3D Optical Body Composition Accuracy across Subgroups of Age, BMI, and Race/Ethnicity

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https://doi.org/10.15221/21.36

Background

Body composition offers important information about health from an individual and population perspective. Body composition consists of whole-body and regional fat and lean mass distributions that are associated with health outcomes [1]. Common body composition modalities include dual-energy X-ray absorptiometry (DXA), bioelectrical impedance analysis (BIA), and air displacement plethysmography (ADP). Although these modalities are commonly accepted in clinical and research settings, they are not without set-backs. DXA uses ionizing radiation, which may limit repeated measures given a certain amount of time. BIA is one of the more accessible technologies, but the accuracy varies depending on the type of device and physiological conditions (i.e., skin moisture, standing, sitting, hydration) [2]. Lastly, ADP is also limited by accessibility and does not report regional body composition values.

Three-dimensional optical (3DO) body scanning is emerging as an alternative for health assessments. The growing 3DO scanner market has made its way into fitness centers, research settings, and homes. Moreover, the technology is becoming more prominent as it can be found in smart phones and video game consoles. Studies have used 3DO imaging to build body composition models from 3DO body shape, which correlate strongly with criterion methods like dual-energy X-ray absorptiometry (DXA) in highly diverse sample sets [3-5]. Although the models were derived on a diverse sample, it is unknown if the accuracy is consistent across different demographic subgroups of interest. Therefore, the objective of this study was to evaluate the accuracy of our 3DO body composition models by age group, body mass index (BMI), and ethnicity.

Methods

Participants were recruited from the Shape Up! Adults, FB4, and Louisiana State University Athlete's Studies. BMI categories included underweight, normal, overweight, and obese. Race/ethnic groups included White, Black, Hispanic, Asian, and Native Hawaiian and other Pacific Islanders (NHOPI). Each participant received whole-body 3DO and DXA scans on a Fit3D Proscanner (Fit3D Inc., San Mateo, CA, USA) and Hologic Horizon/A or Discovery/A system (Hologic Inc., Marlborough, MA, USA), respectively. 3DO scans were templated with a 110,000-vertex mesh for standardization and reposed through Meshcapade (Meshcapade GmbH, Tubingen, Germany) [6]. Principal component (PC) analysis was performed on the 3DO scans to reduce the dimensionality of the data to explain 95% of the shape variance with three PCs. These PCs were used to create whole-body fat and lean models as well as visceral adipose tissue (VAT) using stepwise forward linear regression with five-fold cross-validation [3]. 3DO body composition estimates were subtracted from DXA measures to obtain the difference. Students *t*-test of the differences in each subgroup were considered significant if the P-value was < 0.05. Percent (%) mean differences were categorized low (< 2%), moderate (2-5%), and large (>5%).

Results

In total, 723 participants aged 18-89 years were included in this study (381 females). The mean age was 47 and 44 years for females and males, respectively. Female and male total fat mass achieved a coefficient of determination (R^2) of 0.95 and 0.94 and a root mean square error (RMSE) of 2.74 kg and 3.01 kg, respectively. For age groups, significant differences were identified for young female VAT (-12.3%); senior male total fat mass (-4.4%), total lean mass (1.5%), and percent fat (-1.1%); young males VAT (-7%); and middle-aged male VAT (4.9%). For BMI categories, there were significant differences in underweight female total fat mass (6.8%), total lean mass (-2.2%), percent fat (2.1%); and underweight male VAT (-24%). In the racial/ethnic categories, there were significant differences for Asian female total fat mass (2.9%), total lean mass (-1.3%), and percent fat (1.4%); black female total fat mass (-2.6%), total lean mass (1.5%), and percent fat (-0.99%); NHOPI female total fat mass (-4.8%), total lean mass (2.6%), and percent fat (-2%); and NHOPI male total fat mass (9.3%), total lean mass (2.8%), and percent fat (-2.4%). Of these significant findings, four were categorized with having low differences, nine had moderate differences, and four had large differences.

Conclusion

3DO assessment appears to be comparable to DXA measures not only on the population level but also in most age, BMI, and racial/ethnic subgroups. Even though there were some differences, 3DO and DXA body composition are highly correlated to each other, which makes 3DO a viable method for body composition. Most significant differences were moderate with <5% difference. All large significant differences were in the underweight and NHOPI groups and can be attested to underrepresentation in the sample. Using this overall model will provide accurate results with respect to DXA, but these two subgroups may need specific calibration. Additional demographic adjustments are warranted to help alleviate potential bias that may be causing the observed differences.

References

[1] J. Wells and M. Fewtrell, "Measuring body composition," *Archives of disease in childhood,* vol. 91, no. 7, pp. 612-617, 2006. http://dx.doi.org/10.1136/adc.2005.085522.

[2] N. Achamrah *et al.*, "Comparison of body composition assessment by DXA and BIA according to the body mass index: A retrospective study on 3655 measures," *PloS one,* vol. 13, no. 7, p. e0200465, 2018. https://doi.org/10.1371/journal.pone.0200465.

[3] B. K. Ng *et al.*, "Detailed 3-dimensional body shape features predict body composition, blood metabolites, and functional strength: the Shape Up! studies," *The American journal of clinical nutrition,* 2019. https://doi.org/10.1093/ajcn/nqz218.

[4] I. Y. Tian *et al.*, "Predicting 3D Body Shape and Body Composition from Conventional 2D Photography," *Medical Physics,* 2020. https://doi.org/10.1002/mp.14492.

[5] M. C. Wong *et al.*, "Children and Adolescents' Anthropometrics Body Composition from 3-D Optical Surface Scans," *Obesity,* vol. 27, no. 11, pp. 1738-1749, 2019. https://doi.org/10.1002/oby.22637.

[6] M. C. Wong *et al.*, "A pose-independent method for accurate and precise body composition from 3D optical scans," *Obesity (Silver Spring, Md.).* https://doi.org/10.1002/oby.23256.

[7] M. Loper, N. Mahmood, J. Romero, G. Pons-Moll, and M. J. Black, "SMPL: A skinned multi-person linear model," *ACM transactions on graphics (TOG),* vol. 34, no. 6, p. 248, 2015. https://doi.org/10.1145/2816795.2818013.