Cloth Simulation and Virtual Try-on with Kinect Based on Human Body Adaptation

Yuzhe Zhang, Jianmin Zheng and Nadia Magnenat-Thalmann

Abstract This chapter describes a virtual try-on system with Kinect, which includes three components: data extraction from Kinect, animated body adaptation, garment prepositioning and simulation. With Kinect, some measurements and motion data of the customer can be extracted from captured RGB, depth and motion information. An anthropometry-based method is proposed to generate a customized 3D body from a template model. The method involves three processes. First, a statistical analysis method is proposed to estimate the anthropometric measurements based on partial information extracted from Kinect. Second, a constrained Laplacian-based deformation algorithm is presented to deform the template model to match the obtained anthropometric measurements. Third, a shape refinement method based on the contours is presented. The customized model is then animated by the recorded motion data from Kinect. Meanwhile, a scheme for automatic prepositioning the 2D patterns of garments onto the customized body is proposed. After the step of topological stitching and simulation, the garment is dressed on virtual model of customer finally. With the proposed framework, customers can try-on designed garments in an easy and convenient way. The experiments demonstrate that our try-on system can generate accurate results.

Keywords Cloth simulation · Kinect · Human body adaptation

1 Introduction

Virtual try-on is a technique that allows users to *virtually dress garments onto digital 3D body.* It has many applications. For example, in the scenario of online cloth shopping, a customer picks clothes in the category and the result of dressing

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the clothes on his or her body will be displayed on the screen to check whether the clothes fit or not. This process involves many technical components such as 3D body modeling, adaptation, clothes preposition, and simulation. Also a simple interface and realistic dressing results are expected.

Extensive research has been conducted on the modeling of human body and the simulation of virtual clothes. Substantial progress has been achieved in these areas. The development of virtual human modeling and virtual cloth simulation makes the virtual human and garment realistic and impressive (Volino and Magnenat-Thalmann 2000; Magnenat-Thalmann and Volino 2005; Magnenat-Thalmann 2010). However, these techniques are in general too complicated or need sophisticated equipment, which make the virtual try-on system still far away from practical use. Considering the popularity and cheap price of Kinect, this chapter studies technologies for virtual try-on with Kinect.

1.1 Related Work

Cordier et al. (2003) proposed the concept of made-to-measure online clothing store. This online try-on system includes two databases for body and garments, respectively, and supports interactive manipulators for customers to adjust 3D mannequin by controlling measurements. 3D garment is resized to provide online fitting. It integrates the techniques of virtual human and cloth simulation to achieve the goal of dressing for an individual customer. However, there are some drawbacks in the system. First, the system needs many indirect and complicated interactions for model generation. Second, the body model which is created through only eight measurements is not very accurate. Third, the system generates the initial garment on a generic model in advance and then performs simple deformation according to the shape of the customer's model. The 3D garment may not follow the initial designed 2D patterns of garments.

Founded in 2012, the company Bodymetrics (http://www.bodymetrics.com/) investigates a system for virtual try-on that uses the same Kinect's cameras technology to reconstruct the user's body and uses it to virtually try and order clothing that fits online. However, the try-on result is statistic so that users cannot have a sense of dynamic effect of cloth with regards to their movement.

Body model generation is a research component needed in virtual try-on. Many methods have been proposed, which are divided into four groups: scanner-based methods, photo-based approaches, example-based, and anthropometry-based methods. Scanner-based methods usually reconstruct surface of body model by meshing point clouds from 3D Laser scans, which are accurate but expensive and time consuming. Photo-based methods, such as (Barron and Kakadiaris 2000) and (Seo et al. 2006), reconstruct body model based on multiple images from different views or a single image. In this kind of methods, the 3D surface results are inaccurate. And pose registration is difficult, which can be solved easily by Kinect. Example-based methods, such as (Allen et al. 2003) and (Seo and Magnenat-Thalmann 2004), generate a quite precise and high qualify model, however, it is inconvenient to do local modification and modify models according to user's intention. The approach of parameterizing the human body according to measurements can generate body model in real time and is more suitable for digital fashion applications since anthropometry is also widely used in fashion industry. After Grosso (Grosso et al 1987) first introduced anthropometry-based modeling, many researchers (Shen et al. 1994; Maïm et al. 2009; Kasap and Magnenat-Thalmann 2010, 2011) provided user interactive manipulators to create human models through anthropometric measurements. However, most existing methods treated the anthropometric parameters independently. As a consequence, unrealistic model may result. Thalmann (Magnenat-Thalmann et al. 2004) combined example-based and anthropometry-based method to generate body model satisfying multiple measures, however, it is not a real-time method and lacking further refinement.

Virtual try-on relates the clothes with 3D body. To dress 3D body with garments defined by 2D patterns, a prepositioning step is needed. The traditional manual placement requires intensive interaction for designers to position patterns one by one. Research works have been studied to achieve semi-automatic prepositioning. For example, Groß et al. (Fuhrmann et al. 2003; Groß et al. 2003) place and arrange patterns on an extendable expanded cone surface first and then map this cone surface to trunk or limbs of body which is also approximated by cone surface. Fontana et al. (2006, 2008) set up a hierarchical structure to store the garment information in different levels. During prepositioning, they use several developable surfaces to approximate body model first and map patterns to body according to embedded knowledge. Thanh and Gagalowicz (2005, 2009) provide a tool to map patterns onto front and back 2D silhouette of model. All these approaches try to link patterns with the body model through connectivity of patterns. Based on the summary of three methods, we infer that semantic-based representation to encode linking information between pattern and body is required and the method to encode the position information to transform patterns of garment to different body model automatically is missing.

There is a huge amount of research focused on cloth simulation. Different schemes such as finite elements and particle systems are proposed to produce the dynamic behavior of clothes. There are also a lot of works on numerical methods to improve the efficiency of the simulation or collision detection and response which are to detect the contacts between regions of the clothes with the body and other parts of the clothes to simulate reaction and friction force. A review of cloth simulation can be found in (Volino and Magnenat-Thalmann 2000; Magnenat-Thalmann and Volino 2005; Magnenat-Thalmann 2010).

1.2 Our Work

Our work is inspired by Kinect and its applications (Izadi et al. 2011). Kinect was launched by Microsoft in 2010 and SDK for Window 7 was released in June, 2011. Since Kinect is a controller-free device and can track the movement of a full body in real time, Kinect is changing the way in which people interact with computer. Our goal is to develop efficient techniques with Kinect for automatic generation of virtual mannequin and dressing garment on it.

In this research, we present a Kinect-based virtual try-on system. Figure 1 illustrates the technical components of the proposed system, which are mainly data collection, body generation, and garment dressing. In the stage of data collection, the customer only has to show a T-pose in the front view and a straight posture in the side view in front of the Kinect, then move or pose the body for cloth dressing. The camera and sensor of Kinect will capture the movement of the customer. The system will analyze, filter, and record the data stream to extract useful information. There are three kinds of information extracted from the data captured by Kinect. The first includes some measurements of the customer body such as the breadth of shoulder, waist and hip, and the length of limbs. The second is the contours of the customer in the front and side views. The third is the motion data of the customer. The measurements and the contours of the customer are used to deform and adapt a template body. The initial static mannequin of the customer will then be animated by the motion data captured by Kinect. Finally, the customer can select a garment and the try-on system will automatically position the patterns of the picked garment

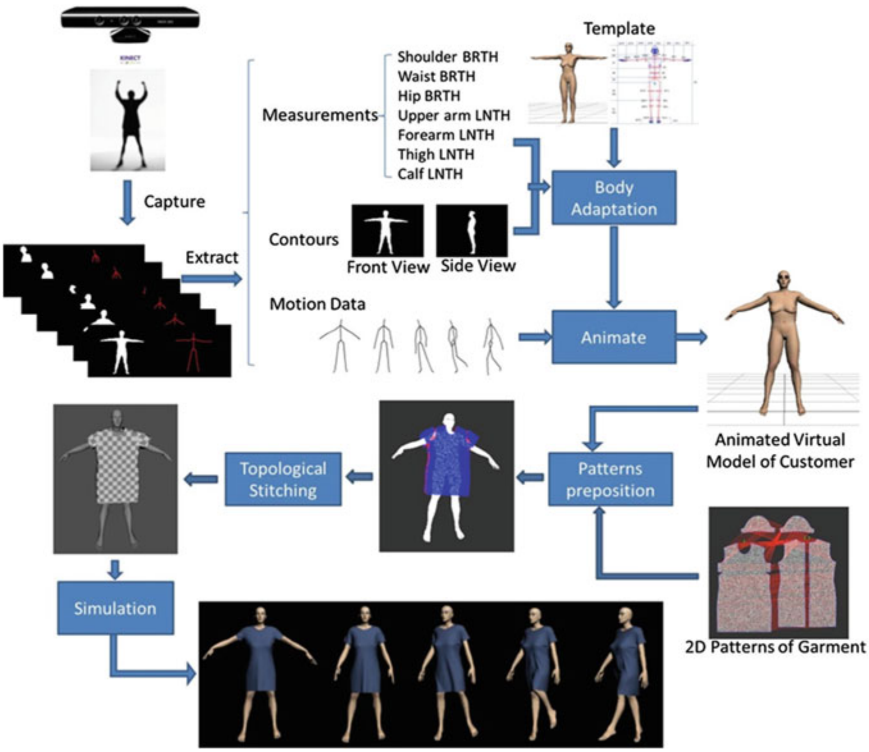

Fig. 1 Workflow of the proposed virtual try-on

around the mannequin of the customer and the dynamic simulation of the virtual body dressed with the picked garment will be displayed.

The main contributions of the paper include:

(1) We present a virtual try-on system with Kinect, which allows users to virtually try-on garments on their own digital body.
(2) We present a body adaptation algorithm based on human anthropometry, which involves statistical analysis of anthropometric measurements, measurement driven surface deformation, and shape refinement based on contours. Compared to the existing anthropometry-based approaches, our approach considers the correlation among the measurements and thus generates more accurate models.
(3) We present an automatic dressing garment method based on prepositioning, topological stitching, and simulation.

This chapter is organized as follows. Section 2 explains data collection from Kinect. The algorithms for measurement prediction, anthropometry-based body deformation, and contour-based shape refinement are presented in Sect. 3. Garment prepositioning and simulation are presented in Sect. 4. Section 5 gives some experiment results and Sect. 6 concludes the research.

2 Kinect-Based Data Collection

Kinect can capture three types of data: RGB frames, depth frames, and skeleton frames. In skeleton frames, the 3D positions of joints of skeleton are captured, which are also mapped into 2D silhouette images. In depth frames, each pixel contains data of player index and depth distance. It is noticed that not all the joints are tracked in some frames. We regard the frames with all joints of skeleton tracked as valid ones, and record these valid silhouette frames and their corresponding 2D and 3D skeletons. Based on these data, contours, measurements and motion data are extracted, which will be used to deform and animate virtual body models.

2.1 Contour Extraction

The front and side silhouette images of the customer are filtered from data stream of Kinect by analyzing the 3D positions of skeleton and 2D images. Then the contours of the body silhouette in front and side views are extracted by computer vision algorithm provided by OpenCV. The contours will be used to compute some measurements of the body. Since different human bodies have various detail shape, especially for the trunk of body, the contours will also be used to optimize the shape of trunk part of mannequin. There is no need to do further optimization for other part of body because that the shape of head and limbs can be represented well by length and girth. Another reason is that the contour of limbs and head includes a lot of noisy due to the low quality of silhouette images by Kinect.

2.2 Measurement Extraction

The real stature is input by the customer, which is used as a reference to normalize the length of skeleton and other measures among valid frames into the same scale. The lengths of upper arm, forearm, thigh, and calf are then calculated by averaging the lengths of their corresponding skeleton among the valid frames. To extract the breadths of shoulder, waist, and hip, the frames with the customer captured in the front view are selected. By intersecting the contour with horizontal lines, breadths of the body silhouette are extracted. For example, the red lines in Fig. 2 are breadths of shoulder, waist, and hip of a silhouette. Although these measurements are not enough to customize template model, they can be used to predict a full set of measurements for customizing body model, which will be explained in Sect. 3.

2.3 Motion Data Collection

We use Brekel Kinect (http://www.brekel.com/?page_id=155), an application using a Microsoft Kinect and PrimeSense's OpenNI and NITE, to capture motions and stream into Autodesk's MotionBuilder in real-time, or export as BVH files. The joints of skeleton can be mapped directly onto those of the template and customized models, enabling captured motion sequences to animate models. Moreover, since there might be some noisy, it is necessary to do further smoothing to delete the frames with extraordinary or discontinuous movement if necessary.

Fig. 2 A body's *front view* and some extracted measurements

3 Anthropometry-Based Body Adaptation

Anthropometric measurements are widely used as a standard in fashion industry. This section describes our anthropometry-based body adaption which customizes an animated body model for an individual person from a standard template according to partial measurements extracted from Kinect. We model the template with anthropometry in preprocessing stage and Fig. 3 shows the processes of anthropometry-based adaptation. First, a full set of anthropometric measurements is calculated from partial ones. Second, the surface and skeleton of a template are deformed according to the full set of measurements. Third, the contours of the customer are used to refine the detailed shape of the deformed body. Finally, the customized body is animated by the motion data.

3.1 Anthropometry-Equipped Template

The template is a T-pose standard human body provided by Make Human (http://www.makehuman.org). The geometry of the template model is defined by a triangular surface mesh. The skeleton and skinning information of the template is also specified.

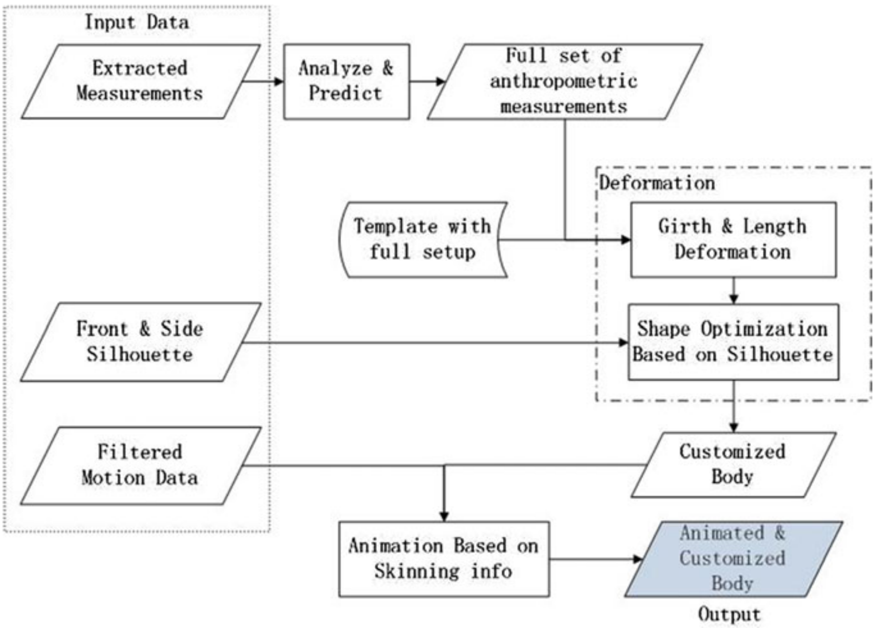

Fig. 3 Process of anthropometry based-body adaptation

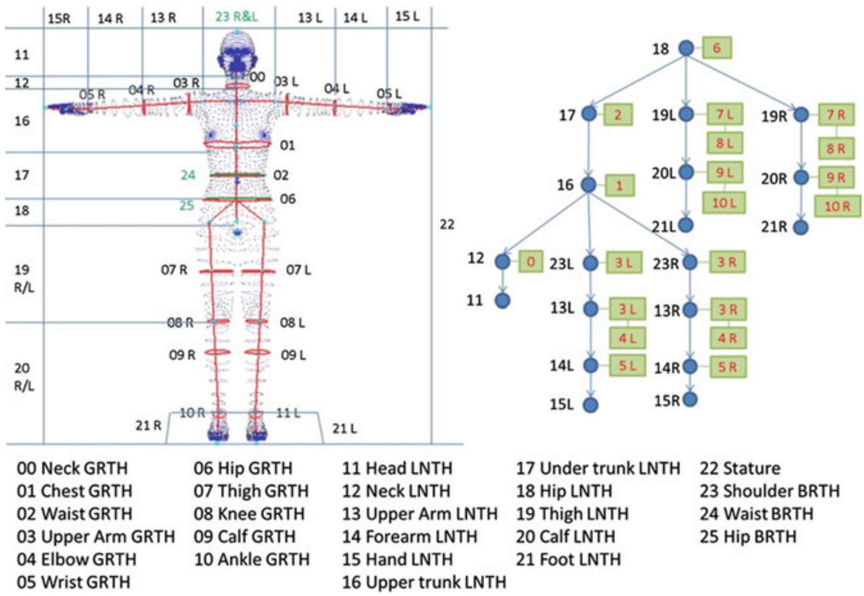

Fig. 4 Template model and structure of anthropometric measurements. *Left* Full measurement template, *Right* Tree structure of length and girth measurements, *Bottom* List of 26 measurements

While there are traditionally more than 100 anthropometric measurements for human body, we select only 26 feature anthropometric measurements as shown on the left of Fig. 4, which are commonly used in practice to characterize the body. They can be categorized into three groups:

(1) Girth G_i is measured as a circumstance of the cross-section in the plane perpendicular to the skeleton of a local part of body.
(2) Length L_i is specified as a distance between two particular points or a distance between two cutting planes.
(3) Breadth B_i is measured as the horizontal breadth of a body segment at the level of specific joint point.

It can be seen that these girth, length and breadth measurements are nicely linked with the template mesh, joints and skeleton. Thus a full setup body template consists of the mesh, 26 anthropometric measurements, skeleton and skinning information.

3.2 Full Measurement Calculation

From Kinect, we can obtain partial measurements based on which we will estimate the full set of measurements. In the following we present a prediction method to achieve this.

To demonstrate our idea and approach, in this chapter we use ANSUR anthropometric body measurement survey (ANSUR) as our training data set, which contains anthropometric measurements for 2,208 females. For each female in the training set, the 26 feature measurements are extracted and they form a feature vector to represent the female. Let $\mathrm{a_i} = \left[\mathrm{a_{i,1}}, \ldots, \mathrm{a_{i,j}}, \ \ldots, \mathrm{a_{i,26}}\right]$ be the feature vector of female *i*, where $\mathrm{a_{i,j}}$ is its *j*-th measurement. Then, the training data for anthropometry analysis can be represented by $\mathrm{A} = [\mathrm{a_1}, \mathrm{a_2}, \ \ldots, \mathrm{a_n}]^{\mathrm{T}}$, in which n is the count of the training set. With reference to Fig. 4.4, each feature vector $\mathrm{a_i}$ should satisfy the constraint C: $\mathrm{a_{i,11}} + \mathrm{a_{i,12}} + \mathrm{a_{i,16}} + \mathrm{a_{i,17}} + \mathrm{a_{i,18}} + \mathrm{a_{i,19}} + \mathrm{a_{i,20}} = \mathrm{a_{i,22}}$. Constraint C means that the height of the body equals the sum of lengths of head, neck, upper trunk, under trunk, thigh and calf.

Using the approach described in Sect. 2, we can extract some measurements from Kinect. We let $\mathrm{w_{(1)}} = \{\mathrm{w_{13}}, \mathrm{w_{14}}, \mathrm{w_{19}}, \mathrm{w_{20}}, \mathrm{w_{22}}, \mathrm{w_{23}}, \mathrm{w_{24}}, \mathrm{w_{25}}\}$ denotes these known measurements for a customer and $w_{(2)}$ denotes the rest unknown measurements. Thus our task here is to calculate $w_{(2)}$ with constraint C.

The correlation coefficient between measurements *i* and *j*, $\mathrm{Cor_{ij}}$, which measures the influence of one anthropometric measurement to another, can be calculated by:

$$\mathrm{Cor}_{ij} = \frac{\sum_{k=1}^{n} \left(a_{k,i} - \overline{a_i}\right)\left(a_{k,j} - \overline{a_j}\right)}{\sqrt{\sum_{k=1}^{n} \left(a_{k,i} - \overline{a_i}\right)^2} \sqrt{\sum_{k=1}^{n} \left(a_{k,j} - \overline{a_j}\right)^2}} \tag{1}$$

where $\overline{a_i}$ and $\overline{a_j}$ are the mean values of measurements *i* and *j*, respectively. The linear correlation between $\mathrm{w_{(1)}}$ and $\mathrm{w_{(2)}}$ is modeled by a matrix $\mathrm{Cor} = \left[\mathrm{Cor}_{ij}\right]$. *Singular value decomposition (SVD)* is performed to obtain

$$\mathrm{Cor} = U \sum V^T \tag{2}$$

where U and V are orthonormal bases for $w_{(1)}$ and $w_{(2)}$, and $\sum$ reflects the correlative relation between the two bases. The calculation of $w_{(2)}$ is done by the following steps:

(1) Assume $\mathrm{w_{tpl(1)}}$ and $\mathrm{w_{tpl(2)}}$ are the sub feature vectors of the template corresponding to $w_{(1)}$ and $w_{(2)}$, respectively. Then $\mathrm{w_{tpl(1)}}$ is projected into the space with bases of U to get $u = U^{-1}\mathrm{w_{tpl(1)}}$. Similarly, $w_{(1)}$ is projected into the space with bases of U to get $u' = \mathrm{U}^{-1}\mathrm{w_{(1)}}$. Based on this, we could detect the variation in U space, which is $\Delta u = u - u'$

(2) We project $\mathrm{w_{tpl(2)}}$ into the space with bases of V to get $\mathrm{v} = V^{-1}\mathrm{w_{tpl(2)}}$. Since $\sum$ reflects the correlative relation between the two bases, the variation of $\mathrm{w_{(2)}}$ in

V space, $\Delta v_k = \Delta u_k$ if $\sum_k^T > 0.5$ (a threshold we choose); and $\Delta v_k = 0$ otherwise. Then the value of $w_{(2)}$ in V space can be obtained by $v' = v + \Delta v_k$.

(3) $w_{(2)}$ can be calculated by projecting back from V space, $w_{(2)}$ = Vv'.

(4) So far $w_{(2)}$ is predicted based on $w_{(1)}$ through correlative analysis. A post processing step is needed to further modify the measurements to satisfy constraint C.

Let $\Delta_{22} = w_{22} - (w_{11} + w_{12} + w_{16} + w_{17} + w_{18} + w_{19} + w_{20})$ and $S=\{11, 12, 16, 18, 19, 20\}$. The value of measurements w_i, whose index is in S, is updated by

$$\frac{w_i}{\sum_{k \in S} w_k} \Delta_{22} + w_i \tag{3}$$

Now a full set of anthropometric measurements w which satisfy constraint C is obtained.

3.3 Anthropometry-Based Deformation

We now describe how to deform the template mesh model to match a given set of anthropometric measurements.

We first organize the measurements in a proper structure. For each girth measurement G, a set of intersection points P_G and edges E_G for the cross-section can be obtained by intersecting the body mesh with the cutting plane. G is represented by the circumference of a sequential intersecting point list of P_G. P_G is considered as the feature constraint of G. For length measurements which correspond to skeleton, a tree structure is organized based on the skeleton. Each length measurement is associated with an inner skeleton and one or several related girth measurements (see the right of Fig. 4 for an illustration).

Then we deform feature vertices through length and girth deformation. The length deformation is to linearly scale the corresponding inner skeleton and to relocate the related girth measurements. Based on the tree structure, the deformation of one node will cause translation of its descendants. For girth deformation, if the value of girth G is changed from g to g', then each feature point P_i in P_G is moved to a new location $p_i' = c + \frac{g'}{g}(p_i - c)$ to achieve the target value of girth, where point c is the center of P_G.

Next, the vertices of the template mesh are deformed through the Laplacian reconstruction (Lipman et al. 2004; Nealen et al. 2005) with some constraints at feature points P_G. For each vertex v_i, its Laplacian coordinates is defined by:

$$\delta_i = v_i - \sum_{j \in N(i)} w_{ij} v_j \tag{4}$$

where $N(i)$ is the set of indices of the vertices that share an edge with v_i, and w_{ij} is determined by cotangent weights (Meyer et al. 2002) satisfying $\sum_{(i,j)\in E} w_{ij} = 1$. Let v be the column vector consisting of all vertices of the mesh and *delta* be the column vector consisting of the Laplacian coordinates of all the vertices. Then $Lv = \delta$, where $L = I - A$ with $A_{ij} = \begin{cases} w_{ij} & i \in N(j) \\ 0 & otherwise \end{cases}$ Assume initially the feature point P_k in P_G is on the edge between vertices v_i and v_j. That is, $P_k = (1 - \lambda_k) * v_i + \lambda_k * v_j$ with constant λ_k. After the girth and length deformations, all the feature points P_k in P_G have been updated into P'_{k}. Then the reconstruction problem is to find new vertex vector v' for v of the mesh, which minimizes the objective function:

$$E(V') = \| \delta - L(v') \|^2 \tag{5}$$

Subject to $(1 - \lambda_k) * v_i + \lambda_k * v_j = P'_k$ for each P_k in P_G. This objective function aims to make the change of the Laplacian of each vertex of the mesh before and after the deformation as small as possible. Since the Laplacians reflect the geometric shape well, the Laplacian reconstruction usually produce nice deformation.

3.4 Shape Refinement

To use the front and side contours to optimize the shape of waist part of deformed model, the corresponding contours on 3D model and how to optimize should be detected. First, the contours are normalized into the same scale with 3D model. Second, four contour lines of model are detected by intersecting model horizontally and vertically as showed in 3rd column of Fig. 5.

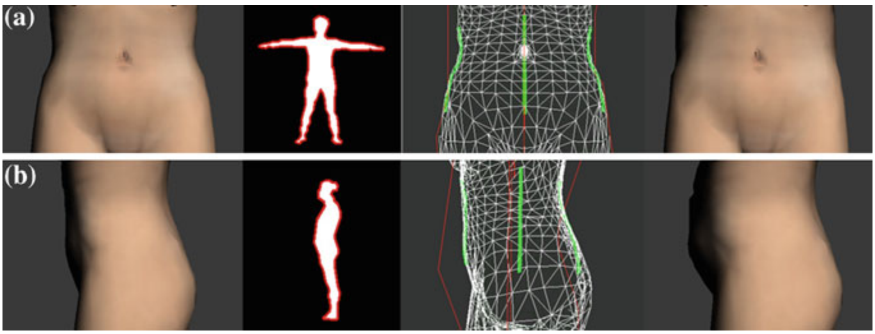

Fig. 5 Shape refinement. From *left* to *right* Initial shapes, 2D contours, 3D contours, refined shapes

(1) Left and right waist contours: intersect model by x–y plane with z equals z value of point at widest of waist girth and extract line below under breast plane and above hip plane.
(2) Front and back waist contours: intersect model by y–z plane with x equals middle of body model and extract line below under breast plane and above hip plane.

Then, each point P_i in these four contours is regards as a constraint $C\_contour_i$. For points on left and right waist contours, the x-offset of point can be calculated by $1/2\Delta width$, in which $\Delta width$ equals the difference between width of model and width of 2D front contour. For points on front and back waist contours, we first project corresponding skeleton into 2D side contour. Then the z-offset of each point is $\Delta thickness$ of difference between thickness of model and target 2D contour, in which thickness means distance from point to skeleton.

The shape refinement is performed by applying the Laplacian reconstruction again on the vertices in related region including upper trunk, under trunk, and thigh parts, with the constraints imposed by the points on the contours. The fourth column of Fig. 5 is the result of refining the initial shape (the first column) according to the contours in the second column.

3.5 Animation of the Customized Model

Since the skinning information is attached in template and the embedded skeleton has been deformed during the length deformation, the standard linear blend skinning (LBS) method is thus used to animate the customized body model. Based on LBS, the position of the transformed vertex j is calculated by

$$v_j' = \sum_i w_j^i T^i \left(v_j\right) \tag{6}$$

Where T_i is the transformation of the i-th bone, and w_{ij} is the weight of the i-th bone for vertex j. Figure 6 compares the real frames of a customer and her animated virtual mannequin guided by Kinect motion data.

4 Garment Prepositioning and Simulation

Once the customized body is generated, the next task for virtual try-on is to dress the body with clothes that are chosen from garment database. This usually involves two steps. The first one is prepositioning, which is to map 2D patterns of garment onto the 3D body and generate initial clothes. The second one is simulation, by which the initial clothes are deformed dynamically to fit the animated body.

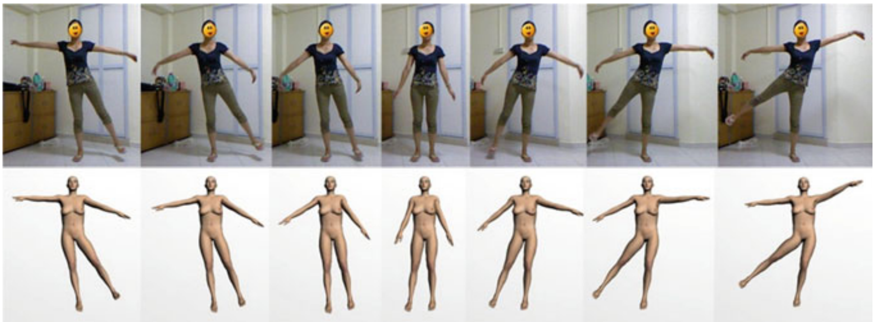

Fig. 6 A real customer and her corresponding animated model

Prepositioning is an important step. A good prepositioning result will reduce the computation of simulation; otherwise, a bad prepositioning will require high computation cost or even leads to failure of simulation as shown in Fig. 7.

To the best of our knowledge, so far the prepositioning is conducted manually or semi-automatically. This is because based on the geometric information of patterns only, it is in general impossible to preposition the patterns around body automatically without interaction. Here we propose an approach to achieve automatic prepositioning. Our basic idea involves four aspects: first, we introduce a new 2D pattern format for garment, which includes geometry, connectivity and semantic information; second, as shown in Fig. 8, the body template is used as a reference to link the correspondence between 2D patterns and the customized body model; third, the 2D patterns are deformed and refined according to the correspondences of skeleton and constraints of seams; and fourth, the 2D patterns are merged into an initial 3D garment by topological stitching along the seams.

4.1 Data Format

Currently garment is defined by 2D patterns in various industry formats. We propose to embed connectivity and semantics knowledge into the existing geometry-based format in order to make automatic prepositioning possible. In our

Fig. 7 Example of bad prepositioning which leads to failure of simulation

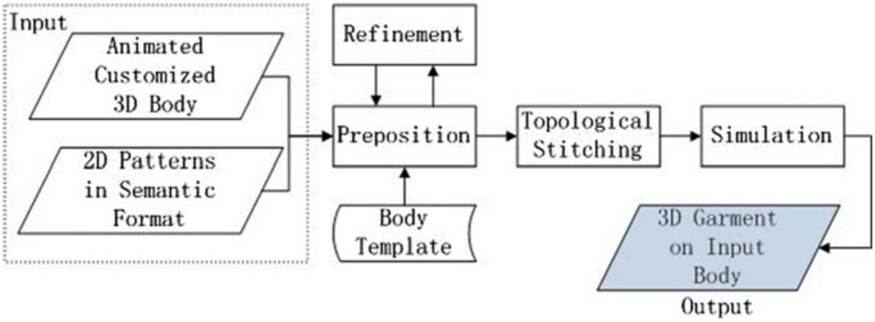

Fig. 8 The process of garment preposition and simulation

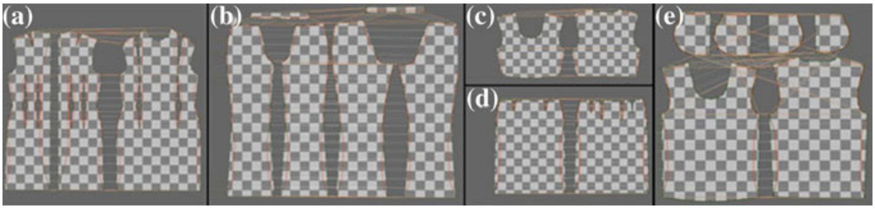

Fig. 9 2D Patterns of garments in category

proposed format, three types of information are involved for 2D patterns of a garment:

(1) Geometrical information: 2D patterns (2D pieces in Fig. 9) are defined by 2D contours and triangulated into 2D mesh.
(2) Topological information: Seams (red lines in Fig. 9) specify the linkage along the contours of one or two patterns.
(3) Semantic information: There are some tags for layer id, side id, etc. The markers to specify with which skeleton of the template the patterns are linked and initial 3D position placed on the template for 2D patterns are recorded.

While geometry is used to define the shape of individual patterns, topological and semantic information is embedded and used to indicate the relationship among patterns. Before prepositioning, there is a stage of preprocessing done previous offline. The goal of preprocess is to define and record semantic information. The patterns of garment are positioned onto the template model by designers either by manually or other tools. We also design a tool for automatic prepositioning of basic types of garment. For complicated garment, it need designers to place or modify manually. After this stage, each pattern P corresponds to a skeleton S_{id} of the template model and a transformation matrix T_{tpl} which places the pattern onto the template.

4.2 Prepositioning

First, since the customer's model is adapted from template, the patterns on the template can be deformed accordingly. Assume that the matrix for deforming the skeleton of the template to that of the customer is T_{skl}. This transformation is applied to the patterns.

Second, by checking the bounding volume for each body segment of the skeleton and considering the layer id of patterns, a translation matrix T_{vol} is applied on patterns to avoid intersection with body and other patterns.

Third, there are three kinds of intersection that should be eliminated through iterations. The first is the intersection of seam lines with the body, which can be detected by testing seams. The other two are the intersection between the pattern and the body and the intersection between two patterns, which can be detected by testing the mesh of patterns and the body model. To eliminate these intersections, the involved patterns are transformed along the direction of the skeleton by analyzing the information of connectivity and geometry. We denote the required transformation by T_{ref}.

To combine these steps, the new position of a pattern on customer's model, P', can be computed from the initial position P by

$$P' = T_{\mathrm{ref}} \times T_{\mathrm{vol}} \times T_{\mathrm{skl}} \times T_{\mathrm{tpl}}(P) \tag{7}$$

The second image in Fig. 10 is the positioned result from initial placement on the template shown in the first image.

4.3 Topological Stitching and Simulation

Assembly of patterns is to stitch the meshes of patterns together along the seams. In the process of stitching, the most important thing is to refine and calculate right topology of garment. First, we push the mesh of all patterns, which includes vertices and faces information, into a temp vertex and a temp face list of garment. Second, since each seam corresponds to two lists of related vertices, we choose one of the two as an updated list, and the other as a reference. For each vertex in the updated list, we detect faces which contain the vertex and modify the vertex index of faces as the index of the reference list. Then we mark the vertices in the updated list as invalid. Third, the valid vertices in the temp vertex list are copied into the vertex list of garment. The vertex index of faces in the temp face list is updated and copied into the face list. The right of Fig. 10 shows the result of stitching. Although the initial 3D garment has a flat shape of garment, it includes not only the geometrical information but also the topological information. In this way, the prepositioning is simply accomplished, without complicated user interaction.

Finally, the simulation of the clothes on the animated body is performed. There have been many research works done on this and some libraries have been

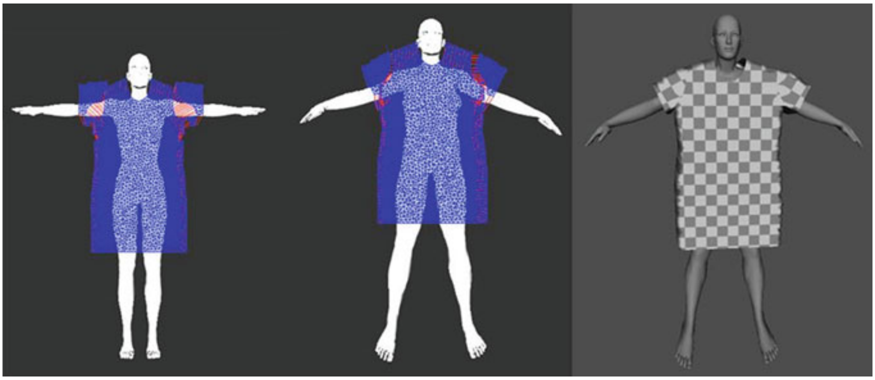

Fig. 10 Example of prepositioning and topological stitching. *left* patterns on the template model; middle: prepositioning on the customized model, *right* topological stitching result

developed to simulate clothes when they are initially placed around the body (Magnenat-Thalmann and Volino 2005; Magnenat-Thalmann 2010). We use the library in Fashionizer (Magnenat-Thalmann 2010), which is a virtual garment creation and simulation software developed by MIRALab, to do the simulation to generate the final dressed 3D body.

5 Experimental Results

Figure 11 is an illustration of our user interface. The customer should show their valid front and side view first. Then, they are required to move and pose in front of Kinect to do motion capture. After that, a virtual body model for the customer will be generated and displayed. For virtual try-on, the customer could pick up one or more garments from the category in the right. A simulation on static model will be shown quickly first, and the final try-on result with motion will be displayed after simulating garment on whole frames.

5.1 Evaluation of Body Generation

To evaluate body generation, we invite several female volunteers of different ages, shapes, and statures to try this system. Experimental results of three customers are compared and listed in Fig. 12.

We compare the three customized models and their real photos in the front and side view, respectively. The stature of customer A and B are nearly the same and A is fatter than B as showing in real photo. Customer C is taller than A and B. Our customized models also reflect this observation. The abdomen of customer C is bulge in photo and the virtual model also owns the same shape with the help of shape optimization.

Fig. 11 User interface of our framework

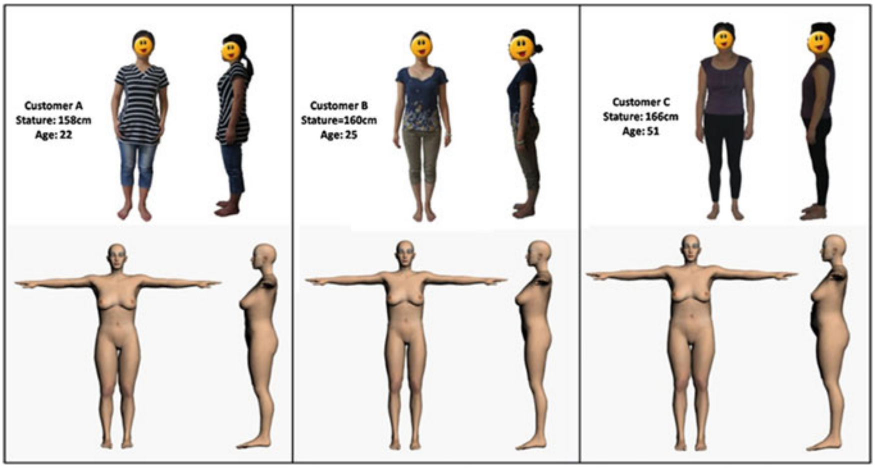

Fig. 12 Experimental results of body generation. 1*st row* photos and information of customers, 2*nd row* virtual models for customers in the front and side views

5.2 Experiment of Garment Try-on

To evaluate virtual try-on effect, we preposition and simulate different set of garments on customers. Several garments of different types are chosen, which include a pair of trousers, a skirt, a T-shirt, a mini-top, and dresses. As shown in Fig. 9, we embed the seams and connectivity into the 2D patterns and record them in our format previously.

Fig. 13 Experimental results of garments prepositioning: initial positioned and stitched garments on models

The experimental results of prepositioning are illustrated in Fig. 13. All the five basic types of garments can be placed on different body model in a good way, since the simulation of initial 3D garments are converged with no failure.

To evaluate the final try-on effect, the experimental results of movement sequences are illustrated in Fig. 14. Customer A dressed with garment (e) and (d) are turning right, and Customer B with garment (c) and (b) walks straight forward, while customer C dressing on garment (a) are turning around. The experimental results demonstrate that our try-on system with Kinect can approximate customer

Fig. 14 Experimental virtual try-on effect of simulated garments on animated models **a** Customer A; Garment e and d **b**Customer B; Garment c and b **c**Customer B; Garment c and b

by generating virtual body in a convenient way, provide accurate preposition results and precise simulation of try-on garments.

Compared with (Cordier et al. 2003), our system simplifies the process of body generation, with which the customer need not to input all the measurements. The information captured by Kinect is enough to generate an accurate virtual model. When comparing our system with Bodymetrics, a sequence of frames with garment dressing on animated model could be displayed in our system, instead of only a static simulation result.

6 Conclusion

This chapter has described a Kinect-based framework for virtual try-on, which includes 3D body model generation and cloth dressing. The framework uses an anthropometry-based modeling template to build a bridge to link the customized model and the patterns of garment. For the body generation part, the main contribution lies in a feasible statistical method to predict a full set of measurements and a robust method through anthropometry-based deformation and contour-based shape refinement, which can produce smooth body models efficiently. By analyzing the data extracted from Kinect, the partial measurements and motion data can be used to make the whole virtual try-on process simple. For the garment dressing part, the main contribution includes defining the format for connectivity and semantic information and proposing a prepositioning algorithm.

Using the proposed framework, a customer should wear tight clothes so that accurate contours and skeleton can be extracted. Since anthropometry-based analysis predicts "normal" results of measurements, some customers with very irregular characteristics need to manually edit the measurements. Since garment simulation is computationally intensive, the whole system cannot achieve real time right now. In addition, some other aspects such as skin and face adaptation and garment resizing are also very interesting topics for future work.

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