

# Experience-based cortical plasticity in object category representation

Marieke van der Linden

DONDERS

series

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**Marieke van der Linden**

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# **Experience-based cortical plasticity in object category representation**

Een wetenschappelijke proeve op het gebied  
van de sociale wetenschappen

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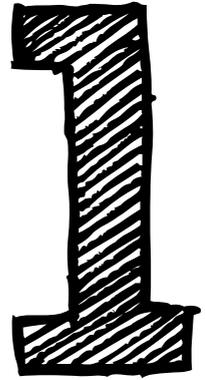




## **Contents**

Chapter 1	
<i>General introduction and outline</i>	9
Chapter 2	
<i>Birds of a feather flock together: Experience-driven formation of visual object categories in human ventral temporal cortex</i>	21
Chapter 3	
<i>Formation of category representations in superior temporal sulcus</i>	43
Chapter 4	
<i>Category training induces crossmodal object representations in the adult human brain</i>	61
Chapter 5	
<i>Task- and experience-dependent cortical selectivity to features informative for categorization</i>	85
Chapter 6	
<i>Summary and discussion</i>	107
Chapter 7	
<i>Nederlandse samenvatting</i>	113
Acknowledgements	122
Biography	123
List of publications	123
Donders Graduate School for Cognitive Neuroscience Series	124





## **General introduction and outline**

**R**ecognizing objects and categorizing them starts already at a very young age and continues throughout adulthood. Experience continuously shapes the borders of existing categories and creates even entirely new categories. As such we can easily assign a novel instance of a known object to its category and at the same time we can discriminate between objects that look similar but are in fact different exemplars of the same category e.g. a pear and an apple. This shows that our visual system is capable of both generalization and discrimination. These are the key points of categorization. Moreover, when more skilled in recognizing fruit, for example because of working in the fruit department of a grocery store, one might even be able to distinguish a Bartlett pear from an Anjou pear (Fig 1.1). This suggests that the neural representation of object categories is plastic, and changes as a result of experience. The research in this thesis was designed to investigate experience-dependent plasticity in the representation of object categories. In the experiments in this thesis subjects were trained to differentiate between categories of computer-generated birds (Chapters 2, 3, and 4) and fish (Chapter 5). These stimuli are very difficult to distinguish without any form of training. We used behavioural measures in combination with a non-invasive brain imaging technique (functional magnetic resonance imaging, see box 1) to get insight on experience-based changes in cortical representations.

### Categorization

Categorization takes place at several levels of abstraction (Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976). The most common and most informative level of categorization is the basic level (e.g. pear), a more general level is the superordinate level (e.g. fruit), and the subordinate level (e.g. Anjou pear) is a more specific level.

Furthermore, conceptual categories (e.g. fruit) might contain things that look quite similar (e.g. orange and grapefruit), but they also often group things that look very different (e.g. a pineapple and a banana). Categories have sharp boundaries between them and members of the same category are largely treated as equivalent even though their appearance varies widely. In contrast, members of a different category (e.g. balls) that share a lot of resemblances with members from another category (e.g. tennis balls and apples) will be treated differently. This means that what belongs to a certain category is not simply defined by visual features alone, it is largely through experience and learning that we know what objects belong to which category. In addition, depending on context, things may be attributable to different categories. For example, an apple may be seen as fruit in the grocery store, but also as a ball-like object by a street juggler, and as belonging to the ingredients for apple-pie by your friend who loves to bake.

This shows that depending on context and experience an object is not always perceived the same



**Figure 1.1**

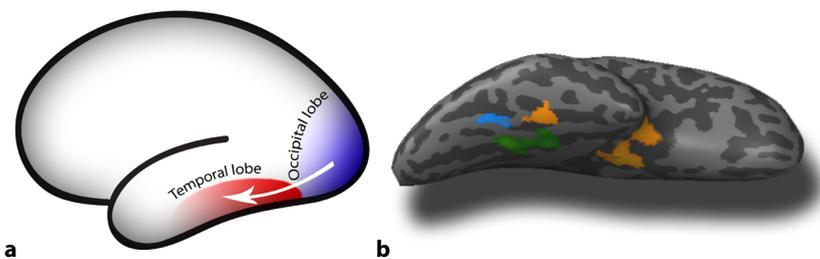
It is easier to discriminate between an apple and a pear as between two types of pears.

way. Whereas the visual percept remains the same, the attributed categories can shift. There is even some evidence that categorization learning influences perception. After categorization training, items learned to be from the same category tended to be rated as being more similar, whereas items from different categories were rated as more distinct (Goldstone, 1998). Clearly a flexible and plastic system is needed for category representations.

### Cortical category-selectivity

Category-selective areas of the human brain exist in the ventral visual pathway (Fig 1.2). This pathway begins in primary visual cortex (V1) and extends from the ventral and lateral surface of the occipital lobe into lateral and inferior areas of temporal lobe, the occipitotemporal cortex (including the fusiform and parahippocampal gyri). Imaging studies have found category-specific activations in occipitotemporal cortex. These category-specific regions can be defined functionally by comparing brain activity of subjects that are viewing images of an object category with brain activity of those same subjects viewing scrambled pictures or objects of another category. Areas in occipitotemporal cortex have been found that respond selectively when subjects view pictures of faces (Haxby, Hoffman, & Gobbini, 2000; Ishai,

Ungerleider, Martin, Schouten, & Haxby, 1999; Kanwisher, McDermott, & Chun, 1997; McCarthy, Puce, Gore, & Allison, 1997), body parts (Downing, Jiang, Shuman, & Kanwisher, 2001), tools (Beauchamp, Lee, Haxby, & Martin, 2002; Chao, Haxby, & Martin, 1999), animals (Chao et al., 1999; Martin, Wiggs, Ungerleider, & Haxby, 1996), chairs (Ishai et al., 1999), houses, and places (Aguirre, Zarahn, & D'Esposito, 1998; Epstein & Kanwisher, 1998; Ishai et al., 1999). It remains unclear what the underlying neuronal architecture of category selectivity is. The organizing principles of the ventral visual pathway are controversial. There are two main and opposing views on its architecture. The first view, proposed by Kanwisher (2000), is that there exist a limited number of modules that are selectively activated by discrete object categories. Most common instances of such modules are the fusiform face area and the parahippocampal place area. The second view (Haxby et al., 2000) proposed that objects are processed according to a map of object features, analogous to those in early visual cortex. Objects that share the same features share the same underlying neuronal architecture. Presently there is no consensus about the functional organization of the ventral visual pathway, however the two views seem to lean more and more towards



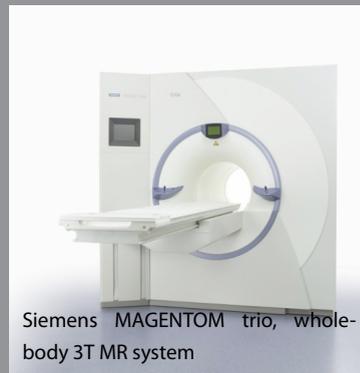
**Figure 1.2**

**(A)** The cortical ventral pathway for visual processing of object categories. **(B)** Example of category selectivity averaged over 24 subjects projected on the ventral view of an inflated right hemisphere. In green viewing houses versus scrambled objects, in yellow viewing faces versus scrambled objects, and in blue viewing fish versus scrambled objects.

### Box 1

#### fMRI

fMRI stands for functional magnetic resonance imaging. It is derived from nuclear magnetic resonance (NMR). Resonance occurs when a nucleus (usually hydrogen) is placed in a magnetic field. The magnetic fields on the hydrogen atoms make them behave like tiny bar magnets. In the absence of other influences, these atomic magnets line up in one of two directions. An MRI machine first creates a magnetic field around the subject, forcing energy changes within the body's own magnetic fields created by the hydrogen (humans consist of approximately 70 % water). The hydrogen atoms are then swept by a radio frequency that causes the nuclei to flip. This causes the radio frequency to be absorbed, which is what is measured. This information is converted into magnetic resonance images. MRI not only allows us to detect different water gradients, but also changes in oxygen concentrations within the body. This is significant in functional MRI. The locus of neural activity related to cognitive processes is detected through a vascular filter. It enables the detection and visualization of local cerebral blood flow increase, which is assumed to be correlated with the activation of nearby neural tissue. Therefore, fMRI is an indirect measure of neural activity. The greatest advantage of fMRI is that it gives a noninvasive view of the inner workings of the human brain. A major advantage of fMRI over other neuroimaging techniques is the high spatial resolution in identifying cortical areas active during a particular cognitive process. The spatial resolution can be in the order of 2 mm. Thus, fMRI allows accurate inferences about where in the brain a particular cognitive process is instantiated. As such, fMRI provides an excellent tool to study dynamic changes in visual processing as a function of experience. In the studies in this thesis we measured signal from tiny sections of the brain as small as 3 mm<sup>3</sup>. We used a 3 Tesla scanner from Siemens (see picture). The subjects lay supine in the scanner and images of birds or fish were projected on a screen that subjects saw via a mirror attached to the head coil. If subjects needed to hear sounds they were provided with a specially padded and MR-compatible headphone. Responses -if necessary- were made by the subjects pressing the buttons of a non ferromagnetic MR-compatible response box.



each other (Bell, Hadj-Bouziane, Frihauf, Tootell, & Ungerleider, 2009; Op de Beeck, Haushofer, & Kanwisher, 2008; Tootell et al., 2008).

### Expertise

Can cortical selectivity to object categories arise as a function of experience? Evidence for this might be found by studying people that are specialized in recognizing objects from a particular category. These so-called experts have the ability to distinguish quickly between similar-looking members of a category based on very subtle differences in appearance. For these experts the subordinate level functions as the basic level for the domain of expertise (Johnson & Mervis, 1997; Tanaka & Taylor, 1991). So, they are just as fast in recognizing a dog as a “Beagle” (subordinate level) as they are in recognizing it to be a dog (basic level). This shows that extensive experience with an object category leads to improved performance. This behavioural improvement is likely to have a neural basis, suggesting plasticity in brain regions subserving object category representations.

Recently, expert object recognition became a research topic in the field of cognitive neuroimaging. By studying perceptual expertise with neuroimaging methods insight is gained on the effects of experience on the cortical representations of objects. In an fMRI experiment (Gauthier, Skudlarski, Gore, & Anderson, 2000) bird and car experts were scanned while they performed a one-back location or identity task. An expertise effect (larger activation for the expert object category than for the non-expert object category) was found in the right middle fusiform gyrus and in the right occipital lobe. Also, a strong correlation between the experts’ performance on a 1-back task outside the scanner and activation of the right fusiform for birds and cars was present. The findings from this study were confirmed in another study (Xu, 2005). However, in an fMRI study by Grill-Spector et al. (2004) no correlation between response of the right fusiform gyrus and success in car identification or detection was found. In yet another study (Rhodes, Byatt, Michie,

& Puce, 2004), Lepidoptera (butterflies and moths) experts showed activation in the right middle fusiform gyrus when viewing Lepidoptera compared with objects of nonexpertise. For novices there was no difference in activation between Lepidoptera and other objects. These studies showed that extensive perceptual experience, or expertise, with a particular category of objects enhances the expert’s ability to distinguish among the different exemplars of the category. Allowing them to distinguish subtle differences between its members and that this improvement seems reflected by cortical changes in the representation of the objects of expertise.

### Plasticity in object representation in monkey cortex

Based on the studies with human experts we assume that the neuroarchitecture underlying category representations shows plasticity as a result of learning and experience. The first evidence on plasticity of object representations came from monkey research. In one of the first studies, monkeys learned to classify and recognize objects while electrophysiological recordings were made from the inferior temporal cortex (Logothetis, Pauls, & Poggio, 1995). It was found that inferior temporal neurons responded selectively to objects that the monkeys had learned to recognize and classify, showing that these neurons displayed experience-dependent plasticity. In another study, Vogels (1999) recorded from single cells in temporal and perirhinal cortex in monkeys that were trained to categorize stimuli as being tree or non-tree. He found that many neurons were selectively activated by the trained exemplars but not by distracter objects. Further evidence for clustering of perirhinal neurons with similar response properties was found by recording from the anterior medial temporal lobe of monkeys (Erickson, Jagadeesh, & Desimone, 2000). The monkeys were presented with novel stimuli and stimuli they had been familiarized with on the previous day. Responses were more similar for nearby neuron pairs than for distant neuron pairs, both for novel and familiar stimuli. The signal correlation for nearby neurons was significantly



**Figure 1.3**

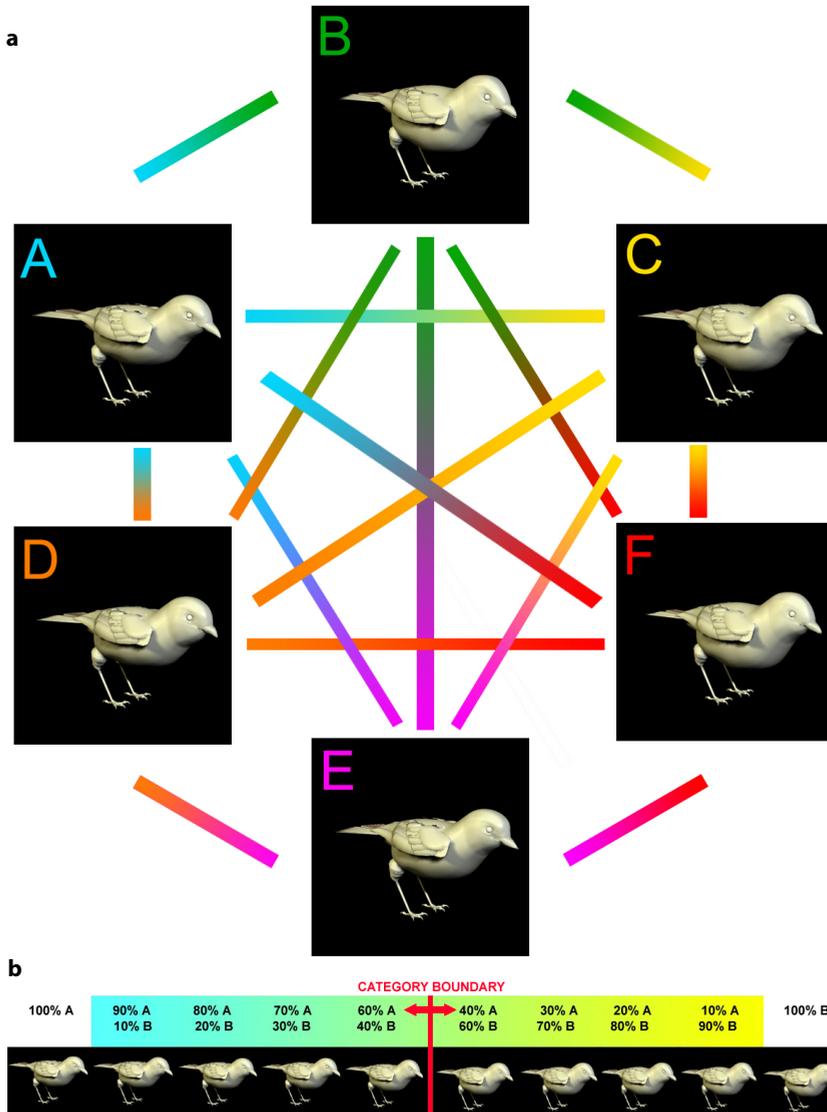
The Greebles form a category of computer-generated novel objects. The two Greebles in the top row are from two different genders and are fairly easy to discriminate. In the bottom row are individuals within the same gender. Adapted from: <http://www.psy.vanderbilt.edu/faculty/gauthier/FoG/Greebles.html>

higher for familiar stimuli than for novel stimuli. The authors concluded that experience with visual stimuli caused nearby neurons to develop similar preferences, suggesting that novel object categories were created after just one day of visual experience with these stimuli. In another study, plasticity was found to follow training on grouping fish or face stimuli in categories based on features that were informative for categorization. After training anterior inferior temporal neurons showed enhanced selectivity for these diagnostic features relative to other stimulus features that were not informative of category membership (Sigala, Gabbiani, & Logothetis, 2002; Sigala & Logothetis, 2002).

These studies indicated that inferior temporal cortex is involved in categorization. Additionally, other studies (Freedman, Riesenhuber, Poggio, & Miller, 2001, 2002) showed that in monkeys the lat-

eral prefrontal cortex might also play an important role. Recordings were made from monkeys' prefrontal cortex while they performed a match-to-category task on a previously trained continuous set of cats and dogs that were parametrically morphed. Along this morph line, one end of the continuum was 100% dog and 0% cat, up to 60% dog and 40% cat then the continuum switched to cat 60% cat 40% dog etc. Monkeys were trained to differentiate between the cats and the dogs. Lateral prefrontal neurons in monkeys were found to encode cat and dog categories after training. Neuronal activity in the lateral prefrontal cortex reflected the category of visual stimuli and changed with learning when a monkey was retrained to assign the same stimuli to new categories. The same study was repeated while recording from monkeys inferior temporal cortex (Freedman, Riesenhuber, Poggio, & Miller, 2003). It was found that neurons in inferior temporal and prefrontal cortex shared many properties but also exhibited differences. Both conveyed information about stimulus category. Inferior temporal neurons often respected the category boundary, but they also distinguished between individual stimuli within a category. Inferior temporal neurons seemed to combine category information with information about physical appearance whereas prefrontal neurons were communicating category membership per se and not distinguishing between the members within a category. Prefrontal cortex showed a greater tendency to encode information in terms of its behavioural relevance, such as stimulus category and match versus non-match.

It seems likely that to some extent these findings can be generalized to humans. There is evidence that humans and macaques share similar brain architectures for visual object processing (Tsao, Freiwald, Knutsen, Mandeville, & Tootell, 2003). However, monkey research alone cannot explain how the human brain learns and represents object categories.



**Figure 1.4**

(A) Pictures of non-existing but plausible bird shapes were constructed in a 3D model manipulation program. From a base-bird we derived six prototype birds (A, B, C, D, E, F) that differed in trunk, tail, beak, head shape, cheeks, brow, and eye position. (B) Exemplars were created by systematically morphing each of the six prototype birds with all other birds. Shown is an example of morphing bird type A and bird type B at morph ratios of 90:10, 80:20, 70:30, and 60:40. The category boundary was set at 50:50.

### Training-induced changes in human cortical category representations

The best way to investigate the plasticity of object category representations is to test this in humans. The studies mentioned in the previous paragraphs tested subjects that became experts in the object category of their interest through many years of experience. There are also studies that have created experts for newly learned object categories in an experimental setting. Gauthier and Tarr (1997) created experts for the subordinate-level recognition of a homogeneous set of stimuli that had a face-like arrangement of parts, the so-called 'Greebles' (Fig. 1.3). After extensive experience with these Greebles, subjects exhibited not only a higher accuracy and shorter response times in categorization, but also sensitivity to configural information with unfamiliar Greebles. Furthermore, it seemed that expertise transferred to the learning of novel Greebles. Even 8 to 13 weeks after training had ended, experts were faster and reached higher accuracy in the learning of new Greebles than novices did (Gauthier, Williams, Tarr, & Tanaka, 1998). This effect was obtained only for novel Greebles sharing the same similarities as those that were previously studied. This pattern of results is similar to the inversion effect (i.e., it is harder to recognize an object that is upside down than upright) found in dog experts, which is largest for their dog breed of expertise (e.g. Irish setter), than for a dog breed in which they are not expert (Diamond & Carey, 1986). These findings show that expertise does not necessarily generalize from one subcategory to the other.

A brain imaging experiment with the same Greebles (Gauthier, Tarr, Anderson, Skudlarski, & Gore, 1999a) showed a training effect in the right middle fusiform gyrus. In this region, an increase of activity was observed over training-sessions. Furthermore, Greeble-related activity in the fusiform and lateral occipital gyri in the left and right hemisphere was larger for experts than for novices. This shows that even a relatively short amount of visual experience with an object category can change responsiveness in human occipitotemporal cortex. A similar con-

clusion was drawn by Op de Beeck et al. (2006). Discrimination training with nonsense objects led to increased responses and changes in their distribution in occipitotemporal cortex. This also fits with the findings of another study (Moore, Cohen, & Ranganath, 2006) that also reported increased activations to trained as compared to not trained nonsense stimuli.

The studies by Gauthier et al. (1999), Op de Beeck et al. (2006), and Moore et al. (2006) used nonnatural nonsense objects as experimental stimuli. In the studies reported in this thesis natural objects (birds and fish) were used. This difference is important to note because of previous reports that showed that experience-related changes in brain activity for nonsense objects were restricted to posterior occipital brain regions (e.g., van Turennout, Ellmore, & Martin, 2000). It seems likely that the nature of the stimuli is important for determining where in the brain changes in the representation will occur as a result of training.

Furthermore, in these previously mentioned studies (Gauthier, Tarr, Anderson, Skudlarski, & Gore, 1999b; Moore et al., 2006; Op de Beeck et al., 2006) subjects did not learn a category boundary. Subjects learned to discriminate between objects within a category. The tasks involved perceptual discrimination, not leading to the formation of new object categories. In contrast, in our studies, training induced the formation of a category boundary between similar looking birds. This is an essential difference in the nature of our training paradigm. To investigate specifically category formation we created a stimulus set (Fig. 1.4) that was similar in design to that of Freedman et al.'s cats and dogs. This stimulus set allowed us to compare birds on different sides of the category boundary while controlling for their physical differences. This stimulus set was used in three out of four studies. In the fourth study a set of fish stimuli was used that was created in a similar fashion. These fish had four visual features that were distinct and easily separable whereas the visual features of the birds were more inseparable.

## Outline of this thesis

The research described in this thesis was designed to gain further insight into the neural mechanisms that underlie the representation of newly learned categories. This research will bridge the gap between monkey electrophysiological recordings of category-selective responses in neurons and experience-dependent changes in brain activity that have been observed in fMRI studies with humans. The studies mentioned in the previous paragraphs have compared trained objects with not-trained objects. Therefore, the neural changes that were observed could also be attributed to mere visual exposure. In Chapter 2 we investigated the neural mechanisms of object category formation in human occipitotemporal cortex while controlling for visual exposure. We compared neural changes mediating the formation of behaviourally relevant object categories with neural changes following visual exposure to objects in the absence of category formation. In order to prevent category formation during visual exposure, subjects were provided with random feedback during training. This manipulation allowed us to investigate neural changes specifically related to the formation of an object category compared with changes occurring as a result of repeated visual exposure. However, category-membership is not only perception-based. Through experience we learn what objects belong to which category. In everyday life we easily group objects that look very differently into the same category (such as a pineapple and an apple). And at the same time we are capable of distinguishing between objects that look similar but belong to different categories (like a mobile phone and a remote control). In Chapter 2 we showed that learning to discriminate between two perceptually different categories of birds was linked to neuronal changes in the occipitotemporal cortex. In this study and the ones described in the previous paragraphs, category-membership was perception-based, i.e. perceptually similar objects belonged to the same category. Therefore, it remained unclear whether these experience-dependent changes could be explained by perceptual categorization alone or

whether they also reflect the formation of conceptual object-categories. In Chapter 3 we investigated with the use of an fMRI adaptation paradigm how cortical representations in the adult human brain are shaped as a result of learning to group perceptually dissimilar objects into the same category. We used specifically fMRI adaptation because it has the potential to probe the sensitivity of neuronal populations. The nature of neural stimulus representations can be revealed when hemodynamic responses are selectively affected by repeating or changing particular stimulus attributes. This makes the adaptation technique a useful tool to make inferences about neural sensitivity in specific cortical regions (Cohen Kadosh, Cohen Kadosh, Kaas, Henik, & Goebel, 2007; Grill-Spector et al., 1999; Pourtois, Schwartz, Seghier, Lazeyras, & Vuilleumier, 2005). We compared birds on the same side of the category boundary (belonging to the same bird type) with birds with a similar physical difference but on opposite sides of the category boundary (belonging to different bird types and belonging to either the same bird category or a different bird category). We were interested in finding training-induced category representations, that were activated in the absence of a categorization task and that were independent of the shape of the birds (i.e. conceptual instead of perceptual).

In Chapter 3 we found that the superior temporal sulcus played a role in the association of perceptually dissimilar object that were conceptually the same. Thus far, the superior temporal sulcus had been found to be involved in cross-modal (audio-visual) processing. More specifically, a recent study showed that familiar cross-modal objects activated the superior temporal sulcus, but not novel artificial cross-modal objects, indicating that cross-modal integration is influenced by familiarity (Hein et al., 2007). Therefore, it seems likely that cross-modal representations, such as found in the superior temporal sulcus, can be shaped as a result of experience with cross-modal objects. In Chapter 4 we investigated the interplay of sound and visual appearance in the formation of cross-modal object categories as

a result of learning which bird sound and shapes define a category. In this study we used the same paradigm that we had successfully applied to visual object category learning in human subjects in the previous studies (Chapter 2 and 3). Subjects learned new cross-modal categories of artificial birds. The novelty in the study from Chapter 4 is that we not only morphed the birds in the visual modality but also in the auditory modality. The boundary between the categories was expressed by information from both auditory and visual modalities. In this study the categories were again perceptual-based: Birds that have the same shape and sound belong in the same category.

In the previous studies we found that neuronal populations became selectively responsive to the trained objects. But what is it exactly about those objects that neurons become selectively responsive to? It seems likely that the task at hand, in this case categorization, determines what parts of the objects induce neural selectivity. We proposed that neurons became selectively responsive to those object features that were informative for categorization. However, the features in our and others' previous studies were not quantified. Finally, in Chapter 5 we tested the hypothesis that the human brain becomes selectively responsive to those object features that are crucial for categorization. We used a training paradigm, similar to that of our previous studies, in which subjects learned to discriminate two categories of fish. Fish from these categories had four distinctive features, but only two of the features were informative for category membership and two of the features were uninformative. In this study we also used the fMRI adaptation paradigm. We examined training- and task-dependent cortical responses to features that were informative for categorization. Finally in Chapter 6 the findings from the research described in this thesis will be summarized and related to each other and to (more recent) research by others.

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## **Birds of a feather flock together: Experience-driven formation of visual object categories in human ventral temporal cortex**

This chapter is based on:  
van der Linden, M., Murre, J.M.J., & van Turennout, M. (2008). Birds of a feather flock together: Experience-driven formation of visual object categories in the human brain. *PLoS ONE*, 3(12), e3995.

**T**he present functional magnetic resonance imaging study provides direct evidence on visual object-category formation in the human brain. Although brain imaging has demonstrated object-category specific representations in the occipitotemporal cortex, the crucial question of how the brain acquires this knowledge has remained unresolved. We designed a stimulus set consisting of six highly similar bird types that can hardly be distinguished without training. All bird types were morphed with one another to create different exemplars of each category. After visual training, fMRI showed that responses in the right fusiform gyrus were larger for bird types for which a discrete category-boundary was established as compared with not-trained bird types. Importantly, compared with not-trained bird types, right fusiform responses were smaller for visually similar birds to which subjects were exposed during training but for which no category-boundary was learned. These data provide evidence for experience-induced shaping of occipitotemporal responses that are involved in category learning in the human brain.

### Introduction

A crucial property of the human object-recognition system is its capacity to group different-looking objects into the same category, and to assign similar-looking objects to different categories. Pineapples and berries look very different, but they are both members of the category 'fruits'. In contrast, berries and beads can look similar, but belong to different categories. Someone more skilled in recognizing fruits might be able to discriminate between similar sub-exemplars of berries (e.g., salmonberries and raspberries), suggesting that the neural representation of object categories is plastic and changes as a result of experience. The present study investigates the neural mechanisms mediating experience-induced formation of visual object categories in the human brain.

There are strong indications both from neuropsychological and functional brain imaging experiments that the ventral temporal cortex is involved in the representation of category-specific information (Damasio, Tranel, Grabowski, Adolphs, & Damasio, 2004; Haxby et al., 2001; Kanwisher, McDermott, & Chun, 1997; Martin, Wiggs, Ungerleider, & Haxby, 1996). Differential neural responses within occipitotemporal cortex have been demonstrated for a wide range of object categories (Aguirre, Zarahn, & D'Esposito, 1998;

Downing, Jiang, Shuman, & Kanwisher, 2001; Epstein & Kanwisher, 1998; Ishai, Ungerleider, Martin, Schouten, & Haxby, 1999). However, the neural mechanisms mediating the formation of category-specific representations in human occipitotemporal cortex are still largely unknown. Animal studies have revealed that learning and experience can shape neural response properties of cells in inferior temporal cortex, possibly resulting in category-specific representations. For example, after monkeys were trained to categorize visual stimuli, inferior temporal neurons responded selectively to stimuli belonging to the trained category (Freedman, Riesenhuber, Poggio, & Miller, 2003). Furthermore, other electrophysiological recordings from monkey cortex revealed increased selectivity in responses from inferior temporal neurons for visual stimulus features diagnostic for trained object categories (Sigala & Logothetis, 2002), as well as for combinations of features in learned objects (Baker, Behrmann, & Olson, 2002). Functional imaging of the human brain has shown that visual as well as functional experience with novel object categories alters neural responses in occipitotemporal cortex (Gauthier, Tarr, Anderson, Skudlarski, & Gore, 1999; Moore, Cohen, & Ranganath, 2006; Op de Beeck, Baker, DiCarlo, & Kanwisher, 2006; Weisberg, van Turennout, & Martin, 2007). Recently,



## Object categories in ventral temporal cortex

2

We designed a stimulus set consisting of six highly similar bird shapes that are difficult to distinguish without training (Figure 2.1). To directly test for neural correlates of category formation, a discrete category-boundary between similar-looking birds was established by training (Figure 2.2*a*). In addition to this categorization training, subjects performed a control task in which they were visually exposed to two other bird types, but to hinder category learning, the feedback they received was random (Herzog & Fahle, 1997). Subjects were not informed that the feedback could be correct or incorrect. This manipulation allowed us to investigate neural changes specifically related to the formation of an object category compared with changes occurring as a result of repeated visual exposure. To investigate neural correlates of object-category formation, pre- and post-training fMRI time-series were obtained while the participants viewed exemplars of the different bird types (Figure 2.2*b*). We predicted that if category formation is mediated by increased neuronal responsiveness in occipitotemporal cortex, this increase should occur only for those birds for which a discrete category-boundary has been established, compared with visually similar birds for which no such boundary has been learned. Critically, this effect should be distinct from general training effects, such as increased familiarity and visual object-learning.

### Materials and Methods

#### Subjects

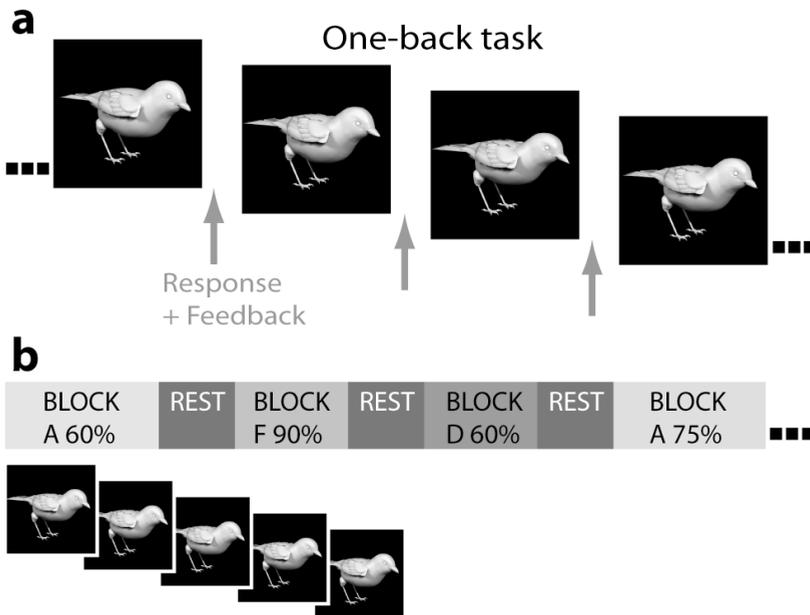
Twelve neurologically healthy right-handed participants, not bird experts (ten females, mean age 20.7 years, range 18-25) with no neurological history participated in the experiment. All subjects had normal or corrected-to-normal vision. Subjects were paid for their participation. All subjects gave written informed consent. The study was approved by the local ethics committee (CMO region Arnhem-Nijmegen, the Netherlands).

#### Stimuli

The stimuli consisted of pictures of birds that were constructed in a 3D model manipulation program (Poser 4 by Curious Labs, Santa Cruz, CA). First, six prototype birds were constructed from a base-bird (Songbird Remix by Daz3d, Draper, UT). Parts of the bird that were manipulated included its back, belly, tail, beak, head shape, cheeks, brow, and eye position. Next, each of the six birds was morphed with all other birds (at ratios of 95:5, 90:10, 80:20, 75:25, 70:30, 65:35, 60:40, and 55:45) analogous to the procedure used by Freedman and colleagues to investigate category formation in the monkey brain (Freedman, Riesenhuber, Poggio, & Miller, 2001). The category boundary was set at 50%. As a result, stimuli that were near opposite sides of a category boundary, though visually similar, belonged to different categories. Morphing happened smoothly between corresponding points on the birds. Each bird was colourless, rendered under the same lighting and camera settings, and exported as an image. Images had identical colour, shading and scale. In addition, using the same software, a set of control images of six different faces was constructed. The images measured 300 by 300 pixels in the training sessions and were slightly reduced in size (250 by 250 pixels) in the scanning sessions.

#### Procedure and experimental paradigm

The six bird types were divided into pairs, and each pair was assigned to one of three conditions: 1) category training, where subjects received correct feedback to their responses, 2) visual exposure, where the amount of exposure to the birds was equal to the amount of exposure to the category trained birds, but category learning was hindered by random feedback, 3) no training. Assignment of bird types to the three conditions was counterbalanced over subjects in such a way that each bird type appeared equally often in each of the training conditions. The experiment was constructed using dedicated experimental software (Presentation by Neurobehavioral Systems, Albany, CA) and was run



**Figure 2.2**

**Training and fMRI paradigms. (A)** During the training sessions participants were presented with a series of bird exemplars. They performed a 1-back task in which they indicated whether two consecutive birds were the same type or not. In the category-training condition implicit category learning was established by providing corrective feedback after each trial. In the visual-exposure condition random feedback was given after each trial, hindering category learning while keeping visual exposure to the birds equal to the category-training condition. **(B)** In the pre and post-training fMRI scanning sessions the bird types were presented in blocks of five exemplars at morph ratios of 60:40, 75:25, and 90:10. Each image was presented for 3 seconds with a mean inter-stimulus-interval of 1 s. Experimental blocks alternated with rest periods of 10 s. Subjects were instructed to view the birds attentively.

on a Pentium 4 with a 2.80 GHz processor and 2 GB of RAM.

### Training

Training included three sessions, each of which lasted approximately two hours, on three consecutive days. During a training session, subjects sat comfortably in a soundproof cabin in front of a 19" computer screen. They performed a 1-back task on a series of bird images, in which they indicated with the index and middle finger of their right hand whether

two consecutive birds were the same bird type or not. Subjects received feedback to their responses consisting of a printed text centred on the screen in coloured Arial font in size 16 (green: "right", red: "wrong", and yellow: "too late"). Bird exemplars were morphed at 55, 65, 70, 80, and 95% with all other bird types (e.g. bird type A at 95% morphed with B, C, D, E, and F at 5%). In total there were 25 exemplars (each bird type was morphed at five morph levels with the other five bird types) for each of the four bird types presented during training.

## Object categories in ventral temporal cortex

Each exemplar was presented 30 times per training session. The average morph distance between birds was 58,67%. The proportion of same and different responses was fifty-fifty. In each trial, stimuli were presented for 1000 ms after which a response could be given during 2250 ms. Feedback was presented for 250 ms. Stimuli onset asynchrony was 4000 ms. A training session consisted of 10 blocks of 150 trials. In each block, 30 trials of category training (correct feedback) were alternated with 30 trials of visual exposure (random feedback). Subjects were not informed on this alternation of correct and random feedback conditions. Each block of 150 trials was followed by a small self-paced pause after which a subject could continue the experiment by pressing a button.

### **fMRI scanning**

Subjects participated in an fMRI scanning session one day prior to training, and in an identical fMRI scanning session one day after training. During scanning, bird exemplars from each of the three conditions (category-training, visual exposure, and no training) were presented and subjects were instructed to view the birds attentively.

Bird exemplars were different from the exemplars encountered during training and included morphs at 60, 75, and 90%. Birds were presented in blocks. Each block contained 5 images of one bird type at a certain morph level. Images within one block were morphed with different bird types so that they were not identical to each other. For example, a block could consist of five images of 60% of bird-type A morphed with 40% of bird type B, C, D, E, or F. Each image was presented for 3 seconds with a mean inter-stimulus-interval of 1 s (varying between 600 and 1400 ms in steps of 200 ms between). Experimental blocks alternated with rest periods of 10 s for sampling the baseline. Experimental blocks were repeated six times, resulting in 108 blocks (6 bird types \* 3 morph levels \* 6 repetitions). In addition, six blocks were included that contained five images of artificial faces. Blocks were presented in pseudorandom order. Total scan time was 54.7 minutes.

Participants read the instructions for the scan session from a piece of paper before going into the scanner. They were instructed that they were going to watch pictures of objects presented in series of five and that these were followed by a few seconds of blank screen. They should watch these pictures carefully. To keep the subjects alert, we included catch trials. After each block a catch trial could occur. The chance of such an occurrence was on average, one out of six blocks. Subjects were instructed that once in a while, after the five pictures in the block were shown, an additional picture could appear after a cue. This picture was either an exemplar of the same bird type, but at a different morph level or an exemplar of a different bird type at the same or a different morph level as the bird exemplars in the previous block. They were instructed to judge whether this picture was the same bird type as the birds presented before the cue. The subjects indicated with a button-press on an MR-compatible response box (Lumitouch by Photon Control, Burnaby, Canada) whether this image was the same as the previously seen images (right index finger) or not (right middle finger). Subjects' heads were fixated and they were shielded from the scanner noise with earplugs. A beamer projected mirror-reversed stimuli on a screen at the end of the bore, which the subject was able to see through a mirror attached to the head coil.

### **Imaging parameters**

For each subject, 1575 whole-brain images (echo-planar imaging, 34 slices, 3 mm thick with 10% gap, repetition time = 2180 ms, voxel size = 3x3x3 mm, echo time = 30, flip angle = 70°, field of view = 19.2 cm, matrix size = 64x64) were acquired on a 3T whole body MR scanner (Magnetom TRIO by Siemens Medical Systems, Erlangen, Germany). In addition, a high resolution structural T1-weighted 3D magnetization prepared rapid acquisition gradient echo sequence image was obtained after the functional scan (192 slices, voxel size = 1x1x1 mm).

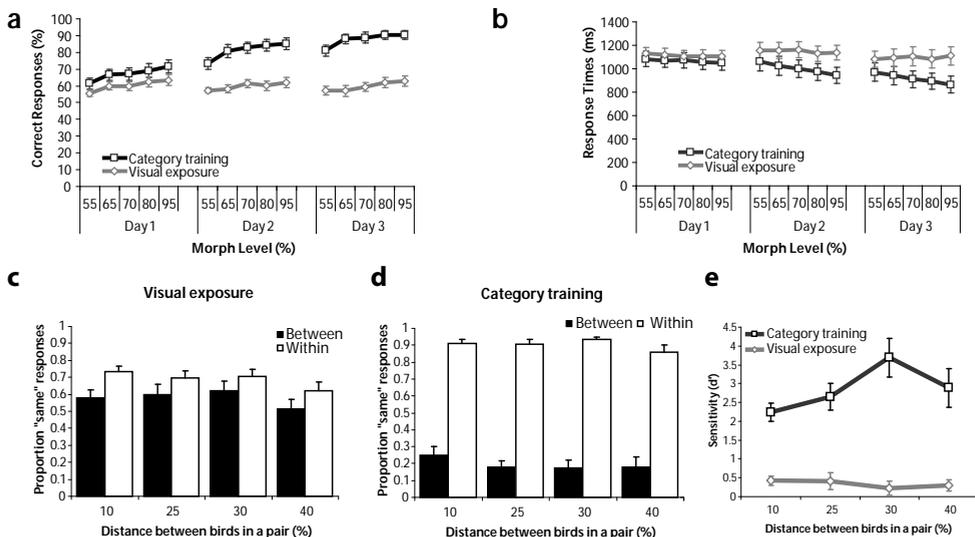
### Training data analysis

Response times for the correct trials and the percentage of correct trials were computed for each subject. These dependent variables were submitted to a training condition  $\times$  morph level  $\times$  session multivariate analysis of variance (MANOVA) with repeated measures. Training condition consisted of two levels (visual exposure and category training), morph level consisted of five levels (55, 65, 70, 80 and 95%), and session consisted of three levels (first, second, and third training session). To investigate the differentiation between training conditions over time, additional 2 (training condition)  $\times$  5 (morph level) MANOVA's were performed for each of the training days. All significant interactions were explored with appropriate F-tests.

The presence of a category boundary was investigated by comparing the proportion of 'same' responses for bird pairs with an equal morph distance for cases in which the birds were from the same or from a different category. This was done for responses in the final training session, separately for the category training and visual exposure condition. Analyses of these data comprised a 2 (within or between category)  $\times$  4 (10, 25, 30, 40 % distance) MANOVA for both the category training and visual exposure condition.

### fMR imaging data analysis

Imaging data analysis was done using BrainVoyager QX (by Brain Innovation, Maastricht, The Netherlands). The first two volumes were discarded to



**Figure 2.3**

**Training results.** (A) Mean percentage of correct responses and (B) mean response latencies to the 1-back task, as a function of morph level, plotted for each of the three training days. (C, D) Proportion of "same" responses (see methods) as a function of physical distance between birds in a pair, separately for bird pairs that belonged to the same category (within) and bird pairs that belonged to different categories (between). The left histogram (C) presents the results for the category-training condition, the histogram on the right (D) the visual-exposure condition. (E) Mean sensitivity ( $d'$ ) for the category-training and visual-exposure 1-back tasks as a function of the physical distance between two birds in a pair. Error bars represent standard error of the mean.

## Object categories in ventral temporal cortex

allow for T1 signal equilibrium. The following pre-processing steps were performed: slice scan time correction (using sinc interpolation), linear trend removal, temporal high-pass filtering to remove low-frequency non-linear drifts of 3 or fewer cycles per time course, and 3D motion correction to detect and correct for small head movements by spatial alignment of all volumes to the first volume by rigid body transformations. Estimated translation and rotation parameters were inspected and never exceeded 3 mm. Co-registration of functional and 3D structural measurements was computed by relating functional images to the structural scan, which yielded a 4D functional data set. Structural 3D and functional 4D data sets were transformed into Talairach space (Talairach & Tournoux, 1988).

Regressors of interest were modelled using a gamma function (tau of 2.5 s and a delta of 1.5) convolved with the blocks of experimental conditions (Boynton, Engel, Glover, & Heeger, 1996) and multiple regression was performed using the general linear model (GLM). In order to correct for multiple comparisons, the false discovery rate (FDR) controlling procedure was applied on the resulting  $p$  values for all voxels. The value of  $q$  specifying the maximum FDR tolerated on average was set to .05. With this value, a single-voxel threshold is chosen by the FDR procedure which ensures that from all voxels shown as active, only 5% or less are false-positives (Benjamini & Hochberg, 1995; Genovese, Lazar, & Nichols, 2002). To further eliminate false-positives in the whole brain analysis, analyses were constrained to only those cortical areas that were responsive to viewing objects as compared with rest. To this end a conjunction analysis with a standard “minimal  $t$ -statistic” approach (Nichols, Brett, Andersson, Wager, & Poline, 2005) was used, which is equivalent to a logical AND of the contrasts at the voxel level. For general training effects we used the contrasts: (Category training + Visual exposure < No training)  $\cap$  (All objects > Rest) to detect training-related decreases in activity and (Category training + Visual exposure > No training)  $\cap$  (All objects > Rest) to detect training-related increases in activity.

For the specific effects of category training we used the contrast: (Category training > Visual exposure)  $\cap$  (All objects > Rest) to detect increases in activity and (Category training < Visual exposure)  $\cap$  (All objects > Rest) to detect decreased activity. To test for a main effect of session we contrasted (All objects pre-training) > (All objects post-training). All contrasts were calculated on data that were normalized using a  $z$ -transformation.

To further investigate responses within voxel populations (> 50 mm<sup>3</sup>) that showed a significant effect of training, voxel-averaged beta-weights (i.e. regression coefficients) were extracted from these populations for each condition and morph level, separately for the pre- and post-training sessions and averaged over subjects. Random effects GLMs were computed using these regionally-averaged beta-weights. Specific effects of interest were tested with linear contrasts. All reported  $t$ -tests are two-tailed. The ROI time-courses were standardized, so that beta weights reflected the BOLD response amplitude of one condition relative to the variability of the signal.

To test for modulation of morph level we extracted the event-related responses to all bird conditions (category training, no training, and visual exposure) at all morph levels (10, 25, 40, 60, 75, and 90 %) from the region in the right middle fusiform gyrus that showed a category training effect. As an example, for the 10 % morph levels of category trained birds (if a subject had bird types A and B assigned to category training) we used responses to the following birds in the calculation: 90A:10B, 90C:10B, 90D:10B, 90E:10B, 90F:10B, 90B:10A, 90C:10A, 90D:10A, 90E:10A, 90F:10A. Each of these bird exemplars occurred six times in the experiment. In total there were 60 trials per morph level per condition. We then used ANOVA's to compute the linear relation between the morph levels and the brain response (beta weights).

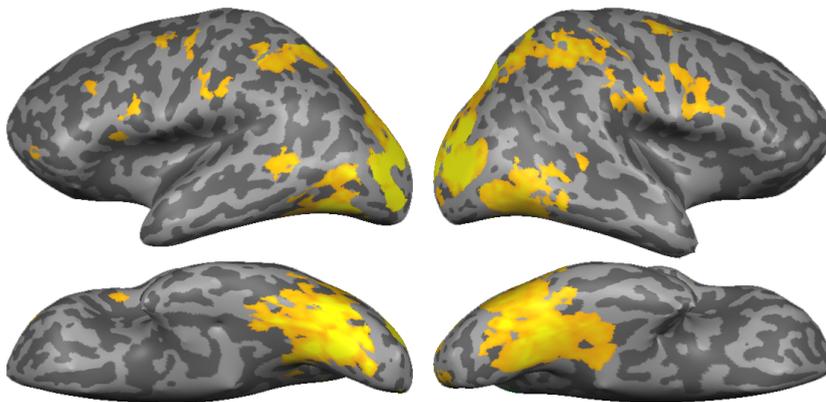
## Results

### Training results

Behavioural training results showed that participants became proficient in categorizing the bird exemplars, but only after receiving correct feedback (Figure 2.3, *a* and *b*). In the first session, percentage of correct responses was equally low in both conditions [ $F(1,11) = 3.76, p = \text{n.s.}$ ]. The percentage of correct responses increased as training progressed over time, but only in the category-training condition [ $F(2,10) = 29.27, p < .001$ , and not in the visual exposure condition [ $F(2,10) = .03, p = \text{n.s.}$ ]. A similar pattern of results was found for response times. In the first session, no differences in response times were observed. Training-related decreases in response times were observed in the category-training condition [ $F(2,10) = 9.04, p < .01$ ], whereas in the visual training condition response times remained stable over time [ $F(2,10) = .52, p = \text{n.s.}$ ]. Significant differences in reaction times and accuracy between category-training and visual exposure

conditions were obtained in session 2 (accuracy: [ $F(1,11) = 26.40, p < .001$ ] reaction times: [ $F(1,11) = 8.60, p < .05$ ]) and session 3 (accuracy: [ $F(1,11) = 40.45, p < .001$ ]; reaction times: [ $F(1,11) = 5.80, p < .05$ ]). By the end of training subjects had developed categorical perception for bird types trained with correct feedback. In the visual-exposure condition performance hovered between 55% and 65%. In the category-training condition, performance improved to around 90% correct for morphs close to the prototype. Even for morph ratios near the category boundary (55:45 morphs), performance exceeded 80% at the end of training. Thus, even though a 55:45 exemplar of, say, bird type A had only 55% of A properties (and 45% of either B, C, D, E, or F properties) it was nonetheless categorized as type A 80% of the time.

In the third training session, a significant effect of morph level [ $F(4,8) = 21.40, p < .001$ ] was obtained. Responses were more accurate for bird exemplars with higher morph levels (close to



■ Pre-training (all objects) > Post-training (all objects)  
 $p < 0.01$  (FDR corr)

**Figure 2.4**

**Main effect of session.** Group-averaged activation maps of the between-session effect overlaid on lateral (top) and ventral (bottom) views of Talairach-normalized inflated hemispheres. In grey with a black outline, regions showing less activity for all objects after training as compared with activity to the same objects before training at  $p < 0.01$  (False Discovery Rate corrected).

## Object categories in ventral temporal cortex

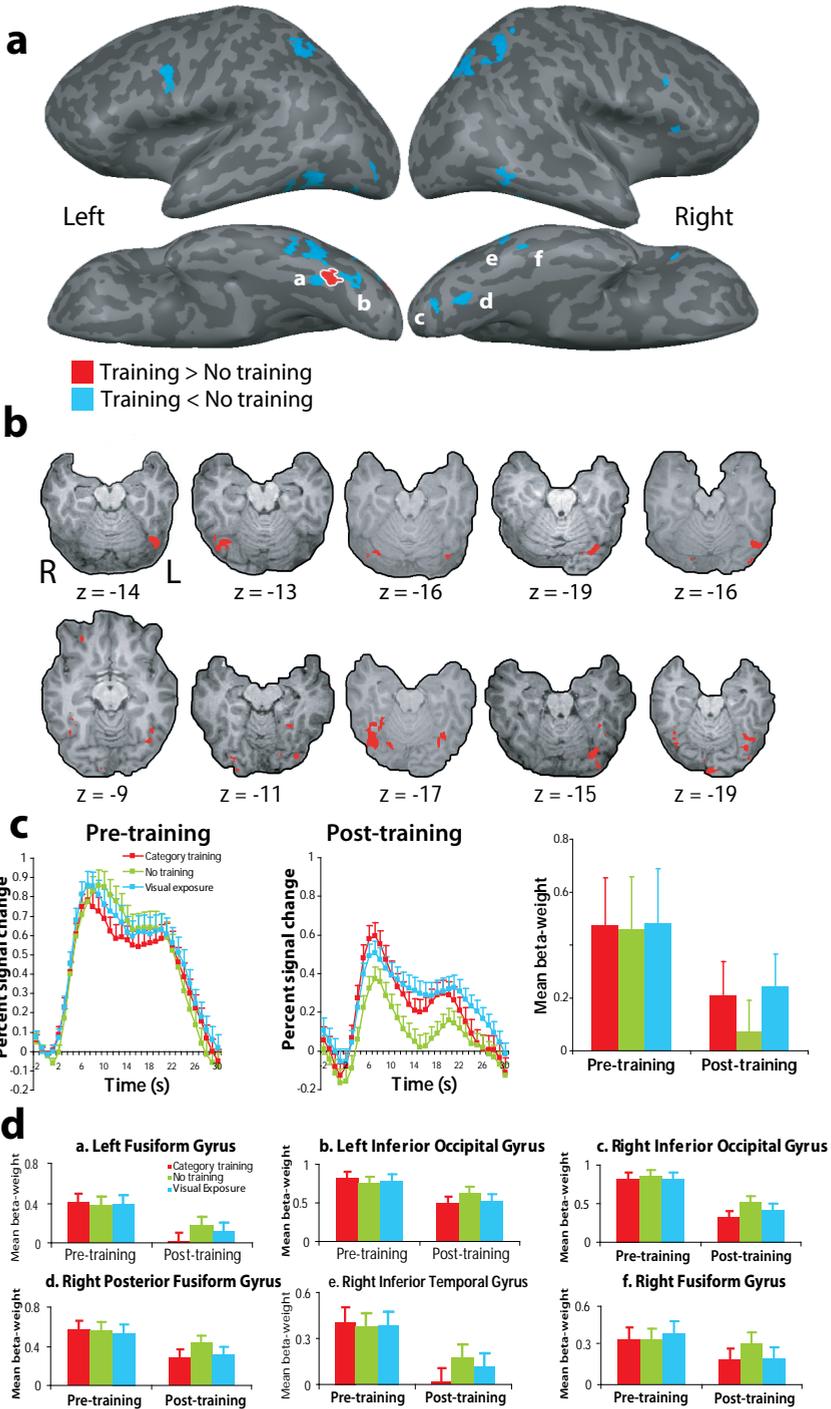
the prototype) than for bird exemplars with lower morph levels (close to the category boundary). This effect of morph level was larger in the category training condition than in the visual exposure condition, as revealed by a condition  $\times$  morph level interaction [ $F(4,8) = 6.02, p < .05$ ]. In addition, responses were faster to bird exemplars closer to the prototype than to bird exemplars closer to the category boundary, but only in the category-training condition [ $F(4,8) = 6.87, p < .05$ ].

The presence of a category boundary was investigated by comparing the proportion of 'same' responses for bird pairs with an equal morph distance for cases in which the birds were from the same or from a different category. This was done for responses in the final training session, separately for the category training and visual exposure condition. As expected, for category training we obtained a significant effect of the category boundary (Figure 2.3*c* and *d*): Subjects were much more likely to rate bird pairs to be the same when they belonged to the same side of the category boundary than equal distance bird pairs belonging to

different sides of the category boundary [ $F(1,11) = 115.86, p < .0001$ ]. For visual exposure the effect was also present [ $F(1,11) = 4.97, p < .05$ ] but smaller [ $F(1,11) = 5.22, p < .05$ ]. Importantly, for category training there was no effect of physical distance [ $F(3,9) = 2.45, p < .05$ ], and no interaction between distance and category boundary [ $F(3,9) = 0.88, p = \text{n.s.}$ ]. The sharp difference in responses for within and between category pairs was maintained over decreasing physical distance between bird pairs (see Figure 2.3*c*), clearly indicating category formation. Furthermore, this result shows that the slightly greater performance for the more extreme morphs does not simply reflect a greater average distance between these morphs and their comparison stimuli. For the visual exposure condition a significant effect of distance [ $F(3,9) = 4.56, p < .05$ ] was obtained. A higher proportion of 'same' responses was observed for bird pairs with a small distance than for bird pairs with a large distance (see Figure 2.3*d*). Calculation of sensitivity ( $d'$ ) in category discrimination showed that the average sensitivity was high for the category-trained bird types ( $d' = 2.87$ ) whereas for

### Figure 2.5

**General effects of training. (A)** Group-averaged activation maps from post-training scanning overlaid on lateral (top) and ventral (bottom) views of Talairach-normalized inflated hemispheres. In red, regions showing an effect of training as compared with no training at  $p < 0.05$  (False Discovery Rate corrected). In blue, brain regions showing decreased activity following training as compared with no training. **(B)** Single-subject data showing a general effect of training. In red the areas that showed a higher response to trained as compared with not trained birds ( $p < .05$ ) overlaid on the axial slices from the corresponding normalized structural images. Structural images are in neurological convention. **(C)** Group-averaged time-course of the BOLD response (percent signal changed) averaged over all voxels in the left fusiform gyrus (Talairach coordinates of the centre of mass:  $x = -33, y = -69, z = -18$ ) that showed a general training effect. Shown are the group-averaged responses for each of three conditions in the pre and post-training scanning session (red: category training, green: no training, blue: visual exposure). Error bars represent standard error of the mean. **(D)** Mean beta-weights (i.e., estimates of signal amplitude) for voxel populations in left and right occipitotemporal cortex showing a general decrease in activity for trained birds as compared with not-trained bird types. Shown are the group-averaged responses for each of three conditions in the pre- and post-training scanning sessions. Error bars represent standard error of the mean.



## Object categories in ventral temporal cortex

the visual-exposure bird types discrimination ability was very poor ( $d' = 0.34$ ), see Figure 2.3*e*.

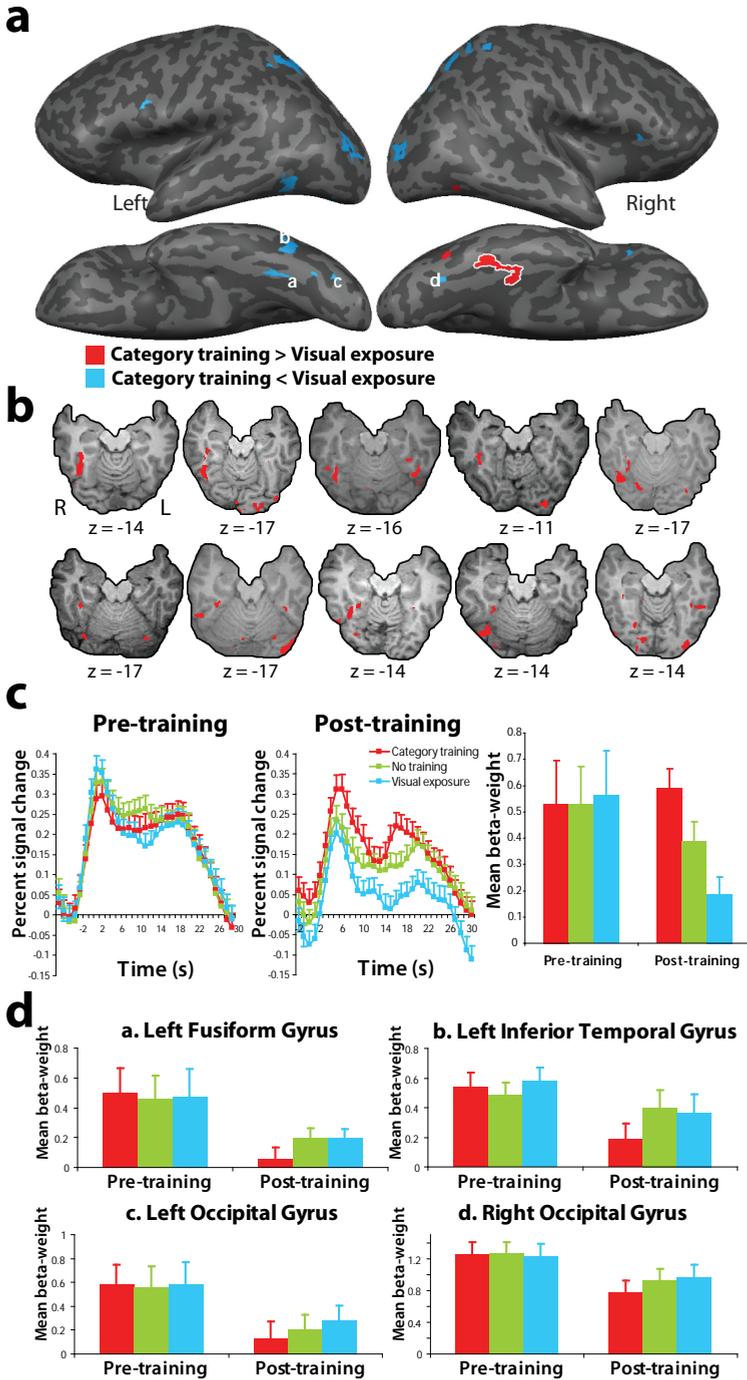
### fMRI results

To test for a main effect of session we compared the responses to all objects post-training versus responses to all objects pre-training. The results showed that after training, responses to all objects were reduced compared with responses to the same objects before training in bilateral lateral occipital gyri extending into bilateral fusiform gyrus and inferior parietal cortex (see Figure 2.4). In addition we observed reduced responses in bilateral superior temporal sulcus, inferior and middle frontal gyri, and bilateral post and precentral gyri. Increased responses were observed in bilateral anterior and posterior cingulate gyrus and bilateral precuneus. Because identical objects were used in the first and the second session, the overall differences in fMRI responses between the two sessions are likely to be related to repetition effects.

To dissociate between effects of training and effects of repetition we performed within-session analyses (Gauthier et al., 1999; Op de Beeck et al., 2006). Since objects were repeated in the training as well as in the control conditions, within-session differences between these conditions can not be due to repetition effects but must result from specific effects of training. Therefore, to examine specific training effects we compared responses to bird types in the different training and control conditions, separately for the pre- and post-training session. Analyses of the pre-training fMRI data showed no significant differences in activity between the bird types. All birds elicited similar patterns of activity, indicating that initially, no differentiation between the birds was made on the basis of their physical features. To test for neural correlates of training-induced category formation, we analyzed post-training responses for the different bird types within object-responsive regions, that is, regions that were active for viewing objects as compared with rest (see methods).

### Figure 2.6

**Specific effects of category training. (A)** Group-averaged activation maps from post-training scanning overlaid on lateral (top) and ventral (bottom) views of Talairach-normalized inflated hemispheres. In red, regions showing a specific effect of category training as compared with visual exposure at  $p < 0.05$  (False Discovery Rate corrected). In blue, brain regions showing decreased activity following category training as compared with visual exposure. **(B)** Group-averaged time-course and mean beta-weights of the BOLD response in the right middle fusiform gyrus (Talairach coordinates of the centre of mass:  $x = 36, y = -35, z = -16$ ) in percent signal change. Shown are the group-averaged responses for each of three conditions in the pre and post-training scanning session (red: category training, green: no training, blue: visual exposure). Error bars represent standard error of the mean. **(C)** Single-subject data showing a specific effect of category training as compared with visual exposure ( $p < .05$ ) in the right middle fusiform gyrus overlaid on the axial slices from the corresponding normalized structural images. Structural images are in neurological convention. **(D)** Mean beta-weights for voxel populations in left and right occipitotemporal cortex showing a specific decrease for category-trained birds as compared with birds from the visual-exposure condition. Shown are the group-averaged responses for category-training, no training, and visual-exposure conditions in the pre- and post-training scanning sessions. Error bars represent standard error of the mean.



### General effects of training

To test for general effects of training, we compared post-training fMRI responses to all trained bird types (category-training and visual-exposure conditions), with post-training fMRI responses to not-trained bird types.

In the post-training session larger responses for trained compared with not trained bird types were obtained in the left posterior fusiform gyrus at a threshold of  $p < .05$  (False Discovery Rate corrected) see Figure 2.5a and 2.5b. Additional random-effects multivariate analyses of the beta weights extracted from this region for each of the training conditions in both scanning sessions revealed a significant interaction between scanning session and training condition [ $F(2,10) = 10.64, p < .005$ ]. The response to category-trained bird types was reduced in the post-training session compared to the pre-training session ( $t(11)=2.90, p < .05$ , for the visual-exposure condition the response was also reduced but did not reach significance ( $t(11)=2.00, p = .07$ ). Whereas before training, conditions did not differ significantly, after training responses were significantly larger for training as compared with no-training conditions. Direct contrasts of post-training conditions showed that compared with no training, responses were enhanced in the category-training condition [ $t(11) = 2.58, p < .05$ ] as well as in the visual-exposure condition [ $t(11) = 3.62, p < .005$ ], see Figure 2.5c. In these voxel populations, no significant difference was found for category-training and visual exposure conditions [ $t(11) = 1.05, p = \text{n.s.}$ ].

In addition to this general training-related enhancement of responses we observed general training-related decreases in activity in frontal, parietal, and occipitotemporal regions at a threshold of  $p < .05$  (False Discovery Rate corrected), see Figure 2.5a, 2.5d, and Table 2.1. Additional random-effects analyses showed a significant interaction between scanning session and training condition in the right inferior temporal, bilateral fusiform, inferior occipital gyri, the right inferior and middle frontal gyrus, and the bilateral intraparietal sulcus. Whereas before training, conditions did not differ significantly,

after training responses were significantly decreased for both for the category-training and the visual-exposure condition, as compared with the no-training condition (Table 2.1). In addition, these analyses revealed that these decreases in brain activity were independent of training condition. No differences were observed between responses in category-training and visual-exposure conditions.

### Specific effects of category training

To directly test for specific effects of category-training, we contrasted post-training responses to category-trained birds with post-training responses to visual-exposure birds. This contrast revealed significantly larger neural responses for category-trained birds in right middle fusiform gyrus and in the right lateral occipital gyrus (Figure 2.6a). A random effects analysis revealed significant greater activity for category-trained birds as compared with visual-exposure birds in the right fusiform gyrus [ $t(11) = 3.26, p < .01$ ], but not in the lateral occipital gyrus [ $t(11) = 2.07, p = \text{n.s.}$ ]. In addition to this increase in activity, decreases in activity for category-trained bird types as compared with visual exposure bird types were observed in occipitotemporal, inferior frontal, and parietal brain regions, see Table 2.2, Figure 2.6a, and 2.6d. See also Table 2.3 for comparisons of category training with no training and visual exposure with no training.

To further analyze the category-specific increase in activity, regions in the right middle fusiform gyrus showing a category-training related increase in activity were defined per subject (Figure 2.6b). Mean beta-weights were extracted from these regions for each condition and morph level, separately for the pre- and post-training session (Figure 2.6c). A random-effects multivariate analysis of the regionally-averaged beta-weights showed a significant main effect of training condition [ $F(2,8) = 9.70, p < .01$ ], as well as a significant interaction between session (pre- and post-training) and training condition [ $F(2,8) = 35.62, p < .0001$ ]. Before training the right fusiform gyrus did not differentiate between the bird types. After training responses

ROI	x	y	z	Pre-training	Post-training	Interaction (session * condition)
<b>Occipitotemporal</b>						
Right Inferior Temporal Gyrus (BA 37)	52	-56	-11	0.72 <sup>ns</sup>	3.41**	2.78*
Right Fusiform Gyrus (BA 37)	48	-46	-14	-0.68 <sup>ns</sup>	4.08***	2.75*
Left Posterior Fusiform Gyrus (BA 37)	-34	-60	-14	-0.83 <sup>ns</sup>	3.88***	3.35**
Right Inferior Occipital Gyrus (BA 19)	27	-69	-10	0.07 <sup>ns</sup>	3.25**	3.12**
Right Inferior Occipital Gyrus (BA 19)	22	-80	4	0.90 <sup>ns</sup>	2.96*	2.56*
Left Inferior Occipital Gyrus (BA 19)	-36	-76	-14	-1.16 <sup>ns</sup>	3.06**	2.52*
<b>Frontal</b>						
Right Inferior Frontal Gyrus (BA 45/46)	41	29	17	-0.65 <sup>ns</sup>	3.43***	2.40*
Right Middle Frontal Gyrus (BA 9)	46	15	35	-1.35 <sup>ns</sup>	2.19*	3.05*
<b>Parietal</b>						
Right Intraparietal Sulcus	28	-61	41	-0.41 <sup>ns</sup>	2.89*	2.37*
Left Intraparietal Sulcus	-28	-54	41	-1.45 <sup>ns</sup>	2.92*	2.66*

<sup>ns</sup> not significant, \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .005$

**Table 2.1**

Brain regions showing a significant decrease in activity after category training and visual exposure as compared with no training, as well as a significant interaction between training condition and scanning session in a random effects analysis. For each region, mean Talairach coordinates, corresponding Brodmann's areas (BA), averaged  $t$ -values ( $df = 11$ ) for the contrast between (category training + visual exposure) and (no training) are reported, separately for the pre- and post-training sessions. In addition, averaged  $t$ -values ( $df = 11$ ) are reported for the interaction between training condition and scanning session.

were significantly larger for the category-trained bird types than for visual-exposure and not-trained birds. Direct comparisons of the responses in the different training conditions revealed that responses for category-trained birds were significantly larger than responses for visual-exposure bird types [ $t(9) = 11.32$ ,  $p < .0001$ ], as well as not-trained bird types [ $t(9) = 3.06$ ,  $p < .05$ ]. In addition, significantly smaller responses were found for the visual-exposure condition as compared with the no-training condition ( $t(9) = 3.00$ ,  $p < .05$ ).

If the category-training related increase in the right middle fusiform gyrus is specifically related to sensitivity of neuronal populations to the diagnostic features of the category, we should see a positive linear relation between morph level and brain response. This relation should be present for the category trained birds, post-training but not pre-training, and also not for birds from the visual exposure condition for which category-learning

was hindered. In addition, if the effect of morph level is specific to category learning it should not be present in the left fusiform gyrus, as this region showed a general training effect. To test this prediction, we investigated whether responses in the right middle and left posterior fusiform showed a linear increase as a function of morph level. As can be seen in Figure 2.7, a clear linear relationship of morph level and brain response was obtained in the post-training scan session for the category trained birds in the right fusiform only. Before training there was no linear relation between morph level and right middle fusiform response in the category training condition [ $F(1,4) = 0.09$ ,  $p = \text{n.s.}$ ;  $R = 0.15$ ], birds from the no training condition [ $F(1,4) = 0.00$ ,  $p = \text{n.s.}$ ;  $R = 0.29$ ], or for birds from the visual exposure condition [ $F(1,4) = 0.11$ ,  $p = \text{n.s.}$ ;  $R = 0.16$ ]. After training there is still no linear relation between brain response and morph level for birds that were not trained [ $F(1,4) = 0.17$ ,  $p = \text{n.s.}$ ;  $R = 0.20$ ]. How-

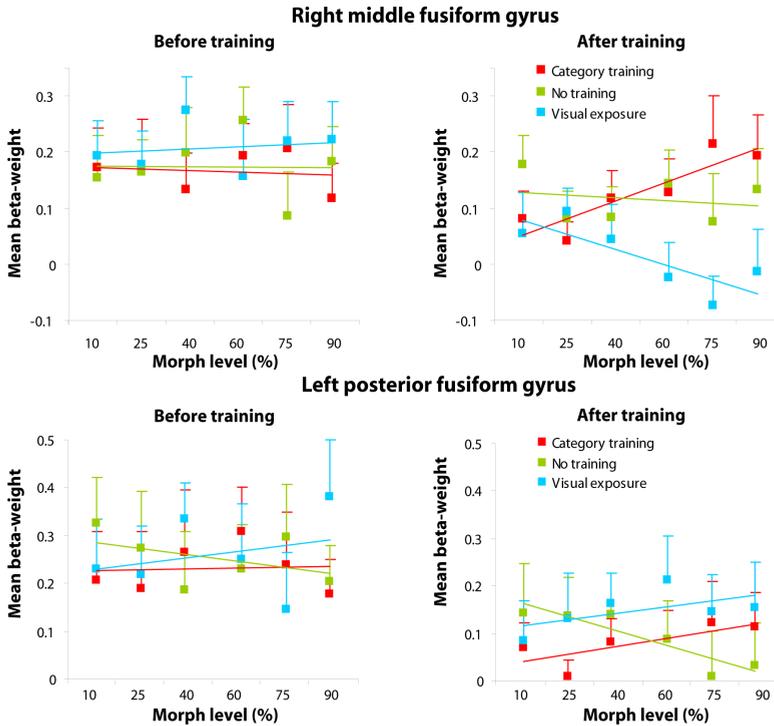
## Object categories in ventral temporal cortex

ever, for birds that were category trained there was a significant linear relation between morph level and beta-weight [ $F(1,4) = 15.87, p < 0.05; R = 0.89$ ] and interestingly for birds in the visual exposure condition there existed a negative linear relation between morph level and brain response [ $F(1,4) = 7.96, p < 0.05; R = -0.82$ ]. The responses in the left fusiform gyrus for category trained and visual exposure bird types showed no linear relation with morph level before [category training:  $F(1,4) = 0.11, p = \text{n.s.}; R = 0.05$ ; visual exposure:  $F(1,4) = 0.30, p = \text{n.s.}; R$

$= 0.27$ ] or after training [category training:  $F(1,4) = 4.95, p = \text{n.s.}; R = 0.74$ ; visual exposure:  $F(1,4) = 1.99, p = \text{n.s.}; R = 0.58$ ]. This finding confirms that the effect of morph level in the right fusiform is specific for category learning and not a general consequence of training.

## Discussion

Our data provide evidence for experience-induced shaping of neural responses in ventral temporal cortex.



**Figure 2.7**

**Fusiform responses as a function of morph level.** The effect of morph level is plotted for voxels in the right middle fusiform gyrus showing a specific training effect and voxels in the left posterior fusiform gyrus that showed a general training effect in the post-training scan. For each training condition (red: category training, green: no training, blue: visual exposure) the regionally-averaged brain responses (mean beta-weight) are plotted as a function of morph level (%) in pre-and post-training scan sessions. Lines represent the optimal linear fit between morph level and brain response. Error bars represent standard error of the mean.

ROI	x	y	z	Pre- training	Post- training	Interaction (session * condition)
<b>Occipitotemporal</b>						
Left Inferior Occipital Gyrus (BA 19)	-21	-82	-20	0.58 <sup>ns</sup>	-3.89 <sup>***</sup>	-2.74*
Left Inferior Occipital Gyrus (BA 18)	-33	-89	10	0.76 <sup>ns</sup>	-2.96*	-4.17 <sup>***</sup>
Left Fusiform Gyrus (BA 37)	-33	-54	-14	0.76 <sup>ns</sup>	-3.22 <sup>**</sup>	-2.61*
Left Inferior Temporal Gyrus (BA 37)	-43	-57	-6	-1.33 <sup>ns</sup>	-6.91 <sup>***</sup>	-3.92 <sup>***</sup>
Right Inferior Occipital Gyrus (BA 19)	30	-70	-3	0.93 <sup>ns</sup>	-3.00*	-3.23 <sup>**</sup>
Right Occipital gyrus (BA 18)	18	-94	6	0.67 <sup>ns</sup>	-2.62*	-2.64*
Right Inferior Occipital Gyrus (BA 18)	27	-83	7	-0.41 <sup>ns</sup>	-2.63*	-2.28*
<b>Frontal</b>						
Left Inferior Frontal Gyrus (BA 44)	-42	2	27	1.27 <sup>ns</sup>	-2.62*	-2.92*
Right Inferior Frontal Gyrus (BA 45)	40	25	16	-0.27 <sup>ns</sup>	4.00 <sup>***</sup>	-3.28 <sup>**</sup>
<b>Parietal</b>						
Left Intraparietal Sulcus	-25	-57	45	1.82 <sup>ns</sup>	-6.88 <sup>***</sup>	-6.13 <sup>***</sup>

<sup>ns</sup> not significant, \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .005$

**Table 2.2**

Brain regions showing significantly less activity for category-trained birds as compared with birds from the visual exposure condition, as well as a significant interaction between training condition and scanning session in a random effects analysis. For each region, mean Talairach coordinates, corresponding Brodmann's areas (BA), averaged  $t$ -values ( $df = 11$ ) for the contrast between category training and visual exposure are reported, separately for the pre- and post-training sessions. In addition, averaged  $t$ -values ( $df = 11$ ) are reported for the interaction between training condition and scanning session.

A main effect of session showed that, compared with the pre-training session, post-training activity in occipitotemporal cortex was reduced for both trained and not-trained objects. Because identical objects were used in the first and the second session, the overall differences in fMRI responses between the two sessions are likely to be related to repetition effects. It is by now well established that repeating an object (even over a delay of a few days) leads to decreases and increases in fMRI responses in a network of brain regions (e.g. (Buckner et al., 1998; Henson, 2003; Meister et al., 2005; van Turennout, Bielamowicz, & Martin, 2003; van Turennout, Ellmore, & Martin, 2000)). The general effect of session that we observed is consistent with these findings.

Before training, all birds elicited similar patterns of activity, indicating that initially, no differentiation between the birds was made on the basis of their physical features. After training activity in

occipitotemporal cortex was modulated as a function of experience. Post-training, activity in the left fusiform gyrus was significantly larger for trained as compared with not-trained bird types. This differentiation in responses occurred after category training as well as after visual exposure. Importantly, category training led to a relative increase in right fusiform responses. Post-training, bird types for which a sharp category-boundary was established during training elicited larger right fusiform responses than not-trained birds. In contrast, visual exposure alone resulted in reduced responses in the right fusiform gyrus. This clearly shows that the increase in activity for category-trained bird types in the right fusiform gyrus was not caused by mere visual exposure, but mediates the formation of category-specific representations.

These results fit well with functional brain imaging data demonstrating increased activity in occipitotemporal cortex as a function of improved

## Object categories in ventral temporal cortex

2

object recognition and visual expertise. Training-related increases in activity in occipital cortex have been reported to follow perceptual discrimination training with nonnatural nonsense objects (Moore et al., 2006; Op de Beeck et al., 2006). In addition, increased activity in the fusiform gyrus has been found after subjects became proficient in individuating a homogeneous set of nonsense objects (Gauthier et al., 1999). Moreover, increased fusiform activity has been reported after subjects had learned to perform functional tasks with a set of novel stimuli (Weisberg et al., 2007). In addition, larger fusiform responses were observed in individuals that were highly skilled in recognizing a particular class of objects such as birds, cars, or Lepidoptera (butterflies and moths) (Gauthier, Skudlarski, Gore, & Anderson, 2000; Rhodes, Byatt, Michie, & Puce, 2004; Xu, 2005). Although these results clearly show the involvement of occipitotemporal cortex in visual object learning they do not necessarily imply category formation. By dissociating between general effects of visual exposure and specific effects of category training we show that increased activity in the right fusiform gyrus is related to category formation.

Functional imaging data of humans (Henson, 2003) as well as electrophysiological recordings from monkey cortex (Freedman, Riesenhuber, Poggio, & Miller, 2006; Peissig, Singer, Kawasaki, & Sheinberg, 2007) have shown increased neural responses in ventral temporal cortex as a function of increased object familiarity. Recently, event-related potential data have shown distinct neural effects for object learning at basic and subordinate levels (Scott, Tanaka, Sheinberg, & Curran, 2006). While training at a basic object level resulted in improved encoding of coarse visual features, training at a subordinate level resulted in additional encoding of more fine-grained visual object features. The present results show that on the first day of training, performance in the 1-back task was slightly above chance in both training conditions suggesting improved object coding as a function of visual experience. During the second and the third training session performance dramatically improved but only when subjects

received correct feedback on their responses. This is in line with the idea that successful categorization of highly similar objects is mediated by learning fine-grained object features indicative of category membership. Indeed, whereas sensitivity in category discrimination was high for the category-trained bird types, for the visual-exposure bird types category-discrimination ability was very poor. In the visual exposure condition, the proportion of same responses was slightly higher for within- as compared with between-category bird-pairs. However, this small effect differed significantly from the sharp boundary effect obtained after category training. Consistent with the behavioural results, we found a clear neural dissociation between general effects of visual training and the formation of an object category. Whereas post-training training-related increases in activity in the left posterior fusiform gyrus occurred independently of category formation, increased responses in the right middle fusiform gyrus were only observed for bird-types for which a sharp category-boundary was established. This dissociation suggests that the left fusiform gyrus is probably involved in the encoding of general shape information, and the right fusiform is encoding fine-grained visual information required for category formation.

Our results are consistent with electrophysiological recordings from the inferior temporal cortex in monkeys suggesting that object category formation is mediated by a learning induced sharpening of neuronal stimulus selectivity (Freedman et al., 2003, 2006; Sigala & Logothetis, 2002). Our behavioural data showed that responses were more accurate and faster for birds at higher morph levels, reflecting that birds close to the prototype are more distinctive than birds close to the category boundary. This implies that the closer to the prototype, the more apparent the features that determine to which category a bird belongs. Recently, it has been shown that neuronal selectivity in monkey inferior temporal cortex is shaped by those object features that were most relevant during categorization training (Sigala & Logothetis, 2002). In addition, single-cell recordings from monkey cortex have demonstrated

that discrimination training enhances the selectivity of neurons in inferior temporal cortex not only for features in isolation but also for whole objects (Baker et al., 2002). In line with these findings from monkey cortex, our findings suggest that after category training, neuronal populations in the right fusiform gyrus differentiated between object features that were informative of a category and features that were uninformative. Right fusiform activity was modulated by morph level. Responses were positively related with the morph-level of category trained birds and negatively related with the morph-level of birds for which category-learning was hindered by random feedback. This means that the higher the percentage of features trained to be relevant for categorization, the larger the responses in the right fusiform gyrus. In contrast, the higher the percentage of features trained to be irrelevant for categorization training, the smaller the right fusiform responses. Moreover, the left fusiform gyrus that showed a general training effect did not show a positive linear relation between morph level and responses, indicating that the effect of morph level is specific for category learning and does not occur as general consequence of visual exposure. One of the neural mechanisms that could explain this pattern of enhanced responsiveness to relevant category features and suppressed responses to irrelevant features involves increased tuning of neuronal populations to informative combinations of visual features. Op de Beeck et al. (2006) have shown that the largest effects of training occur in regions that already process stimulus properties that are relevant during training. This suggests that increased tuning of neuronal populations concerns those features that were most relevant during training. However, since the present fMRI data reflect overall magnitude of response of relatively large neuronal clusters, no direct conclusions can be drawn on whether the results indeed reflect increased neural tuning. One way to investigate neuronal sensitivity with fMRI is by using an adaptation paradigm. Recent studies using this paradigm showed narrow shape tuning of neural populations in occipitotemporal cortex to

sub-exemplar faces (Gilaie-Dotan & Malach, 2007; X. Jiang et al., 2006) and trained car stimuli (Xiong Jiang et al., 2007). This suggests that neural populations in this brain region are highly specialized to dissociate between fine-grained visual features, which fits nicely with our interpretation of the results.

The location of our post-training training-related increase in activity in the right fusiform gyrus seems to be close to the location of the fusiform face area (FFA), a region that has been claimed to be specifically involved in face recognition (Grill-Spector, Knouf, & Kanwisher, 2004; Kanwisher et al., 1997). This claim has been challenged by findings relating FFA activity to increased expertise in object recognition (Gauthier et al., 2000; Gauthier et al., 1999). However, since we did not localize the FFA in our subjects we should be cautious about whether the current results directly address the debate regarding the function of the FFA. It is unclear whether the exact same region is involved here. The FFA is neighboured by regions that prefer other stimuli, such as bodies (Peelen & Downing, 2005; Schwarzlose, Baker, & Kanwisher, 2005). Also, birds have faces and previous studies have shown that the FFA responds to animal faces to a considerable extent (Chao, Martin, & Haxby, 1999; Tong, Nakayama, Moscovitch, Weinrib, & Kanwisher, 2000). Our subjects might have found the features in the bird's head extra useful for categorization. Therefore, the training-effects may have occurred in regions that process facial features. Note however, that not all features informative of a bird's category were located in its head and we cannot be certain that during training the facial features received indeed the most attention. Nevertheless, should the increase we observe for category-trained birds be attributed to the presence of a face in the stimuli, this does not deter from our novel finding of an increase that is specific to only those bird types for which category boundaries were formed during training.

In addition to training-related increases in activity, in some areas neural responses were significantly

reduced for bird types from both category training and visual exposure conditions. These opposite patterns of responses in different brain regions might reflect two different learning mechanisms. While the underlying mechanism for the relative increase in the right middle temporal gyrus might be increased neuronal tuning for those object features relevant for category learning, a different mechanism could explain lower responses for trained compared with not-trained birds. Reduced occipitotemporal responses have consistently been reported to follow repeated exposure to visual objects (Henson, 2003), even over a delay of several days (van Turennout et al., 2003; van Turennout et al., 2000). This so-called repetition-suppression effect has been argued to reflect a learning process in which stimulus representations are optimized. Repeated exposure to the same stimulus causes neurons coding non-specific stimulus features to drop out of the responsive pool, while neurons tuned optimally to the stimulus continue their activity (Desimone, 1996; Grill-Spector, Henson, & Martin, 2006; Wiggs & Martin, 1998). As a consequence, the total number of responsive neurons decreases, leading to a reduced overall response. In line with this idea, the reduced neural response for trained birds could reflect the formation of sharper object representations. Since reduced responses occurred in both the visual exposure and the category-training condition, this sharpening process is not related to object-category formation but probably reflects object-specific visual learning. In addition to general training-related decreases in activity, some occipitotemporal regions showed reduced responses for category-training as compared with visual-exposure conditions. This shows that applying random feedback not only hindered category learning (Herzog & Fahle, 1997), but also affected sharpening of object-specific representations. Although repetition suppression occurs as a result of repeated visual exposure, differences in encoding as a result of receiving correct or random feedback, might have led to differential changes in stimulus-specific representations (Vuilleumier, Schwartz, Duhoux, Dolan, & Driver, 2005; Zago,

Fenske, Aminoff, & Bar, 2005).

Our data provide evidence for learning-related formation of visual object category representation in occipitotemporal cortex. However, occipitotemporal cortex is not the only brain region that has been implicated in object-category learning. Monkey data have shown that neurons in prefrontal cortex respond selectively to members of a learned category, irrespective of within category variations (Freedman et al., 2001). These data were obtained while monkeys were actively involved in a categorization task. Although in our paradigm subjects may have been implicitly categorizing the birds throughout the scan session in order to successfully perform the task, this did not elicit training-specific increases in prefrontal cortex. Recently, it has been shown that prefrontal cortex shows a category-dependent response only when human subjects were performing a categorization task and not when performing a displacement detection task (Xiong Jiang et al., 2007). The exact relationship between the nature of a categorization task and category-selective responses in human cortex remains to be determined. Data from network models on object category learning suggest that during learning, the top-down influence of prefrontal cortex enhances the selectivity of the neurons in inferior temporal cortex encoding the behaviourally relevant features of the stimuli (Rougier, Noelle, Braver, Cohen, & O'Reilly, 2005; Szabo et al., 2006). Presumably, category-learning requires collaboration between these different brain structures, with the occipitotemporal cortex storing characteristic features of objects belonging to a learned category, and the prefrontal cortex being involved in explicit retrieval of category information.

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## **Formation of category representations in superior temporal sulcus**

This chapter is based on:  
van der Linden, M., van Turennout, M., & Indefrey, P. (2010). Formation of category representations in superior temporal sulcus. *Journal of Cognitive Neuroscience*, 22(6), 1270-1282.

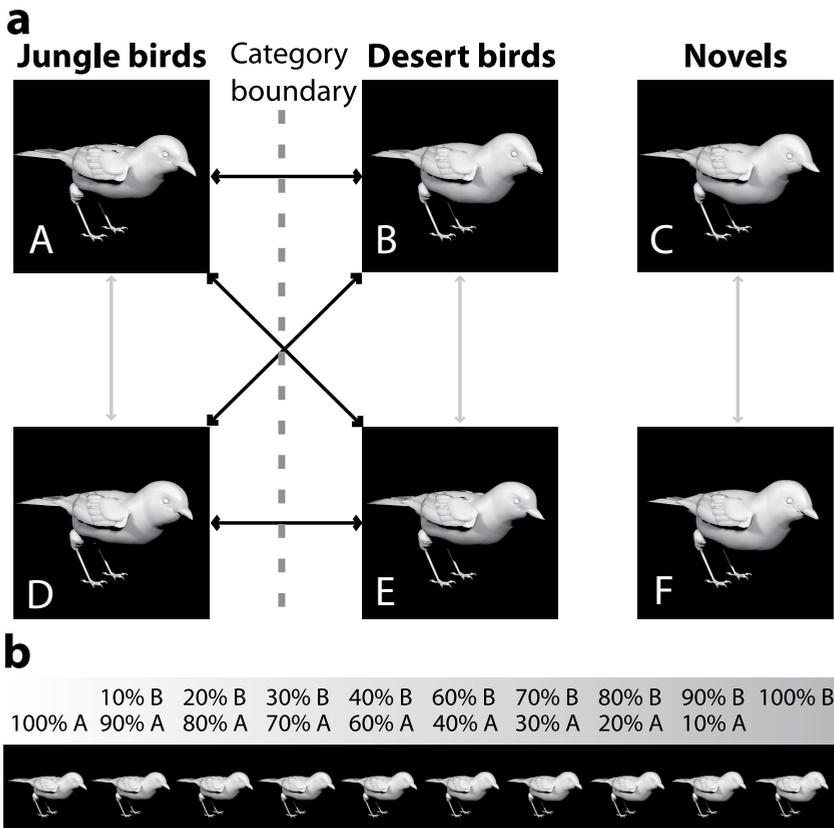
 The human brain contains cortical areas specialized in representing object categories. Visual experience is known to change the responses in these category-selective areas of the brain. However, little is known about how category training specifically affects cortical category-selectivity. Here, we investigated the experience-dependent formation of object categories using an fMRI adaptation paradigm. Outside the scanner, subjects were trained to categorize artificial bird types into arbitrary categories (jungle birds and desert birds). After training, neuronal populations in occipitotemporal cortex, such as the fusiform and lateral occipital gyrus were highly sensitive to perceptual stimulus differences. This sensitivity was not present for novel birds, indicating experience-related changes in neuronal representations. Neurons in superior temporal sulcus showed category-selectivity. A release from adaptation in superior temporal sulcus was only observed when two birds in a pair crossed the category boundary. This dissociation could not be explained by perceptual similarities, because the physical difference between birds from the same side of the category boundary and between birds from opposite sides of the category boundary was equal. Together the occipitotemporal cortex and the superior temporal sulcus have the properties suitable for a system that can both generalize across stimuli and discriminate between them.

### Introduction

Learning to categorize the world starts at a very young age. Infants of only 4 months of age can form categorical representations (Mareschal and Quinn, 2001). This process continues throughout adulthood, with learning and experience shaping the borders of existing categories and forming entirely new categories. Brain imaging studies investigating the formation and alteration of cortical object category representations in the adult human brain have linked increased perceptual expertise to neuronal changes in occipitotemporal cortex. When subjects gain experience with discriminating a novel object category, increases in activity have been found in the right middle fusiform gyrus (Gauthier et al., 1999; Weisberg et al., 2007), lateral occipital gyrus (Op de Beeck et al., 2006), and the middle occipital gyrus (Moore et al., 2006). Activity in occipitotemporal cortex has also been found to be selectively enhanced for objects from a category with which subjects have extensive experience, such as birds and cars (Gauthier et al., 2000; Xu, 2005), or Lepidoptera (Rhodes et al., 2004). These findings indicate that experience with an object category modulates the underlying neuronal representation. However,

it is not clear whether these experience-dependent changes could be explained by visual experience alone or whether they reflect the formation of object-categories. Previously, we found that learning to categorize highly similar bird types led to a selective increase in activity in the right middle fusiform gyrus (van der Linden et al., 2008). Critically, this increase was not present for bird types to which the subjects were exposed to the same amount, but for which a category's distinguishing features could not be learned because of random feedback. We attributed this selectivity to increased responsiveness of neurons in the right middle fusiform gyrus to those object features that facilitate categorization.

Taken together, increased perceptual expertise is linked to neuronal changes in occipitotemporal cortex. However, in all these studies category-membership was perception-based, i.e. perceptually similar objects belonged to the same category. Recently, Jiang et al. (2007) used fMRI to investigate how cortical representations in the adult human brain are shaped when perceptually dissimilar objects are grouped in the same category. In their fMRI study, a discrete boundary between similar-looking nonnatural objects (cars) belonging to different cat-



**Figure 3.1**

**Creation of the stimulus set. (A)** Each of the six prototype birds (i.e. A-F) was morphed with all other birds to create exemplars for each of the different bird types. Four bird types were grouped into two arbitrary bird categories, desert birds (e.g. A and D) and jungle birds (e.g. B and E). Two bird types (e.g. C and F) were not used during training and acted as novel controls during scanning. The assignment of birds into categories was counterbalanced over subjects. **(B)** By systematically morphing each of the six prototype birds with all other birds the different exemplars for each bird type were created. Shown is an example of morphing bird type A and bird type B at morph ratios of 90:10, 80:20, 70:30, 60:40.

egories was established by training. Car stimuli were morphed with each other, allowing comparison of cars on the same side of the category boundary (belonging to the same car type) with cars with a similar physical difference but on opposite sides of the category boundary (belonging to different car

types and belonging to either the same category or a different category). They found sharpening of the representation after categorization training in the lateral occipital gyrus. However, the response in this region was perception-based and not selective for category-membership. The prefrontal cortex did

show category-selectivity that was not perception-based, however this selectivity was task-dependent and only obtained when the subjects performed a categorization task.

In the present study we used an fMRI adaptation paradigm (Grill-Spector et al., 2006), similar to Jiang et al. (2007), to investigate experience-dependent formation of cortical category representations. Grill-Spector and Malach (2001) have shown that fMRI adaptation can be used to probe the sensitivity of neuronal populations. The nature of neural stimulus representations can be revealed when hemodynamic responses are selectively affected by repeating or changing particular stimulus attributes. This makes the adaptation technique a useful tool to make inferences about neural sensitivity in specific cortical regions (Grill-Spector et al., 1999; Pourtois et al., 2005; Cohen Kadosh et al., 2007).

Previous studies have demonstrated that regions involved in representing stimuli from a certain class adapt selectively to repeated presentation of objects from this class. For example, the fusiform face area shows sensitivity to repeated presentation of faces (Andrews and Ewbank, 2004), and the parahippocampal place area to the repetition of places (Epstein et al., 2003; Ewbank et al., 2005). In addition, fMRI adaptation paradigms have been successfully applied to identify cortical areas sensitive to identity change (Loffler et al., 2005; Rotshtein et al., 2005; Jiang et al., 2006; Gilaie-Dotan and Malach, 2007) and category change (Jiang et al., 2007). Regarding the category of animals, the lateral fusiform gyrus and the superior temporal sulcus (STS) showed reduced activity only for repeated animals and not for repeated tools (Chao et al., 2002). Additional tasks, such as animal picture processing, reading animal names, and answering questions about animals produced category-related activity in the same regions (Chao et al., 1999). Because not only pictures of the animals, but also words and questions elicited category-related activations in STS the activity in the temporal cortex seems to reflect stored information about animals rather than the physical features

of the animals, which are believed to be stored in the fusiform gyrus.

We trained subjects to successfully categorize four bird types that were highly similar into two arbitrary bird categories (desert birds and jungle birds). During scanning the subjects did not categorize the bird types. We were interested in finding training-induced category representations, that were activated in the absence of a categorization task and that were independent of the shape of the birds. We hypothesized to find experience-dependent selectivity to the birds in the occipitotemporal cortex and superior temporal sulcus.

## Materials and Methods

### Subjects

28 Healthy right-handed participants (24 females, mean age 21.9 years, range 18-35) with no neurological history participated in the experiment. Two subjects were excluded because of excessive motion (i.e. more than 3 mm). After training, 18 subjects (15 females, mean age 22.5 years, range 18-35) were able to categorize at least three bird types. These subjects were included in a within subject analysis. All subjects had normal or corrected-to-normal vision. Subjects were paid for their participation. All subjects gave written informed consent.

### Stimuli

The stimuli consisted of pictures of computer-generated birds that were constructed in a 3D model manipulation program (Poser 4 by Curious Labs, Santa Cruz, CA). First, six prototype birds were constructed from a base-bird (Songbird Remix by Daz3d, Draper, UT), see Figure 3.1a. Parts of the bird that were manipulated included its trunk, tail, beak, head shape, cheeks, brow, and eye position. Next, to create different exemplars for each category each of the six prototype birds was morphed with all other birds at ratios of 95:5, 90:10, 80:20, 75:25, 70:30, 65:35, 60:40, and 55:45 (Fig. 3.1b). The category boundary was set at 50%. As a result, stimuli that were close to, but on opposite sides of the category boundary were visually similar, but

belonged to different categories. Morphing happened smoothly between corresponding points on the birds. Each bird was colourless, rendered under the same lighting and camera settings, and exported as an image. Images had identical shading and scale. The images measured 300 by 300 pixels in the training sessions and were slightly reduced in size (250 by 250 pixels) in the scanning sessions. In addition, a set of scrambled bird pictures was constructed to function as a low-level visual baseline in the scan session.

### Procedure

Four bird types were arbitrarily assigned to two categories (jungle birds and desert birds), see Figure 3.1*a*. The two bird types constituting a category were counterbalanced across subjects. In addition, two bird types were not trained, and acted as novel controls in the scan session.

### Training

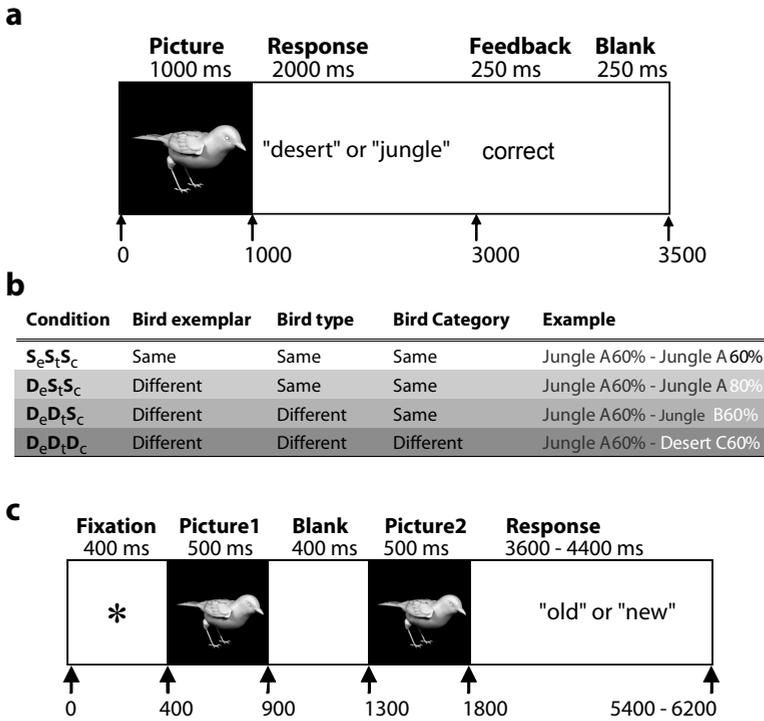
Subjects were instructed to categorize four bird types in two bird categories (desert and jungle birds). During training the subjects performed a categorization task on pictures of different exemplars of the bird types, see Figure 3.2*a*. They indicated for each bird picture whether it was a jungle bird or a desert bird with a button press of the index or middle finger of the right hand. After each response they received feedback whether their response was correct, false, or too late. The assignment of bird category to finger was switched every block of training to avoid mapping of a bird category to a finger. Each bird picture was shown for 1 second, after which the subject had 2 seconds to give a response. Feedback was presented for 250 ms and was followed by a blank screen of 250 ms, after which the next trial commenced. Each block of training lasted ten minutes and contained 160 exemplars (40 per bird type). Each exemplar was shown once during a block. Each training session contained eight blocks. Training sessions took place on consecutive days. Subjects were scanned after completing three training sessions.

### fMRI scanning session

An adaptation paradigm was used during scanning. The adaptation condition was determined by the relation between the two birds that were rapidly presented in a pair. Four types of adaptation conditions were used (Fig. 3.2*b*). In the first condition, birds in a pair consisted of the exact same exemplar from the same bird type and the same category ( $S_e S_e S_e$ ), e.g. Jungle bird type A 60% and Jungle bird type A 60%. In the second condition, birds in a pair were different exemplars of the same bird type and the same category ( $D_e S_e S_e$ ), e.g. Jungle bird type A 60% and Jungle bird type A 80%. In the third condition, the birds in a pair were different exemplars of different bird types, but of the same category ( $D_e D_e S_e$ ), Jungle Bird type A 60% and Jungle bird type B 60%. In the fourth condition, birds were different exemplars of different bird types and belonged to different categories ( $D_e D_e D_e$ ), Jungle bird type A 60% and Desert bird type C 60%. Importantly, the physical distance between birds from the same ( $D_e S_e S_e$  and  $D_e D_e S_e$ ) and opposite sides ( $D_e D_e D_e$ ) of the category boundary was kept equal. This physical difference was 20% for half of the trials and 30% for the other half. For each adaptation condition there were 20 trials per morph level distance. In addition, there were 40 pairs of scrambled images that functioned as a baseline.

For the novel birds the adaptation conditions were  $S_e S_e S_e$ ,  $D_e S_e S_e$  and  $D_e D_e D_e$ . Novel birds were not trained. As such, novel bird types could not be grouped into one and the same category. Therefore, there was no  $D_e D_e S_e$  condition for novel birds. During scanning the subjects performed an old/new task. They indicated for each second bird in the pair, whether they remembered it from the training session or not. Subjects responded with the index (“yes”) and middle finger (“no”) of the right hand on an MR-compatible response box (Lumitouch by Photon Control, Burnaby, Canada). To balance the number of “yes” and “no” responses we included  $D_e D_e D_e$  filler-pairs of which the first bird was trained and the second bird was novel.

## Category representation in superior temporal sulcus



**Figure 3.2 (A) Training design.** During the training sessions participants were presented with a series of bird exemplars. They performed a categorization task in which they labelled each exemplar as either a “desert bird” or a “jungle bird” by pressing a button. Category learning was established by providing corrective feedback after each trial. **(B)** fMRI adaptation design. The experimental design included four adaptation pair types:  $S_e S_t S_c$  (birds in a pair are the exact same bird exemplar, the same bird type, and the same category),  $D_e S_t S_c$  (birds in a pair are different bird exemplars, but the same bird type and the same category),  $D_e D_t S_c$  (the birds in pair are different bird exemplars and different bird types, but from the same category), and  $D_e D_t D_c$  (birds in a pair are different bird exemplars, different bird types, and different categories). The morph distance between birds within a pair was always 0% for  $S_e S_t S_c$  repetitions and 20% or 30% for all other conditions. **c.** fMRI adaptation trial timing. A trial started with an asterisk (fixation) for 400 ms after which the first bird picture (picture1) was shown for 500 ms, followed by a blank screen interval (blank) of 400 ms and the second bird picture (picture2) of a bird for 500 ms. After the onset of the second picture the subject could respond. They pressed a button indicating whether they recognized the second bird from the training sessions (“old” or “new” bird). The inter-stimulus interval was jittered between 3600 ms and 4400 ms in steps of 200 ms.

A trial started with an asterisk for 400 ms after which a bird picture was shown for 500 ms, followed by a blank screen interval of 400 ms and another picture of a bird for 500 ms. After the onset of the second picture the subject could respond. The inter-stimulus-interval was jittered between 3600 ms and 4400 ms in steps of 200 ms, see Figure 2c. The order of trials was pseudo-random in order to have an optimal distance between two pairs of the same condition and morph level difference.

### fmRI scanning parameters

For each subject, 939 whole brain EPI (echo planar imaging) images (35 slices, 3 mm thick, no gap, TR=2250 ms, TE = 30, flip angle = 70°, FOV = 19.2 cm, matrix = 64x64) were acquired on a 3T whole body MR scanner (Magnetom TRIO by Siemens Medical Systems, Erlangen, Germany). In addition, a high resolution structural T1-weighted 3D magnetization prepared rapid acquisition gradient echo (MPRAGE) sequence image was obtained after the functional scan (192 slices, voxel size = 1x1x1 mm).

### fmRI Analysis

Data analysis was done using BrainVoyager QX (by Brain Innovation, Maastricht, The Netherlands). The first two volumes were discarded to allow for T1 signal equilibrium. The following preprocessing steps were performed: slice scan time correction (using sinc interpolation), linear trend removal, temporal high-pass filtering to remove low-frequency non-linear drifts of 3 or fewer cycles per time course, and 3D motion correction to detect and correct for small head movements by spatial alignment of all volumes to the first volume by rigid body transformations. Estimated translation and rotation parameters were inspected and never exceeded 3 mm. Co-registration of functional and 3D structural measurements was computed by relating T2\*-weighted images and the T1-weighted MPRAGE measurement, which yields a 4D functional data set. Structural 3D and functional 4D data sets were transformed into Talairach space (Talairach and Tournoux, 1988) and

spatially smoothed with a Gaussian kernel (FWHM = 6 mm). The expected BOLD signal change was modelled using a gamma function (tau of 2.5 s and a delta of 1.5) and convolved with the second event (Boynton et al., 1996). Statistical analyses were performed in the context of the general linear model. Both fixed and random-effects group analyses were performed. The statistical threshold was set at  $p < 0.05$  False Discovery Rate (FDR) corrected and with a cluster threshold of 50 mm<sup>3</sup>.

We defined areas that showed adaptation for bird pairs consisting of the exact same exemplar of the same bird type and the same category ( $S_e S_t S_c$ ) relative to bird pairs consisting of birds from different categories ( $D_e D_t D_c$ ) using the contrast  $S_e S_t S_c < D_e D_t D_c$ . We did this for novel, trained, and both novel and trained birds. Next, clusters showing a significant adaptation effect were selected for a more sensitive region of interest (ROI) analysis. The ROI time-courses were standardized, so that beta weights (regression coefficients) of predictors, as indices of effect size, reflect the BOLD response amplitude of one condition relative to the variability of the signal. Beta weights were obtained for all voxels within these regions of interest, per subject and per adaptation condition ( $S_e S_t S_c$ ,  $D_e S_t S_c$ ,  $D_e D_t S_c$ , and  $D_e D_t D_c$  for trained and  $S_e S_t S_c$ ,  $D_e S_t S_c$ , and  $D_e D_t D_c$  for novel bird types). Random effects analyses were performed on the subject-averaged beta-weights by applying paired  $t$ -tests, with a threshold set at  $p < 0.05$ . All  $t$ -tests were two-tailed.

To test for category-selectivity a conjunction analysis of three contrasts for fixed effects was performed with a standard “minimal  $t$ -statistic” approach (Nichols, Brett, Andersson, Wager, & Poline, 2005), which is equivalent to a logical AND of the contrasts at the voxel level. In order to obtain a statistical threshold for the conjunction analysis, we estimated the probability of finding a voxel that is significant in each and all three contrasts (i.e., the joint probability). We conjoined all contrasts where there is a difference in category membership ( $S_e S_c < D_e D_t D_c$ )  $\cap$  ( $D_e S_t S_c < D_e D_t D_c$ )  $\cap$  ( $D_e D_t S_c < D_e D_t D_c$ ). The least significant contrast determines

## Category representation in superior temporal sulcus

the  $p$ -value of the conjunction, i.e.  $p < 0.05$  FDR corrected.

### Behavioural data analysis

For the training data response times for the correct trials and the percentage of correct trials were computed for each subject. These dependent variables were collapsed over bird categories and submitted to a training session  $\times$  morph level analysis of variance (ANOVA) with repeated measures. Training session consisted of three levels (first, second, and third training session) and morph level consisted of eight levels (55, 60, 65, 70, 75, 80, 90, and 95 percent). All significant interactions were explored with additional ANOVA's for each training session. Greenhouse–Geisser corrections were applied when sphericity was violated, but uncorrected degrees of freedom are reported for ease of interpretation.

For the old/new task during scanning we computed percentage of correct responses and reaction times to the correct responses. The design matrix contains one missing level. Trained birds consisted of  $S_e S_t S_c$ ,  $D_e S_t S_c$ ,  $D_e D_t S_c$ , and  $D_e D_t D_c$  pairs. For the Novel birds we had  $S_e S_t S_c$ ,  $D_e S_t S_c$ , and  $D_e D_t D_c$  pairs, but no  $D_e D_t S_c$  pairs, because this is a dissociation that is only present after training. We submitted the overlapping levels to a training type (Trained, Novel)  $\times$  pair type ( $S_e S_t S_c$ ,  $D_e S_t S_c$ ,  $D_e D_t D_c$ ) analysis of variance with repeated measures. This way we established whether there was an effect of training and/or condition. Second, we performed paired  $t$ -tests to compare the pair types within the trained and novel birds with each other and we compared overlapping conditions between trained and novel bird pairs.  $T$ -tests were two-tailed and not corrected for multiple comparisons. Greenhouse–Geisser corrections were applied when appropriate.

## Results

### Behavioural data

#### Training

During training, subjects made two-alternative category responses for four bird types from each of 16 levels of morphing (Fig. 3.3*a* and *b*). Subjects

categorized the bird types in three training sessions. Performance increased significantly over training sessions [ $F(2,34) = 39.03$ ,  $p < 0.001$ ], see Figure 3.3*a*. Subjects' performance was already slightly above chance level during the first block of training [ $t(17) = 3.84$ ,  $p < 0.005$ ]. However, the first 40 trials of the first block were at chance level [ $t(17) = 0.34$ ,  $p = ns$ ]. Subjects were more accurate in categorizing birds with higher morph levels [ $F(7,119) = 132.984$ ,  $p < 0.001$ ]. Furthermore, the effect of morph level was highest in session three and lowest in session one, as revealed by a significant interaction between morph level and training session [ $F(14, 238) = 3.98$ ,  $p < 0.005$ ].

Reaction times decreased significantly over training sessions [ $F(2,34) = 10.47$ ,  $p < 0.001$ ], see Figure 3.3*a*. Reaction times were faster for birds consisting of higher morph levels [ $F(7,119) = 34.16$ ,  $p < 0.001$ ]. The effect of morph level was greatest in session three and lowest in session one, as revealed by a significant training session by morph level interaction [ $F(14,238) = 3.48$ ,  $p < 0.01$ ].

At the end of training, in the third training session, categorical perception was established, see Figure 3*b*. The difference between the correctly assigned category labels is larger for pairs with a 10% difference that crossed the category boundary (45 and 55 percent morph levels) than for pairs with an equal distance, that were from the same side of the category boundary (70 and 80 percent morph levels [ $t(17) = 18.95$ ,  $p < .0001$ ] and with 60 and 70 percent morph levels [ $t(17) = 18.68$ ,  $p < 0.0001$ ]).

#### Old/New Task

During scanning the subjects were presented with the birds, rapidly presented in pairs. Subjects performed an old/new task and indicated whether they remembered the second bird being present in the training session ('old') or not ('new'). Subjects had a relatively high rate of false alarms, they were biased to respond 'old' to new bird types, see Figure 3.3*c*. This was confirmed by a low  $d'$  (0.50 with a standard error of mean of 0.14).

We found that the task during scanning did not induce a category effect, but there was an effect of bird type on the behaviour. The percentage of correct responses was significantly greater for trained than novel bird pairs [ $F(1,17) = 16.79, p < 0.005$ ] and differed significantly between the different pair types [ $F(2,34) = 11.41, p < 0.001$ ]. The interaction between training and pair type was significant [ $F(2,34) = 3.53, p < 0.05$ ]. For the trained bird pairs,

the subjects responded ‘old’ more often to birds from a pair that consisted of exemplars from the same bird type than for exemplars of different bird types ( $S_e S_t S_c > D_e D_t D_c$  [ $t(17) = 4.26, p < 0.001$ ],  $D_e S_t S_c > D_e D_t D_c$  [ $t(17) = 3.78, p < 0.001$ ,  $S_e S_t S_c > D_e D_t S_c$  [ $t(17) = 5.05, p < 0.001$ ;  $D_e S_t S_c > D_e D_t S_c$  [ $t(17) = 4.37, p < 0.001$ ]). There was no significant difference between bird pairs containing exemplars from the same bird type ( $S_e S_t S_c > D_e S_t S_c$  [ $t(17) =$

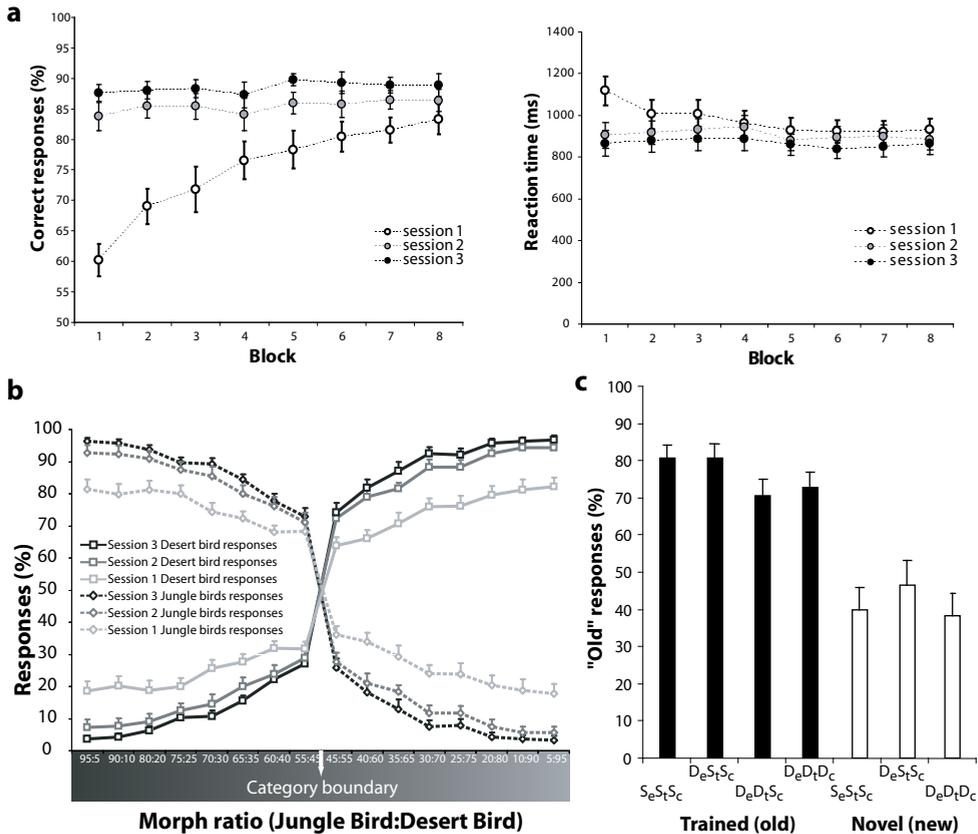


Figure 3.3

**Behavioural results. (A)** Results of categorization training. Plots present the percentage of correct responses and reaction times for each block of training for all three training sessions. **(B)** The percentage of birds that were categorized (y-axis) as either a desert bird (blue) or jungle bird (red) is shown as a function of the 16 morph ratios between jungle and desert birds (x-axis). **(C)** Results of the behavioural ‘old-new’ task during scanning. Percentage of ‘hits’ and ‘false alarm’ responses (y-axis) is plotted as a function of pair type (x-axis) for trained (‘old’) and novel birds (‘new’). Error bars present the standard error of mean.



Anatomical description	BA	x	y	z	mm <sup>3</sup>	t avg	Trained	Novel
							$S_e S_t S_c < D_e D_t D_c$	$S_e S_t S_c < D_e D_t D_c$
L precentral G	4	-21	-20	53	468	3.82	4.57***	1.02 <sup>ns</sup>
	4/6	-40	-3	30	1350	3.28	3.20**	2.63*
R precentral G	4/6	30	-16	46	98	3.50	4.63***	1.99 <sup>ns</sup>
L intraparietal S	7	-24	-55	51	244	3.59	4.03***	1.95 <sup>ns</sup>
R intraparietal S	7	27	-67	39	1774	3.58	4.55***	2.27*
L supramarginal G	40	-34	-32	34	106	3.49	4.27***	1.65 <sup>ns</sup>
R superior frontal G	8	4	22	45	269	3.48	2.91**	0.12 <sup>ns</sup>
R middle frontal G	4/6	29	14	43	316	3.65	3.21**	2.79*
R inferior frontal G	44	47	12	29	1233	3.23	2.94**	0.82 <sup>ns</sup>
R caudate nucleus		18	-14	28	160	3.43	4.30***	0.53 <sup>ns</sup>
L caudate nucleus		-15	-21	24	159	3.51	5.24***	0.10 <sup>ns</sup>
R superior temporal S	22/42	44	-35	9	2262	3.36	4.71***	0.12 <sup>ns</sup>
L superior temporal S	22	-47	-41	6	1039	3.38	3.52**	0.02 <sup>ns</sup>
L ant superior temporal S	21	-55	-14	-9	1223	3.22	2.66*	1.50 <sup>ns</sup>
R middle occipital G	19	25	-81	12	621	3.60	5.22***	0.30 <sup>ns</sup>
Cuneus	18	4	-79	8	4097	3.65	3.28**	0.02 <sup>ns</sup>
L lingual G	19	-9	-46	3	1546	3.69	4.34***	1.02 <sup>ns</sup>
R lingual G	19	8	-55	-2	489	3.56	3.66**	0.52 <sup>ns</sup>
R lingual G	19	19	-83	-12	1378	3.64	3.50**	0.96 <sup>ns</sup>
L lateral occipital G	37	-37	-66	-9	10149	3.58	5.43***	1.18 <sup>ns</sup>
R lateral occipital G	37	44	-59	-10	5181	3.34	5.09***	0.58 <sup>ns</sup>
L fusiform G	36/37	-36	-41	-19	843	3.36	6.24***	1.01 <sup>ns</sup>
R fusiform G	36/37	37	-38	-20	520	3.29	4.22***	0.58 <sup>ns</sup>

\* $p < 0.05$ , \*\* $p < 0.01$ , \*\*\* $p < 0.001$

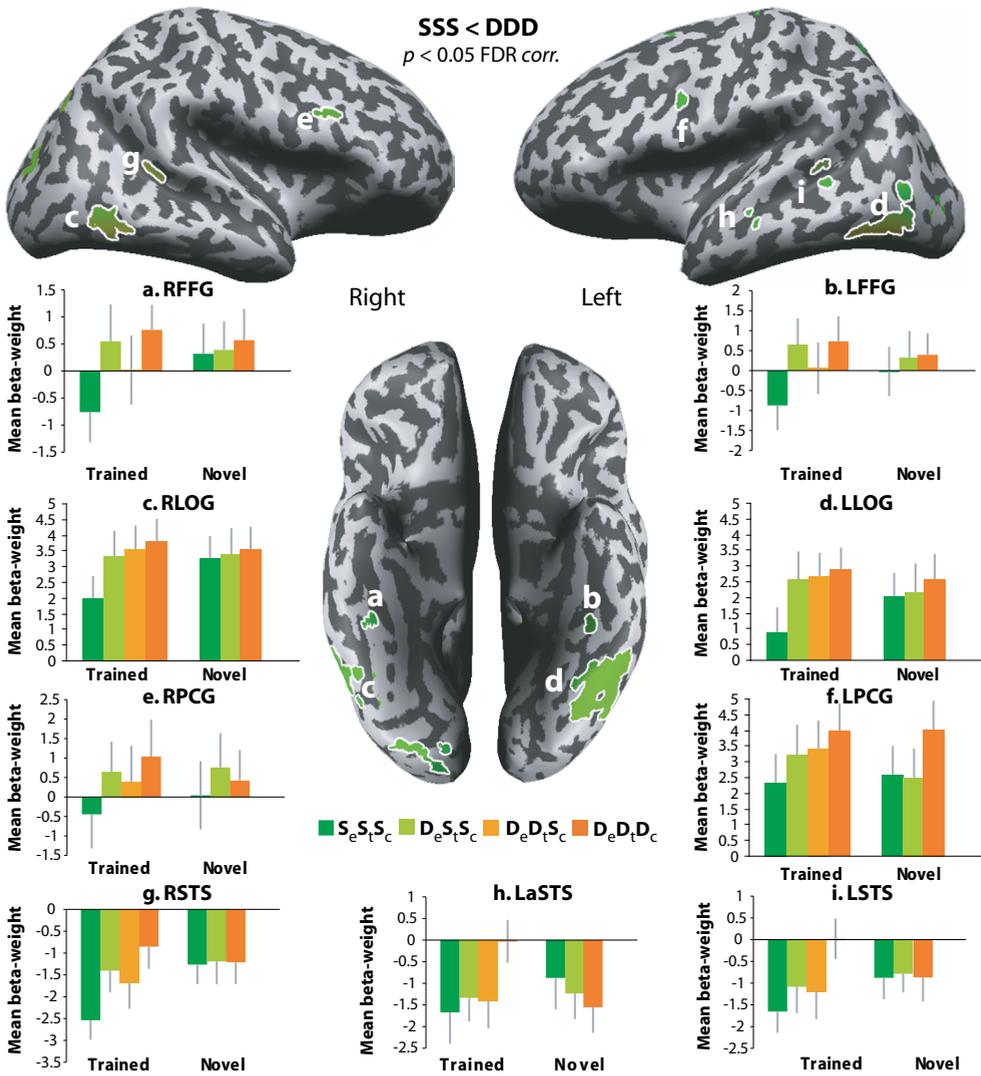
**Table 3.1**

Regions showing an adaptation effect for trained bird pairs consisting of the same exemplars ( $S_e S_t S_c$ ). Mean Talairach coordinates, volume in mm<sup>3</sup>, and averaged  $t$ -values for regions showing an adaptation effect for trained  $S_e S_t S_c$  bird types at  $p < 0.05$  (*corr.*). In addition, we present  $t$ -values obtained in a random effects ROI analysis ( $df = 17$ ) on the subject-averaged beta weights comparing bird pairs consisting of the same exemplars with bird pairs consisting of birds from different categories ( $S_e S_t S_c < D_e D_t D_c$ ) for both trained and novel birds. Ant: anterior L: left, R: right, G: gyrus, S: Sulcus

the subject-averaged beta-weights of  $S_e S_t S_c$  and  $D_e D_t D_c$  pairs were compared for trained and novel birds separately, see Table 3.1. We tested whether these areas showed a training-induced selectivity

i.e. adaptation that is only present for trained bird types, or whether these areas are involved in general shape representation i.e. showing also adaptation for novel birds. In addition we also tested if these areas

### Category representation in superior temporal sulcus



**Figure 3.5**

Brain regions showing adaptation following  $S_e S_t S_c$  bird pairs (trained and novel birds collapsed,  $p < 0.05$  corr.) presented on Talairach-normalized inflated left and right hemispheres. Top: lateral view, bottom: ventral view. Histograms present mean beta-weights for  $S_e S_t S_c$  (dark green),  $D_e S_t S_c$  (light green),  $D_e D_t S_c$  (orange), and  $D_e D_t D_c$  (dark orange) bird pairs for both novel and trained bird types (x-axis). LFFG: left fusiform gyrus (Talairach coordinates of centre of mass: -36, -41, -19), RFFG: right fusiform gyrus (37, -38, -20), LLOG: left lateral occipital gyrus (-37, -66, -9), RLOG: right lateral occipital gyrus (44, -59, -10), LPCG: left precentral gyrus (-40, -3, -30), RPCG: right precentral gyrus (47, 12, 29), LaSTS: left anterior superior temporal sulcus (-55, -14, -9), LSTS: left superior temporal sulcus (-47, -41, 6), RSTS: right superior temporal sulcus (44, -35, 9).

showed category selectivity, i.e. selectivity for birds belonging to the same category. The results confirm our previous analysis. As expected all regions showed a significant adaptation effect for trained bird pairs that contained the same exemplars from the same bird type and the same category ( $S_e S_e S_e$ ) relative to bird pairs consisting of different exemplars from different bird types and different trained categories ( $D_e D_e D_e$ ). In addition, adaptation for novel bird pairs consisting of the same exemplars ( $S_e S_e S_e$ ) was present in left precentral gyrus, right middle frontal gyrus and right intraparietal sulcus, and this adaptation effect was not significantly different from the adaptation to trained birds. In the occipitotemporal regions, no adaptation was present for novel bird pairs from the  $S_e S_e S_e$  conditions, the adaptation effects for trained  $S_e S_e S_e$  bird pairs were significantly greater than for novel  $S_e S_e S_e$  bird pairs. The only area that showed adaptation for  $D_e S_e S_e$  and  $D_e D_e S_e$  for the trained bird types was the left anterior superior temporal sulcus ( $D_e S_e S_e$ : [ $t(17) = 2.39, p < 0.005$ ],  $D_e D_e S_e$ : [ $t(17) = 3.18, p < 0.01$ ]).

### Category-selectivity

Although  $S_e S_e S_e$  bird pairs inherently include both repetitions of the same bird type and category, of primary interest was whether bird pairs consisting of different exemplars and different bird types, but still belonging to the same bird category ( $D_e D_e S_e$ ) would produce reduced activity in comparison to two birds from different categories ( $D_e D_e D_e$ ). To test directly for regions showing category-selectivity we used a conjunction analysis to find regions that showed adaptation to  $S_e S_e S_e$ ,  $D_e S_e S_e$  and  $D_e D_e S_e$  bird pairs relative to  $D_e D_e D_e$  bird pairs [ $(S_e S_e S_e < D_e D_e D_e) \cap (D_e S_e S_e < D_e D_e D_e) \cap (D_e D_e S_e < D_e D_e D_e)$ ], see Figure 3.6. These results confirmed the findings from our ROI analysis. Two regions in the left superior temporal sulcus showed category-selectivity. They showed adaptation for birds from the  $S_e S_e S_e$ ,  $D_e S_e S_e$ , and  $D_e D_e S_e$  condition relative to birds from the  $D_e D_e D_e$  condition. In the left superior temporal sulcus responses were smaller for  $S_e S_e S_e$  [ $t(17) = 3.50, p < 0.005$ ],  $D_e S_e S_e$  [ $t(17)$

$= 2.34, p < 0.05$ ], and  $D_e D_e S_e$  bird pairs [ $t(17) = 2.96, p < 0.01$ ] compared to  $D_e D_e D_e$  bird pairs. In the left anterior temporal sulcus responses were also smaller for  $S_e S_e S_e$  [ $t(17) = 2.43, p < 0.05$ ],  $D_e S_e S_e$  [ $t(17) = 2.83, p < 0.05$ ], and  $D_e D_e S_e$  bird pairs [ $t(17) = 3.51, p < 0.005$ ] than for  $D_e D_e D_e$  bird pairs. In addition we investigated whether the adaptation scores differed between the different pair types. We found no differences in adaptation scores between the different conditions (left superior temporal sulcus:  $S_e S_e S_e > D_e S_e S_e$  [ $t(17) = 0.37, p = ns$ ];  $S_e S_e S_e > D_e D_e S_e$  [ $t(17) = 0.39, p = ns$ ];  $D_e S_e S_e > D_e D_e S_e$  [ $t(17) = 0.02, p = ns$ ]; left anterior temporal sulcus  $S_e S_e S_e > D_e S_e S_e$  [ $t(17) = 0.30, p = ns$ ];  $S_e S_e S_e > D_e D_e S_e$  [ $t(17) = 0.35, p = ns$ ];  $D_e S_e S_e > D_e D_e S_e$  [ $t(17) = 0.81, p = ns$ ]).

No adaptation effect was found for novel birds, responses to novel  $S_e S_e S_e$  and  $D_e S_e S_e$  bird pairs did not differ in left superior temporal sulcus [ $S_e S_e S_e$   $t(17) = 0.15, p = ns$ ;  $D_e S_e S_e$   $t(17) = 0.08, p = ns$ ] and left anterior temporal sulcus [ $S_e S_e S_e$   $t(17) = 1.04, p = ns$ ;  $D_e S_e S_e$   $t(17) = 0.58, p = ns$ ].

### Discussion

In the present fMRI study we investigated the neural mechanisms that underlie experience-related formation of object categories. Subjects learned to categorize four artificial bird types into two bird categories. Behavioural training results showed that after three days of training, subjects were indeed successful in categorizing the birds. One day after training subjects were scanned using a rapid fMRI adaptation paradigm. We used the adaptation approach to investigate changes in neural tuning as a function of category learning. We hypothesized that category training would induce neurons in the occipitotemporal cortex and superior temporal sulcus to display selectivity for trained but not for novel bird stimuli. This is indeed what we found.

In the fusiform gyrus adaptation occurred for identical exemplars of trained bird types, but not for identical exemplars of novel bird types. Similar adaptation effects were found in the bilateral lateral occipital gyri. These results show that training to

## Category representation in superior temporal sulcus

3

categorize birds induces neural sensitivity to small shape changes, whereas for novel birds no differential neural responses between two similar looking exemplars of the same bird type were observed. These results are in line with our previous fMRI results on the involvement of the right fusiform gyrus in category formation (van der Linden et al., 2008). We found that after visual category training, responses in the right fusiform gyrus were selectively increased for bird types for which a discrete category-boundary was established. Importantly, this increase was not observed for visually similar birds to which subjects were exposed during training but for which no category-boundary was learned. In addition, we found that the increase was linearly related to the distance to the category boundary: the further away from the boundary, the higher the responses. These results suggested that visual category training leads to an increase in selectivity for visual features that are relevant for categorization. The present adaptation results provide more specific evidence for this hypothesis. Category training induced an increase in neural selectivity for fine-grained visual object features. The increased selectivity might be attributed to an increase in neural tuning to the visual features that are relevant for categorization.

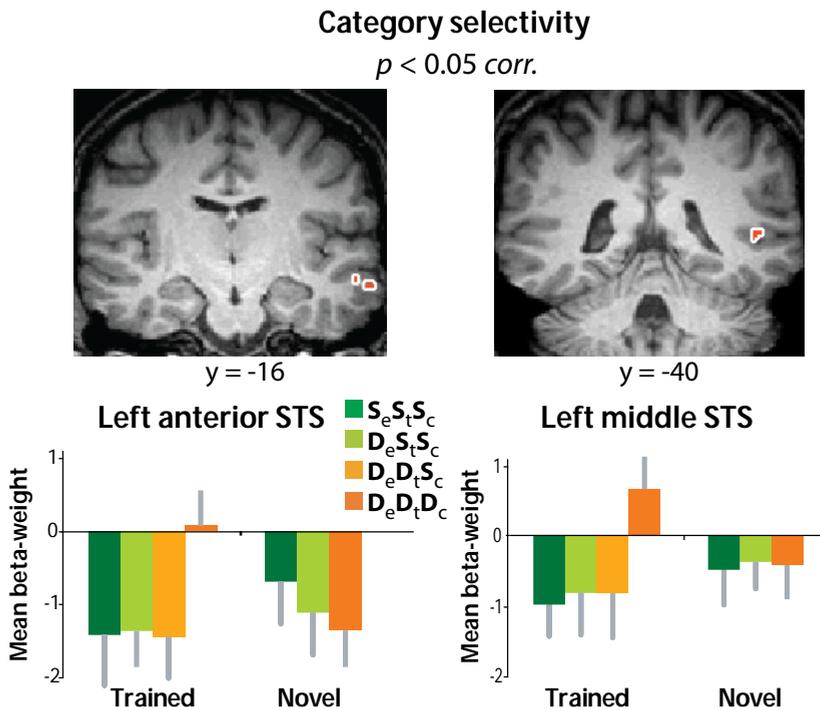
Our finding is different from the finding of Jiang et al. (2007), who found no adaptation in the middle fusiform gyrus for pairs of cars that consisted of the same exemplars during a shape-displacement task, neither before nor after training. However, our results agree with other fMRI studies that found an effect of experience on response strength of the right middle fusiform gyrus to objects of expertise (Gauthier et al., 2000; Rhodes et al., 2004; Xu, 2005) or to novel objects that subjects trained with (Gauthier et al., 1999; Weisberg et al., 2007). In addition, our results are in line with electrophysiological recordings from the inferior temporal cortex in monkeys suggesting that object category formation is mediated by a learning-induced neuronal stimulus selectivity (Freedman et al., 2003, 2005, 2006).

The fusiform gyrus showed adaptation only to

the repetition of identical trained birds. A relatively small shape change (20%) led to a release of adaptation. This indicates that the right middle fusiform gyrus shows a high level of perceptual specificity. This is in line with other fMRI adaptation studies showing that the fusiform gyrus is narrowly tuned for shapes and shows very little invariance (Jiang et al., 2006; Gilaie-Dotan and Malach, 2007). Future research should be able to elucidate which amount of shape change will still give rise to an adapted response and at which level a release of adaptation takes place. Such an investigation, as has been used for face stimuli (Loffler et al., 2005; Gilaie-Dotan and Malach, 2007), could potentially give more information on the underlying neuronal representation of non-face objects.

In accordance with Jiang et al. (2007) we found adaptation for identical stimuli in the lateral occipital gyrus. This observation held for trained but not for novel birds, in line with Jiang et al.'s finding that there was no adaptation for identical cars in a pre-training scan. Just like Jiang et al. we found evidence for narrow shape-tuning in the lateral occipital gyrus. A small change in the stimulus leads to a release of adaptation. The lateral occipital gyrus has also been found to show an increase in response strength after discrimination training with novel objects (Op de Beeck et al., 2006). Both the fusiform and lateral occipital gyrus showed narrow shape-tuning, and showed no effect when two exemplars that belonged to the same bird type or category were presented. We found no other areas that displayed sensitivity to the repetition of two exemplars from the same perceptual bird type. Possibly the training procedure was too short to induce such a category effect in the occipitotemporal areas, or the training did not facilitate the learning of the category boundary between perceptual bird types. Jiang et al. do not report having investigated brain regions that show sensitivity to car type.

Importantly, we did find a region that responded in a category-specific manner in the absence of an explicit categorization task. The task we used had the function to keep subjects attentive. Without

**Figure 3.6**

Brain regions showing a category-selective response ( $p < 0.05 \text{ corr.}$ ) are presented on coronal slices corresponding to the location of regions h and i in Figure 3.5. The graphs present the mean beta-weights from the left superior temporal sulcus (Talairach coordinates of centre of mass: -46, -40, 6) and left anterior superior temporal sulcus (-59, -16, -11).

such a task the adaptation effects might have been more difficult or impossible to detect. In this general sense it is possible that the tasks had an influence on STS adaptation. Crucially, however the task did not require application of the trained categories hence the fact that we observed effects of the trained categories cannot be attributed to a task requirement to use these categories as in the study by Jiang et al (2007). Our task alone cannot explain that the left superior temporal sulcus (STS) showed adaptation when two birds from the same trained category were presented but release from adaptation for the trained bird types for objects belonging to different categories. This dissociation could also not be ex-

plained by perceptual similarities or dissimilarities, because the physical difference between birds from the same and opposite sides of the category boundary was equal.

This finding provides evidence for the STS being involved in the representation of category information. Neuroimaging studies have shown that regions in the STS are responsive to biological stimuli such as faces, human bodies (Puce et al., 1995; Kanwisher et al., 1997), and animals (Chao et al., 1999; Chao et al., 2002). For face-stimuli the STS has been found to respond in a category-selective way to identity (Rotshtein et al., 2005) and emotions (Furl et al., 2007). Therefore, the role of the

## Category representation in superior temporal sulcus

STS in representing category information might be limited to biologically relevant stimuli. This would also explain why Jiang et al. (2007), who used non-natural stimuli found no adaptation effect for cars belonging to the same category. Alternatively, our training paradigm might also have led to a different encoding of the category information than the Jiang et al. paradigm. In our experiment subjects learned categories by labeling birds, whereas in Jiang et al.'s experiment subjects learned by discrimination. The emphasis in discrimination is on the differences that exist between exemplars by directly comparing one exemplar to the other. Discrimination is relative (always compared to another object) while labeling is absolute ('desert' or 'jungle'). Labeling category members facilitates the formation of associations between different exemplars within a category. The STS has been found to be involved in associating familiar sounds and shapes to facilitate crossmodal object representations (Beauchamp et al., 2004; Hein et al., 2007). Moreover, the STS has been suggested to play an important role in associative learning, linking different types of stimuli regardless of the modality (Tanabe et al., 2005).

In Jiang et al.'s (2007) study the prefrontal cortex responded in a category-selective manner, but only when subjects performed an explicit categorization task. Using intracranial recordings in monkeys it has also been shown that the prefrontal cortex is involved in categorization (Freedman et al., 2001), and more specifically that the prefrontal cortex is involved in explicit category decisions based on functional or behavioural relevance (Freedman et al., 2003). In the present study, using an old-new task, we found no category-selectivity in the prefrontal cortex which confirms that the prefrontal cortex may only be involved during active categorization.

We propose that the model for perceptual categorization as outlined by Jiang et al. (2007) could be extended with our data so that it includes conceptual categorization as well. As a result of training the occipitotemporal cortex becomes sensitive to those features that are relevant for perceptual categorization. This is also confirmed by monkey

electrophysiological recordings (Sigala and Logothetis, 2002), where neurons became more sensitive to features relevant for categorization compared with features that were irrelevant for categorization. This narrow shape-tuning allows for discrimination between highly similar objects, but does not necessarily imply a category-selective representation. Categorization of objects extends beyond their physical differences in appearance and takes into account those features that are common in a category. The STS seems to be a candidate area to fulfill this role within the model. We found a category-selective response in the STS for stimuli that subjects learned to categorize. The STS is located on the border of visual and auditory association areas and receives input from visual as well as auditory cortex. The STS is widely regarded as a multisensory binding site. Recently, Hocking and Price (2008) concluded that the STS is involved in conceptual matching of stimuli regardless of their modality. Although our results are limited to the visual modality alone, they suggest that the STS is involved in conceptually linking different objects within a category allowing for true category-specificity that extends beyond mere physical similarities of objects.

Jiang et al. (2007) propose that within their model the prefrontal cortex receives input from the occipitotemporal cortex and is involved in explicit category decisions. We cannot confirm this with our data, but monkey electrophysiological recordings also support this role for the prefrontal cortex (Freedman et al., 2001, 2002, 2003). Jiang et al. (2007) also speculate that the prefrontal cortex could exert a top-down influence on the responses in occipitotemporal cortex. Modeling studies also suggest that the prefrontal cortex might be involved during learning by having a top-down influence that enhances the selectivity of the neurons in occipitotemporal cortex encoding the behaviourally relevant features of the stimuli (Rougier et al., 2005; Szabo et al., 2006).

To conclude, adaptation effects in occipitotemporal cortex, i.e. the fusiform and lateral occipital gyrus, showed that these regions are very sensitive to

perceptual stimulus differences. This suggests that neurons in occipitotemporal cortex are narrowly tuned to specific object-features and do not generalize across different objects from the same category. Moreover, this sensitivity is training-induced, it arose as a result of experience with the birds and was not present for very similar novel birds. In addition, we found neuronal populations in superior temporal sulcus to show a high level of invariance to perceptual dissimilarities between birds, displaying a selective response to different category members. This indicates that neurons in the superior temporal sulcus formed associations between different stimuli and generalized across objects within a category. Together the occipitotemporal cortex and the superior temporal sulcus have the properties suitable for a system that can both generalize across stimuli and discriminate between them.

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## Category representation in superior temporal sulcus

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## **Category training induces crossmodal object representations in the adult human brain**

This chapter is based on:  
van der Linden, M., van Turenout, M., & Fernández, G. (2011). Category training induces crossmodal object representations in the adult human brain. *Journal of Cognitive Neuroscience*, 23(6), 1315-1331

## Crossmodal category representation

The formation of crossmodal object representations was investigated using a novel paradigm that was previously successful in establishing unimodal, visual category learning in monkeys and humans. The stimulus set consisted of six categories of bird shapes and sounds that were morphed to create different exemplars of each category. Subjects learned new crossmodal bird categories using a 1-back task. Over time the subjects became faster and more accurate in categorizing the birds. After three days of training, subjects were scanned while passively viewing and listening to trained and novel bird types. Stimulus blocks consisted of bird sounds only, bird pictures only, matching pictures and sounds (crossmodal congruent), and mismatching pictures and sounds (crossmodal incongruent). fMRI data showed unimodal and crossmodal training effects in the right fusiform gyrus. In addition, the left superior temporal sulcus showed crossmodal training effects in the absence of unimodal training effects. Importantly, for both the right fusiform gyrus and the left superior temporal sulcus the newly formed crossmodal representation was specific for the trained categories. Learning did not generalize to incongruent combinations of learned sounds and shapes, their response did not differ from the response to novel crossmodal bird types. Moreover, responses were larger for congruent than for incongruent crossmodal bird types in the right fusiform gyrus and superior temporal sulcus providing further evidence that categorization training induced the formation of meaningful crossmodal object representations.

## 4

### Introduction

We can rapidly discriminate a pigeon from a chicken. By looking at it, but also by listening to it. The image and sound of an object are tightly linked and provide clues for its categorization. In this study we investigated the formation of crossmodal object representations in the human brain resulting from crossmodal category learning.

Increased visual experience with object categories has been linked to neuronal changes in category-selective areas in occipitotemporal cortex. Specifically, learning to discriminate objects from a novel category modulates activity in the right middle fusiform gyrus (Gauthier, Tarr, Anderson, Skudlarski, & Gore, 1999; van der Linden, Murre, & van Turennout, 2008; Weisberg, van Turennout, & Martin, 2007) and lateral occipital gyrus (Op de Beeck, Baker, DiCarlo, & Kanwisher, 2006). Activity in occipitotemporal cortex has also been found to be selectively enhanced for objects from a category with which subjects have extensive experience, such as birds and cars (Gauthier, Skudlarski,

Gore, & Anderson, 2000; Xu, 2005), or Lepidoptera (Rhodes, Byatt, Michie, & Puce, 2004). In a previous study (van der Linden, van Turennout, & Indefrey, 2010) we found the superior temporal sulcus to be involved in the formation of associations between perceptually different exemplars within a category.

For the formation of crossmodal object representations the role of association also seems crucial. Early in life we need to learn which shapes and sounds of objects belong together. Indeed, the superior temporal has also been found to be involved in associating familiar sounds and shapes to facilitate crossmodal object representations. Common crossmodal objects, such as animals and tools, elicited enhanced responsiveness of posterior superior temporal sulcus compared to unimodal stimuli (Beauchamp, Lee, Argall, & Martin, 2004). Crossmodal categories that are acquired later in life, such as letters and speech sounds, were also found to activate the superior temporal gyrus and sulcus (van Atteveldt, Formisano, Goebel, & Blomert, 2004;

van Atteveldt, Formisano, Blomert, & Goebel, 2007; van Atteveldt, Formisano, Goebel, & Blomert, 2007). Recently, it became clear that familiar crossmodal objects activated the superior temporal sulcus, but not novel artificial crossmodal objects, indicating that audiovisual integration is influenced by familiarity (Hein et al., 2007). Therefore, it seems likely that crossmodal representations, such as found in the superior temporal sulcus, can be shaped as a result of experience with crossmodal objects. This has been tested by Naumer et al. (2009). After training subjects to associate eight nonsense objects with sounds they found more activity in frontal, parietal, and cingulate areas of the brain compared to pre-training.

However, showing that an area responds more to crossmodal trained than to crossmodal pre-training or novel stimuli does not automatically mean that this region is also involved in a meaningful crossmodal representation. It could simply mean that mere exposure alone is enough to induce plasticity in these areas. If crossmodal integration is successful and the representation is meaningful the brain regions involved should show a dissociation between congruent (sound and shape match, meaningful) and incongruent (sound and shape do not match, meaningless) crossmodal stimuli. Therefore, congruency effects are usually investigated to make inferences about crossmodal integration and representations (Calvert, Campbell, & Brammer, 2000; Taylor, Moss, Stamatakis, & Tyler, 2006; van Atteveldt et al., 2004). Naumer et al. (2009) reported congruency effects for newly learned crossmodal objects in inferior frontal cortex and posterior middle temporal gyrus. The interplay of learned associations between vision and sound has been subject of a number of fMRI studies (for a review see (Amedi, von Kriegstein, van Atteveldt, Beauchamp, & Naumer, 2005; G. Calvert & Lewis, 2004)). However, there has so far been no direct investigation of changes that occur in the brain as a result of acquiring entirely new crossmodal object categories.

In the present study we used a paradigm that has

successfully been applied to visual object category learning in human subjects (Jiang et al., 2007; van der Linden et al., 2008; van der Linden et al., 2010) and monkeys (Freedman, Riesenhuber, Poggio, & Miller, 2001, 2003). Subjects will learn new crossmodal categories of artificial birds (see Figure 1). The novelty in the present study is that we not only morphed the birds in the visual modality but also in the auditory modality. The boundary between the categories is expressed by information from both auditory and visual modalities. Our categories are perceptual-based: Birds that have the same shape and sound belong in the same category. We expect that at the end of training crossmodal object representations have been formed. Training-induced improvements in unimodal object recognition usually result in increased cortical responses to the trained compared to responses to novel objects (Gauthier et al., 1999; Moore, Cohen, & Ranganath, 2006; Op de Beeck et al., 2006; van der Linden et al., 2008; Weisberg et al., 2007). We expect regions that are involved in training-dependent crossmodal representations to show more activity for trained crossmodal congruent birds than for novel crossmodal birds. However, some training-related decreases in activation as a result of repeated stimulus exposure can also occur (Grill-Spector, Henson, & Martin, 2006). Regions showing training-related increases in activity should enclose at least the right fusiform gyrus and the superior temporal sulcus. Importantly, if these regions are involved in a meaningful representation of crossmodal objects they should show no training effect for incongruent stimuli. Moreover, these areas should show a congruency effect, dissociating between congruent and incongruent crossmodal bird stimuli (Doehrmann & Naumer, 2008). In addition, the inferior frontal gyrus will likely show the opposite pattern of response. The inferior frontal gyrus' responses are modulated by the meaningfulness (or semantics) of crossmodal stimuli (Doehrmann & Naumer, 2008) and usually shows a higher response to incongruent stimuli (Hein et al., 2007; Belardinelli et al., 2004).

### Materials and Methods

#### Subjects

Sixteen healthy participants (5 males, mean age 21.6 years, range 18-26) participated in the experiment. All subjects had normal or corrected-to-normal vision and no hearing problems. Subjects were paid for their participation. All subjects gave written informed consent.

#### Stimuli

##### Shapes

The same stimuli were used as in Van der Linden et al. (2008; 2010). The stimuli consisted of pictures of computer-generated birds that were constructed in a 3D model manipulation program (Poser 4 by Curious Labs, Santa Cruz, CA). First, six prototype birds were constructed from a base-bird (Songbird Remix by Daz3d, Draper, UT), see Fig 4.1a. Parts of the bird that were manipulated included its trunk, tail, beak, head shape, cheeks, brow, and eye position. Next, each of the six birds was morphed with all other birds. The category boundary was set at 50 % (Fig. 4.1c). As a result, stimuli that were close to, but on opposite sides of the category boundary were visually similar, but belonged to different categories. Morphing happened smoothly between corresponding points on the birds. Each bird was colourless, rendered under the same lighting and camera settings, and exported as an image. Images had identical colour, shading and scale. The images measured 300 by 300 pixels in the training sessions and were slightly reduced in size (250 by 250 pixels) in the scanning sessions.

##### Sounds

For the auditory stimuli six sound fragments were taken from real bird calls, see Table 4.1. These sound fragments were converted to wave files with a sampling rate of 44 KHz and multiplied with a Gaussian, see Figure 1b. The length and loudness of the sounds was matched, each sound measured 500 ms and the loudness was set to 80 dB for all wave files. Finally, the wave files were morphed with each other in the same ratios as the visual stimuli using

the formula: morphed sound A:B = (morph ratio \* amplitude soundA) + ((1-morph ratio) \* amplitude sound B), see Figure 1c. All described manipulations were done using Praat software (<http://www.praat.org>).

English	Latin
Northern Pintail	<i>Anas acuta</i>
European Scops Owl	<i>Otus scops</i>
Long-eared Owl	<i>Asio otus</i>
Meadowlark	<i>Sturnella</i>
Eagle Owl	<i>Bubo bubo</i>
Little Owl	<i>Athene noctua</i>

**Table 4.1**

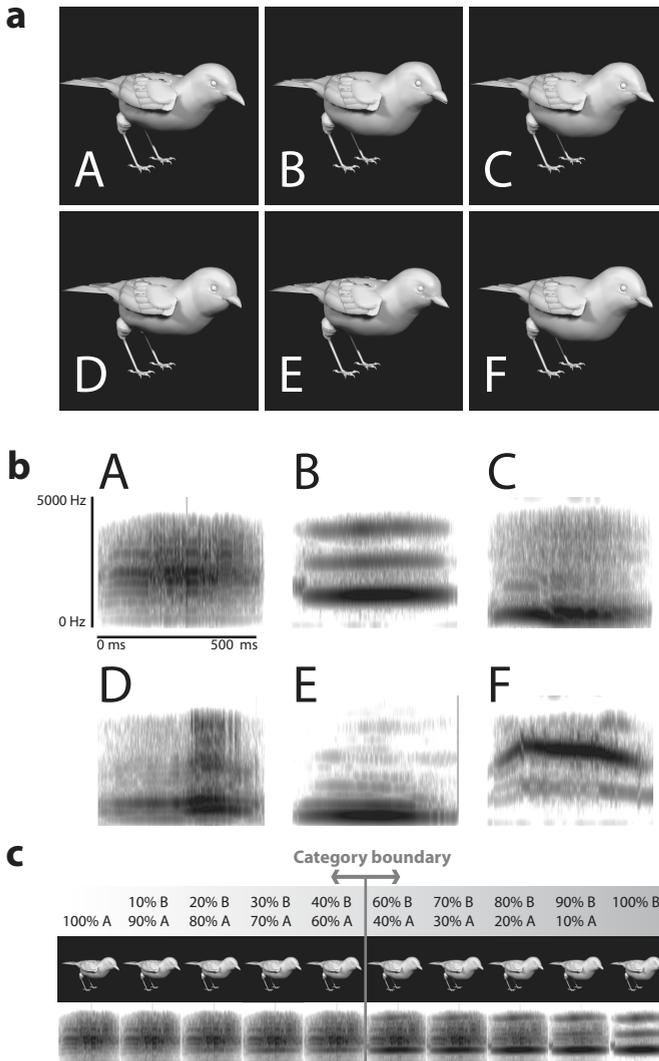
Overview of the birds whose calls were used in the experiment.

#### Procedure

Bird shapes and sounds were paired to create cross-modal bird stimuli. The pairing of sounds and shapes was arbitrary. The morph ratio between shape and sound always corresponded (i.e. bird type A70% morphed with 30%B would also have the sound of 70% A morphed with 30% B). Three bird types were assigned to be trained and three bird types acted as novel controls during scanning. The bird types constituting the trained and novel conditions were counterbalanced across subjects. Birds were only morphed with each other within a condition, so if the trained bird types were A, B, and C the exemplars would consist of morphs of 55, 65, 70, 80, and 95 percent of A:B, B:A, A:C, C:A, B:C, and C:B.

#### Training

Training included three sessions on separate days, each of which lasted approximately one and a half hours. During a training session, subjects sat comfortably in a soundproof cabin in front of a 19" computer screen to view the bird shapes. Subjects

**Figure 4.1**

**Construction of the stimulus set.** (A) Pictures of non-existing but plausible bird shapes were constructed in a 3D model manipulation program. From a base-bird we derived six colourless prototype birds (A, B, C, D, E, F) that differed in trunk, tail, beak, head shape, cheeks, brow, and eye position. Each bird was rendered under the same lighting and camera settings to make sure that shading and scale was identical for all birds. (B) Spectrogram of the bird sounds corresponding to the bird shapes. (C) Exemplars and their corresponding sounds were created by systematically morphing each of the six prototype birds with all other birds. Shown is an example of morphing the shapes (top) and sounds (bottom) of bird type A with bird type B at morph ratios of 90:10, 80:20, 70:30, 60:40. The category boundary was set at 50:50.

wore a headphone to listen simultaneously to the bird sounds. During training they performed a 1-back task on a series of crossmodal bird stimuli (Figure 4.2a), in which they indicated with the index and middle finger of their right hand whether two consecutive birds were the same bird type or not. Subjects received feedback to their responses consisting of a printed text centered on the screen in coloured Arial font in size 16 (green: “right”,

red: “wrong”, and yellow: “too late”). During one block of training two crossmodal bird types would be presented. There were 10 exemplars (each bird type was morphed at five morph levels with the other two bird types) for each of the three trained bird types. Each exemplar was presented 45 times per training session. The proportion of birds from the same and different categories was fifty-fifty. In each trial, stimuli were presented for 1000 ms after

## Crossmodal category representation

which a response could be given during 2250 ms. Feedback was presented for 250 ms. Stimuli onset asynchrony was 4000 ms. A training session consisted of 9 blocks of 100 trials. Each block of 100 trials was followed by a small self-paced pause after which a subject could continue the experiment by pressing a button. After five blocks of training the subjects had a longer break during which they left the sound-proof cabin and drank coffee or tea.

### **fMRI scanning session**

Subjects participated in an fMRI scanning session one day after training. During scanning, subjects were presented with trained and novel bird stimuli in blocks (Figure 4.2*b*). Stimulus blocks consisted of bird sounds only, bird shapes only, matching pictures and sounds (crossmodal congruent), and mismatching pictures and sounds (crossmodal incongruent). Bird exemplars consisted of morph levels that were different from the morph levels that the subjects trained with to avoid simple repetition effects. Morph levels were 60, 75, and 90% and were presented pseudorandom within the blocks. Each block contained 9 bird stimuli at 3 morph levels. Each image was presented for 1 second and each sound for 500 ms (with a simultaneously presented fixation cross of 1 s) with a mean inter-stimulus-interval of 2 s (varying random between 1500 and 2500 ms).

Experimental blocks lasted 25 s and alternated with rest periods of 10 s for sampling the baseline. Blocks were presented ten times per condition in pseudorandom order. For each morph level there were 30 trials. Total scan time was 47 minutes. Subjects were instructed to view and listen attentively to the birds. We were interested in investigating the automatic activation of cortical object representations, therefore we have chosen a passive paradigm to minimize task-related activation. Task instructions have an effect on the automatic integration of sound and percept (de Gelder & Bertelson, 2003) and can even overrule it (Nienke M. van Atteveldt et al., 2007). A passive task is widely used to investigate automatic processing of unimodal and

crossmodal stimuli (Belardinelli et al., 2004; Calvert et al., 2000; Hein et al., 2007; van Atteveldt et al., 2004), also for studies that combined the scanning session with a learning phase (Naumer et al., 2009).

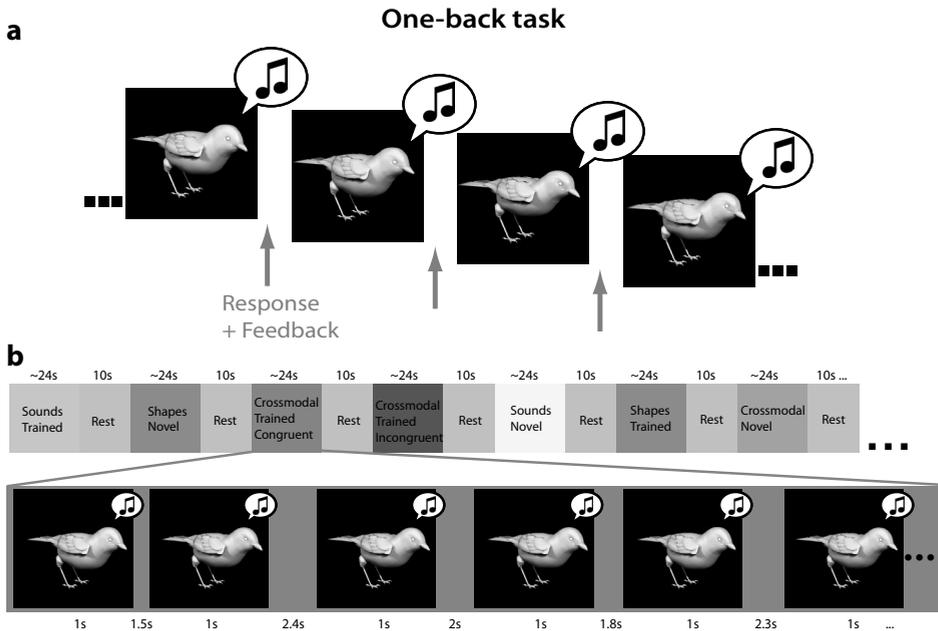
During scanning subjects' heads were fixed with cushions attached to the head coil. An LCD projector projected mirror-reversed stimuli on a screen at the end of the bore, which the subject was able to see through a mirror attached to the head coil. Auditory stimuli were presented using headphones (Commander XG, Resonance Technology Inc., Northridge, CA) with padding that also attenuated gradient noise. Before starting the experiment the sound level was determined by exposing the subject to the gradient noise accompanying epi-scanning and presenting the bird sounds simultaneous. The subjects indicated at which sound level they could clearly hear the bird sounds. This sound level was then used throughout the experiment.

### **Imaging parameters**

For each subject, 1300 whole-brain images (echo-planar imaging, 32 slices, 3 mm thick with 10% gap, repetition time = 2170 ms, voxel size = 3×3×3 mm, echo time = 30, flip angle = 75°, field of view = 19.2 cm, matrix size = 64×64) were acquired on a 3T whole body MR scanner (Magnetom TIM TRIO by Siemens Medical Systems, Erlangen, Germany). In addition, a high resolution structural T1-weighted 3D magnetization prepared rapid acquisition gradient echo sequence image was obtained after the functional scan (192 slices, voxel size = 1×1×1 mm).

### **Behavioural data analysis**

Mean response times for the correct trials and the mean proportion of correct trials were computed for each subject. These dependent variables were submitted to a training session × morph level multivariate analysis of variance (MANOVA) with repeated measures. Training session consisted of three levels (first, second, and third training session) and morph level consisted of five levels (55, 65, 70,

**Figure 4.2**

**Training and fMRI paradigms. (A)** During the training sessions participants were presented with a series of crossmodal bird exemplars. They performed a 1-back task in which they indicated whether two consecutive birds were the same type or not. Category learning was established by providing corrective feedback after each trial. **(B)** In the post-training fMRI scanning session the bird types were presented in blocks of ten exemplars at mixed morph ratios of 60:40, 75:25, and 90:10. Stimulus blocks consisted of bird sounds only, bird pictures only, matching pictures and sounds (crossmodal congruent), and mismatching pictures and sounds (crossmodal incongruent). Blocks consisted of either trained or novel birds. Each bird was presented for 1 second with a mean inter-stimulus-interval of 2 s. Experimental blocks alternated with rest periods of 10 s. Subjects were instructed to view and listen to the birds attentively.

80, and 95%). Differences between training sessions were explored with multivariate analyses of variance with two levels for training session and five levels for morph level. We investigated the differences within training sessions by examining the effect of block on accuracy with a session  $\times$  block  $\times$  morph level MANOVA. Analyses of separate sessions were performed using a block  $\times$  morph level MANOVA. Block consisted of 9 levels (there were 9 blocks of training per session).

### fMRI imaging data analysis

Imaging data analysis was done using BrainVoyager QX (by Brain Innovation, Maastricht, The Netherlands). The first three volumes were discarded to allow for T1 signal equilibrium. The following preprocessing steps were performed: slice scan time correction (using sinc interpolation), linear trend removal, temporal high-pass filtering to remove low-frequency non-linear drifts of 3 or fewer cycles per time course, and 3D motion correction to detect and correct for small head movements by spatial

## Crossmodal category representation

alignment of all volumes to the first volume by rigid body transformations. Estimated translation and rotation parameters were inspected and never exceeded 3 mm. Co-registration of functional and 3D structural measurements was computed by relating functional images to the structural scan, which yielded a 4D functional data set. Structural 3D and functional 4D data sets were transformed into Talairach space (Talairach & Tournoux, 1988).

The inhomogeneity-corrected structural scans were used for individual subjects' cortex reconstruction (Kriegeskorte & Goebel, 2001). For each individual subject the gray and white matter were segmented. The border between white and gray matter was used to produce a surface reconstruction of each hemisphere. To improve the spatial correspondence between subjects' brains beyond Talairach space matching, the reconstructed hemispheres were aligned using curvature information reflecting the gyral/sulcal folding pattern. Folded cortical representations of each subject and hemisphere were morphed into a spherical representation. These spherical representations were aligned to one another using an algorithm accounting for an optimal fit of the main gyrification with minimal distortion between the individual cortices. Alignment of major gyri and sulci was achieved reliably using this method. Cortex-based inter-subject alignment enabled us to align the time courses for multi-subject GLM data analysis. Group-averaged functional data were then projected on inflated representations of the left and right cerebral hemispheres of a single subject.

Cortex-based statistical analysis was performed using multiple linear regression. For every cortical surface vertex, the time course was regressed on a set of predictors representing our eight experimental conditions. Regressors of interest were modeled using a gamma function ( $\tau$  of 2.5 s and a  $\delta$  of 1.5) convolved with the blocks of experimental conditions (Boynton, Engel, Glover, & Heeger, 1996). Because for novel birds there existed no representation of congruent or incongruent combinations these were collapsed. In addition six regressors of no

interest representing the motion parameters were included in the model. Multiple regression, fixed effects, was performed using the general linear model (GLM). Unimodal and crossmodal activations were investigated with the following contrasts: First, unimodal activation for sounds presented in isolation: Sounds (Trained + Novel) > Rest. Second, unimodal activation for shapes presented in isolation: Shapes (Trained + Novel) > Rest. Third, crossmodal activations: Crossmodal (Congruent Trained + Incongruent Trained + Novel) > Rest. Crossmodal training effects were investigated with the contrast: Crossmodal Congruent Trained > Crossmodal Novel. Congruency effects were investigated with the contrast Crossmodal Trained Congruent > Crossmodal Trained Incongruent. The effect of morph level for trained birds was investigated with the contrast 90 % morph level (trained sounds + trained shapes + crossmodal congruent + crossmodal incongruent) > 60% morph level (trained sounds + trained shapes + crossmodal congruent + crossmodal incongruent) and for novel birds with the contrast 90 % morph level (novel sounds + novel shapes + crossmodal novel) > 60% morph level (novel sounds + novel shapes + crossmodal novel).

In order to correct for multiple comparisons, the false discovery rate (FDR) controlling procedure was applied on the resulting  $p$  values for all voxels. The value of  $q$  specifying the maximum FDR tolerated on average was set to 0.001 for overall crossmodal and unimodal activations and to 0.01 for crossmodal training and congruency effects. With a  $q$  value of 0.01, a single-voxel threshold is chosen by the FDR procedure which ensures that from all voxels shown as active, only 1% or less are false-positives (Benjamini & Hochberg, 1995; Genovese, Lazar, & Nichols, 2002). In addition a cluster threshold of 25 mm<sup>3</sup> was applied.

Significantly activated clusters were further explored with a ROI analysis in which we tested for unimodal and crossmodal training effects and for a crossmodal congruency effect. The subject-averaged responses for each condition averaged over all significantly activated voxels in a region were submitted

to two-tailed paired *t*-tests ( $df = 15$ ). The tests for unimodal training effects were Trained Shapes versus Novel Shapes and Trained Sounds versus Novel Sounds. The test for crossmodal training effects was Crossmodal Congruent Trained versus Crossmodal Novel and Crossmodal Incongruent Trained versus Novel Crossmodal. Congruency effects were tested by testing for Crossmodal Congruent Trained versus Crossmodal Incongruent Trained. For these tests an alpha level of 0.05 was used.

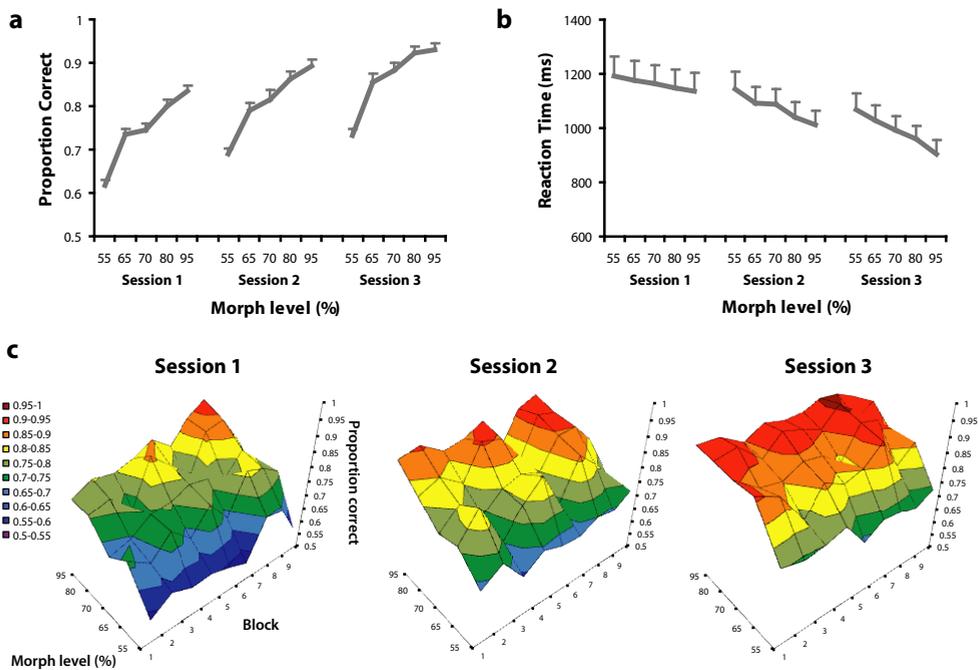
We used a PPI analysis (Friston et al., 1997) to search for regions that were connected to the left superior temporal sulcus as a result of crossmodal training. The superior temporal seed region was defined as the area that responded more to crossmodal congruent than to crossmodal novel birds ( $p < 0.05$  FDR corr). We used the timecourse from the left

superior temporal sulcus ROI as our seed region and convolved this with the vector of our contrast of interest (crossmodal congruent > crossmodal novel). This PPI regressor was then entered into a general linear model together with the timecourse of the seed region and the vector that represented the contrast itself. The GLM estimated those voxels where there was a significant change in connectivity between crossmodal congruent and crossmodal novel birds. The threshold of this analysis was at  $p < 0.05$  (FDR corrected).

## Results

### Training

Analysis of the behavioural training data showed that participants became skilled in categorizing the bird exemplars (see Figure 4.3). The proportion of



**Figure 4.3**

**Training results.** Mean proportion of correct responses (A) and mean response latencies (B) to the 1-back task, as a function of morph level, plotted for each of the three training sessions. Error bars represent standard error of the mean. (C) Accuracy (proportion of correct responses) plotted as function of morph level and blocks for all three training sessions.

## Crossmodal category representation

correct responses increased as training progressed over time [ $F(2,14) = 72.05, p < 0.001$ ], Fig 4.3a. Performance increased significantly from the first to the second training session [ $F(1,15) = 48.10, p < 0.001$ ] and from the second to the third training session [ $F(1,15) = 30.43, p < 0.001$ ]. Within the first training session accuracy increased from the first to the last block [ $F(8,8) = 8.67, p < 0.005$ ]. In the second training session there was a trend towards increased performance over blocks [ $F(8,8) = 3.10, p < 0.07$ ], but not in the third training session [ $F(8,8) = 1.21, p = ns$ ]. In the third session performance did not even differ between the first and the last block [ $F(1,15) = 2.05, p = ns$ ], see Figure 4.3c. Even though it was not our goal to have learning saturation we did observe that training accuracy did not further increase during the last training session. We also found an effect of morph level. Responses were least accurate for birds closest to the category boundary [ $F(4,12) = 398.78, p < 0.001$ ]. The effect of morph level was present in all training sessions (first session: [ $F(4,12) = 138.22, p < 0.001$ ]; second session: [ $F(4,12) = 197.93, p < 0.001$ ], and third session: [ $F(4,12) = 113.07, p < 0.001$ ]).

We also found that our subjects became faster over training sessions [ $F(2,14) = 7.44, p < 0.01$ ], Fig 4.3b. Subjects were significantly faster in the second training session than in the first training session [ $F(1,15) = 13.70, p < 0.005$ ] and faster in the third training session than in the second training session [ $F(1,15) = 7.06, p < 0.05$ ]. Subjects responded faster to birds closer to the prototype [ $F(4,12) = 9.99, p < 0.005$ ].

### fmRI results

Subjects trained for three days with the crossmodal bird categories. After training the subjects were scanned. Subjects were presented with unimodal and crossmodal bird stimuli presented in blocks during scanning. These were different exemplars than the subjects trained with. For unimodal bird types the stimuli consisted of either bird shapes or bird sounds presented in isolation. The crossmodal bird types consisted of trained congruent (sound

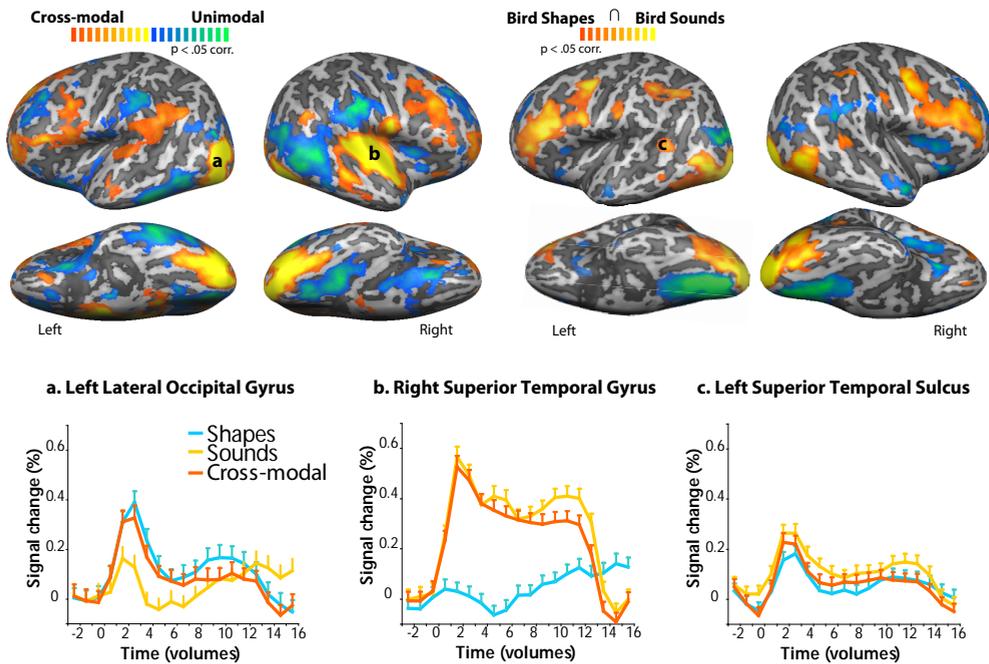
and shape are matching), incongruent (sound and shape do not match), and novel crossmodal bird types. Compared with unimodal bird stimuli, the crossmodal bird types activated bilateral inferior and middle frontal gyri, supramarginal gyrus, middle and superior temporal gyri, lateral occipital gyrus, and right superior temporal sulcus, see Figure 4.4. We also investigated which areas are responsive to both modalities, that is to shapes and sounds presented in isolation. These areas overlap with areas that prefer crossmodal over unimodal stimuli (bilateral inferior and middle frontal gyri, bilateral lateral occipital gyri), but they exclude the superior and middle temporal gyri and include both left and right superior temporal sulci.

### Crossmodal training effects

To investigate crossmodal training effects we compared the responses to congruent crossmodal birds from the trained categories with responses to novel crossmodal bird stimuli at  $p < 0.01$  (FDR corrected), see Figure 4.5a. The regions that were obtained from this analysis were further explored with two-tailed paired  $t$ -tests ( $df = 15$ ). We tested whether the regions showing a crossmodal training effect for congruent bird types also showed a training effect for incongruent bird types. In addition, we tested whether these regions showed a training-effect for shapes and sounds presented in isolation (see Table 4.2).

As expected, the left superior temporal sulcus showed a crossmodal training effect for congruent crossmodal bird types, see Figure 4.5b. Other regions that showed a significant crossmodal training effect were the right fusiform gyrus, left superior temporal gyrus, bilateral supramarginal gyrus, left inferior frontal gyrus, bilateral precentral gyrus, left anterior cingulate gyrus and sulcus, bilateral superior frontal gyrus, bilateral insula, and left parieto-occipital sulcus. In addition to these increases, we found that the right middle temporal gyrus showed a training-related decrease in activity.

Training effects do not necessarily indicate that the areas that showed such an effect are truly repre-



**Figure 4.4**

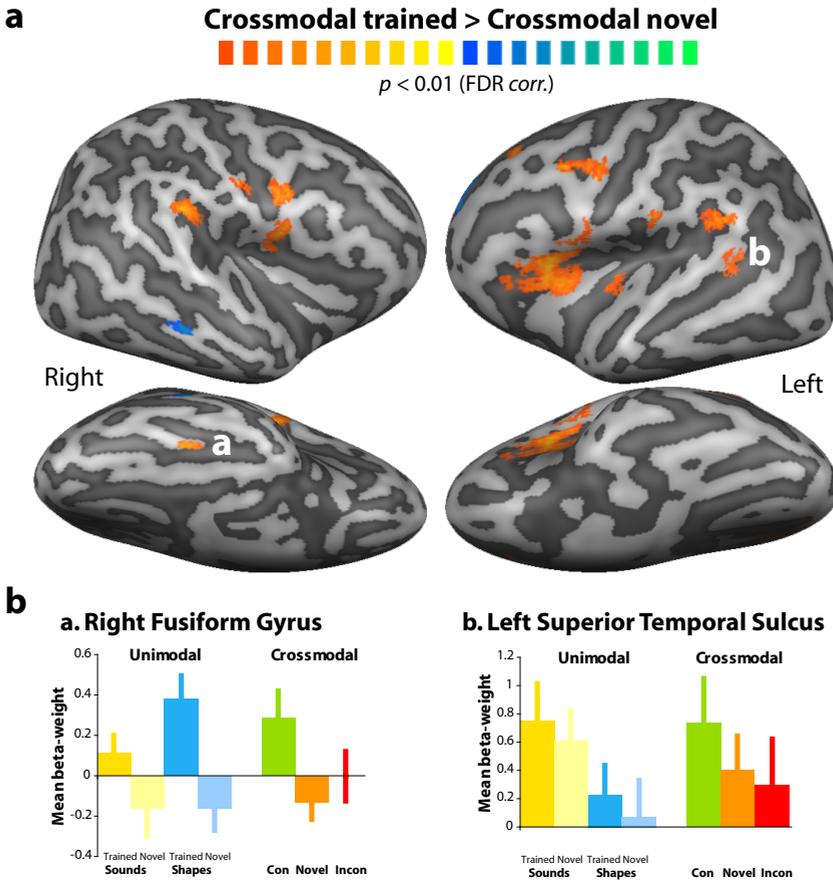
**Crossmodal activation.** Group-averaged activation maps from the post-training scanning session overlaid on lateral views of Talairach-normalized inflated hemispheres. On the left in yellow colours the activity to all crossmodal birds (crossmodal novel + crossmodal congruent + crossmodal incongruent) compared with all unimodal birds (shapes novel + shapes trained + sounds novel + sounds trained) in blue colours. On the right, in yellow colours, the areas that respond to both sounds and shapes. All activation maps are thresholded at  $p < 0.05$  (False Discovery Rate corrected). Response plots show averaged timecourses of the BOLD response (in percent signal change) during unimodal (shapes or sounds) and crossmodal stimulation. Error bars represent standard error of the mean.

senting the newly learned categories. Mere exposure might also contribute to finding ‘simple’ training effect. If areas are part of a meaningful crossmodal representation the training effect should not generalize to incongruent, but trained, bird-sound combinations. Therefore, we tested whether any of these regions showed a general training effect (see Table 4.2). We found that none of the regions showed a general crossmodal training effect. The response to incongruent trained bird types was never larger than the response to novel bird types.

### Unimodal training effects

Next to these crossmodal training-effects we tested the areas that showed a crossmodal training effect for unimodal training effects. The only region that showed unimodal training effects was the right fusiform gyrus, see Figure 4.5b and Table 4.2. The right fusiform responded more to trained bird shapes compared to novel bird shapes. In addition, responses were larger for trained bird sounds than for novel bird sounds.

## Crossmodal category representation



**Figure 4.5**

**Crossmodal training effects.** (A) Group-averaged activation maps from the post-training scanning overlaid on lateral (top) and ventral (bottom) views of Talairach-normalized inflated hemispheres. In orange tones regions that showed more activity for trained congruent crossmodal bird types compared with novel crossmodal bird types at  $p < 0.01$  (False Discovery Rate corrected). In blue, brain regions showing less activity following presentation of trained congruent crossmodal bird types compared with novel crossmodal bird types. (B) Voxel-averaged plots of the mean beta-weights in left superior temporal sulcus (a; Talairach coordinates:  $x = -48, y = -51, z = 12$ ) and right fusiform gyrus (b;  $x = 38, y = -29, z = -19$ ). Shown are the averaged responses for unimodal bird stimuli (sounds in yellow and shapes in blue) and crossmodal bird stimuli. For unimodal stimuli divided in trained (dark colours) and novel bird types (light colours). For crossmodal divided in trained congruent (con in green), trained incongruent (incon in red), and crossmodal novel bird types (orange). Error bars represent standard error of the mean.

To further investigate the spatial distribution of the different training effects in the right fusiform gyrus we overlaid separate unimodal and crossmodal contrasts in the right fusiform gyrus, see Figure 4.6. As can be seen in Figure 4.6 the areas are overlapping each other largely. The training effect for the

shapes extends the largest region ( $x = 37, y = -23, z = -20, 1306 \text{ mm}^3$ ). The auditory training effect is smaller and located slightly more posterior ( $x = 38, y = -35, z = -19, 279 \text{ mm}^3$ ). The crossmodal training effect and congruency effect are closest together in location and size (crossmodal training effect:  $x = 38,$

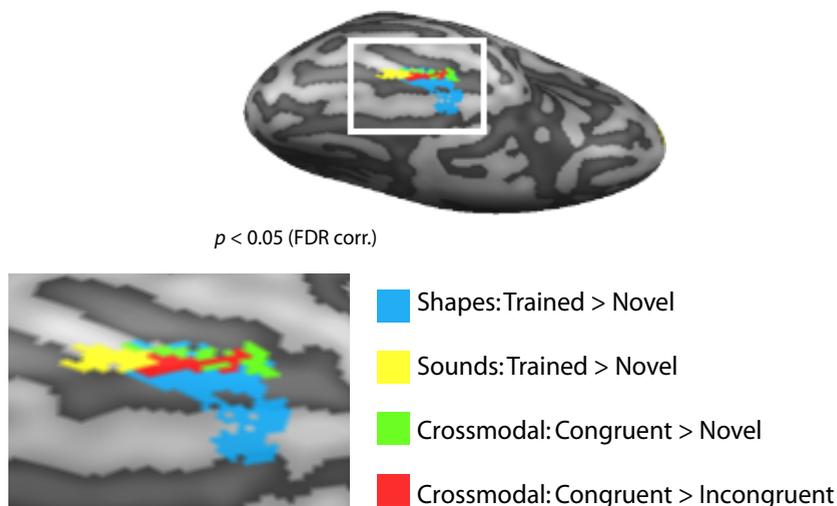
Area	x	y	z	mm <sup>3</sup>	AT > AN	VT > VN	CCT > CN	CIT > CN	CCT > CIT
<i>Training-related increases</i>									
R Fusiform G	38	-29	-19	245	2.19*	3.13**	3.39***	0.99	2.61*
L Superior Temporal S	-48	-51	12	415	0.75	0.84	3.31**	-0.56	3.13**
L Supramarginal G	-52	-48	30	862	0.72	0.50	3.13**	0.49	1.88
R Supramarginal G	52	-36	34	787	-1.25	-1.20	2.83*	-0.93	2.49*
L Superior Temporal G	-35	-23	6	293	0.18	-1.74	2.40*	-0.93	3.64***
L Inferior Frontal G	-30	26	13	219	1.12	0.32	1.92	0.92	0.93
	-50	0	10	519	0.68	-0.34	2.60*	-2.55*	4.95***
L Postcentral G	-60	-24	21	387	1.45	-0.44	2.85*	-0.91	3.80***
R Postcentral G	52	-12	34	280	-0.11	-0.35	2.67*	-0.35	3.26**
L Precentral G	-47	-9	42	1147	1.88	-0.22	2.51*	1.11	1.37
R Precentral G	53	-6	30	757	1.24	-0.55	3.57***	0.15	2.63*
L Anterior Cingulate G	-2	24	8	420	1.60	-2.36*	2.54*	0.12	2.47*
L Posterior Cingulate G	-7	-45	32	618	-0.50	-1.03	2.08	1.54	1.21
L Cingulate S	-15	-37	38	60	0.26	-1.64	2.75*	0.14	2.17*
L Superior Frontal G	-7	2	53	791	0.59	0.05	2.40*	0.00	1.73
R Superior Frontal G	8	-1	48	594	0.72	-0.10	2.53*	0.49	1.41
L Parieto-occipital S	-10	-64	12	1645	-0.95	-0.70	2.87*	0.14	4.46***
L Insula	-32	6	16	2417	0.91	-0.61	2.57*	0.06	2.83*
R Insula	50	-4	14	1060	0.59	-1.15	2.76*	-1.14	4.25***
<i>Training-related decrease</i>									
R Middle Temporal G	60	-35	-6	228	0	-0.58	-2.77*	-0.26	-2.32*

**Table 4.2**

**Regions showing a crossmodal training effect.** Mean Talairach coordinates, volume in  $\text{mm}^3$ , and averaged  $t$ -values for regions showing a crossmodal training effect at  $p < .01$  *FDR corr.* In addition, we present  $t$ -values obtained from paired  $t$ -tests ( $df = 15$ ) on the subject-averaged beta weights. We tested for both unimodal training effects, auditory training effect: trained sounds > novel sounds (AT > AN) and visual training effect: trained shapes > novel shapes (VT > VN). Next, we tested for crossmodal training effects: crossmodal congruent trained > crossmodal novel (CCT > CN) and crossmodal incongruent trained > crossmodal novel (CIT > CN). And finally, for the congruency effect: crossmodal congruent trained > crossmodal incongruent trained (CCT > CIT).

*L = left, R = right, G = gyrus, S = Sulcus, \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.005$ , \*\*\*\*  $p < 0.001$ .*

## Crossmodal category representation



**Figure 4.6**

### Right fusiform training effects.

Overlap of regions in the right fusiform gyrus that show a crossmodal training effect (in green: congruent crossmodal trained > crossmodal novel), unimodal training effects (in blue: trained shapes > novel shapes and in yellow: trained sounds > novel sounds), as well as a congruency effect (in red: trained congruent crossmodal > trained incongruent crossmodal), presented at  $p < 0.05$  (corr.) for display purposes.

$y = -24, z = -18, 279 \text{ mm}^3$ ; congruency effect:  $x = 38, y = -27, z = -18, 250 \text{ mm}^3$ .

### Congruency effects

We found that most areas that showed a training effect also responded significantly more to the congruent bird types than to the incongruent ones. The fusiform gyrus showed higher responses for congruent crossmodal birds than for incongruent crossmodal birds (Table 4.2). Next to the right fusiform gyrus, the left superior temporal sulcus also showed a congruency effect, see Figure 4.5*b* and Table 4.2. Other regions that showed a congruency effect were left superior temporal gyrus, right supramarginal gyrus, bilateral precentral gyrus, left cingulate sulcus, left parieto-occipital sulcus, and bilateral insula, see Table 4.1. Again, the right

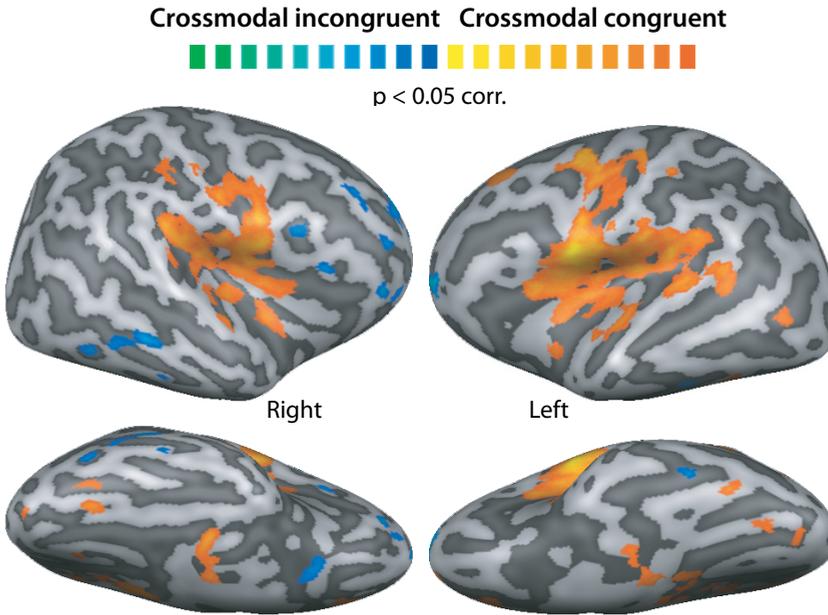
middle temporal gyrus, which also showed a training-related decrease, showed the reverse effect and responded more to incongruent than to congruent crossmodal birds, see Table 4.2.

The ROI analysis of congruency effects might be in part biased due to the contrast we used to test for training effects. The contrast already contained crossmodal congruent birds and therefore will yield those areas that have a preference for crossmodal congruent birds. If one then compares responses to congruent crossmodal birds with responses to birds from another condition within these areas it is more likely to obtain a difference. Therefore, we also directly tested for congruency effects in the brain by contrasting congruent crossmodal birds with crossmodal incongruent birds at  $p < 0.01$  (FDR corrected), see Figure 4.7 and Table 4.3. This analysis

Area	x	y	z	mm <sup>3</sup>	CCT >		
					CN	CIT>CN	CCT > CIT
<i>Congruent &gt; Incongruent</i>							
L Perirhinal Cortex	-9	-32	-17	511	1.18	-2.04	3.87***
R Perirhinal Cortex	17	-21	-19	678	1.19	-3.12**	4.48****
R Posterior Fusiform G	31	-55	-16	365	1.28	-1.55	3.27**
L Lateral Occipital G	-41	-63	3	218	1.06	-1.75	2.53*
L Cuneus	-7	-74	13	215	3.01**	-0.33	3.96***
R Posterior Cingulate G	7	-38	7	392	1.10	-1.84	2.53*
L Posterior Cingulate G	-8	-60	10	557	2.93*	-0.02	4.10****
L Parieto-occipital S	-17	-67	16	155	2.32*	0.08	3.36***
R Parieto-occipital S	10	-58	19	240	2.01	-0.62	2.65*
L Anterior Cingulate	-2	22	6	504	2.34*	-0.36	2.89*
R Anterior Cingulate G	9	-10	39	959	1.50	-1.05	3.02**
L Insula	-34	-16	11	2501	2.36*	-2.43*	4.14****
	-36	-6	-8	220	0.78	-1.86	2.67*
R Insula	35	-12	0	412	0.95	-1.67	3.63***
	34	-7	16	1228	2.31*	-1.18	3.32***
L Superior Temporal S	-46	-48	9	324	2.69*	-0.56	3.14**
L Superior Temporal G	-56	-49	14	1087	2.76*	-0.79	2.91*
	-57	-37	14	1027	1.31	-2.02	2.97**
	-54	-17	10	860	1.23	-2.28*	2.91*
R Superior Temporal G	37	-21	9	475	2.15*	-1.70	3.39***
L Supramarginal G	-49	-44	27	1168	2.13	-1.29	3.04**
	-55	-29	22	2722	1.95	-1.79	4.05***
	-38	-28	21	2452	1.83	-2.42*	4.41****
R Supramarginal G	52	-34	19	346	1.18	-2.09	3.56***
	52	-34	33	1036	2.48*	-0.58	2.70*
L Inferior Frontal G	-34	4	17	1615	2.21*	-0.54	3.27**
L Precentral G	-52	-5	14	3314	1.77	-2.71*	4.10****
	-43	-13	48	1458	1.88	-1.27	4.54****
R Precentral G	52	-8	30	2611	3.09**	-1.19	4.02***
	51	-8	15	2812	2.47*	-1.86	3.97***
L Postcentral G	-44	-15	33	1259	1.81	-2.09	3.70***
R Posterior Lateral S	43	-29	22	3032	1.72	-2.24*	3.44***
L Superior Frontal G	-9	-15	46	4633	1.79	-1.70	4.01***
L Superior Frontal S	-22	19	45	894	2.53*	-2.24*	2.54*
<i>Incongruent &gt; Congruent</i>							
R Middle Temporal G	57	-38	-4	261	-2.04	0.81	-2.40*
R Inferior Frontal G	44	38	-1	194	-2.51*	0.59	-2.23*
L Middle Frontal G	-26	53	11	827	-1.51	1.78	-2.59*

**Table 4.3****Regions showing a congruency effect.**

Mean Talairach coordinates, volume in mm<sup>3</sup>, and averaged *t*-values for regions showing a crossmodal congruency effect at  $p < .01$  *FDR corr.* *T*-values for the paired *t*-tests ( $df = 15$ ) on the subject-averaged beta weights of the congruency effect are presented: crossmodal congruent trained > crossmodal incongruent trained (CCT > CIT). In addition, we present *t*-values obtained for the crossmodal training effect: crossmodal congruent trained > crossmodal novel (CCT > CN)  
L = left, R = right, G = gyrus, S = Sulcus, \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.005$ , \*\*\*\*  $p < 0.001$ .



**Figure 4.7**  
**Congruency effects.** Group-averaged activation maps from the post-training scanning overlaid on lateral (top) and ventral (bottom) views of Talairach-normalized inflated hemispheres. In orange tones regions that showed more activity for trained congruent crossmodal bird types compared with trained incongruent crossmodal bird types at  $p < 0.01$  (False Discovery Rate corrected). In blue, voxel populations showing more activity following presentation of trained incongruent crossmodal bird types compared with trained congruent crossmodal bird types.

confirmed the congruency effects that were obtained in the ROI analysis. In addition, some areas, including the right inferior frontal gyrus, were revealed that preferred incongruent stimuli above congruent stimuli. Within the areas showing congruency effects we also tested for crossmodal training effects (Table 4.3). In addition, testing the areas that showed a congruency effect for a training effect also confirmed the previous analysis of the crossmodal training effects, being the right fusiform gyrus, the left superior temporal sulcus and gyrus, bilateral insula, left inferior frontal gyrus, right supramarginal

gyrus, and right precentral gyrus. The right inferior frontal gyrus showed the reverse pattern and preferred novel stimuli above crossmodal congruent trained stimuli, see Table 4.3. We also found some additional regions that showed a congruency effect in the absence of a crossmodal training effect, see Table 4.3. In addition, some areas showed responses that were lower for incongruent than for novel crossmodal birds. These areas were right perirhinal cortex and posterior lateral sulcus, and left superior temporal gyrus, insula, supramarginal gyrus, precentral gyrus, and superior frontal sulcus.

### Effects of morph level

To investigate the effect of morph level on the brain's responses we collapsed over all trained conditions and tested for areas that showed greater activity for morph level 90 than for morph level 60 at  $p < 0.01$  (FDR corrected), see Figure 4.8*a*. The areas that showed an overall effect of morph level fit nicely with those areas that responded more to trained than to novel birds and more to congruent than incongruent bird types. No areas were found that responded more to the 60% morph levels than to the 90% morph levels. For the novel bird types we performed the same analysis, but no areas preferred the higher morph level at  $p < 0.01$  (FDR corrected) and not even at  $p < 0.05$  (FDR corrected) or  $p < 0.001$  (uncorrected). We investigated responses from two areas in the right superior temporal sulcus (Fig 4.8 *b and c*), the left superior temporal sulcus (Fig 4.8*d*), and the right occipitotemporal cortex (Fig 4.8*e*) with a MANOVA. This ROI analysis confirmed the overall effect of morph level for trained items in all these areas and not for the novel items. Interestingly, the incongruent items also showed an effect of morph level in these areas.

### Effective connectivity analysis

We did an exploratory PPI analysis to see which areas showed greater connectivity from the left superior temporal sulcus during presentation of crossmodal congruent birds than during presentation of crossmodal novel birds (Figure 4.9*a*). We found that the bilateral supramarginal gyrus and anterior cingulate gyrus showed more connectivity with left superior temporal sulcus, in addition we found a group of left-lateralized areas that included inferior frontal areas, left middle frontal, and post-central gyrus. Most interesting was that in the right occipitotemporal cortex the right fusiform gyrus showed increased connectivity from the left superior temporal sulcus for the crossmodal congruent bird types (Fig 4.9*b*).

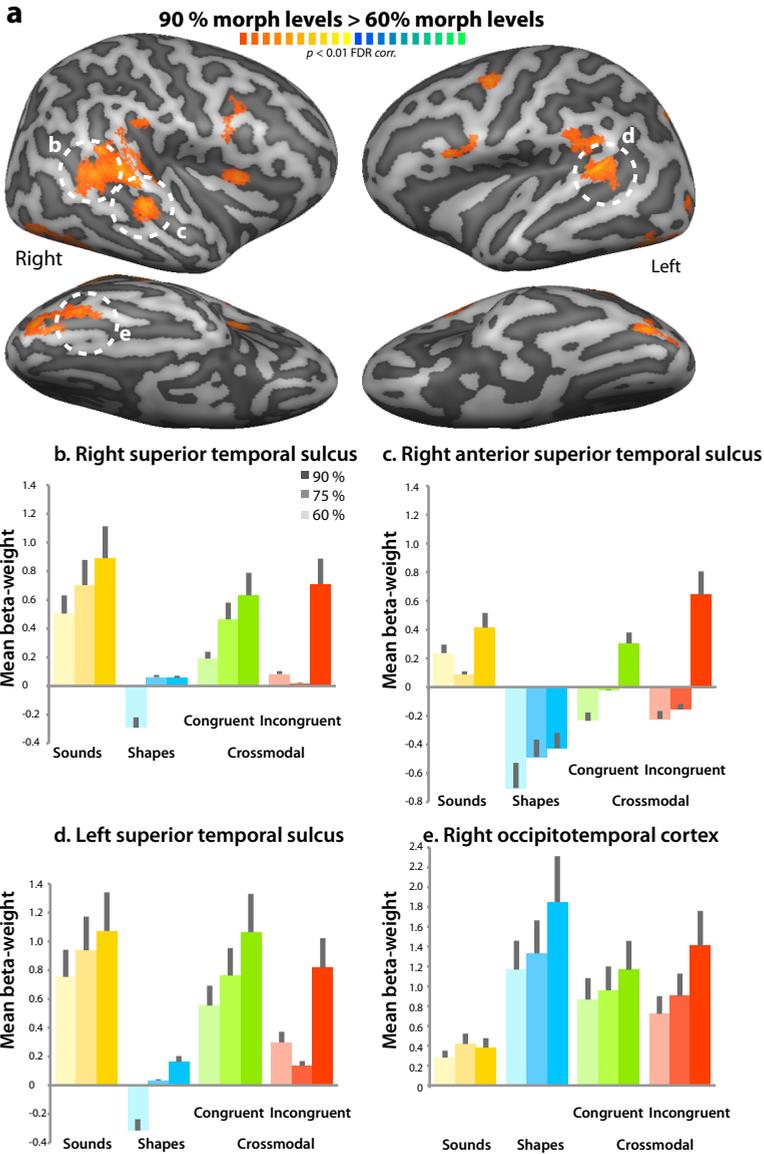
### Discussion

In this study we used a novel audiovisual training paradigm to investigate the formation of cross-modal object representations in the adult human brain. We trained subjects to dissociate between three highly similar crossmodal bird categories. Our behavioural results indicate that our 1-back discrimination task was successful in inducing the formation of new category representations. Behavioural data from our study follow the pattern that is typical of category learning i.e. responses to stimuli that were close to the category boundary were faster and more accurately than would be expected based on the physical properties of the stimuli. Even for morph ratios near the category boundary (55:45 morphs), performance exceeded 70% at the end of training. Thus, even though a 55:45 exemplar of, say, bird type A had only 55% of A properties (and 45% of another bird type) it was nonetheless categorized as type A 70% of the time. This demonstrates that subjects had developed categorical perception of the bird types. Such a behavioural pattern has previously been found for training with a discrimination task (Op de Beeck et al., 2006; van der Linden et al., 2008) as well as for categorization training (Gillebert, Op de Beeck, Panis, & Wagemans, 2009; Jiang et al., 2007; van der Linden et al., 2010).

After three days of training, on the fourth day, the subjects were scanned. We presented them with the trained crossmodal birds in congruent and incongruent audiovisual combinations and with novel audiovisual bird categories. The subjects also listened and viewed novel and trained bird sounds and shapes in isolation. We found crossmodal training effects in frontal and temporal regions known to be involved in crossmodal object representations.

Many studies have determined that the superior temporal sulcus plays a very important role in crossmodal integration. Anatomically the superior temporal sulcus is conveniently located near the borders of auditory and visual association cortices. Functionally it has been found to respond to audio-

## Crossmodal category representation



**Figure 4.8**

**Effects of morph level.** (A) Shown in orange colours are areas that responded more to 90% morph levels than to 60% morph levels of the trained bird types at  $p < 0.01$  (False Discovery Rate corrected). The activations are overlaid on lateral (top) and ventral (bottom) views of Talairach-normalized inflated hemispheres. Plots show the voxel-averaged mean beta-weights in (B) right superior temporal sulcus, (C) right anterior superior temporal sulcus, (D) left superior temporal sulcus, and (E)

right occipitotemporal cortex. Shown are the averaged responses for the trained bird types for the unimodal bird stimuli (sounds in yellow and shapes in blue) and crossmodal bird stimuli (green for congruent and red for incongruent stimuli). Colour saturation represents the morph levels, the most saturated colour represents the 90% morph level and the least saturated colour the 60% morph level. Error bars represent standard error of the mean.

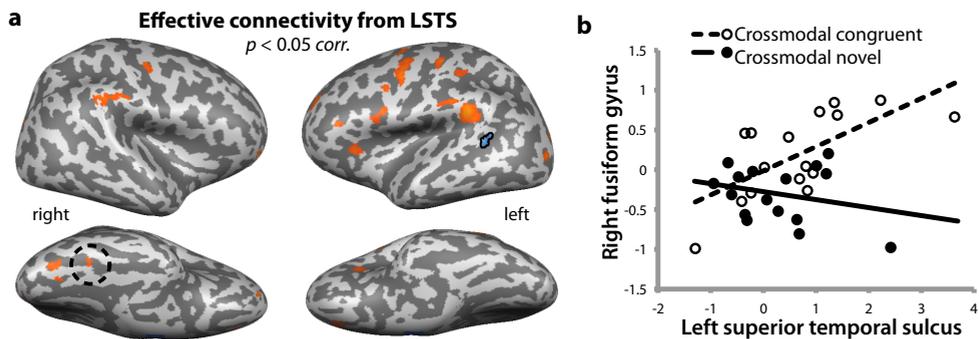
ry, visual, and audiovisual linguistic stimuli (Callan et al., 2004; Calvert et al., 2000; van Atteveldt et al., 2004; van Atteveldt et al., 2007a; van Atteveldt et al., 2007b), and to common shapes, sounds, and audiovisual objects (Beauchamp, Argall, Bodurka, Duyn, & Martin, 2004; Beauchamp, Lee et al., 2004; Hein et al., 2007; Taylor et al., 2006). We found that the superior temporal sulcus becomes involved in crossmodal object representation after a relatively short amount of category training. What is even more important is that this training-effect did not generalize to incongruent pairings of trained bird sounds and shapes. The superior temporal sulcus did not show differential responses to incongruent bird types compared with novel bird types. This indicates that the formation of crossmodal representations was meaningful, namely restricted to those combinations of sounds and shapes that were associated together during category training and did not just occur for any combination of familiar trained sounds and shapes. Congruency effects have been found before in the left superior temporal sulcus (Calvert et al., 2000). However, the reversed effect has also been found in the superior temporal sulcus during active matching (Hocking & Price, 2008; Taylor et al., 2006).

Although there seems great consensus that the superior temporal sulcus is a site for crossmodal integration it is also possible that the superior temporal sulcus is involved in integrating or associating information regardless of modality. Recently it was found that the superior temporal sulcus responded in equal amounts to visual-visual, auditory-auditory, and audiovisual matching (Hocking & Price, 2008). In addition in a study where subjects learned associations between crossmodal stimuli that were presented segregated in time, the superior tempo-

ral sulcus increased its responsiveness as learning progressed for visual-visual and audiovisual associations (Tanabe, Honda, & Sadato, 2005). In a previous study we also found that the superior temporal sulcus is involved in learned associations between birds from different perceptual categories (van der Linden et al., 2010). The results from the present study further support the theory that the superior temporal sulcus is involved in associative learning or linking different types of information regardless of modality. In general one can say that repeated simultaneous presentation of sound and image during training results in the association of these unimodal representations. It is likely that our training paradigm with morphed crossmodal birds made the association of sound and shape extra salient. Especially for the more difficult birds around the category border combining the information of both modalities probably provided stronger clues to category membership than each modality in isolation would have provided. Therefore, training strengthened the association between sound and shape representation and the successful association of these unimodal representations into a congruent crossmodal category can explain the crossmodal training and congruency effects in the superior temporal sulcus.

Another region that showed a crossmodal training effect was the right fusiform gyrus. We found that crossmodal training with the birds resulted in increased activity for crossmodal birds with congruent sounds and shapes as compared with crossmodal novel birds. Importantly, this training-related increase in responses was not present for incongruent trained bird types. Moreover, the response to crossmodal congruent bird types was larger than the response to incongruent trained bird types. This fits

## Crossmodal category representation



**Figure 4.9**

**Effective connectivity analysis.** (A) Areas that show increased connectivity at  $p < 0.05$  (False Discovery Rate corrected) from the seed region in the left superior temporal sulcus (represented in blue with a black outline) for crossmodal congruent birds as compared to crossmodal novel birds are presented in orange colours. (B) Scatterplots of the correlation of activity (mean beta-weights) between the right fusiform gyrus on the y-axis and the left superior temporal sulcus on the x-axis. Black dots and the solid black line represent the crossmodal novel birds ( $R^2 = 0.07$ ) and the open dots with the dotted line represent the crossmodal congruent birds ( $R^2 = 0.45$ ).

4

the results of Naumer et al. (2009) who also report a congruency effect for trained crossmodal nonsense objects. Interestingly, in our study, in the right fusiform gyrus a training-related increase was present for trained shapes in the absence of sounds as well as for trained sounds in the absence of shapes. The finding of a crossmodal training effect combined with a training effect for bird shapes presented in isolation fits well with a previous fMRI study in which we found increased fusiform responses for bird types that subjects successfully learned to visually dissociate (van der Linden et al., 2008). Increased activity in the fusiform gyrus has also been found after subjects became proficient in individuating a homogeneous set of nonsense objects (Gauthier et al., 1999). In addition, larger fusiform responses were observed in individuals that were highly skilled in recognizing a particular class of objects such as birds, cars, or Lepidoptera (butterflies and moths) (Gauthier et al., 2000; Rhodes et al., 2004; Xu, 2005). The fact that the right middle fusiform gyrus showed no training effect for incongruent crossmodal bird stimuli also fit with our previous finding that the right fusiform gyrus showed only increased responsiveness

for birds for which a meaningful representation had been formed and not for birds to which the subjects were exposed in an equal amount, but for which they were hindered in forming a representation of the categories (van der Linden et al., 2008). It is likely that the fusiform gyrus is involved in coding for the visual features of the bird types that were informative during crossmodal training.

Because the fusiform is part of the ventral visual stream, finding unimodal auditory training-effects in the fusiform gyrus is somewhat surprising. However, Beauchamp et al. (2004) also reported auditory activation in the ventral visual stream for sounds of common objects presented in isolation. Responses in the fusiform gyrus seem to emerge when sounds are presented for which a visual association exists. During recognition of voices that were associated with a face as a result of familiarity the fusiform gyrus showed larger responses than for unfamiliar voices (von Kriegstein, Kleinschmidt, Sterzer, & Giraud, 2005). The same was found for voices that were associated with a face as a result of training (von Kriegstein & Giraud, 2006). In our study, hearing the sound of a bird that was trained

might have activated the associated visual representation. Such a representation did not exist for novel birds, therefore novel bird sounds did not activate the fusiform gyrus. This gave rise to the observed auditory training effect in the right fusiform gyrus. Activation of the visual representation of a bird by its sound could also explain why the fusiform gyrus shows a congruency effect. In line with this reasoning is the finding of tighter connection strength for crossmodal trained birds than for crossmodal novel birds between left superior temporal sulcus and the right fusiform gyrus. This could reflect that training increased top-down influence of the superior temporal sulcus on the right fusiform gyrus. Therefore, when presented with a congruent crossmodal bird, both its sound, via feedback connections of the superior temporal sulcus into the fusiform gyrus, and shape activated the newly formed visual representation of the bird. This might boost activation in this area. For incongruent birds the shape might have activated the visual representation in the fusiform, but the combined sound did not match this representation, therefore no increase in activation was observed.

The inferior and middle frontal gyrus showed the reverse effect of the temporal areas and responded more to incongruent crossmodal birds compared with congruent crossmodal bird types. This result corroborates with other studies (Belardinelli et al., 2004; Hein et al., 2007). Rather than being involved in crossmodal binding, the inferior frontal cortex is linked to semantic retrieval (Martin & Chao, 2001; Wagner, Pare-Blagoev, Clark, & Poldrack, 2001). Presenting subjects with incongruent crossmodal stimuli could have reflected increased load on semantic memory because retrieval of a semantic representation was unsuccessful. This failure to retrieve a semantic representation could also explain why we found larger responses to novel birds compared with trained congruent birds in this area. Our findings of temporal areas showing congruency effects and the frontal areas showing the reversed effect is the same pattern that was recently described in a review paper (Doehrmann & Naumer, 2008)

that evaluated the role of semantics on audio-visual integration in frontal and temporal regions.

We found that several areas, among which the superior temporal sulcus and the occipitotemporal cortex, that showed an effect of morph level. Responses were greater to birds with a higher percentage morph level. These areas were for the most part the same areas that preferred trained over novel and congruent over incongruent bird types. The effect of morph level is experience-dependent, we found it only for the trained bird types and not for novel birds. Interestingly, the incongruent crossmodal birds also showed an effect of morph level. This indicates that even the incongruent recombinations of trained sounds and birds activated some general representation of the birds and that this representation was influenced by categorization training, the response is higher to those birds that are further away from the category boundary.

Our analysis of effective connectivity showed that several areas showed increased connectivity with the left superior temporal sulcus as a result of training. These areas included left frontal areas, right occipitotemporal cortex and bilateral supramarginal gyrus. These areas are overlapping those areas that showed crossmodal congruency and training effects. We already discussed the putative roles of frontal and occipitotemporal areas in crossmodal processing. The supramarginal gyrus has been recently found to be involved in successful category learning of sounds (Desai, Liebenthal, Waldron, & Binder, 2008; Liebenthal et al., 2010). In addition, faster learners of non-native speech sounds have greater white matter volume in bilateral supramarginal gyrus than slow learners (Golestani, Paus, & Zatorre, 2002). Taken together with the findings from the present study this suggests that the supramarginal gyrus is involved in learning auditory categories.

One particular concern in this study is the role of attention on the processing of the stimuli. Like in many other studies (Belardinelli et al., 2004; Calvert et al., 2000; Hein et al., 2007; Naumer et al., 2009; van Atteveldt et al., 2004) we used a pas-

## Crossmodal category representation

sive task and blocked presentation. An alternative explanation therefore might be that the congruency effect is attributed to differences in attention. However, when Van Atteveldt et al. (2007) compared passive blocked presentations of crossmodal stimuli with a passive event-related paradigm, the congruency effects did not disappear. When comparing the passive paradigm to an active matching paradigm they found that the congruency effects disappeared during active matching and even resulted in incongruency effects in several other brain regions. In addition, novel stimuli in all modalities are usually associated with higher attentional engagement and thus higher BOLD responses (Downar, Crawley, Mikulis, & Davis, 2002). Therefore, one can expect that novel birds and new recombinations of trained sounds and shapes, i.e. the incongruent bird types, would show larger responses than the trained birds. However, in our study there were very few regions that preferred novel or incongruent stimuli.

To summarize, with this caveat in mind, the present study revealed plasticity in the adult human brain resulting from the successful association of bird sounds and bird shapes into coherent crossmodal categories. The representation of these meaningful crossmodal categories were revealed by crossmodal training and congruency effects. These crossmodal training effects indicate that the cortical representation of audiovisual object categories is experience-dependent, being more involved in processing trained bird types than similar novel birds. Moreover, this representation is category-specific; it is based on learned associations between sounds and shapes that define a category. Learning did not generalize to incongruent combinations of trained sounds and shapes. We observed crossmodal, auditory, and visual training effects in the right fusiform gyrus that did not generalize to incongruent combinations of sound and shape. Given the involvement of the right fusiform gyrus in learning to categorize visual objects (Gauthier et al., 1999; van der Linden et al., 2008), we conclude that the right fusiform gyrus was involved in the visual representation of the learned bird shapes. Another region showing

crossmodal training and congruency effects was the left superior temporal sulcus. Rather than being just a binding site for visual and auditory properties of objects the superior temporal sulcus is involved in the representation of associated objects (Hocking & Price, 2008; Tanabe et al., 2005; van der Linden et al., 2010). We conclude that this area was involved in the formation of new meaningful links between sound and shapes of birds. The present study thus provides the first evidence that the adult human brain is indeed plastic enough to learn new crossmodal categories by the associations of sounds and shapes. Moreover, the combination of sound and shapes that define a category is crucial for the formation of cortical crossmodal representations.

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## Crossmodal category representation

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## **Task- and experience-dependent cortical selectivity to features informative for categorization**

This chapter is based on:  
van der Linden, M., Wegman, J., & Fernández, G. (submitted). Task- and experience-dependent  
cortical selectivity to features informative for categorization.

## Cortical selectivity to informative features

**M**onkey research has suggested that the brain responds selectively to features that are informative for categorization. In humans increased neuronal selectivity to trained objects has been found. We hypothesize that this selectivity is limited to those object features that are informative for categorization. Our human subjects were trained with fish that had features that were informative for category membership and features that were uninformative. Using an fMRI adaptation paradigm we investigated the cortical selectivity to informative and uninformative features. During categorization the right inferior frontal gyrus was selectively responsive to informative features. Responses were also larger for those fish features with values close to the category boundary. In addition, inferior frontal cortex showed category-selective responses. Moreover, selectivity to the informative features correlated with performance on the categorization task during scanning. This shows that prefrontal cortex uses informative features to actively categorize objects, while ignoring those features that do not contribute category information. Occipitotemporal cortex also showed selectivity to the informative features during the categorization task. Interestingly, this area showed a positive correlation of performance during training and selectivity to the informative features and a negative correlation with selectivity to the uninformative features. This indicates that training enhanced sensitivity to trained items and decreased sensitivity to uninformative features. The absence of sensitivity for informative features during a colour-change detection task indicates that there is a strong component of task-related processing of these features.

### Introduction

When you are swimming in the ocean and suddenly a dorsal fin surfaces next to you, you don't take the time to have a closer look at the fish type you stumbled upon. You are too busy to get out of the water assuming that you are dealing with a shark. However, there are a number of other sea creatures with a dorsal fin, such as whales and dolphins. Therefore seeing only the dorsal fin will not be informative for which type of fish you encountered. You need to see more features of the fish in order to categorize it. In the present experiment we investigated if and how our brain distinguishes between features that are informative and features that are uninformative for categorization. More specifically, we trained subjects to discriminate between two types of fish categories. The fish had four features (mouth, tail, dorsal, and ventral fin) that could vary, but only two of those features were informative for category membership.

Experience with an existing object category

leads to changes at the neuronal level in the occipitotemporal cortex (Gauthier, Skudlarski, Gore, & Anderson, 2000; van der Linden, Murre, & van Turennout, 2008) but also experience with novel objects leads to changes in this part of cortex (Gauthier, Williams, Tarr, & Tanaka, 1998; Moore, Cohen, & Ranganath, 2006; Op de Beeck, Baker, DiCarlo, & Kanwisher, 2006; Weisberg, van Turennout, & Martin, 2007). The nature of the underlying neuronal mechanism of these changes have been investigated using fMRI adaptation (Grill-Spector & Malach, 2001). Adaptation effects in several brain regions were found following categorization training with objects. This suggests that neuronal clusters in the occipitotemporal (Gillebert, Op de Beeck, Panis, & Wagemans, 2009; Jiang et al., 2007; van der Linden, van Turennout, & Indefrey, 2010) and prefrontal cortex (Jiang et al., 2007) became selectively responsive to the trained objects. But what is it exactly about those objects that neurons become selectively responsive

to? It seems likely that the task at hand, in our case categorization, determines what parts of the objects induce sensitivity in the neurons. We hypothesize that neurons become selectively responsive to those object features that are informative for categorization. However, the features in our and others' previous studies were not quantified. A few studies have investigated categorization based on informative and uninformative features in macaque inferior temporal cortex (De Baene, Ons, Wagemans, & Vogels, 2008; Sigala & Logothetis, 2002) and found indeed selective responses to informative features. In humans, using separable stimulus dimensions such as curvature and thickness enhances processing of such a dimensions if it was relevant for categorization (Op de Beeck, Wagemans, & Vogels, 2003).

In the present study we used a stimulus set similar to that of Sigala and Logothetis (2002). Subjects trained for three days with fish that they categorized based on two features that were informative for categorization. At the same time they were exposed to two other distinctive features that the fish had, but these features were uninformative for categorization. We combined this training regimen with an fMRI adaptation paradigm to investigate neuronal selectivity to informative and uninformative features. The effects of categorization on feature processing were investigated by having subjects perform a categorization task during scanning. We expected that training leads to increased neuronal sensitivity to those features that are informative for categorization. Therefore, repetition of fish with the same informative features will give rise to an adaptation effect, even if the uninformative features are differing. Presenting the same uninformative features should not elicit an adaptation effect, because there should be no training-related sensitivity to these features. We used an active categorization task, therefore we expected that next to the occipitotemporal cortex, prefrontal areas also respond selectively to the informative features. Selective responses to trained items -with no distinction between features- has been shown in human (Jiang et al., 2007) and macaque (Freedman, Riesenhuber, Poggio, & Mill-

er, 2001, 2002, 2003) prefrontal cortex.

To investigate whether the processing of informative features is depending on active categorization or whether it is also, in part, an automatic process we presented the same fish stimuli while subjects performed a feature colour-change detection task. In half of the trials subjects attended an informative feature and in the other half they attended an uninformative feature. If neuronal selectivity is automatic we expected to see adaptation for repetition of the informative features, even when subjects attended the uninformative features. If neuronal selectivity is partly driven by attention we expected to see adaptation for those trials in which subjects attended to the informative features and not to the uninformative features. If, however, neuronal selectivity is task-dependent we might find no adaptation for the informative features, but only for repetitions of the same colour.

## Materials and Methods

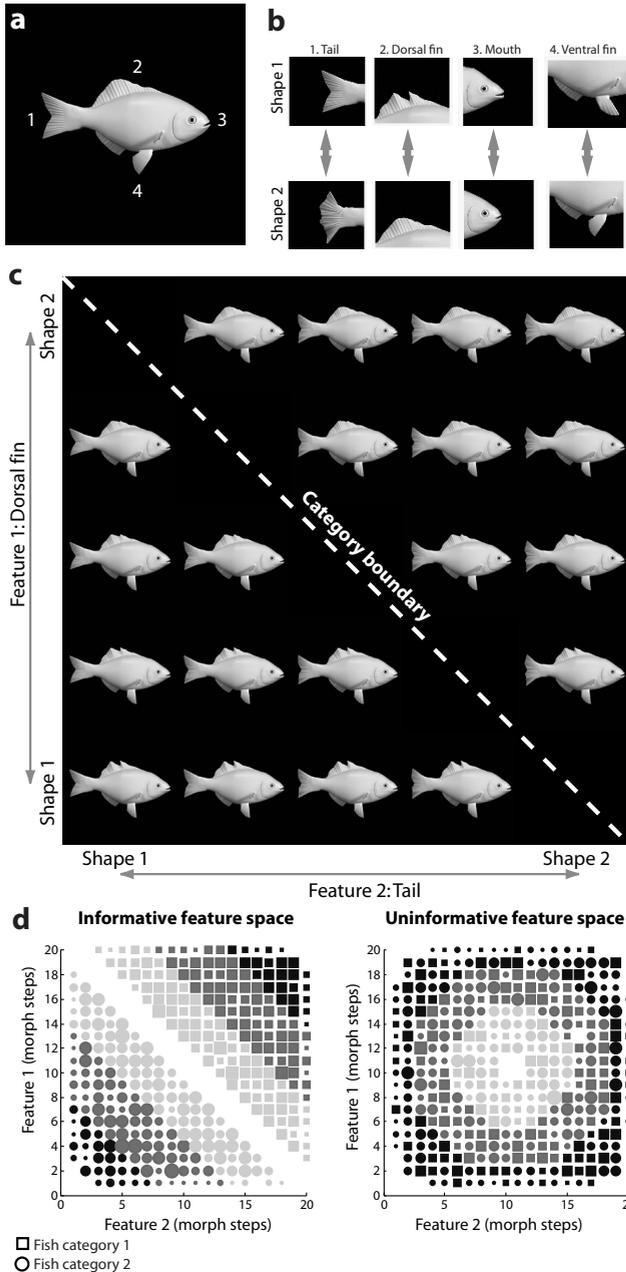
### Subjects

Twenty-four healthy participants (9 males, mean age 22.4 years, range 20-25) participated in the experiment. All subjects had normal or corrected-to-normal vision. Subjects were paid for their participation. All subjects gave written informed consent according to the guidelines of the local ethical committee.

### Stimuli

The stimuli consisted of pictures of computer-generated fish (Pacific Perch by Daz3d, Draper, UT) that were constructed in a 3D model manipulation program (Poser 7 by e frontier, Scotts Valley, CA). Four features of the fish were manipulated: ventral fin, dorsal fin, tail, and head, see Figure 1*a*. These four features could each take the shape of two extremes (Fig. 1*b*). To create different fish exemplars the features were morphed between these two extremes. Morphing was done parametrically in 20 steps (corresponding to a 5% physical difference per step), creating 20 possible shapes of a feature. As such, the stimulus space of the informative features

## Cortical selectivity to informative features



**Figure 5.1**

**The stimulus set. (A)** We designed a fish stimulus with four features that could be manipulated. These four features were its tail (1), dorsal fin (2), mouth (3), and ventral fin (4). **(B)** The fish exemplars were created by parametrically varying the shape of the features. Each of the four features could take a shape in between two extremes, e.g. the dorsal fin could vary from a spiked shape to a more smooth shape. **(C)** For each subject two features would be informative of category membership (e.g. dorsal fin and tail). The category boundary was defined as a linear combination of both features. In total the informative feature space consisted of  $20 \times 20$  feature combinations, excluding the most extreme shapes and those fish immediately bordering the category boundary (in this example the space is  $5 \times 5$ ). **(D)** Fish exemplars did not only vary on their informative features, the uninformative features differed too. The uninformative feature space also contained  $20 \times 20$  possible feature combinations. The uninformative fish features did not determine fish category membership, therefore, in order to prevent subjects from correlating uninformative features with a category boundary we selected the uninformative features of a fish

exemplar in a circular relation to the centre of the space. So, a fish from the light grey space in the informative feature space would have uninformative features from the light grey space in the uninformative feature space.

contained 400 fish exemplars. For each subject two features were informative for categorization. These feature combinations were counterbalanced over subjects. A category boundary was placed within this feature space. The boundary was expressed as a linear relation between two informative feature shapes, see Figure 1*c*. Stimuli that were on or within a distance of less than 5% of the category boundary were not included in the stimulus set and neither were the feature extremes. Each of 400 fish exemplars with morphed informative features would also have morphed uninformative features. The space for the uninformative features also contained 400 exemplars. As such there were 160,000 possible exemplars, each with a unique feature combination.

We rendered each feature separately for the 20 morph steps. Each feature was colourless and rendered against a black background under the same lighting and camera settings. The software used for presenting the fish stimuli to the subjects constructed fish exemplars from the shapes of the four features. The total fish images measured 250 by 250 pixels in both the training and scanning session.

## Procedure

### Training

Training included three sessions, each of which lasted approximately two hours, on three consecutive days. During a training session, subjects sat comfortably in a soundproof cabin in front of a 19" computer screen. Subjects performed a 1-back task on a series of fish images, in which they indicated with appropriate button presses by their right index and middle finger whether two consecutive fish belonged to the same fish category or not. Subjects received feedback to their responses consisting of a printed text centred on the screen in coloured Arial font in size 16 (green: "right", red: "wrong", and yellow: "too late"). The proportion of "same" and "different" responses was fifty-fifty. In each trial, stimuli were presented for 400 ms after which a response could be given during 1850 ms. Feedback was presented for 250 ms. A training session consisted of 9 blocks of 150 trials each. Each block was

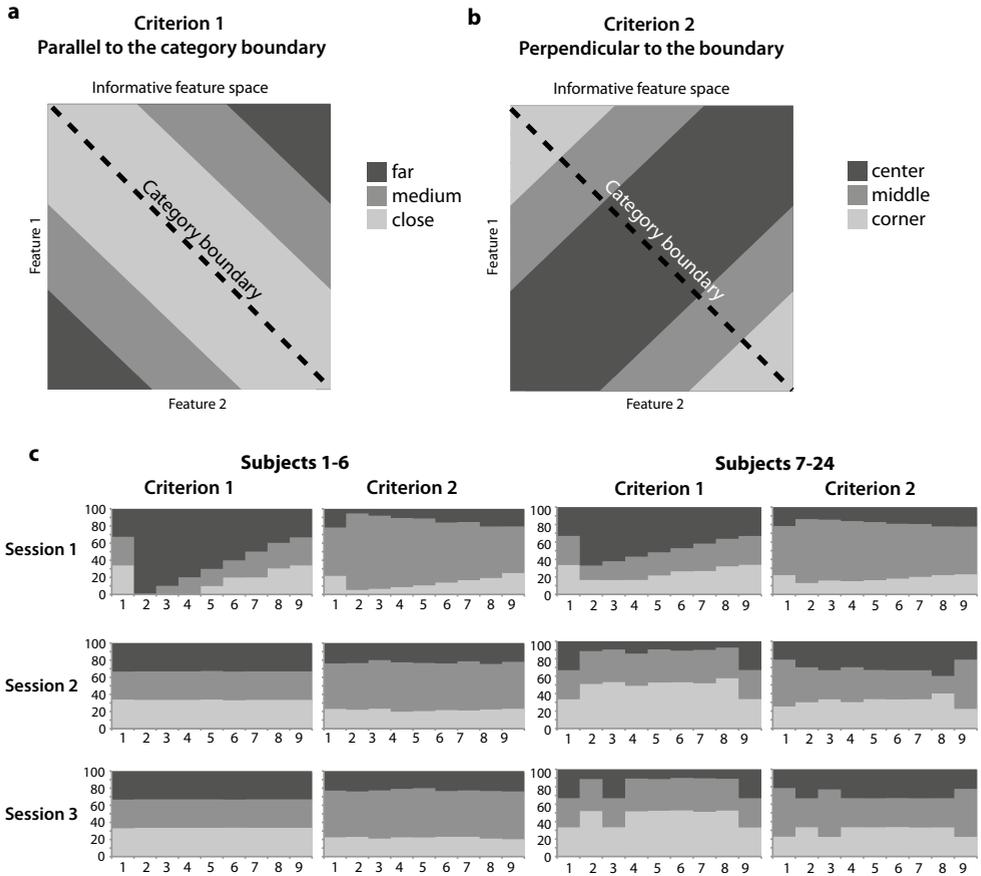
followed by a small self-paced pause after which a subject could continue the experiment by pressing a button.

We used an adaptive training paradigm. Difficulty of trials increased over sessions by selecting fish exemplars using different criteria. The first criterion was based on the distance of the fish exemplars parallel to the category boundary (close, medium, or far, see Figure 2*a*). The second criterion was the place of the fish exemplars perpendicular to the category boundary (centre, medium, or corner, Fig 2*a*). During the first week of training (six subjects) we used only the first selection criterion. For these subjects the first training session started easy (with fish far from the category boundary) and in the next blocks more difficult fish exemplars (close to the category boundary) and less easy exemplars (far from the category) were added as training progressed, see Figure 2*b*. However, using this criterion, subjects could employ a 1-dimensional strategy, utilizing only one informative feature to categorize the exemplars and still achieve reasonable performance, see Figure 3. This would then lead to suboptimal conditions to find selectivity to the informative features in the fMRI experiment. To encourage the next eighteen subjects of our study to combine information from both informative features, in the following training sessions we used the second criterion to select fish exemplars for training. Again, subjects would start with more easy fish (centered perpendicular to the category boundary) and would be introduced to more difficult fish during the course of training (from the corners of the fish space), see Figure 2*c*. For all 24 subjects the first and last block of each training session had identical distributions of fish over the feature space based on the first criterion (1/3 far, 1/3 medium, 1/3 close). Because of this, these blocks could be compared and performance of these blocks was our measurement for training success.

### fMRI scanning session

After three training sessions on three consecutive days, the subjects participated in two fMRI experi-

## Cortical selectivity to informative features



**Figure 5.2**

**Training paradigm.** (A) During the first weeks trials in the training session were added to the training set based on the distance of the fish exemplars parallel to the category boundary (close, medium, or far). (B) During the second, third and fourth training weeks (subjects 7 – 24) fish were added to the training set based on their place perpendicular to the category boundary (centre, middle, or corner). (C) The distribution of fish for each of the two criteria for each the three sessions of training is plotted for both sets of subjects. Colours in the diagrams represent the colours of the distances in both criteria (light colours more difficult trials, dark colours easier trials). On the y axis the percentage of trials is presented and on the x axis the nine blocks of training within a session.

ments. In the first experiment (*not this thesis*) they were scanned in a 7T scanner in Essen, Germany. They performed a feature-colour-change detection task for about one hour followed by the same localizer that was used in the present experiment. The

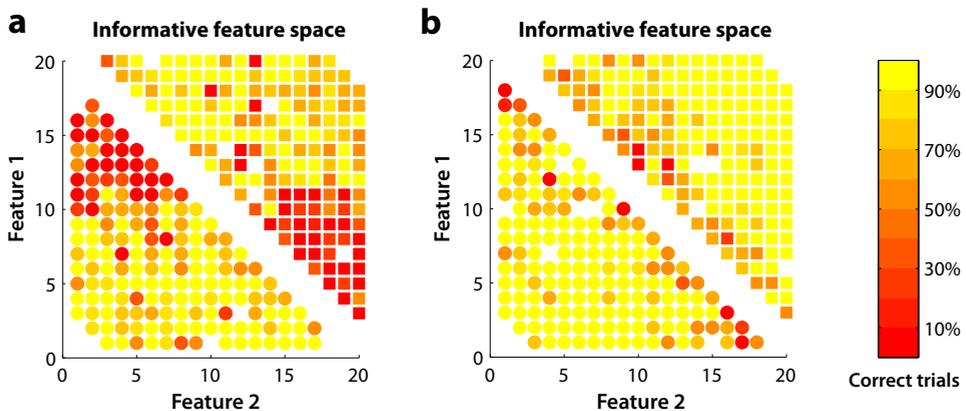
next day the subjects participated in the experiment described here.

An adaptation paradigm with two tasks was used during scanning. The two tasks were a categorization task and a feature colour-change detection task

(Fig. 5.4a). Subjects were presented with pairs of fish. In the categorization task subjects indicated whether the second fish in a pair belonged to the same fish category as the first fish. In the other task we wanted to avoid subjects actively categorizing the fish, in order to tap into automatic processing of the features. Therefore, we used a feature colour-change detection task. In each fish one feature would be coloured. The subjects indicated for each second fish in the pair whether the coloured feature had the same or a different colour as in the first fish. For half of the trials the subjects attended a coloured informative feature and in the other half of the trials they attended a coloured uninformative feature. Each task was performed in a separate run. The order of the tasks was counterbalanced over subjects. In both runs an adaptation trial started with a fish picture that was shown for 400 ms, followed by a blank screen interval of 400 ms and another picture of a fish for 400 ms. After the onset of the second picture the subject could respond. The inter-stimulus-interval was randomly jittered between 3500

and 4500 ms. The order of trials was pseudo-random to have an optimal distance between pairs of the same adaptation condition.

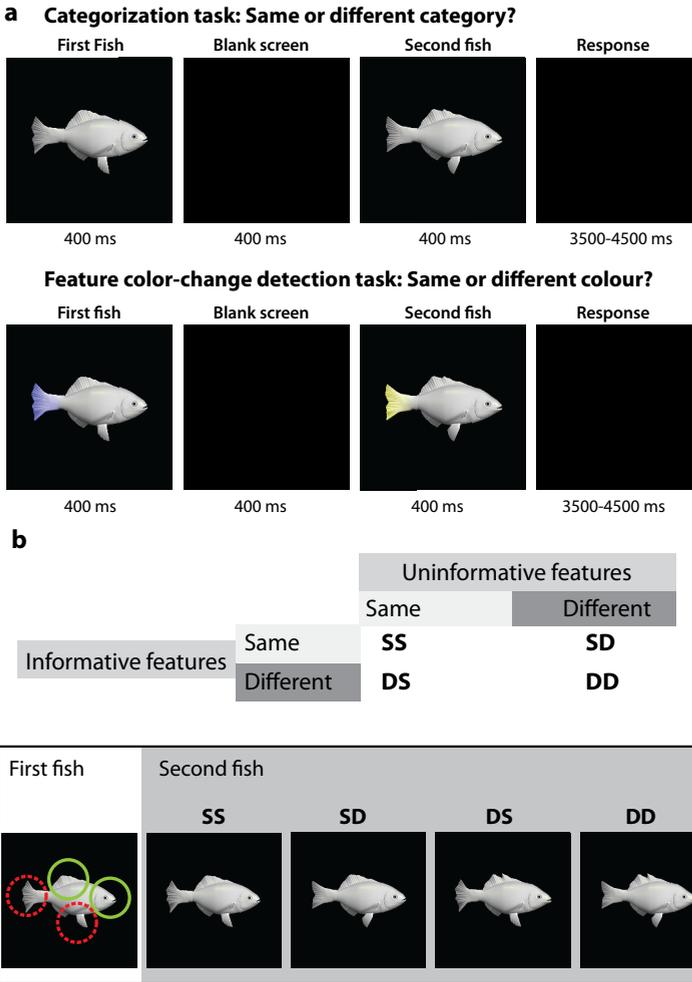
The adaptation condition was determined by the relation between the two fish that were rapidly presented in a pair. We used a 2 (same or different informative features)  $\times$  2 (same or different uninformative features) design, see figure 5.4b. The informative features of the second fish could either be the same or different from the first fish. In addition, the uninformative features of the second fish would also either stay the same or be different. There were four adaptation conditions. In the first condition the informative and uninformative features stay the same (identical repetition, SS). In the second condition the second fish has the same informative features as the first fish, but different uninformative features (SD). In the third condition the second fish has different informative features, but the same uninformative features (DS). In the fourth condition the second fish has different informative and uninformative features (DD). For



**Figure 5.3**

**Subject strategies.** (A) An example of a subject using a 1-dimensional strategy (using only one informative feature for categorization, in this case feature 1). Even though this subject used a 1-dimensional strategy she still categorized 73% of the fish correct in the third training session. (B) An example of a subject using a 2-dimensional strategy (using both informative features for categorization). The score for this subject was 87.2% correct in the third training session.

## Cortical selectivity to informative features



**Figure 5.4**  
**Adaptation paradigm.** (A) Two fish were presented in rapid succession for 400 ms each. In between the two fish pictures a blank screen of 400 ms was presented. Subjects were required to respond after presentation of the second fish picture. The response interval was jittered with a length of a random interval between 3500 and 4500 ms. Two tasks were used during scanning, a categorization task (top) and a feature colour-change detection task (bottom). In the categorization task subjects indicated whether the second fish belonged to the same fish category as the first fish. In the feature colour-change detection task the subjects indicated for each second fish whether the feature that was coloured had the same or a different colour as the same feature in the first fish. For half of the trials the subjects attended an informative feature and in the other half of the trials they attended an uninformative feature. (B) A 2 × 2 adaptation design was used during scanning. The informative features of the two fish could either be the same or different. In addition, the uninformative features of the fish would also either be the same or different. This yields four adaptation conditions: SS, same informative and same uninformative features; SD, same informative features, but different uninformative features; DS, different informative features, but the same uninformative features; DD, different informative and different uninformative features. Below is an example of what the different adaptation conditions look like for a fish for which the mouth and dorsal fin are informative features (grey solid circles) and the tail and ventral fin are uninformative features (grey dashed circles).

each adaptation condition there were 60 trials. 20 Trials per distance to the category boundary (close, medium, and far).

Subjects responded with the index (“same”) and middle finger (“different”) of the right hand on an MR-compatible response box (Lumitouch by Photon Control, Burnaby, Canada). In the categorization task the correct response in the SS and SD condition was always “same”. In the DS and DD half of the trials were also from the same category. Therefore, the ratio of “same” and “different” responses was 75:25. We used the same ratio of “same” and “different” responses for the feature colour-change detection task. To increase sensitivity we did not use fish stimuli from the corners of the fish space perpendicular to the category boundary. Fish could belong to close, medium, and far distances parallel to the category boundary.

### **Localizer scan**

We used a localizer scan to be able to compare the location of areas that show adaptation to the computer-generated fish with the location of areas that show responses to natural fish stimuli. In addition we can compare these locations with the location of other well-known areas such as the FFA and LOC. A blocked design was used with stimuli from five categories: 32 faces (16 male, 16 female), 32 houses, 32 common objects, 32 fish (not computer-generated, but natural fish), and 32 scrambled pictures. Images had grey backgrounds and measured 500 x 500 pixels. Images were randomly assigned to blocks of 17 images (each image was displayed for 400 ms and followed by a blank screen of 600 ms, except for the last image). Each block lasted 16.4 s. Within each block 16 images were unique and one image was repeated. The subjects’ task was to detect this repetition by pressing a button with the index finger of the right hand. Each block was followed by a blank screen interval of 10 s. Each image was presented twice to the subject, but within different blocks. There were four blocks for each category of objects. The localizer run lasted 8.7 minutes.

### **Similarity rating**

After participating in the fMRI experiment the subjects judged the perceived similarity of fish stimuli in a behavioural experiment. Subjects were instructed to rate the overall similarity of pairs of fish by pressing a key from 1 (very dissimilar) to 5 (very similar). Twenty-five fish exemplars were used for all subjects. Fish stimuli consisted of a combination of five points from the mouth-tail space and five points from the dorsal-ventral fin space. An asterisk, presented for 250 ms, marked the start of each trial. This was followed by the presentation of the first fish stimulus (400 ms), a scrambled fish image (350 ms), and the second fish stimulus (400 ms). The subjects could respond for 1250 ms. Each combination of stimuli was presented one time in each unique order, giving 600 trials.

### **Imaging parameters**

Whole-brain images (echo-planar imaging, 35 slices, 3 mm thick with 10% gap, repetition time = 2220 ms, in plane resolution = 3.3×3.3 mm<sup>2</sup>, echo time = 30 ms, flip angle = 80°, field of view = 21.1 cm, matrix size = 64×64) were acquired on a 3T whole body MR scanner (Magnetom TIM TRIO by Siemens Medical Systems, Erlangen, Germany). In addition, a high-resolution structural T1-weighted 3D magnetization prepared rapid acquisition gradient echo sequence image was obtained after the functional scan (192 slices, voxel size = 1×1×1 mm).

### **fMRI analysis**

Data analysis was done using BrainVoyager QX (by Brain Innovation, Maastricht, The Netherlands). The first two volumes were discarded to allow for T1 signal equilibrium. The following preprocessing steps were performed: slice scan time correction (using sinc interpolation), linear trend removal, temporal high-pass filtering to remove low-frequency non-linear drifts of three or fewer cycles per time course, and 3D motion correction to detect and correct for small head movements by spatial alignment of all volumes to the first volume by rigid

## Cortical selectivity to informative features

body transformations. All volumes were aligned to the first volume of the colour-change-detection-task scan session. This ensured between-session alignment of all three functional sessions. Co-registration of functional and 3D structural measurements was computed by relating T2\*-weighted images and the T1-weighted MPRAGE measurement, which yields a 4D functional data set. Structural 3D and functional 4D data sets were transformed into Talairach space (Talairach & Tournoux, 1988) and spatially smoothed with a Gaussian kernel (FWHM = 6 mm).

The expected BOLD signal change was modeled using a gamma function (tau of 2.5 s and a delta of 1.5) and convolved with the second event (Boynton, Engel, Glover, & Heeger, 1996). Statistical analyses were performed in the context of the general linear model. Both fixed and random-effects group analyses were performed. The statistical threshold was set at  $p < 0.001$  at the voxel level and a cluster threshold of  $50 \text{ mm}^3$ .

First, we looked at the difference between the two tasks (categorization and feature colour-change detection), comparing each task with rest and the two tasks with each other (categorization > feature colour-change detection). Next, we defined areas that showed adaptation following the repeated presentation of the same fish using the contrast  $SS < DD$ . The contrasts that we used from the localizer session were faces versus houses, fish versus objects, and objects versus scrambled images.

Next, significantly activated clusters were selected for a more sensitive region of interest (ROI) analysis. The ROI time-courses were standardized, so that beta weights (regression coefficients) of predictors, as indices of effect size, reflect the BOLD response amplitude of one condition relative to the variability of the signal. Beta weights were obtained for all voxels within these regions of interest, per subject and per adaptation condition (SS, DS, DS, and DD), per distance (medium, close, or far from the category boundary), and per category (same or different category). Random effects analyses were performed on the subject-averaged adaptation scores

and beta weights by applying  $t$ -tests, with a threshold set at  $p < 0.05$ . All  $t$ -tests were two-tailed.

For the correlation analysis we paired the proportion of correctly categorized fish during scanning or during the third training session (first and last block averaged) with the score for selectivity to the different feature types. Selectivity was defined as the amount of adaptation. So, for informative features this was defined as the subject-averaged beta-weight for those trials where the informative features were different minus the subject-averaged beta-weights of trials where the informative features remained the same [(DD + DS) minus (SS + SD)] and for the uninformative features it was defined as [(DD + SD) minus (SS + DS)].

### Training data analysis

Mean response times for the correct trials and the percentage of correct trials of the first and the last block of a training session were computed for each subject. These dependent variables were submitted to a training session  $\times$  block  $\times$  distance multivariate analysis of variance (MANOVA) with repeated measures. Training session consisted of three levels (first, second, and third training session), block of two levels (first and last), and distance to the category boundary consisted of three levels (close, medium, and far). Differences between training sessions were explored with multivariate analyses of variance with two levels for session and three levels for distance. Significant differences between sessions and blocks were explored with paired  $t$ -tests. We used a one-sample  $t$ -test to test the difference of the first block of the first training session with chance level. All reported  $t$ -test were 2-tailed.

### fMRI behavioural data analysis

Percentage of correct responses and reaction times on correct trials were computed for both the categorization task and the feature colour-change detection task. To investigate the effect of distance on reaction times and percentage of correct responses for both tasks we used a distance  $\times$  informative feature  $\times$  uninformative feature multivariate analysis of vari-

ance (MANOVA) with repeated measures. Distance had three levels (close, medium, and far), informative and uninformative features had two levels each (same and different).

In the categorization task we also investigated differences between fish with different informative features that belonged to either the same or different fish categories. We used an uninformative features  $\times$  category MANOVA with repeated measures. Uninformative features had two levels (same and different) and category also had two levels (same and different). To investigate the effect of attention for the feature colour-change detection task we used an attention  $\times$  informative feature  $\times$  uninformative feature MANOVA with repeated measures. Attention had two levels (attended informative feature and attended uninformative feature), informative and uninformative features had two levels each (same and different).

### Similarity rating data analysis

Similarity ratings (on a scale of 1-5) were entered in a MANOVA with repeated measures with four levels for feature (mouth, tail, dorsal fin, and ventral fin), four levels for the distance between two features (1, 9, 10, or 19 steps), and two levels for feature type (informative or uninformative). Significant interac-

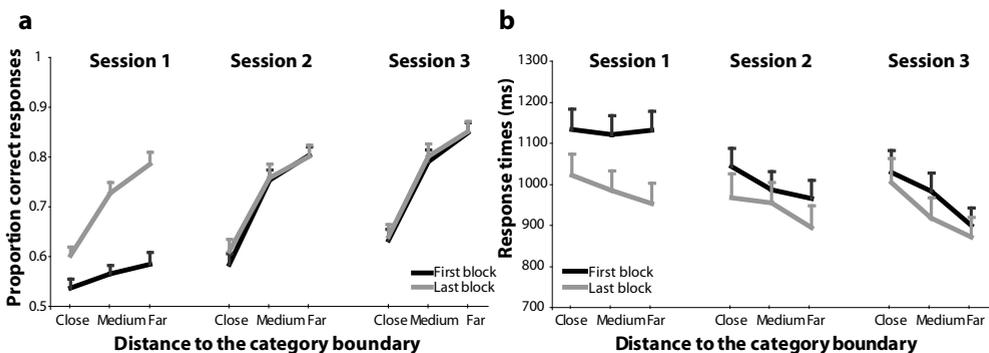
tions were further explored with MANOVAs and t-tests (paired and two-tailed).

## Results

### Training

Subjects trained for three days with the fish and had one training session per day. The percentage of correct responses increased over training sessions [ $F(2,22) = 27.66, p < 0.001$ ], see Figure 5a. In the first block of the first session subjects performed above chance [ $t(23) = 35.00, p < 0.001$ ] and performance improved from the first to the last block [ $F(1,23) = 40.93, p < 0.001$ ]. Performance also improved from the first to the second training session [ $F(1,23) = 23.83, p < 0.001$ ] and from the second to the third training session [ $F(1,23) = 15.12, p < 0.005$ ]. Within the second and third training session there were no differences in performance between the first and last blocks.

Performance was significantly modulated by the distance of the fish exemplars to the category boundary [ $F(2,22) = 136.65, p < 0.001$ ]. Subjects are better at categorizing fish that are further away from the category boundary. In the first block of the first training session the distance effect was already present [ $F(2,22) = 3.64, p < 0.05$ ]. In the last block of the first session the effect of distance [ $F(2,22) =$



**Figure 5.5**

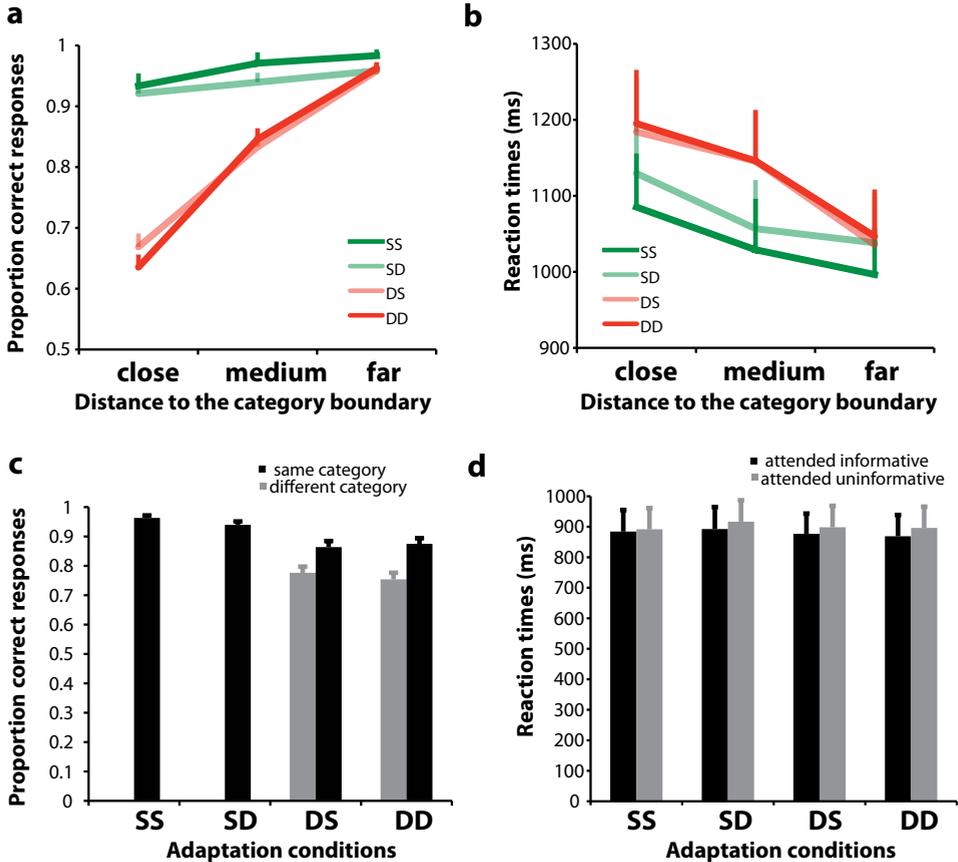
**Training data.** Proportion correct responses (A) and response times (B) are plotted for the first and last block of each training session as a function of the distance of the fish exemplars to the category boundary.

## Cortical selectivity to informative features

38,98,  $p < 0.001$ ] was greater than in the first session, as revealed by a significant block  $\times$  distance interaction [ $F(2,22) = 16,46$ ,  $p < 0.001$ ]. In the second and third session the effect of distance remained strong and did not differ between the first and last block of a session.

Reaction times (Fig. 5b) became faster over

training sessions [ $F(2,22) = 6,43$ ,  $p < .01$ ]. During the first training session subjects were faster in the last block than in the first block [ $F(1,23) = 9.71$ ,  $p < 0.01$ ], but for the consecutive training sessions no differences between the first and last blocks were observed. Reaction times improved from the first to the second session of training [ $F(1,23) = 12.71$ ,  $p <$



**Figure 5.6**

**Behavioural data. (A)** Proportion of correct responses of the categorization task as a function of the distance of the fish exemplars to the category boundary. **(B)** Reaction times of the categorization task as a function of the distance of the fish exemplars to the category boundary. **(C)** Proportion of correct responses in the categorization task plotted separately for adaptation conditions from the same and different fish categories. **(D)** Reaction times from the feature colour-change detection task as a function of the attended feature (informative or uninformative) for the different adaptation conditions (SS, SD, DS, and DD).

0.005], but not from the second to the third training session.

Subjects responded faster to fish that were further away from the category boundary [ $F(2,22) = 10.03, p < 0.005$ ]. We observed a significant 3-way interaction between training session, block, and distance [ $F(4,20) = 4.36, p < 0.05$ ]. In the first block of the first training session no effect of distance to the category boundary was present yet. In all subsequent blocks a significant effect of distance of the fish to the category boundary was obtained.

### **fMRI behavioural Categorization task**

Subjects performed well in the scanner (an average of 88.4% correct responses with a standard deviation of 4.1%). Accuracy was highest for fish that were far from the category boundary [ $F(2,22) = 166.65, p < 0.001$ ], see Figure 5.6*a*. Trials that had the same informative features had a higher accuracy than trials with different informative features [ $F(1,23) = 198.36, p < 0.001$ ]. This effect, albeit smaller, was also present for fish that had the same uninformative features than fish with different uninformative features [ $F(1,23) = 4.94, p < 0.05$ ]. The effect of distance to the category boundary was largest for fish with different informative features, as revealed by an interaction between informative feature and distance [ $F(2,22) = 46.12, p < 0.001$ ].

Subjects responded fastest to fish far from the category boundary [ $F(2,22) = 12.21, p < 0.001$ ], see Figure 5.6*b*. Subjects responded faster to trials in which the fish had the same informative features than when the fish had different informative features [ $F(1,23) = 26.86, p < 0.001$ ]. When the uninformative features were also the same the responses were even faster than when the uninformative features were different [ $F(1,23) = 4.10, p = 0.055$ ]. The effect of distance to the category boundary was largest for fish with different informative features [ $F(2,22) = 7.44, p < 0.005$ ].

Fish with the same informative features were from the same category. However, fish with different informative features could belong to the same

or a different category. Accuracy was higher for those fish with different informative features that belonged to the same category [ $F(1,23) = 10.52, p < 0.005$ ] than for fish with different informative features that belonged to different categories, see Figure 5.6*c*. It did not matter for these fish whether their uninformative features were the same or different. The reaction times did not differ between fish from the same or different categories.

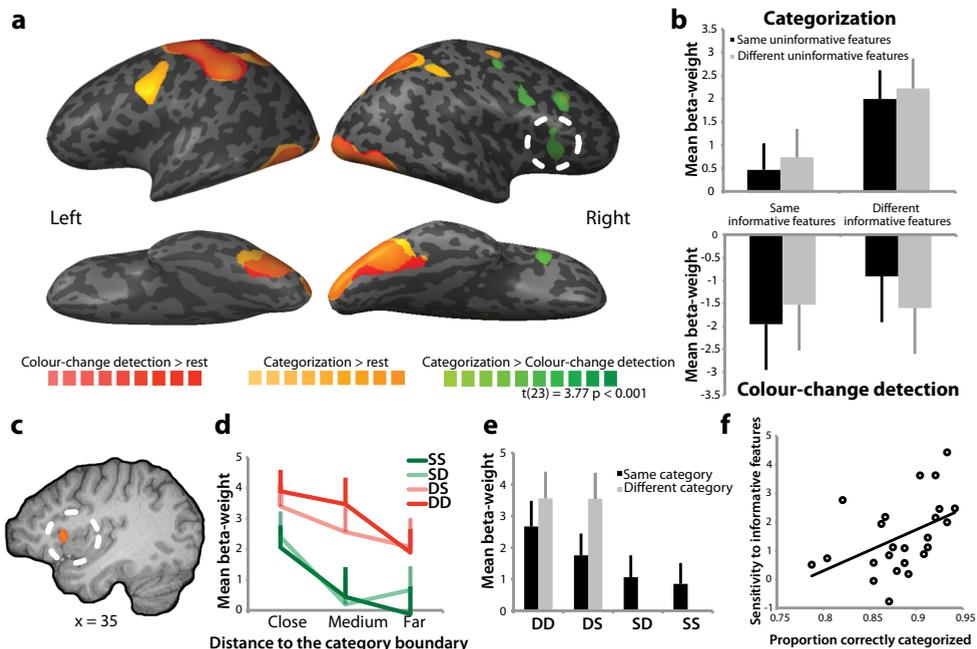
### **Feature colour-change detection task**

Performance accuracy in the feature colour-change detection task was very high. The mean percentage of correct responses was 98.4% (standard deviation = 1.8%), but did not differ between conditions. Also no significant effects were found for the reaction times for the different adaptation conditions, nor for the different distances of the fish to the category boundary. However, a significant effect of attention on reaction times was found, Fig 5.6*c*. Subjects were on average 20 ms faster when they attended the informative features [ $F(1,23) = 9.74, p < 0.01$ ], Fig. 5.6*d*.

### **fMRI Categorization versus feature colour-change detection**

After three days of training the subjects were scanned. We used an fMRI adaptation paradigm with two tasks. A categorization task and a feature colour-change detection task. Both tasks activated largely the same brain areas (occipitotemporal, parietal, and motor cortices [ $t(23) = 3.77, p < 0.001$ ]), see Figure 5.7*a*. When comparing the categorization task with the feature colour-change detection task we found that right frontal cortex was more active for the categorization task than for the feature colour-change detection task [ $t(23) = 3.77, p < 0.001$ ], see Figure 5.7*a*. We tested for effects of adaptation (Figure 5.7*b*) in the right inferior frontal gyrus (Figure 5.7*c*). We found that the inferior frontal gyrus showed adaptation when presented with two identical fish [ $SS < DD: t(23) = 4.73, p < 0.001$ ], but more importantly only the responses

## Cortical selectivity to informative features



**Figure 5.7**

**fMRI results. (A)** Overlay of the group-averaged activation maps of two tasks during scanning (in red colour-change detection task and in yellow categorization task) versus rest and the comparison between the two tasks in green (categorization versus colour-change detection task). Results are projected on inflated Talairach-normalized hemispheres in lateral (top) and ventral views (bottom). Light grey colours represent the gyri and dark grey colours the sulci. **(B)** Results from the ROI analysis showing the mean beta-weights (i.e., estimates of signal amplitude) from the voxel population in the right inferior frontal gyrus for the four adaptation conditions (same or different informative features with same or different uninformative features) for the two tasks (top: categorization task, bottom: colour-change detection task). Error bars represent the standard error of the mean. **(C)** Region of interest in the right inferior frontal gyrus where categorization > colour-change detection, overlaid on the coronal slices of a normalized structural image of a single subject in neurological convention (Talairach coordinates of the centre of mass:  $x = 35$ ,  $y = -19$ ,  $z = 8$ , volume = 400 mm<sup>3</sup>, average  $t(23) = 4.18$ ,  $p < 0.0005$ ). **(D)** Mean beta-weights from the ROI in right inferior frontal gyrus that was more active for categorization than for colour-change detection. Shown are the group-averaged responses for all adaptation conditions (Green: SS, same informative and same uninformative features, light green: SD, same informative and different uninformative features, light red: DS, different informative and same uninformative features, and red: DD different informative and different uninformative features) as a function of the distance of the fish to the category boundary (close, medium, and far). **(E)** Group-averaged beta-weights from the same ROI plotted as a function of category membership. In grey responses to fish from different categories and in black responses to fish from the same category. **(F)** Correlation between performance during categorization in the

scanner and the sensitivity of the right inferior frontal gyrus to the informative features (adaptation effect: responses to fish with different informative features minus response to fish with the same informative features).

to the informative features were adapted [SS + SD < DS + DD:  $F(1,23) = 33.20, p < 0.001$ ]. Changing the uninformative features did not alter the response [SS + DS < SD + DD:  $F(1,23) = 0.88, p = ns$ ]. This area was not active during the colour-change detection task, see Figure 5.7*b*. In addition we tested whether there was an effect of distance of the fish to the category boundary on the responses of the right inferior frontal gyrus, see Figure 5.7*d*. Indeed, we found that responses were higher to those fish that were closer to the category boundary [ $F(2,22) = 8.06, p < 0.005$ ].

Given that prefrontal cortex is usually associated with active categorization, we tested whether there was a category effect in this area, Figure 5.7*e*. We compared fish that had different informative features and belonged to different categories with fish that also had different informative features, but belonged to the same category. We found that responses were higher for fish from different categories than for fish from the same category [ $F(1,23) = 6.42, p < 0.05$ ] and that it made no difference whether the uninformative features were the same or different [ $F(1,23) = 1.01, p = ns$ ].

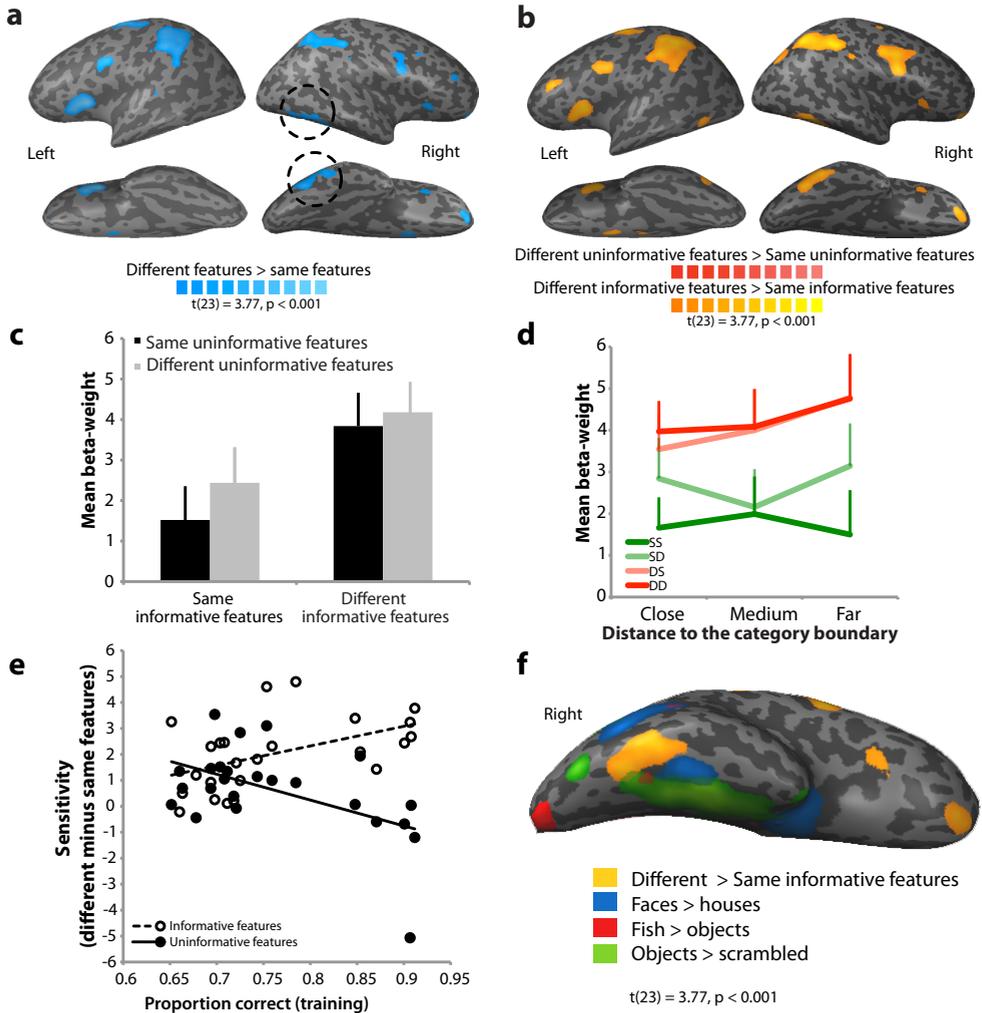
We were also interested in seeing whether responses in this area correlated with performance during training or with performance during scanning and whether this holds for the informative features or also for the uninformative features. A significant correlation was found between subject-averaged categorization scores during scanning and sensitivity to the informative features [ $r = 0.46, p < 0.05$ ], Figure 5.7*f*. There was no correlation between categorization scores and sensitivity to the uninformative features [ $r = .02, p = ns$ ]. There was no correlation with performance during training [informative features:  $r = -0.31, p = ns$ , uninformative features:  $r = -0.35, p = ns$ ]. Next, we analyzed the two tasks separately.

### **Categorization task**

First, we investigated areas that showed adaptation when presented with exactly the same objects compared to different objects (SS < DD), Figure 5.8*a*. We found that this effect was driven entirely by the informative features, Figure 5.8*b*. No selectivity was obtained for the uninformative features. We extracted responses from the right occipitotemporal cortex from the area that was obtained by the SS < DD contrast. For this area the effect driven by informative features and not uninformative features (Fig 5.8*c*). There was no effect of distance [ $F(2,22) = 0.93, p = ns$ ] on the responses from the right occipitotemporal cortex (Fig 5.8*d*). We hypothesized that training increases the sensitivity to informative features. Indeed, we found that there was a correlation between training success and increased selectivity to informative features [ $r = 0.48, p < 0.05$ ], fig 5.9*e*. Most interestingly, we obtained the reversed effect for the uninformative features. Training led to decreased selectivity to uninformative features [ $r = -0.52, p < 0.01$ ]. We found no correlation of occipitotemporal sensitivity with categorization during scanning.

Because the area we found seems more located in the inferior temporal cortex than in the fusiform or lateral occipital gyrus, we compared its location to the results from our localizer. We contrasted faces with houses which usually activates an area in the fusiform gyrus, the fusiform face area (FFA) and we looked for object selective cortex, usually found in the lateral occipital complex (LOC) by contrasting objects with scrambled pictures. Indeed our area falls in between the FFA and the LOC, see Figure 5.8*f*. We also compared it to the area that responds more to natural fish stimuli than to objects. This area falls posterior to the FFA and just outside the area that is selective to the informative features.

## Cortical selectivity to informative features



**Figure 5.8**

**Categorization task adaptation effects.** (A) Blue colours represent the overlay of the group-averaged activation map of areas that showed adaptation to two identical fish (SS) compared with the presentation of two different fish (DD). Results are projected on inflated Talairach-normalized hemispheres in lateral (top) and ventral views (bottom). Light grey colours represent the gyri and dark grey colours the sulci. (B) Overlay of areas that responded selectively to informative features (SS + SD < DS + DD) in yellow. No areas showed selectivity to the uninformative features (SS + DS < SD + DD), in red. (C) Results from the ROI analysis showing the mean beta-weights (i.e., estimates of signal amplitude) from the voxel population in the right occipitotemporal cortex (Talairach coordinates of the centre of mass:  $x = 47, y = -49, z = -10, \text{volume} = 2665 \text{ mm}^3$ , average  $t(23) = 4.15, p < 0.0005$ ) for the four adaptation conditions (same or different informative features with same or

different uninformative features) for the two tasks (top: categorization task, bottom: colour-change detection task). Error bars represent the standard error of the mean. **(D)** Mean beta-weights from the ROI in right occipitotemporal cortex that showed adaptation to the presentation of identical fish. Shown are the group-averaged responses for all adaptation conditions (Green: SS, same informative and same uninformative features, light green: SD, same informative and different uninformative features, light red: DS, different informative and same uninformative features, and red: DD different informative and different uninformative features) as a function of the distance of the fish to the category boundary (close, medium, and far). **(E)** Correlation between performance during training and the sensitivity of the right occipitotemporal cortex to the informative features (open dots) and the correlation of training performance with sensitivity to the uninformative features (closed dots). **(F)** Representation of the location of the occipitotemporal area that was selectively responsive to informative features with respect to the area that responds to natural fish stimuli and the location of the fusiform face area (FFA) and the lateral occipital complex (LOC).

### **Feature colour-change detection task**

No areas were found that showed adaptation to the features. We did find areas that showed adaptation for the same colour (Fig. 5.9).

### **Similarity ratings**

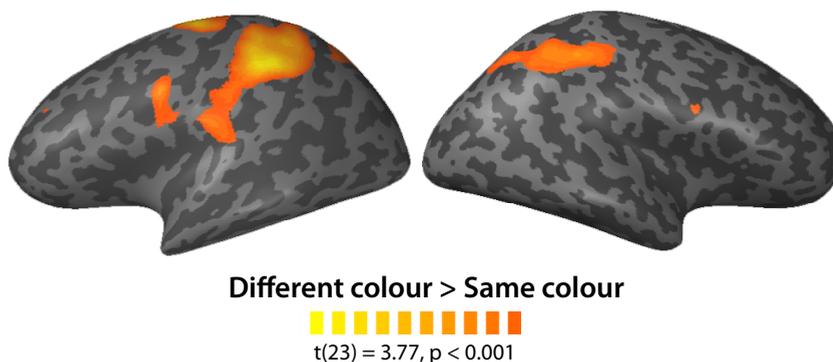
After the fMRI experiment the subjects were asked to rate pairs of fish on their similarity, see Figure 5.10. No rating differences were obtained for the four different features (mouth, tail, dorsal fin, and ventral fin). As expected, subjects were more likely to rate fish more similar if there was a small physical difference between the features and as more dissimilar if the fish in a pair had greater physical difference between their features [ $F(3,9) = 7.77$ ,  $p < 0.01$ ]. This distance effect was strongest for the informative features as was revealed by an interaction between distance and feature type [ $F(3,9) = 5.25$ ,  $p < 0.05$ ]. So, pairs of fish were rated more similar if their informative features were close together in fish space and were rated as being more dissimilar if they were further away in fish space [ $F(3,9) = 6.61$ ,  $p < 0.05$ ]. In addition, informative features were rated as being more similar at distance 1 than uninformative features at the same distance [ $t(11) = 4.17$ ,  $p < 0.005$ ] and more dissimilar than uninformative features at a distance of 19 [ $t(11) = -3.37$ ,  $p < 0.01$ ]. At distances 9 and 10 there was no difference in rating between informative and uninformative features. The ratings of the informative features differed be-

tween steps 1 and 9 [ $t(11) = 4.18$ ,  $p < 0.005$ ] and between 10 and 19 [ $t(11) = 3.55$ ,  $p < 0.01$ ], but not between 9 and 10.

### **Discussion**

We used a training paradigm in which subjects learned to discriminate two categories of fish. Fish from these categories had four distinctive features, but only two of the features were informative for category membership and two of the features were uninformative. Subjects were able to categorize the fish well after three days of training and performed best on fish that were furthest away from the category boundary. After training subjects were asked to rate fish on their similarity. As expected, informative features determined perceived similarity between exemplars, as pairs of fish were rated more similar when they had a smaller physical difference and rated as being less similar when they had a greater physical difference in informative feature values. In contrast, the similarity ratings for pairs of fish was unaffected by differences in uninformative features. Also, informative features with a small difference were rated as being more similar than uninformative features with the same difference. In addition, informative features with a greater distance were rated as being more dissimilar than uninformative features with the same difference. This pattern of results indicates that training led to increased sensitivity to differences in features that

## Cortical selectivity to informative features



**Figure 5.9**

**Feature colour-change detection task.** In orange the areas that showed adaptation to the same colour are represented. Results are projected on inflated Talairach-normalized hemispheres in lateral (top) and ventral views (bottom). Light grey colours represent the gyri and dark grey colours the sulci.

were informative for categorization or a decrease in sensitivity for features that were uninformative for categorization. Thus, only the informative features were weighted when subjects made a decision about the similarity of the fish.

After three training sessions the subjects were scanned. We used an fMRI adaptation paradigm (Grill-Spector, Henson, & Martin, 2006) to test for selective responses to informative and uninformative features. Fish were presented in pairs that had identical or different informative and uninformative features. The idea is that if neuronal clusters are sensitive to a certain type of feature they will show a reduced response when this feature is repeated. We used two tasks, a categorization task and a feature colour-change detection task. We found that both categorization task and colour-change detection task activated largely the same areas. Only the inferior frontal cortex was more active during categorization. Prefrontal cortex is assumed to be involved in active categorization in monkeys and humans (Freedman et al., 2001, 2002, 2003; Jiang et al., 2007) which fits with this result. We investigated the selectivity of responses in the right inferior frontal gyrus and found that the area responded selectively to informative features. Responses in the right inferior frontal

gyrus were reduced when informative features were repeated. The responses in this region were unaffected by whether the uninformative features stayed the same or differed. Interestingly, responses in the right inferior frontal gyrus were greater for those trials that were close to the category boundary. This could mean that the frontal cortex is involved in representing category boundaries, but it seems more likely that this finding indicates more effortful processing of the categories. Trials close to the category boundary are found to be more difficult, producing more errors and longer reaction times. Perhaps more top-down feedback from the inferior frontal cortex is necessary to activate the appropriate features. Difficulty to categorize these stimuli would thus lead to more activity in this area. In addition, responses of the right inferior frontal gyrus were category-specific. We found a dissociation between responses to fish from the same and from different categories. However, this finding, also reported by Jiang and colleagues (2007), can also be explained by categorization effort. Behavioural data showed lower accuracy scores and longer reaction times when objects belonged to different categories than when they belonged to the same category. This is an indication that they were more difficult to categorize.

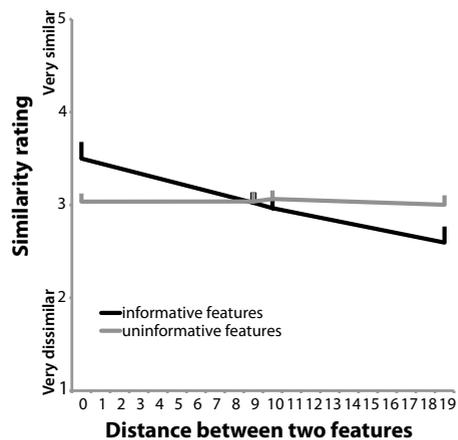
rise. Furthermore, we found a correlation of frontal adaptation scores with the behaviour of the subjects during scanning. Better categorization performance was linked with higher adaptation scores. For the uninformative features no correlation was found and also not between performance during training and adaption effects in right inferior frontal gyrus. Together, these findings provide new and additive evidence that prefrontal cortex is indeed involved in active categorization with a focus on those features that are relevant for categorization, while selectively ignoring those features that proved to provide no useful category information.

Occipitotemporal cortex is usually found to show training-related changes in activation following category training (Moore et al., 2006; Op de Beeck et al., 2006; van der Linden et al., 2008; van der Linden, van Turennout, & Fernández, 2011). More specifically, categorizing stimuli has been shown to induce cortical selectivity in occipitotemporal cortex. These occipitotemporal areas included the fusiform gyrus (van der Linden et al., 2010) and the lateral occipital gyrus (Gillebert et al., 2009; Jiang et al., 2007). In the present study we revealed that this selectivity is experience-dependent and not present for the entire trained object, but specific for those features that are informative for categorization. This novel finding bridges the gap between monkey electrophysiological recordings that showed selective responses to informative features (De Baene et al., 2008; Sigala & Logothetis, 2002) and human fMRI data that revealed increased and selective responses to trained objects (Gauthier et al., 1998; Gillebert et al., 2009; Jiang et al., 2007; Moore et al., 2006; Op de Beeck et al., 2006; van der Linden et al., 2008; van der Linden et al., 2010; Weisberg et al., 2007). The area in occipitotemporal cortex that we found to be sensitive to informative features is a region that appears closer to the lateral part of the inferior temporal cortex than to the fusiform or lateral occipital gyrus. Interestingly, although the occipitotemporal cortex appeared to show similar responses as the inferior frontal cortex at first glance, a closer look into the data provided a different pattern of selectivity.

For example we did not find any relation between occipitotemporal responses and the distance to the category boundary nor did this area show category specificity. Also, performance during scanning was unrelated to the selectivity of the occipitotemporal cortex. However, performance during training did relate to the sensitivity of the area. Subjects that were better during training showed greater selectivity to the informative features and what is most interesting is that this was paired with less selectivity for the uninformative features. This pattern of results indicates that training can increase sensitivity to informative features but also that at the same time uninformative features are ignored. To take this a bit further, we might speculate that learning to categorize objects is an active process whereby an optimal sharpening of tuning could be achieved by increasing selectivity to informative features and by reducing or suppressing selectivity to uninformative features. This is similar to the interpretation of re-

**Figure 5.10**

**Similarity ratings.** Similarity ratings on a scale of 1 to 5 (1 = very dissimilar, 5 = very similar) for pairs of fish as a function of the distance between the features of the fish. One step corresponds to one step in feature space. Similarity ratings are plotted separately for informative and uninformative features.



## Cortical selectivity to informative features

sults proposed before (van der Linden et al., 2008), where it was suggested that the additional decreased responses to objects that were trained with random feedback (thereby obstructing category learning) were due to a suppression of the responses to those features that proved to be uninformative for categorization. However, in that study it was impossible to disentangle the informative from the uninformative features like in the present study. Though, this also provided a certain caveat. Separable dimensions can be attended to separately. In our fish stimuli it is easy to attend to the fins and ignore the rest of the features, so called selective attention. However, neuronal selectivity to features has and can only be found using separable features and not when using integral features (De Baene et al., 2008; Op de Beeck, Wagemans, & Vogels, 2001; Sigala & Logothetis, 2002). Although selective attention can be put forward as an explanation for adaptation to repeated presentation of identical informative features, there is no reason to assume more attention to fish features that are closest to the category boundary, as was found in the inferior frontal gyrus. Occipitotemporal cortex did not show such an effect of distance to the category boundary, but this area showed a correlation with behaviour outside the scanner, also a finding that cannot readily be explained by selective attention during categorization in the scanner.

Only during the categorization task did we find selective responses to informative features. Also during the colour-change detection task no selectivity to any of the repeated features was present; the brain showed only adaptation when presented with features that had the same colour. Even though the behavioural data suggested that there was slight advantage for the informative features during the colour-change detection task, we found no evidence for automatic cortical processing of the informative features. The category representation adapts to task demands. Ultimately what is perceived and processed of an object is determined by the goal of the observer (Tanaka, 2004).

To conclude, we showed for the first time in humans that the informativeness of features for categorization is reflected in neuronal selectivity in occipitotemporal and inferior frontal cortex. Both areas seemed to play a different role. The inferior frontal gyrus was involved in active categorization of the stimuli and the responses were modulated by categorization effort. The occipitotemporal cortex showed selectivity for informative features that was dependent on the performance of the subjects during training. Success in training led to greater selectivity for the informative features in combination with less selectivity for the uninformative features. Importantly, these effects were highly task-dependent.

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## **Summary and discussion**

## Summary and discussion

 bject categorization is an acquired skill. From early on in life, we learn to assign perceptually similar objects to the same category. We even learn that different looking objects can still belong to the same category because they are conceptually the same. This process continues throughout adulthood with learning and experience shaping the borders of existing categories and forming entirely new categories. Although brain imaging has demonstrated object-category specific representations in the occipitotemporal cortex, the crucial question of how the brain acquires this knowledge has remained unresolved. The goal of the research described in this thesis was to address a fundamental question in visual neuroscience: what are the neural mechanisms underlying category formation? How does our brain deal with discriminating between perceptually similar objects while also being able to generalize perceptually dissimilar but conceptually similar objects? In this chapter, I will summarize and discuss the research described in this thesis. I will describe how these findings relate to each other and to (more recent) research by others. To conclude I will formulate an answer to the research question that this thesis addressed.

Category representation involves more than the encoding of simple object features. Whereas members of the same category can look very different (e.g., the face of a young girl and the face of an old woman are very different, but clearly belong to the category 'female'), members of different categories can look very similar (although a male and a female face often have very similar features, we can easily keep them apart). To measure the establishment of such sharp groupings and divisions, we employed a training paradigm similar to the one used by Freedman and colleagues (Freedman, Riesenhuber, Poggio, & Miller, 2001, 2002, 2003, 2006) to study object category formation in monkey cortex. They used a morphed stimulus set with an arbitrary category boundary placed between these morphed exemplars. We reconfigured this paradigm so we could use it to investigate human subjects in an

fMRI experiment. In Chapter 2 we used a training paradigm in which subjects learned to discriminate between similar looking bird categories. Two types of feedback were provided to the subjects: correct feedback to help the subjects learn to categorize the birds and random feedback that was detrimental to category learning. This way we could separate between representations that were formed by category learning and those formed by visual exposure. After three days of training, fMRI results showed that responses in the occipitotemporal cortex, more specifically in the right fusiform gyrus were selectively increased for bird types for which a discrete category-boundary was established. Importantly, decreased activity was observed for visually similar birds to which subjects were exposed during training but for which no category-boundary was learned. This result clearly shows that the increase in activity for category-trained bird types in the right fusiform gyrus was not caused by mere visual exposure, but mediates the formation of category-specific representations. The novel contribution of this study was that it allowed this direct contrast between stimuli as a function of whether they were assigned to a trained category or not. Previous studies on this topic have not distinguished between mere visual exposure and behaviourally relevant responses. Thus, they have not been able to attribute any changes in cortical function to simply being exposed to the stimulus versus defining a neural substrate concerned with category learning per se. Recently however, Gillebert et al. (2009) performed a similar study and found that categorization training and not visual exposure alone led to increased selectivity for trained objects in the occipitotemporal cortex. This nicely corroborates our findings.

As we showed in Chapter 2 and was also shown by other studies (Gauthier, Skudlarski, Gore, & Anderson, 2000; Gauthier, Tarr, Anderson, Skudlarski, & Gore, 1999; Moore, Cohen, & Ranganath, 2006; Op de Beeck, Baker, DiCarlo, & Kanwisher, 2006; Rhodes, Byatt, Michie, & Puce, 2004; Weisberg, van Turenhout, & Martin, 2007; Xu, 2005) increased perceptual expertise is linked to neuro-

nal changes in occipitotemporal cortex. However, in all these studies, including my own, category-membership was perception-based, i.e. perceptually similar objects belonged to the same category. Thus, we investigated how cortical representations in the adult human brain are shaped when perceptually dissimilar objects are grouped in the same category in Chapter 3. In this study, a discrete boundary between similar-looking natural objects (birds) belonging to different categories was established by training. The same morphed bird stimuli were used as in Chapter 2. This allowed comparison of birds on the same side of the category boundary (belonging to the same bird type) with birds with a similar physical difference but on opposite sides of the category boundary (belonging to different bird types and belonging to either the same category or a different category). Outside the scanner, subjects were trained to categorize the birds into conceptual categories (jungle birds and desert birds). Although with this paradigm the focus was on the grouping of birds into categories instead of discriminating between bird categories as was the case in Chapter 2 the results for the occipitotemporal cortex were similar. After training, neuronal populations in occipitotemporal cortex, such as the fusiform and lateral occipital gyrus were highly sensitive to perceptual stimulus differences. Because this time we used an fMRI adaptation paradigm, we could infer that neuronal populations in occipitotemporal cortex had become selectively responsive to the trained items. This extends our results from Chapter 2 where we already speculated that neuronal selectivity was the underlying mechanism of the experience-dependent increase in responsiveness to the trained birds. However, since the fMRI data in Chapter 2 were expressed as the size of the response of large neuronal clusters, no inferences could be made on whether the results indeed reflect increased neural selectivity. In this study, we showed that training does lead to increased selectivity for trained but not novel birds types in the occipitotemporal cortex. A very similar study by Jiang et al. (2007) who used morphed cars also found increased selectivity in oc-

cipitotemporal cortex. They also found that during active categorization the frontal cortex showed sensitivity to category membership of the trained cars. Whereas Jiang and colleagues were only able to find evidence for categorical representations in frontal cortex when participants were actively categorizing the cars, we found in our study evidence for category selectivity when participants were performing an orthogonal task. A release from adaptation was observed in the superior temporal sulcus only when two birds in a pair crossed the conceptual category boundary. This dissociation could not be explained by perceptual similarities, because the physical difference between birds from the same side of the category boundary and between birds from opposite sides of the category boundary was equal. Thus, we concluded that occipitotemporal cortex together with the superior temporal sulcus have the properties suitable for a system that can both generalize across stimuli and discriminate between them.

In Chapter 3 we found a region in the superior temporal sulcus to be involved in conceptual category representation. Because this region is usually found active in cross-modal representations and has more recently been suggested to be involved in associating objects regardless of the modality, the training paradigm of Chapter 2 was extended to the cross-modal domain. Hence, we investigated in Chapter 4 the formation of cross-modal object category representations in the brain. The stimulus set consisted of the same six highly similar bird shapes that were used in the two previous studies (Chapter 2 and 3). These bird shapes became associated to sounds. The sounds were newly created for this experiment from real bird cries and were also morphed -like the bird shapes- to create different exemplars of each category. Subjects learned novel cross-modal categories in a 1-back “same-different bird type” task. This was the same task as we used in *Chapter 2*. After training, subjects were scanned while passively viewing and listening to the birds. Stimulus blocks consisted of bird sounds only, bird pictures only, matching pictures and sounds (cross-modal congruent), and mismatching pictures and sounds

## Summary and discussion

(cross-modal incongruent). Our fMRI data showed visual object category learning in occipitotemporal cortex and more specifically in the right fusiform gyrus. The observed increase to trained bird shapes relative to novel bird shapes replicated the findings in Chapter 2 where we also observed increased responses in the fusiform gyrus. The responses of the fusiform gyrus to the other conditions that we used in Chapter 4 form an interesting addition to our understanding of visual object representations in the fusiform gyrus and the role of the superior temporal sulcus in category representations. Firstly, the right middle fusiform gyrus showed a training effect for trained cross-modal birds relative to novel cross-modal birds. We found no training effect for incongruent cross-modal birds. This pattern of results fits also with our previous finding that the right fusiform gyrus showed only increased responsiveness for birds for which a meaningful representation had been formed and not for birds to which the subjects were exposed in an equal amount, but for which they were hindered in forming a representation of the categories. This strengthens our hypothesis that only task-relevant object features are stored in the occipitotemporal cortex. Secondly, we found an auditory training effect in the fusiform gyrus. We suspect that it is not the representation of a trained sound that is stored in the fusiform gyrus, but that hearing the sound of a trained bird category activates its visual representation, which is stored in the fusiform gyrus. This finding is in line with human voices activating the matching face representations (von Kriegstein & Giraud, 2006). This shows that via different routes the visual representation can be accessed and that the fusiform representation is under influence of feedback connections. Finally, the finding of cross-modal congruency and cross-modal training effects in superior temporal sulcus can also be linked to the findings of Chapter 3. Like in the previous chapter, the newly formed cross-modal representation in left superior temporal sulcus was also category-specific. Learning did not generalize to incongruent combinations of learned sounds and shapes, their response did not differ from the res-

ponse to novel cross-modal bird types. Moreover, responses were larger for congruent than for incongruent cross-modal bird types providing further evidence for a training-induced formation of meaningful cross-modal object categories. We can conclude from Chapter 3 and 4 that the superior temporal sulcus is involved in the representation of associated objects and capable of forming new meaningful links between shapes of different categories and also between sounds and shapes of objects. Chapter 4 thus provides evidence that the adult human brain is indeed plastic enough to learn new cross-modal categories by the associations of sounds and shapes. Moreover, the combination of sound and shapes that define a category is crucial for the formation of cortical cross-modal representations.

In the fourth study (Chapter 5) we tested the hypothesis that category learning involves increased sensitivity to those features that are relevant for category membership. The studies in Chapters 2, 3, and 4 have shown that categorization training leads to increased cortical selectivity in the adult human brain to trained items. We investigated whether this selectivity can be linked to those features that are relevant for category membership. We trained subjects with computer-generated fish stimuli. We switched from birds to fish stimuli with four separable features. These stimuli were parametrically modified along four feature dimensions. We used the same task during the training sessions that we successfully used in Chapter 2 and 4. For each participant two features were informative for category membership and two features were uninformative. Like in Chapter 3, we used an fMRI adaptation paradigm. With this paradigm, we could specifically investigate cortical selectivity to informative and uninformative features. We used two tasks to investigate active categorization and automatic processing of the informative features using a categorization task and a feature colour-change detection task. We found that, during the categorization task, the right inferior frontal gyrus was indeed selectively responsive to the informative but not to the uninformative features. Responses in this area were also larger

for those fish features that were close to the category boundary. In addition, inferior frontal cortex showed category selectivity and selectivity to the informative features correlated with performance on the categorization task during scanning. This all suggests that the prefrontal cortex is involved in behaviourally-relevant manner. Prefrontal cortex uses the informative features of objects to do so, while ignoring those features that do not contribute category information. Occipitotemporal cortex also showed selectivity to the informative features during the categorization task. Interestingly, this area showed a positive correlation of performance during training and selectivity to the informative features and a negative correlation with selectivity to the uninformative features. This indicates that training enhanced sensitivity to trained items and decreased sensitivity to uninformative features. This is a crucial result, because it is an addition to the findings from the previous chapters where we already suggested this mechanism to be at work. The absence of sensitivity for informative features during the colour-change detection task indicated that there is a strong component of task-related processing of these features. In this light, we also need to review the tasks used in the previous chapters. We found training-related and even category-selective responses in these chapters, even though we did not use an explicit categorization task. It seems that the absence of a task (in Chapter 2 and 4) or the old-new task in Chapter 3 may not have tapped into automatic processing of the birds' informative features, but instead processing of these informative features might have been implicitly facilitated by the (absence of a) task. To conclude, in Chapter 5 we bridged the gap between monkey electrophysiological recordings that showed selective responses to informative features (De Baene, Ons, Wagemans, & Vogels, 2008; Sigala & Logothetis, 2002) and human fMRI data such as in the previous chapters and in several other studies (Isabel Gauthier, Williams, Tarr, & Tanaka, 1998; Gillebert et al., 2009; Jiang et al., 2007; Moore et al., 2006; Op de Beeck et al., 2006; Weisberg et al., 2007) that demonstrated in-

creased and selective responses to trained objects.

## Conclusion

What are the neural mechanisms underlying category formation? The question and its answer are broader than only this thesis can cover, but I believe that some important contributions to answer this question can be found in the chapters. Together, the research in this thesis provides novel insights in how the human brain learns, stores, and uses category knowledge, enabling us to become skilled in categorization. The studies reveal the neural mechanisms through which perceptual as well as conceptual category knowledge is created and shaped by experience. Our results clearly show that neuronal sensitivity to object features is affected by categorization training. These findings fill in a missing link between electrophysiological recordings from monkey cortex demonstrating learning-induced sharpening of neuronal selectivity and brain imaging data showing category-specific representations in the human brain. Moreover, we showed that it is specifically the features of an object that are relevant for its categorization that induce selectivity in neuronal populations. Category-learning requires collaboration between many different brain areas. Together these can be seen as the neural correlates of the key points of categorization: discrimination and generalization. The occipitotemporal cortex represents those characteristic features of objects that define its category. The narrowly shape-tuned properties of this area enable fine-grained discrimination of perceptually similar objects. In addition, the superior temporal sulcus forms associations between members or properties (i.e. sound and shape) of a category. This allows the generalization of perceptually different but conceptually similar objects. Last but not least is the prefrontal cortex which is involved in coding behaviourally-relevant category information and thus enables the explicit retrieval of category membership.

## Summary and discussion

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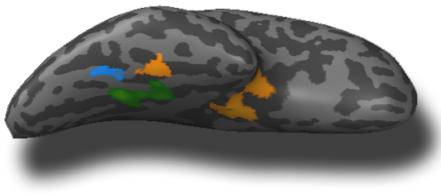


**Nederlandse samenvatting**

## Nederlandse samenvatting

**N**et categoriseren van de dingen om ons heen is een aangeleerde vaardigheid die voortborduurt op onze aangeboren eigenschap om de wereld te willen ordenen. Vanaf het prilste begin van ons leven leren we om objecten toe te wijzen aan categorieën. Het makkelijkst leren we dat perceptueel soortgelijke objecten tot dezelfde categorie behoren (bijvoorbeeld appel en peer). Maar we leren ook dat verschillend uitziende objecten ook tot dezelfde categorie kunnen behoren, omdat ze conceptueel hetzelfde zijn (bijvoorbeeld aardbei en ananas). Dit proces gaat ons hele leven door. Leren en ervaring geven de grenzen van de bestaande categorieën vorm en kunnen zelfs leiden tot de vorming van geheel nieuwe categorieën.

Waar in het brein bevinden zich dan de neurale mechanismen die ervoor zorgen dat wij kunnen categoriseren? Onderzoek van de menselijke hersenen heeft aangetoond dat specifieke categorierepresentaties zich in de occipitotemporale cortex bevinden (zie Figuur 7.1). Maar de cruciale vraag hoe deze representaties in de hersenen ontstaan zijn is nog niet beantwoord. Het doel van het onderzoek in dit

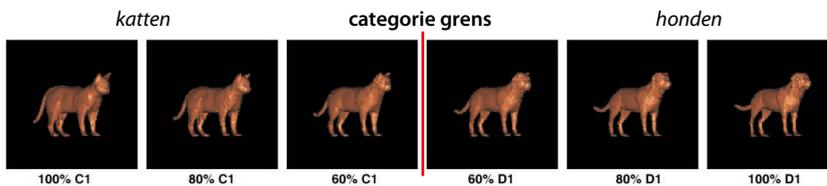


**Figuur 7.1**

Onderaanzicht van een rechter hersenhelft van het menselijk brein. Deze hersenhelft is “opgeblazen”, zodat ook de dieperliggende structuren zichtbaar zijn. In dit voorbeeld zien we in groen gebieden die betrokken zijn bij de representatie van huizen, in geel de representatie van gezichten en in blauw de representatie van vissen. Deze gebieden zijn verkregen door de gemiddelde hersenactiviteit te nemen van 24 proefpersonen die plaatjes van deze drie categorieën hebben bekeken in de MRI-scanner.

proefschrift was om te onderzoeken wat de neurale mechanismen zijn die ten grondslag liggen aan de vorming van categorierepresentaties door leren en ervaring. Andere vragen die daarbij ook opkomen zijn: Hoe gaat ons brein om met het onderscheiden van perceptueel soortgelijke voorwerpen die tot verschillende categorieën behoren en hoe kan ons brein aan de andere kant twee objecten die perceptueel verschillend zijn toch conceptueel groeperen? In dit hoofdstuk zal ik het onderzoek dat ik heb gedaan om deze vragen te beantwoorden samenvatten en bespreken. Ik zal beschrijven hoe de bevindingen uit mijn proefschrift zich tot elkaar verhouden en tot (meer recent) onderzoek door anderen. Tot slot zal ik een antwoord formuleren op de onderzoeksvraag die in dit proefschrift aangepakt werd.

Categorie representatie houdt meer in dan enkel de codering van de visuele kenmerken van een object. Zo kunnen leden van dezelfde categorie er heel anders uitzien (bijvoorbeeld, het gezicht van een jong meisje en het gezicht van een oude vrouw zijn zeer verschillend, maar beiden behoren duidelijk tot de categorie ‘vrouwelijk’), terwijl leden van de verschillende categorieën juist erg op elkaar kunnen lijken (hoewel een mannelijke en een vrouwelijk gezicht voor een groot deel exact dezelfde kenmerken hebben, kunnen we ze toch gemakkelijk uit elkaar houden). Om het ontstaan van dergelijke scherpe groeperingen en scheidingen te onderzoeken, gebruikten we een trainingparadigma dat lijkt op een eerder gebruikt paradigma van Freedman en collega’s (Freedman, Riesenhuber, Poggio, & Miller, 2001, 2002, 2003, 2006) om de vorming van object categorieën in de hersenschors van apen te onderzoeken. Ze gebruikten hiervoor een gemorphede stimulus set van honden en katten. Bij het morphen vloeien als het ware de twee prototypen (de hond enerzijds en de kat anderzijds) van beide categorieën in elkaar over via verschillende mengverhoudingen (bv 30% kat en 70% hond). Tussen deze exemplaren is door de onderzoekers bij de 50% mengvorm de grens aangebracht die de categorieën scheidt (zie Figuur 7.2). Ik heb dit paradigma aangepast, zodat deze ook toegepast kan worden op onderzoek bij



**Figuur 7.2**

Voorbeelden van het morphen tussen het prototype van de categorie katten (C1) en het prototype van de categorie honden (D1). Exemplaren van de beide categorieën bestaan uit mengvormen tussen de kat en de hond, zo bestaat 80% C1 ook uit 20% D1. De grens tussen de categorieën ligt bij 50%, rechts van de grens de honden, links van de grens de katten. Figuur aangepast naar het origineel uit Freedman et al. (2001).

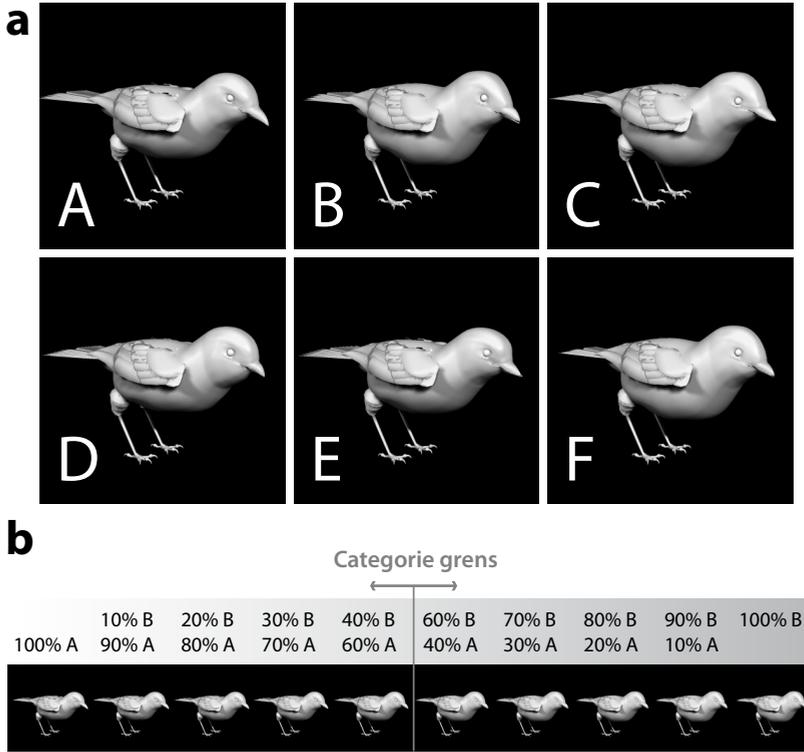
mensen in een fMRI experiment.

In hoofdstuk 2 hebben we gebruik gemaakt van een trainingparadigma waarin proefpersonen gedurende drie dagen leerden om sterk op elkaar lijkende vogelcategorieën te onderscheiden (zie Figuur 7.3). Tijdens het leren ontvingen de proefpersonen twee soorten feedback. Feedback (“goed” of “fout”) die klopte bij het antwoord dat gegeven werd. Waardoor proefpersonen dus in staat werden gesteld om bepaalde categorieën te leren. Daarnaast feedback die niet gerelateerd was aan het antwoord van de proefpersoon. Deze willekeurige feedback zorgde ervoor dat bepaalde andere categorieën niet geleerd werden. Op deze manier konden we onderscheid maken tussen representaties in het brein die werden gevormd door het leren van een nieuwe categorie en representaties die gevormd werden door alleen maar te kijken naar de vogels, zonder het leren van een categorie. Voor en na de training werden onze proefpersonen gescanned. Na drie dagen training lieten de fMRI resultaten zien dat een gebied in de rechter occipitotemporale cortex, de gyrus fusiformis, selectief reageerde op vogels die men had leren te categoriseren. Tegelijkertijd werd er juist minder activiteit waargenomen in de occipitotemporale cortex voor vergelijkbare vogels die proefpersonen ook gezien hadden tijdens de training, maar waarvan

zij niet in staat waren geweest om de categorieën te leren. Dit resultaat toont duidelijk aan dat de toename van activiteit in de rechter gyrus fusiformis niet werd veroorzaakt door visuele blootstelling, maar specifiek is voor de vorming van de representatie van categorieën.

Het nieuwe inzicht dat dit onderzoek oplevert is dat er een onderscheid kan worden gemaakt in de manier waarop de stimuli visueel verwerkt zijn tijdens de trainingsfase. Eerdere studies over dit onderwerp hebben geen onderscheid gemaakt tussen louter visuele blootstelling en het leren van nieuwe objecten. Daardoor was het bij deze studies niet mogelijk om eventuele wijzigingen in corticale activiteit toe te schrijven aan het leren van categorieën omdat ze ook verklaard konden worden uit het feit dat proefpersonen de stimuli vaker gezien hadden. Onlangs echter hebben Gillebert et al. (2009) een soortgelijk onderzoek uitgevoerd en gevonden dat categorisatie, en niet visuele blootstelling alleen, leidt tot een grotere selectiviteit voor getrainde objecten in de occipitotemporale cortex. Dit bevestigt onze bevindingen.

Zoals we zagen in Hoofdstuk 2, en ook is aangetoond door andere studies, is toegenomen perceptuele expertise gekoppeld aan neuronale veranderingen in de occipitotemporale cortex (Gauthier,



**Figuur 7.3**

**De stimulus set.** (A) Zes prototypen van de vogelcategorieën (A, B, C, D, E, F) die in hoofdstukken 2, 3 en 4 zijn gebruikt. De vogels verschillen in rug, buik, staart, snavel, kopvorm, wangen, wenkbrauwen en oogpositie. Vogelexemplaren voor elke categorie werden gemaakt door te morphen tussen alle prototypes. (B) Een voorbeeld van alle vogelexemplaren die zijn ontstaan door te morphen tussen vogel A en vogel B. De categoriegrens ligt op 50%. Alle vogels die voor meer dan 50% uit vogel A bestaan behoren tot categorie A. De vogels die voor meer dan 50% uit vogel B bestaan behoren tot categorie B.

Skudlarski, Gore, & Anderson, 2000; Gauthier, Tarr, Anderson, Skudlarski & Gore, 1999; Moore, Cohen, & Ranganath, 2006 ; Op de Beeck, Baker, DiCarlo & Kanwisher, 2006; Rhodos, Byatt, Michie & Puce, 2004; Weisberg, Van Turenout & Martin, 2007; Xu, 2005). Echter, in al deze studies, waaronder ook mijn eigen studie, was categorielidmaatschap gebaseerd op overeenkomsten in visuele kenmerken. Dat wil zeggen dat voorwerpen die er

hetzelfde uitzien tot dezelfde categorie behoorden. In Hoofdstuk 3 onderzocht ik hoe corticale representaties in de volwassen menselijke hersenen worden gevormd voor perceptueel verschillende objecten die toch thuishoren in dezelfde categorie. In deze studie leerden de proefpersonen een discrete grens tussen hetzelfde uitzijende natuurlijke objecten (de zes vogelsoorten A, B, C, D, E en F uit Figuur 7.3) die behoorden tot verschillende ca-

tegorieën (woestijnvogels of oerwoudvogels). We hebben voor deze studie weer dezelfde vogel stimuli gebruikt. Dit maakte de vergelijking mogelijk tussen vogels aan dezelfde kant van de categoriegrens (behorende tot dezelfde vogelsoort) met vogels die visueel evenveel verschilden, maar zich aan de overkant van de categoriegrens bevonden (en die dus bij een andere vogelsoort hoorden van dezelfde vogelcategorie of van een andere vogelcategorie). De proefpersonen werden getraind om vogels te categoriseren in conceptuele categorieën (oerwoudvogels en woestijnvogels). Met dit trainingsparadigma lag de focus op het groeperen van vogels in categorieën in plaats van het onderscheid maken tussen vogelcategorieën zoals in Hoofdstuk 2. Toch zijn de resultaten die gevonden werden in de occipitotemporale cortex vergelijkbaar. Na training zien we dat neuronale populaties in de occipitotemporale cortex, zoals in de gyrus fusiformis en in de laterale occipitale gyrus, zeer gevoelig zijn geworden voor perceptuele verschillen in de stimuli. Omdat we dit keer gebruik gemaakt hebben van een zogenaamd fMRI adaptatieparadigma kunnen we concluderen dat neuronale populaties in occipitotemporale cortex selectief reageerden op de getrainde items. Dit is een mooie aanvulling op de resultaten van Hoofdstuk 2, waar al werd gespeculeerd dat neuronale selectiviteit het onderliggende mechanisme is van de toename in de corticale response voor de getrainde vogels. Echter, aangezien de fMRI activiteit in Hoofdstuk 2 werd uitgedrukt als grootte van de respons van neuronale clusters, konden geen conclusies worden getrokken of de resultaten inderdaad verhoogde neuronale selectiviteit weerspiegelden. In deze studie hebben we laten zien dat training leidt tot een grotere selectiviteit voor getrainde vogelsoorten in de occipitotemporale cortex. Een zeer vergelijkbare studie van Jiang en collega's (2007) die gebruik maakten van gemorpheerde auto's heeft ook zulke toegenomen selectiviteit in occipitotemporale cortex aangetoond. Zij vonden ook dat tijdens actieve categorisatie de frontale cortex gevoeligheid toonde voor de categorie waartoe de auto's behoorden. Hoewel Jiang en collega's alleen bewijs vonden

voor categorische representaties in de frontale cortex wanneer de deelnemers actief de auto's categoriseerden, hebben we in onze studie al wel bewijs voor categorie selectiviteit gevonden bij proefpersonen die een andere taak uitvoerden die niets te maken had met het categoriseren van de vogels. We vonden een response in het brein, in de superieure temporale sulcus, die specifiek werd waargenomen wanneer de proefpersonen twee vogels achter elkaar zagen die tot verschillende conceptuele categorieën behoorden. Deze dissociatie kan niet verklaard worden door perceptuele verschillen tussen de vogels, omdat het fysieke verschil tussen vogels aan dezelfde kant van de categoriegrens en tussen vogels van verschillende kanten van de categoriegrens even groot was. Geconcludeerd kan worden dat de occipitotemporale cortex samen met de superieure temporale sulcus over eigenschappen beschikken die geschikt zijn voor een systeem dat zowel kan generaliseren over stimuli als ook onderscheid kan maken tussen stimuli.

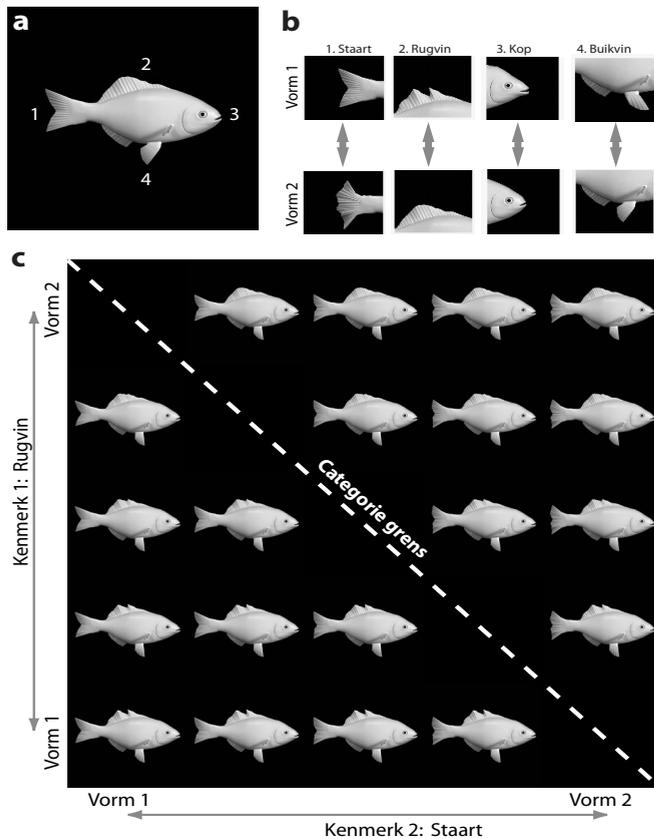
In Hoofdstuk 3 vonden we dat de superieure temporale sulcus betrokken was bij conceptuele categorie representaties. Dit hersengebied blijkt ook vaak actief te worden als mensen multimodale (bijvoorbeeld audiovisuele) stimuli verwerken. Dit zou kunnen betekenen dat de superieure temporale sulcus betrokken is bij associaties leggen tussen twee stimuli waarbij de modaliteit er niet toe doet. Om multimodale categorievorming te onderzoeken hebben we het trainingsparadigma van Hoofdstuk 2 uitgebreid tot het audiovisuele domein. In Hoofdstuk 4 hebben we de representatie van nieuw geleerde audiovisuele categorieën onderzocht. De stimulusset bestond weer uit dezelfde zes sterk op elkaar lijkende vogels. Deze vogelsoorten kregen elk hun eigen geluid toebedeeld. De vogelgeluiden waren speciaal voor dit experiment gecreëerd op basis van bestaande vogelkreten. Net als de vogelplaatjes werden ook de geluiden gemorphed. Zag een proefpersoon dus tijdens de training een vogel die voor 70% uit A bestond en voor 30% uit B, dan hoorde hij of zij tegelijkertijd ook het geluid van 70% B en 30% A. De proefpersonen leerden de nieuwe

## Nederlandse samenvatting

audiovisuele vogelcategorieën in een zogenaamde 1-terugtaak. Hierbij geven zij steeds aan of de vogel die zij zien “dezelfde of een andere vogelsoort” is als degene die zij daarvoor hebben gezien en gehoord. Dit was dezelfde taak als in Hoofdstuk 2. Na de training werden de proefpersonen gescand, terwijl zij passief keken en luisterden naar de vogels. Ze hoorden of alleen vogelgeluiden, of zagen alleen vogelplaatjes, of ze kregen audiovisuele vogels aangeboden waarbij het vogelplaatje en het vogelgeluid overeenkwamen met wat ze geleerd hadden (congruent, bv vogelplaatje A met het geluid van vogel A), of kregen een audiovisuele vogel aangeboden waarbij het plaatje en het geluid niet overeenkwamen (incongruent, vogelplaatje A met het geluid van vogel B). Wederom vonden we dat het kijken naar de plaatjes van de geleerde vogels meer activiteit gaf in de rechter gyrus fusiformis. Dit komt dus overeen met de bevindingen van Hoofdstuk 2, waarin we ook hogere responsen waarnamen in de rechter gyrus fusiformis voor de getrainde vogels. De activiteit die we observeerden in de rechter gyrus fusiformis voor de verschillende audiovisuele stimuli vormden een interessante aanvulling op ons begrip van visuele object representaties in de gyrus fusiformis. Ten eerste, de rechter gyrus fusiformis vertoonde een trainingeffect voor getrainde audiovisuele vogels ten opzichte van nieuwe audiovisuele vogels. Interessant daarbij is dat we geen training effect vonden voor incongruente audiovisuele vogels. Dit patroon van resultaten past ook bij onze eerdere vaststelling (Hoofdstuk 2) dat de rechter gyrus fusiformis alleen maar reageert op vogels waarvoor een betekenisvolle representatie is gevormd, en niet voor vogels waaraan de proefpersonen ook zijn blootgesteld tijdens training, maar waarvoor geen representatie van de categorieën gevormd is. Dit versterkt onze hypothese dat alleen taak-relevante objectkenmerken worden opgeslagen in de occipitotemporale cortex. In de tweede plaats vonden we een auditief training effect in de gyrus fusiformis. We vermoeden dat niet het getrainde geluid wordt opgeslagen in de gyrus fusiformis, maar dat het geluid van een getrainde vogelsoort de visuele repre-

sentatie die in de gyrus fusiformis ligt opgeslagen activeert. Dit komt overeen met de bevinding dat het horen van een menselijke stem de bijbehorende gezichtrepresentatie activeert in de gyrus fusiformis (von Kriegstein & Giraud, 2006). Dit toont aan dat via verschillende routes de visuele representatie kan worden geactiveerd en dat de representatie onder invloed staat van feedbackverbindingen. Ten slotte vonden we audiovisuele trainingeffecten en audiovisuele trainingeffecten in de superieure temporale sulcus. Deze kunnen ook gekoppeld worden aan de resultaten van Hoofdstuk 3. Net als in het vorige hoofdstuk is ook hier de nieuw gevormde audiovisuele representatie in de linker superieure temporale sulcus categoriespecifiek. De geleerde vogelsoorten hebben niet geleid tot een generalisatie naar incongruente combinaties van de geleerde vogelgeluiden en vogelvormen. De superieure temporale sulcus reageerde hetzelfde op de incongruente vogelsoorten als op totaal nieuwe vogelsoorten. Bovendien zijn de responsen in dit gebied groter voor congruente audiovisuele vogelsoorten dan voor incongruente audiovisuele vogelsoorten. Dit levert ook weer bewijs voor het ontstaan van een nieuwe, door training gevormde, audiovisuele categorie. We kunnen concluderen uit Hoofdstuk 3 en 4 dat de superieure temporale sulcus betrokken is bij de representatie van objecten die bij elkaar horen. Tevens kunnen nieuwe betekenisvolle verbanden gevormd worden tussen verschillend uitzijnde objecten van dezelfde categorie en tussen geluiden en beelden die bij een categorie horen. Hoofdstuk 4 levert dus het bewijs dat het volwassen menselijk brein inderdaad flexibel genoeg is om nieuwe audiovisuele categorieën te leren door de associatie van geluiden en beelden. Bovendien is de juiste combinatie van geluid en beeld cruciaal voor de activatie van de corticale audiovisuele representatie.

In de vierde studie (Hoofdstuk 5) testten we de hypothese dat het leren van categorieën de gevoeligheid in het brein verhoogt voor specifiek die kenmerken die categorielidmaatschap definiëren. De studies in de Hoofdstukken 2, 3 en 4 hebben aangetoond dat training leidt tot een verhoogde



**Figuur 7.4**

**De stimulus set.** (A) De visstimuli van Hoofdstuk 5 bestonden uit vissen met vier kenmerken die allen in vorm konden variëren. De kenmerken zijn de staart (1), rugvin (2), kop (3), en buikvin (4). (B) Verschillende vissen werden gemaakt door tussen twee vormen van elk kenmerk te variëren in stapjes. De rugvin kan variëren van gestekeld tot glad. (C) Voorelkeproefpersoon waren twee kenmerken informatief voor categorisatie (in dit voorbeeld de rugvin en de staart). De categorie grens wordt weergegeven als een lineaire combinatie van beide kenmerken. In totaal zijn er in de ruimte van informatieve kenmerken  $20 \times 20$  vormcombinaties mogelijk, de meest extreme vormen en de vormen direct op de grens tellen niet mee (in dit voorbeeld is de ruimte maar  $5 \times 5$ ).

corticale selectiviteit in het volwassen brein voor de geleerde items. We hebben onderzocht of deze selectiviteit kan worden gekoppeld aan die kenmerken die relevant zijn voor het categorielidmaatschap. We trainden proefpersonen met computer-gegenereerde vis stimuli. We zijn overgestapt van vogels naar vissen, omdat deze stimuli vier duidelijk gescheiden kenmerken hebben (staart, rugvin, buikvin en kop, zie Figuur 7.4). Deze vier kenmerken konden variëren in stapjes tussen twee vormen. Tijdens de training werd dezelfde taak gebruikt die al met succes ook in Hoofdstuk 2 en 4 is gebruikt. Voor elke proefpersoon waren twee kenmerken informatief voor categorie lidmaatschap en twee kenmerken wa-

ren dat niet. Net als in Hoofdstuk 3, gebruikten we na de training een fMRI adaptatieparadigma. Met dit paradigma kunnen we specifiek onderzoeken of er corticale selectiviteit is voor informatieve en niet-informatieve kenmerken. We gebruikten tijdens de scan twee taken om onderscheid te maken tussen actieve categorisatie en automatische verwerking van de informatieve kenmerken. Hiervoor gebruikten we een categorisatietask en een taak waarbij de proefpersoon kleurverandering moest detecteren. We vonden dat tijdens de categorisatietask de rechter frontaalkwab inderdaad selectief reageerde op de informatieve kenmerken. Dit gebied reageerde ook sterker op vissen met kenmerken die vlak bij de

## Nederlandse samenvatting

categoriegrens lagen. Bovendien vertoonde de frontaalkwab selectiviteit voor categorieën en selectiviteit voor de informatieve kenmerken die gerelateerd was aan de prestaties van de proefpersonen op de categorisatietask tijdens het scannen. Bij elkaar genomen suggereert dit dat de frontaalkwab betrokken is bij actief categorisatiegedrag. De frontaalkwab maakt gebruik van de informatieve kenmerken van objecten om te kunnen categoriseren, tegelijkertijd zien we dat de kenmerken die niet informatief zijn voor categorisatie als het ware genegeerd worden. De occipitotemporale cortex bleek ook selectiviteit voor de informatieve kenmerken te vertonen tijdens de categorisatietask. Interessant is dat dit gebied een positieve relatie laat zien tussen de prestaties van de proefpersonen tijdens de training en selectiviteit voor de informatieve kenmerken en dat die prestatie een negatieve relatie heeft met de selectiviteit van de niet-informatieve kenmerken. Dit geeft aan dat training een grotere gevoeligheid voor informatieve kenmerken veroorzaakt en juist een verminderde gevoeligheid voor niet-informatieve kenmerken. Dit is een cruciale bevinding, want het is een aanvulling op de resultaten uit de voorgaande hoofdstukken waarin we al veronderstelden dat dit weleens het onderliggende mechanisme zou kunnen zijn voor de corticale leereffecten. Het ontbreken van enige gevoeligheid voor informatieve kenmerken tijdens de kleurverandering detectietask wijst op een sterke taakgerelateerde verwerking van deze kenmerken. Hierdoor komen wellicht de taken die tijdens het scannen in de vorige hoofdstukken gebruikt zijn in een ander licht te staan. We vonden traininggerelateerde en ook categorieselectieve activiteiten van het brein in deze hoofdstukken, hoewel we in die experimenten geen taak gebruikten waarvoor actieve categorisatie nodig was. Het zou dus zo kunnen zijn dat het ontbreken van een taak (in Hoofdstuk 2 en 4) of de “oud-nieuw” taak uit Hoofdstuk 3 niet geleid heeft tot automatische verwerking van de informatieve kenmerken, maar dat het afwezig zijn van een taak de verwerking van deze informatieve kenmerken impliciet vergemakkelijkt heeft. Tot slot, in Hoofdstuk 5 hebben we de kloof overbrugt

die er was tussen elektrofysiologische metingen bij apen die selectiviteit van het brein voor informatieve kenmerken aantoonde (De Baene, Ons, Wage-mans, & Vogels, 2008; Sigala & Logothetis, 2002) en fMRI metingen die bij mensen zijn gedaan, zoals in de voorgaande hoofdstukken en in verscheidene andere studies die lieten zien dat visuele training leidt tot toegenomen corticale activiteiten (Gauthier, Williams, Tarr, & Tanaka, 1998; Gillebert et al., 2009; Jiang et al., 2007; Moore et al., 2006; Op de Beeck et al., 2006; Weisberg et al., 2007).

## Conclusie

Wat zijn de neurale mechanismen die ten grondslag liggen aan categorie vorming in het brein? De vraag en het antwoord zijn breder dan alleen dit proefschrift kan beslaan, maar een aantal belangrijke bijdragen aan de beantwoording van deze vraag kan worden gevonden in de hoofdstukken. Het onderzoek in dit proefschrift biedt nieuwe inzichten in hoe het menselijk brein kennis over categorieën vergaart, opslaat en gebruikt. De studies laten zien welke neurale mechanismen ten grondslag liggen aan perceptuele en conceptuele categorieën kennis en hoe die ontstaan en gevormd worden door ervaring. Onze resultaten tonen duidelijk aan dat neuronale gevoeligheid voor kenmerken wordt beïnvloed door training in categoriseren. Deze bevindingen vormen de schakel tussen elektrofysiologische metingen van het apenbrein die laten zien dat training leidt tot toegenomen neuronale selectiviteit en fMRI onderzoek van de menselijke hersenen waaruit de categorie-specifieke representaties in het menselijk brein blijken. Bovendien hebben we aangetoond dat de kenmerken die relevant zijn voor categorisatie van een object selectiviteit veroorzaken in neuronale populaties. Het leren van nieuwe categorieën vereist samenwerking tussen verschillende hersengebieden. Samen kunnen deze gebieden gezien worden als de neurale correlaten van de belangrijkste onderdelen van het categoriseren: onderscheiden en generaliseren. De occipitotemporale cortex herbergt de karakteristieke kenmerken van objecten die een categorie definiëren. De ei-

genschappen van dit gebied stellen het in staat tot een fijngevoelig onderscheid tussen visueel sterk op elkaar lijkende objecten. Daarnaast is de superieure temporale sulcus in staat om associaties te vormen tussen leden of eigenschappen (bijvoorbeeld geluiden en beelden) van een categorie. Hierdoor kunnen perceptueel verschillende, maar conceptueel vergelijkbare objecten gegroepeerd worden. Tot slot is de frontaalkwab betrokken is bij het coderen van gedraggestuurde categorie-informatie en stelt dit gebied ons in staat om beslissingen te nemen over categorielidmaatschap.

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## Biography

Marieke van der Linden was born in Nijmegen and grew up in Beugen (Noord-Brabant, The Netherlands). She attended pre-university secondary education (VWO) at the Elzendaal College in Boxmeer. From 1996 she studied at the Radboud University in Nijmegen. After receiving her first year diploma (propeadeuse) in Psychology she began her master's studies in Cognitive Science. She started her research experience in 2000 at the Max Planck Institute for Psycholinguistics in Nijmegen. There she worked as a research assistant in the human electrophysiology lab of the "neurocognition of language" group headed by Prof. Dr. Peter Hagoort. In 2002 she obtained her master's degree and combined her work at the Max Planck Institute with working at the then newly founded Donders Institute for Brain, Cognition, and Behaviour. There she worked in the "learning and plasticity" group under supervision of Dr. Miranda van Turennout. In 2004 she started her PhD research in the same group. Marieke is married to Dr. Gijs van Elswijk, they have one son (Oscar, 2008) and are expecting their second child. They live in Eindhoven.

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