Body Weight And Age Analysis From Human Body Images

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ABSTRACT

Human body images encrypt plenty of useful biometric information, such as pupil color, gender, weight, etc. Among this information, body weight is a better indicator of health conditions. the recent health science studies, this work investigates the feasibility of analyzing body weight from 2-dimensional (2D) frontal view human body image. A visual-body-to-BMI dataset is collected and cleaned to aid the study, which contains 5900 images of 2950 subjects along with the debacle corresponding gender, height, and weight. Some absorbing results are obtained, demonstrating the usefulness of analysing body weight from 2D body images. In addition, the proposed method out complete two state-of-art facial images-based weight analysis approaches in most cases.

Keywords*: Body weight analysis, visual analysis of Body mass index (BMI), measurement features, visual-body-to-BMI dataset.*

I. INTRODUCTION

The Photos from social networks contain oodles of hard biometric and soft biometric information, such as pupil color, gender, height, weight, age, etc. Such biometric information can be utilized for lone identification. Among the soft biometric measures, body weight and fat are fine indicators of health conditions. Body mass index (BMI) is an important soft biometric measure that is related to people's daily lives. Given an individual's height and weight, BMI = (weight / (lb) / height (in2))*703 .BMI is an important ocular characteristic to describe a person. It is widely used for measuring the adiposity, especially for the overweight issue. In medical science, both BMI and body weight can be used to estimate the risk for some diseases, such as breast and endometrial cancers. Currently, computer vision has been a favored means for providing new techniques to automatically detect various diseases. Considering the inconvenience of measuring BMI with special devices, exploring an automatic BMI estimation method from visual images data could make it efficient to monitor the health conditions in a large-scale setting .

II. Literature Review and Objectives

1.Min Jiang, Guodong Guo, Human body images encode plenty of useful biometric information, such as pupil color, gender, weight, etc. Among this information, body weight is a good indicator of health conditions. Motivated by the recent health science studies, this work investigates the feasibility of analyzing body weight from 2-dimensional (2D) frontal view human body images. The widely used body mass index (BMI) is employed as a measure of body weight. To investigate the problems at different levels of difficulties, three feasibility problems, from easy to hard, are studied. More specifically, a framework is developed for analyzing body weight from human body images. Computation of five anthropometric features is proposed for body weight characterization. Correlation is analyzed between the extracted anthropometric features and the BMI values, which validates the usability of the selected features. A visual-body-to-BMI dataset is collected and cleaned to facilitate the study, which contains 5900 images of 2950 subjects along with the labels corresponding gender, height, and weight. Some interesting results are obtained, demonstrating the feasibility of analyzing body weight from 2D body images. In addition, the proposed method outperforms two state-of-art facial images based weight analysis approaches in most cases

2.Elise Klæbo Vonstad , Beatrix Vereijken , Kerstin Bach , Xiaomeng Su , and Jan Harald Nilsen In exercise gaming (exergaming), reward systems are typically based on rules/templates from joint movement patterns. These rules or templates need broad ranges in definitions of correct movement patterns to accommodate varying body shapes and sizes. This can lead to inaccurate rewards and, thus, inefficient exercise, which can be detrimental to progress. If exergames are to be used in serious settings like rehabilitation, accurate rewards for correctly performed movements are crucial. This article aims to investigate the level of accuracy machine learning/deep learning models can achieve in classification of correct repetitions naturally elicited from a weight-shifting exergame. Twelve healthy elderly (10F, age 70.4 SD 11.4) are recruited. Movements are captured using a marker-based 3-D motion-capture system. Random forest (RF), support vector machine, k-nearest neighbors, and multilayer perceptron (MLP) are the employed models, trained and tested on whole body movement patterns and on subsets of joints. MLP and RF reached the highest recall and F1-score, respectively, when using combined data from joint subsets.

3.Shahzad Muzaffar and Ibrahim (Abe) M. Elfadel Change patterns in body weight are significant indicators of a variety of medical conditions and in some instances, such as congestive heart failure, strong predictors of critical care interventions. The continuous monitoring of body weight can therefore help care givers and patients reduce the risks that are inherent in ignoring body weight changes or in measuring them infrequently. One possible approach to continuous body weight monitoring is to use shoe-integrated sensors.Such approach is however hampered by the lack of patient's adherence to medical protocols and by the detrimental impact of motion artifacts on weight measurements during body movement. The objective of this paper is to show that both problems can be readily addressed by pushing body weight measurement into the background of the patient's daily routine and by adapting piezoresistive flexible force sensors to the specific requirements of accurate body weight measurement during motion.The proposed solution is enabled by two major innovations.

4.Tan Halim Supranata , Poh Steven Sean Davin Body weight is an indicator that shows many things from someone's body. There are two ways to measure our body weight, analog and digital depend on body scales that is being used. Traditional body scales are accurate, but also get some weaknesses such as the likelihood of the result being misread by the user. This research is about detecting someone's weight through his photograph. Elliptical tube volume and body surface area are two different methods that are used for this research. Both methods assume human body consists of many small size tubes. For elliptical tube volume, human's body weight is measured by applying volume's tube formula. But for body surface area, the human's body weight is measured by applying surface area of a tube. From the results of the study, the elliptical tube volume method's accuracy is 93,271body surface area method's accuracy is 92,854volume method is more accurate than the body surface area method.

III. MATERIALS AND METHODS

To the best of our knowledge, there is no previous approach that can estimate the BMI values from 2D body images only. Thereby, we compare with two methods which predict BMI values from face images. One is a geometric feature based method and another is a VGG-face feature based method [28]. They are denoted as PIGF (psychology inspired geometric feature) and VGG feature, respectively. These two methods both require clear frontal face images as the input, while some images in visual-body-to-BMI dataset do not meet this requirement. For a fair comparison, we select 2000 images which contain the clear frontal view face and then crop the face images. The 2000 images are split into training and test sets, which contains 1500 and 500 images, respectively. The input of our approach is a single body image, and the input of the other two methods is a face image cropped from the same body image. The comparison of the results is shown in Table VII. It can be seen that the proposed method outperforms the PIGF and VGG-face feature based methods in most cases, except on the male set. Moreover, the proposed method does not require a clear frontal view face image as input, which is useful for more general applications.

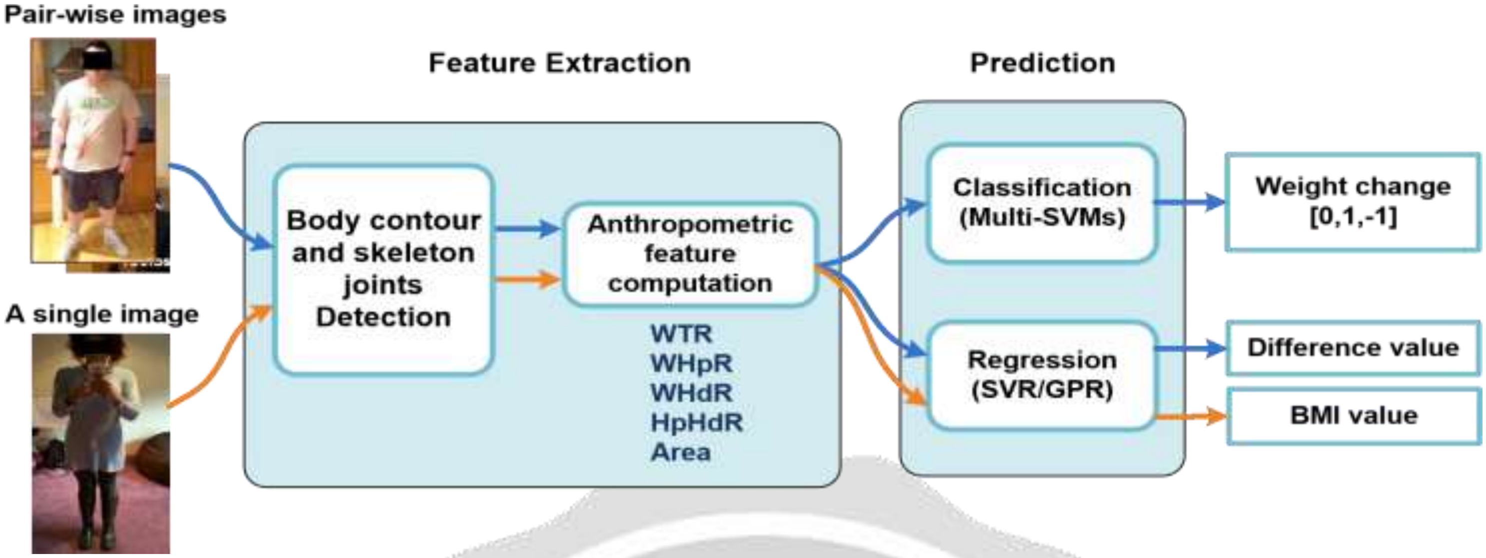
Furthermore, considering the features learned in deep neural networks (DNN) are demonstrated to be transferable and effective when used in other visual recognition tasks [48], we compare our anthropometric features with that the deep features. In this experiment, we employ the VGG-Net [49] model which is pre-trained on ImageNet database [50] to extract the deep feature. Then an SVR model is trained based on the extracted

3.1 FEATURE EXTRACTION

we present the details about feature extraction for the proposed approach. Body contour and skeleton joints (CSJ) detection is the first step for feature extraction. The output of the detection is used for anthropometric feature computation.

A. Contour and skeleton joints detection

Body contour and skeleton joints (CSJ) detection are based on deep networks for contour and skeleton joints detection. Fig. 6 shows the body contour and skeleton joints detected by the CSJ detector. The brick red area represents the detected body part. The asterisks represent the detected skeleton joints.



B. Anthropometric feature computation

Several anthropometric indicators suggested in health science [13]–[16] are used as measures for the obesity. Some listed indicators include waist-thigh ratio, waist-hip ratio, abdominal sagittal diameter, waist circumference, and hip circumference. Taking into account these indicators, we have five anthropometric features automatically detected and computed from body images, including waist width to thigh width ratio (*WTR*), waist width to hip width ratio (*WHpR*), waist width to head width ratio (*WHdR*), hip width to head width ratio (*HpHdR*), and body area between waist and hip (*Area*). Among these features, *Area* is inspired by our human perception.The measurement of the waist circumference and the hip circumference cannot be directly obtained from 2D images. We consider the particular body part as a cylinder. Then we use the width of the body part (on a 2D image) to approximately represent the circumference of a particular body part.

Body part	Abbrev.	Body part	Abbrev.
Nose	n	Hip	h
Left ear	le	Left hip	lh
Right ear	re	Right hip	rh
Center shoulder	cs	Left hip boundary	lhb
Waist	w	Right hip boundary	rhb
Left waist	lw	Thigh	t
Right waist	rw	Left thigh boundary	ltb
Left waist boundary	lwb	Right thigh boundary	rtb
Right waist boundary	rwb	Knee	k
Left knee	lk	Right knee	rk

There are 18 detected skeleton joints shown in the figure labeled with asterisks. In the following, we use the coordinates of 8 detected skeleton joints for computing anthropometric features. These 8 skeleton joints are the nose, left ear, right ear, center shoulder

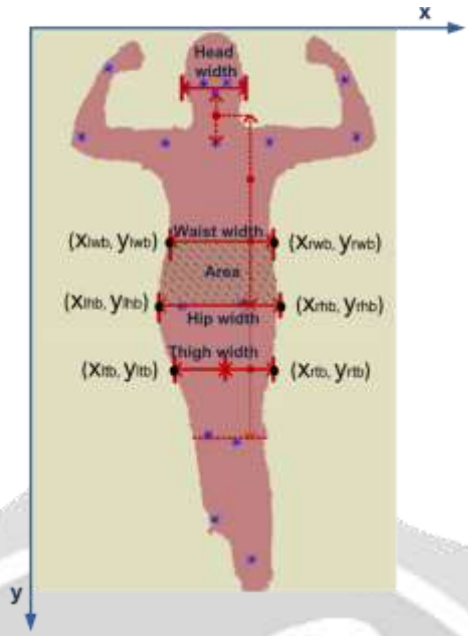


Fig. The anthropometric features computed for body weight analysis. The 18 skeleton joints (labeled by asterisks) are nose, left eye, right eye, left ear, right ear, center shoulder, left shoulder, right shoulder, left elbow, left hand, right elbow, right hand, left hip, right hip, left knee, right knee, left ankle and right ankle. The area filled with green dash dots denotes the feature *Area*.

3.2. Support vector machine

Support vector machines (SVMs) are supervised learning algorithms that analyze data for classification or regression. There are two main categories for SVMs: support vector classification (SVC) and support vector regression (SVR). They have been widely utilized in many problems . The SVM can do nonlinear classification using kernel functions. Gaussian radial basis Function (RFB) kernel is one of the most popular kernels. In this work, the RBF kernel achieves a better performance in classification and regression than other kernels. The SVC is a binary classifier. To get multi-class classification, a set of binary classifiers are constructed with each trained to separate one class from another. For n classes, this results in $\frac{(n-1)n}{2}$ binary classifiers. Since our classification on BMI difference has three classes {*0,1,-1*} for a pair of images, 3 binary classifiers are trained accordingly. The SVR uses the same principle, similar to the SVC, but with differences in the optimization.

3.3. Gaussian processing regression

A Gaussian process (GP) is a collection of random variables and a finite number of variables which have a joint Gaussian distribution [45]. GPR means Gaussian process regression. The prior mean and covariance of the GP need to be specified. The prior mean is assigned constantly with zero, or the mean of the training data. The prior covariance is specified by passing a kernel object. The hyper-parameters of the kernel are optimized by maximizing the log-marginal-likelihood. A rational quadratic kernel is employed for GPR. Given a set of training examples

(a_1, b_1), ...(a_n, b_n), the rational quadratic kernel is defined as:

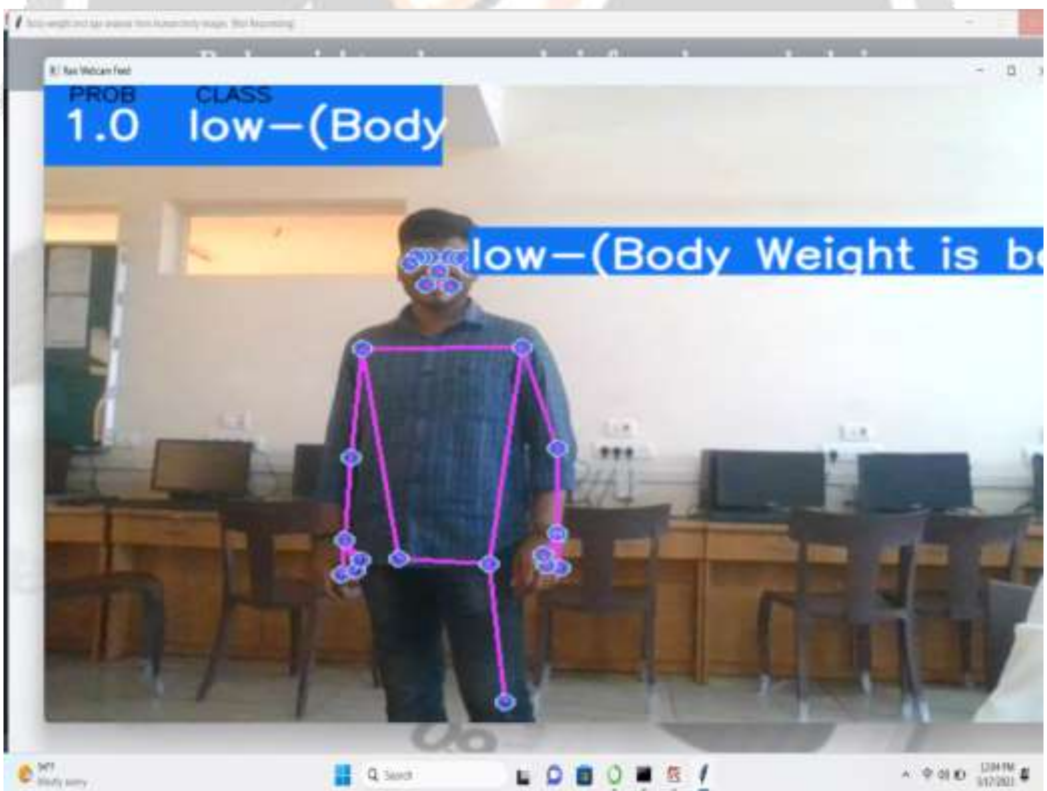
$$k(a_i, a_j) = \left(1 + \frac{D(a_i, a_j)^2}{2\alpha\iota^2}\right)^{-\alpha},$$

here ι is a length-scale parameter, α is a scale mixture parameter, and $D(\cdot)$ denotes the distance between two sample points.

IV. RESULT AND DISCUSSION

we first analyze the errors generated in feature extraction. Then the statistical analysis will be given, discussing whether the errors are acceptable for the application of BMI estimation from a single image. Finally, we analyze the influencing factors for the proposed method and possible reasons for the failure cases.

For feature extraction and regression, the widths of head, waist, hip and thigh are estimated from the 2D body images, and used to calculate the four anthropometric features (*WTR*, *WHpR*, *WHdR*, *HpHdR*). To analyze the error, we randomly selected 300 images from the dataset and manually labeled the widths of head, waist, hip, and thigh for each image. Then the labeled widths are used as the ground truth values (v) to calculate the relative error (ε) of the estimated values ($\hat{v}$) by: $\varepsilon = \frac{|v-\hat{v}|}{v}$. The mean relative errors of the extracted widths are shown in Table IX. The four errors are within a relatively low range. Since it is hard to label the area between waist and hip, where the relative error of estimated *Area* is not given. To demonstrate whether the errors are acceptable for BMI estimation from a single body image, we further calculate the accuracy of the predicted category. According to the estimated BMI values, we can classify the body belong to which BMI category (underweight, normal, overweight and obese). The accuracy of the predicted category is the proportion of the total number of predictions that are correct. This measurement is helpful to decide if the errors are acceptable. For example, given a body image with ground truth BMI value of 24.5, the estimated value is 20. Though the absolute error is 4.5 which is larger than the MAE (3.8), the predicted category (normal) is correct. On the other hand, this measurement has a limitation.



V. CONCLUSION

This project Accuracy is impacted by a number of variables, including people's attire, hair, and picture processing. Results are also influenced by gender because men and women often dress differently, which gives males a better accuracy than women. These variables still have a significant impact on accuracy, with a variation of roughly 4 kg. Future studies can be conducted to lessen the impact of clothes and hair on computations.

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