

Deep Physics-aware Inference of Cloth Deformation for Monocular Human Performance Capture

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Abstract

Recent monocular human performance capture approaches have shown compelling dense tracking results of the full body from a single RGB camera. However, existing methods either do not estimate clothing at all or model cloth deformation with simple geometric priors instead of taking into account the underlying physical principles. This leads to noticeable artifacts in their reconstructions, such as baked-in wrinkles, implausible deformations that seemingly defy gravity, and intersections between cloth and body. To address these problems, we propose a person-specific, learning-based method that integrates a finite element-based simulation layer into the training process to provide for the first time physics supervision in the context of weakly-supervised deep monocular human performance capture. We show how integrating physics into the training process improves the learned cloth deformations, allows modeling clothing as a separate piece of geometry, and largely reduces cloth-body intersections. Relying only on weak 2D multi-view supervision during training, our approach leads to a significant improvement over current state-of-the-art methods and is thus a clear step towards realistic monocular capture of the entire deforming surface of a clothed human.

1. Introduction

Human performance capture plays a critical role in various computer graphics and vision applications such as virtual try-on, avatar re-targeting, movies as well as video games. With rapid progress in display and capture technology, expectations on the quality of geometric reconstruction and tracking are constantly increasing. Here, not only the geometric details are of major importance but also that the deformed and posed reconstructions follow the physical behavior of real objects which includes realistic wrinkle patterns as well as coherent interaction of body and clothing. While professional content production studios can rely on involved multi-camera setups to capture high-fidelity hu-

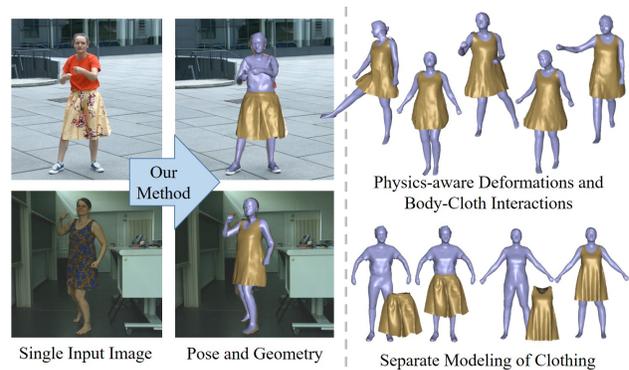


Figure 1: Our method estimates body pose as well as physically plausible surface deformation from a single image. Importantly, body and clothing are represented as separate meshes which allows accurate modeling of body-cloth interactions.

man performances, there is an ever growing desire to democratize performance capture for everyday applications, such as virtual try-on, by using much simpler and cheaper capture devices.

Hence, research has shifted from expensive and complex multi-view capture setups [52, 6, 10, 7, 8, 50, 14, 17, 38, 44, 72, 73, 77, 50] to depth cameras [61, 22, 46, 28, 21, 36, 80, 16, 82, 83, 81, 76] over the past decade. Unfortunately, the latter are sensitive to bright sunlight and thus not suited for outdoor use-cases. Due to this and the advances in deep learning, the most recent research has shifted its attention onto *single RGB camera* setups, offering the most flexible and low cost setup. Previous monocular methods have made a substantial progress in recovering the 3D unclothed body [31, 49, 32], hand pose [74, 43, 88] as well as facial identity and expression [34, 66, 67]. First attempts have also been made to jointly track the above body parts [48, 78, 30]. However, so far only few methods [24, 23, 79] have managed to coherently track the dense surface deformations with clothing included from monocular views, which is essential for a lot of applications and for an immersive experience. These person-specific methods densely deform and pose a geometry to match the body pose as well as the cloth-

ing deformation in the input image while assuming an initial template of the person is given. Recent learning-based monocular methods [24] only assume image-based supervision, making it challenging for them to densely supervise deformations. This manifests in simplified model assumptions like a single geometry for body and clothing as well as the usage of simple geometric priors which do not obey physics principles. As a result, they cannot account for body-cloth interactions, deformations do not follow physical rules, and they have notable artifacts such as baked-in wrinkles from the initial scan.

To this end, we propose a learning based approach for capturing body pose as well as the physically plausible clothing deformation from a single RGB image (see Fig. 1). Our method is comprised of two networks dedicated to regress body pose in terms of joint angles and surface deformations in form of embedded deformation. Importantly, during training we only assume weak supervision in form of multi-view imagery, i.e. 2D skeletal joint detection and foreground masks. As discussed before, this type of supervision can hardly ensure physically plausible results. Thus, at the core of our approach, we propose an efficient simulation layer that for the first time allows physically plausible self supervision *during* the training in such a weakly supervised setting. We achieve this by integrating a finite element based simulator into a learning architecture which takes intermediate predictions of cloth and body positions and velocities to perform a forward simulation. The simulation result is then used to supervise the deformations of our deformation network during training. As cloth-body collisions are explicitly handled in the proposed layer, we can accurately model clothing as a separate piece of geometry in contrast to previous monocular methods. In summary, our contributions are:

- A monocular human performance capture approach, which outputs body pose and physically plausible cloth deformations for dressed subjects.
- A simulation network layer that allows on-the-fly simulation supervision *during* training, which also enables separate modeling of cloth and body geometry.

In contrast to prior work, our method reconstructs physically more accurate deformations without baked in wrinkles and with correct body-cloth collision handling. Our quantitative evaluations indicate that incorporating physical simulation during training provides significant improvements over state-of-the-art methods.

2. Related Work

As our goal is recovering a dense surface of the human, we focus on previous works that achieve this by using parametric body models or template meshes, and works that

treat body and clothing as separate mesh layers. We do not discuss the large body of work on 2D [11, 12, 60, 75] and 3D skeletal pose estimation [42, 41, 25, 54, 53, 87, 65, 69, 55] as they are not concerned with the problem of surface reconstruction.

Reconstruction of Parametric Body Models. The works [86, 29, 56, 19, 4, 37, 31, 70] that fall into this category use parametric body models such as SMPL [39]. Some works fit the model parameters to sparse 2D and 3D joint predictions [4] or to regressed vertex positions [35] by minimizing corresponding energies. Others [31] directly regress these parameters from images. A set of recent works [48, 78] extended body models to account for changing hand pose and facial expression which was then used to jointly capture hands, face and body. While motion and shape of the naked body can be reconstructed, clothing was not considered.

Unified Reconstruction. One stream of previous work treats body and clothing as a single geometry. Volumetric representations [85, 71] use an occupancy grid to represent the body, meaning that resolution is limited by the grid. Implicit methods [57, 27, 58] methods overcome this limitation by treating the subject’s surface as an implicit function. However, both approaches require post-processing to recover an explicit surface representation, e.g., through the marching cubes algorithm. The resulting concerns in terms of temporal consistency make these approaches all but impractical for applications such as texture replacement or motion retargeting. Closely related to our work are template-based methods [23, 24, 79, 13, 15] which track a template based on image observations. Using a mesh with fixed topology as reference, surface correspondence over time is directly given. With input data originating from images only, however, they must replace missing information with simplifying assumptions and geometric priors that do not reflect real physical behavior. Geometric priors alone cannot ensure physically plausible result, leading to static wrinkles present in template that remain visible across all poses, and deformations that do not respect gravity. Most importantly, all these methods treat clothing and body as a single piece of geometry so that they cannot account for dynamic body-cloth interactions. To address these limitations, we propose a simulation layer that encourages cloth deformations to not only satisfy image constraints, but to also exhibit physically plausible behavior.

Cloth as a Separate Part. In contrast to the above methods, there is also a line of work that reconstructs body and clothing as separate geometries. Bhatnagar et al. [3] recover static geometry for clothing and body from a set of RGB images. ClothCap [51] uses multi-view capture to

produce a clothed human body that can be used for re-targeting. Stoll et al. [63] recover cloth material parameters from multi-view video sequences to reproduce the observed garment deformation. Similar to our work, but requiring a depth camera, is SimulCap [84], which performs quasi-static physics simulation with depth matching constraints to reconstruct the clothing layer. While all of the above methods rely either on multi-view setups or depth cameras, our approach requires only a single RGB camera.

As a potential alternative to simulation, geometric detail such as wrinkles can be added in a data-driven, pose-dependent manner [18, 59, 47, 20]. Different from these geometry-driven methods, we integrate physics-based simulation into our training framework thus encouraging physical plausibility with only a single image as input.

3. Method

Our template-based method leverages a deep neural architecture, which takes a single background-segmented person image as input and regresses posed and deformed surface meshes for body and clothing which match the performance in the input image (see Fig. 2). Before training, a 3D template of the person with separate cloth and body geometry as well as a multi-view recording of the subject performing various motions has to be acquired (Sec. 3.1). The technical core of our architecture is formed by two prediction networks, *PoseNet* and *SimNet*, that are trained to regress body pose and cloth deformation, respectively (Sec. 3.3). *PoseNet*, introduced by Habermann et al. [24], regresses skeleton joint angles and the root rotation from the input image using multi-view 2D joint detections as weak supervision. The proposed *SimNet* predicts the surface deformation of the cloth template by regressing embedded graph parameters from the same input image. In addition to multi-view image data, *SimNet* leverages our cloth simulation layer as supervision, which encourages physically plausible deformations (Sec. 3.2).

3.1. Data Processing

Template Acquisition. Similar to [24], we acquire a single scan for body and clothing (e.g. using photogrammetric scanning). We perform surface registration against a parametric body mesh model using the method of Bhatnagar et al. [1, 2] to obtain an estimate for body parts occluded by clothing, such as the legs under a skirt, which are merged with the visible body parts from the scan to form a complete body mesh. We also mark the arms of the body mesh as inactive when resolving collisions in our simulation. A separate cloth mesh is created manually from the scan, a task that could also be automated [63, 51]. Skeleton parameters and skinning weights, required for posing the two meshes, are determined automatically as described in [24]. Two separate embedded graphs [64, 62] for body and cloth-

ing are computed by subsampling the original body and cloth meshes. For more details, we refer to the supplemental document.

Video Capture. We capture the subject to be tracked in a multi-view green screen studio with calibrated and synchronized cameras. We ask the person to perform various tasks such as walking and dancing to best sample the space of possible poses. Next, we run OpenPose [12, 11, 60, 75] on all frames and views to obtain multi-view 2D joint predictions. Color keying is used to segment the foreground from the greenscreen background and compute distance transform images D_c from the foreground masks [5].

3.2. Cloth Simulation Layer

Our simulation layer uses the publicly-available cloth simulation framework ARCSim [45] as its basis, but we make several adjustments that we describe below.

Material Model and Parameter Selection. ARCSim uses a data-driven material model defined by a total of 39 parameters. While parameter values for several real-world fabrics are provided, we found that none of them were ideally suited for the materials that we use in our examples. Manually adjusting parameters to obtain better approximation proved very difficult. For this reason, we resorted to a simpler, isotropic material model (see, e.g., [68]) that is defined through three parameters: Young’s modulus and Poisson’s ratio for in-plane behavior, and a single bending stiffness coefficient. We determine parameter values through best-guess initialization and a few iterations of simulation-based tuning to better approximate the qualitative behavior observed in the input video sequences. Although we found this manual approach to be sufficient for our examples, this task could be further automated [63].

Time Integration. During training, the initial state and velocities that are fed into the simulation layer can exhibit large deformations that, when using ARCSim’s default integration method, can lead to instabilities. To improve stability, we resort to an optimization-based formulation of fully implicit Euler (see, e.g., [40]) combined with adaptive regularization and a back-tracking line search. Finally, we make several code adaptations to enable batch operations for efficient training and integrate the simulation engine in a customized TensorFlow¹ layer. We refer to this layer as the simulation function \mathcal{S} later, which takes cloth and body vertices as input and returns the cloth positions for the next time step.

¹<https://www.tensorflow.org/>

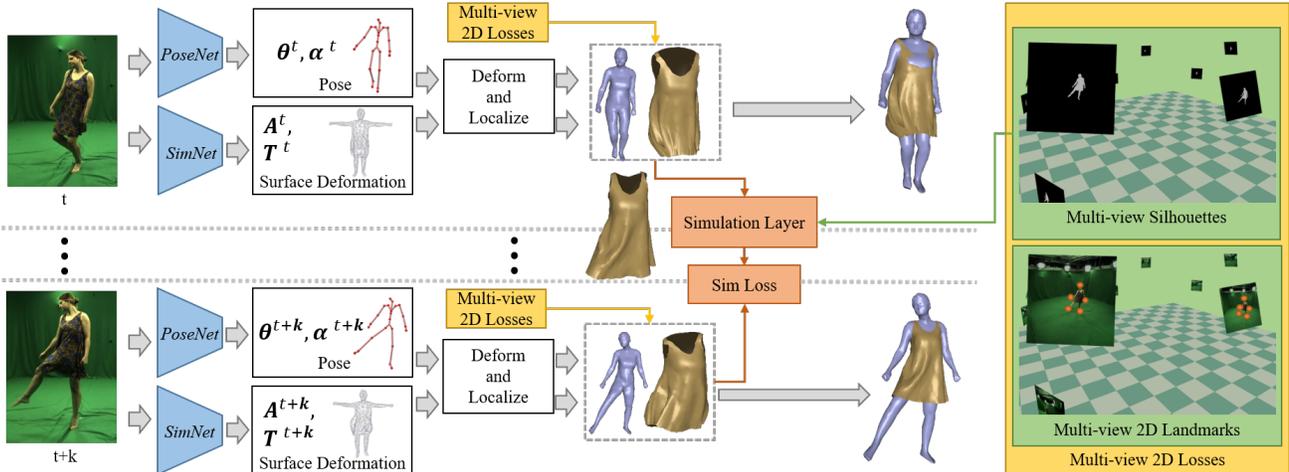


Figure 2: Overview. Our method takes a single image as input and two separate networks, *PoseNet* and *SimNet*, regress the skeletal pose as well as embedded deformation parameters for the clothing. Combining the outputs of the two networks allows posing and deforming the body and clothing geometry. During training, we use multi-view image losses for *PoseNet*, whereas *SimNet* is additionally supervised by our proposed simulation loss to encourage physically plausible deformations. To evaluate the simulation loss, we run on-the-fly cloth simulation on small windows of subsequent frames from the training sequence and penalize the difference between regressed deformations and simulation outputs.

Silhouette Constraint. Although our simulation model captures the characteristic behavior of clothing, it is still an approximation and deviations from the input images must be expected due to external forces such as air drag, viscous damping, and friction that are not modeled. To better track the real-world behavior, we therefore introduce an additional multi-view silhouette constraint, integrated into the simulation layer. Specifically, this constraint ensures that the vertices $\tilde{\mathbf{V}}_{\text{cloth}}^t$ of the simulated cloth geometry matches the image silhouettes from all camera views for frame t . Therefore, we construct a 3D ray going through the camera origin and the silhouette pixel p and search for the boundary vertex $\tilde{\mathbf{V}}_{\text{cloth},p}^t$ that minimizes the distance to this ray. The closest point on the ray is used as 3D point correspondence for the boundary vertex, included as soft constraint into the simulation.

$$E_{\text{cons}} = \sum_p \|\tilde{\mathbf{V}}_{\text{cloth},p}^t - \mathbf{V}_{\text{ray},p}^t\|^2. \quad (1)$$

Next, we introduce our pose regressor and the surface deformation network which leverages our simulation layer as an additional form of supervision.

3.3. Pose and Deformation Regression

We separate the task of regressing the full surface deformation into predicting pose and surface deformation independently. Therefore, our method consists of two ResNet50 based CNNs [26], *PoseNet* and *SimNet*, which regress skeleton pose and embedded deformation parameters from a segmented input image, respectively.

3.3.1 Pose Regression and Deformation Model

To pose and deform template vertices as well as sparse body markers, the deformation layer of Habermann et al. [24] denoted as

$$\mathbf{V}_{\text{loc}}, \mathbf{K}_{\text{loc}} = f(\boldsymbol{\theta}, \boldsymbol{\alpha}, \mathbf{A}, \mathbf{T}) \quad (2)$$

is used, which is a combination of dual quaternion skinning [33] and embedded deformation [64, 62]. It takes the pose in terms of skeleton joint angles $\boldsymbol{\theta} \in \mathbb{R}^3$ and camera-relative root joint rotation $\boldsymbol{\alpha} \in \mathbb{R}^3$ as well as the embedded graph node rotation $\mathbf{A} \in \mathbb{R}^{K \times 3}$ and translation $\mathbf{T} \in \mathbb{R}^{K \times 3}$ where each row encodes rotations in terms of Euler angles and translation vectors for each of the K nodes. The output is the posed and deformed vertices \mathbf{V}_{loc} and markers \mathbf{K}_{loc} in camera and root relative space where the i th row contains the updated position of vertex i . The body pose parameters $\boldsymbol{\theta}$ and $\boldsymbol{\alpha}$ are regressed using *PoseNet* [24].

3.3.2 Physics-aware Deformation Regression

To not only pose the template but also account for surface deformation, we propose a dedicated network *SimNet* which predicts the translation vectors \mathbf{T} and rotation angles \mathbf{A} of the embedded graph (EG) from the segmented input image. *SimNet* is supervised using a combination of both image-based and physics-based metrics, which ensure that deformations match image-based observations while minimizing violations of physical equilibrium conditions. In the remainder of this chapter we assume *PoseNet* is fixed and provides the posed and deformed vertices \mathbf{V} and markers \mathbf{K} in global space. As \mathbf{V} and \mathbf{K} are a function of the *Sim-*

Net output (\mathbf{T}, \mathbf{A}) , we can supervise SimNet by supervising \mathbf{V} and \mathbf{K} .

Warm Start. To jump start our training including the simulation layer, we first pre-train *SimNet* without running simulation but use a geometric regularizer (ARAP [62]). This adds robustness to the training since geometric regularizers are more stable than simulation and significantly reduces overall training time. Once the network predicts reasonable shapes, we add the simulation loss to supervise the physical deformation. The loss is defined as

$$L_{\text{warm}} = L_{\text{sil}} + L_{\text{lm}} + L_{\text{reg}} + L_{\text{att}} \quad (3)$$

which comprises multi-view losses as well as geometric priors. The individual loss terms are defined as follows.

Multi-view Image Losses. First, a multi-view 2D landmark loss

$$L_{\text{lm}} = \sum_c \sum_m \|\Pi_c(\mathbf{K}_m) - \mathbf{p}_{c,m}\|^2 \quad (4)$$

is used, which ensures that projected landmark matches the 2D detection $\mathbf{p}_{c,m}$ for all views c and landmarks m . Here, Π_c denotes the projection function of camera c . To densely supervise the surface, we also introduce a silhouette loss

$$L_{\text{sil}} = \sum_c \sum_{b \in \mathcal{B}_c} \rho_{c,b} \|\Pi_c(\mathbf{V}_b) - \mathbf{D}_c\|^2, \quad (5)$$

which ensures that the set of mesh boundary vertices \mathcal{B}_c matches the zero contour line in the distance transform image \mathbf{D}_c for all camera views. $\rho_{c,b}$ is a weighting term ensuring that silhouettes are only matched if the normal of the surface aligns with the gradient of the distance transform [23].

Regularization Loss. To regularize deformations and to avoid drifting of the surface, we use the as-rigid-as-possible prior [62] which ensures that local embedded deformations are smooth. We further adopt the original formulation by using rigidity weights [24] allowing us to model material dependent deformation behaviours, e.g. the skirt can deform more freely than the skin.

Attachment Loss. Note that our entire mesh \mathbf{V} can be split into body and garment meshes, denoted as $\mathbf{V}_{\text{cloth}}$ and \mathbf{V}_{body} in the remainder of this section. To ensure a coherent movement of the two, an attachment loss

$$L_{\text{att}} = \sum_{i \in \mathcal{A}} \|\mathbf{V}_{\text{cloth},i} - \sum_{j=0}^2 \gamma_{i,j} \mathcal{C}(\mathbf{V}_{\text{cloth},i}, \mathbf{V}_{\text{body}})_j\|^2 \quad (6)$$

is included, which ensures that the cloth is attached to the body at some anchor positions, e.g. the waistband of a skirt has to be attached to the hip of the body mesh. Here, \mathcal{A} are the selected vertices on the garment that act as anchor points, \mathcal{C} is a function that takes the cloth vertex id i and returns the 3 vertices of its closest triangle on the undeformed body mesh, and γ_{ij} are precomputed barycentric weights computed from the closest point on this triangle and its three vertices.

Physics-aware Training. Although our previous training allows the surface to already match image evidence, it can neither account for collision of body and clothing nor ensure physically plausible cloth deformations. To this end, we introduce an additional simulation-based loss function, whose goal it is to explicitly supervise collision behaviour as well as physical plausibility. Substituting the ARAP loss by the simulation loss, our final loss is defined as

$$L = L_{\text{sil}} + L_{\text{lm}} + L_{\text{sim}} + L_{\text{att}}. \quad (7)$$

As our previously introduced simulation layer \mathcal{S} is directly integrated into a learning framework, we can perform on-the-fly simulation during training. As training samples we use short frame sequences of length \mathcal{F} starting at random frames t' . In the following, we refer to a specific frame in this window using the superscript \cdot^t , where $t \in \{t', \dots, t' + \mathcal{F}\}$. Our physics loss

$$L_{\text{sim}} = \sum_i \sum_{t=t'+1}^{t'+\mathcal{F}} \|\mathbf{V}_{\text{cloth},i}^t - \tilde{\mathbf{V}}_{\text{cloth},i}^t\|^2 \quad (8)$$

now ensures that deformed cloth vertices $\mathbf{V}_{\text{cloth},i}^t$ match the simulation result for all frames within the frame window except the first one. Here, $\tilde{\mathbf{V}}_{\text{cloth},i}^t$ are the simulated cloth vertex positions which are defined as

$$\tilde{\mathbf{V}}_{\text{cloth}}^t = \begin{cases} \mathbf{V}_{\text{cloth}}^t, & t = t' \\ \mathcal{S}(\mathbf{V}_{\text{cloth}}^{t-1}, \mathbf{V}_{\text{cloth}}^t, \mathbf{V}_{\text{body}}^{t-1}, \mathbf{V}_{\text{body}}^t), & t = t' + 1 \\ \mathcal{S}(\tilde{\mathbf{V}}_{\text{cloth}}^{t-2}, \tilde{\mathbf{V}}_{\text{cloth}}^{t-1}, \mathbf{V}_{\text{body}}^{t-1}, \mathbf{V}_{\text{body}}^t), & t > t' + 1 \end{cases}$$

where \mathcal{S} takes current and previous body and cloth positions to approximate garment and body velocities. Note that for $t = t'$ no velocities are available, thus we set $\tilde{\mathbf{V}}_{\text{cloth}}^t = \mathbf{V}_{\text{cloth}}^t$. Similarly for $t = t' + 1$, we have to approximate cloth velocity using $\mathbf{V}_{\text{cloth}}^{t-1}, \mathbf{V}_{\text{cloth}}^t$. For the remaining frames in the window, the velocities can be acquired from previous simulation steps using forward differences (FD). We can now evaluate the simulation loss on these $\mathcal{F} - 1$ frames (excluding the first frame of the window) and thus supervise our *SimNet* deformation predictions. We opted to not backpropagate gradients through the simulation inputs with respect to the EG parameters as this would

make it harder to guarantee convergence during training. Even though the first frame in a training sample sequence does not receive supervision, that frame is supervised by our multi-view supervision, such that in practice all frames are supervised. In addition to the shape of the cloth, the networks also generate the body shape. In the next section, we demonstrate that incorporating physics during training provides stronger and more physically plausible supervision leading to significantly less collisions, and physically implausible forces.

4. Results

We evaluate our approach on various outdoor and indoor environment settings with three subject-cloth combinations under a wide range of motions (see Fig. 3). To bridge the domain gap between training data recorded in the capture studio and in-the-wild testing sequences, e.g. different light conditions and cameras, we apply a domain adaptation step. Here, PoseNet and SimNet are refined for 300 iterations on the testing sequence leveraging the losses introduced before but *using only a single camera*. For in-the-wild captures with varying and dynamic backgrounds, we segment the input images using OSVOS [9]. While the result is almost collision free thanks to *SimNet*, minute intersections can still remain, which is why we run a final collision resolution step (see also supplemental video). Following [24], we smooth the final results temporally using a Gaussian filter of size 5 frames. To visualize our result overlaid onto the input image, we leverage the single view global alignment of Habermann et al. [24] that computes the global translation in closed form.

Dataset. Our training dataset contains 3 green screen studio capture sequences ($S4$, $F1$, $F2$) with actors performing a large range of motions. For testing, we recorded an additional multi-view green screen sequence to evaluate our reconstruction on reference views and multiple in-the-wild captures using a single camera with a resolution of 1920×1080 for every subject. Sequence $S4$ is from [24], and we additionally acquired two training sequences and templates, $F1$ and $F2$, with 18 cameras at a resolution of 1285×940 , where each sequence contains around 20,000 frames. We will release the dataset for future research.

Qualitative Results. In Fig. 3, we test our method on various in-the-wild environments while the subjects perform a wide range of motions. Our method does not only provide accurate image overlays and plausible 3D body and cloth geometries but our reconstruction also shows physics-aware cloth deformations and plausible body-cloth interactions. In Fig. 4, we show that our SimNet predicts different physically plausible wrinkle patterns related to the charac-

ter motion. This is due to our separate modeling of body and cloth geometry and the fact that body-cloth interactions are taken into account by our simulation supervision during training. We further visualize the underlying body geometry without clothing. Note that also the occluded parts are predicted accurately.

4.1. Comparisons

We compare our approach to the state-of-the-art template-based monocular human performance capture methods [23, 24]. LiveCap [23] determines poses using inverse kinematics with predicted 2D and 3D joint positions as targets and computes surface deformations such as to optimize a single-view image loss. DeepCap [24] uses weak supervision from multi-view images during training to predict pose and embedded deformation parameters from a single segmented image.

4.1.1 Qualitative Comparisons

In Fig. 5, we compare our method with state-of-the-art template-based methods [23, 24]. Unlike our approach, both LiveCap and DeepCap only use geometric priors on the deformations during optimization and training, respectively. Consequently, the resulting cloth deformation contains static wrinkles from the initial template (see top left corners) that persist across all poses. By using simulation supervision and separate modeling of cloth and body geometries, the wrinkles generated by our method are less constrained by the template and, consequently, exhibit more variety and better physical plausibility.

4.1.2 Quantitative Comparisons

We evaluate our results using the green screen testing sequence of $S4$ for all metrics below. For a fair comparison, we use the same cloth-body geometry, obtained through manual clean-up of the input scans, for all approaches.

Out-of-balance Force Evaluation. In Tab. 1, we list the magnitude of the out-of-balance forces, which are defined as the difference between inertial forces and the sum over internal, external, and collision forces. This physical measure indicates to what extent the results deviate from Newton’s second law of motion, and vanishes for physically-correct motion. The acceleration of the body and the garment for a given frame is determined using a centered difference approximation based on network predictions for three consecutive frames. To reduce the global translation error irrespective of our network predictions, we apply the ground truth global translation for all methods as described by Habermann et al. [24]. Our method performs not only better on average compared to other approaches but also



Figure 3: Reconstructions obtained with our method for various in-the-wild environments and challenging motion combinations. Our results show good overlay quality throughout, attesting to the pose and clothing estimation accuracy of our method. Furthermore, diverse and physically plausible cloth deformations are observed for a wider range of poses.

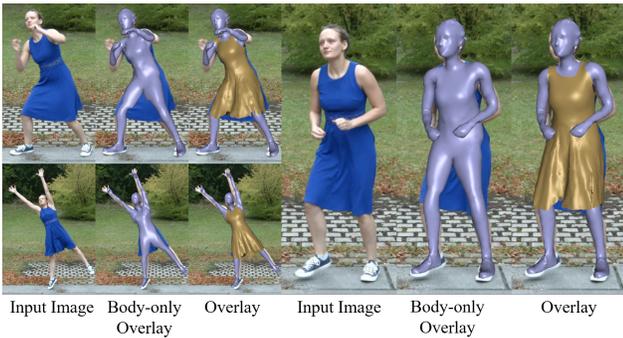


Figure 4: Physically plausible deformation. Here we show our reconstructed body geometry as well as our final model with body geometry and clothing. Despite minor distortions in occluded regions, our reconstructed body geometry matches the image evidence. Thanks to the separate template geometry modeling, our cloth reconstruction is able to reproduce the folding and unfolding behaviour of the dress which is driven by the underlying body motions.

significantly reduces the peak value. LiveCap [23] performs significantly worse due to the inherent ambiguity of the single-image setting combined with the inability of geometric priors to capture physical behavior. As a result, the cloth geometry returned by their method exhibits large distortions, in particular in regions occluded from view, resulting in large internal forces. DeepCap [24] leverages neural

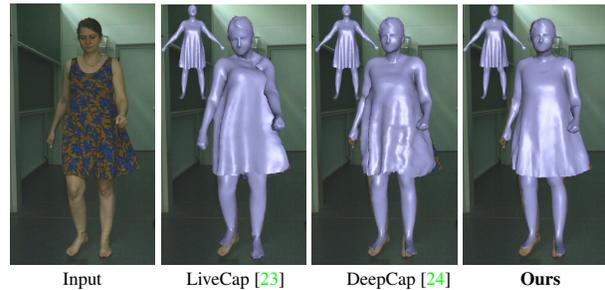


Figure 5: Comparison with state-of-the-art template-based monocular methods [23, 24]. Using simulation supervision during training, our method produces physically more realistic results without baked-in wrinkles from the initial template mesh (shown in the top left corners).

network models trained with multi-view supervision. Despite substantial improvements compared to LiveCap, our physics-aware method leads to another 50% decrease in error.

Garment-body Intersection Distance. In Tab. 2, we further compare the garment-body intersection distance to LiveCap [23] and DeepCap [24]. Their simplified one-piece templates sidesteps this issue, however, when we evaluate with our more accurate mesh model, e.g. separate geometry for clothing and body, collisions severely affect the reconstruction quality. We show that our network predictions significantly reduce cloth penetration.

Methods	Avg	Max
LiveCap[23]	79.85	1140
DeepCap[24]	2.119	29.84
Ours	1.017	7.063

Table 1: Out-of-balance force evaluation. We compare our method to LiveCap [23] and DeepCap [24] with respect to out-of-balance force magnitude. It can be seen that our physics-aware method outperforms state-of-the-art geometry-based methods.

Average Penetration Depth (cm)	
Methods	Distance
LiveCap[23]	25.58
DeepCap[24]	23.83
Ours	4.165

Table 2: Penetration Depth. We compute average penetration depths for cloth-body intersections across a 10,000 frame testing sequence. Not taking collisions into account, both LiveCap [23] and DeepCap [24] produce severe penetrations. Our method handles collisions during training, which leads to substantially reduced penetration depths.

IoU Percentage. To measure reconstruction quality from different camera views, we compare our results with previous methods using the intersection over union (IoU) metric (see Tab. 3). The IoU metric indicates the overlapping percentage of the camera projection images of our reconstruction and the foreground segmentation of input images (ground truth). To be consistent with [24], the evaluation is performed for every 100th frame of the testing sequence from $S4$. We apply the same ground truth global translation and temporal filter as in DeepCap [24]. Comparing to body-only reconstruction methods, our method achieves significantly better performance. It should be noted that, compared to the other approaches, the cloth geometry in our method is more constrained due to physics. For example, the strap of a dress cannot detach from the body to match the image silhouettes. Nonetheless, we achieve comparable IoU accuracy while maintaining better physical plausibility.

Methods	AMVioU (%)	RVioU(%)	SVioU(%)
HMR[31]	65.10	64.66	70.84
LiveCap[23]	59.96	59.02	72.16
DeepCap[24]	82.53	82.22	86.66
Ours	80.83	80.53	84.83

Table 3: IoU percentage comparison. Average multi view ($AMVioU$), reference view ($RVioU$) and single view ($SVioU$) values correspond to IoU evaluation on all views, all views except input view, and input view, respectively. Our reconstruction provides comparable accuracy with state-of-the-art methods while delivering more physically plausible results.

4.2. Ablation Study

Simulation during Training. Here we verify that, with simulation supervision in the training process, physically unrealistic cloth deformations and other artefacts resulting from merely image-based supervision can be reduced. As can be seen in Fig. 6, the strap of the dress remains on the body, and the bottom of the dress does not distort to match the silhouette.

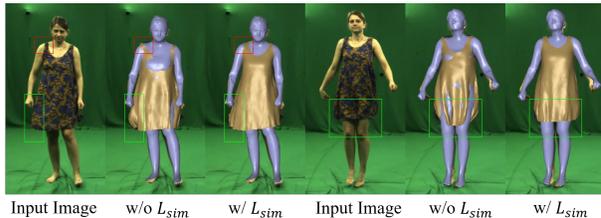


Figure 6: Simulation during training. We evaluate our deformation network with and without simulation loss on a testing sequence. It can be seen that penetrations and deformation artefacts are largely reduced when using simulation.

5. Conclusion

We propose a physics-aware deep learning-based method for monocular human performance capture. With physics-based simulation running on-the-fly as a network layer, we enforce physics plausibility to compensate the shorthand of using only multi-view images. We show more visually pleasing results and much improved physics-metrics over state-of-the-art methods.

Limitations & Future Work. Simulation is the computational bottleneck of our training process. However, using GPU-accelerated simulation, we believe that training time can be substantially reduced. On a related note, the simulation layer is not differentiable in our current implementation. Nevertheless, a fully-differentiable physics solver would improve data efficiency and it would open the door to automatic material parameter estimation from video input. Our method is able to faithfully track body pose and cloth deformations for dynamic input motion, but it cannot produce dynamic effects from a single input image—an inherently ill-posed problem. To further improve physical fidelity and reconstruction quality, we would like to extend our method to regress dynamically-consistent cloth motion by leveraging deep temporal architectures, which take short videos as input instead of single frames.

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