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Modification and refinement of three-dimensional reconstruction to estimate body volume from a simulated single-camera image

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Abstract

Objective: Body volumes (BV) are used for calculating body composition to perform obesity assessments. Conventional BV estimation techniques, such as underwater weighing, can be difficult to apply. Advanced machine learning techniques enable multiple obesity-related body measurements to be obtained using a single-camera image; however, the accuracy of BV calculated using these techniques is unknown. This study aims to adapt and evaluate a machine learning technique, synthetic training for real accurate pose and shape (STRAPS), to estimate BV.

Methods: The machine learning technique, STRAPS, was applied to generate three-dimensional (3D) models from simulated two-dimensional (2D) images; these 3D models were then scaled with body stature and BV were estimated using regression models corrected for body mass. A commercial 3D scan dataset with a wide range of participants (n = 4318) was used to compare reference and estimated BV data.

Results: The developed methods estimated BV with small relative standard errors of estimation (<7%) although performance varied when applied to different groups. The BV estimated for people with body mass index (BMI) < 30 kg/m^2 (1.9% for males and 1.8% for females) were more accurate than for people with BMI ≥ 30 kg/m^2 (6.9% for males and 2.4% for females).

Conclusions: The developed method can be used for females and males with BMI < 30 kg/m^2 in BV estimation and could be used for obesity assessments at home or clinic settings.

KEYWORDS

body composition, body image, computer vision, machine learning, monitoring, obesity

1 | INTRODUCTION

Contactless reconstruction of individualized three-dimensional (3D) models for understanding body shape and size is an emerging technique in the medical field because of the discreet and rapid nature.[1] Conventional anthropometric measures (e.g., stature, segment length, girth measurements) and body volume (BV) can be estimated virtually from the reconstructed 3D models, to subsequently estimate the body fat quantity (e.g., body fat percentage) and distribution.[2–5] Conventional techniques such as manual measurement and underwater weighing to obtain these measures can be difficult to apply because of the requirement of technical expertise and a complicated test environment. Conventional anthropometric measures enable obesity-related measurements such as waist girth and waist-to-hips ratio to determine abdominal adiposity which is related to health risks such as cardiovascular disease, diabetes, cancer, and low back pain, and so forth.[6–8] BV can be used to calculate body density for estimation of body fat percentage,[9] which address some limitations of body mass index (BMI), to enable accurate obesity and health risk assessment.[10–13] Further, advanced shape parameters such as principal components can also be obtained to provide further information to improve the estimation of body composition[14,15] and somatotype.[16] Finally, body shape visualization with 3D human model reconstruction can improve people's motivation to control weight with diet and physical activity.[17–19]

Recently, computer vision and machine learning techniques have been developed to estimate 3D body shape and pose from single or a small number of two-dimensional (2D) images, captured from general-purpose digital cameras.[5,20] Such techniques facilitate the portable and cost-effective reconstruction of 3D human models for anthropometric measurement and body shape visualization. 3D body shape, estimated using 2D images, can provide accurate length, breadth, and girth measurements. Smith et al.[21] showed that the errors of stature, waist and hip girth measurements obtained from 2D images are less than 2 cm; for context, this is better than that achieved by general practitioners.[22,23] Sengupta et al.[24] presented a machine learning technique that generates 3D human models from a single image, with low reconstruction errors (scale-corrected per-vertex Euclidean error < 2 cm). Like traditional 3D scanning systems, multiple anthropometry measurements can be acquired from the 3D human models generated from a single or a small number of 2D images.

By applying these techniques, individualized body models can be generated without expensive, large, 3D body scanning systems. Only a consumer-level digital camera (e.g., smartphone, etc.) is required, which provides several advantages (e.g., the ubiquitous, portable and accessible nature of smartphones and digital cameras) when compared to conventional 3D scanning systems (which typically cost > $10k) and simplified systems such as Fit3D and Styku, which require specialized facilities.[5] However, the accuracy of BVs estimated from the 3D human models generated from single or a small number of 2D images is still unknown. Consequently, it is uncertain whether machine learning techniques can be used to estimate body fat percentage for obesity assessment.

A few commercial mobile applications enable the estimation of BV from 2D images. Sullivan et al.[25] recently showed the high accuracy of a commercially available application for BV acquisition from a single image (standard error of estimation < 1.0 L). However, the validation tests were conducted with limited participant groups.[25] The maximum BMI of participants was 30.9 kg/m^2 and thus no participants were in obesity class II or III (i.e., BMI ≥ 35 kg/m^2[26]). Furthermore, no individualized 3D human models can be generated using this technique, so body visualizations and other obesity-related measures (e.g., waist and hip girths), or other rich body shape parameters,[15,27] cannot be achieved by this approach.

Tian et al.[28] developed an approach that can estimate 3D body shape from images and predict body composition. The results showed it enables accurate estimation of body fat percentage comparing with dual-energy x-ray absorptiometry scans (root mean square error <3.5%). However, the estimation and prediction could be sensitive to the pose variant and silhouettes segmentations.[28] Further, the use of handles (to fix arm positions) and manual annotation that was applied in the previous study,[28] decreased the convenience of assessing obesity from a 2D image.

Among 3D body reconstruction from a single image, Sengupta et al.[24] presented an advanced machine learning technique, synthetic training for real accurate pose and shape (STRAPS), which can generate 3D human models from a single image with different poses. The qualitative results of STRAPS demonstrate better 2D projection that matches silhouettes than the results shown in Tian et al.[28] Furthermore, the low reconstruction error of the STRAPS technique might lead to improved BV estimation compared with other machine learning techniques that are validated against conventional anthropometry. To the best of the authors' knowledge, the generation of 3D models and volumes using single camera images that allow pose variants (e.g., do not need a specific handles) including STRAPS and other machine learning techniques have not been validated using reference BV data. Therefore, the aim of this study was to apply and adapt the STRAPS technique to generate 3D human models for BV estimation. Furthermore, an evaluation of BV estimates was performed using a large dataset comprising a wide range of participant body shapes.

2 | METHODS

2.1 | Datasets and participants

The commercial 3D dataset obtained from the world engineering anthropometry resource (WEAR) was used in this study. This dataset was collected in the Civilian American and European Surface Anthropometry Resource Project[29] and consists of 3D body scanning and manually measured anthropometric data from 4431 participants. Data from participants without complete 3D scan data in a standing position (e.g., data missing, incomplete scanning data, or data captured with non-close-fitting clothes), or without manually measured anthropometric data (stature, body mass) were excluded. Thus, data from 4318 participants (stature range 124.8–218.3 cm, body mass range: 37.9–181.4 kg, BMI range: 15.2–57.1 kg/m^2) were used in this study. The scan and anthropometric data were separated into training and test sets. The training set was used to determine model coefficients. The test sets were categorized with two BMI levels with the threshold 30 kg/m^2 to evaluate the model accuracy. Table 1 shows the descriptive characteristics of participants in this study.

2.2 | Reference body volume acquisition

The raw 3D scanning data in the WEAR dataset contains holes and noise as shown in Figure 1A. Automatic post-processing techniques adapted from the previous development[30] were applied to obtain watertight 3D models from the large datasets for BV acquisitions. The test–retest of whole BV obtained from the automatic post-processing techniques are less than 1 L.[30] The automatic technique enables accurate BV compared with manual post-processing[30] the acquired BVs (error < 1 L) were thus used as reference values for validation. First, the screened Poisson reconstruction techniques[31] were applied to fix the incomplete scans such as the tops of heads, hands, and feet as shown in Figure 1B. Then, the reconstructed meshes were clustered to remove random points from the main meshes. The floor plane was setup and the hole-filling algorithm[32] in the open source Python module, "pymeshfix" (https://pypi.org/project/pymeshfix/), was applied to reconstruct mesh on foot region and ensure the body mesh was watertight for reference BV acquisitions as shown in Figure 1C. The reference BVs ($BV_{reference}$) were calculated by the open source Python module, "trimesh" (https://pypi.org/project/trimesh/), which implements the method presented by Eberly.[33]

2.3 | Body image rendering

The color images are required for machine learning techniques to estimate joint positions and silhouettes as input data of the STRAPS techniques. As no color image data were collected in the WEAR dataset, the 2D images were generated with the 3D scanning data. The vertex colors of the watertight meshes were determined by the closest point color on the raw 3D scanning data as shown in Figure 1D. The colored watertight meshes were then used for generating body images as shown in Figure 2A,B. The open source Python module "pyrender" (https://pypi.org/project/pyrender/) was used to render body images. A virtual camera was set to provide a frontal view of the human model. The captured images were then cropped to minimize the effect of the background.

2.4 | Individualized 3D model generation

After generating the body image, the joint locations and silhouettes were predicted by machine learning techniques, Keypoint-RCNN[34] and PointRend,[35] respectively as shown in Figure 2C–F. The STRAPS technique was then used to estimate the pose and shape parameters of a deformable mesh to fit the silhouettes and joint locations. Once the pose and shape parameters of the deformable mesh are determined, individualized 3D human models can be obtained as shown in Figure 2G–J.

TABLE 1 The descriptive characteristics of the selected participants in this study

	Male	Female
Training set		
N	1661	1787
Stature (cm)	178.0 ± 8.4 (147.5–207.3)	164.5 ± 7.5 (124.8–194.2)
Body mass (kg)	83.3 ± 17.2 (45.8–181.4)	68.0 ± 16.5 (37.9–156.5)
BMI (kg/m^2)	26.2 ± 4.7 (16.5–55.1)	25.1 ± 5.7 (15.2–55.2)
Testing set with BMI ≥ 30		
N	56	68
Stature (cm)	178.5 ± 6.9 (161.7–193.9)	163.5 ± 7.4 (150.1–186.0)
Body mass (kg)	107.1 ± 15.2 (80.8–156.7)	97.2 ± 18.2 (71.9–156.5)
BMI (kg/m^2)	33.5 ± 3.7 (30.0–51.0)	36.3 ± 5.9 (30.1–57.1)
Testing set with BMI < 30		
N	332	414
Stature (cm)	177.6 ± 8.6 (156.6–218.3)	165.0 ± 7.5 (144.5–194.8)
Body mass (kg)	77.1 ± 11.6 (48.2–125.3)	62.8 ± 9.7 (43.3–103.4)
BMI (kg/m^2)	24.4 ± 2.8 (16.1–29.9)	23.0 ± 2.8 (17.0–29.9)

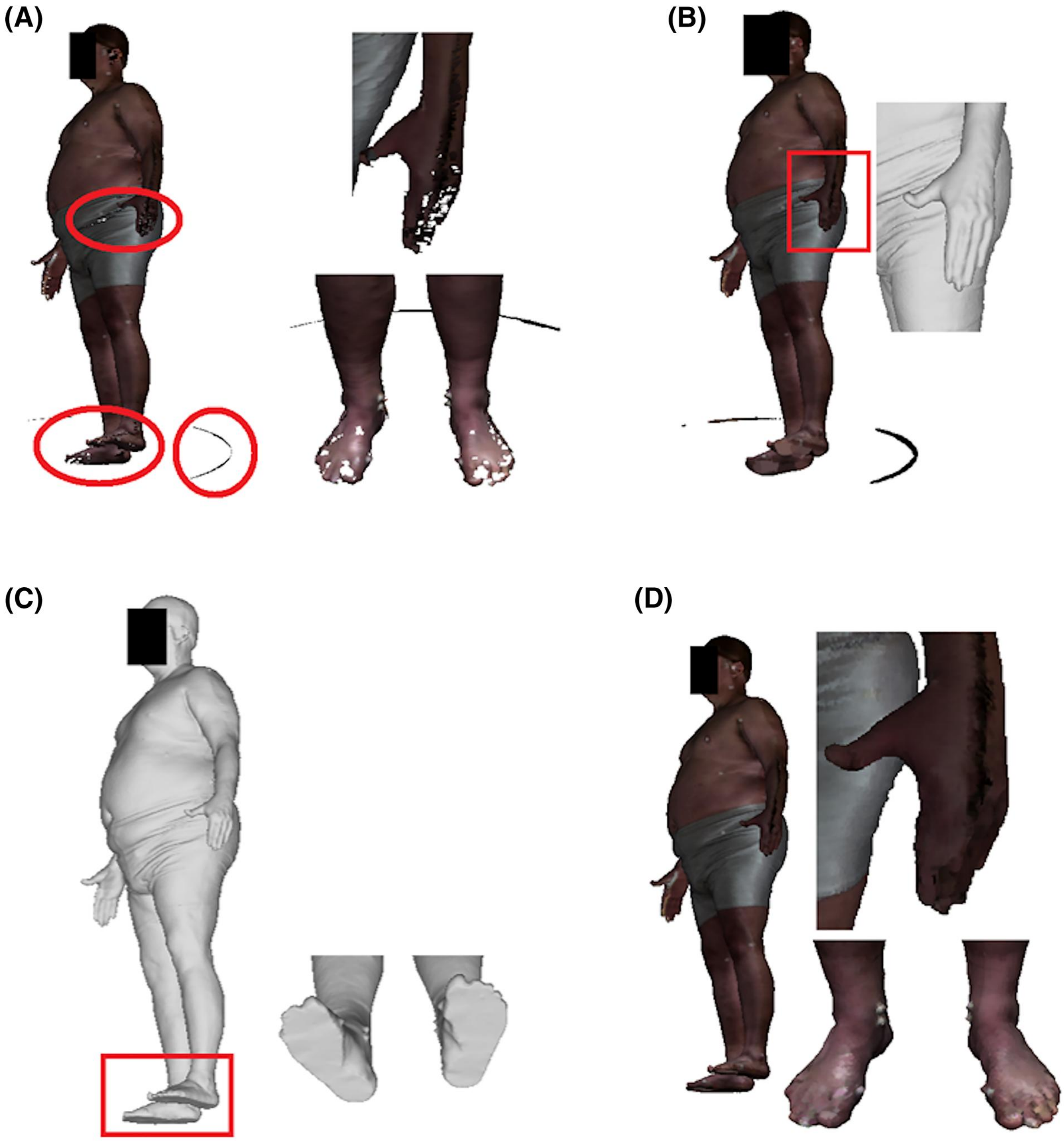

FIGURE 1 Automatic post-processing for the raw 3D scanning data in the WEAR dataset. (A) The raw 3D scanning data in the WEAR dataset contains holes on hands, bodies, feet, and noise such as the floor. (B) Screen Poisson reconstruction techniques applied and fixed the incomplete scanning on the tops of heads, hands, and feet. (C) Cluster techniques were used to remove random noise (e.g., mesh for the floor). Floor plane was set up and hole-filling techniques was applied to reconstruct mesh on foot. (D) Vertices color assigned to the reconstructed watertight meshes

2.5 | Body volume estimation

The models generated by the STRAPS technique are clean and watertight, and BV can be calculated directly. To avoid mesh self-intersection (e.g., arm meshes inside of the body meshes for people with obesity) which might lead to failure volume estimation, BV (BV_{straps}) was measured by generating 3D models that were reposed to a standard "T-pose" by eliminating body pose parameters (i.e., setting body poses equal to zeros) without post-processing (e.g., filling holes and deleting noise). The method presented by Eberly[33] that was used to calculate reference BV data was also used to estimate BVs. Like other methods that generate 3D human models from a small number of images, the STRAPS technique suffers from an unknown absolute scale. To overcome this, the scale of the 3D models was adjusted by the ratio of reposed model height and real stature manually measured, as

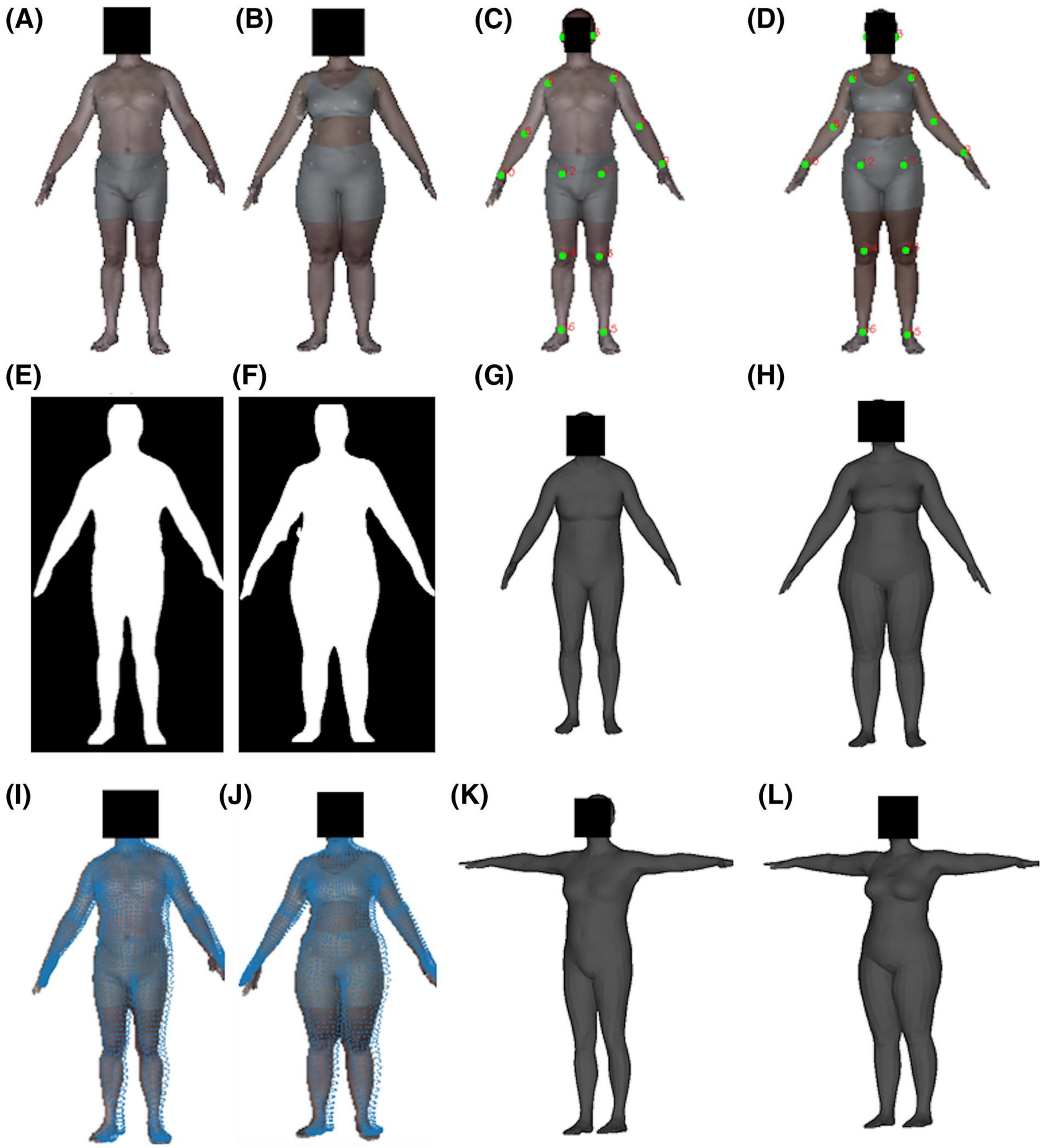

FIGURE 2 Body image rendering and 3D human model generation. (A, B) Examples of rendering images for male and female participants, respectively. (C, D) Joint location estimated by Keypoint-RCNN method. (E, F) Silhouettes generated from the PointRend method. (G, H) Front views of individualized 3D human models predicted by the STRAPS technique. (I, J) Vertices of the generated model overlay on 2D body image. (K, L) Reposed and scaled 3D human models used for body volume calculation

shown in Figure 2K,L. Scaled BVs (BV_{scale}) were measured using the scaled model. Because of ambiguous depth of single images, the BV obtained from scale models (BV_{scale}) might still contain some error. Body mass (*M*) and scaled BV (BV_{scale}) were used as the input to gender-specific linear regression models to minimize the depth ambiguity and obtain corrected BV ($BV_{regression}$). The coefficient of the regression model was determined with the training datasets.

2.6 | Evaluation tests

The estimated BVs (BV_{straps}, BV_{scale}, and $BV_{regression}$) of the test datasets were compared with the reference BVs. The formula presented by Siri et al.[9] was used to estimate body fat percentage ($BF_{reference}$, $BF_{regression}$) from BVs ($BV_{reference}$, $BV_{regression}$) to identify the difference between the reference and proposed methods in acquiring body composition. As there was no breath control in the 3D scanning protocol of the WEAR dataset, the BVs were corrected by subtracting the tidal, expiratory reserve, and residual volumes.[36] Standard error of the estimation (SEE) and Bland and Altman limits of agreement were conducted to determine the accuracy of the proposed methods.

2.7 | Statement on ethics approval

The ethics approval of this study was given by the University Ethics Committee.

3 | RESULTS

Participants exhibited a wide BMI range from 15.2 to 57.1 kg/m^2. Around 16% of participants had obesity (BMI $\geq$ 30 kg/m^2) and 55% of participants were of normal weight (BMI < 25 kg/m^2). The evaluation test results are shown in Table 2. BVs were overestimated from the model generated from the STRAPS technique (mean errors > 10 L; standard deviations of errors > 10 L) and usually underestimated from the results of stature correction (mean errors < −2 L; standard deviations of errors > 3 L apart from females without obesity). The BVs estimated using the STRAPS technique had higher SEEs (>15 L), absolute mean errors (>10 L), standard deviations of errors (>10 L), and wider limits of agreement than the ones estimated with stature correction and the regression model applications (SEEs < 15 L; absolute mean errors < 10 L and standard deviations of errors < 10 L). After applying the regression model, the SEEs and standard deviations of errors were less than 3 L (relative SEEs < 3%) for BV across all the groups apart from the men with obesity (relative SEE = 6.9%).

The bias (absolute mean errors) and the standard deviation errors of BV (−1.1 ± 7.6; limit of agreement = (−15.9, 13.7)) and body fat percentage (−3.5 ± 24.8; limit of agreement = (−52.1, 45.0)) for male participants with obesity were higher than the ones for other groups. BV estimates for males and females with obesity had higher SEEs (>2 L) and standard deviation errors (>2 L) than the ones for the group without obesity (<2 L).

4 | DISCUSSION

The STRAPS technique was applied and adapted to generate 3D human models for BV estimation. An evaluation using a wide range of body morphologies was conducted and shows that the developed methods enable accurate BV estimated for people with BMI < 30 kg/m^2 (relative SEE 1.9% for males and 1.8% for females). Cloud computing techniques can be applied to implement these developed techniques so the individualized models could be generated in a short period (typically within 1 min) with an inexpensive, ubiquitous, portable, and accessible device such as a smartphone. Thus, the developed method can be used for females and males with BMI < 30 kg/m^2 in BV estimation and could be used for obesity assessments at home or clinic settings for regular obesity assessment and visualization.

The error of BV acquired from the STRAPS technique is a large SEE (SEE > 10 L), which led to more than 10% relative SEE. The probable reason is that the reference meshes were reconstructed from 2D images with computer vision techniques indirectly instead of obtained from the 3D body scanning technique directly and the scale ambiguities were not considered while computing the reconstruction error in the previous study.[24] Further research to develop new machine learning techniques to estimate 3D body shapes and poses should consider using volumetric capturing[37] and scale correction to conduct direct comparison for quantifying reconstruction error to improve the BV estimation.

Using stature can improve the accuracy of BV estimation to reduce the limits of agreement (standard deviation errors decrease to less than 10 L). This improvement by involving stature confirms that using single 2D images contains some scale ambiguities.[5] However, BV estimated with the correction with stature for males and females with obesity contains higher SEEs and limits of agreement than BVs for the group without obesity. The body shapes variation of the group with obesity might be more complicated than for the non-obesity group so it is hard to predict from a 2D image with current models. Further model improvement might be required to acquire correct BV values for specific groups such as participants with obesity. Using body mass in a regression model can further reduce the SEEs of BV estimation which shows that using a few manual anthropometric measurements enhances the reconstruction of individual human models from 2D images. It is highly recommended that further development that estimates 3D body shape from a 2D image should combine with a few manual anthropometric data which could be measured precisely with minimal training such as stature and body mass to improve the model accuracy.

The BV obtained from the STRAPS technique with a regression model enabled accurate estimation for people without obesity (SEE $\leq$ 1.5; relative SEE < 2%). The SEE was a little higher than for commercial mobile apps (SEE < 1.0).[25] Comparing the results of the groups with obesity and without obesity, accuracy decreases as BMI increases (Table 2). The proportion of participants in overweight and obesity and the BMI range in evaluation tests for this study (45%; 15.2–57.1 kg/m^2) is higher than the ones in the previous study (31%; 18.6–30.9 kg/m^2).[25] Most participants in the previous study were in the normal-weight group[25] so the commercial mobile apps might lead to poor accuracy when applied to those with different degrees of obesity. It is necessary to conduct evaluation tests with a large representative sample that contains many participants with obesity before using commercial tools for obesity assessment. The techniques that estimate 3D human models from 2D images can provide more useful information (conventional anthropometric measures, body visualization, BVs) than commercial software which merely estimate BVs. Considering the advantages of multiple measurements[6–13] and body visualization,[17–19] further development to refine the accuracy of BVs estimated from 3D human models generated from 2D images should be encouraged and continue. More effort

TABLE 2 Evaluation tests result for body volume and body fat percentage evaluation

	Mean ± std	SEE (%SEE)	Mean error ± std	LOA
Males with obesity (51.0 ≥ BMI ≥ 30, *n* = 56)				
$BV_{reference}$	109.4 ± 20.3	-		-
BV_{straps}	126.9 ± 22.8	21.7 (19.9)	17.5 ± 13.0	−7.9, 43.0
BV_{scale}	99.7 ± 14.6	12.2 (11.2)	−9.7 ± 7.6	−24.5, 5.2
$BV_{regression}$	108.3 ± 15.6	7.6 (6.9)	−1.1 ± 7.6	−15.9, 13.7
$BF_{reference}$	41.1 ± 27.0	-		-
$BF_{regression}$	37.6 ± 3.8	24.8	−3.5 ± 24.8	−52.1, 45.0
Females with obesity (57.1 ≥ BMI ≥ 30.1, *n* = 68)				
$BV_{reference}$	101.3 ± 20.4	-	-	-
BV_{straps}	163.5 ± 7.4	40.5 (40.0)	36.8 ± 17.1	3.3, 70.3
BV_{scale}	94.3 ± 15.8	10.4 (10.3)	−7.0 ± 7.7	−22.1, 8.0
$BV_{regression}$	100.9 ± 18.9	2.5 (2.4)	−0.4 ± 2.4	−5.2, 4.4
$BF_{reference}$	53.0 ± 10.3	-	-	-
$BF_{regression}$	51.6 ± 3.0	9.4	−1.3 ± 9.4	−19.8, 17.1
Males without obesity (29.9 ≥ BMI ≥ 16.1, *n* = 332)				
$BV_{reference}$	77.9 ± 11.6	-	-	-
BV_{straps}	90.5 ± 14.8	16.8 (21.6)	12.6 ± 11.2	−9.3, 34.4
BV_{scale}	75.6 ± 11.6	4.2 (5.4)	−2.3 ± 3.5	−9.2, 4.6
$BV_{regression}$	78.0 ± 11.9	1.5 (1.9)	0.1 ± 1.5	−2.8, 3.0
$BF_{reference}$	32.4 ± 9.5	-	-	-
$BF_{regression}$	32.6 ± 5.3	9.3	0.2 ± 9.4	−18.2, 18.5
Females without obesity (29.9 ≥ BMI ≥ 17.0, *n* = 414)				
$BV_{reference}$	64.9 ± 10.2	-	-	-
BV_{straps}	85.9 ± 17.0	23.7 (36.5)	20.9 ± 11.1	−0.9, 42.8
BV_{scale}	65.4 ± 11.5	3.4 (5.2)	0.5 ± 3.3	−6.1, 7.0
$BV_{regression}$	65.0 ± 10.4	1.2 (1.8)	0.0 ± 1.2	−2.3, 2.4
$BF_{reference}$	43.6 ± 9.5	-	-	-
$BF_{regression}$	43.5 ± 5.3	9.1	0.0 ± 9.1	−17.8, 17.8

Note: Unit for BMI is kg/m^2; relative SEE is %; body volume is the liter (L) and body fat percentage is %.
Abbreviations: $BF_{reference}$, body fat percentage obtained from 3D scanning data; $BF_{regression}$, body fat percentage acquired with $BV_{regression}$; $BV_{reference}$, body volume obtained from 3D scanning data; $BV_{regression}$, body volume after body mass adjustment; BV_{scale}, body volume after stature correction; BV_{straps}, body volume estimated with the synthetic training for real accurate pose and shape techniques; LOA, lower and upper bound of the limit of agreement; Mean ± std, mean value with standard deviation; Mean error ± std, mean error value and standard deviation error; SEE, standard error of the estimate; %SEE, relative standard error of the estimate.

should be made to improve the accuracy for the group with obesity before applying it to obesity assessment.

The evaluation test in this study showed that the developed methods have different performances in estimating BV ($BV_{regression}$) and body fat percentage ($BF_{regression}$) when applied to different groups. The accuracy of BV and body fat percentage for male participants with obesity are worse than the ones for other participants (males without obesity and females). This suggests that using a linear regression model might not be appropriate to estimate volume for males with obesity. The current formula used for calculating body fat percentage is sensitive to BV error[3] which leads to poor accuracy in body fat percentage for the male group with obesity. Multiple views or non-linear correction models should be considered in the future development to minimize the depth ambiguity, especially for males with obesity. Wong et al.[38] presented a novel method that estimated body fat percentage from 3D body shape instead of volume. However, the model is not publicly available. The method was developed with a simplified 3D scanning system (Fit3D ProScanner[37]) which might not be compatible with the conventional 3D scanning system (Cyberware and Vitronic scanner[29]) and STRAPS estimation which generated 3D models in different resolutions. Public and updated formulae or models that can estimate body fat percentage from different 3D reconstruction techniques including conventional and simplified scanner and 2D image estimation (e.g., STRAPS) should be developed and used to reduce the sensitivity of BV error for obesity assessment. For instance, Pointnet++[39] which can process 3D point clouds in different resolutions could be applied to develop the public method for estimating body fat percentage from 3D reconstruction results.

Evaluation tests were conducted with the synthesized data generated with the datasets established for more than 20 years. Similar techniques are widely used in computer vision for developing machine learning models.[21,24] Although the BV obtained from 3D scanning data enables reference data acquisition, some assumptions and errors still exist in 2D image rendering, mesh post-processing, and residual lung volume estimation. Some random errors caused by camera optics or hardware were ignored. To the authors' knowledge, there are no public datasets that include 2D images and reference BV data, obtained directly obtained using medical methods such as air displacement plethysmography and dual-energy x-ray absorptiometry. This is the first study that has applied and adapted methods to generate 3D models using single images that allows pose variants, to compare to validated BV data across a large dataset. The evaluation tests in this study demonstrate a protocol and a benchmark for future computer vision and machine learning research to improve BV estimation and body visualization from single 2D images. Further studies can use the protocols presented here to evaluate the developed methods with synthesized data before collecting data directly. This provides an alternative solution for research institutes without access to devices for medical measurements.

5 | CONCLUSION

This study adapted computer vision techniques to generate individualized 3D models for the estimation of BV; a wide range of body morphologies was used to assess the validity of BV estimates. The proposed approach generated body visualizations and accurate BV estimates could be made using a consumer-level digital camera for females and males without obesity (BMI < 30 kg/m^2). The proposed approach does not require expensive 3D scanning equipment, and as such, could be used in home or clinic settings for obesity management and monitoring. Further research should be conducted to improve estimation for individuals with obesity, eliminate gender differences, and validate using directly collected data.

AUTHOR CONTRIBUTIONS

Chuang-Yuan Chiu conceived and designed the experiments with the support of **Marcus Dunn**, **Ben Heller**, **Sarah M. Churchill**, and **Tom Maden-Wilkinson**. **Chuang-Yuan Chiu** analyzed data. All authors contributed to manuscript drafting, revision, and final approval.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest with regard to this paper for any author.

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