Advancements in Body Composition Assessment Using Mobile Devices

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Abstract

Advancements in mobile technology and artificial intelligence have transformed body composition assessment, providing a practical alternative to traditional methods like air displacement plethysmography (ADP), dual energy X-ray absorptiometry (DXA), and expensive optical booth scanners for 3D body measurement. This paper evaluates the competitiveness of Size Stream's mobile 3D body scanning applications against these alternatives and compares their performance with two-point and four-point bioimpedance devices. Based on a substantial dataset of 209 samples across 118 subjects, body composition was assessed using a four-compartment model, incorporating DXA, bioimpedance analysis, body volume measurements, and body weight. Our findings demonstrate that mobile device 3D scanning achieves impressive accuracy and reliability, closely aligning with full booth results and outperforming conventional bioimpedance scales. The paper details the methodology, data analysis, and comparative metrics, highlighting the potential of mobile devices as viable tools for body composition assessment. This advancement not only enhances accessibility but also ensures precision and accuracy in health and fitness applications.

Keywords: 3D body scanning, machine learning, mobile scanning, body fat measurement, body composition

1. Introduction

Body composition data plays a crucial role in managing and monitoring health. While some individuals may wish to track their progress in weight loss or muscle gain as part of a diet or training program, others may seek measurements for medical reasons. Body fat percentage is closely linked to various diseases and health risks, making it a more informative metric than body mass index (BMI), which is often inadequate for certain body types, particularly those with high muscle mass. Transitioning from BMI to these more precise measurements can provide users with critical information and provide them with a much more accurate assessment of their health. Especially important is the ability to continually monitor this information over time.

Measuring body fat can be challenging for the average consumer. The gold standard for body fat measurement is the four-compartment (4C) model that integrates multiple measurements using an array of technologies including dual energy X-ray absorptiometry (DXA) and air displacement plethysmography (ADP) [1]. However, these large and costly systems require professional operation in healthcare or research settings, making them impractical for regular monitoring or home use. Many people turn to bioimpedance devices for body fat measurement, most commonly in the form of foot-to-foot scales; but these devices can be lacking in accuracy, or in some cases expensive and complicated to use [2]. Optical body scanners offer another alternative, using 3D body shape analysis to provide a better understanding of fat distribution, which has been shown to provide accurate body fat measurements [3]. Yet, like DXA and the more accurate bioimpedance devices, these technologies can also come with high costs and accessibility challenges.

Mobile phone 3D body scanners present a promising solution to this problem, offering the body fat estimation quality of 3D body optical body scanners, but as an accessible and affordable option for everyday users [4]. In this paper, we introduce our latest body fat estimation technology, which leverages the accuracy of our 3D booth scanner within our mobile phone solution. We present results from our latest algorithms, tested on 209 scans from a cohort of 118 individuals, which demonstrate favorable performance compared to similar 3D body scanning technologies and bioimpedance scales. Body Fat measurements are a key part of Size Stream's suite of body composition metrics which can be easily accessed with just a mobile phone camera.

2. Methods

2.1. Mobile scanning and pairing with 4C Body Fat measurements

In coordination with Texas Tech University (Lubbock, Texas, USA) [4], we received a number of paired scans, where participants had utilized our 3D booth scanning system (Size Stream, Cary, NC, USA), our mobile phone scanning system, and had also been measured via 4C-calculated body fat mass [1], [3]. The DXA scans were performed using a Lunar Prodigy scanner (General Electric, Boston, MA, USA) with the enCORE software. Bone mineral (Mo) was estimated by dividing DXA bone mineral content by 0.9582. Total Body Water (TBW) was obtained using a BIS system (SFB7, ImpediMed, Carlsbad, CA, USA). Body Volume (BV) and Body Mass (BM) were measured using air displacement plethysmography (ADP) using a BOD POD® device (Cosmed USA, Concord, CA, USA). In total, the 4C equation from [1] was used to estimate whole-body fat mass:

$$\text{FatMass (kg)} = 2.748 \cdot \text{BV} - 0.699 \cdot \text{TBW} + 1.129 \cdot \text{Mo} - 2.051 \cdot \text{BM}$$

Equation 1. Four component (4C) formula for measuring total body fat mass from Wang et al. [1].

An initial set of 246 scans from 129 subjects were paired with 4C body fat measurements from the Texas Tech study. Data quality was assessed visually from the mobile scan images, looking for obvious errors such as subjects wearing baggy clothing or more than one person in the image. In addition, there were some clear data entry issues with respect to patient metadata (such as age), and these scans were discarded. After data cleaning, a total of 209 scans from 118 subjects remained with 84 female (Table 1.)

Gender	Subjects	Scans	Age		Weight (kg)		BMI		Body Fat %		Fat Mass (kg)	
			Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
All	118	209	23.24	6.51	69.97	13.84	24.78	4.16	26.66	9.11	18.82	8.41
Female	84	138	22.57	6.02	65.56	11.93	24.60	4.29	30.98	7.31	20.92	8.35
Male	34	71	24.56	7.24	78.55	13.34	25.14	3.91	18.25	5.80	14.73	6.94

Table 1. Population statistics for the study.

2.2. New formulations for body fat mass

Images from the mobile phone scans were processed with our computer vision algorithms to construct 3D models and take body measurements. Although our mobile scanning technology roughly equals that of our optical 3D booth scanners, the regressors were adapted for a slightly better fit. Three of our internal body composition metrics were utilized in the slightly modified regressor: Body Fat Mass, Lean Body Mass, and FatMassIndex. Performance metrics shown in subsequent figures (Figure 1, Tables 2,3) were determined via a 10-fold cross validation scheme. With this method, 10% of the subjects were randomly chosen for testing, and the other 90% were used to train a linear regressor utilizing the 3 variables in Equation 2. This process was repeated 10 times until there were unbiased estimates for all subjects. The final formula (Equation 2) was determined via regression with the entire dataset, performs slightly better than the 10-fold estimates, and utilizes the following coefficients:

$$\begin{aligned} Total\ Fat\ Mass\ (kg) \\ &= 4.51 + 1.63 \cdot Gender + 1.20 \cdot BodyFatMass - 0.07 \cdot LeanBodyMass \\ &- 0.005 \cdot FatMassIndex \end{aligned}$$

Equation 2. Regressed formula using Size Stream fitness metrics for Body Fat prediction. Here Gender refers to a simple variable set to 1 for male and 0 for female.

Each component used in the final regressor are created from the 3D body measurements as follows:

1. $\text{BodyFatMass} = \text{Weight (kg)} \cdot \text{BodyFat\%}$
2. $\text{BodyFat\% (Abdomen} < 40.75) = 48.837 - 7.2745 \cdot \text{Gender} + 1.192 \cdot \text{RThigh} - 17.387 \cdot \text{MSI}$
3. $\text{BodyFat\% (Abdomen} \geq 40.75) = -1.1789 - 3.5143 \cdot \text{Gender} + 1.3664 \cdot \text{Abdomen} - 0.0069449 \cdot \text{BodySurfaceArea}$
4. $\text{Muscle to Stomach Index (MSI)} = \frac{\text{RBicep+LBicep+RCalf+LCalf+RThigh+LThigh}}{\text{MaximumStomach}}$

Equation 3. Regressed formulae for body fat mass using 3D body measurements. Gender = 1 for male, 0 for female. Except for BodySurfaceArea (which is in inches^2), all units are in units of inches of circumference, with right or left designated as L or R; i.e., RBicep=RightBicepCircumference

$$\text{LeanBodyMass} = \text{Weight (kg)} - \text{BodyFatMass}$$

Equation 4. Formula for Lean Body Mass

1. $\text{FitnessIndex} = \frac{\text{MuscleFactor}}{\text{BodyFat\%}}$
2. $\text{MuscleFactor (male)} = \frac{\text{RBicep+Chest+RThigh+RCalf+Seat}}{\text{StomachMax}}$
3. $\text{MuscleFactor (female)} = \frac{\text{RBicep+Chest+RThigh}}{\text{StomachMax}}$

Equation 5. Definition of Size Stream Fitness Index using body measurements. Gender = 1 for male, 0 for female. R and L refer to left and right, all units are circumference in inches.

Although we present only results for Body Fat here, Size Stream currently provides a wide range of body composition metrics that relate to health and fitness. The full list includes Body Fat %, Total Fat Mass (kg), Body Mass Index, Lean Body Index, Fat Mass Index, Waist to Height Ratio, Waist to Hip Ratio, Resting Metabolic Rate (kcal/day), Lean Body Mass (kg), Fitness Index, Bone Mineral Content (pounds), Lean Mass Legs (pounds), Visceral Adipose Tissue (pounds), and Body Surface Area (inches^2).

3. Results

3.1. Performance and Bland-Altman plots

The performance of our mobile phone measurement algorithm for the 209 scans is plotted below (Figure 1A, 1B). The R^2 for Body Fat % and Total Fat Mass were 0.804 and 0.898, respectively, showing a high correspondence with the 4C measures. Multiple scans were taken for many individuals as part of the Texas Tech study, sometimes a few months apart. For this reason, presented numbers include all of these scans separately. However, if multiple scans and 4C body fat measurements are instead averaged together, the performance across the 118 individuals are essentially unchanged, with R^2=0.804, 0.902 for body fat percentage and total fat mass, respectively. The error is fairly consistent over a range of both body fat percentage and total fat mass, as can be seen in the Bland-Altman plots (Figure 1C, 1D). However, both show a slight overprediction at low body fat, and slight underprediction at high body fat. Overall, we find the results to compare favorably with both similar 3D body scanning technologies (Table 2) and bioimpedance scale devices (Table 3).

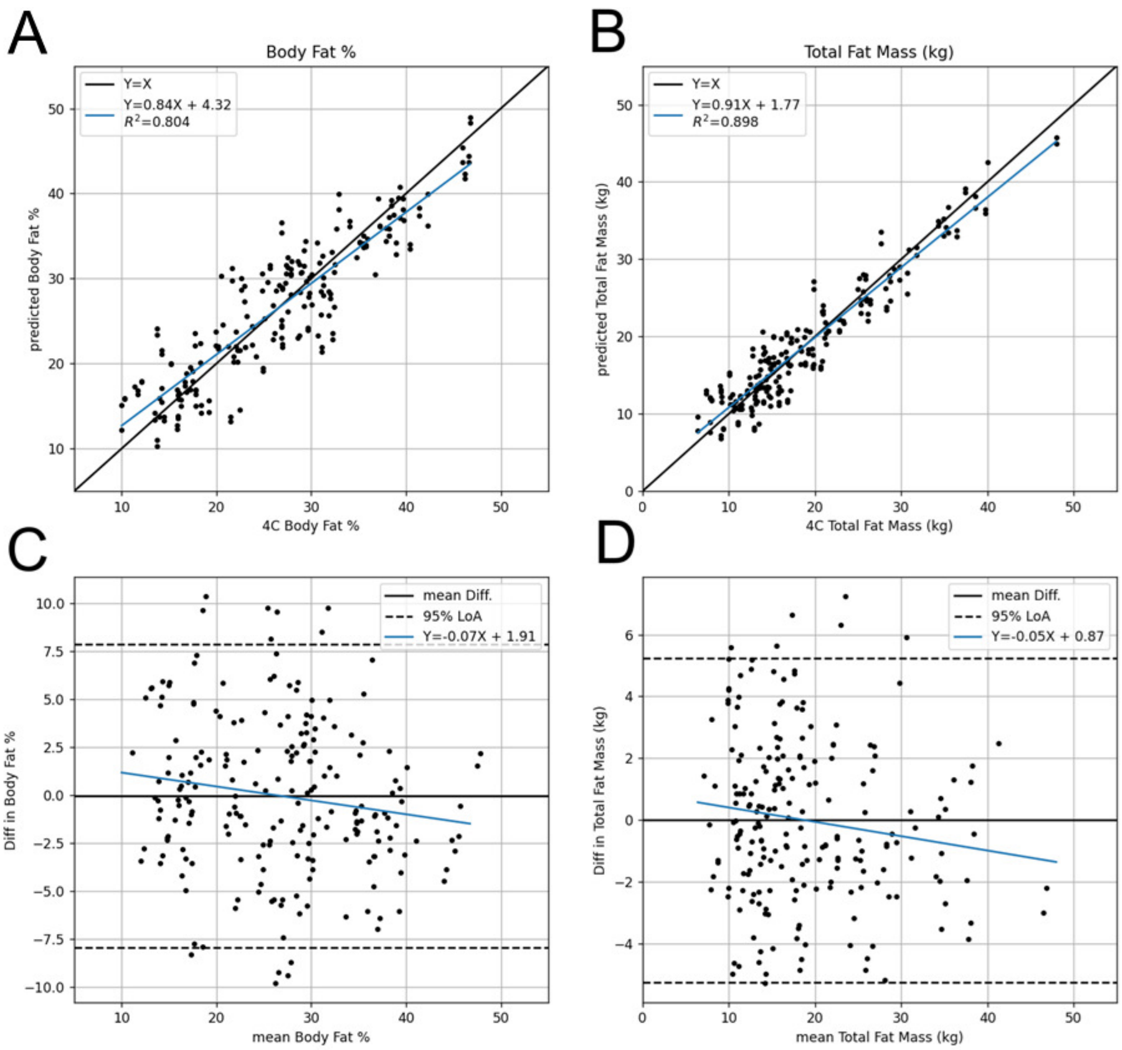

Fig. 1. Performance of the new regressor for Body Fat across 204 mobile phone scans compared to 4C body fat measurement (209 scans, 118 individuals). These predictions reflect the results of a10-fold cross validation scheme, and perform slightly worse than the final regressor (Equation 2).

3.2. Comparison to other 3D body scanning solutions

Through prior efforts at Size Stream with our SS20 optical 3D booth scanners, formulas have been adapted to calculate several body composition metrics from body measurements, including total fat mass [3]. The performance has since been slightly improved internally, and up-to date numbers are presented below (Table 2). We also offer comparison to a similar work which utilizes a 4-photo 3D mobile body scanning solution to predict DXA scan results [5]. Overall, the mobile phone system is roughly comparable to our booth scanner solution, offering an R^2 = 0.804 for body fat % and R^2 = 0.898 for total fat mass compared to 0.82 and 0.91 for our booth scanner, respectively. In addition, the root mean square of error is under 3 kg for total fat mass, and just above 4% for body fat percentage.

Name	Scanner Type	n	Body Fat %				Total Fat Mass (kg)			
			Bias (95%LoA)	RMSE	R	R^2	Bias (95%LoA)	RMSE	R	R^2
Qiao et. al 2024	Mobile phone scan, 4-photo	119	1.62 (-9.2; 12.5)	5.54	0.84	0.71	0.93 (-6.4; 8.3)	3.76	0.91	0.83
Size Stream Mobile	Mobile phone scan, 2-photo	118	-0.02 (-7.9; 7.9)	4.03	0.90	0.80	-0.01 (-5.2; 5.2)	2.67	0.95	0.90
Size Stream SS20	Booth scanner	175	0.15 (-7.1; 7.2)	3.68	0.91	0.82	0.12 (-5.2; 5.4)	2.74	0.95	0.91

Table 2. Comparison to other 3D body scanning solutions. The predictions for Size Stream Mobile reflect the results of a 10-fold cross validation scheme, and perform slightly worse than the final regressor (Equation 2).

3.3. Comparison to bioimpedance devices

Bioimpedance devices offer another simple method to measure body fat percentage. Most similar to our technology in terms of ease of use and cost are the foot-to-foot bioimpedance scales, which additionally offer a simple method to measure body fat percentage at home. We refer to a survey study of these devices for comparison [2], and find our method to be substantially more accurate than a large cohort of 10 foot-to-foot bioimpedance scales. Although we approximately fall in line with the more expensive and difficult to use hand-to-hand and hand-to-foot (octapolar) devices, two of these devices did offer substantially better performance than our solution, one a research-grade medical device (Table 3). We find the constant error to also be quite low; our solution provides the smallest bias of any of the devices in the table.

Name	Scanner Type	Bioimpedance	Body Fat %		
			R^2	CE	SEE
Weight Watchers	Bioimpedance device	Foot-to-foot	0.33	0.90	7.50
HAWANA	Bioimpedance device	Foot-to-foot	0.36	2.90	7.30
RENPHO	Bioimpedance device	Foot-to-foot	0.42	-1.40	7.00
Vitagoods Form Fit	Bioimpedance device	Foot-to-foot	0.45	-1.10	6.80
INEVIFIT	Bioimpedance device	Foot-to-foot	0.47	1.40	6.60
Wyze	Bioimpedance device	Foot-to-foot	0.57	3.60	6.00
Tanita UM-081	Bioimpedance device	Foot-to-foot	0.62	0.60	5.60
Withings Body Cardio	Bioimpedance device	Foot-to-foot	0.62	-0.40	5.60
Tanita BC-554 Ironman	Bioimpedance device	Foot-to-foot	0.62	0.70	5.60
Seca 804	Bioimpedance device	Foot-to-foot	0.75	11.70	4.50
Omron HBF-516	Bioimpedance device	Hand-to-foot (octapolar, consumer grade)	0.78	3.30	4.30
Omron HBF-306	Bioimpedance device	Hand-to-hand	0.80	-3.50	4.10
Size Stream Mobile	Mobile phone 3D scan		0.80	-0.02	4.02
Tanita BC-568 Inner Scan	Bioimpedance device	Hand-to-foot (octapolar, consumer grade)	0.81	-1.40	4.00
InBody H20N	Bioimpedance device	Hand-to-foot (octapolar, consumer grade)	0.88	-0.10	3.10
Seca mBCA 515-514	Bioimpedance device	Hand-to-foot (octapolar, research grade)	0.88	-0.20	3.20

Table 3. Comparison to bioimpedance device technologies for Body Fat %. Shown for comparison are the coefficients of determination ($(R)^2$) for each prediction, as well as the constant error (CE) and standard error of the estimate (SEE). The predictions for Size Stream Mobile reflect the results of a 10-fold cross validation scheme, and perform slightly worse than the final regressor (Equation 2).

4. Discussion

Interest in measuring and tracking body fat percentage, as opposed to more rudimentary measures such as BMI, appears to be growing significantly in recent years. This shift reflects a broader understanding of health and fitness, emphasizing the importance of body composition. In addition, smartwatches and other advanced devices have showcased the clear utility of technology in continual monitoring of more advanced fitness and health metrics, making it easier for individuals to stay informed about their body. Finally, the rising popularity of weight loss medications underscores the importance of accurately measuring and monitoring body fat, creating a compelling use case for more precise methods.

Although accurate body fat measurement has been historically locked behind expensive and cumbersome technologies, recent advances in bioimpedance measurement devices have provided a more convenient method to measure at home. 3D body measurement may be a next step in this progression, as it allows for the accuracy of the higher-quality bioimpedance devices with an arguably more simple and accessible process; a quick scan that requires only your mobile phone's camera.

In this paper, we have shown that the accuracy of our mobile scanning technology is approaching the accuracy of Size Stream's larger booth scanning systems to provide an array of body composition metrics. In addition, we find the technology to be substantially more accurate than several bioimpedance scales, rivaling the accuracy of some of the more sophisticated devices. With continued work at Size Stream and with our partners we hope to continue improving the performance to acquire even more accurate measurements.

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