WHAT CAN COMPUTER VISION TELL YOU ABOUT YOUR WEIGHT?

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ABSTRACT

Extreme overweight and obesity are spreading widely like an epidemic. Populations feels the urge for preventive tools and methods to increase people self-awareness and 3D body analysis could be employed to create self-diagnostic methods. We propose a system based on the Microsoft Kinect RGBD sensor to help people to detect weight problems and, possibly, to guide them through improvements in their lifestyle. Our application extrapolates anthropometric measures from the body silhouette and 3D information. Measures are used to estimate body weight thanks to a statistical model trained on the data of a large medical database. Thanks to the knowledge acquired while analyzing the user, the system provides through its interface, healthiness measures and information that are necessary for a correct lifestyle that would mitigate the effects of weight problems.

Index Terms— Obesity, weight control, 3D body analysis, Kinect, weight estimation

1. INTRODUCTION

Poor diet, lifestyle choices, and a under regulated food market are the main causes of the widespread obesity worldwide. Obesity is when a person is carrying too much body fat with respect to his/her height and gender. Generally, a person is considered obese if his/her body mass index ($BMI = \frac{weight[kg]}{(height[m])^2}$) is 30 kg/m^2 or greater.

United States spends more than \$300 billions each year to treat obesity, diabetes, and cardiovascular diseases [1]. Overweight is one of the main causes of this spending as it has been identified as one of the main factors that generates those diseases. US is not alone since according to the statistics of the World Health Organization [1], many countries experience an increase of overweight people whose number has reached a size proper to epidemics.

Even worse, people develop the overweight status at younger age compared to the past, this situation provides them more time to develop a morbid condition. Data extrapolated from [2] shows that the percentage of European children population (7–11 years) falling in the overweight range is terribly large (more than 10 countries has a percentage larger than 20%). For these subjects the risk of becoming obese in the near future is very high. For this reason various activities have been set up from nations and organizations like the vast number of European research projects and associations[2] that contribute to study the problem and to promote awareness campaigns.

Obesity can be treated by losing weight, which can be achieved through a healthy, calories-controlled diet, and increased exercise. However, the lifestyle changes necessary for weight loss can be challenging and not feasible to achieve without the proper support and control. For these reasons we need friendly technologies that could help people to develop their self-awareness so as to achieve a better state of health.

Computer vision, by now entered in our daily life could be a favored mean for providing such new techniques. Algorithms like silhouette analysis [3], automatic extraction of the weight [4] and measures of the body [5], as well as the 3D model reconstruction of the human body [6], may be used as self-diagnostic tools or telemedicine equipment.

Computer vision has been already applied to the medical domain and to body analysis. In [7] 3D model-

[1] *http://www.who.int/topics/obesity/en/*

[2] http://ec.europa.eu/research/health/medical-research/diabetes-and-obesity/index_en.html

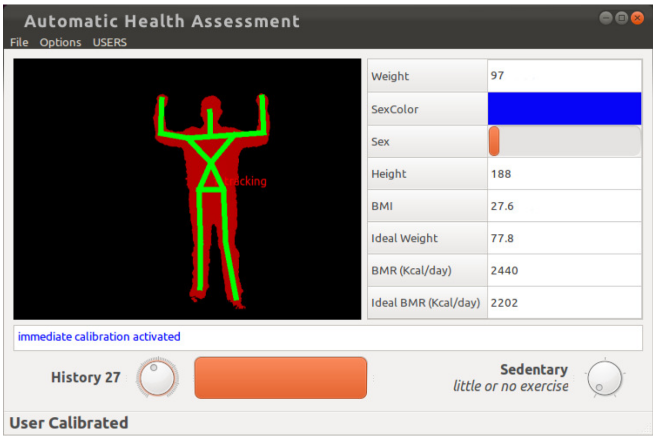

Fig. 1. The interface of our automatic health self-assessment tool.

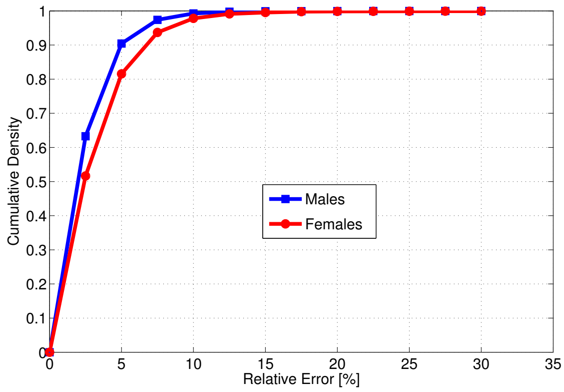

Fig. 2. A graph of the cumulative density function of the relative error. The two groups (Males and Females) are trained and tested separately.

ing is used to show body variations as the BMI increase or decrease. This mechanism allows people to acquire a better confidence about healthy body statuses. Another example is the work from [8] that draw great attention from many scientific websites[3] where a computer vision based weight estimation algorithm is compared against mechanical ones existing on board of the International Space Station. In this paper we aim at revising our anthropometric system so as to provide to the user a better understanding and awareness of his/her own body condition. Through the use of computer vision techniques and resorting to commercial 3D equipment (e.g. the Microsoft Kinect sensor), we extract information about the user's body in order to estimate anthropometric measures, weight, height, gender, and successively BMI and subjective/objective ideal weight. The result of our work is a system (see fig. 1) that shows to the subject its current position in a scale of *healthiness* and provides hints on how to reach the goal of the *ideal weight*. Thanks to computer vision we are able to provide such information to the user in a contact-less way and by using affordable 3D devices.

The rest of the paper is organized as follow. In Section 2 we present the techniques that allow the extraction of the measures and the weight estimate, as well as the gender classification. In Section 3 we explore the medical concepts of subjective and objective *body weight* and we summarize some of the methods to obtain those two values. In Section 4 the final application is described that provide to the user insights on *ideal weight*, BMI, and lifestyle choices to help reducing weight problems.

[3] *http://www.newscientist.com/article/mg21228443.700-kinect-weighs-astronauts-just-by-looking-at-them.html*

2. VISUAL WEIGHT ESTIMATION

Our system takes advantage of anthropometric measures that are used to compute a statistical model able to estimate one's weight. Training data are provided by the publicly available medical database NHANES, collected in US, that contains several anthropometric measurements for more than 28000 subjects. Our technique is built similarly to the work of [4] where a statistical model for weight estimation is built from anthropometric measures. To better exploit the non-linear relation between body measures and the body weight, we resorted to a Neural Network regressor instead of a multilinear one. To push further the weight estimation we divide our data set by classes of sex.

Since missing data are typical in database of this size, we filter out all the entries that are not complete. Successively, NHANES database is split in training, validation, and test set respectively of 30%, 35%, 35%, and Matlab Neural network toolbox is used to create our estimator. We firstly test our system obtaining the results shown in figure 2 where the cumulative distribution of the relative error is shown. Considering the males population, the majority of the database (90%) falls in the interval of $\pm 5\%$ relative error. That is, if we consider a person weighing 90 kg the correspondent error is of 4.5 kg.

Exploiting the capabilities of the Microsoft Kinect

Table 1. The table summarize the statistics about the measurements extracted from a 3D video.

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

RGBD sensor, our system is able to capture the 3D information of user's silhouette. The silhouette is analyzed and used to extrapolate the anthropometric measures needed to estimate user's weight. The procedure is derived from the one of [8] where the body parts of the user are segmented and measured separately. Each measure is repeated several times and the median value is considered to remove outliers.

A database of 15 subjects was recorded under minimum controlled conditions where the subjects were asked to wear without loose garments and without heels. The Kinect is able to perceive only the frontal surface and since we do not cope with the entire 3D reconstruction of the body, our system had been tuned to estimate what is on the back of the person; this system improves on other similar 2D based systems [4]. Table 1 summarizes the absolute and relative errors of the six anthropometric measures collected by our system; we report also the statistics of the weight estimation. The higher error for the arm circumference is due both to the poor resolution of the Kinect and to the quantization of depth measurements. Because of these two characteristics of the sensor the arm appears as a flat surface at the distance of 2–3 meters.

Height estimation's precision is definitely the best results among the other measured values. Its precision is of foremost importance in our case as both the BMI and other values computed by our system depend on height's measure.

To further automate the process, we perform gender recognition thanks to the same set of six anthropometric measures. By using a neural network classifier we are able to recognize the gender of subjects from the limited set of anthropometric measures in NHANES data set, we achieve a preliminary average accuracy of over 80%.

It is reasonable to hypothesize that age is independent from body measures, for this reason we consider it as a manual input. In the future the use of combined different sensors, techniques, and modality (e.g. face recognition) could increase the precision of each single step of our system, or make completely automatic.

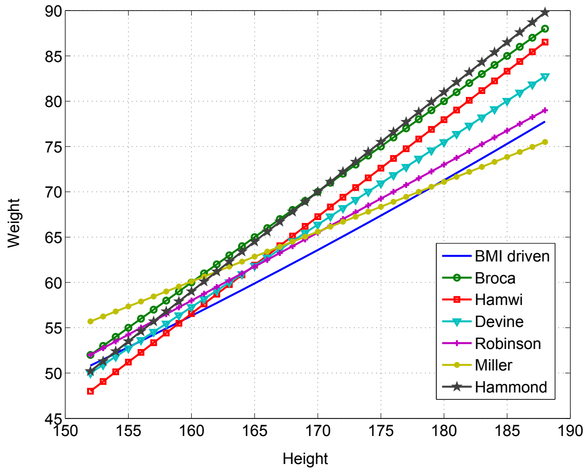

Fig. 3. The graph shows the outcome of the different equations analyzed in [9].

3. SUBJECTIVE AND OBJECTIVE IDEAL WEIGHT

The medical community agrees that by considering: bones density, height, and sex of a person, there is a weight's range which minimizes the risk of contracting illnesses like cardiovascular diseases, and some form of cancer.

While several methods exist to compute with precision the amount of fat in one's body (e.g. bio-electrical impedance) and the bone mineral density (e.g. Dual-energy X-ray absorptiometry) but those techniques require specific machines and trained technicians. For this reason specific equations where analyzed in the recent years to obtain an approximation of the optimal body weight.

However, the medical literature contains two contrasting definitions of the ideal body weight (IBW) problem. IBW was introduced in 1959 when MetLife insurance company proposed the height-weight tables. By considering the sex and height of a subject, the tables assessed the weight able to provide the lowest mortality rate. Since its introduction, this term passed through many formulation and became something not clearly defined. During the last years several works tried to reformulate it so as to have a clear idea of what this value represents.

While on the one side a *healthy* weight can be scientifically defined as the right combination of body cell mass, extra-cellular water, and nonfat connective tissue [10]; on the other hand IBW does not seems to have a clear and scientific definition.

We thus may refer to two different terms one of which is an objective evaluation, the other is a subjective one. One is a scientific measurable quantity, while the other is more subtle as it depends on a personal belief. To make a neat distinction between the two concepts, we will refer respectively to objective IBW (oIBW), and subjective IBW (sIBW).

In [11] the authors identified sIBW as the value that replies to the question: "Ideally, how much would you like to weigh at the moment?". Crawford and Campbell demonstrate that people are poorly educated about the healthy weight range. This is especially true for men, whose definition of sIBW is always higher than the healthy weight.

Other works concentrated on finding formulas to express oIBW. An interesting summary of the state of the art is made in [9], the authors group all the known equations (see Figure 3) and compare them with the height-weight tables produced for MetLife. The results of the comparison is that the formulas are quite similar even if some of those are of unknown source like Broca and Hamwi, which makes difficult to clarify their validity.

The study concludes that Robinson's formula is the closest one to the results of the MetLife height-weight tables, and the one that fits closely to the values provided by considering 22 kg/m^2 BMI (the center of the normoweight range):

$$\textit{oIBW [kg]} = (52 - 3s) + [(h - 152) \times (0.75 - 0.08s)]$$

where $s = \{0 \rightarrow \textit{male}, 1 \rightarrow \textit{female}\}$ and h represents subject's height. Nevertheless, the article suggests to refer directly to the BMI range between 18.5 and 24.9 kg/m^2 that corresponds to the *normal* range. Considering this range the oIBW becomes 22 kg/m^2, that is to say the value associated with the lowest morbidity for both men and women. If we consider the example in Figure 1 where subject's height is 1.88 m, and we revert *BMI* formula ($\textit{weight[kg]} = \textit{BMI} \times (\textit{height[m]})^2$), we obtain a normal range of 65–88 kg, and an oIBW (at 22 kg/m^2) of 78 kg.

Table 2. Comparison of *BMR* equations.

Gender	BMR equation (kcal/day)
men	$10 \times$ *weight (kg)* $+ 6.25 \times$ *height (cm)* $- 5 \times$ *age (y)* $+ 5$
women	$10 \times$ *weight (kg)* $+ 6.25 \times$ *height (cm)* $- 5 \times$ *age (y)* $- 161$

4. APPLICATION DESCRIPTION

The application we conceived exploits the anthropometric measures extracted thanks to the Kinect sensor to provide to the users a better vision of their health status.

Measuring just the current health status would not help the person to correctly tackle eventual weight problems. For this reason our system provides helpful insights about the current basal metabolic rate (BMR) that is to say the quantity of energy expended per day [12]. This value affect how our weight varies. Indeed, eating more than the BMR we gain weight, while eating less we loose weight.

Similarly to the IBW, many equations have been developed to help dietetics to compute BMR without necessarily resort to more expensive and time consuming exams. Nowadays, for historical reasons, the most common equation is the one from Harris-Benedict. However, this has been demonstrated to overestimate in many cases the real value of BMR. To be up to date with the literature, we resort to the estimation through the use of Mifflin-St. Jeor equation that has been validated as the most accurate [13] in general conditions.

Table 2 summarize the formulas used in our system, different for the two classes (male/female). However, to compute the real energy that a body need during the entire day, this value has to be multiplied by an appropriate factor proportional to the amount of daily activity (1.2 for sedentary, up to 1.9 for extra active users).

- 1.200 = sedentary (little or no exercise)
- 1.375 = lightly active (light exercise/sports 1-3 days/week, ca. 590 Cal/day)
- 1.550 = moderately active (moderate exercise/sports 3-5 days/week, ca. 870 Cal/day)

- 1.725 = very active (hard exercise/sports 6-7 days/week, ca. 1150 Cal/day)
- 1.900 = extra active (very hard exercise/sports and physical job, ca. 1580 Cal/day)

By comparing the current BMR with the one provided by the oIBW, we can provide a range of possibilities for losing (or respectively increasing) weight so as to reach the ideal weight goal. In the case of Figure 1 example the estimated calories intake for the subject is 2440 kcal/day, the system suggest that the BMR at the oIBW should be circa 2202 kcal/day. By reducing of 200 kcal/day his/her BMR and by keeping the same activity level, the subject could reach his/her oIBW. Reporting a 5% error in the weight due to the computer vision estimation will make oscillate the value of ± 50 kcal/day, which still make our system a helpful information.

5. CONCLUSION

We successfully combined computer vision techniques to measure anthropometric traits from 3D videos recorded with a Kinect sensor; opening new possible applications to computer vision algorithm. Anthropometric measures are automatically extracted and subsequently used to figure out the user's weight thanks to a statistical model that exploits updated work on data analysis on a large medical database. An interesting review of medical literature about *ideal weight* and *basal metabolic rate* is exploited to create our automatic health self-assessment tool. The application's purpose is to provide useful insights that are carriers of greater information about user's health status. Thanks to these values the user can detect weight problems and act so as to reach the lifestyle goals that mitigates those effects.

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