Received: 18 March 2018 | Accepted: 21 March 2018
DOI: 10.1002/cav.1811

SPECIAL ISSUE PAPER

WILEY

A fast garment fitting algorithm using skeleton-based error metric

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Funding information
National Natural Science Foundation of China, Grant/Award Number: 61732015; National Key R&D Program of China, Grant/Award Number: 2017YFB1002600; Key Research and Development Program of Zhejiang Province, Grant/Award Number: 2018C01090; National Natural Science Foundation of China, Grant/Award Number: 61472355

Abstract

We present a fast and automatic method to fit a given 3D garment onto a human model with various shapes and poses, without using a reference human model. Our approach uses a novel skeleton-based error metric to find the pose that best fits the input garment. Specifically, we first generate the skeleton of the given human model and its corresponding skinning weights. Then, we iteratively rotate each bone to find its best position to fit the garment. After that, we rig the surface of the human model according to the transformations of the skeleton. Potential penetrations are resolved using collision handling and physically based simulation. Finally, we restore the human model back to the original pose in order to obtain the desired fitting result. Our experiment results show that besides its efficiency and automation, our method is about two orders of magnitudes faster than existing approaches, and it can handle various garments, including jacket, trousers, skirt, a suit of clothing, and even multilayered clothing.

KEYWORDS

cloth simulation, garment fitting, pose recovery, skeleton-based error metric

1 | INTRODUCTION

Dressing a given clothing onto a human model of arbitrary poses and shapes is essential in many applications, including online shopping, entertainments, and virtual fitting room.[1] A typical 2D-to-3D scheme consists of 3D patterns positioning, sewing, and draping,[2,3] which is time consuming and labor intensive. Most existing 3D garment fitting methods[4–9] have focused on finding the correspondences between an initial reference human model and a targeted human model. However, they are not suitable when the reference human model is missing. To address this issue, Li et al.[10] removed the need of the reference human model, but their method needs to generate a garment skeleton manually. Later, Huang et al.[11]

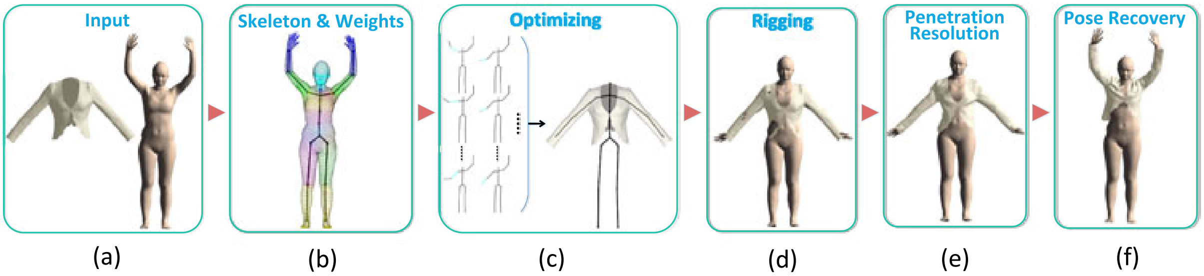


FIGURE 1 Overview of our garment fitting pipeline

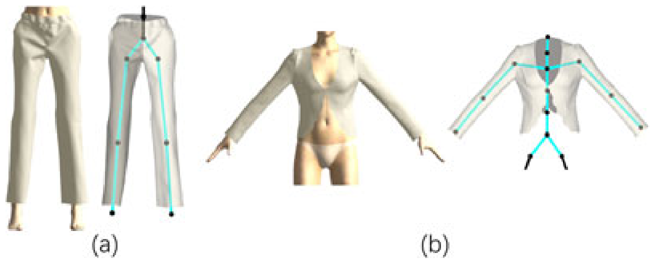


FIGURE 2 The cyan bones are taken into account in the subsequent fitting process, and these bones lie approximately at the center of the corresponding garment parts

further proposed an automatic method to align 3D garment with a human model without the use of the reference human model. Unfortunately, they can only process zygomorphic short-sleeved shirt and trousers. Recently, Tisserand et al.[12] proposed an error metric to take into account both positions and normals for garment fitting. In their method, to calculate the error metric, it needs to iterate every point on the garment and on the human model. As a result, the complexity of its error metric is $O(n_H \cdot n_G)$, where n_H and n_G denote the number of the vertices of the human model and that of the clothing, respectively.

Inspired by the work of Tisserand et al.,[12] we propose a novel, fully automatic algorithm for fitting any given clothing, including multilayered clothing and a suit of clothing, onto a 3D human model of arbitrary poses and shapes without using a reference human model. Specifically, given a 3D clothing and a 3D human model with an arbitrary pose, we first generate the skeleton of the human model and its corresponding skinning weights.[13] Then, we iteratively rotate each joint of the skeleton, as well as translate globally, to find the optimal position and pose that fits the garment best. After that, we rig the surface of the mannequin using dual quaternion linear blend skinning and use physically based simulation (PBS) and common collision handling algorithms[14] to resolve potential interpenetrations between the human model and the garment. Finally, we recover the pose of the mannequin gradually using spherical linear interpolation during PBS. Figure 1 illustrates the pipeline of our approach.

Our method is based on the key observation that, in real life when the clothing is worn on a human body, the bones of the human body lie approximately at the center of the corresponding clothing parts, for example, forearms lie approximately at the center of sleeves, and legs lie approximately at the center of the trousers. As shown in Figure 2, it is reasonable to assume that the mannequin will fit in the garment if and only if the skeleton is in the appropriate position and pose. As a result, determining the position and pose of the skeleton is the key to solve the target garment fitting problem.

Compared with the work of Tisserand et al.,[12] our error metric uses the skeleton of the human model; therefore, to calculate the error, we iterate several sampling points on the skeleton and every point on the garment. As a result, the complexity of our method is $O(n_G)$. Moreover, the method of Tisserand et al.[12] needs to rig the surface mesh of the human model at every iteration, whereas our method only needs to do this once for an application. Altogether, our method is about two orders of magnitudes faster than that of Tisserand et al.[12] according to our experiments.

2 | RELATED WORK

In typical virtual try-on systems (e.g., Clo3D), the dressing process is 2D pattern based that can be divided into three steps: 3D patterns positioning, sewing, and draping.[2,3] The three steps can be described briefly as follows: (a) **Positioning**: 3D patterns are placed manually around the corresponding body parts and are rolled along the corresponding bones if necessary. This step is typically done in a manual or semiautomatic way. (b) **Sewing**: Corresponding 3D patterns are sewn together by either the sewing forces or the sewing springs with zero rest lengths. (c) **Draping**: Physics-based simulation is usually used to simulate the realistic behavior of clothing. After the above three steps, a 3D clothing can be dressed onto a specific human body. However, redressing a 3D clothing onto a different human body of an arbitrary shape and pose using 2D pattern-based methods is time consuming and labor intensive with nontrivial manual intervention. Therefore, in the recent years, researchers started to focus on directly manipulating 3D garment models to fit to a target 3D human body.

Existing 3D garment fitting methods can be roughly classified into two categories based on whether it uses a reference human model.

With a reference human model. Zhong[5] proposed a method based on pose duplication, where the skeletons of the reference human model and the target human model are extracted according to anthropometric features, and then, the pose difference is compensated by an affine transformation. Li et al.[6,9,10] developed a series of works to delicately customize 3D garments for a target human model, including tetrahedralizing and deforming input garments to match the skeleton with the target human model[10] and generating curve nets for the reference human model and the input garment for the correspondence establishment.[9]

Different from the above works, Lee et al.[8] proposed an automatic garment fitting method by dividing the reference human model into five parts and assigning the vertices of the input garment mesh to one of these parts based on spatial relationships between the two models. This method can obtain realistic fitting results of the input garment on the target mannequin without resizing the input garment. However, it cannot handle long and wide skirts, as well as garments that are not held by the torso. It is noteworthy that while the above methods[6,8–10] deform the input garment to fit the target human model, our method, along with many other methods,[5,11,12] deforms the target human model to fit the garment.

Recently, Guan et al.[7] proposed a data-driven method to fit a given garment to a target human model of arbitrary shapes and poses. In this method, given a garment, they first generated a series of simulation results on human models of various shapes and poses. Then, a DRAPE model for this garment was trained from these results. While it can dress human models of various shapes and poses at run time, its offline computing part is very time consuming.

Without a reference human model. Relatively few research works have been done in this direction. Li et al.[15] used curvature and torsion to match feature points on the clothing with the human body, and thereby, the transformation matrix for the clothing can be computed. However, this method cannot handle human models of various poses. Actually, the pose of the input human model is required to strictly match that of the source human model originally wearing the garment. Huang et al.[11] proposed an automatic method to align 3D garment with a human model through feature points calculation and postural alteration, based on the assumption that the garment is zygomorphic and confined to short-sleeved shirt and trousers. This assumption limits its use in many practical applications. Recently, Tisserand et al.[12] reported an automatic method to position garments on a human model based on joint rotations. It adaptively searches for the possible poses of the target human model to find the optimal pose that minimizes the defined surface metric, which takes into account both coordinates and normals of vertices on the garment mesh and the human model mesh.

Our method is inspired by the work of Tisserand et al.,[12] but we design a different and much more effective error metric based on the skeleton of the target human model. Note that the complexity of computing the surface metric in the work of Tisserand et al.[12] is dependent on both the number of the vertices of the garment mesh and that of the human model. By contrast, the computational complexity of our error metric is independent of the number of the vertices of the target human model. As a result, our method is much more efficient than the work of Tisserand et al.[12]

3 | OUR ALGORITHM

In this section, we first introduce the skeleton structure of the human model we use and then define our novel error metric. Finally, we introduce how to optimize the resulting error metric to obtain the optimal skeleton position and pose for garment fitting.

3.1 | Human structure and skinning

We use the acclaimed skeleton file from the Carnegie Mellon University Motion Capture Database (mocap.cs.cmu.edu) as the starting point of the human structure. We remove the bones of hands, feet, and head, and use the remaining 17 bones and the corresponding 16 joints (Figure 3). The reason for the removal of these bones is that they are not covered by any clothing in real life and thus irrelevant to our fitting algorithm.

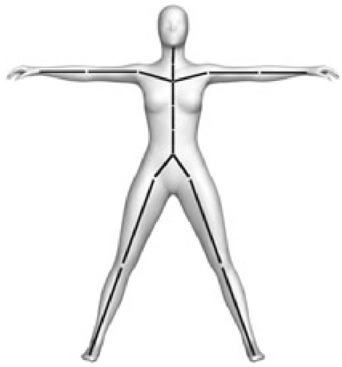


FIGURE 3 The used skeleton structure with 17 bones and 16 joints

Given the above skeleton structure, we use the work of Baran et al.[13] to compute the embedded skeleton of the given human model and the corresponding skinning weights. The surface of the human model is rigged by dual quaternion blend skinning.[16] Then, we define an error metric that needs to be used in our approach.

3.2 | Error metric

Our error metric is based on the observation that, in real life, when a garment is worn on a person, the skeleton of the person lies approximately, if not exactly, at the center of the corresponding part of the garment. See Figure 2 for examples.

To obtain this optimal position of the skeleton of the human model, we first define an error metric and then optimize it by deforming the skeleton. Our error metric is based on the observation that the minimum distance from a point on the skeleton to the surface of the garment will be maximized when the skeleton lies at the center of the garment.

Error metric for a bone. For each bone, we generate a few sampling points evenly distributed on the bone. Empirically, we use five sampling points for each bone. The error metric for the bone is the sum of the error metrics of the sampling points. We denote the error metric for a sampling point p as $\delta(p)$; then, the error metric for a bone B_i is defined as follows:

$$E_{B_i} = \sum_{p \in S} \delta(p), \tag{1}$$

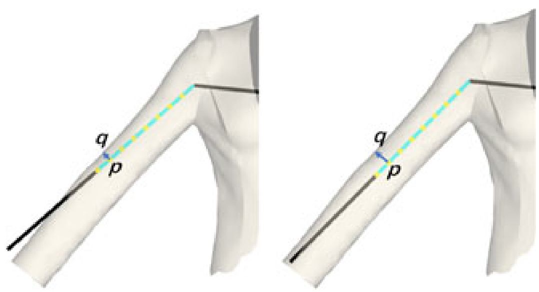
where S is the sampling point set on the bone B_i.

For each sampling point p on the bone, the error metric $\delta(p)$ can be defined as the minimum distance between p and the vertices on the garment, as follows:

$$\delta(p) = \min_{q \in M_g} ||p - q||, \tag{2}$$

where M_g denotes the garment mesh, and q is a vertex on M_g.

Ideally, $\delta(p)$ needs to be as large as possible, which means that the bone lies at the center of the surface of the garment. This further means that the surface of human body lies at the center of the surface of the garment, as shown in Figure 4. However, this is true only if the bone is inside the garment. When the bone is outside the garment, the error metric defined in Equation (2) will lose its effectiveness. As shown in Figure 5, a larger value of E_{B_i} indicates a worse fitting result.



(a) (b)

FIGURE 4 As the error metric defined by Equation (2) becomes larger, the position of the cyan bone becomes more reasonable. (a) Smaller error metric of cyan bone, and (b) larger error metric of cyan bone

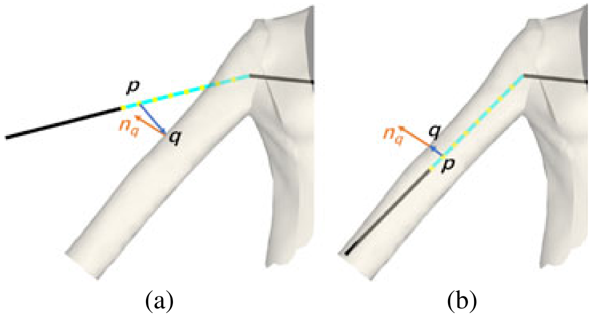


FIGURE 5 Illustration of the improved error metric for a point on the bone

The above problem can be solved by taking into account the normals of the vertices of the garment mesh. Suppose that p is a sampling point on the bone, and q is the closest (by Euclidean distance) vertex on the garment mesh to p. Assume that $\vec{pq}$ is the vector from p to q, and $\vec{n_q}$ is the normalized normal of vertex q. As shown in Figure 5, if the dot product of $\vec{pq}$ and $\vec{n_q}$ is positive, then p will lie inside the garment mesh; otherwise, p will be outside of the garment mesh.

Ideally, we hope to have a large value of E when the garment is worn on the human body, and thus, a small value of E is expected when the bone is outside of the garment. To this end, we penalize the outside case with a negative scaling factor. The final version of our error metric for one sampling point is defined as follows:

$$\delta(p) = \begin{cases} \min_{q \in M_g} ||p - q||, & \vec{pq} \cdot \vec{n_q} > 0 \\ s \cdot \min_{q \in M_g} ||p - q||, & \vec{pq} \cdot \vec{n_q} < 0 \end{cases}, \tag{3}$$

where s is the penalizing factor. In our experiments, it is empirically set to -100.

Complexity analysis. To compute the error metric for one sampling point p, we have to iterate every vertex on the garment mesh to find the closest vertex to p as defined in Equation (3). Thus, the computational complexity for one sampling point is $O(n_G)$, where n_G is the number of the vertices of the garment mesh. Therefore, the complexity of our error metric is $O(k \cdot n_G)$, where k is the number of sampling points, which is constant for a specific case. By contrast, Tisserand et al. employed the positions and normals of vertices.[12] The total error metric in their method is the sum of error metrics of all the vertices on the garment mesh. To compute the error metric for one vertex q on the garment mesh, it has to iterate every vertex on the human mesh to find the nearest neighbor of q. Thus, its computational complexity is $O(n_H \cdot n_G)$, where n_H is the number of the vertices of the human model. In this sense, our algorithm is much more efficient than that of Tisserand et al.[12]

3.3 | Joints selection

According to the type of the input garment, the bones used in the algorithm could be different. The typical rule is that only those bones that will be covered by the garment should be taken into account. For example, the bones used for long-sleeved T-shirts consist of lower back, upper back, thorax, left/right clavicle, left/right humerus, and left/right radius, and the bones used for trousers consist of left/right femur and left/right tibia. As shown in Figure 2, the cyan bones are covered by the garment and thus should be taken into account in the garment fitting process. Similar to the work of Tisserand et al.,[12] our method also requires garment type as an input, and then, the bones that should be taken into account can be determined accordingly.

In this paper, we denote the set of the bones taken into account in a specific scenario as B, and then, the total error E for B is the sum of the error metrics of all the bones in B. Our goal is to find the optimal pose of the skeleton that maximizes E, as follows:

$$E = \sum_{B_i \in B} E_{B_i}. \tag{4}$$

3.4 | Optimization

As mentioned above, the used skeleton consists of 17 bones and 16 joints (Figure 3). Each joint has one to three degrees of freedom (DOFs). For example, the knee joint only has one DOF, whereas the hip joint has three DOFs. In addition, there are three DOFs for the global translation, and three DOFs for the global rotation. As a result, there are 43 DOFs in total, which means that the solution space of our problem is R^{43}, and every point in R^{43} is a pose of the skeleton. The main idea

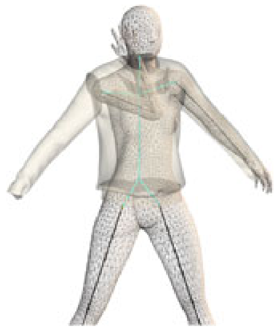


FIGURE 6 An example result without constraints on the rotations of bone

of our optimization step is to exhaustively search for every possible pose of the skeleton and find the one that maximizes the error metric defined in Equation (4).

However, due to the curse of dimensionality, conducting exhaustive search in the original solution space is too time consuming and infeasible. Therefore, we decide to use a relaxation method similar to the work of Tisserand et al.,[12] that is, dividing the whole optimization problem into several subproblems that can be solved sequentially. These subproblems can be solved iteratively to obtain an approximately optimal solution. Specifically, the subproblems in this case have three types: global translation, global rotation, and rotation for each joint. Moreover, we should solve the global translation first, then the global rotation, and finally the rotation for each joint. For each subproblem, we use a grid search method to find the optimal pose of skeleton. The grids to be searched are sorted according to the distance from that grid to the anchor grid that represents the initial pose, that is, the closer the pose is to the initial pose, the earlier it will be searched. The grid size is chosen based on the precision we want to get. In practice, we initialize the grid size with a large value and decrease it at the next iteration. We apply a similar strategy to the size of the search space. With this strategy, we are able to obtain more accurate results than the case of using a fixed grid size all the time.

Global translation. We initialize the position of the root joint as the barycenter of the garment. The search space is roughly limited to the axis-aligned bounding box of the garment. This is reasonable for garments such as trousers and skirts in which the root joint is supposed to be covered. However, for short, upper, and outer garments such as T-shirts, the root joint is supposed to lie outside the garment. For such a case, we will move down the axis-aligned bounding box slightly. We initialize the grid size as the average length of the edges on the garment. The objective function for this step is the total error metric in Equation (4).

Global rotation. In most cases, global rotation may not be needed, because both the clothing and the human model usually have vertical poses. When this is not the case, a small search space and a small grid size are required for the consideration of accuracy. In our experiments, we use 0.2 radian for each DOF and set the initial grid size to 0.02 radian. The objective function for this step is also the total error metric E defined in Equation (4).

Bone rotation. To find the best position of a bone, we exhaustively search for every possible pose of that bone and find the joint position that optimizes the error metric of that bone, that is, E_{B_i} defined in Equation (1). Note that if we rotate it, one of its two joints is fixed, which means that the trajectory of the other joint is a spherical surface. Therefore, instead of searching the possible poses of the bone and then calculating the joint position, we directly search for possible joint positions. This is advantageous because the DOF is decreased by one. As aforementioned, subproblems can be solved sequentially. With the hierarchical structure of the skeleton, the rotation of a parent joint can affect the positions of all the child joint(s). Hence, the parent joint need to be rotated/solved first followed by the child joint(s). Fortunately, the bones from different body parts can be rotated independently. For instance, the rotation of the left humerus is independent of that of the right humerus and thus can be solved in parallel. Our skeleton-based error metric cannot decide which body part should wear in which clothing part itself. As a result, occasionally some weird poses may have better metric values. As shown in Figure 6, the right arm is folded into the chest, and the pose is invalid in real world. To solve this problem, we define constraints for the rotations of bones to prevent such poses. For the case in Figure 6, the angle between the left forearm and the left clavicle needs to be smaller than $\frac{\pi}{2}$, and the same for the right side. Figure 7 illustrates the solving of each subproblem.

4 | PENETRATION AND POSE RECOVERY

Penetration handling. After the above optimization step, the skeleton will lie in a reasonable position inside the garment, as shown in Figure 8c. We then rig the surface mesh of the human body using dual quaternion blend skinning[16]

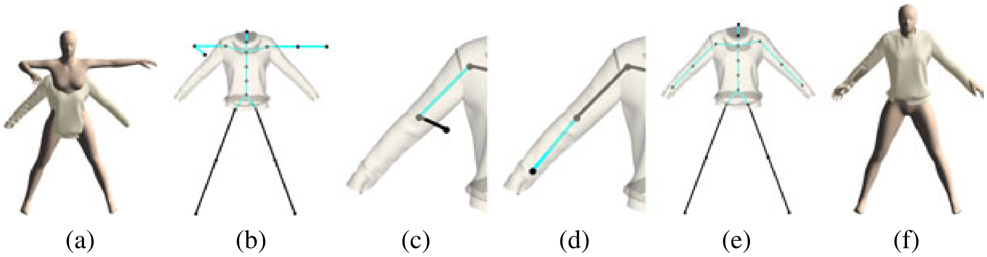


FIGURE 7 Illustration of solving each subproblem (at the first iteration). (a) Input with centroid alignment, (b) global translation, (c) rotation of the right humerus, (d) rotation of the right radius, (e) result of one iteration of our algorithm, and (f) the rigging result of the mannequin surface

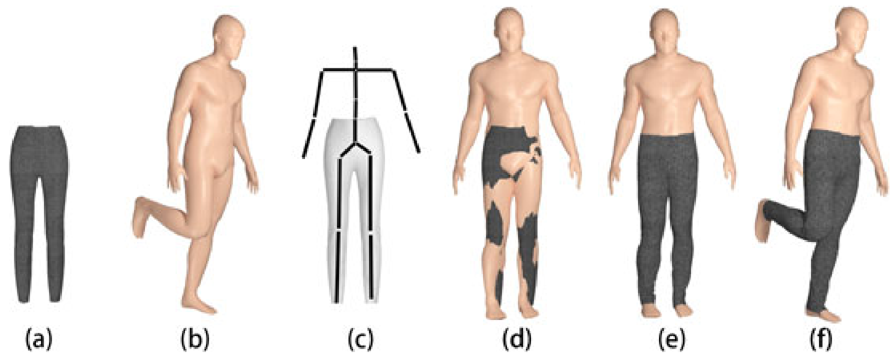


FIGURE 8 Penetration handling and pose recovery. (a) Input trousers, (b) input mannequin with the right leg lift, (c) the coarse result after skeleton fitting and surface mesh rigging, (d) penetration result, (e) penetrations solved using common collision handling algorithms without any manual intervention, and (f) pose recovery result

accordingly (Figure 8d). Note that while our method rigs the surface mesh only once for one application, the method of Tisserand et al.[12] does it once for each optimization step, which is computationally inefficient. In an ideal case, the rigged surface mesh of the mannequin is supposed to be completely inside the garment without any interpenetration. Unfortunately, this is not always true for most cases, because penetrations could happen frequently, as shown in Figure 8d. Fortunately, penetrations can be straightforwardly solved by collision handling algorithms (e.g., the work of Zhang et al.[14]) while performing PBS (in our approach, we employ a position-based dynamic approach[17]), as shown in Figure 8e.

Human body pose recovery. Note that after the above optimization step, we change the original pose of the input human body to fit the input garment. As a result, the final fitting result we obtain is that for the modified pose. It is trivial to obtain the fitting result in the original pose using any PBS and rigging. Basically, at every time step, we rig the surface of the human body gradually toward the original pose and then use PBS with collision handling to drape the garment. See Figure 8f for an example result.

5 | EXPERIMENTAL RESULTS

We implemented our approach in C++ and reported its performances on an off-the-shelf computer with Intel Core i7-7700 CPU 4.20GHz and 16GB memory.

To generate the search space of joint positions, we evenly sample the spherical surface using its parametric presentation with ϕ and θ, where $\phi \in [0, \pi]$ and $\theta \in [0, 2\pi]$. The initial distance between any two sampling points is half of the average edge length of the clothing mesh. In our experiments, we do not sample the entire sphere. With a control parameter ϕ_0, we only sample the surface where $\phi \in [0, \phi_0]$ and $\theta \in [0, 2\pi]$. The initial value of ϕ_0 is $\frac{2}{3}\pi$. In the next iteration, we decrease ϕ_0 by half and thus double the sampling density.

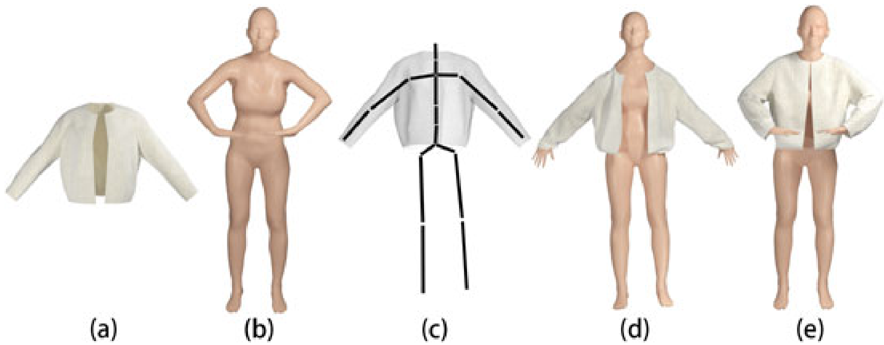


FIGURE 9 Fitting result of a blouse. (a) Input clothing, (b) input body, (c) skeleton fitting result, (d) penetration solved result, and (e) pose recovery result

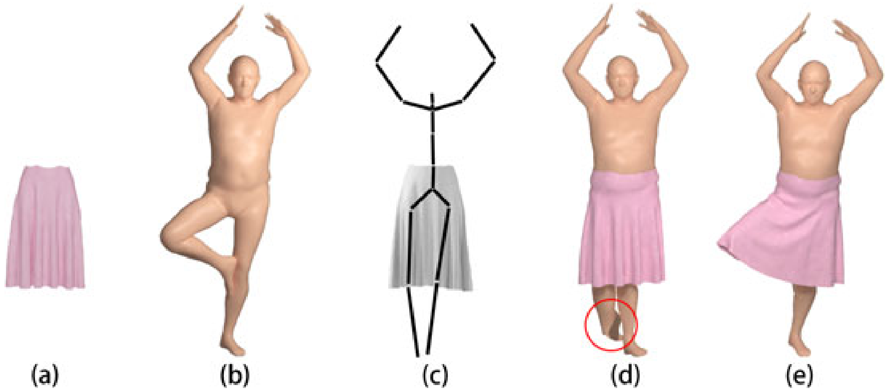


FIGURE 10 Fitting result of a dress. (a) Input clothing, (b) input body, (c) skeleton fitting result (note that the skeleton lies approximately at the center of corresponding clothing parts), (d) penetration solved result (the right foot is abnormal because of its inaccurate skinning weights), and (e) pose recovery result

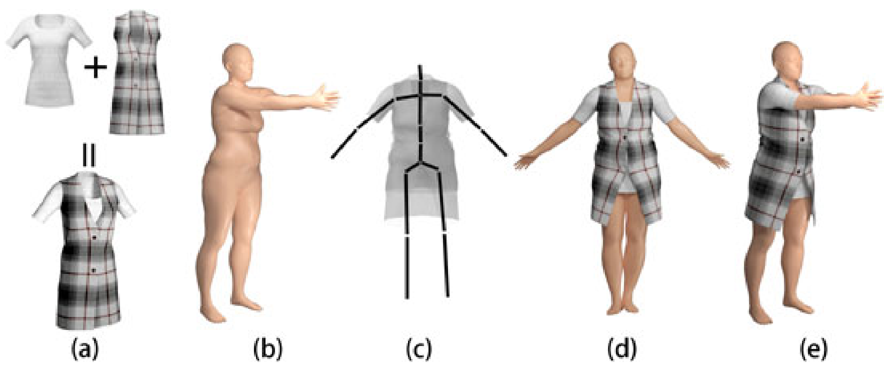


FIGURE 11 Fitting result of a two-layered clothing. (a) Input clothing, (b) input body, (c) skeleton fitting result, (d) penetration solved result, and (e) pose recovery result

Different types of garments. Our method is able to handle many kinds of clothing, including coats, hoodies, trousers, skirts, and many others (cf. Figures 1, 7–10, and 13). Our method is also able to handle multilayered clothing (shown in Figure 11) and a suit of clothing that also contains multilayered parts (Figure 12). Like the work of Tisserand et al.,[12] for a specific clothing, we also need the clothing type as input to determine which bones should be considered in the fitting process. For example, we use the hipbone, femur, and tibia for trousers (Figure 8) and the clavicle, humerus, and radius bones for a hoodie.

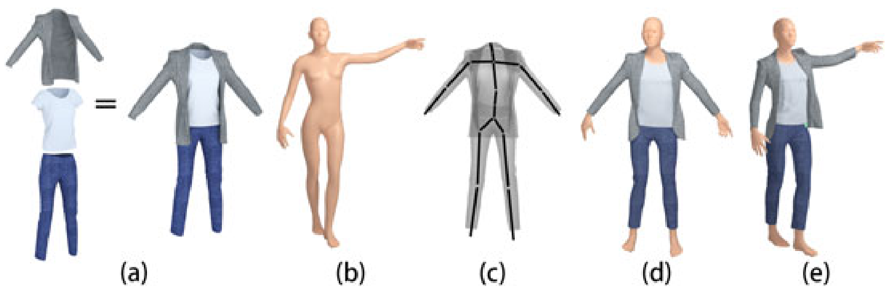


FIGURE 12 Result of a suit of clothing composed of vest, coat, and trousers. (a) Input clothing, (b) input body, (c) skeleton fitting result, (d) penetration solved result, and (e) pose recovery result

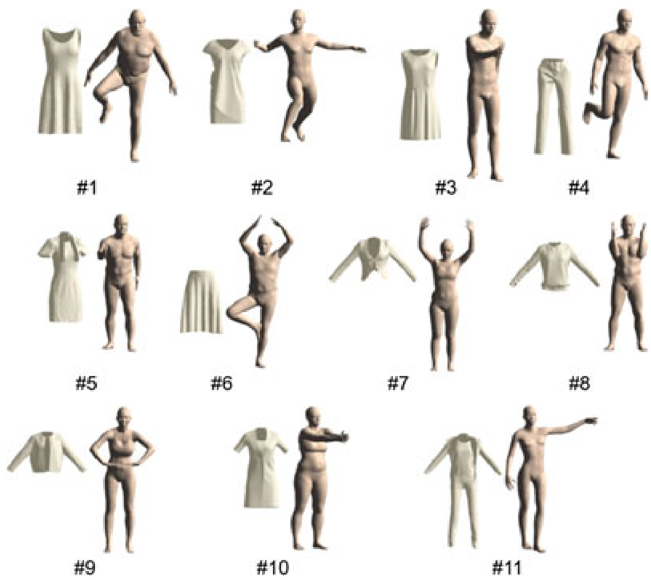


FIGURE 13 The test clothing and bodies

As aforementioned, we use the method of Baran et al.[13] to compute the skeleton and skinning weights of the human model. Because this technique requires the human model to be a 2D manifold, our method has such a requirement too. Also, the skinning weights play an important role in our method. If they are not correctly computed, the skinning result may look unnatural, as shown in Figure 10d, where the left foot is distorted due to the incorrect skinning weights of that region. In such a case, skinning weights correction would be needed.

We tested our method on many human models from the FAUST dataset[18] and MakeHuman software,[19] with various poses and shapes. Our experiments results show that our method is effective for all the test cases. Please see the supplemental demo video for animation results. As shown in Figure 13, compared with the work of Tisserand et al.,[12] our method correctly fits all the 11 examples, whereas the work of Tisserand et al.[12] failed the last test case, where the left arm is incorrectly fitted.

Runtime performances. We compared our method with the work of Tisserand et al.[12] To this end, we implement its error metric and insert it into our framework. As shown in Table 1, for all the examples, our method is about two orders of magnitudes faster than the work of Tisserand et al.[12] The test clothing and bodies are shown in Figure 13. The efficiency of our method results from two factors. First, our method uses the skeleton, rather than the surface mesh, to compute the error metric. This results in the computational burden of $O(n_G)$ rather than $O(n_H \cdot n_G)$ in the work of Tisserand et al.[12] Second, we rig the surface mesh of the human body only once for each garment fitting, whereas Li et al.[10] did this for each candidate search pose during garment fitting. Note that the computation time of our method is independent of the density of the human model, except the time for computing the skeleton and skinning weights, which makes it possible to fit a high-resolution human model with hundreds of thousands of vertices.

TABLE 1 Runtime statistics of our work and the method by Tisserand et al.[12]

garment & body	#vertices/#faces of the garment	#vertices/#faces of the body	time for our method (seconds)	time for Tisserand et al.[12] (seconds)
1	4,218 / 7,847	6,890 / 13,776	0.88	163.99
2	4,556 / 8,292	13,380 / 26,756	1.52	798.85
3	15,680 / 30,196	6,890 / 13,776	11.06	1, 975.07
4	18,482 / 35,655	6,890 / 13,776	10.75	3, 940.91
5	5,385 / 9,717	6,890 / 13,776	0.43	288.55
6	8,490 / 16,506	6,890 / 13,776	1.09	567.41
7	3,035 / 5,495	6,890 / 13,776	0.64	137.86
8	15,727 / 30,318	6,890 / 13,776	25.65	3, 681.60
9	7,423 / 13,912	6,890 / 13,776	4.66	754.98
10	8,215 / 14,838	6,890 / 13,776	0.71	505.16
11	11,725 / 21,399	13,380 / 26,756	6.55	2, 885.38

6 | DISCUSSION AND CONCLUSION

We propose an automatic method to fit a garment on a human body with any pose and shape. The key part of our method is the introduced novel error metric that efficiently calculates the fitness between the garment and the skeleton of the human body. Our method does not change the size of the input garment and hence gives a fitting result of a garment of certain size. This feature is particularly useful for various virtual try-on applications.

Our current work has some limitations: First, currently we use the method of Baran et al.[13] to compute the skeleton and the skinning weights of the human model. Because it requires the human model to be a 2D manifold, some manual work might be needed if a nonmanifold human model is inputted. Second, similar to the work of Tisserand et al.,[12] the joints involved in the optimization step need to be selected manually according to the type of the garment. In the future, we plan to develop an automated method to identify the type of clothing and thus the involved joints. Lastly, our current method does not pay special attention to the interpenetration issue. In some extreme cases, such as a very obese guy wearing a garment of relatively small size, interpenetration cannot be solved by common collision handling algorithms in PBS. In the future, we would like to address this issue.

ACKNOWLEDGEMENTS

Xiaogang Jin is supported by the National Natural Science Foundation of China No. 61732015, the National Key R&D Program of China No. 2017YFB1002600, and the Key Research and Development Program of Zhejiang Province No. 2018C01090. Dongliang Zhang is supported by the National Natural Science Foundation of China No. 61472355.

We thank Xuan Luo from Jiangnan University for designing the garments in Figures 11–12.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

How to cite this article: Wu N, Deng Z, Huang Y, Liu C, Zhang D, Jin X. A fast garment fitting algorithm using skeleton-based error metric. *Comput Anim Virtual Worlds*. 2018;e1811. https://doi.org/10.1002/cav.1811