Pacific Graphics (2014)
J. Keyser, Y. J. Kim, and P. Wonka (Editors)

Short Papers

Automatic Garment Modeling From Front And Back Images

Lifeng Huang[1] and Chengying Gao[†1]

[1]School of Information and technology, Sun Yet-Sen university, China
[1]School of Software, Sun Yet-Sen university, China

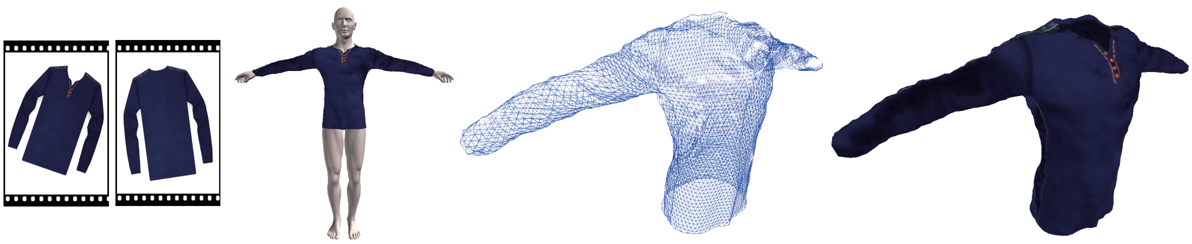

Figure 1: *The 3D garment model built in our approach. From left to right: input garment photos in front view and back view,3D garment draped in male model with standard pose, 3D meshed garment model with geometry details.*

Abstract

We present a system which can automatically generate a realistic garment model from two images of an existing garment. Without the requirement of tailoring expertise and tedious operation, our method takes the front and back images of a real garment as input, and the system will make reasonable geometric modeling as well as physical simulation of the garment. Combining with mannequin's skeleton information, we propose a panel positioning method to place garment panels in appropriate positions. A key feature of our system is to automatically interpret sewn information, which effectively simplifies user interaction. In addition, panel deformation method based on mannequin's pose allows easy data capture. It extends the flexibility and utility of our method. The experiments demonstrate the effectiveness on generating models of various garment styles.

Categories and Subject Descriptors (according to ACM CCS): I.3.5 [Computer Graphics]: Computational Geometry and Object Modeling—I.3.7 [Computer Graphics]: Three-Dimensional Graphics and Realism—

1. Introduction

In recent years, online shopping has become a major way of shopping. However, until now, several famous E-Commerce such as Ebay, Taobao and Vipshop only support basic functions such as viewing apparel items in 2D images. Limited details make it difficult to exhibit the full view of garment. As a result, the product-return rate remains high, and most consumers are unsatisfied with their online shopping experience. Thus, it's significant to develop a 3D garment modeling approach to display the existing real garments.

Most existing garment modeling techniques were proposed for designation rather than exhibition of existing garment. Some sketched-based methods [RMSC11, TCH07] are difficult to reconstruct the real-life garments. Other approaches [BGK*13, FRC06] require multiple 2D patterns, which are hard to attain freely for online vendors. Few works [ZCF*13,ZSZ*12] handle the problem of virtual fitting for existing garments. But they also require significant amount of user interaction, which is tedious and unintuitive, especially for experienceless users.

We aim at a simple and fully-automatic solution to model real garments for novice. Inspired by [ZCF*13], we proposed a garment modeling method based on images. We only require two photos in front and back view of an existing garment as input. Combining with 3D joints of mannequin's skeleton, we estimate basic garment information such as

† Corresponding author: mcsgcy@mail.sysu.edu.cn (Chengying Gao)

DOI: 10.2312/pgs.20141250

size and position dressed on 3D mannequin. By exploiting a seams interpretation approach, the stitching correspondence between edges is obtained automatically. Moreover, we propose a panel-deformation method, which can match garment to mannequin's pose. It is easy to use without tailoring experiences for novices.

Our main contributions are as follows: 1) we propose a simple and automatic garment modeling method from images of the existing garment. To the best of our knowledge, fully automatic 3D garment modeling from images has not been addressed before; 2) we propose a seams interpretation method to set stitching correspondence automatically. Compared with previous approaches, this method does not require significant expertise; 3) we propose a panel warping method which does not require the input garment exactly matching the mannequin pose. Therefore, it allows users to capture garment data easily.

2. Related Work

Most existing approaches used for virtual garment modeling are proposed for garment design rather than exhibition of those ready-to-wear garments. Some garment modeling approaches [UKIG11, FRC06] can generate sophisticated and compelling models, while they require tailoring expertise to set stitching correspondence between 2D patterns. Moreover, [BSBC12] is effective to save time to avoid redesign 2D patterns. However, identifying the sewing corresponding relationship among numerous patterns is still a huge challenge to novice without domain expertise.

Sketch-based methods [WWY03, TCH07] allow users directly sketch on top of a mannequin to model 3D garments. A context-aware sketch modeling method [RMSC11] provides more realistic-looking models with loose region and complex details. However, the trivial details such as wrinkles and hemlines are too complicated to sketch out in reality. In addition, camera-based approaches [BPS*08, HSR11a, WCF07] usually bring clothes animation with remeshing, high quality rendering and deformation techniques. The methods [SGDA*10, VPB*09] used in motion capture can build rough garment model wearing in the actor. In short, expensive instruments and complicated computation bring some difficulties to the users. Different from former methods, our system does not require cumbersome setting and complicated operations.

Some image-based methods [HSR11b, ZSZ*12] have to set cameras to capture input images. [ZCF*13] proposed an effective method to create 3D garment model from a single image. Nevertheless, it can hardly generate realistic model because it assumed that the garment is symmetric in front and back. It also needs more time to create mannequins with different poses for each garment image. The requirement of complicated human-computer interaction makes it difficult for online retailers to use. Thus, we seek to use only two images of a garment to generate its garment models automatically.

3. Our Method

Our system converts the images of existing garment into 3D model automatically (Figure 3). It involves three steps: Alignment and Contour Segmentation (section 3.2), Seams Interpretation (section 3.3), Deformation and Simulation (section 3.4).

3.1. Data Preparation

For each garment we provide its category(see Table 1) and two photos, one in front view and other in back view. Both images are captured in a rough "front-parallel" view to minimize distortion. But we do not have any strict requirement on the view angle and focal length. We require the background color in the photo to be pure (i.e. monochromatic) and differ from the main color of the garment to be captured. Moreover, it is better to flat garments to restore the accurate outlines. At last, the inner side of the garment is often visible at collar and sleeves. As the example shown in Figure 2, the yellow inner side of collar from the back panel is visible. Thus, we use a white paperboard to cover these redundant parts to facilitate contour detection in the next step.

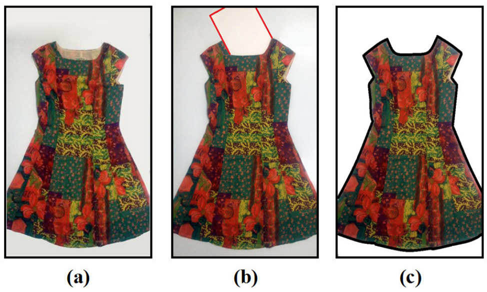

Figure 2: *The data preparation of garments. We use the white paperboard (colored in red) to cover the back collar. It is facilitate to obtain more accurate outlines.*

3.2. Alignment and Contour Segmentation

In the first step, we convert garment images into 2D panels. Then we calculate the size of garment and set its sewing position dressed on 3D mannequin.

We utilize the method [PP11] to extract the garment outlines which are seen as 2D panels from photos. Because it is difficult to keep the same angle and focal length in two photos, we need to align the panels between two images. The angle makes them hard to align during simulation. And different focal length causes the different size of two panels. Thus, we utilize 2D oriented bounding box (2D-OBB) to figure out the rotation angle to make outline upright. Moreover,

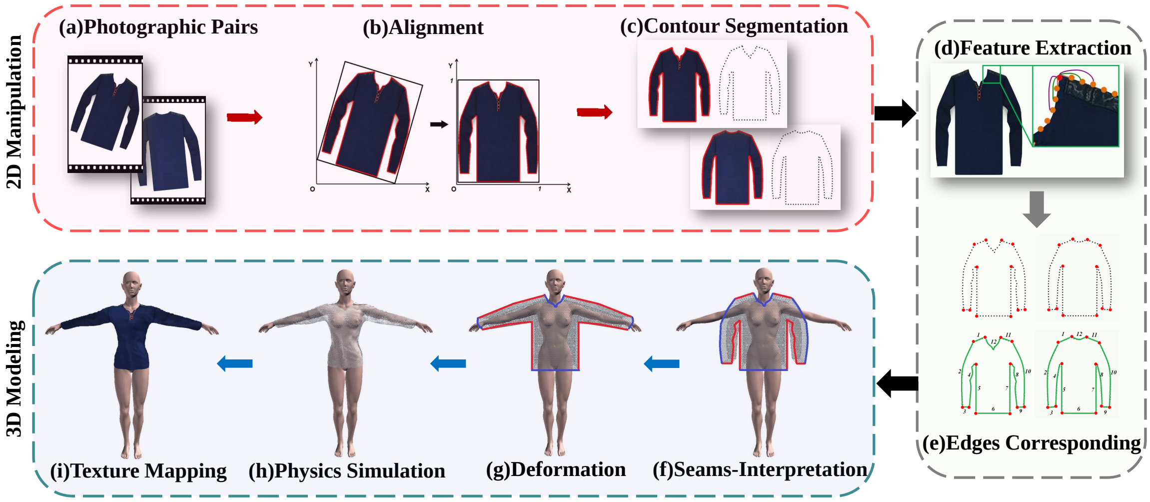

Figure 3: *Pipeline of our method. Firstly we input two garment images, one is front view and other is back view, and then the garment outlines are aligned while they are not upright. We also obtain size and sewing position based on its corresponding joints. After that we figure out the key vertices among a series of boundary points by features detection, and then establish the corresponding relationship between the stitching edges. Combining with pose vector, we deform the panels and then classify the silhouettes and borders. At last, triangulation, simulation and texture mapping are essential to generate 3D garment model.*

we will normalize the outlines to avoid the problem caused by different focal length.

Then we focus on alignment between panels and mannequin, which need to obtain garment size and set its sewing position. We classify common garments into several categories(Table 1). For each kind of garment, we collect more than 20 Middle size (Asian yards) women's wears, and then record the ratio between the shoulder-width(waist-width) and length in Table 1.For each category, we also record its corresponding 3D joint position of mannequin's body. Based on the garment's category, the system estimates the size of garment and places the panels around corresponding 3D joint positions. We utilize both average value of real garments(Table 1) and skeleton length to calculate the size of garment. And its size will be adjusted if the ratio data is out of range.

Table 1: The size of key parts in women's wears.

Category	Shoulder	Waist	Length	Ratio
Upper Cloth(no sleeve,NS)	31-36	-	55-61	1.65-1.72
Upper Cloth(short sleeve, SS)	33-37	-	54-62	1.62-1.74
Upper Cloth(long sleeve, LS)	32-37	-	54-63	1.61-1.80
Under Cloth(middle-pants, MP)	-	32-37	60-73	1.84-2.16
Under Cloth(long-pants, LP)	-	33-39	81-96	2.31-2.66
Dress (middle-dress, MD)	33-39	-	79-92	2.35-2.62
Dress (long-dress, LD)	35-39	-	98-112	2.81-3.02

For finding intersection points between edges in section 3.3, we segment the outlines into a series of evenly spaced boundary points with a tiny interval (Figure 3(c)). The pixel interval of each two adjacent boundary points contribute to obtain the curvature changes, and to distinguish their relative position.

3.3. Seams Interpretation

Before identifying the stitching correspondence between the sewing edges in two panels, we have to segment the integrated outline into separated edges, which are distinguished by intersection points. Thus, we focus on seeking theses intersection points by multi-feature detection in first place. These points are regarded as key points in panels.

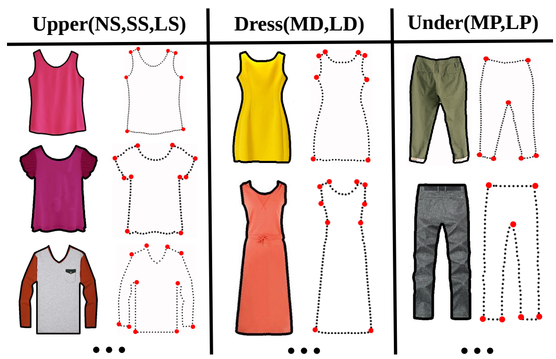

Figure 4: *Examples of manually annotation for each type garment. The annotation data is treated as training set.*

We first manually mark key points to form a training data set for automatic key point detection. Figure 4 provides some examples of our manually marked key points. For each category of garment, we manually annotate all key points for more than 20 clothes to build training data. And we extract the feature vector at each point to build a classifier. We define feature vector of point p_i as F_{p_i}:

$$G(F_{p_i}) = G(\{S, tP_i, (1-t)C_i\}) = \{0,1\} \quad (1)$$

where $S = \{NS, SS, LS, MD, LD...\}$ is regarded as the shape composed of discrete points-sets; C_i represent the trend of curvature changes in p_i, which is calculated based on a series of its adjacent points; P_i describes relative position of p_i. G is the result of classifier to judge whether p_i is key point. We set default weight $t = 0.3$.

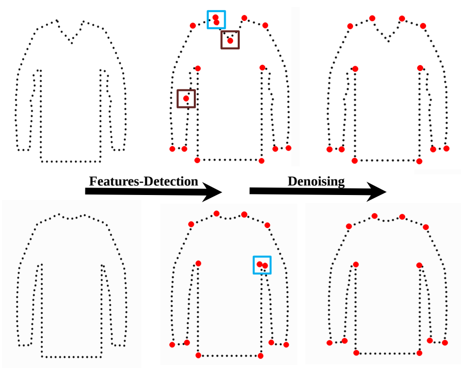

Figure 5: *Few errors contained in the classifier result: duplicated detection(bounded in blue) and false detection(bounded in brown). The system utilizes relative position and symmetric constraint to remove the errors.*

According to the former definition, each edge is consisted of two intersection points, and the edges are one-to-one corresponded in two panels. Thus, we assumed that the key points are almost symmetric located in front and back panels. Thus, we remove both asymmetric and repeated key points until two panels own the same number of key points (Figure 5). Then we figure out the correspondence between key points in front and back panel. By considering the similarity between key points, we calculate the minimized difference:

$$min \sum_{i=1,j=1}^{N_{kp}} (1-\lambda_2)[(1-\lambda_1)\frac{C_{p_i}-C_{p_j'}}{C_{p_i}+C_{p_j'}} + \lambda_1 \frac{l_{p_i}-l_{p_j'}}{l_{p_i}+l_{p_j'}}] \quad (2)$$
$$+\lambda_2 D(p_i, p_j') \qquad (p_i \in F, p_j' \in B)$$

where the F is the set of key points in front panel, B is the set of key points in back panel, N_{kp} is the number of key points. C_{p_i} and $C_{p_j'}$ refers to the curvature changes in $Eq(1)$. l_{p_i} and $l_{p_j'}$ are the length between one key point and both its former and next key point. $D(p_i, p_j')$ is the Euclidean distance between these two points. We set weight variables $\lambda_1 = 0.5, \lambda_2 = 0.5$.

Since we obtain the correspondence between key points in front and back panel, the edges composed of two adjacent key points are one-to-one corresponded (Figure 3(e)). The edges are classified as boarders if they cross the mannequin (colored in blue). Otherwise the edges are considered as silhouettes which need to sew together (colored in red). The result is shown in Figure 3(f),

3.4. Deformation and Simulation

Generally, it is difficult to match the sleeve garment (or pants) to the pose of mannequin (Note that some garments without sleeves or trouser legs do not have this problem). Such as (Figure 3(f)), the sleeve part does not exactly match the arm position. Thus, we warp these part(sleeve and trouser leg) based on pose vector, a representation of skeleton information by the corresponding concatenation of joint positions.We consider that sleeve part is loose state at first, and then it becomes tensile state after warping. Thus, We triangulate the sleeve region at first, and warp it at next step. It can avoid over-distorted of each triangulation mesh and keep the invariance property of the garment structure. Considering the garment is made of various elastic material, we will contract or stretch the sleeve within a certain extent (Figure 6). The boundary vertices of sleeve part are rotated based on arm vector. To each inner vertices of sleeve, rotation angle and the stretching length is calculated by interpolation, and the changed space between each two vertices is limited in a certain ratio: $(1+r)^{-1} \leq l_i/l_i' \leq (1+r)$. We set default ratio $r = 0.4$. Moreover, the trouser legs can be deformed to match mannequin's shin bones by similar method.

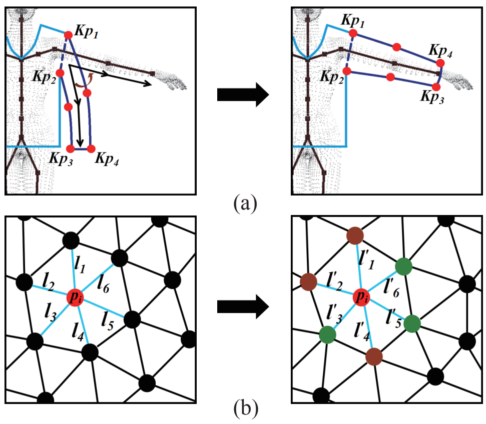

Figure 6: *The deformation of sleeve part. (a) The deformation based on pose vector; (b) The change of space between vertices. To avoid over-distorted, the changed space between each two vertices is limited in a default ratio. Some vertices are contract to become closer(colored in green), and some are stretched to be farther(colored in brown).*

Once we have pose-matched panels, we use a garment simulator in [VMT05] to generate the 3D garment dressing

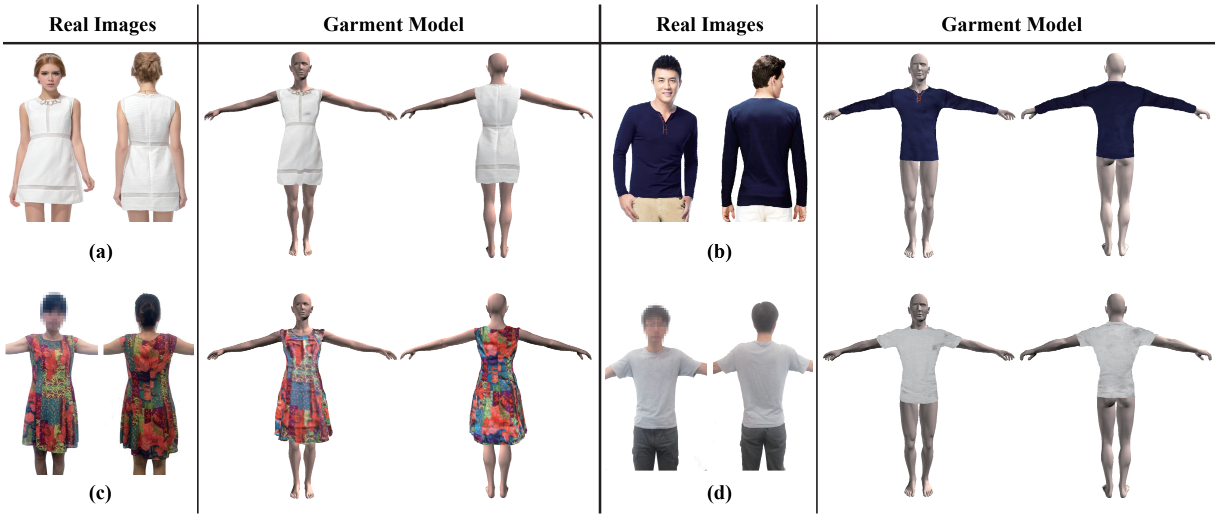

Figure 7: *The comparison between realistic images and our garment model. a) one-piece dress with necklace; b) T-shirt with long sleeves; c) long dress with complicated patterns; d) T-shirt with short sleeves. The 3D garment models generated in our system are similar to the contrasted photos.*

on mannequin automatically. Only two panels are stitched together in our system. Less patterns improve the convergence speeds and enhance simulation speed. After 3D garment model has been built, the images are used in texture mapping, which provides more realistic-looking model. We do not utilize Shape-from-Shading(SfS) algorithm [sTS] to recover details because those shades are generated in flatten garment, not the real geometric features in a dressed garment.

4. Experiments and Discussion

We select 50 garments from internet randomly, and then test them in our system. More than 80% (42/50) clothes are handled properly in our system. These garments include different types such as dress, underwear and long pants for male or female. Moreover, garments with complicated patterns and tiny accessories(buttons, necklace, zipper and so on) have been simulated in our test (Figure 7, Figure 8).

We also provide real images of the garment wearing on a person for the reference (Figure 7). Garment models draped in mannequin and realistic images are put side by side to make comparison. The 3D garment model is generated from physical simulation, and then it is mapped from real images. We also consider distinguishing the loose state and tensile state of deformed parts. It will generate analogous wrinkles when garment dressed on mannequin with lifted arm (Figure 1,Figure 7(d) and Figure 8(b)). In addition, the meshed model shows its reasonable geometry details in Figure 1. Thus, the modeling approach in our system is believable and available.

The texture mapping from images is useful to represent garment in visual sense. Instead of spending much time to modeling for complicated decorative accessories, we directly mapping them on garment models, which makes it more realistic (Figure 1,Figure 7). However, the folded garments with shadows in image are mapped on garment model as well. It obscures the geometry (e.g. Figure 8(d))so that we spread clothes to remove unwanted wrinkles with less shade.

Limitation Though most casual garments (T-shirt, underwear, pants and dress) can be modeled well in our system, it is difficult to restore the precise outline of garments with excessive wrinkles, such as pleated skirt. The wrinkles generated during simulation and others mapped from texture are mixed together, which obscures the geometry (Figure 8(d)). Moreover, because of the limited number of garments we have collected, the size data recorded in Table 1 is not generally enough. Finally, the sophisticated accessories such as shirt collar are difficult to reconstruct from images.

5. Conclusion

We presented an automatic method for garment modeling based on garment's images. It can assist online retailers to obtain garment models conveniently. The approach, which consist of seams-interpretation and panel-warping method, extracts the garment outlines, positioning panels and sets sewing information automatically. The garment picture in front and back views can simply display its special features such as material and own ornaments. Thus, the texture mapping makes 3D model more intuitive.

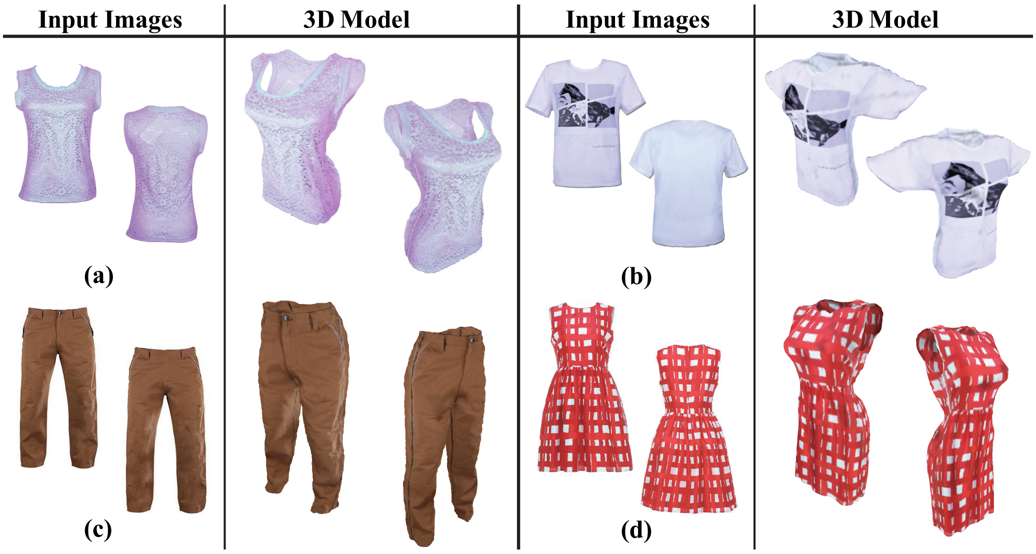

Figure 8: *More result of our method. (a)Underwear with complicated patterns; (b)T-shirt with picture of horse. The sleeve parts is deformed to match mannequin's arm; (c)The long pants. The system warps the trouser leg to match mannequin's leg; (d)Middle dress with wrinkles, which obscure the geometry.*

Acknowledgement

The authors would like to thank Guiqing Li and Ping Tan for their valuable suggestions. This work is supported by the National Science Foundation of China Grant No.61100080.

References

[BGK*13] Berthouzoz F., Garg A., Kaufman D. M., Grinspun E., Agrawala M.: Parsing sewing patterns into 3d garments. *ACM Transactions on Graphics (TOG) 32*, 4 (2013), 85. 1

[BPS*08] Bradley D., Popa T., Sheffer A., Heidrich W., Boubekeur T.: Markerless garment capture. In *ACM Transactions on Graphics (TOG)* (2008), vol. 27, ACM, p. 99. 2

[BSBC12] Brouet R., Sheffer A., Boissieux L., Cani M.-P.: Design preserving garment transfer. *ACM Transactions on Graphics (TOG) 31*, 4 (2012), 36. 2

[FRC06] Fontana M., Rizzi C., Cugini U.: A cad-oriented cloth simulation system with stable and efficient ode solution. *Computers & Graphics 30*, 3 (2006), 391–406. 1, 2

[HSR11a] Hauswiesner S., Straka M., Reitmayr G.: Free viewpoint virtual try-on with commodity depth cameras. In *Proceedings of the 10th International Conference on Virtual Reality Continuum and Its Applications in Industry* (2011), ACM, pp. 23–30. 2

[HSR11b] Hauswiesner S., Straka M., Reitmayr G.: Image-based clothes transfer. In *Mixed and Augmented Reality (ISMAR), 2011 10th IEEE International Symposium on* (2011), IEEE, pp. 169–172. 2

[PP11] Papari G., Petkov N.: Edge and line oriented contour detection: State of the art. *Image and Vision Computing 29*, 2 (2011), 79–103. 2

[RMSC11] Robson C., Maharik R., Sheffer A., Carr N.: Context-aware garment modeling from sketches. *Computers & Graphics 35*, 3 (2011), 604–613. 1, 2

[SGDA*10] Stoll C., Gall J., De Aguiar E., Thrun S., Theobalt C.: Video-based reconstruction of animatable human characters. In *ACM Transactions on Graphics (TOG)* (2010), vol. 29, ACM, p. 139. 2

[sTS] sing Tsai P., Shah M.: Shape from shading using linear approximation. *Image and Vision Computing 12*, 487–498. 5

[TCH07] Turquin E., Cani M.-P., Hughes J. F.: Sketching garments for virtual characters. In *ACM SIGGRAPH 2007 courses* (2007), ACM, p. 28. 1, 2

[UKIG11] Umetani N., Kaufman D. M., Igarashi T., Grinspun E.: Sensitive couture for interactive garment modeling and editing. *ACM Trans. Graph. 30*, 4 (2011), 90. 2

[VMT05] Volino P., Magnenat-Thalmann N.: Accurate garment prototyping and simulation. *Computer-Aided Design and Applications 2*, 5 (2005), 645–654. 4

[VPB*09] Vlasic D., Peers P., Baran I., Debevec P., Popović J., Rusinkiewicz S., Matusik W.: Dynamic shape capture using multi-view photometric stereo. *ACM Transactions on Graphics (TOG) 28*, 5 (2009), 174. 2

[WCF07] White R., Crane K., Forsyth D. A.: Capturing and animating occluded cloth. In *ACM Transactions on Graphics (TOG)* (2007), vol. 26, ACM, p. 34. 2

[WWY03] Wang C. C., Wang Y., Yuen M. M.: Feature based 3d garment design through 2d sketches. *Computer-Aided Design 35*, 7 (2003), 659–672. 2

[ZCF*13] Zhou B., Chen X., Fu Q., Guo K., Tan P.: Garment modeling from a single image. In *Computer Graphics Forum* (2013), vol. 32, Wiley Online Library, pp. 85–91. 1, 2

[ZSZ*12] Zhou Z., Shu B., Zhuo S., Deng X., Tan P., Lin S.: Image-based clothes animation for virtual fitting. In *SIGGRAPH Asia 2012 Technical Briefs* (2012), ACM, p. 33. 1, 2