Garment Replacement in Monocular Video Sequences

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We present a semi-automatic approach to exchange the clothes of an actor for arbitrary virtual garments in conventional monocular video footage as a post-process. We reconstruct the actor’s body shape and motion from the input video using a parameterized body model. The reconstructed dynamic 3D geometry of the actor serves as an animated mannequin for simulating the virtual garment. It also aids in scene illumination estimation, necessary to realistically light the virtual garment. An image-based warping technique ensures realistic compositing of the rendered virtual garment and the original video. We present results for eight real-world video sequences featuring complex test cases to evaluate performance for different types of motion, camera settings, and illumination conditions.


General Terms: Animation

Additional Key Words and Phrases: image based techniques, garment simulation, lighting reconstruction, video augmentation

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1. INTRODUCTION

Digital workflows have greatly advanced video post-processing capabilities. However, photo-realistically modifying recorded real-world scene content is still a time-consuming, highly labor-intensive, and monetary costly process. In this work we address the challenge of realistically exchanging the attire of human actors in already captured, conventional, uncalibrated monocular video footage. Previous approaches addressed this long standing problem by re-rendering the entire human actor by a virtual dummy [Divivier et al. 2004] or by altering only the texture print on the garment leaving the garment itself unchanged [Scholz and Magnor 2006]. To go beyond these approaches, a precise dynamic 3D body model reconstruction is usually required. This is the approach most often pursued in contemporary movie productions [Landgrebe 2012] but comes at the expense of a costly hardware setup and extensive manual labor. Earlier approaches in research have achieved impressive results based on multi-view recordings to estimate the necessary 3D body information from either a laser scanned model [de Aguiar et al. 2008] or using a statistical body model [Hasler et al. 2009]. The need for multi-view recordings, however, complicates acquisition, and such methods are not applicable to already recorded, conventional video footage. The input video and reconstructed body model generally do not match identically because of the limited fitting precision of the statistical body model and can therefore be used only as approximate guidance for video editing [Jain et al. 2010]. For virtual garment replacements, unfortunately, such imprecisions are unacceptable as they will inevitably produce noticeable visual artifacts.

In the following, we present a semi-automatic approach for perceptually convincing garment replacement in real-world video footage. In contrast to previous work, we intentionally concentrate on the difficult case of conventional monocular video recordings of actors wearing normal clothes. We do not use any additional input information besides the plain RGB images. While the problem is ill-posed, we are able to achieve high-quality results excelling in quality and general applicability over previous approaches that rely on additional information from depth cameras or multiview settings. Inspired by state-of-the-art literature [Jain et al. 2012], we aimed at achieving best-possible realism with user interaction times of approximately one minute per edited frame. This paper makes the following contributions:

(1) a complete and flexible pipeline for garment replacement in monocular video sequences,
(2) a novel set of error terms for human pose estimation tailored specifically to track human motion in monocular video sequences while offering the possibility to interactively add soft pose constraints to resolve ambiguities,
(3) an approach to reconstruct dynamic scene illumination from a person’s video recording alone, and
(4) an image-based body and silhouette matching algorithm for compositing and alignment of the virtual garment with the recorded actor based on an imprecise body model.

As potential applications of our approach we envision movie post-production and youth protection by sanitizing nudity in movie scenes.

2. RELATED WORK

Virtual clothing. Typically, virtual clothing systems follow one of three principles: they render a virtual avatar that is dressed with the virtual garment [Divivier et al. 2004; Hauswiesner et al. 2011] avoiding the problem of augmenting the real person with the virtual garment; the system changes only the texture of the garment [Scholz and Magnor 2006; Scholz et al. 2005; Pritchard and Heidrich 2003; Guskov et al. 2003]; or additional sensor data from multi view recordings [Hauswiesner et al. 2013] or depth sensors [Fitnect 2012; Giovanni et al. 2012] is used to render the garment on top of an actor in a video stream. To simulate even small wrinkles or wide apparel image-based clothing simulations provide a powerful tool [Xu et al. 2011; Hilsmann and Eissert 2012; Hilsmann et al. 2013]. For garment replacement in still images Yoon et al. [2011] proposed a semi-automatic system using a priori skeletal and silhouette information to properly drape a character. In this paper we propose a novel approach that tackles the problem of realistically augmenting a standard, monocular video of a human actor with virtual clothing requiring only minimal user interaction.

Shape and Pose Reconstruction. The simulation of virtual garments requires a proxy for the inherent collision detection and
plausible reconstruction of garment motion. In recent years, statistical deformable body models have received a lot of attention due to their flexibility and robustness [Anguelov et al. 2005; Hasler et al. 2009]. With these models, human shape and motion can be reconstructed from multiview video data [Hasler et al. 2009; Balan et al. 2007; Guan et al. 2010; Hasler et al. 2009]. Recent work shows that it is possible to solve the underconstrained problem of reconstructing complex 3D human poses [Agarwal and Triggs 2004; Guan et al. 2009] or approximate 3D geometry [Töppe et al. 2011] even from single images. Overcoming the problem of self-occlusions and ambiguities in monocular videos, however, requires additional information in the form of body markers on the actor [Rogge et al. 2011], a proper annotation of body joints [Ramakrishna et al. 2012] or by obeying to the laws of physics [Wei and Chai 2010; Vondrak et al. 2012]. Similar to [Zhou et al. 2010] reshaping bodies in still images, MovieReshape [Jain et al. 2010] manipulates the body shape of a human actor by transforming the deformation of a body model to a smooth deformation of the input video to prevent complex matting, segmentation, and occlusion problems. In a semi-automatic approach the required body shape and motion is reconstructed from silhouette comparisons and tracked features on the body surface. However, solving the problem of robust shape and motion reconstruction with the precision required for realistic garment replacement in arbitrary monocular videos seems currently still infeasible. In this work, we therefore relax the requirement of precise pose reconstruction from monocular video and instead fine-tune the garment simulation result in image space during compositing.

Lighting Reconstruction. For convincing realism of the final video augmentation, it is necessary to reconstruct not only the body model, but also scene illumination. In computer graphics the conventional approach is to estimate a radiance map from a light probe placed in the scene [Debevec 1998] or a fisheye lens recording [Frahm et al. 2005], but both require special preparations during recording and hence are not applicable to already captured video footage. However, given a reference geometry and input video allows to draw inferences from shading differences within a surface about the reflectance properties, normals and approximate lighting conditions [Gibson et al. 2001; Chen et al. 2011]. We extend the approach of Gibson et al. [2001] to estimate the albedo distribution function for a person’s surface in the input video. We make use of the 3D information from the estimated parameterized body model to formulate the lighting reconstruction problem as a linear system that can be solved in a physically plausible way using a non-negative least-squares solver.

3. Overview
We propose a semi-automatic approach to solve the highly underconstrained problem of augmenting monocular videos of a human actor with virtual garments by combining coarse pose estimation with an image-based refinement algorithm for more accurate garment alignment. We first fit a parameterized body model to the silhouettes of a recorded human actor (Sect. 4). This serves as a crude approximation to the actor’s shape and motion. We propagate the model through the video by optimizing shape and pose parameters with a specifically designed error functional. Ambiguities are solved by allowing for soft user constraints. Based on the body model we reconstruct the BRDF of the actor and estimate the scene illumination (Sect. 5). The model serves as a proxy to simulate and render the virtual garment (Sect. 6). As the body model and the actor’s shape only roughly match, we first apply a global image-based refinement by tracking the motion of both, model and actor, and using the discrepancy between these to fit the virtual garment to the human actor in image space (Sect. 7). This prevents a “floating” of the garment on the human actor. Small mismatches along the silhouettes are then corrected by a line matching algorithm. Both correction steps are combined in a single image-space warping procedure. The warped depth values of the body model handle occlusions during the final compositing step. Fig. 2 gives an overview of the proposed algorithm.

Input and Assumptions. The input to our algorithm is an arbitrary uncalibrated, monocular video sequence depicting a human actor. We assume that a matte $M_t$ of the actor can be extracted from the video for each frame at time $t$. For our experiments we made use of the Grab-Cut algorithm by Rother et al. [2004] and Video SnapCut by Bai et al. [2009] available in Adobe AfterEffects™. Hair occluding any body parts must be removed from the matte.

Our work focuses on the garment simulation and compositing and we require the actor not to wear loosely fitting clothes. Estimating body poses from actors wearing loose clothes has been done in [Balan and Black 2008]. We further assume that the actor’s surface is largely diffuse.

4. Shape and Pose Reconstruction
In the following we propose specifically tailored error functions to track an actor and estimate his/her shape in a monocular video sequence.
We pose our shape estimation problem as an optimization of global shape parameters $\Lambda = (\lambda_1, \ldots, \lambda_M)$ and pose parameters $\Phi = (\phi_1, \ldots, \phi_N)$. For the shape optimization it is sufficient to concentrate on optimizing the $M = 30$ most important shape parameters in the statistical model. For the MakeHuman model we can reduce the number of shape parameters from 50 to 35 by using the same parameter values for shaping symmetrical body parts, such as the left and right arm or the left and right leg. During pose estimation, we optimize all available parameters in both models. We proceed by first optimizing the shape for a single reference frame (Sect. 4.3) followed by optimizing the pose parameters $\Phi_t = (\phi_{1,t}, \ldots, \phi_{N,t})$ for each frame $t$ in the video (Sect. 4.4).

### 4.3 Body Shape Estimation

We pose our shape estimation problem as an optimization of global shape parameters $\Lambda$ based on an image-based energy function $E_{\text{Shape}}(\Lambda; \Phi_t, M_t)$ for a specific frame time $t$:

$$\operatorname{argmin}_{\Lambda} E_{\text{Shape}}(\Lambda; \Phi_t, M_t) = E_s + \alpha E_h$$

We set $\alpha = 30$ in all our experiments.

The first term $E_s$ measures the misalignment of the segmented actor’s silhouette with the silhouette of the re-projected body model $B$ using the camera projection $P$ estimated in Sect. 4.1, similar to

$$E_s(\Phi_t, \Lambda, M_t) = \sum_{p=1}^{\#\text{pixels}} |M_t(p) - P(B(\Phi_t, \Lambda))(p)|$$

The parameterized body model $B(\Phi_t, \Lambda)$ or in short form $B_t$ represents the template body model $B$ deformed by the pose and shape parameters $\Phi_t, \Lambda$.

The second component $E_h$ penalizes differences in height between the actor silhouette and the projected body model in image space:

$$E_h(\Phi_t, \Lambda, M_t) = |y_{\text{min}, M_t} - y_{\text{min}, B_t}| + |y_{\text{max}, M_t} - y_{\text{max}, B_t}|$$

where $y_{\text{min}, M_t}$ and $y_{\text{max}, M_t}$, and $y_{\text{min}, B_t}$ and $y_{\text{max}, B_t}$ are the minimum and maximum y-values of non-zero pixels in the respective mattes $M_t$ of the actor and of the body model $B_t$ at frame time $t$. Fig. 3 shows a comparison with and without the error term $E_h$.

The pose parameters $\Phi_t$ for the shape estimation are set by the user in a simple click-and-drag fashion for a single frame $t$, having
a matte $M_t$ describing body shape and joint length properly. We then keep $\Phi_t$ fixed for the optimization of $\Lambda$ in Eq. (1) for which we use a multidimensional linear optimizer [Nelder and Mead 1965]. Once $\Lambda$ has been computed, it is kept fixed throughout the video sequence. For efficiency reasons when using the MakeHuman model, we first estimate the so-called macro parameters for height, weight, gender, and tone as these are linear projections of the other parameters and therefore influence them. We then use the result as an initialization to optimize all 35 parameters. We explicitly decouple shape and pose estimation, as the size and orientation of the actor are unknown a priori and have to be initialized by hand. Manually setting the pose parameters for a reference frame during this initialization step is more efficient and less time consuming than optimizing pose and shape in a coupled manner for every video frame. If required for more precise shape estimation one could easily define several keyframes for a joint shape optimization or optimize shape and pose together using keyframes as soft constraints, as described in Sect. 4.4.

### 4.4 Pose and Motion Estimation

Estimating the pose for each frame $t$ is more intricate as the monocular projection is ambiguous with respect to the pose parameters $\Phi_t$. We solve ambiguities and physical implausibilities by enforcing temporal coherence of the pose from one frame to the next, incorporating an interpenetration check as a separate error term and allowing for soft user constraints at keyframes which we describe in detail in the following.

**Error Term.** We formulate the error term for pose estimation as:

$$
\arg \min_{\Phi_t} E_{\text{Pose}}(\Phi_t; \Lambda, M_t) = E_s + \beta E_i + \gamma E_t ,
$$

We set $\beta = 2.5$ and $\gamma = 500$. $\Lambda$ is known from the previous shape optimization, Sect. 4.3. The first term $E_s$ is equivalent to the silhouette error term in Eq. (1). The second term $E_i$ penalizes strong temporal deformations by comparing the joint angles between frames:

$$
E_i(\Phi_{t-1}, \Phi_t) = |\sum_{i=1}^{N} e^{d(p_i - \phi_{i,t-1} - \phi_{i,t})} - 1 |	ag{5}
$$

$\phi_{i,t}$ is the $i$th pose parameter in frame $t$. The third term $E_t$ penalizes self-interpenetrations of the body mesh. For every vertex $v_j \in B_t$ the penetration depth $d_p(v_j, \Phi_t, \Lambda)$ is accumulated:

$$
E_t(\Phi_t, \Lambda) = \sum_{j=1}^{V} d_p(v_j, \Phi_t, \Lambda)
$$

where $d_p(v_j, \Phi_t, \Lambda) = 0$ for all vertices $v_j \in B_t$, that are not penetrating any body surface. Otherwise, $d_p$ is the Euclidean distance to the closest surface point of the penetrated body part.

The algorithm is initialized with the shape and pose $B_t$ estimated during shape optimization, Sect. 4.3. The optimizer then proceeds to estimate each individual succeeding frame in sequential order. To optimize preceeding frames, $\Phi_{t-1}$ is exchanged with $\Phi_{t+1}$ in $E_t$, Eq. 5.

**Soft user constraints.** To solve ambiguities resulting from the monocular input, we allow for additional soft constraints at each joint. In any frame where errors occur, the user may mark interactively invalid pose parameters, either for single joints or whole kinematic chains and specify a range of frames $R$ that are to be re-optimized, Fig. 4.

This is done using an interactive 3D editor allowing the user to select the invalid body parts at a specific frame and to move them towards the correct position, overwriting the falsely reconstructed pose parameters for this frame. For re-initialization of the optimizer, we linearly interpolate the pose parameters of the body model in $R$ between the user-specified keyframe and the already well-optimized frames at the boundaries of the range $R$. We additionally remove small jittering artifacts in the joints by temporally smoothing the pose parameters. Using a simple boxfilter with a one-frame radius in temporal direction proved to be sufficient in our cases.

### 5. SCENE RECONSTRUCTION

Once the actor’s shape and pose are reconstructed from the monocular input video, we can use the 3D information to reconstruct approximate scene lighting. Our approach consists of two steps. In the first step, we determine diffuse BRDF parameter values for all pixels within the actor’s silhouette $M$ from the monocular input video (Sect. 5.1). In the second step, we make use of the reconstructed BRDFs to estimate scene illumination on a per frame basis, allowing for changing lighting conditions (Sect. 5.2).
5.1 Albedo Estimation

Inspired by [Ziegler et al. 2004], we derive a time-dependent representation of the actor’s surface shading by reprojecting each visible vertex of the statistical body model $B$ into each frame of the input video. We then estimate the diffuse component of a parametric BRDF model by averaging each vertex color over time. Our basic assumption is that for a fixed surface point only its intensity values should change over time due to changes in surface orientation but not its chromaticity or saturation. Thus, averaging colors should properly describe the saturation and chromaticity of the diffuse surface and reduce the influence of shadows affecting color brightness. We are aware that more sophisticated approaches for BRDF reconstruction exist [Theobalt et al. 2007], but these generally require more than one viewpoint or known scene lighting.

5.2 Scene Illumination Estimation

We estimate scene illumination on a per-frame basis. The idea is to distribute virtual point lights in the scene and adjust their intensities so that the rendered image of the body model using the reconstructed diffuse BRDF closely matches the appearance in the original video frame $I_t$, Fig. 5. The problem can be formulated as a linear system

$$\text{argmin} \|Ax - b\|_2$$

(7)

describing the shading equations for a set of $L$ light sources which can be solved in a least-squares sense. Here, $x$ is a column vector of size $3L \times 1$ that describes the RGB color components for all $L$ virtual light sources and $b$ is the vectorized version of the reference image $I_t$. Each row of the matrix $A$ represents the influence of each single light source on a single sample pixel according to the utilized shading model. Although this approach is capable of reconstructing the illumination using more complex BRDF models, we found it sufficient to use the albedo estimate of Sect. 5.1 as this reduces the complexity of the linear system and yields plausible results in all of our test scenes.

In contrast to the work in [Gibson et al. 2001], we initially distribute the light sources uniformly over a hemisphere using a deterministic golden spiral point distribution [Swinbank and Purser 2006], Fig. 5.

The hemisphere is aligned with the camera orientation surrounding the reconstructed body model at an infinitely far distance. The positions are kept fixed and we apply a non-negative least squares solver [Lawson and Hanson 1995] to solve the linear system in Eq. (7). We use $L = 400$ initial light source positions in all our test scenes. While the solver avoids negative light emission it also minimizes the amount of non-zero lights during optimization. Therefore, only a minimum amount of light sources remains active to illuminate the scene properly. For our test sequences, this varied between one to six light sources, depending on scene and frame.

The visual appearance of the actor model compared to the input image is mainly influenced by the light sources on the frontal hemisphere. We found it sufficient in terms of quality of the results to limit the reconstruction to the frontal light source positions, as this reduces the complexity of the linear system.

The resulting light source positions can be interpreted as an environment map or used directly as point light sources when rendering the virtual garment. Examples can be seen in Fig. 6.

6. CLOTH ANIMATION AND RENDERING

The reconstructed body model is used to run a physical cloth simulation using the commercially available Marvelous Designer™.

The body model assures that the garment interacts plausibly with the human actor. We export the animated garment model, the predefined camera configuration, and the reconstructed virtual point lights into Mental Ray™ for rendering. Along with the pixel color, we also render into a separate depth buffer which we later use for depth-based compositing with the input video. Finally, we make use of differential rendering [Debevec 1998] to transfer all illumination effects caused by the artificial garment into the original scene. For this we use the shading difference of the reconstructed body model rendered with and without the virtual garment to extract information about shadows and ambient occlusion caused by the garment and apply them to the original actor during the compositing step (Sect. 7.3).

7. IMAGE-BASED REFINEMENT

To obtain convincing compositing results, we propose to refine the rendering result of the virtual garment in image space for pixel accurate alignment with the actor in the input video. We first correct for remaining differences in body shape between the actor and the body model (Sect. 7.1), then align the silhouettes between the rendered virtual garment $G$ and the silhouette of the actor $M$ (Sect. 7.2), and, finally, warp and composite $G$ into the input video (Sect. 7.3). This approach follows the intuition that similar body shapes create similar wrinkles and deformations in garment simulations [Guan et al. 2012].

7.1 Image-based Garment Motion Correction

The optimized body model (Sect. 4) provides a robust but usually not pixel-precise representation of the human actor. To create a convincing illusion of the actor wearing the virtual garment, the garment needs to move precisely according to the actor in the video. A mismatch in the motion between the reconstructed body model and the actor otherwise results in an unnatural “floating” of the gar-

Fig. 5: Scene illumination estimation. We use the estimated diffuse surface color on the body model (a), 3D surface position (b) and orientation (c) and the original video (d) to reconstruct scene illumination for each video frame. Virtual point light sources are distributed across the frontal hemisphere (e). For each light source, intensity and color is determined to match the actor’s illumination in the video frame.
ment on the actor. In our approach we establish a correspondence field between the body model and the actor that we use to correct for the differences in motion between both in image space.

The user starts by selecting keyframes in the video where the rendered clothes visually fit the actor as desired. Less than ten key frames have proven to be sufficient for all our test sequences. From there all further correction is done automatically. The motion of the rendered body model in image space is known. For a continuous motion estimation of the original actor, we compute the optical flow inbetween adjacent frames of the input video. To this end we make use of the long-range optical by [Lipski et al. 2010] which uses a robust belief propagation algorithm and SIFT-feature descriptors per pixel, extended with RGB information, to compute a pixel precise matching. We compute trajectories for each pixel \( \mathbf{x}, \mathbf{y} \) in each keyframe by concatenating the frame-to-frame flow fields for the respective.

Visualization of the reconstructed light positions as environment maps ((d) and (e)). Grey circles mark all possible light source positions used for optimization. The bigger dots mark color and position of light sources of the illumination reconstruction result. A greenish light source has been reconstructed at similar positions for both sample frames, recreating the indirect illumination reconstruction result. A greenish light source has been reconstructed at similar positions for both sample frames, recreating the indirect illumination from the floor and static illumination. A brighter white light source was reconstructed at positions resembling the direct illumination of the moving light source in the Dyn. Light sequence.

Reconstructed scene illumination. Reconstructed illumination of the Dyn. Light sequence depicting dynamic illumination with a moving light source. Top: The illumination estimate improves the realism of the composite, especially in the case of an animated light source, as the reconstructed light positions illuminate the shirt from the correct direction ((a) and (c)), while the default illumination of the used render tool (Mental Ray®) introduces inconsistencies between background shadows and shading of the virtual garment (b), as directions of the incident light do not match. Bottom: Visualization of the reconstructed light positions as environment maps ((d) and (e)). Grey circles mark all \( L \) possible light source positions used for optimization. The bigger dots mark color and position of light sources of the illumination reconstruction result. A greenish light source has been reconstructed at similar positions for both sample frames, recreating the indirect illumination from the floor and static illumination. A brighter white light source was reconstructed at positions resembling the direct illumination of the moving light source in the Dyn. Light sequence.

\[
\mathbf{D}(x', y', t) = \mathbf{T}_1(x, y, t) - \mathbf{T}_B(x, y, t)
\]

Where \( (x, y) \) is a pixel position in a keyframe and \( (x', y') \) is the pixel position according to \( \mathbf{T}_B(x, y, t) \). Assuming that the motion of the actor is locally smooth, we can safely apply an outlier removal to all \( \mathbf{D} \) using a small median filter. \( \mathbf{D} \) is only sparsely populated, due to discarded trajectories, occlusion and disocclusion. To keep the change subtle and to avoid visible artifacts we interpolate and smooth the values of \( \mathbf{D}(x, y, t) \) by applying a domain transform filter [Gastal and Oliveira 2011], which is a versatile and edge-preserving filter function capable of processing high resolution images in real time. The depth of the rendered garment serves as the edge function for the filter. Applying the resulting smooth warp field to the rendered garment \( \mathbf{G} \) for each frame nicely adapts the motion of the garment from the body model to the real actor. To avoid drifts due to imprecise optical flow computations, the same procedure is applied in backward direction between two keyframes and the warps are averaged.

7.2 Silhouette Matching

While the last step corrected for general screen-space motion differences stemming from shape deviations between the body model and the actor, we now need to track non-matching silhouettes over time and correct them so that the garment correctly overlaps the actor in the video. Detecting semantically meaningful silhouettes for matching is an ill-posed problem as the cause for mismatching silhouettes between garment and actor may also be intended for wider apparel. We, therefore, opted for a semi-automatic approach. For preview and misalignment detection, we warp the garment according to the warp field from the last step.

We track a set of silhouettes as follows: The user begins by selecting an input frame at a time \( t_k \) in the video sequence and specifies two points \( s_{\text{start}} \) and \( s_{\text{end}} \) along the silhouettes of the garment and also along the silhouettes of the actor that are to be matched, Fig. 8. Since the silhouettes of both \( \mathbf{G}_{\text{tip}} \) and \( \mathbf{M}_{\text{tip}} \) are known, the segments \( S_{\mathbf{G}_{\text{tip}}} \) and \( S_{\mathbf{M}_{\text{tip}}} \) connecting start and endpoints in the respective mattes can be found by tracing both silhouette contours from \( s_{\text{start}} \) to \( s_{\text{end}} \). For the matching, we treat both lines \( S_{\mathbf{G}_{\text{tip}}} \) and
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7.3 Warping and Compositing

We use radial basis functions to establish a smooth warp field that matches the silhouettes of G and M for all frames between time $t_0$ and $t_1$. Let $s_i, i \in 1, \ldots, K$ be the $i^{th}$ pixel along $S_G$, of length $K$ and $w_i(s_i)$ be the associated warp vectors to match $s_i$ to its correspondence on $S_M$. The warp $w(p)$ for the position $p$ of each pixel in the image of the rendered garment G is estimated as an inverse multi quadratic weighting of all warps along the silhouette segment with a Gaussian falloff:

$$w(p) = \frac{1}{\sum_{i=1}^{K} \frac{1}{\|p-s_i\|^2}} \cdot w_i(s_i) \cdot e^{-\frac{1}{2\sigma^2} \sum_{i=1}^{K} \frac{|p-s_i|^2}{\|p-s_i\|^2}}, \quad (9)$$

where $\sigma = 8.3$ and $s_i$ is the closest point to $p$ along any silhouette segment $S_{G_i}$.

This warp field is then concatenated with the warp field from the image-based body model correction (Sect. 7.1) and applied to the original rendering of G and the depth map of the rendered body model. Finally, the virtual garment is composited into the input video by comparison of the depth values of the warped garment G and warped body model B.

Further, we use differential rendering [Debevec 1998] to darken those regions of the input video that are in shadow of the garment using the shadow matte generated during the garment rendering step (Sect. 6).

8. RESULTS

We tested a variety of video sequences in our experiments, Tab. I, which differ in resolution, duration, motion complexity of the actor, scene illumination, and camera motion. The sequence Ballet depicts a ballet dancer performing a fast pirouette motion, while the Dancer scene contains a combination of slow and fast movements. The Hulk sequence allows evaluating complex interactions of the actor and virtual garment, while the Yoga sequence depicts time-coherent realistic folding of clothes. We use Dyn. Light as an example for a scene with a moving light source. While the scenes Ballet and Yoga are taken from videos available online [Howcast Media, Inc. ; Stock Footage, Inc.], Dancer, Dyn. Light, and Hulk are own recordings. The Haidi sequence taken from the i3DPPost dataset [Starck and Hilton 2007; Gkalelis et al. 2009] comprises a straight walking motion. The sequence Into The Blue is a short clip taken from the eponymous movie [MGM, Inc. 2005] while Parkour is taken from the short film Aaron Martin - Parkour provided by Yannick Wolff [Wolff ]. Both clips demonstrate the applicability of our approach to professional shots with strong camera motion. All scenes have a resolution of 1080p except for Ballet (720p) and Dancer (4k).

The MakeHuman body model was used in the scenes Into The Blue and Parkour. In all other scenes we used the body model of [Hasler et al. 2009]. We found the MakeHuman model allowed for a slightly more precise adjustment of gender specific body proportions.

The number of manually edited frames during shape and pose optimization, cf. Tab. I, includes the initial positioning of the body model for shape reconstruction as well as the corrections of falsely reconstructed joint orientations after automatic pose reconstruction (Sect. 4). The amount of required manual guidance of the body and silhouette matching algorithm (Sect. 7), is included in Tab. I, 3rd column. Scenes with more complex or fast motions require more corrections of the pose estimation (Ballet, Dancer) than scenes with slower motions (Dyn. Light, Yoga). Pose correction was necessary in frames with ambiguous silhouettes resulting from body self-occlusions in the scenes Haidi, Hulk, Into The Blue, and Parkour. Editing pose keyframes, however, is not overly time consuming, taking less than a minute per edited frame in general.

User guidance for image-based refinements is needed in frames with strong silhouette deformations. Correcting a silhouette mismatch in a single frame only takes a few seconds, and since the silhouette start and end position are interpolated linearly, corrections for slow moving objects are completed quickly. However,
Fig. 9: Results. Original (top) and augmented frames (bottom) of our test sequences (a) Ballet © Howcast Media, (b) Haidi, (c) Hulk, (d) Parkour © Yannick Wolff, (e) Into The Blue © MGM, (f) Dyn. Light, (g) Dancer, and (h) Yoga © Stock Footage.

more editing time is necessary for fast non-linear motions. By only applying a few corrections the overall quality of most sequences increases considerably and the majority of the time listed in the fourth column of Tab. I was spent on correcting details. This is especially the case in the Ballet scene due to the fast, motion blurred rotation of the dancer.

On average, manual interaction using the provided tools takes approximately one minute per edited frame. Total editing time for an entire sequence varies between 60 and 90 minutes. We think this amount of manual interaction is permissible to achieve best-possible results, as state-of-the-art approaches allow comparable amounts of user guidance in the range of one to ten minutes per edited frame [Jain et al. 2012].

The results, cf. Fig. 9, as well as the accompanying video show that our approach allows augmenting an uncalibrated, monocular video with virtually rendered garments in a variety of different settings. The selected scenes illustrate nicely that our approach can handle tight as well as loose-fitting virtual garments sufficiently. As we reconstruct the scene illumination on a per frame basis, changing directions of incident light are modeled properly, cf. Fig. 9(f) and our accompanying video. Since we use the reconstructed body model as collision proxy in the garment simulation, complex interactions of body and garment can be generated, and convincingly composed into the original video, cf. Fig. 9(c). In the case of the Parkour sequence, we removed parts of the actors loose fitting shirt by applying a fast diffusion based inpainting technique [Oliveira et al. 2001] and adjusting the actor's silhouette accordingly.

9. DISCUSSION AND FUTURE WORK

The results demonstrate that the hybrid 3D/image-based technique provides an easy-to-use and versatile way to convincingly augment general monocular videos of human actors with virtual garments. While our approach presents only a first step towards realistic video editing and augmentation, our solution provides a generally applicable framework that enables to solve the problem of garment replacement for a variety of different settings. Given the methods and techniques available today, we are convinced that the only way to attain even more realistic results would come at the price of investing disproportionately more manual work. In this work we tried to find an optimal balance between automatic processing and manual guidance to obtain highest-possible visual quality for still passable manual labor costs. The problem tackled in this paper is ill-posed, and many opportunities for future improvements exist.

Body and Shape Reconstruction. Shape optimization requires a “cooperative” silhouette. In cases where only a frontal view is provided, gender-specific shape characteristics can not be derived adequately. This problem is currently handled by allowing the user to adjust or constrain individual shape characteristics.
Scene Reconstruction. BRDF reconstruction from monocular video sequences with unknown scene lighting is an ill-posed problem. In the worst case, some color channels cannot be reconstructed at all, e.g., a white dress under red illumination. This is no limitation of our algorithm but rather a physical limitation and constructed at all, e.g., a white dress under red illumination. This is a problem. In the worst case, some color channels cannot be reconstructed. Our matching and warping technique explicitly enforces temporal consistency in the warping step, we did not encounter visually disturbing artifacts in our examples. However, in cases where the mismatch is too large the warping will become visible.

Clothing and Rendering. Our algorithm demands close-fitting clothes in the original video. Supporting arbitrary apparel in the input video requires more robust pose estimators that can deal with the additional uncertainties due to loose-fitting clothes [Hasler et al. 2009]. It also requires more sophisticated segmentation and inpainting techniques to remove the clothing from the input video [Granados et al. 2012]. Besides these limitations to the input video, certain pose parameters of the body model strongly influence the result of the garment simulation, as garment geometry might get stuck in between parts of the body geometry. The physics simulation is not able to resolve disadvantageous geometry collisions, resulting in a jittering mesh animation. This can be seen in the arm pit regions of the Parkour sequence.

Real-Time Implementation. Our approach is currently limited to off-line processing due to the high computational demands for fitting the body model parameter, manual interaction and garment rendering. While rendering can be accelerated, precise real-time pose estimation is not yet possible. Still, porting the solver to the GPU or making use of temporal predictions to find better initial poses will let the solver converge more quickly. Real-time implementations of our approach can open up other fields of applications, such as virtual try-on systems, e.g., for internet shopping using only a simple webcam, or visualizing people in different apparel using augmented reality eye wear.

10. CONCLUSION

We have presented a hybrid 3D/image-based approach to augment actors in general monocular video recordings with arbitrary garments without any additional input information or intrusive markers on the actor. The approach requires considerably less user interaction than state-of-the-art approaches. Our specifically tailored error function takes the silhouette, height, and information on self-intersection into account. Our matching and warping technique robustly removes visual artifacts caused by inaccuracies of the body model. A high degree of realism is achieved by our automatic per-frame scene illumination reconstruction. The 3D/image-based approach enables us to create realistically looking results in a flexible and versatile way. We applied our approach to scenes containing a variety of different motions, resolutions, video qualities and lighting conditions. The algorithm forms a solid basis for further research including partial occlusions, real-time implementations for virtual try-on systems, and realistically editing and augmenting real-world footage.

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