# A 3D Method for Human Body Modeling and Composition Assessment

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## Background and Introduction

- Excess body fat is a key underlying factor in the development of numerous chronic diseases, including type II diabetes, heart disease, stroke, and cancer.
- The various techniques for Percentage of Body Fat (%BF) assessment have their pros and cons.
- Accurate instruments like dual X-ray absorptiometry (DXA, Figure1(b)), volumetric air-displacement plethysmography (i.e. BOD POD®, Figure1(a)) could be very expensive (~\$100K and \$40K respectively) and they are large and immobile equipment operated by trained professionals.
- Some methods are inexpensive like Body Mass Index (BMI), skinfold (Figure 1(d)) and bioelectrical impedance(Figure1(c)), but they can be unreliable and inaccurate.



### Objective

The primary objective of this project is to develop an accurate, reliable, convenient and cost-effective method of scanning body surface shapes and to use this technique to accurately assess %BF.

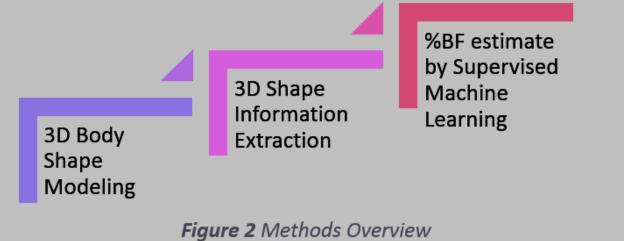
- For this project, we are developing a highly innovative approach for non-rigid registration which will make it possible to capture human shapes using one commodity depth camera (Microsoft Kinect®).
- A supervised Machine Learning Algorithm is then used to map the resulted 3D body representation to accurate %BF. The use of Machine Learning techniques in calculating %BF is a significant innovation and will be a major improvement on the currently used methods such as Siri or Brozek equations.

#### Methods

There are two specific tasks associated with the project:

- development of a whole-body surface capture system based on surface scanning and non-rigid registration;
- using the developed system to scan a number of human subjects and use the resulting shape information to develop an accurate estimate of %BF based on density. This section presents details for both tasks.

The overall system pipeline is shown in Figure 2. In the following sections we will discuss the methods in detail.



### Method: Capture 3D Body Shape

#### 1. Baseline approach

We used Kinect Fusion, a commercial software to generate surfaces using a mobile Kinect camera as our baseline approach. To improve the reconstruction quality, accuracy, and software usability, we adopt nonrigid registration method to improve the system design.

#### 2. Improved approach

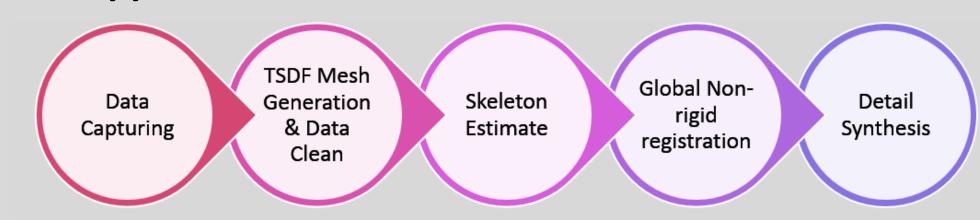


Figure 3 Pipeline for 3D Human Body Modeling by Non-Rigid Registration

We use 2 static Kinects, one covers the upper body and the other covers the lower body. We take 8 pose in total for capturing, with 45° rotation for each pose

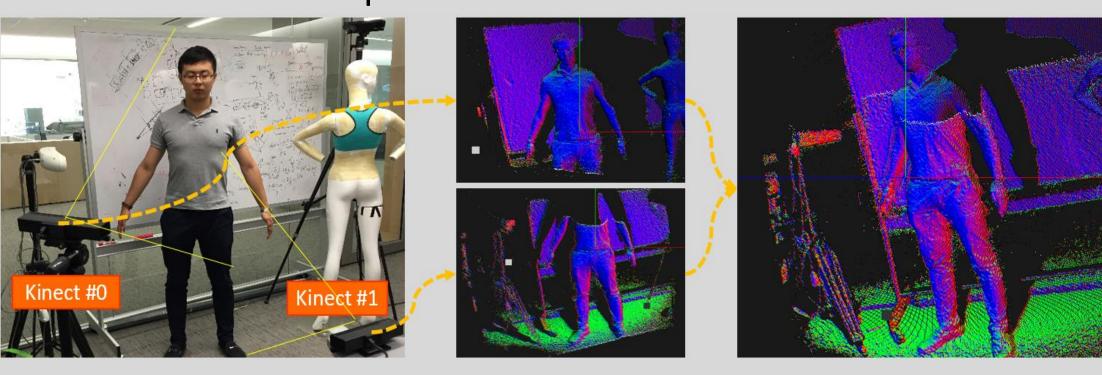


Figure 4 Capture System Setup

For each pose, we fuse the depth images into TSDF volume and then, generate meshes using Marching Cubes, after which we estimate the skeleton joints using the silhouette information.

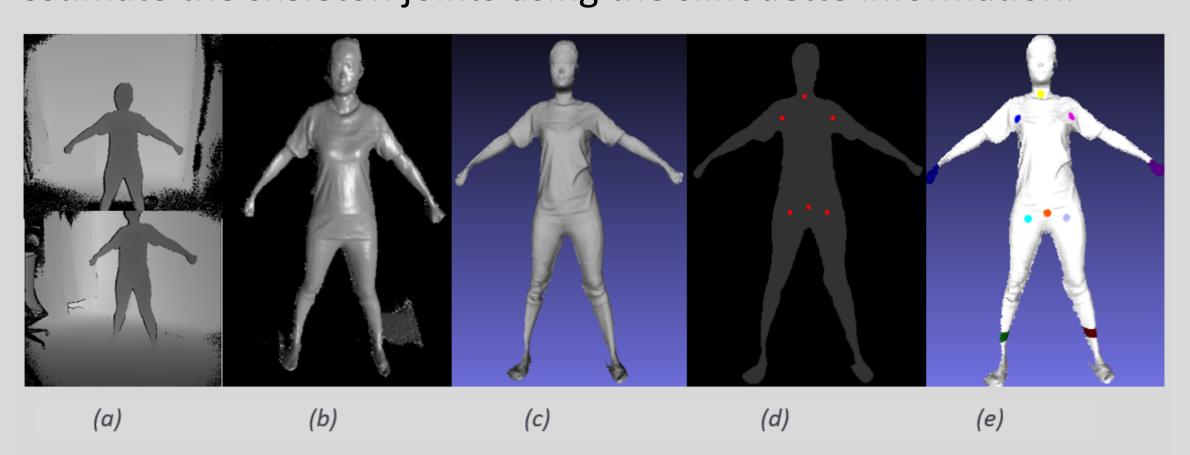


Figure 5 Front end processing. (a)Depth images captured by Kinects (b) Rendered TSDF volume (c) Generated meshes using Marching Cubes from TSDF volume and data cleaning. (d) Skeleton estimation using silhouette information. (e) Skeleton estimation results.

- Then we conduct an articulate based ARAP non-rigid registration to stitch all the meshes. The articulate based ARAP non-rigid registration is the key to preserve the volume during mesh deformation, in which we maximize the utilizing of rigid alignment.
- In the final step, we synthesis the high frequency detail of the source mesh onto the watertight surface, since the watertight surface reconstructed by Poisson Surface Reconstruction tends to over smooth the surface.
- Preliminary accuracy validation: we evaluated the proposed method with a static mannequin, with which the volume has been measured by Bod Pod as ground truth. The result indicates that our proposed method has a very high degree of accuracy compared with the baseline method, see Figure 6.

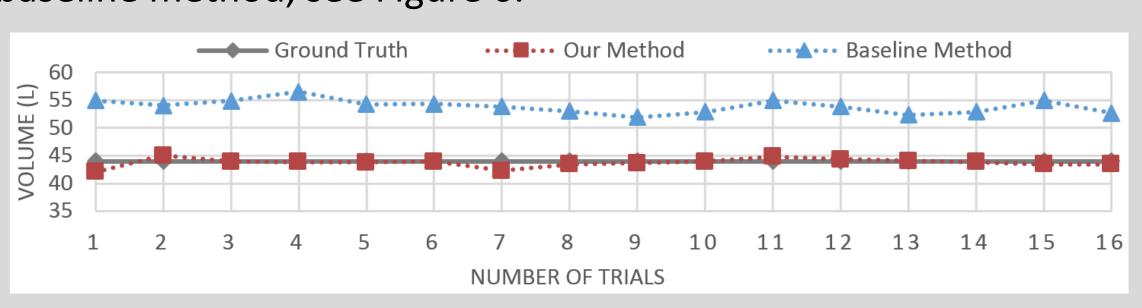


Figure 6 Volume accuracy comparison for our method and the baseline method with known ground truth.

### Method: Calculating BF%

The analysis is based on our baseline 3D modeling approach (i.e. Kinect Fusion), with which we preliminarily conducted a human subject test with sample size of 19. The subjects were first scanned by Kinect for 3D shape modeling and then the ground truth volume and %BF were obtained by BOD POD and DAX. We will further develop the BF% estimation algorithm based on our new 3D modeling approach after we conduct new human subject testing with a larger sample size.

#### 1. Modeling Accuracy Validation:

- We have conducted experiments to verify the accuracy and reliability of scanning shapes with the Kinect®. Three classes of objects were scanned (simple inanimate, complex inanimate, and human subjects).
- We analyzed the large consistent error for the complex concave inanimate and human subjects and concluded that the errors came from surface reconstruction and volume integration algorithms that are being used in the commercial software.
- We were able to reduce this to 1.406% for the complex concave inanimate objects and 0.780% for human subjects by manual segmentation of the raw volumetric representations. (Table 1)

		Simple/Convex	Complex/Concave	Human Subject
		Inanimate Object	Inanimate Object	Human Subject
	Error	0.296%	1.406%	0.78%
	CV	1.234%	1.973%	1.008%

Table 1 Shape variant average volume error and coefficient of variation

#### 2. Calculating %BF:

We have done preliminary analyses using a sample of 19 subjects. Their %BF was obtained using both BOD POD® and DXA. Additionally, each subject was scanned using Kinect® and a 3D virtual model representing the subject was constructed and used to extract height, volumes and surface areas (full body, segmented torso, segmented thigh) and circumferences (chest, waist, hip, and thigh), see Figure 7.

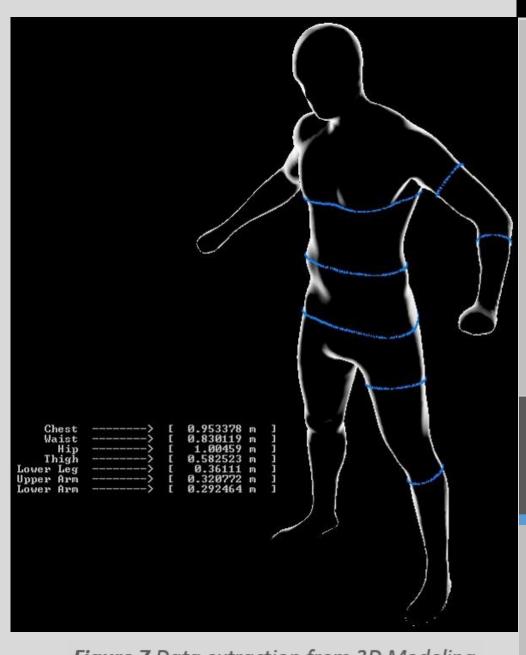


Figure 7 Data extraction from 3D Modeling.

The plot in Figure 8 shows the absolute Pearson correlation between the various parameters and the %BF given by DXA. All of the features were derived from the 3D model. Body S/V ratio was significant (p=0.03) and improved the model R2 from 0.69 to 0.81 (0.52 to 0.67 for the adjusted R2). Torso S/V ratio was not significant (p=0.17). Thigh S/V was significant (p=0.04) and improved the model R2 from 0.69 to 0.80 (0.52 to 0.65 for the adjusted R2).

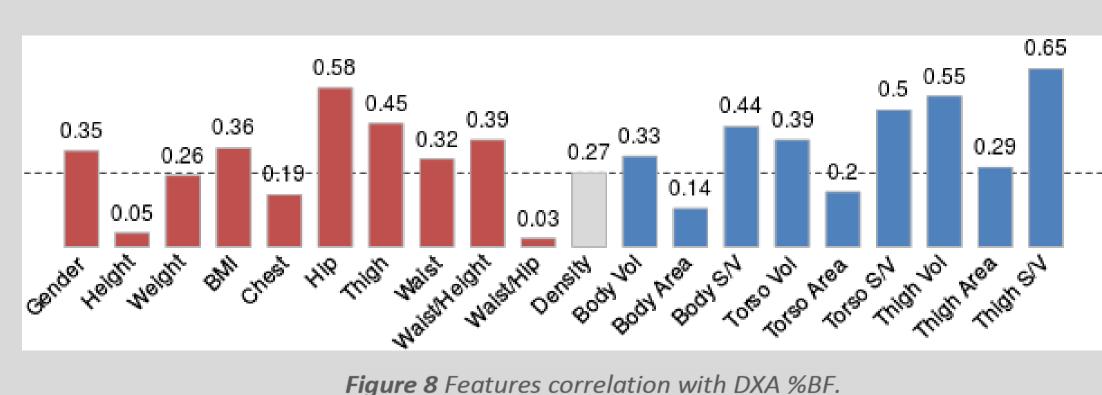
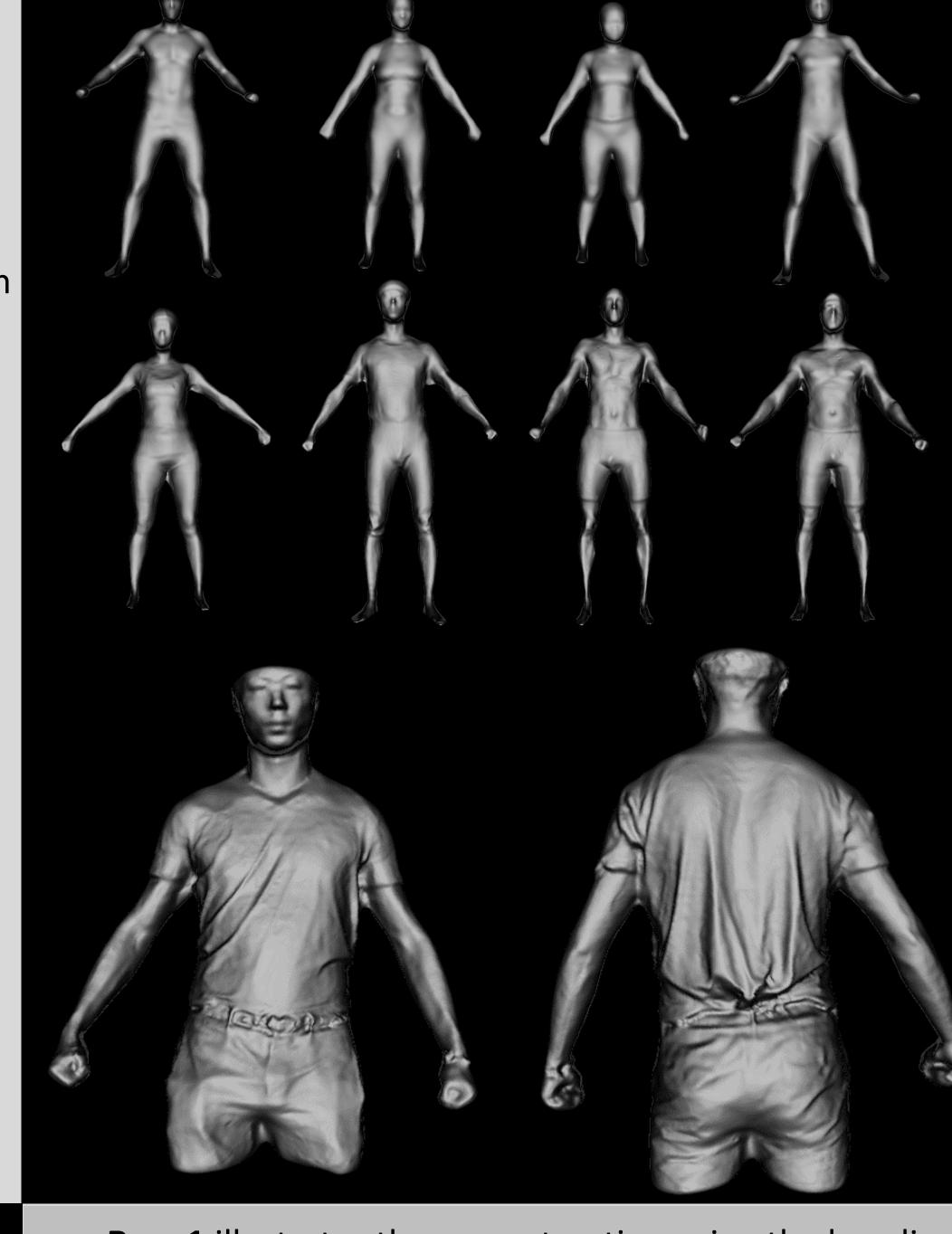


Figure 8 Features correlation with DXA %BF

#### Results



- **Row 1** illustrates the reconstruction using the baseline method (i.e. Kinect Fusion)
- Row 2 illustrates the reconstruction using the improved method with non-rigid registration.
- Row 3 illustrates the reconstruction using the improved method with non-rigid registration and detail synthesis.

#### Conclusion and Future work

- Developed an innovative non-rigid registration method for accurate and robust human body modeling. Developed a new formula to calculate %BF which is more economical and convenient than DXA or BOD POD®, and more accurate and easier to use than
- skinfold and bioelectrical impedance methods. Provided a valuable resource for clinicians and fitness professionals, this technology can become a revolutionary research tool.
- For future work, we will further validating the accuracy of the proposed non-rigid registration method. Also, we are going to conduct the subject test with sample size around 120 with the new modeling method, base on which we will further develop the %BF assessment algorithm with Machine Learning.

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