Perception and prediction of simple object interactions

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Abstract

For humans, it is useful to be able to visually detect an object's physical properties. One potentially important source of information is the way the object moves and interacts with other objects in the environment. Here, we use computer simulations of a virtual ball bouncing on a horizontal plane to study the correspondence between our ability to estimate the ball's elasticity and to predict its future path. Three experiments were conducted to address (1) perception of the ball's elasticity, (2) interaction with the ball, and (3) prediction of its trajectory. The results suggest that different strategies and information sources are used for passive perception versus actively predicting future behavior.

CR Categories: J.2 [Computer Applications]: Physical sciences and engineering—Physics; J.4 [Computer Applications]: Social and behavioral sciences—Psychology

Keywords: Perception of physics, elasticity, object interaction, dynamic property, path prediction

1 Introduction

When an inanimate object moves and interacts with other objects in its surroundings, its spatiotemporal trajectory depends on a variety of factors. Some of these factors are extrinsic to the object, such as gravity, air currents, or the layout of the scene. The object's behavior is, however, also determined to a large extent by intrinsic properties such as its shape, internal structure, and material constitution. This suggests that the human visual system might be able to extract the intrinsic properties of an object from observations of its movements through a scene. Conversely, given estimates of the object's intrinsic properties, it might also be possible to predict the object's future behavior. From an applied perspective, knowledge about human perception of dynamic events could be useful in reducing the complexity of costly collision-detection algorithms in computer animation [O'Sullivan et al. 2003].

A large body of research has already shown that humans are able to judge dynamic properties of objects, at least to some extent, from visually observable motion patterns [Hecht 1996; Gilden and Proffitt 1989; Gilden and Proffitt 1994; Proffitt and Gilden 1989; Runeson et al. 2000; O'Sullivan and Dingliana 2001; O'Sullivan et al. 2003; Twardy and Bingham 2002]. For example, Gilden and Proffitt [1994] studied observers' ability to estimate the mass ratio of two colliding balls. They found that participants use simple heuristics based on the direction and speed after collision to estimate the mass ratio of the two objects. Under some circumstances these heuristics support excellent estimates. The estimates were, however, systematically biased under certain critical conditions, such when the observers' assumptions are infringed. Other researchers, most notably Michotte [1963], have emphasized our ability to detect higher order attributes from motion behaviors, such as the apparent *causal influence* of one object on another or *animacy* (i.e. attributing 'volition' to an object; see [Scholl and Tremoulet 2000] for a review).

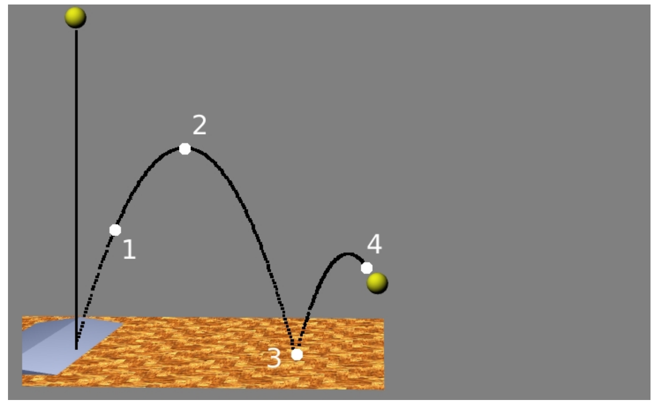

Figure 1: Schematic graph of the different stopping points in the trajectory used in the experiments.

One of the most important factors in determining an object's bouncing behavior is its elasticity. Elasticity measures how an object deforms and returns to its initial state in response to stress and strain, and depends on a range of complex properties of the material composition and internal microstructure. These properties cannot be directly observed visually. For elementary collision mechanics such is the case in a simple bouncing event, however, elasticity is defined simply as the ratio of incident to outgoing velocity[1]. Assuming conservation of energy, this ratio can never be above 1 or less than zero, and leads to several easily measurable regularities, most notably: (i) the ratio of bounce heights; (ii) the ratio of bounce periods; and (iii) the ratio of velocities immediately preceding and following each bounce. A number of previous studies have measured observers' ability to estimate elasticity from observations of bouncing or collision events. For example, Warren et al. [1987] have shown that participants rely on these three ratios in order to estimate an object's elasticity.

It seems likely that one of the primary ecological motivations for estimating an object's dynamic properties would be to predict its future behavior in order to guide an action towards that object. Yet,

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[1] This is known as Newton's Law of Restitution.

to our knowledge, the interaction between estimates of elasticity and our ability to intercept an elastic object has never directly been examined.

Interestingly, studies in the field of "naive physics" have shown that humans make large systematic errors when asked questions that involve cognitively predicting the behavior of an object. This effect was found to vanish when the question was presented in a dynamic sequence, in which participants could easily identify physically incorrect events visually [Kaiser et al. 1992]. This demonstrates that judging a seen event is quite different from predicting it cognitively. It seems reasonable that a similar dichotomy may occur with perception versus action. Indeed, although it is still rather controversial, there is a large body of work that has tried to extend this observation to the neural level [Goodale and Milner 1992; Goodale 2000; Ward 2002; Franz 2001]. More specifically, it has been claimed that there are two independent visual processing streams, the dorsal and the ventral streams, which are dedicated to perception and action, respectively. Regardless of the neural implications, it is very possible that different criteria, mechanisms, or strategies are involved depending on whether we passively observe an event or actively interact with that event. This issue is of particular pertinence to real-time interactive physics simulations, where the computational costs entailed by accurately reproducing physics become critical.

Here, we present a series of experiments that measure the extent to which humans use estimates of elasticity to predict and interact with objects. The experimental environment was constrained to a simple object interaction, such as a ball bouncing on a surface. Our goals were to identify relevant information that users rely on to estimate elasticity, and to measure how well users can exploit their estimates of elasticity to predict and interact with computer generated objects. Specifically, we conducted the following three experiments:

- **Experiment 1**: Participants used visual information to perceive and report the elasticity of an object.
- **Experiment 2**: Participants performed an active task where they virtually intercepted the ball using a paddle they could control.
- **Experiment 3**: Participants predicted and reported the ball's trajectory by positioning the same paddle at the point of expected interception in the scene.

2 General Method

2.1 Stimulus

Stimuli were created using the 3D virtual developing tool Virtools Dev 3.5[2]. The physical simulation of the balls was calculated through the Physics Pack of Virtools. It is based on the popular *"Havoc"* engine, which uses only rough estimations for the simulation. In a series of pilot tests, we examined the correlation of this simulation with a real world situation in order to find the appropriate parameters for the virtual scene.

The calculation of the ball's trajectory was performed without air resistance, friction, or deformations of the ball. These parameters actually formulate the degree of elasticity of an object but for this simulation we focused on the inner energy transfer to have only one manipulation factor for the elasticity. Addressing the interaction of all parameters is a topic of a different research. In common computer simulations, such as computer games, these factors are often eliminated as well for processing time reasons.

[2]http://www.virtools.com/

In our environment, a small yellow ball was set at a fixed starting position. When subjects pressed the space bar, the ball was released from the starting point with zero initial velocity and fell straight down under normal gravity. At the point of initial contact, the floor was slightly inclined to give the ball a horizontal velocity component. The ball continued to bounce along the plane until it bounced off the virtual edge and fell off the screen (see Figure 1). A shadow of the ball was cast on the floor when the ball came close to it. The elasticity of the ball was varied from trial to trial, causing the ball to follow different trajectories.

2.2 Elasticities

Nine different elasticities were used: 0.31, 0.39, 0.43, 0.47, 0.51, 0.54, 0.58, 0.62, 0.74. The elasticities were linearly scaled except for the lowest and the highest elasticities. For all except the two extreme values, the balls bounced twice, first on the inclined ramp and then on the horizontal plane, before passing the virtual edge of the floor. It is important to note that, for these stimuli, the distance between the bounces on the horizontal plane as well as the heights of the bounces were linearly related to the elasticity of the ball. The ball with the lowest elasticity bounced a total of three times, while the most elastic ball bounced only once. These two extreme elasticities tested the ability of the observers to generalize beyond the simple linear relationships that held for the other values. The highest elasticity was chosen to provide a ball falling unexpectedly close to the edge of the virtual plane. The lowest elasticity shared the same disappearance position as the second elasticity but had one additional bounce. For some later analysis these two extremes were partially excluded due to their different behavior.

2.3 Stopping points of the ball

To control the visual information available to the observers, we stopped the ball's motion at one of four points along the ball's trajectory, as shown in Figure 1.

At the **first** stopping point, the ball bounced once on the plane and stopped when it reached a certain height above the ground plane. Visually, this point was located at the same height for all elasticities, but varied a small amount horizontally. Naturally, the speed with which this point was reached varied as a function of the ball's elasticity. The primary information for elasticity provided in this condition was the ratio of velocities before and after the first bounce. The faster the ball reached the stopping point, the more elastic the ball was.

The **second** stopping point was the highest point after the first bounce, where the vertical velocity is zero. Therefore, in addition to the ratio of velocities present in the first condition, this condition also included a ratio of heights. Since the initial height was always the same, a greater height after the first bounce corresponds to a higher elasticity.

The **third** stopping point was when the ball hit the plane for the second time. In addition to the previous two cues, this condition also included the period of the bounce (i.e., through the time between the two bounces). The longer the time between the two contacts (and the closer the ball came to the virtual edge), the more elastic the ball. Since the ball with the highest elasticity did not bounce twice, this elasticity was not used for this stopping point.

The **fourth** stopping point was located shortly after the ball reached the second apex. Again, this condition included all of the visual cues in the previous conditions as well as a new cue. From this position, the ball fell in a more or less straight line over the edge of the plane. Since the definition of this point contained the second bounce and the second height, the highest elasticity was also not considered for this point.

2.4 Apparatus

All experiments were conducted on a laptop using Virtools to generate and present the experimental environment.

3 Experiment 1

Our primarily goal for the first experiment was to investigate the role of the information present at each of the stopping points in judgments of the ball's elasticity. Therefore, participants had to rate the elasticity of each ball on a 7 point Likert scale [Likert 1932]. This experiment provided us with a baseline about our ability to perceive and describe the ball's elasticity from its movement.

3.1 Method

3.1.1 Stimulus

In each condition, the ball moved normally up to a stopping point, rested there for one second, and disappeared from the scene. Both the four stopping points as well as the elasticities of the balls were presented in randomized order without repetition. This yielded a total of 35 trials (note that the top elasticity is not in the third condition).

3.1.2 Design

The stimuli were shown to the entire group of participants simultaneously in one session. The experiment was presented on a projector screen in a seminar room where the tables were formed in a U-shape, so that each participant had the same distance to the screen.

The motion of the ball was initiated by the experimenter. Participants rated the elasticity of the ball after each trial (using a 7 point Likert scale) by recording their decision on a sheet of paper. When all participants were ready, the experimenter started the next trial.

Before the start of the real experiment, the experimenter showed three demonstration trials, one each with the lowest, middle, and highest elasticity. Each ball bounced along its full trajectory. Providing anchors of the extremes of the Likert scale in this manner helps to avoid possible scaling effects.

3.1.3 Participants

The group consisted of 11 graduate students from the University Montpellier-1. The gender was about equally spread. They were not payed for the contribution.

3.2 Results

Figure 2 shows the ratings for each stopping point. The red line illustrates the linear regression calculated over all data points. The highest elasticity was excluded from the calculations in the third and the forth conditions (red star). The two graphs in Figure 3 show the values of the slopes for the linear regressions and the R^2 for each condition.

Overall, performance in the first stopping point condition was poor. The mean slope was substantially shallower than optimal performance (which would be if the bottom elasticity was rated as 1 and the top elasticity as 7) and the correlation coefficient was low. In

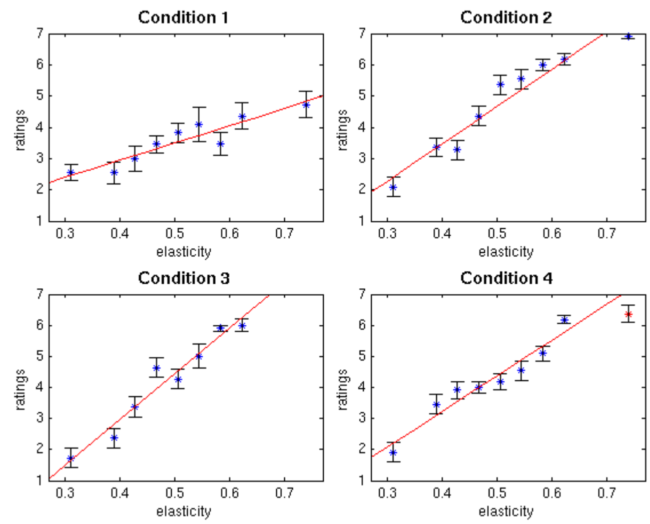

Figure 2: Mean ratings as a function of the actual elasticity of the ball (1: least elastic, 7: most elastic). Error bars depict the standard error of the mean. The conditions represent the different stopping points.

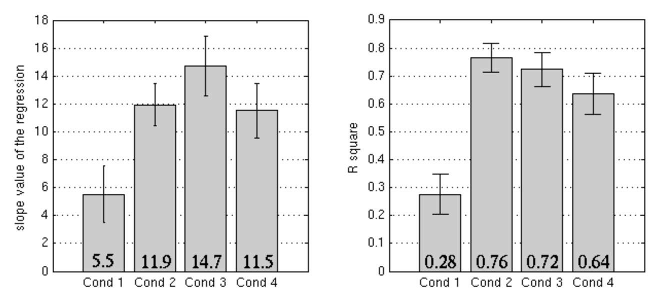

Figure 3: (Left) - Slope values calculated through a linear regression for each condition. Error bars depict the 95% confidence interval. (Right) - R square for each condition. Error bars depict the standard error of the mean.

other words, the participants were not able to judge the elasticities accurately with the limited visual information solely from the ratio of velocities.

The ratings in the other conditions were quite similar to each other. The slopes were close to optimal. The correlation coefficients for these conditions are quite high and not statistically different ($t(10)<1.35$; $p>0.2$; n.s.[3]). This shows that with the visual information given from the ball's trajectories from the second stopping point on (the ration of heights), participants were able to differentiate between the elasticities accurately and spread the ratings on the whole range of the Likert scale.

3.3 Discussion

In this experiment, we validated our method and investigated which visual information the participants used to rate the ball's elasticity. Participants were less sensitive to the velocity information available at the first stopping point, although they were able to make some use of it since the mean slope for this condition was non-

[3]The analysis has been done with a 2-tailed dependent measures t-test (α=95%). Further t-test statistics in this paper were always done with this analysis

zero (t(10)=3.86; p<0.003). In contrast, the additional information of the height ratio available by the second stopping point yielded a better and more accurate differentiation of the elasticities. Since the last two conditions showed the same trend as condition two, the additional period information available after this point (i.e., the period and the straight line at the end of the trajectory) do not seem to have played a significant role (although this lack of an effect is almost certainly due to a ceiling effect.) Furthermore, no difference in the analysis was found between including or excluding the extrem elasticities.

As all participants saw the same ordering of the balls, one could argue with a possible ordering effect. Since the succession of the balls were totally random and the results fit a linear model, unclear answers in the first trials would add only noise. Furthermore, the demonstration of the extrem balls at the beginning prevent a scaling calibration of the participants.

To summarize, the results are quite consistent with the findings of Warren et al. [1987] who found that (i) velocity information is a relatively weak cue, (ii) period information allows a better judgment, and (iii) height ratio is a very strong cue. Here we found that velocity is indeed not particularly useful for elasticity judgments, and that the height ratio is a very strong cue. In particular, the height ratio seems to be sufficient for accurate elasticity judgments. As Warren et al. also found, repetitions of velocity and height ratio information in subsequent bounces does not appear to aid perception of elasticity substantially. Overall, then, participants are able to perceive and describe the elasticity of a ball from its trajectory.

4 Experiment 2

Experiment 1 clearly demonstrated that we can use the visual information present in a ball's trajectory to infer its elasticity. In terms of physics, given an estimate of the elasticity of the ball, and its trajectory up to the second stopping point, it should be possible to predict the ball's future path correctly. To test whether humans can successfully extrapolate the trajectory of the ball, we asked participants to perform an anticipation interception task in which they had to position a virtual paddle so that the ball would hit it (see Figure 4). If unconstrained, this task could be performed trivially by simply following the ball with the paddle until the point of contact. To prevent participants from using this strategy, on each trial we froze the paddle when the ball reached one of the stopping points used in Experiment 1. This way, participants were required to move the paddle to the expected place of interception as soon as they could. We have shown in Experiment 1 that, from the second stopping point on, participants can accurately judge elasticity. Here, we wanted to see if this estimate would support successful interception performance.

4.1 Method

4.1.1 Stimulus

The 3D virtual environment was the same as in Experiment 1, with one exception. To intercept the ball, a grey virtual paddle was set to the right of the horizontal plane. The paddle was moved by the mouse. Each ball started from the same position as in the previous experiment. At the different stopping points the paddle's motion was frozen and balls followed their paths up to the end. The ball's color was altered when it passed the paddle to enhance feedback. If the ball hit the paddle, it briefly turned green. If the ball did not hit the paddle, it turned red. In addition to the four stopping points used in Experiment 1, a control condition in which the paddle was never frozen was used. The stopping points and the elasticity values were presented in randomized order (44 trials). The full experiment contained three repetitions of each trial and yielded a total of 132 trials.

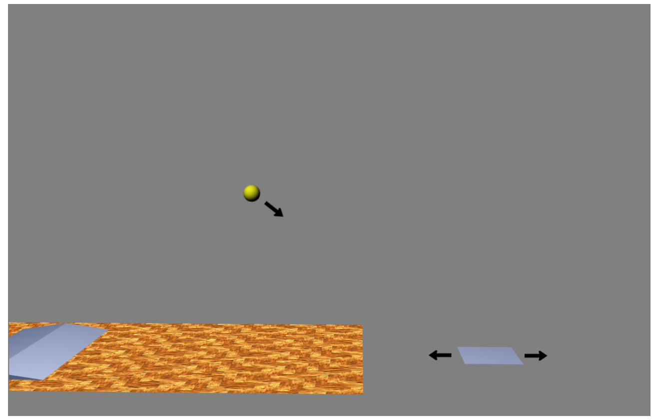

Figure 4: Screen shot of the second experiment. The arrows indicates the motion of the ball or the possibility to move the paddle.

4.1.2 Design

The participants' task was to set the virtual paddle as quickly as possible to the position where they expected the ball to hit the paddle. Participants pressed the space bar to initiate the ball's fall. The paddle could be moved at any time before the trial was started as well as during the trial up to the appropriate freezing point (where it was frozen by the program). After the ball passed through the horizontal plane of the flow, the paddle briefly changed color and was reactivated. Participants were never told at which point the paddle would be frozen. They were asked to put the paddle to either the extreme left side or the extreme right of the screen before the start of the following trial. Each participant was run individually through the experiment in a small, half dimmed room. The order of the balls was randomized for each participant.

In a familiarization phase before the actual experiment, participants practiced the handling of the paddle. During this phase, the ball's elasticity was picked randomly and the paddle was never frozen. After they became accustomed to drive the paddle, they started the experiment.

4.1.3 Participants

Ten under graduate students from the University of Montpellier-1, none of whom had participated in Experiment 1, participated in this experiment. The gender was about equally spread. They were not payed for the contribution.

4.2 Results

Figure 5 shows the mean distances of the paddle's positions at the different stopping points and the actual ball's position at its final destination. The distance from the edge of the horizontal plane to the ball's final destination increased linearly with elasticity, except for the highest elasticity. Note that for the highest elasticity, the ball's final destination was very close to the plane, as it was for the lowest elasticity due to an additional rebound. In the sixth panel the correlation coefficients are shown for each condition. Since the ball with the highest elasticity was an exception, it was not included in the calculations of the correlations and will be discussed separately.

As expected, the condition in which the paddle was not blocked

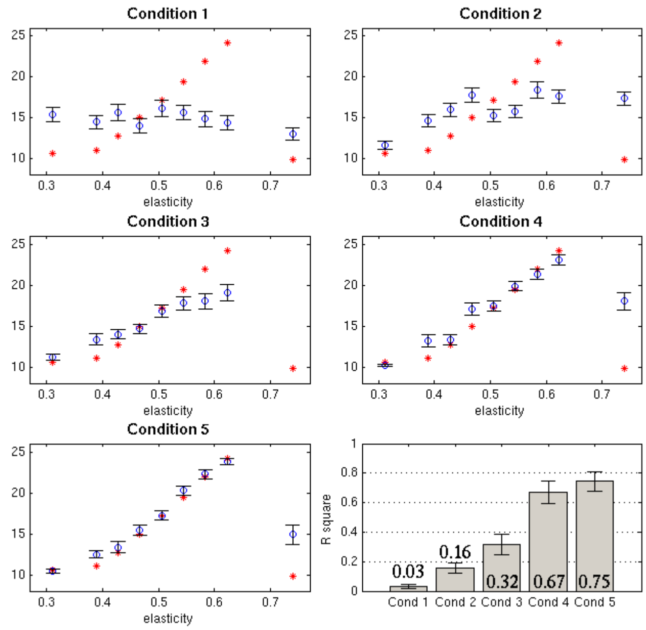

Figure 5: Mean position of the paddle distance to the plane edge for the different elasticities of the balls. The red stars show the ball's position. Error bars depict standard error. Conditions represent the different stopping points. The sixth panel depicts the R square of the five conditions.

(condition 5) showed the best performance. The mean of the paddle's position was nearly identical to the ball's position for all elasticities except for the highest one. This is reflected in the high correlation coefficient.

When the paddle was frozen at the first stopping point, participants were not able to correctly locate the interception point. The correlation coefficient was very low and nearly zero ($t(9)=2.25$; $p>0.05$). This poor performance, however, can be probably be attributed to the inherent latency in executing the movements: Participants were unable to move the paddle to the intended location within the restricted time interval between the first bounce and the stopping point. This time window was between 300 ms and 400 ms, which is barely long enough to complete a response.

At the second stopping point the correlation was also quite low. The third condition showed slightly better performance ($t(9)=3.08$; $p<0.01$). The fourth condition showed a very good correlation, and is similar to the last condition ($t(9)=1.69$; n.s.).

It is important to note that the participants had to position the paddle before the stopping point. Thus, the information present at the stopping points was not the critical information for this task. The second stopping point, for instance, did not include the full height information after the first bounce (since, as soon as the ball reached this point, the paddle was frozen). A further insight into the performance of the task, therefore, is revealed by the relation between the paddle movements and the stopping points. For that, we calculated the velocity of the paddle as a function of time. In Figure 6, the sum of the velocities is depicted as a peri-stimulus time histogram. The velocity v was calculated by the difference in the paddle position x at time t_n and t_{n+1}:

$$v_t = \sqrt{(x_{t+1} - x_t)^2} \tag{1}$$

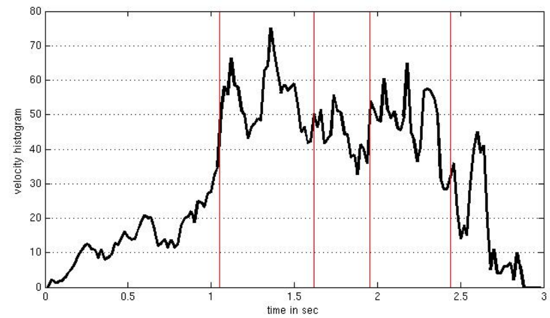

Figure 6: Histogram of the paddle velocities at each time frame. The red lines depict the time of the stopping points.

The histogram illustrates the time frames during which the paddle could be moved. For the histogram curve, the sum was divided by the number of trials in each condition. The red lines demonstrate the stopping points. Since the stopping points are spatial stopping points, the line represents the point with the longest duration.

As expected, during the time preceding the first stopping point the paddle was hardly moved, confirming the interpretation that participants were unable to move the paddle in this small time window. Directly after the first stopping point a first peak of paddle motion can be seen, followed by a second peak.

Prior to the second stopping point, the only information about the elasticity that was available was the velocity ratio. Since the participants expected the paddle to be frozen at any time, the movements of the paddle seem to reflect first assumptions about the ball's trajectory. The correlation of the ball's position and the paddle, however, is still quite low for the second stopping point, suggesting that these motions are just rough approximations.

The third stopping point included the height ratio information. The velocity histogram shows fewer movements of the paddle for this point. The correlation coefficient increased but was still surprisingly low. The paddle movements seem to represent first corrections of its location whereas the participants seem to still have only a rough idea of where the interception point should be even if the height information is contained in the path.

Between the third and forth stopping points, there are several peaks in the paddle motion, indicating further corrections of the paddle. The information provided here include the second bounce and the path to reach the second height. The correlation coefficient increased, indicating that this information seems to provide a good predictability for the remaining trajectory of the ball.

After the forth stopping point, a final peak in the paddle's motion can be observed. This indicates final corrections to set the paddle at the optimal position, which was directly underneath the ball.

For the highest elasticity, which was not included in the velocity calculations, the paddle was almost never set close to the ball's position. The best approximation was for the first condition in which the mean tendency was to set the paddle in this region, suggesting this was mere coincidence. The same behavior seems to occur in the second condition. For the other conditions, it seems that participants firstly set the paddle as far from the plane's edge as possible and were then surprised by the ball's movements and tried to move the paddle back towards the plane.

4.3 Discussion

In this experiment, participants had anticipate the path of a ball by moving a virtual paddle to a future interception point. They had to set this paddle as fast as they could since the motion of the paddle was blocked at specific, but non-predictable, points.

As to be expected, the correlation of the ball's position and the setting of the paddle increased when the participants had more time to move the paddle. They performed best when the paddle was not frozen. The poor performance for the first stopping point may be due to a motor response limit.

The analysis of the paddle's velocity shows that participants did not simply track the ball's motion but made small, rapid movements at particular points. The presence of notable peaks and lulls in the participants' responses suggests that they performed the task with a series of refinements as more information became available.

This constant correction contradicts the hypothesis that participants used the elasticity of the ball as the main information source. The findings of Experiment 1 showed that, from the second stopping point on, participants had an excellent idea of the ball's elasticity. Physically, this knowledge can support the prediction of the full motion behavior of the ball. Nevertheless, it seems that this knowledge was not used here to perform the anticipated interception task. The information that increased performance the most was provided by the second bounce and the immediately following path. Thus, the ball provided simple heuristic cues since it was quite close to the paddle and a simple following and catching strategy seems to have been used.

This interpretation is confirmed by the results from the highest elasticity conditions. Experiment 1 showed that the participants could easily identify the highest elasticity. Here, this information seems not to have been used to set the paddle correctly. A common strategy seems to be to follow the ball: the more elastic the ball appears, the more the participants put the paddle to the right-hand end of the screen.

In summary, asking participants to perform an anticipation intercepting task under time constraints forced them to use rapid approximations, which were corrected if time allowed. These estimates were not driven by the inferences of the ball's elasticity. In the following experiment, we investigated if this behavior is due to the active task or to the lack of knowledge about elasticity.

5 Experiment 3

In Experiment 1, participants could easily detect its elasticity from its trajectory. In Experiment 2, the participants did not use this information to perform an anticipation interception task. Their good performance may have been due to a "feedback" (online error-correction) strategy. In this experiment, we wanted to know how well participants could predict the ball's path when they were not presented with time constraints. Would they use the ball's elasticity as additional information source, or would they use a correction strategy as they did in Experiment 2? Thus, the third experiment was a combination of the previous two experiments. Participants were given restricted visual information, as in Experiment 1, and unlimited time to predict the ball's trajectory by setting the virtual paddle at the interception position with the ball.

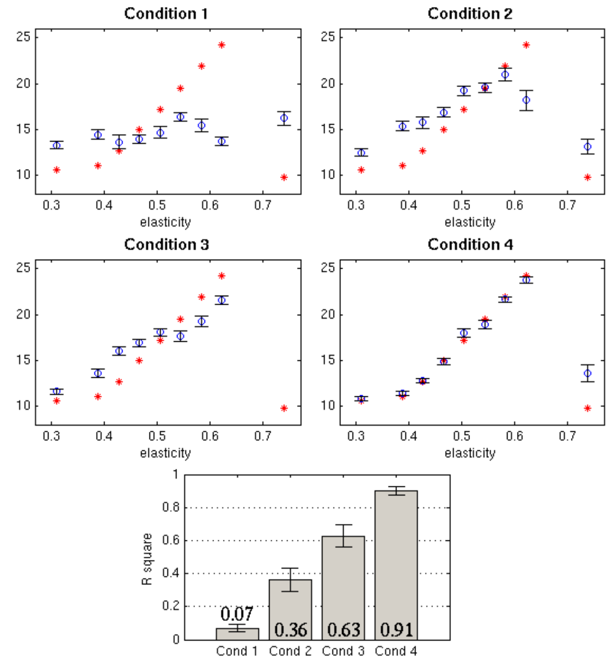

Figure 7: Mean positions of the paddle distance (from the right edge of the plane) shown for the different elasticities. The red stars show the ball's position. Error bars depict the standard error. Conditions represent the different stopping points. The fifth panel shows the correlation coefficients for each condition.

5.1 Method

5.1.1 Stimulus

The virtual environment was identical to that used in Experiment 2. The ball's path, however, was identical to that used in Experiment 1: the ball moved normally up to the different stopping points and were then frozen in motion. Participants had to move the paddle to the predicted interception point. The stopping points and each elasticity value were presented in randomized order. With two repetitions, the experiment contained 70 trials.

5.1.2 Design

The participant's task was to set the virtual paddle at the position where they expected the ball to hit the paddle. They started each trial with the space bar. The ball moved to its stopping point. When the participant had positioned the paddle, they pressed the mouse button. The ball jumped directly to the position where it would be at interception. The paddle's color turned green if the ball hit the paddle and red otherwise. The next trial was then initiated by pressing the space bar.

The order of the balls was randomized for each participant. The participants started the experiment directly with the first trial.

5.1.3 Participants

Twelve under graduate students from the University of Montpellier-1 participated in this experiment. None of the participants participated in either of the two previous experiments. The gender was about equally spread. They were not payed for the contribution.

5.2 Results

The results are shown in Figure 7. For each elasticity, the position of the ball (red star) and the mean value of the paddle's position is depicted. The correlation is shown in the bottom graph. The highest elasticity was not included in the analysis for any condition.

In the fourth condition, as expected, the correlation between the position of the paddle and the ball was very high. This demonstrates that the participants could easily extrapolate the path of the ball from the last stopping point. This was to be expected since, in this condition, the ball fell in a more or less straight line to the paddle and provided a simple path to predict.

The first condition shows, again, a low correlation (difference to zero: $t(11)=3.11$; $p>0.01$), indicating that the participants found it hard to predict the ball's trajectory using only the velocity ratio. The pattern of responses resembles random estimates. For the second and the third conditions, the correlation increased, suggesting that with more information, the prediction of the ball's motion was more accurate.

Surprisingly, as in Experiment 2, this does appear to hold for the highest elasticity. Even in the fourth condition, in which the ball fell more or less directly through the floor, participants were not able to position the paddle correctly.

5.3 Discussion

In this experiment, participants had to predict, and then move the paddle to, the location where the ball would hit the paddle. In contrast to Experiment 2, no time constrains and no interruption in the paddle's motion were present. The ball's trajectories, and thus the available visual information about elasticity, were the same as in Experiment 1.

The results show that the correlation coefficients increased with increasing trajectory length. This was to be expected, at least within a range of a small prediction error. Performances showed, however, that the participants were not really able to predict the ball's path for the first two conditions, and were only somewhat better in the third condition.

Similar to Experiment 1, the very low correlation coefficient of the first condition shows that the velocity ratio does not seem to contain a lot of useful information for path prediction. If participants used their knowledge of the ball's elasticity, then performance should be very high for the last three conditions. Surprisingly, this is not the case, indicating that the elasticity does not seem to be used to any great degree in the performance of this task.

This interpretation can again be confirmed by the performances with the most elastic balls. The paddle was never set correctly for these conditions. This may be due to a confusion between the perception of a high elasticity and the prediction of the ball to fall due to this elasticity at a further distant position.

Nevertheless, the correlation coefficients of the paddle's and the ball's position for conditions two, three, and four were about 0.2 higher in this experiment than in Experiment 2 ($p<0.01$ for all conditions). This shows that both the time factor and the elasticity knowledge seem to increase the performance in the individual conditions but did not change the participant's overall strategy.

6 General Conclusions

In this study, we conducted three experiments to investigate the influence of knowledge about an object's elasticity on the perception and prediction of its future behavior in a simple object interaction. Elasticity is a fundamental physical property of an object, and is particularly important for the prediction of an object's trajectory. Similar to other studies, Experiment 1 showed that the elasticity of a bouncing ball can be easily detected from its trajectory after it has reached the first peak of the rebound. For this task, observers could use several simple heuristics (e.g. bounce height), which vary reliably with elasticity, to perform the task well. This is consistent with the findings of Warren et al. [1987] and Gilden and Proffitt [1994].

In the anticipation interception task of Experiment 2, it was shown that the longer the time window within which the virtual paddle could be moved, the better the positioning of this paddle to the interception point was. If the participants had used the elasticity information (which Experiment 1 showed they could perceive) to extrapolate the ball's path, the performance in Experiment 2 should be more accurate after the height ratio became available. It seems, however, that knowledge about the object's elasticity was not sufficient to accurately perform the anticipation interception task. The underlying strategy seems to have been more related to a error-correction strategy from the ball's motion than to a physically correct calculation.

The third experiment examined whether observers could predict the ball's path using the same visual information as in Experiment 1, by asking participants to set the paddle at the position of interception without time pressure. Just as was found in Experiment 2, the more of the ball's path that was seen, the better the outcome of the prediction.

Together, these findings suggest that the visual information used, and the strategy applied, depends crucially on the task that the observer is performing and the information that is available. While observers can easily extract visual information from the trajectory of the ball to passively rate its elasticity, this information is not used in actively predicting its path. In both cases the observer can rely on heuristics, however, these heuristics are different depending on the context. Thus, it seems that the criteria, mechanisms, or strategies used in passively observing an event are different from those used when we actively interact with that event.

These findings should be taken into account in the development of interactive interfaces and animation systems based on the simulation of physical objects, in an industrial context or in computer games. Depending on the task to be performed by the user, it may be possible to make approximations without causing visually objectionable appearance, or inaccurate responses from the user. The differences between passively observering and actively interacting with a virtual object could be exploited to reduce computational costs in interactive applications [O'Sullivan et al. 2003].

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