The Journal of The Textile Institute

ISSN: 0040-5000 (Print) 1754-2340 (Online) Journal homepage: https://www.tandfonline.com/loi/tjti20

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THE JOURNAL OF THE TEXTILE INSTITUTE
https://doi.org/10.1080/00405000.2019.1610205

Comparison of three-dimensional reconstruction approaches for anthropometry in apparel design

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ABSTRACT

The anthropometry is the fundamental knowledge for apparel design. While quite a few techniques have been developed for this purpose, it also becomes an obstacle for conducting a customized apparel design. Not only because most of them are expensive but they are also not quite clarified in their accuracy, speed, implement, and complexity. This article investigates three existing anthropometric approaches including two-dimensional–three-dimensional (2D-3D) mapping, point-cloud approach, and dense-reconstruction approach. With conducting three experiments in terms of these approaches, 3D reconstructive model have been built and then used for anthropometry. The results in this study have addressed the aforementioned issues; in particular, the accuracy and reliability of the anthropometric measurements built on these three approaches have been clarified. There are two main contributions out from this study. The first one is the provision of several references for users or customers to select anthropometric approaches in different apparel design scenarios. The second one is the provision of the fundamental knowledge of anthropometry for the development of conducting a customized apparel design online.

ARTICLE HISTORY
Received 23 October 2018
Accepted 16 April 2019

KEYWORDS
Apparel design; point cloud; reconstruction; anthropometry; measurements

Introduction

For apparel design, the start point is to understand the measurement of a body (Paquette, 1996). The measurement is obtained through measuring a subject's body, which is called anthropometry (Simmons & Istook, 2003). Anthropometry is essential for a customized design of apparel, in particular, the customized design of apparel in this online-shop era (Protopsaltou, Luible, Arevalo, & Magnenat-Thalmann, 2002). Generally, there are two anthropometric measurements, including contact anthropometry and non-contact anthropometry (Linney et al., 1997). The former is to capture the anthropometric measurements through contacting a subject's body. For example, the strip of parchment was used in the early time to mark the dimensions of an individual; the cloth tape measure is usually used by tailor to record the measurement of an individual (Mohan et al., 2012). The latter is to capture the anthropometric measurements without contacting a subject's body. This non-contact anthropometry is based on measuring a virtual three-dimensional (3D) model, which is generated by scanning a subject's body. This generation of a virtual 3D model is called 3D body reconstruction. This non-contact anthropometry is regarded as more intelligent and automatic (Istook & Hwang, 2001; Straub & Kerlin, 2014).

In non-contact anthropometry, to generate a virtual 3D model, several approaches have been proposed (Izadi et al., 2011; Geiger et al., 2011). For instance, Popovic, Goswami, & Herr (2005) used a 14-actuator circle to build a virtual 3D model of a biological limb. Although the reconstructed 3D biological limb with this method is precise, it requires special equipment to collect body parameters and thus is not practical for general users. Similarly, quite a few equipment, such as laser scanning (Brenner, 2005; Tiebe, Yang, Khan, Grzegorzek, & Scarpin, 2016), multiple camera array (Pesce et al., 2015), and time-of-fly cameras (Newcombe et al., 2011) are also commonly used to reconstruct 3D objects, but they are absent in terms of handy, practical, and economical. In the apparel domain, the aforementioned disadvantages make the anthropometry to be inefficient, thus, restrict the development of the customized apparel design.

To overcome the aforementioned issues, 3D body reconstruction in terms of two-dimensional (2D) images (2D-to-3D) have been developed. The technique of 2D-to-3D requires 2D images only from normal cameras (e.g. camera in a laptop or camera in a smart phone) as the input. Technically, 2D-to-3D can be implemented mainly by three approaches, including (1) 2D-3D mapping (Figure 1 (upper)); (2) point-cloud approach (Figure 1 (middle)); and (3) dense-reconstruction approach (Figure 1 (lower)). 2D-3D mapping is faster than point-cloud approach, as the former only requires two images (in some applications, it needs the third image or background image for the segmentation). However, 2D-3D mapping can easily fail due to a bad

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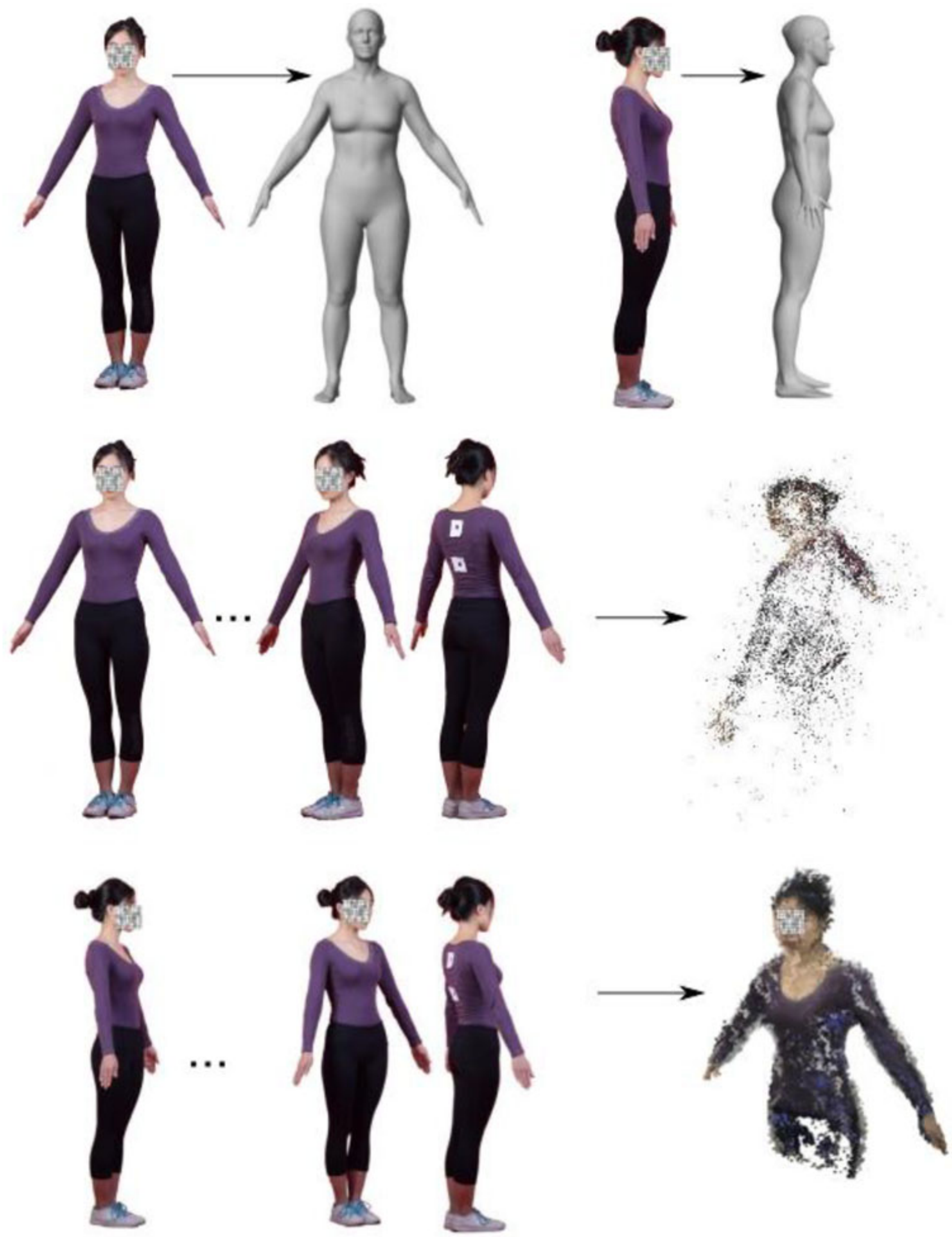

Figure 1. 3D reconstruction by using the 2D-3D mapping (Lahner et al., 2016) (upper) and the point-cloud approach (Zheng & Wu, 2015) (middle) and dense-reconstruction approach (Wendel, Maurer, Graber, Pock, & Bischof, 2012).

segmentation, boundary generation, and matching (Yang, Tiebe, Shirahama, Łukasik, & Grzegorzek, 2017). Point-cloud approach is easier than 2D-3D mapping due to avoid applying a virtual 3D standard model and model-matching process. However, the speed of the point-cloud approach is limited, as a set of a subject's images from different angles are required. Moreover, it requires rich textures from a human body for an accurate image matching and 3D body reconstruction. Theoretically, dense reconstruction preserves more fine-grained object features such as texture and geometry, but it has the slowest speed compared with the other two approaches. The main reason is that dense reconstruction normally requires both image matching, dense point cloud generation, as well as polygon transformation. In the commercial market, quite a few apps or programs have been developed in terms of aforementioned three approaches. For example, Nettelo is a mobile 3D scan, and was developed based on 2D-3D mapping. Only couple of images are required for the virtual 3D body simulation. Other apps, such as 3DsizeME, were developed in terms of point-cloud approach, where the conduction of it needs the installation of a structured sensor. These apps' development used their underlying algorithm, and thus the processing and the result of apps inherit the drawback and advantage aforementioned.

Although several strengths and weakness for these three approaches have been clarified, other essential attributes, such as their accuracy and implement, are absent. However, these attributes along with the complexity and speed of the three approaches are important criteria for designers to select a proper anthropometry in conducting a customized apparel design. In this article, main technique of 2D-to-3D anthropometry, including 2D-3D mapping, point-cloud

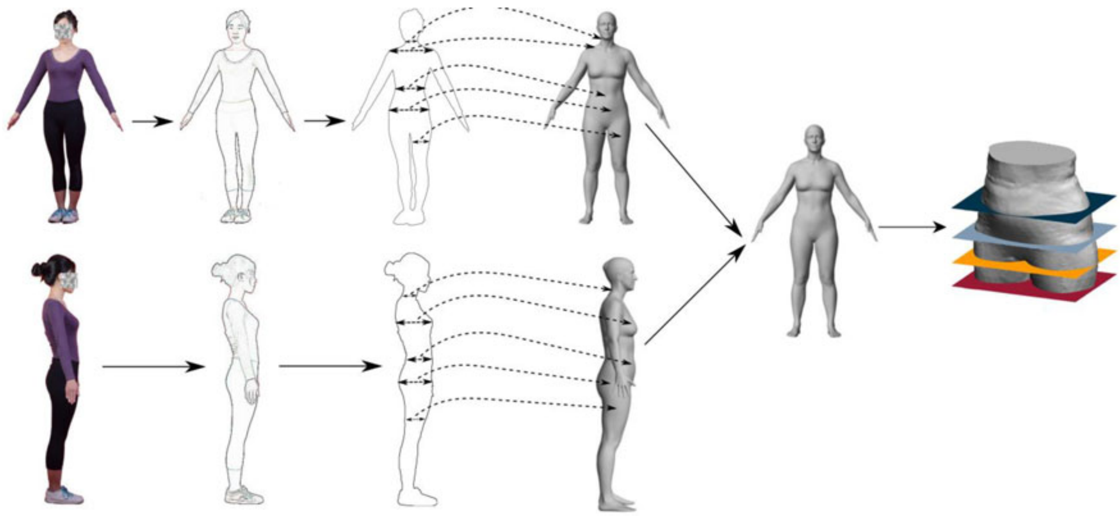

Figure 2. A general idea of reconstructing a virtual 3D model applying 2D-3D mapping.

approach, and dense-reconstruction approach, have been investigated. Several experiments with applying these approaches were conducted. The anthropometric results were compared with the ground truth, and suggestions were given in selecting a proper anthropometry in different scenarios.

Methodologies for 3D body reconstruction

In this section, methodologies of 2D-3D mapping, point cloud, and dense reconstruction for reconstructing a virtual 3D model for the purpose of the anthropometry are presented.

2D-3D mapping-based methodology

The reconstruction of 3D model with the 2D-3D mapping is normally addressed by the body boundary (or edge) matching. As shown in Figure 2, a general idea is described below:

1. Two images of a subject, including the front and side images, are needed. To get accurate boundary, Canny method (Canny, 1987) is normally used for extracting the edge of a body, due to its state-of-the-art and adaptable to various environments. The noises in the images are first removed by applying Gaussian filter (Young & Van Vliet, 1995), then filtered with a Sobel kernel (Boyle & Thomas, 1988) in both horizontal and vertical directions, so that the gradient and direction for each pixel can be observed. A full scan of the filtered images is then conducted to remove any unwanted pixels, which may not constitute edges, and then updated edges are generated. Each pixel is checked in terms of whether it is a local maximum in its neighborhood in the direction of gradient. By the end of this step, the processed images are illustrated in the second column in Figure 2.
2. The purpose of this stage is to remove small noisy pixels on the assumption that edges are long lines. Two threshold values are defined including minimal and maximum values. If the intensity gradient of an edge is more than the maximum value, it will be kept for the output. Otherwise, it will be discarded. In the end, the connected and smooth edges of a body silhouette are generated, as shown in the third column in Figure 2.
3. A one-to-one matching of different body parts using Hungarian algorithm (Jain et al., 2005) is used for the 2D silhouette to 3D body (2D-3D) mapping. It should be noted that standard body shape boundary for 2D-3D mapping cannot be directly used, as the information inside the body shape could be lost (e.g. gaps between the legs). As a result, the boundary information of an individual both inside and outside is kept, as shown in the fourth column in Figure 2.
4. Once the virtual 3D model is generated, it is available for the anthropometry. As shown in the fifth and sixth columns in Figure 2, the main idea is to measure different body parts using a set of bounding ellipses. Each of the assigned bounding ellipses is tightened to fit the true dimensions of the body parts, and the mesh skeleton is extracted to control the direction of ellipses (Tierny, Vandeborre, & Daoudi, 2006). Moreover, a threshold is proposed to balance the ratio between the surfaces that drooped-out and covered by a bounding ellipses (Choi & Ashdown, 2011).

Point cloud-based methodology

Point cloud-based method for 3D reconstruction consists of two main aspects: camera motion estimation and point-cloud generation. In the first aspect, the camera poses for taking each image is estimated using a sparse set of points matched across the views (Figure 3 (left)). In the second one, a point tracking method is applied to track a set of points across the views, whose sequences are iterated over, and to reconstruct a 3D point cloud (Figure 3 (right)). This 3D point-cloud model may have noises due to the

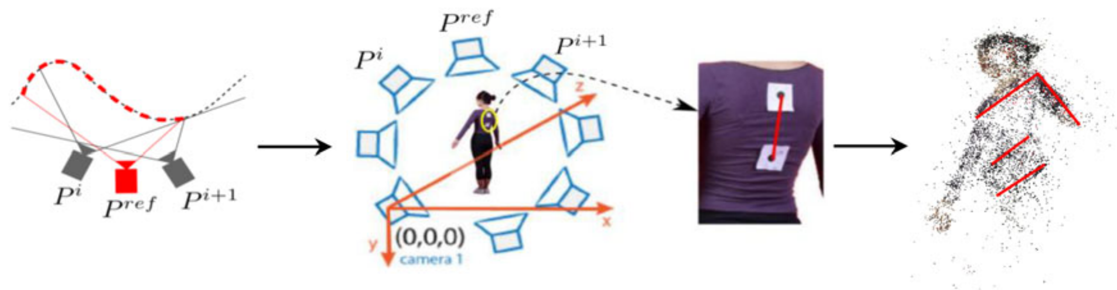

Figure 3. General idea of point cloud generation for anthropometry.

mismatches from background and foreground. However, these noises are removed with applying a noise reduction technique (Carr et al., 2001). Two reference markers on the back of a subject is used for transferring the parameters from the 3D point cloud to the body parameters from the subject in terms of the ratio of the distances between two reference markers (Figure 3 (middle)).

In this study, structure from motion (SfM) (Wu, 2013) is used for point cloud generation. SfM is a photogrammetric range imaging technique for estimating 3D structures from 2D image sequences that may be coupled with local motion signals. In a typically incremental SfM system, two view reconstructions are first estimated upon successful feature matching between two images (images are taken from different angles around a human body), which is called image matching. The 3D model is then reconstructed by initializing from good two-view reconstructions, repeatedly adding matched images, triangulating feature matches, and bundle-adjusting the structure and motion (Snavely, Seitz, & Szeliski, 2006). Image matching is usually noisy and inefficient because the views are captured from different angles, and it is one of the most time-consuming steps as the full pairwise matching takes O(n2) time for n input images. O(n2) denotes the computational complexity of the used algorithm. n2 means the algorithm is in quadratic complexity. To overcome aforementioned issues, a preemptive feature matching for the purpose of exploiting the scales of invariant features is applied to the match image (Wu, 2013; Lowe, 2004). Based on the image matching, as illustrates in Figure 3 (left), pairwise point matches is applied to estimate the camera pose of the current view relative to the previous view. Then, the pairwise matches are linked into longer point tracks spanning multiple views of the target body. These tracks then serve as inputs to multi-view triangulation and the refinement of camera poses and the 3D points using the bundle adjustment (BA) method (Agarwal, Snavely, Seitz, & Szeliski, 2010). The 3D point cloud model is then available for the anthropometry (Zhang, Xi, & Yan, 2005).

Dense reconstruction-based methodology

Different from sparse reconstruction, dense reconstruction preserves more detailed body features in terms of shape and texture. Normally, a dense reconstruction is upgraded from a sparse point cloud by adding additional constraints and refinements. Moreover, the reconstructed dense model is finally transferred into the mesh format for anthropometry (Figure 4). 3D dense reconstruction algorithms can be roughly subdivided into two categories depending on how they deal with 3D medialization problem. On one hand, there are volume-based approaches (Gool, 2003). Examples are voxel coloring, photo hulls, and level sets. They use a large number of images integrated into a single scheme. These approaches use a discretized volume and restrict possible depth values (3D points) to a predefined accuracy. On the other hand, there are pixel-based approaches (Alvarez, Deriche, Sanchez, & Weickert, 2002), and they do not need 3D discretization and compute depth (disparity) with higher precision for every pixel. These approaches are often based upon the iterative solution of a partial differential equation minimizing an energy function. Combing the features of two categories, several researchers proposed the hybrid approaches. For example, Pollefeys, Koch, Vergauwen, and Van Gool (2000) presented an approach by combining state-of-the-art algorithms for uncalibrated projective reconstruction, self-calibration, and dense correspondence matching. However, the computational complexity of this method is too high to be used in practice. In this article, an approach named Clustering Views for Multi-view Stereo (CMVS) (Schonberger & Frahm, 2016) for dense reconstruction was applied, as this approach is more accurate, dense, and robust multi-view stereopsis. The keys to its performance are effective techniques for enforcing local photometric consistency and global visibility constraints. Moreover, this method contains a simple but effective function for turning the resulting patch model into a mesh appropriate for image-based modeling so that fine surface details, deep concavities, and thin structures can be preserved. The general idea of this approach is summarized in Figure 4. Particularly, from left to right: a set of sample input images, detected features and reconstructed patches after the initial matching, final patches after expansion and filtering, polygonal surface (mesh model) extracted from reconstructed patches, and automatic anthropometry (colorful circles).

Experiments

In this section, the experiments regarding 2D-3D mapping, point cloud, and dense reconstruction are conducted to obtain a subject's measurement, respectively. The measurement includes weight, height, bust, waist, hip, arm length, and shoulder width. Moreover, the contact anthropometry by using the cloth tape measure was used as the ground truth, which was used as the comparison with the other

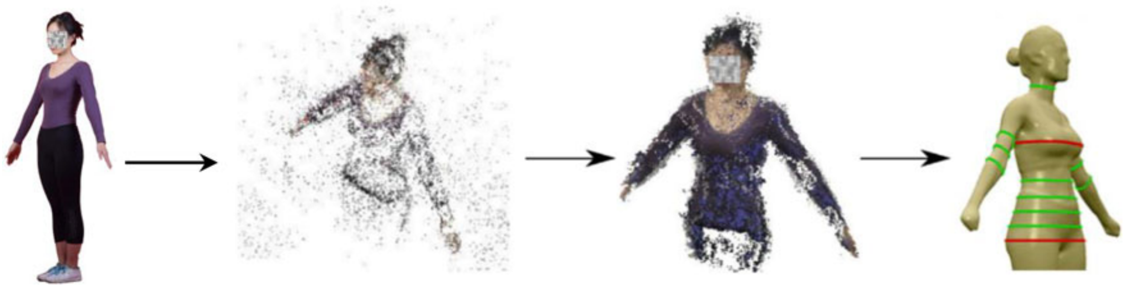

Figure 4. 3D body dense reconstruction using CMVS (Schonberger & Frahm, 2016).

non-contact anthropometry. Five subjects (four females and a female manikin) were participated in these experiments. They were asked to wear apparel without pattern and apparel with pattern. The purpose of using a manikin is to avoid the pose error, respiration, and so on during the experiments, and it adds the value to the results of the experiments.

2D-3D mapping

A mobile program called Nettelo was used in this experiment. Nettelo was developed under the 2D-3D mapping algorithm. Nettelo captures three photos including a subject and an experimental background, and then uses them to do the 3D model reconstruction. The procedure of this experiment is as follows:

1. Prepare subjects. The dress code for the four females includes wearing tight apparel, tying their hair up, and baring their feet, while a manikin was worn with tight apparel.
2. Prepare a mobile phone. The mobile phone was placed in a flat horizontal surface and kept vertically straight. The height of the mobile phone was leveled with the area between hip and bust of a subject. A small object was placed on the floor around 2 m away from the phone camera as a reference for the measurement.
3. Conduct a front scan. A subject was asked to vertically stand in front of the phone camera and face it. Except the manikin, females had to open the arms, keep them straight about 45 degrees from their body, keep their feet parallel, and with the reference object between their feet.
4. Conduct a side scan. A subject's left side had to face the camera. Except the manikin, females' arms were brought back down. The reference object was still between their feet and in the same position.
5. Conduct a background scan. The background scan was without a subject in it.
6. Reconstruct the 3D model (Figure 5). After obtaining three scans (front, side, and background) of each subject, Nettelo automatically reconstructed the 3D models, and calculated the body parameters. This approach took about 15 minutes to obtain body parameters for a single subject. In total, four females and a manikin's body parameters were generated and recorded. It is noted that the manikin only had the upper body parameters.

Point cloud

In this experiment, a Canon 550D camera and a tripod were used for the image taking. Same subjects and same dress code in the 2D-3D mapping experiment were used. Two reference markers distanced at 16 cm were worn on the back of each subject. Each subject took turns to stand on a rotated platform. Except the manikin, each female opened the arms, kept them straight about 45 degrees from her body, and keep her feet closed. The camera was settled in three angles including the 0 degree (horizontal level), –20 degree, and 45 degree. When the platform was rotating, the experimenter took photos of a subject. Totally, 44 images were taken, which represented almost all angles around a subject. For each collected image, we use scale-invariant feature transform (SIFT) to generate feature points. Based on this, we search correspondences between images using the Lukas–Kanade tracker. We also use RANSAC (random sample consensus) algorithm to remove the outlier correspondences and BA algorithm to refine the camera positions. Finally, the feature trajectories over time are then used to reconstruct their 3D positions and the camera's motion. By clustering the feature points in 3D space based on their positions, a 3D point-cloud model is generated (Figure 6). The processes are applied in Virtual SfM (Wu, 2013). This approach took about 45 minutes to obtain body parameters for a single subject. In the end, body parameters for five subjects (four females and a manikin) with wearing different type of apparel were calculated in terms of the dense 3D model (Choi & Ashdown, 2011). In practice, we use the Visual SFM (Wu, 2013) for generating the point cloud (as shown in Figure 6). After that, MeshLab (2019) is used for postprocessing and anthropometry (red lines in Figure 6).

Dense reconstruction

As mentioned in Dense reconstruction-based methodology section, CMVS for 3D dense reconstruction were used. This algorithm (CMVS) took the output of a SfM software as input, then decomposed the input images into a set of image clusters of manageable size. Because of this, the same input images from point cloud method for end-to-end reconstruction were used.

1. Similar to point cloud method, SIFT features in each image are generated. After these features had been found in each image, they were matched across multiple

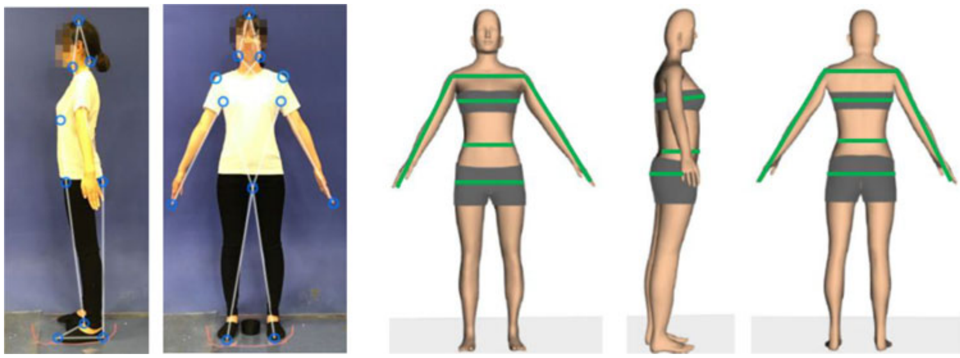

Figure 5. Based on the physical interesting points, a virtual 3D model with its front, side, and back reconstructing through 2D-3D mapping. Green lines illustrate how virtual measurements of waist, bust, hip, and arm length.

Figure 6. Examples of the 3D point cloud image.

pictures to reconstruct a sparse set of patches, which were then stored in the grid of cells overlaid on each image. To reconstruct the dense set, we iteratively added new neighbors to existing patches until they covered the surfaces visible in the model body. Intuitively, two patches were considered to be neighbors when they were stored in adjacent cells of the same image and their tangent planes were close to each other.

2. Two filtering steps were applied to the reconstructed patches to further enforce visibility consistency and remove erroneous matches. The first filter focused on removing patches that lie outside the real surface and the second filter focused on outliers lying inside the actual surface. After this step, the reconstructed dense model was cleaner. However, one of the risks is that some small body parts (such as fingers, hair, etc.) could be removed if the filter power is set too high. In our work, subjects were asked to tight their hairs, and join their fingers to reduce the negative influence of this part.
3. We used two phases to turn our collection of patches into surface meshes for anthropometry applications. Concretely, after initializing a polygonal surface from a predetermined bounding volume, the convex hull of the reconstructed points. We repeatedly moved each vertex according to three forces. They included a smoothness term for regularization; a photometric consistency term, which was based on the reconstructed patches in the first phase, but was computed solely from the mesh in the second phase; and, when accurate silhouettes were available, a rim consistency term pulling the rim of the deforming surface toward the corresponding visual cones. Finally, the meshes were generated after refining the surfaces in its desired resolution. The generated sample 3D models were presented in Figure 7. For each model, this approach took about an hour to obtain body parameters for a single subject. In practice, we use the Altizure platform (2019) to generate the initial dense model (as shown in Figure 7). For fair comparison with the point cloud method, we use MeshLab for postprocessing and anthropometry in the final step (red lines in Figure 7).

Cloth tape measurement–ground truth

Cloth tape measurement is a contact anthropometry. The experimenter directly uses the cloth tape to measure a subject's body, and obtain the body parameters. In this study, cloth tape measurement was treated as the ground truth. It was the comparison with other non-contact anthropometry. In total, the measurements of five subjects including four females and a manikin were calculated.

Results and discussion

General comparison of three 3D reconstruction approaches

Table 1 shows the relative errors of three 3D reconstruction approaches, including 2D-3D mapping, point-cloud approach, and dense-reconstruction approach, for the anthropometry on different subjects. The standard deviation

Figure 7. 3D mesh models through dense reconstruction.

Table 1. Relative errors in 3D Reconstruction.

Subject	3DR	Wei	W	B	H	AL	SW	Hei	M	SD
Manikin (pattern)	2D-3D	–	0.015	0.023	0.022	–	–	0.006	0.017	0.008
	PC	0.145	0.068	0.103	0.056	–	–	0.038	0.082	0.043
	DR	0.182	0.046	0.057	0.044	–	–	0.031	0.072	0.062
Model 1 (plain)	2D-3D	–	0.172	0.083	0.084	0.078	0.000	0.013	0.072	0.062
	PC	0.219	0.203	0.119	0.218	0.157	0.184	0.044	0.163	0.064
	DR	0.181	0.134	0.083	0.179	0.078	0.158	0.025	0.120	0.059
Model 1 (pattern)	2D-3D	–	0.078	0.071	0.017	0.039	0.026	0.000	0.039	0.031
	PC	0.086	0.172	0.114	0.086	0.059	0.066	0.013	0.085	0.050
	DR	0.029	0.133	0.095	0.050	0.039	0.079	0.009	0.062	0.043
Model 2 (Plain)	2D-3D		0.090	0.000	0.011	0.167	0.000	0.026	0.049	0.067
	PC	0.106	0.075	0.102	0.154	0.042	0.086	0.046	0.087	0.039
	DR	0.064	0.179	0.141	0.057	0.002	0.057	0.060	0.080	0.060
Model 2 (Pattern)	2D-3D	–	0.015	0.047	0.034	0.104	0.000	0.000	0.033	0.039
	PC	0.234	0.112	0.082	0.080	0.177	0.057	0.026	0.110	0.072
	DR	0.085	0.052	0.059	0.057	0.115	0.029	0.013	0.059	0.034
Model 3 (Plain)	2D-3D	–	0.055	0.081	0.138	0.057	0.056	0.048	0.072	0.034
	PC	0.158	0.111	0.102	0.241	0.132	0.111	0.024	0.126	0.065
	DR	0.088	0.096	0.067	0.001	0.113	0.128	0.018	0.073	0.048
Model 3 (Pattern)	2D-3D	–	0.000	0.035	0.115	0.094	0.028	0.000	0.045	0.049
	PC	0.088	0.058	0.083	0.192	0.138	0.083	0.018	0.094	0.056
	DR	0.053	0.049	0.064	0.138	0.113	0.056	0.018	0.070	0.041
Model 4 (Plain)	2D-3D	–	0.015	0.024	0.000	0.021	0.025	0.007	0.015	0.010
	PC	0.152	0.061	0.108	0.023	0.096	0.100	0.020	0.080	0.048
	DR	0.065	0.015	0.072	0.011	0.043	0.050	0.013	0.039	0.026

3DR: 3D reconstruction; Wei: weight; W: waist; B: bust; H: hip; AL: arm length; SW: shoulder width; Hei: height; M: mean; SD: standard deviation; PC: point cloud; DR: dense reconstruction.

(SD) for each test was checked and is close to 0. The mean (M) value in Table 1 indicates that 2D-3D mapping in each experiment has the smallest value, thus shows best accuracy among all approaches, while the point-cloud approach has the largest mean value in each experiment triggering the most errors. The reason may lie in that 2D-3D mapping is more robust of the noise in the reconstruction phase, and the other two approaches are likely to be affected by removing the noises, particularly, several necessary points can be removed, and thus lead the imprecise virtual 3D model.

Moreover, the accuracy (by checking mean values) of dense-reconstruction approach is better than point-cloud approach may due to that the latter one contains many sparse noises, which makes the virtual 3D model hard to be smoothed, while the former one with dense noises reconstructs a mesh, which is easier to remove noises and smooth the surface of the virtual 3D model. The anthropometric measurements from both point-cloud approach and dense-reconstruction approach are also consistent with the phenomena of the sparse or scattered noises in point cloud and the dense noises in dense reconstruction that point-cloud approach produces bigger measurements than that of dense-reconstruction approach (Baidu cloud, 2018). It should be noted that some existing filters could be used to remove such noise. For this, we use the Statistical Outlier Removal in Point Cloud Library (Rusu & Cousins, 2011) to remove the noisy data for the four female participants. After noise removal, we apply the anthropometry again. The mean performance changes are listed in Table 2.

We can clearly observe that the performance of both point cloud and sparse methods on models wearing apparel without patterns are reduced after noise removal. This is because the point clouds on those models are quite sparse and it is easy to break or shorten body parts after some points are wrongly filtered. For the models wearing apparel with patterns, the performance improved is not obvious and quite random. Particularly, performance on three dense reconstructed models is dropped. It is also interesting to

Table 2. Performance changes (+/– %) after noise removal.

Subjects (apparel without pattern)	PC (%)	DR (%)	Subjects (apparel with pattern)	PC (%)	DR (%)
Female 1	–10	–2	Female 1	+1	+0.5
Female 2	–7	–2.3	Female 2	–2	–1
Female 3	–5	–4	Female 3	+0.7	–0.1
Female 4	–5	–3	Female 4	+0.5	–0.1

–: performance drop; +: performance improve; PC: point cloud; DR: dense reconstruction.

mention that the performance changes of dense reconstruction are less than the point cloud. This is because the point cloud surface is smoothed during the dense reconstruction and it is more stable to noise removal.

The speed to process 2D-3D mapping, point-cloud approach, and dense-reconstruction approach is consistent with that in the existing studies (Young & Van Vliet, 1995), showing 2D-3D mapping is the fastest, point-cloud approach is the second fastest, and the last is dense-reconstruction approach. 2D-3D mapping only requires couple of pictures to be processed, while the other two needs quite many. Meanwhile, dense-reconstruction approach smooths the reconstructive model twice, which is also time-consuming. However, 2D-3D mapping is stricter with the experimental conditions, including the pose of a subject, the distance between subject and a camera, and the photo taking background, while the other two only need a camera to take pictures of a subject from different angles.

Anthropometry in different surface

Table 1 also illustrates that the surface of a subject influences the anthropometric results. In this study, both apparel without pattern and apparel with pattern were worn by subjects, and Table 1 shows that almost all subjects who worn apparel with pattern show more accurately anthropometric results than subjects who worn plain apparel in 2D-3D mapping, point-cloud, and dense reconstruction approaches. It is because that apparel with pattern contains rich texture on the surface of a subject, and they can produce more interesting and necessary points for the reconstruction phase, thus a precious viral 3D model can be reconstructed.

Anthropometry for different body parameters

As shown in Table 1, almost all 2D body parameters, including height, shoulder width, and arm length have more accurate anthropometry than 3D body parameters, such as waist, bust, and hip by conducting the three 3D reconstruction approaches. The first reason is that to measure the 3D body parameters requires pictures from different angles, and the lightness of the pictures are thus diffident, which may trigger quite many errors in the viral 3D model reconstruction. The second one is that 3D body parameters may be more sensitive to the noises than 2D body parameters.

Conclusions

In this article, three approaches of 3D body reconstruction for anthropometry, namely 2D-3D mapping, point-cloud method, and dense-reconstruction approaches were investigated in their accuracy, speed, and complexity. Three experiments regarding the aforementioned approaches were conducted. The following conclusions can be drawn from the results: (1) all three approaches are accurate and practical for anthropometry, particularly, 2D-3D mapping shows better accuracy of anthropometric measurements; (2) the reference of selecting anthropometric approaches by users in different scenarios is proposed. For example, the online-shopping customers can choose dense-reconstruction approach to obtain the anthropometric measurement at their homes, and an apparel designer in the retail store can use 2D-3D mapping to quickly obtain a customer's anthropometric measurement; (3) the realization of customizing apparel online becomes quite promising in the future with these 3D reconstruction approaches. The future work can be studying on the online apparel manufacture system, that a customer input his/her anthropometric measurements, and a very fast-customized apparel can be delivered to the customer within couple of hours.

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