BUILDING THE SPACE SCALE
OR HOW TO WEIGH A PERSON WITH NO GRAVITY

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ABSTRACT

Since the very beginning of space exploration, cosmonauts have suffered from weight losses which need to be particularly monitored during long term missions in space stations to insure their health and well being. In 1965-6 Thornton successfully built a device able to measure the body mass of cosmonauts in the micro-gravity space environment using passive linear spring-mass oscillators. Since then, space stations have been equipped with labs containing, among others, bulky devices like Thornton's. In this work we report recent advancements in computer vision algorithms allowing us to estimate the weight of a person within 4% error using 2D and 3D data extracted from a low-cost Kinect RGBD camera output.

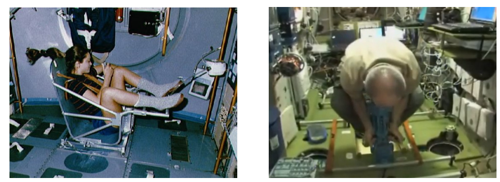
***Index Terms*—** Body mass estimation, anthropometry, soft biometrics, Kinect

1. INTRODUCTION

On April 12, 1961, the Soviet cosmonaut Yuri Alekseyevich Gagarin orbited the Earth, for the first time in the history of mankind; since then, in the last 40 years more than 500 cosmonauts [1] have been sent to the space.

One of the findings throughout the history of spaceflights concerns the loss of body mass that affects cosmonauts [2]. Typically, these losses are small (about 2%), but they can reach up to 10 to 15 percent of preflight body mass in particular cases. Most of the observed loss of body weight is accounted for by loss of muscle and adipose tissue [3]. As a matter of fact, micro-gravity severely changes the human physiology leading to loss of muscle mass and muscle volume, weakening muscle performance, especially in the legs.

To avoid some of these phenomena, since the 70's, cosmonauts are given precise exercises and feeding routines which were, in the following years, gradually adjusted and incremented to the current levels [3]. As a result, in a typical day on board of the International Space Station, crew members spend twelve hours working, two exercising, two preparing and eating meals, and eight hours sleeping. Weight, or more generally body mass, has been always considered as a good indicator of correct nutritional status and well being; however, a problem still exists on how to measure and track cosmonauts' weight in micro-gravity conditions.



(a) (b)

Fig. 1. The images shows the Thornton first experimental device (a), and the last and still used Russian BMMD device (b).

Over the centuries, two main methodologies have been adopted to measure the weight of an object: the spring scale and the balance. Unfortunately, both of these techniques make the assumption that a relatively strong and constant gravity acceleration field is affecting the object we want to weigh.

Because in space this assumption is not true, in order to measure mass during spaceflights, an acceleration field must be artificially generated. In 1965/66 the US cosmonaut and researcher William Thornton, developed and tested a device (Fig. 1.a) that, making use of a passive calibrated linear spring, was able to estimate mass of objects by computing their characteristic frequency of vibration. Since then, similarly designed devices are sent into space to measure the mass of cosmonauts, garbage containers, and scientific specimens.

The current technology for weighing cosmonauts involves a precisely calibrated spring attached to a support to which the cosmonaut is rigidly fastened and which is moved several times to estimate the kinematics of the structure and thus the mass of the cosmonaut (see Fig. 1.b).

Such a system assumes the cosmonaut to be a rigid body during accelerations and decelerations, and it requires both space and energy, two resources which are quite scarce in space explorations. The precision of such a system, has been recently debated [4, 5, 6], especially due to deviation from the baseline which can be in the order of 6 to 7 kilograms for the latest NASA device, the SLAMDD, and in the order of 2 kilograms for the latest Russian BMMD device currently serving the European International Space Station.

2. VISION BASED WEIGHT ESTIMATION

Vision is a very interesting way to estimate the weight of a subject; in fact, such approach is used in hospitals during emergencies. In space, cameras (possibly 3D) could easily be integrated into the walls and automatically record cosmonauts in their daily life autonomously tracking their weight several times a day unobtrusively, accurately, and even without the need for cooperation.

To the best of our knowledge only two works have tried to exploit vision based algorithms to estimate the weight of a subject. In [7] the authors use the evidences from crime scenes to collect footprints and link them with the weight of the suspects. The study concludes that the body weight has a strong correlation with the footprint.

In [8], Velardo and Dugelay demonstrate that it is feasible to estimate the mass/weight of a person by means of soft biometric analysis through computer vision techniques with reasonable error ratios. Velardo's technique makes use of 7 anthropometric measures (height, upper leg length and circumference, upper arm length and circumference, waist and calf circumferences) to estimate the mass of the body by means of multiple linear regression methods.

The system elaborates pictures to estimate people weight. The estimate differs from the true value with an average error of 4.3%. Supposing a 80 kilograms average weight of cosmonauts this translates into an error of ± 3.44 kilograms which is in-line with the results of the much more expensive, energy and space consuming, NASA SLAMDD device [4, 5, 6].

The main limit of [8] is that features are computed off-line by manually tagging subjects' anthropometric measures.

In this work we present our preliminary results as well as our plans for the development of next generation vision based weighing device. Similarly to Velardo and Dugelay we took inspiration from the anthropometric measures contained in the National Health and Nutrition Examination Survey (NHANES) database [1].

The NHANES data set was collected from a large population of individuals (more than 28000 people), over a period of 6 years (from 1999 to 2005) by the U.S. Centers for Disease Control and Prevention. The purpose of the survey was monitoring American population, and assessing health and nutritional conditions of adults and children in the United States. From all the measurements available in the database, we retained only the ones that are directly measurable on the subject (i.e. discarding values like the skin-fold's measures).

The paper is organized as follows: in Section 3 we discuss our improvements on the estimation from anthropomeasures, in Section 4 we introduce our automatic system to estimate measures from 3D data, and we will present our results. In Section 5 we summarize our work and present our future research.

Table 1. Gender estimation confusion matrix.

	Male	**Female**
Male	**83.4%**	16.6%
Female	22.3%	**77.7%**

3. FROM ANTHROPOMEASURES TO WEIGHT

In order to understand the limits of a vision-based system for human weight estimation the first part of this work is dedicated to push the estimates of weight further than it was done by Velardo and Dugelay [8] by limiting the sex and age of the subject and by testing more complex classification methods.

In the future a biometric system such as face recognition could recognize the subject and give us the exact age, sex, expected anthropometric measures, and many other a-priori knowledge that could help the weight estimate. At present we are constraining the database to represent as closely as possible the space environment. In particular, considering that about 65% of the cosmonauts are selected by the US and age between 26 and 46 years (the average age being 34 years) [2] we notice that the algorithm can be designed and targeted to work by exploiting such prior information.

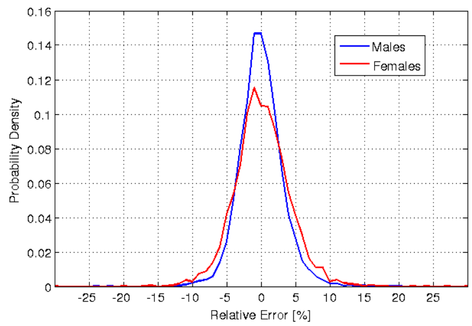
To top that, we can exploit the visual appearance of the subject to figure out the sex of the cosmonaut using computer vision algorithms. As an example, by using a binary Artificial Neural Network (ANN) classifier that learns how to recognize the gender of subjects from the limited set of anthropometric measures represented by NHANES, we can achieve a preliminary accuracy of over 80% (see Tab. 1). Possible improvements in that direction may be introduced by increasing the set of measures, or, for example, by coupling other modalities (e.g. RGB image analysis).

We report here the weight estimation result obtained by selecting (from the 28.000 subjects of the NHANES database) entries corresponding to the two separated male and female classes which only includes people older than 20 years. For the sake of brevity we will discuss only the results for the male class, the considerations are equal for the female class since the performance do not vary considerably.

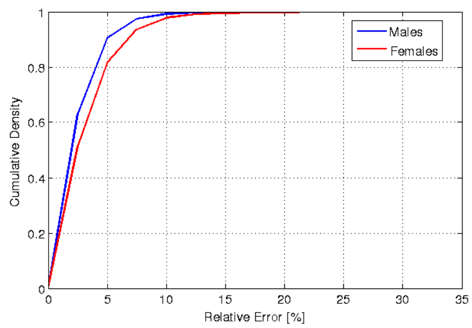
The results shown in Fig. 2 are obtained using an ANN with a single hidden layer consisting of 5-neurons and a hyperbolic tangent sigmoid transfer function. We obtain that, over the entire male class, the mean absolute relative error is 0.023, thus in average the system error falls within the range of $\pm 2.3\%$.

[1] www.cdc.gov/nchs/surveys.htm

[2] http://astronauts.nasa.gov/content/faq.htm



(a)



(b)

Fig. 2. In our theoretical test a subset of people divides the database respectively by age (older than 20 years), and by gender. Figure (a) shows the probability density function of the error as percentage over the actual weight of the subject, while figure (b) depicts the cumulative density function.

In figure 2.a the probability density function is Gaussian shaped with a standard deviation of 0.032 meaning that 95.5% of estimates fall into the range of $2 \times \sigma = 6.4\%$ relative error. This is better visible in figure 2.b that shows the cumulative density function of the absolute relative error. For the male class the entire dataset is covered considering a relative error of $0.1 = 10\%$ (almost $3 \times \sigma = 9.6\%$, thus 99.7% of the dataset). These results improve the ones proposed by Velardo and Dugelay in [8], such improvement is due to a cumulation of factors. From the one side, it is clear that being the ANN approach a non linear regression technique, it is more capable of modeling non linear relationships among measures and weight of the subjects. On the other hand by selecting only a specific gender and age subset helps the regressor to find a more suitable way of estimating weight.

The result just presented in this section is interesting because it shows us what could be a theoretical limit to weight estimation through visual analysis. To our knowledge this limit could be further improved if additional anthropomeasures are considered, thus increasing the complexity of the computer vision algorithms and sensors.

4. AUTOMATIC VISION-BASED WEIGHT ESTIMATION

In order to build an automatic vision-based weight estimation we set up a system using a Microsoft Kinect sensor. We are able to extract height, weight, and gender information from the user according to our previous conclusions on anthropometric measures.

As a first step we capture the output of the Kinect sensor with the OpenNI framework from Primesense [3] and exploit the OpenCV [4] and PCL [5] open source libraries to extract the silhouette of the people moving in front of the 3D sensor. Background subtraction and blob tracking algorithms automatically segment and track each single user so that the analysis can be performed separately and in parallel for each person. The segmentation algorithm takes advantage of the continuity of human body surface to classify vertices belonging to the same object. Once the user presence is recognized, his/her bounding volume is extracted thanks to the point cloud coordinates. A simple sorting allow us to extract the information about the minima and the maxima in the 3D point cloud, which are rearranged as corners of the bounding volume.

To automatically measure height, we look for in the upper-central part of the bounding volume where presumably the head is located. Here we extract the 3D information for the outermost points of the silhouette. A similar approach is performed for the lower part were the feet are located. Height is then measured as distance between these two extrema (head and feet locations). Afterwards, we exploit the skeleton tracker embedded in the NITE framework to locate the limbs of each user. In our system, the user has the possibility to trigger the automatic estimation assuming the calibration pose required by the skeleton tracker (i.e. both arms up with the elbow flexed $90°$, also known as Ψ pose). As the calibration pose is hold for a few seconds the system immediately triggers the measurement step which computes lengths and estimates the required circumferences of the limbs. In order to stabilize and filter out the outliers we apply a median filtering approach, over time, for all the repeated measures; this processing step is needed due to the noise produced around the edges of the silhouette by the 3D sensor.

Once all the measures are extracted the weight is estimated. One important factor that influences the precision of such a system is the accuracy of the estimated measures. While in case of direct measurements on the subjects' body the source of error is primarily due to the tape meter and measuring pose, in a scenario that gives to the user no constraints of movements (basically just a pose to hold) the sources of error are numerous. Both the sensor and the slight motion of the user concur to increase imprecision. We tried to overcome the flickering due to the sensor error by smoothing the

[3] www.openni.org
[4] http://opencv.willowgarage.com/
[5] www.pointclouds.org

Table 2. The estimation of extrapolation factors that link real with sensed circumferences.

Measure	**Extrapolation factor**
Arm circumference	2.7
Waist circumference	1.5
Leg circumference	2.8

Table 3. The estimation error for the automatic analysis of 10 out of 15 people of the 3D dataset we recorded using the Kinect sensor.

Measure	**Absolute Error**	**Relative Error**
Height	1.9 cm	1.1%
Arm length	3.6 cm	12.3%
Arm circumference	3.2 cm	10.7%
Waist circumference	8.4 cm	10.0%
Leg length	2.9 cm	6.2%
Leg circumference	1.7 cm	3.4%
Weight (absolute)	**2.7 Kg**	**3.6%**

depth values with an hybrid approach where both the 2D and 3D information are used together. We smooth the depth map convolving its 2D projection with a Gaussian kernel (3×3) and then we remove the outliers at the edges by taking only the pixel belonging to the binary mask provided by the background separation algorithm.

Although the technology of Primesense's sensor employed in the Kinect provides more resolution than an equivalent time of flight camera, at a 3 meters distance (so that the user is completely visible), does not provide much depth resolution. This leads to the impossibility of recovering with enough accuracy the dimensions of the arms, that at this distance appear almost as flat surfaces.

In order to validate the results of our limb measurement and weight estimator, and following the guidelines of [8], we recorded a database composed of 15 different subjects. Each of them was recorded using the Kinect sensor while performing the calibration pose. Each subject was casually dressed. The calf circumference is not considered in the process because trousers represents a big limiting factor as they particularly hide the shapes at the ankles.

For the circumferences considered in our system (arm and leg circumferences, and waist) we have to find correspondence between the sensed and the real dimensions. To do so, a set of 5 random candidates was used to "train" our system by computing multiplicative factors that could link extracted measures from real values. The corresponding values are shown in table 2.

Provided the results of the "training" step, we performed the estimation of the set of measures from the remaining 10 subjects. The resulting estimation errors are summarized in table 3. Bigger error in the estimate of the arm dimensions and waist circumference are understandable. The clothes for the waist, and the limited depth precision for the arms have a big impact in the estimation performance of this two body parts. Nevertheless, our system is capable of providing an error range of ± 2.7 kilograms, exactly in the same range provided by its more complex equivalents and close to the theoretical value obtained in Section 3.

5. FURTHER WORK AND DISCUSSION

We have introduced the issue of determining the mass of people in space micro-gravity environment and presented a solution to this challenge based solely on computer vision techniques. Our technology relies on RGBD cameras such as the Microsoft Kinect. The current development makes use of estimated anthropomeasures extracted from a frontal 3D view of the user. Thanks to our algorithms we are able to extract limbs measurements and to estimate subjects' weight up to 2.7 kg average absolute error. Future work will focus on further ameliorating the quality of the 3D reconstruction by both using multiple (and therefore closer) Kinect sensors and implementing algorithms specifically targeted at registering non rigid structures like human body. In this way we plan on being able to build a complete 3D model of a person from different viewpoint and different body-postures. Finally, by combining estimates from the BMMD, our Space Scale, and other technologies, we additionally plan to be able to evaluate over time the quality of body mass lost in term of either bone, blood, muscular, or fat masses.

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