Evaluating the Accuracy of an Hallucinatory Algorithm to Predict Body Shape Changes from Dieting and Physical Activity

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Background

Accurate renderings of the human body can be generated from 3-dimensional optical (3DO) scanning systems. Commercial devices are readily available at fitness centers around the world, and personal computers can visualize the renderings using readily available software. The most common way these scans are used is to generate automated anthropometry such as circumferences and volumes of arms, legs and trunk. Moreover, our research group and others have shown how accurate estimates of body composition can be estimated using these anthropometry measures (1) (2). Previous work in our group has shown that we can accurately estimate body composition from 3DO by associating the variance in the scan meshes to fat and lean masses by transforming the scans meshes from real space to a principal component space. This has the benefit of reducing the variance into a small number of components that are conducive for including in predictive equations.

Visualizing body shape at some future time point can also be useful in a variety of ways including motivational support for health interventions where fat and muscle mass changes are anticipated to create positive body image reinforcement. Although there are a variety of "hallucinatory" algorithms available, most, if not all, are created using cross-sectional population modeling or non-data driven bloating/shrinking artistic approaches.

In this paper, we explored the accuracy of hallucinated future body shapes from baseline 3DO scans and the expected, or desired, changes in body fat and lean masses. We apply our approach to a curated sample of individuals who completed dietary or physical activity interventions as part of clinical studies. Both body composition and 3DO scans were acquired at baseline and at the end of the intervention.

Methods

Participants were recruited as having participated in one of three interventional studies: a time-restricted eating study (TREAT, (3)), a 10-week dietary intervention study (FB4,(4)), 16-week exercise intervention in older adults study (REALPA,(5)). Hallucinated predictive 3DO scans were created using the observed changes in DXA fat and lean mass, and the hallucinated scans were compared to the actual end of study scans. In all studies, participants received similar 3DO and DXA scans at baseline and at the end of intervention.

Whole Body 3DO Scanning

Each participant underwent 3DO whole-body surface scans on a Fit3D ProScanner (Fit3D, Inc). Participants followed a standard positioning protocol and wore skin-tight undergarments to minimize the effects of clothing on observed body shape. The ProScanner uses light-coding depth sensors to capture 3D shape as the participant rotates 360◦ on the scanner platform. Each scan took approximately 40 seconds to complete. The iterative closest point algorithm was used to spatially align point clouds captured by the sensor as the participant rotated (14). The final point cloud was converted to a triangle mesh with approximately 300,000 vertices and 900,000 faces representing the human body shape. The 3DO scans were co-registered to a standard 110,000-point mesh (Meshcapade GmbH, Tubingen, Germany). After registration, Principal Component Analysis (PCA) was performed to produce a statistical shape model that captured >95% of shape variation in the template space with only a small number of PCs (2). We will refer to this PC space as the **Shape Model PCA**. Each detailed 3DO body scan could then be represented in the 3DO PC space as a short vector of weights.

DXA scans

*P*articipants underwent a whole-body DXA scans, on either Hologic Horizon/A or Discovery/A systems according to the manufacturer's guidelines (Hologic, Inc, Marlborough, MA). Body composition measurements from DXA included total and regional (trunk, arms, legs) fat mass, bone mineral content, and lean mass.

Hallucinatory Prediction Scans

Allen et al. (6) extended the original work by Blanz and Vetter (7) to relate several variables simultaneously by learning a linear mapping between the controls and the PCA weights. If we have l such controls, the mapping can be represented as a (k-1) x (l+1) matrix, M:

$$\mathbf{M}[f_1 \dots f_l \; 1]^{\mathrm{T}} = \mathbf{p}$$

where *fi* are the feature values of an individual, and **p** are the corresponding PCA weights. We can draw feature information from the demographic data associated with 3DO scans. After assembling the feature vectors into an (l+1) k feature matrix F, we solve for M as

$$\mathbf{M} = \mathbf{P}\mathbf{F}^{+}$$

where $\mathbf{F}^{+}$ is the pseudoinverse of **F**. We can then create a new feature vector, e.g., the desired fat and lean mass for a given age, and create an average individual with those characteristics. In addition, we can create delta-feature vectors of the form:

$$\mathbf{\Delta f} = [\Delta f_1 \dots \Delta f_l \; 0]^{\mathrm{T}}$$

where each Δf_i is the difference between a target feature value and the actual feature value for an individual. By adding $\Delta\mathbf{p} = \mathbf{M}\Delta\mathbf{f}$ to the PCA weights of that individual, we can edit their features, e.g., making them gain or lose weight, become taller or shorter, or change their fat and lean masses. This was done for one of the authors and is shown in Figure 1, where the center scan is the actual scan, and the other representations are hallucinations for different fat and lean masses.

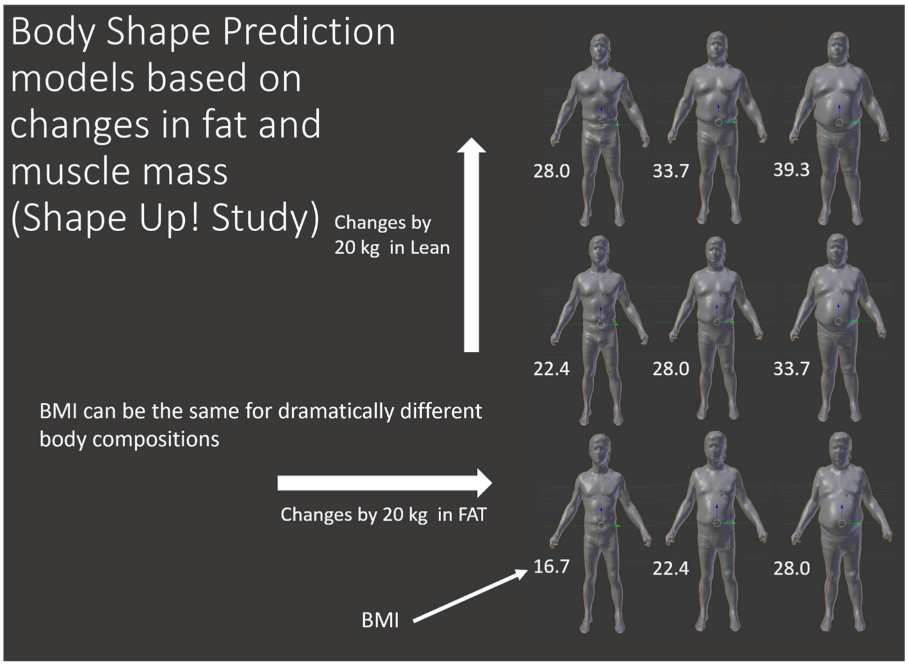

Figure 1. Hallucinated scans of one male. Actual scan is in the middle.
The numbers shown for each image is the target

Statistical Analysis

Hallucinated prediction scans were created from all baseline 3DO scans using changes in fat mass, lean mass, and age. The prediction scans were subtracted from the actual follow-up 3DO scan creating an error vector for each mesh point. Thus, each participant had a difference map for each of the 110,000 mesh points. These difference maps were then transformed into a PC space to reduce dimensionality and to describe the modes of error observed. The **Mesh Error PCA** modes were compared to participant demographics and body composition characteristics to explore reasons for the errors using linear regression techniques.

Results

There were 377 adults (167 male) in our shape model (from Ng et al. (2)) and 106 participants (67 male) in our intervention dataset. Their general description is found in Table 1. The Shape Model PCA had 99% of the shape variance described in the first 15 PCs.

Table 1. Participants descriptions at their initial and final visits.

	Visit 1		Visit 2	
	Female (N=39)	**Male (N=67)**	**Female (N=39)**	**Male (N=67)**
Age				
Mean (SD)	46.2 (13.8)	37.5 (12.4)	46.4 (13.8)	37.7 (12.4)
Median [Min, Max]	45.9 [24.0, 76.7]	34.8 [19.0, 70.5]	46.2 [24.4, 77.1]	35.1 [19.3, 70.9]
Ethnicity		10 (14.9%)		
Asian	3 (7.7%)	2 (3.0%)	3 (7.7%)	10 (14.9%)
Black	7 (17.9%)	5 (7.5%)	7 (17.9%)	2 (3.0%)
Hispanic	6 (15.4%)	0 (0%)	6 (15.4%)	5 (7.5%)
White	23 (59.0%)	50 (74.6%)	23 (59.0%)	50 (74.6%)
Height (cm)				
Mean (SD)	165 (7.24)	177 (6.86)	165 (7.22)	177 (6.97)
Median [Min, Max]	164 [149, 185]	177 [162, 194]	164 [149, 185]	177 [162, 194]
Weight (kg)				
Mean (SD)	88.8 (15.9)	103 (17.8)	82.5 (12.8)	93.0 (17.6)
Median [Min, Max]	83.5 [64.0, 134]	100 [70.2, 169]	81.7 [63.0, 116]	88.5 [64.8, 175]
Body Mass Index				
Mean (SD)	32.5 (5.52)	33.6 (8.42)	30.3 (4.49)	29.8 (5.57)
Median [Min, Max]	31.4 [24.2, 50.3]	31.2 [23.7, 82.1]	30.0 [23.8, 43.7]	28.8 [22.2, 57.3]

Figure 2 is an example of a female and male participant's 3DO follow-up scans with the heat map showing the mesh errors in the hallucinated prediction scans based on their individual fat and lean changes. For the participants who underwent the interventions, the Mesh Error PCA space took 17 PCs (females) and 20 PCs (males) to describe 95% of the difference (error) variance. Table 2 and Table 3 show the correlation of each Mesh Error PC values to selected body composition and demographic variables for female and male respectively. Even though age was included in the predicted mesh, it remained highly significant for both females and males. Further, PC6 in females and PC4 in males were highly significant to many adiposity measures. Least square means with Tukey adjustments were used to evaluate if there were differences in the Mesh Error PCA values by study. We found that there were no significant error Mesh error differences between studies for Total Fat, Total Lean, percent fat, visceral adipose tissue (VAT), height or weight. However, there were unique Mesh Error PCA differences by age (TREAT vs. REALPA, $p < 10^{-5}$; FB4 vs. REALPA, $p < 10^{-7}$).

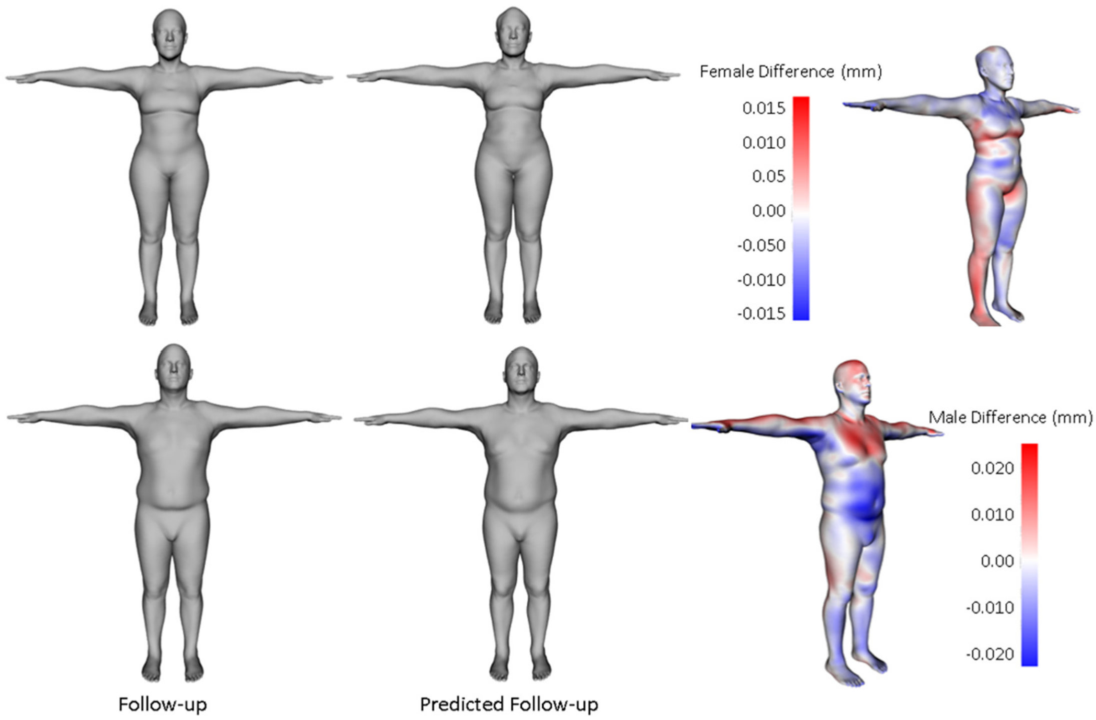

Figure 2. Example difference images of the actual follow-up scan and the hallucinated prediction scan of a male and female participant after undergoing a time restricted eating intervention. The man gained 2 kg total fat and lost 2 kg total lean. The woman gained 05 kg total lean and no difference in total fat.

Table 2. Correlations (r) of female participant descriptors and the Mesh Error PCA values (hallucinated predicted - actual follow-up). Only PC value columns and values are shown that have some statistically significant correlations out to PC 20.

	PC1	**PC4**	**PC5**	**PC6**	**PC7**	**PC10**	**PC14**	**PC16**
Age	-0.46**				0.33*			
Height								
Weight				0.38*				
BMI				0.48*				
Total Fat				0.42**				0.32*
Total Lean								
Percent Fat		-0.40*						
Visceral Fat (VAT)								
Waist Circumference				0.38*				
Hip Circumference			0.36*					
Waist to Hip Ratio				0.35*			-0.44**	
Bicep Circvumference				0.35*		-0.37*		
MidThigh Circumferenc							0.32*	

** P < 0.05, ** P < 0.01*

Table 3. Correlations (r) of male participant descriptors and the Mesh Error PCA values (hallucinated predicted - actual follow-up). Only PC value columns and values are shown that have some statistically significant correlations out to PC 17.

	PC1	PC3	PC4	PC5	PC6	PC7	PC8	PC10	PC12	PC15	PC16
Age	-0.54****			-0.25*							
Height							-0.34*	0.30*			
Weight			0.42***								-0.29*
BMI			0.42**						-0.32*		
Total Fat			0.51****			-0.36**			-0.27*		
Total Lean		-0.29*	0.27*							-0.30*	-0.35**
Percent Fat			0.43***			-0.36**					
Visceral Fat (VAT)	-0.31*		0.32**	-0.28*							
Waist Circumference			0.47****			-0.30*			-0.26*		
Hip Circumference			0.39**								-0.28*
Waist to Hip Ratio			0.30*		0.29*						
Bicep Circvumference	-0.26*		0.38**								-0.46****
MidThigh Circumference	-0.41***									-0.28*	-0.38**

** $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$, **** $P < 10^{-4}$*

Discussion and Conclusion

We present both a method to visualize predicted body shapes due to changes in body composition and a means of evaluating the accuracy of the predictions compared to actual body shapes in individuals that have undergone a variety of dietary and physical activity interventions. We modeled the change in body shape based on a model created with cross-sectional data only. We found that although the predicted and actual images are visually similar to each other, there are systematic errors in the prediction associated with age and many of the body composition variables. A better understanding of these biases will allow us to improve our visualizations further. We also found that these prediction errors were not unique between the three interventional studies except for the errors associated with age. REALPA was unique in its errors in predicted body shape with age. REALPA was the only study exclusively in older adults. This required further examination as well.

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References

1. Wong MC, Ng BK, Kennedy SF, Hwaung P, Liu EY, Kelly NN, Pagano IS, Garber AK, Chow DC, Heymsfield SB. Children and adolescents' anthropometrics body composition from 3-D optical surface scans. Obesity. 2019;27(11):1738-49.
2. Ng BK, Sommer MJ, Wong MC, Pagano I, Nie Y, Fan B, Kennedy S, Bourgeois B, Kelly N, Liu YE. 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;110(6):1316-26.
3. Lowe DA, Wu N, Rohdin-Bibby L, Moore AH, Kelly N, Liu YE, Philip E, Vittinghoff E, Heymsfield SB, Olgin JE. Effects of time-restricted eating on weight loss and other metabolic parameters in women and men with overweight and obesity: the TREAT randomized clinical trial. JAMA internal medicine. 2020;180(11):1491-9.
4. Dickinson S, Mehta T, Ebbeling C, Allison D, Ludwig DS. Macronutrients and body fat accumulation: A mechanisic feeding study. Open Science Framework. 2018.

5. Resistance Exercise and Low-Intensity Physical Activity Breaks in Sedentary Time to Improve Muscle and Cardiometabolic Health (REALPA): clinicaltrails.gov; 2021 [cited 2021 10-10-21]. Available from: https://clinicaltrials.gov/ct2/show/NCT03771417.
6. Allen B, Curless B, Popović Z, editors. The space of human body shapes: reconstruction and parameterization from range scans. ACM transactions on graphics (TOG); 2003: ACM.
7. Blanz V, Vetter T, editors. A morphable model for the synthesis of 3D faces. Proceedings of the 26th annual conference on Computer graphics and interactive techniques; 1999.