Simulating Microgravity Effects and Changes on Body Shape

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A Step Towards Measuring Body Composition in Space

Background

- Long duration space flights induce loss of muscle and bone mass, which in turn leads to greater risks of injury and death.
- Few body composition measurement technologies are suitable for in-flight use to capture status and changes in body fat, lean and bone masses.
- The terrestrial criterion method is dual-energy X-ray absorptiometry (DXA). However, DXA is not feasible for long duration missions
- 3D optical (3DO) whole body imaging is being explored as a more accessible alternative to DXA by many groups by relating the variance in body shape to the underlying distributions of fat, lean, and bone tissues[1].
- Our group has two large on-going NIH (NIDDK) studies in kids (R01DK111698) and adults (R01DK109008) to relate body shape to health status and body composition from 3DO. Current results have shown this method to be accurate and precise.
- However, the accuracy of 3DO body composition in space may be impacted by fluid redistribution due to microgravity, and to date is unknown.
- We hypothesized that 3DO body composition can be calibrated for extra-terrestrial use, and be more easily deployable because of its low power consumption and ability to be performed on co-use equipment

Objective

- In this study, we seek to demonstrate the feasibility of our system to accurately and precisely measure body composition under simulated microgravity environments.

Methods

- Picking the right sensor - 5 depth sensors (Table 1) have been tested for depth accuracy, field of view, and overall feasibility. (Figure 6)
- Simulating microgravity - Volunteers are scanned in 2D and 3D at different inversion angles. (**Figure 1**)
- New challenges to current model – background removal, non-standardized camera placement, fluid redistribution, incomplete scanning, pose variability.
- Machine learning and deep learning models are being explored and trained on anthropometrics and body models, specifically Catboost was used with 5-fold cross validation taking in anthropometrics to predict total fat mass with the same data as the Ng 2019 Shape up paper[1]
- The graph neural network was DGCNN with L1 loss, removal of face information, sampling of vertices, and predicting on fat mass
- The Spin model was used to test 3d reconstruction from single rgb images (Figure 4)
- Inversion table data collected at various intervals

Results

- D435 sensor has best depth accuracy with a % error of 0.86 (Table 1) while Azure Kinect has wide field of view.
- Catboost and DGCNN train root mean squared error – 1368, standard deviation – 109. test root mean square error – 2436, standard deviation – 791 (Table 5) slightly better than Ng's results (table 4) and Graph NN brief training loss of 8000 on partial data set
- 3d models constructed with single sensors and segmentation of person tested

Conclusions

- We have successfully demonstrated to date sensor quality tests, deep learning prediction of total fat mass, inversion table setup, and 3d reconstruction. Further studies in more volunteers are new being implemented with the tested protocols and then will be validated on parabolic flights this summer.

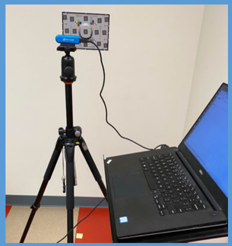

Figure 1. Sensor Testing Setup

Figure 2. Example 2D Image of participant on inversion table. This image is at 60 degrees.

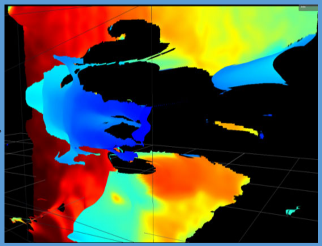

Figure 3. Inversion Table Image colored by depth distance from the sensor

Figure 4. Foreground/background detection

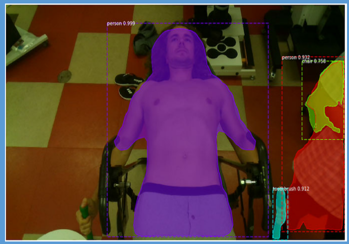

Figure 5. Person segmentation on inversion table

Figure 7. Single Kinect windows 3d reconstruction

Figure 8. Multi Realsense sensor 3d reconstruction

Figure 8. Spin model from single rgb image

Table 1: Sensor Comparison

Sensor	% error at 1.1 feet	% error at 2.1 feet	% error at 3.1 feet	% error at 4.1 feet	% error at 5.1 feet	Average % error at each feet
D435	3.641	0.170	0.129	0.154	0.226	0.864
Azure Kinect	x	1.807	1.913	1.702	0.044	1.366
D415	0.753	0.568	0.966	0.244	6.166	1.739
Kinect Windows	x	7.302	0.269	0.516	1.697	2.446
Kinect XBOX	x	x	2.574	2.483	2.409	2.489

Columns are by one feet intervals; x specifies sensor was unable to capture at that distance

Table 2: Azure Kinect Depth Specs (Source documentation)

Mode	Resolution	FOI	FPS	Operating range*
NFOV unbinned	640x576	75°x65°	0, 5, 15, 30	0.5 - 3.86 m
NFOV 2x2 binned (SW)	320x288	75°x65°	0, 5, 15, 30	0.5 - 5.46 m
WFOV 2x2 binned	512x512	120°x120°	0, 5, 15, 30	0.25 - 2.88 m
WFOV unbinned	1024x1024	120°x120°	0, 5, 15	0.25 - 2.21 m
Passive IR	1024x1024	N/A	0, 5, 15, 30	N/A

Table 3: Intel D4 Processor (Source documentation)

Format	Resolution	Frame Rate	Comment
Z [16 bits]	1280x720	6,15,30	Depth
	848X480	6,15,30,60,90	
	640x480	6,15,30,60,90	
	640x360	6,15,30,60,90	
	480x270	6,15,30,60,90	
	424x240	6,15,30,60,90	
Y8 [8 bits]	1280x720	6,15,30	Luminance Left and Right Imager
	848x480	6,15,30,60,90	
	640x480	6,15,30,60,90	
	640x360	[illegible]15,30,60,90	

Table 4: Ng 2019 Shape up paper results

				Model type							
				3D PC-only; 5-fold CV		Anthro-only; 5-fold CV		3D PC + Anthro; 5-fold CV		Simple Anthro (10); no CV	
Output variable	Sex	n	PC-only model	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
Fat mass, kg	M	177	PC1, 2, 3, 4, 5, 8, 9, 10, 13, 15	0.88	3.38	0.88	3.51	0.91	3.07	0.82	3.88
	F	230	PC1, 2, 3, 4, 8, 9, 11	0.93	2.96	0.95	2.66	0.95	2.63	0.94	2.84

Table 5: Catboost fat mass training and test results on total fat mass using Shape Up Adults data

	iterations	test-RMSE-mean	test-RMSE-std	train-RMSE-mean	train-RMSE-std
0	0	24583.988336	1346.137968	24611.077377	335.515052
1	1	23954.612166	1341.481161	23977.641413	320.422257
2	2	23332.202447	1336.817610	23360.064226	318.256459
3	3	22778.629031	1346.884986	22769.748008	306.131040
4	4	22185.000104	1330.592870	22174.481380	295.515801
...	...	...	...	...	...
995	995	2435.762452	790.463304	1368.520825	108.975341
996	996	2435.756712	790.465094	1368.454910	109.008941
997	997	2435.712977	790.657594	1368.204666	109.079069
998	998	2435.699738	790.638334	1368.092496	109.120926
999	999	2435.749463	790.611023	1367.707004	109.137616

1000 rows × 5 columns

Features include: race, age, height, weight, BMI, waist circumference, hip circumference, biceps girth, thigh girth, waist/hip girth ratio, waist/height ratio.

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References

1. Ng Et Al. Am J Clin Nutr. Detailed 3-dimensional body shape features predict body composition, blood metabolites, and functional strength: the Shape Up! Studies. 2019;00:1–11.
2. S. Izadi Et Al. KinectFusion: Real-Time 3DReconstruction and Interaction Using a Moving Depth Camera. InProceedings of ACM Symposium on User InterfaceSoftware and Technology (UIST), 2011.