Accurate body composition measures from whole-body silhouettes

Bowen Xie,^{a)} Jesus I. Avila,^{a)} Bennett K. Ng, and Bo Fan
*Department of Radiology and Biomedical Imaging, University of California,
San Francisco, California 94115-0628*

Victoria Loo
Department of Political Science, Yale University, New Haven, Connecticut CT 06520-8301

Vicente Gilsanz
Children's Hospital Los Angeles, Los Angeles, California CA 90027

Thomas Hangartner
*Department of Biomedical, Industrial, & Human Factors Engineering, Wright State University,
Dayton, Ohio OH 45435*

Heidi J. Kalkwarf
Cincinnati Children's Hospital Medical Center, Cincinnati, Ohio OH 45229

Joan Lappe
Department of Endocrinology, Creighton University, Omaha, Nebraska NE 68131

Sharon Oberfield
Department of Pediatrics, Columbia University, New York, New York NY 10032

Karen Winer
*The Eunice Kennedy Shriver National Institute of Child Health and Human Development,
Bethesda, Maryland MD 20892-7510*

Babette Zemel
Children's Hospital of Philadelphia, Philadelphia, Pennsylvania PA 19104

John A. Shepherd^{b)}
*Department of Radiology and Biomedical Imaging, University of California,
San Francisco, California 94115-0628*

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Purpose: Obesity and its consequences, such as diabetes, are global health issues that burden about 171×10^6 adult individuals worldwide. Fat mass index (FMI, kg/m^2), fat-free mass index (FFMI, kg/m^2), and percent fat mass may be useful to evaluate under- and overnutrition and muscle development in a clinical or research environment. This proof-of-concept study tested whether frontal whole-body silhouettes could be used to accurately measure body composition parameters using active shape modeling (ASM) techniques.

Methods: Binary shape images (silhouettes) were generated from the skin outline of dual-energy x-ray absorptiometry (DXA) whole-body scans of 200 healthy children of ages from 6 to 16 yr. The silhouette shape variation from the average was described using an ASM, which computed principal components for unique modes of shape. Predictive models were derived from the modes for FMI, FFMI, and percent fat using stepwise linear regression. The models were compared to simple models using demographics alone [age, sex, height, weight, and body mass index z-scores (BMIZ)].

Results: The authors found that 95% of the shape variation of the sampled population could be explained using 26 modes. In most cases, the body composition variables could be predicted similarly between demographics-only and shape-only models. However, the combination of shape with demographics improved all estimates of boys and girls compared to the demographics-only model. The best prediction models for FMI, FFMI, and percent fat agreed with the actual measures with R^2 adj. (the coefficient of determination adjusted for the number of parameters used in the model equation) values of 0.86, 0.95, and 0.75 for boys and 0.90, 0.89, and 0.69 for girls, respectively.

Conclusions: Whole-body silhouettes in children may be useful to derive estimates of body composition including FMI, FFMI, and percent fat. These results support the feasibility of measuring body composition variables from simple cameras such as those found in cell phones. © 2015 American Association of Physicists in Medicine. [<http://dx.doi.org/10.1118/1.4926557>]

Key words: silhouettes, body composition, dual-energy x-ray, absorptiometry, active shape modeling

NOMENCLATURE

DXA	Dual-Energy X-ray Absorptiometry
FMI	Fat Mass Index
FFMI	Fat-Free Mass Index

1. INTRODUCTION

With the globalization of high-caloric foods, the rate of obesity in children of developing regions such as Southeast Asia and China has increased from 2% to 10% over the last 20 yr.¹ In many developing countries, there is a dual burden of malnutrition, where under- and overnutrition occurs simultaneously.² Body mass index (BMI) is often used as a measure of under- and overnutrition since it describes the body weight relative to height and it can be measured with little or no cost. Studies have shown that increased BMI is associated with increased risk for diabetes³ and metabolic syndrome;⁴ however, because BMI is only a measure of overall insufficient or excess weight, it does not discern the relative amounts of fat and lean masses.^{5–7} For example, there can be a twofold variation in fat mass for a given BMI in children.^{8,9} Furthermore, the distribution of fat changes in children and adolescents throughout their development, and BMI cannot directly monitor these changes.⁹ The relationship of BMI to percent body fat changes as a function of age and sex.¹⁰ Must and Anderson have suggested using BMI z-scores (BMIZ) instead of BMI to represent what is normal for BMI as a function of age and sex trends,¹¹ and BMIZ is commonly reported instead of BMI in pediatric studies.

Unlike BMI and BMIZ, the fat mass index (FMI, kg/m²) and fat-free mass index (FFMI, kg/m²) describe body mass in terms of fat and lean masses independently. FMI is a significant determinant of diabetes type and overcomes the limitation of BMI and BMIZ not directly measuring fat and lean masses.¹² FFMI is associated with strength and muscle mass and is used in sarcopenia prediction models.¹³

To measure FMI and FFMI, total body mass must be subdivided into fat and fat-free masses. Previous approaches to measuring FMI and FFMI include bioelectrical impedance analysis (BIA),^{14,15} underwater weighing,¹⁶ air-displacement plethysmography,¹⁷ deuterium dilution,^{18,19} and dual-energy x-ray absorptiometry (DXA).^{20–22} Of these, DXA is considered a reference method because few assumptions are made in its determination of fat and lean masses. DXA is not widely used to characterize body composition in large populations or in a clinical setting because the technique is typically more costly than other body composition methods and it uses ionizing radiation.¹⁶ However, all of the techniques listed require measurement devices that range from thousands to tens of thousands of dollars, making FMI and FFMI impractical in low-resource environments.

An alternative approach is to quantify fat and lean masses using anthropomorphic body shape measures of either skinfold thicknesses or body circumferences. Body shape measures including waist, hip, and thigh circumferences, as well as sagittal abdominal diameter, are already used in epidemiological studies for their high association with diabetes²³ and meta-

bolic syndrome.^{24–27} In adult models of metabolic syndrome, BMI loses its predictive power when waist circumference is added to the model.²⁸ Skinfold thicknesses provide an estimate of subcutaneous fat thickness by measuring the thickness of pinched (doubled over) skin, but models of whole body percent body fat derived from skinfold thickness are not accurate compared to more direct methods like DXA.²⁹

In this study, we propose that the silhouette of a person is a reasonable representation of overall body shape, and that shape can be used to estimate fat and lean body masses. Silhouettes, or shadow images that represent the outline of objects, have the advantage of being easily created with minimal processing using low-resolution cameras, which are now ubiquitous. For a proof-of-concept, we created silhouettes from an existing DXA whole-body dataset of a large cohort of children. This approach allows for testing the silhouette imaging concept and its accuracy to DXA before recruiting a large population of children to have new DXA and optical scans. Here, we present a method to derive fat and fat-free indices from silhouettes and show their agreement with the true indices acquired using whole-body DXA scans.

2. MATERIALS AND METHODS

This study is an *in vivo*, cross-sectional, comparative study using a convenience sample; the sample population of children varies in age, BMIZ, and sex.

2.A. Participants

The participants were recruited as part of the bone mineral density in children study (BMDCS). BMDCS was a prospective cohort study of 1554 children of mixed ethnicity ranging in age from 5 to 16 yr. Begun in 2002 and sponsored by the National Institute for Children's Health and Diseases (NICHD), BMDCS was designed to study the bone health of healthy children as they aged over a 6-yr period. The scans used in the present study were the baseline scans from five different locations in the United States from July 2002 to November 2003.²⁰ The selection criteria for the children were defined by the BMDCS through telephone questionnaires and physical examination. A complete description of recruitment and the study have been published.²⁰ Two hundred children (100 male) were selected to represent a wide range of body shapes and demographic descriptors. Weights were measured on digital scales, and heights were measured using stadiometers. All measures including DXA were acquired while the participants were dressed in examination gowns without shoes. BMIZ for each participant was calculated using growth charts from the Centers for Disease Control and Prevention.³⁰ Our selection criteria was to choose the extremes (low and high values) for age, height, and weight from both sexes, then use a random selection criteria for the remaining individuals.

2.B. DXA acquisition

Our selected children were scanned on one of four Hologic Discovery/A systems (Hologic, Inc., Bedford, MA). A

fifth BMDCS study site was not used in our pilot because the children were scanned on a Hologic Discovery/W. The DXA scans created using the Discovery/W have a slightly different projection of the body due to differences in the fan-beam geometry compared to the Discovery/A. All scans were centrally analyzed at the University of California, San Francisco using Hologic APEX 3.0 software. FMI and FFMI were derived from the total body fat and lean masses as follows: $FMI = \text{fatmass}/\text{height}^2$ and $FFMI = (\text{leansofttissuemass} + BMC)/\text{height}^2$. Note that $BMI = FMI + FFMI$ using this definition. Participants were centered on the scanner table with their arms out to the side and feet pointed downward, which followed the manufacturer's standard scan and positioning protocols.³¹ Further details of the acquisition and analysis procedures are described elsewhere.²⁰

2.C. Silhouette images

In-house algorithms written in MATLAB (MathWorks Inc.) were used to extract high-energy x-ray attenuation images from raw DXA image files.³² All pixels above a threshold value defined the silhouette and set to "1." All pixels with values below the threshold were set to "0" (see Fig. 1). Linear spatial transformations (translation and rotation) were then used to align all images to each other. Images were then cropped above the head to remove unused pixels and at the ankles to remove the variance of the position of the feet. Due to the standardized geometry of DXA device, pixel dimensions were identical across all patients. Quality control was performed

on the silhouettes by manually reviewing each and checking for abnormalities in the body positioning that was markedly different from the standard DXA positioning.

2.D. Active shape modeling (ASM)

We built a 50-point ASM to describe body shape,³³ see Fig. 2. The selection criteria for the 50 points were as follows: (a) points were placed on vertices along the body outline (inseam, underarms, elbows, etc.), (b) additional 3-point sets were used to capture major body contours (thighs, shoulders, neck, etc.) defining the start, apex, and end of the contour, and (c) point locations were picked that were easily visualized such that their placement was accurate and precise across the sample. The 50 points chosen were considered to be the minimum number of points that satisfied these criteria, but an alternative number of points were not tested at this time. The ASM of the silhouettes was built using the active shape modeling toolkit (Visual Automation Limited, Manchester, U.K.), a software program that generates image parameters based on principal component analysis of fiducial markers on images, the details of which can be found in Gregory *et al.*³⁴ and Cootes *et al.*³³ In brief, the 50 points were manually placed on the first few images. Then, the software used these initial placements to build a limited ASM. With this limited ASM, the software predicted the placement of the points in subsequent images. All points were manually reviewed and adjusted as necessary. This process was repeated, i.e., initial placement by the limited ASM, manual inspection, then the rebuilding of the ASM, for

FIG. 1. (left) Image of the high energy attenuation portion of the DXA scan. Bone and the density of soft tissue can clearly be distinguished as shades of gray. (right) Silhouette representation of the same DXA image.

Fig. 2. Delineation of 50 points of interest on silhouettes for active shape modeling.

every 10 images analyzed until all of the images were added to the model.

From the dataset formed from the point positions of all 50 points on all images, modes of variation were generated using principal component analysis. The result was a model that described the unique modes of variation in the form of a set of eigenvectors (i.e., modes of variation) where each successive eigenvector explains less of the variation than the previous. By combining the average point placements with the linear combinations of the eigenvector basis, the location of the fiducial markers for any particular image can be generated. The coefficients that are used in the linear combination (i.e., how much each eigenvector is scaled) are the output parameters of each image. These output parameters were used for statistical analysis. It is convenient to visualize principal components in this context by generating series of shape images in which a single principal component is varied while all others are held fixed at their average value. Such images are shown in Fig. 3. In each row, the middle image is the overall “average shape” generated from the test data set. Extreme images are generated by varying the principal component of interest to its +3 and -3 standard deviation values and combining with the average image. These extreme images are shown on the left and right of the average image. For example, it is readily apparent that PCA mode 1 (pc1) captures shape information related to body width and height.

2.E. Statistics

All statistics were performed in SAS version 9.3 (SAS Institute, Cary, NC). The BMDCS study population was separated into two groups by sex. FFMI was defined as $\text{Lean soft tissue mass} + \text{BMC}/\text{height}^2 \text{ kg/m}^2$, where BMC = bone mineral content, FMI was defined as $\text{Fat mass}/\text{height}^2 \text{ kg/m}^2$, and percent fat was defined as $\text{Fat mass}/\text{total mass} * 100$. Note that $\text{BMI} = \text{FMI} + \text{FFMI}$ using these definitions. The ASM parameters of each silhouette (i.e., the coefficients of the eigenvector basis) were placed in a matrix, with each column corresponding to the principal component number and each row the silhouette number corresponding to each of the children. Limiting our analysis to the components needed to describe 95% of the image variation, stepwise linear regression with n -fold (leave-one-out) cross-validation (GLMSELECT procedure in SAS) was used to generate a predictive model for FFMI, FMI, and percent body fat. Separate model equations were made from both PCA components and demographic variables. A cross-validation stop criterion was defined on the Schwarz Bayesian criterion (SBC). Statistical significance was defined as the $p < 0.05$ threshold. The final models for FFMI, FMI, and percent body fat were generated using three different approaches. As a reference point, we first derive prediction equations using demographic variables only (age, sex, height, weight, and BMIZ). We compared these to equations derived using principal components only. Finally, we combined principal components and demographic variables.

3. RESULTS

In a total of 200 participants, 11 were excluded during quality control for reasons including movement and poor positioning. Of the remaining 189 participants, 93 were male. The children were mainly white (112) but also include Asian (8), Hispanic (24), and black (45). Summary statistics about the selected test population are provided on Table I. Twenty-six principal components were required to explain 95% of the variance in silhouette shapes. All subsequent analysis was limited to these 26 components. Table II shows the correlations between the principal components, demographic, and adiposity measures. Several of the components (e.g., pc0, pc1, and pc5) showed significant correlation with multiple demographic and adiposity variables. Additionally, a few components (e.g., pc9) were not found to be significantly correlated with any demographic or adiposity variables. It can be seen in Fig. 3 that pc9 appears to capture a variance in positioning of the left shoulder, a “tilt” along the longitudinal-axis, irrelevant to our analyses. Other patient positioning artifacts such as arm and leg abduction/adduction can be observed in several of the other principal components.

The body composition prediction equations for boys and girls are shown in Tables III and IV, respectively. In general, the demographic information only had a modest ability to predict percent body fat in boys and girls ($R^2 = 0.457$ and 0.61, respectively.) Using only principal components to predict %fat was also modestly correlated (0.73 and 0.59,

FIG. 3. Silhouette representations of the first 10 (i.e., 0–9) modes used to model FFMI in both boys and girls. The average silhouette is shown in the middle and the silhouettes representing –3SD (left) and +3SD (right) are also shown.

respectively.) For %fat, a combination of demographics and principal components created the best models (0.75 and 0.69, respectively). For the boys, the equation (omitted) for %fat (PCA + demo) included two additional PC terms (PC3 and 13) but no demographic variables. These coefficients remained due

to the progression of the stepwise selection algorithm and were interpreted as artifacts.
For all measures of FFMI, FMI, and percent body fat, the combination of principal components with demographics performed equally or better than either principal components

TABLE I. Summary statistics of the test population separated by sex.

Demographic variable	Girls (<i>n</i> = 96)				Boys (<i>n</i> = 93)			
	Mean	Standard deviation	Min	Max	Mean (SD)	Standard deviation	Min	Max
Age (yr)	10.3	3	6	16	10.5	3.2	6	16
Height (cm)	141.2	15.5	108	173	144.6	19.3	111	185
Weight (kg)	38.9	14.9	17.2	81.8	40.9	17.7	18.1	87.4
BMI (kg/m ²)	18.8	3.8	13.3	30.1	18.6	3.5	13.7	28.8
BMIZ	0.4	0.9	-1.8	1.9	0.3	1	-2	1.9
FMI (kg/m ²)	5	2.1	2.1	10.4	3.9	1.7	1.7	10
FFMI (kg/m ²)	13.3	2.1	10.4	20.3	14.2	2.6	10.5	21.6
Percent body fat	25.5	6.1	14.3	39.3	20.4	6	9.7	38.1

alone or demographics alone. No conclusion can be drawn whether the principal components alone fair better or worse than the demographics alone. They performed about equally well for %fat and FMI in girls (Table IV) but the principal component alone model performed better for %fat and FMI in boys (Table III), while the demographics-only model had a slight advantage in FFMI prediction.

Regression plots of the best models versus the actual measures are shown in Fig. 4.

4. DISCUSSION

In this study, we evaluated the possibility of using silhouettes, or whole body shadow images, to estimate fat and lean body composition indices. We found that the addition of the shape descriptors in the form of principal components did improve on the estimates of body composition over a demographics-alone model for both boys and girls. Additionally, the demographics-only and the PCA-only models had

TABLE II. Correlation of the most significant principal components with demographic and adiposity variables (*R*²).

Principal comp. No.	Age		Height		Weight		BMI z-score		%Fat		FFMI		FMI	
	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls
pc0	0.659 ^a	0.479 ^a	0.688 ^a	0.469 ^a	0.784 ^a	0.700 ^a	0.615 ^a	0.698 ^a	0.364 ^a	0.647 ^a	0.716 ^a	0.695 ^a	0.622 ^a	0.780 ^a
pc1	0.534 ^a	0.454 ^a	0.544 ^a	0.510 ^a	0.339 ^a	0.243 ^b	-0.284 ^c	-0.374 ^a	-0.173	-0.286 ^c	0.137	0.105	-0.100	-0.180
pc2	0.183	0.094	0.210 ^b	0.147	0.170	0.090	0.105	0.000	-0.083	0.051	0.175	0.035	0.023	0.055
pc3	0.069	-0.098	0.081	-0.082	0.116	0.034	0.117	0.316 ^c	0.033	0.266 ^c	0.124	0.065	0.070	0.224 ^b
pc4	-0.261 ^b	-0.189	-0.244 ^b	-0.196	-0.179	-0.055	0.218 ^b	0.249	0.456 ^a	0.166	-0.234 ^b	0.020	0.337 ^c	0.154
pc5	-0.028	0.352 ^a	0.014	0.307 ^c	0.079	0.388 ^a	0.228 ^b	0.204 ^b	0.217 ^b	0.193	0.083	0.350 ^c	0.265 ^b	0.300 ^c
pc6	-0.165	0.0003	-0.224 ^b	-0.064	-0.103	0.108	0.195	0.186	0.278 ^c	0.112	-0.059	0.173	0.258 ^b	0.169
pc7	-0.118	-0.176	-0.097	-0.149	-0.183	-0.108	-0.099	-0.029	-0.004	0.031	-0.219 ^b	-0.101	-0.085	-0.024
pc8	-0.019	-0.170	-0.039	-0.230 ^b	0.009	-0.174	0.020	0.008	-0.022	-0.011	0.035	-0.132	-0.016	-0.061
pc9	-0.091	0.080	-0.119	-0.042	-0.086	-0.013	-0.009	-0.037	0.106	0.051	-0.073	-0.023	0.078	0.024
pc10	0.152	0.178	0.165	0.219 ^b	0.268 ^c	0.133	0.376 ^a	-0.016	0.319 ^c	0.127	0.260 ^b	0.000	0.413 ^a	0.110
pc11	0.131	0.074	0.107	0.096	0.084	0.062	-0.048	0.054	-0.028	0.046	0.043	0.030	-0.021	0.016
pc12	0.121	-0.165	0.141	-0.258 ^b	0.154	-0.170	0.082	-0.078	-0.134	-0.169	0.184	-0.057	-0.059	-0.148
pc13	-0.120	-0.111	-0.056	-0.114	-0.060	-0.151	-0.001	-0.124	0.273 ^c	-0.107	-0.161	-0.140	0.206 ^b	-0.148
pc14	0.058	0.137	0.051	0.111	-0.006	0.130	-0.216 ^b	0.021	-0.080	0.051	-0.071	0.109	-0.104	0.096
pc15	0.046	0.294 ^c	-0.015	0.204 ^b	0.009	0.195	0.070	-0.039	-0.060	-0.117	0.071	0.224 ^b	-0.041	-0.011
pc16	0.319 ^c	0.164	0.335 ^c	0.157	0.335 ^c	0.111	0.0488	-0.039	-0.288 ^c	-0.158	0.375 ^c	0.141	-0.130	-0.069
pc17	-0.130	0.035	-0.142	0.119	-0.217 ^b	0.133	-0.278 ^c	0.095	-0.043	-0.047	-0.250 ^b	0.171	-0.096	0.046
pc18	-0.044	-0.015	-0.050	0.072	-0.077	0.004	-0.058	0.039	0.005	0.022	-0.078	-0.034	-0.044	-0.015
pc19	0.215 ^b	-0.154	0.142	-0.169	0.155	-0.116	0.090	-0.074	-0.205 ^b	-0.111	0.265 ^b	-0.053	-0.065	-0.075
pc20	-0.059	0.086	-0.078	0.093	-0.053	0.142	-0.180	0.017	-0.018	0.098	-0.097	0.112	-0.017	0.160
pc21	-0.029	0.007	-0.055	0.086	-0.067	0.056	-0.077	0.082	0.090	-0.027	-0.110	0.055	0.040	-0.015
pc22	0.104	0.036	0.032	0.057	0.025	0.023	-0.024	0.012	0.094	0.043	-0.020	-0.007	0.113	0.008
pc23	-0.123	0.232 ^b	-0.153	0.163	-0.111	0.183	0.095	0.130	-0.067	0.019	-0.011	0.256 ^b	-0.067	0.086
pc24	-0.129	-0.076	-0.135	-0.079	-0.188	-0.043	-0.176	0.096	-0.230 ^b	0.110	-0.139	-0.045	-0.275 ^c	0.070
pc25	-0.073	-0.120	-0.067	-0.092	-0.078	-0.177	0.015	-0.146	0.056	-0.170	-0.080	-0.176	0.025	-0.191
pc26	-0.069	0.136	-0.059	0.169	-0.009	0.062	0.099	-0.147	0.052	-0.093	0.024	-0.031	0.069	-0.075

^aIndicates *p* < 0.001.

^bIndicates *p* < 0.05.

^cIndicates *p* < 0.01.

TABLE III. Prediction equations, R^2 adj. (see definition below table), and root-mean-square error (RMSE), for demographic variables, FFMI, FMI, and percent fat from PCA modes and demographic information using the boys' data.

Variable (method)	Boys prediction equation	R^2 adj	RMSE
%fat (demo)	$-94.943 + 1.761 \cdot \text{height} - 0.007 \cdot \text{height}^2 + 0.44 \cdot \text{weight} + 1.421 \cdot \text{BMIZ}$	0.457	4.411
%fat (PCA)	$21.818 + 13.218 \cdot \text{pc0} - 6.225 \cdot \text{pc1} + 21.929 \cdot \text{pc4} + 17.214 \cdot \text{pc5} + 14.52 \cdot \text{pc6} + 30.348 \cdot \text{pc10} - 28.108 \cdot \text{pc12} - 49.375 \cdot \text{pc16} - 42.53 \cdot \text{pc19} + 32.767 \cdot \text{pc21}$	0.728	3.119
%fat (PCA + demo)	(No demographic variables added significantly to the model)		
FMI (demo)	$3.523 + 1.266 \cdot \text{BMIZ}$	0.519	1.186
FMI (PCA)	$4.291 + 6.025 \cdot \text{pc0} - 1.461 \cdot \text{pc1} + 2.45 \cdot \text{pc3} + 4.989 \cdot \text{pc4} + 6.007 \cdot \text{pc5} + 4.508 \cdot \text{pc6} - 2.237 \cdot \text{pc8} + 8.5 \cdot \text{pc10} - 5.873 \cdot \text{pc12} - 8.393 \cdot \text{pc16} - 6.109 \cdot \text{pc19} + 7.043 \cdot \text{pc21}$	0.861	0.637
FMI (PCA + demo)	(no demographic variables added significantly to the model)		
FFMI (demo)	$14.979 - 0.061 \cdot \text{height} + 0.197 \cdot \text{weight}$	0.884	0.875
FFMI (PCA + demo)	$14.093 - 3.536 \cdot \text{pc4} - 3.335 \cdot \text{pc10} + 4.013 \cdot \text{pc12} - 5.218 \cdot \text{pc13} + 7.87 \cdot \text{pc16} + 7.814 \cdot \text{pc19} - 5.581 \cdot \text{pc21} + 0.176 \cdot \text{age} - 0.05 \cdot \text{height} + 0.126 \cdot \text{weight} + 0.692 \cdot \text{BMIZ}$	0.946	0.599

Note: Demo: R^2 and RMSE were calculated using only demographic variables; PCA: R^2 and RMSE were calculated using only the PCA coefficients derived from the active shape model; PCA + demo: R^2 and RMSE were calculated using both PCA & demo; R^2 adj: the coefficient of determination adjusted for the number of parameters used in the model equation.

comparable R^2 adj. and root-mean-square error (RMSE), with the exception of girls' FFMI. Even though these silhouettes were made from DXA whole-body scans, this study suggests that shadow imaging using simpler optical imaging devices, such as simple cell phone cameras, could be used to generate similar silhouettes and associations to body composition. To our knowledge, this is the first study of its kind to show that the

shape of silhouettes can be used to quantify body composition measures.

Clearly, some principal components generated by our analysis were related to the positioning of the individual. DXA whole-body scans are acquired with standardized positioning, but the standardization was not intended for direct image registration. It would easily be possible to eliminate many of the

TABLE IV. Prediction equations, R^2 adj. (see definition below table), and root-mean-square error (RMSE), for demographic variables, FFMI, FMI, and percent fat from PCA modes and demographic information using the girls' data.

Variable (method)	Girls prediction equation	R^2 adj	RMSE
%fat (demo)	$23.586 + 5.257 \cdot \text{BMIZ}$	0.606	3.830
%fat (PCA)	$24.998 + 17.594 \cdot \text{pc0} - 7.372 \cdot \text{pc1} + 11.857 \cdot \text{pc3} + 18.405 \cdot \text{pc5} + 19.104 \cdot \text{pc10}$	0.586	3.926
%fat (PCA + demo)	$23.577 + 7.099 \cdot \text{pc0} + 19.925 \cdot \text{pc10} - 18.239 \cdot \text{pc15} - 21.687 \cdot \text{pc16} - 32.043 \cdot \text{pc17} + 4.111 \cdot \text{BMIZ}$	0.691	3.392
FMI (demo)	$4.217 - 0.0002422 \cdot \text{height}^2 + 0.137 \cdot \text{weight} + 0.913 \cdot \text{BMIZ}$	0.851	0.795
FMI (PCA)	$4.766 + 7.609 \cdot \text{pc0} - 1.022 \cdot \text{pc1} + 2.038 \cdot \text{pc2} + 3.375 \cdot \text{pc3} + 2.599 \cdot \text{pc4} + 7.732 \cdot \text{pc5} + 6.181 \cdot \text{pc6} + 8.311 \cdot \text{pc10} - 5.523 \cdot \text{pc13} - 5.651 \cdot \text{pc17}$	0.886	0.694
FMI (PCA + demo)	$5.19 + 1.43 \cdot \text{pc0} + 5.079 \cdot \text{pc10} - 3.931 \cdot \text{pc12} - 4.834 \cdot \text{pc15} - 4.907 \cdot \text{pc16} - 6.405 \cdot \text{pc17} - 5.28 \cdot \text{pc19} - 0.00032333 \cdot \text{height}^2 + 0.153 \cdot \text{weight} + 0.586 \cdot \text{BMIZ}$	0.895	0.667
FFMI (demo)	$10.767 + 0.165 \cdot \text{age} - 0.00029077 \cdot \text{height}^2 + 0.173 \cdot \text{weight}$	0.881	0.712
FFMI (PCA)	$13.288 + 6.962 \cdot \text{pc0} + 1.807 \cdot \text{pc1} + 2.258 \cdot \text{pc2} + 8.859 \cdot \text{pc5} + 4.099 \cdot \text{pc6} + 9.11 \cdot \text{pc15} + 9.64 \cdot \text{pc16}$	0.732	1.069
FFMI (PCA + demo)	$10.649 - 3.135 \cdot \text{pc10} + 5.363 \cdot \text{pc17} + 0.192 \cdot \text{age} - 0.00028224 \cdot \text{height}^2 + 0.166 \cdot \text{weight}$	0.892	0.679

Note: Demo: R^2 and RMSE were calculated using only demographic variables; PCA: R^2 and RMSE were calculated using only the PCA coefficients derived from the active shape model; PCA + demo: R^2 and RMSE were calculated using both PCA & demo; R^2 adj: the coefficient of determination adjusted for the number of parameters used in the model equation.

FIG. 4. Comparison between FMI (top), FFMI (middle), and percent fat (bottom) values acquired from DXA scans and predicted by the PCA models constructed from silhouettes with boys (left) and girls (right). The associated R^2 adj. values are found in Tables III and IV.

positioning variation modes (leg abduction/adduction, torso twisting, arm raising, etc.) if the DXA scans were acquired with this detail in mind. Likewise, for an optical acquisition protocol, positioning of the arms and legs could be more tightly controlled to reduce the contribution of positioning to the overall total variation or omitted if it is found that they provide little to no benefit in the model. In DXA scans, there is a tendency to not repeat a scan if there are minor positioning issues because of radiation exposure.

This study was a pilot demonstration and not intended to be a final model since, ultimately, it is not useful to use DXA images as the primary data source for silhouettes. Silhouette

models should be derived for a specific imaging technology, since magnification and projection differences may change the presentation of the silhouette. The silhouettes used in this study were low spatial resolution compared to cell phone cameras. The DXA-based silhouette images were created with a maximum of 21 800 pixels ($1.0 \times 6.5 \text{ mm}^2$ pixel size), or in common camera terminology, the equivalent to a 0.022 megapixel resolution. This resolution is worse than that of the cheapest 640×480 (i.e., 0.31 Megapixel) cell phone camera. Most current cell phones have cameras with resolution of 1 megapixel or above. Besides spatial resolution, one must also consider the pose (position + orientation) of subjects, their

clothing, and the imaging background. These three factors require standardization for optical imaging as it was for the DXA imaging to create a successful ASM. For optical imaging, clothing would have to be thinly layered and fit snugly so as to not significantly alter patients' body outline. In addition, patients should be optically imaged using standardized anatomical positioning to minimize the variance unrelated to body composition (as seen in some of the PCA modes). Unlike DXA, repositioning and reimaging could be performed repeatedly until an ideal image is acquired. The distance between the imaging plane and the camera would also need to be equivalent across all images. To adjust for differences in optical characteristics of different cameras, a calibration object of known dimensions (e.g., a meter stick or piece of letter-size paper) may be placed coplanar with the subject. Postacquisition scaling can then be performed to normalize pixel dimensions. Finally, a "green screen" technique could be used to insure the removal of background was consistent. Given that the above-mentioned factors are mitigated, cell phone images should perform equally or better than DXA images for generating silhouettes. The optical extension of this study could be useful in clinical applications, low resource settings (e.g., point-of-care centers), or when traveling with light equipment is desired (e.g., visiting patients' homes to acquire adiposity measurements). 3D optical images, such as available from the Microsoft Kinect,³⁵ may be advantageous to 2D images in that they collect more detail on body curvature, especially that curvature that cannot be seen in a silhouette. The strengths and limitations of 2D versus 3D approaches for fitness and nutritional assessment have yet to be explored.

This study had several limitations. First, the participants were imaged in a supine position. We envision that the practical application will use a standing position. Body shape will be different for standing versus supine, but all the concepts derived here should be just as applicable. There is the possibility of overfitting, given the number of variables included in our models. To address this, we used a cross-validation (leave-one-out) approach. Ideally, future validations of the optical imaging approach should use separate populations. Additionally, we did not address body shape difference by ethnicity. The sample size for each ethnicity was small. A larger and more diverse sample (separated into ethnicities) will be used in future studies to determine if there are unique body shapes by ethnicity.

5. CONCLUSION

We have demonstrated the potential to derive FMI, FFMI, and percent fat estimates from whole body silhouettes that could be useful for the assessment of adiposity and muscularity. The technique presented here may be appropriate to apply to images acquired with simple cell phone cameras.

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^aB. Xie and J. I. Avila contributed equally to this work.

^bAuthor to whom correspondence should be addressed. Electronic mail: john.shepherd@ucsf.edu; Telephone: 415-891-7437; Fax: 415-476-8723.

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