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Quantifying Obesity from Anthropometric Measures and Body Volume Data

Chuang-Yuan Chiu and Ross H. Sanders

Abstract— **Obesity has become a serious problem in several developed and developing countries. Three-dimensional photonic scanning (3DPS) is a useful tool to obtain accurate anthropometric measures and body volume data for body shape quantification. Some traditional models have been developed to estimate body fat percentages from anthropometric measures or body volume data for body composition classification and obesity quantification. However, these traditional models are very sensitive to the errors in anthropometric measures and body volume data. Small errors in anthropometric measures or body volume data reduces accuracy of body fat percentages estimated from 3DPS and may lead to misclassifications when quantifying levels of obesity. In this study, pattern recognition techniques, neural networks, were applied to develop a new model which can classify obesity levels from a combination of anthropometric measures and body volume data without estimating body fat percentages. The developed model and the traditional models were applied to determine 2209 male participants' body composition classes for obesity quantification. The accuracy of the new and the traditional models was determined by comparing the estimated body composition classes with the real body composition classes obtained from dual energy X-ray absorptiometry scanning output. The results showed that the accuracy of the developed model was better than the traditional models. Therefore, the developed model provides more accurate results in body composition classification for obesity quantification.**

Index Terms—**anthropometry, body composition, classification, neural network, obesity**

I. Introduction

Obesity has become a serious problem in several developed and developing countries [1]. According to the World Health Organization report [2], more than 600 million adults were obese worldwide. Body mass index (BMI) was generally used to quantify people's obesity levels. However, Shah and Braverman [3], Batsis, et al. [4] and Pilutti and Motl [5] indicated that BMI might underestimate people's obesity levels since BMI cannot be used to quantify body shape [6] and determine body composition [7].

To complement BMI, several techniques have been developed to quantify body shape and body composition. Among these methods, three-dimensional photonic scanning (3DPS) is a technique which enables body shape and body composition to be quantified within a rapid scanning session. Wang, et al. [8] and [9] showed that 3DPS can be used to obtain accurate anthropometric measures (e.g. heights, body masses, segmental lengths, and circumferences) and body volume data (whole body volumes and regional volumes) for quantifying body shape. The results of body shape quantification obtained from 3DPS could be used to calculate useful indicators (e.g. waist-to-height ratio[10] and abdominal volume index[11]) for estimating the risks of disease related to obesity.

Apart from BMI and body shape quantification, body composition, usually represented in body fat percentages, is another indicator for assessing the level of obesity. Researchers usually used traditional models to estimate body fat percentages of individuals from body volume data [12, 13] or anthropometric measures [14, 15] and then complete the body composition classification to assess the level of obesity as shown in Fig. 1. Okorodudu, et al. [16] indicated that most researchers regard body fat percentages of 25% and 35% as the cut-points for defining obesity for male and female participants (i.e. obese men: body fat percentages > 25%; non-obese men: body fat percentages ≤ 25%; obese women: body fat percentages > 30%; non-obese women: body fat percentages ≤ 30%).

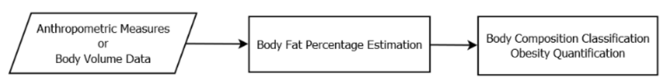

Fig. 1 A traditional model for obesity quantification from the parameters which can obtain from 3DPS.

The body volumes and anthropometric measures obtained from 3DPS have been used to estimate body fat percentages [17, 18]. Adler, et al. [18] measured whole body volumes from 3DPS in conjunction with body masses to estimate body fat percentages of individuals. Garlie, et al. [17] measured body fat percentages from the circumference data acquired from 3DPS.

However, the traditional models were very sensitive to the errors in anthropometric measures and body volume data [8, 17, 18]. Small errors in anthropometric measures or body volume reduces the accuracy of body fat percentages estimated from 3DPS. Adler, et al. [18] indicated that there are large differences between body fat percentages obtained from 3DPS and those estimated from air displacement plethysmography (limit of agreement of error from 1.4% to 12.6%). Compared with the results obtained from dual energy X-ray

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absorptiometry (DXA), the error of body fat percentages estimated from 3DPS is also considerably high (limit of agreement of error from -4.69% to 5.99%) [17].

The poor accuracy of the body fat percentages estimated from 3DPS could lead to misclassifications of body composition and obesity level. For example, if a man's real body fat percentage is 24.9% but the estimated value is 25.1%. Then, according to the classification system commonly used, the person would be classified as obese despite the actual real value being below the threshold (25%).

For studies with large populations, the classification results were usually more important than continuous measures of body fat percentages. For instance, it was usually essential for health surveys to indicate the proportion of obese people rather than showing participants' body fat percentages [19]. To improve accuracy in obesity quantification and avoid classification errors, pattern recognition techniques could be applied to develop a new model which completes the body classification from both anthropometric measures and body volume data without estimating people's body fat percentages as shown in Fig. 2. Schranz, et al. [20] indicated that using the combination of body dimensions including anthropometric measures and body volume data can determine sports performance more accurately than merely using anthropometric measures. Taking the combination of anthropometric measures and body volume data as input could provide more useful information in body composition classification for obesity level than the traditional models which only considered either body volume or anthropometric measures. By using the new model, the effect of the error in body fat percentage estimation on the body composition classification is eliminated. Therefore, the new model might improve the accuracy of estimating obesity levels when using 3DPS.

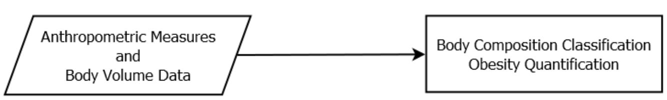

Fig. 2 A new model for obesity quantification from the parameters which can obtain from 3DPS.

Nevertheless, to our knowledge, this kind of new model has not been developed. The first step for building this kind of model is to determine whether the combination of parameters increases the accuracy of the binary classification (obese and non-obese). Hence, the first aim of this study was to develop a new model that can estimate the level of obesity from a combination of anthropometric measures and body volume data without estimating body fat percentages. The second aim of this study was to examine the accuracy, sensitive (true positive rate) and specificity (true negative rate) of the developed model.

II. METHOD

A. Participants

To develop a new model, data were collected from the 2005-2006 datasets of National Health and Nutrition Examination Survey (NHANES). In total the data extracted from 1990 males aged 18-80 years(height: 175.5 ± 7.9 cm, mass: 86.9 ± 19.9 kg, body fat percentage: 27.0 ± 6.4%; 62.86% obese, 37.14% non-obese) with complete information in DXA scan output (regional fat masses, fat-free masses, bone mineral contents, total body fat masses, fat-free masses, bone mineral contents, body fat percentages), self-reported survey (genders, ages, races) and anthropometric measures (heights, masses, segmental lengths, circumferences) were used.

To determine the accuracy of the new model and the traditional models, 2209 males, aged 18-80 years participants (height: 175.4 ± 7.9 cm, mass: 85.3 ± 18.7 kg, body fat percentage: 27.5 ± 6.5%; 67.41% obese, 32.59% non-obese) with complete information in DXA scan output, self-reported survey and anthropometric measures were extracted from the 2003-2004 datasets of National Health and Nutrition Examination Survey (NHANES) as the test sample.

B. Data Preprocess

Participants' ages and anthropometric measures (heights, body masses, segmental lengths, circumferences) were obtained from the datasets of NHANES directly. Body volume data (total body volumes, the regional volumes) and body composition classes were calculated from the information in DXA scan output. The regional volumes and total volumes for each participant were calculated by (1) presented in the previous study [21]. The real body composition classes for obesity quantification were determined by the extracted body composition values with the most popular classification method (obese men: body composition > 25%; non-obese men: body composition ≤ 25%) [16].

$$\text{Volume (l)} = 0.01 + \frac{Fat\ (g)}{0.88} + \frac{Lean\ (g)}{1.05} + \frac{BMC\ (g)}{4.85} \quad (1)$$

C. Model Development

To develop the new model which can complete body composition classification from body volume data and anthropometric measures, participants' ages, body masses, heights, upper leg lengths, calf circumferences, upper arm lengths, arm circumferences, waist circumferences, thigh circumferences, head volumes, trunk volumes, left arm volumes, right arm volumes, left leg volumes, right leg volumes, whole body volumes, were extracted as the input features (p) of the model. The output (q) of the model was a body composition class, which defined as 0 and 1 represented by non-obese class (body fat percentages ⩽ 25%) and obese class (body fat percentages > 25%) separately. The developed mode (f) can be represented in (2).

$$f(p) = q, q \in \{0,1\} \quad (2)$$

Pattern recognition techniques, neural networks [22], were applied to develop the models for body composition classification. In this study, 85% sample (1691 participants) and 15% sample (299 participants) were randomly selected as the training and validation sets for generating the neural network models. Twenty hidden layers were applied in the model as shown in Fig. 3. The model was built with Matlab Neural Pattern Recognition Tool (nprtool; https://www.mathworks.com).

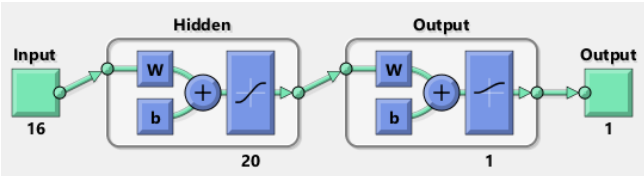

Fig. 3 The developed neural network model for body composition classification in this study (W: weight, b: bias).

D. Evaluation Test

To determine the accuracy, sensitive (true positive rate) and specificity (true negative rate) of the developed model for body composition classification and obesity quantification, the body composition classes estimated by the developed model compared with the real body composition classes acquired from DXA scanning output. The accuracy was represented by the ratio of the number of cases correctly identified as obese (TP) or non-obese (TN) to the number of total participants (PN) as shown in (3). The sensitivity was the ratio of the number of cases correctly identified as obese (TP) to the number of truly obese participants (P) as shown in (4). The specificity was denoted by the ratio of the number of cases correctly identified as non-obesity to the number of truly non-obese participants as shown in (5). The definition of accuracy, sensitivity, and specificity was referred to the illustration in the previous study [23].

$$Accuracy = \frac{TP + TN}{PN} \quad (3)$$

$$Sensitivity = \frac{TP}{P} \quad (4)$$

$$Specificity = \frac{TN}{N} \quad (5)$$

The accuracy, sensitivity and specificity of the traditional models were also calculated to compare with the ones of the developed model. To achieve this, each participant's body fat percentage was calculated by the equations presented by Siri [12] and Brožek, et al. [13]. The calculated body fat percentage of each participant was used to compare against the 25% cut-off for classifying as obese or not obese. The body composition classes estimated from the traditional models compared with the real classes acquired from DXA scanning output.

III. Result

TABLE I shows the accuracy, sensitivity and specificity of the developed model and the traditional model. The accuracy of the developed model was higher than 0.8 while the accuracy of the traditional model was lower than 0.75. The sensitivity of the traditional model was close to one and the sensitivity of the developed model was higher than 0.85. The difference of the sensitivity and specificity of the developed model was smaller than 0.1 but the differences of the sensitivity and specificity of the traditional models were larger than 0.8.

TABLE I
Analysis result of the comparison test

	Developed model	*Traditional Model (Siri [12])*	*Traditional Model (Brožek, et al. [13])*
Accuracy	*0.839*	*0.728*	*0.737*
Sensitivity	*0.862*	*0.999*	*0.999*
Specificity	*0.790*	*0.168*	*0.194*

IV. Discussion

The aim of this study was to 1) develop a new model that can complete classification of obesity levels from a combination of anthropometric measures and body volume data without estimating body fat percentages; 2) examine the accuracy, sensitive, and specificity of the developed model for obesity quantification.

The test results showed that the accuracy of the developed model was higher than the accuracy of the traditional model. It confirms that using the combination input of anthropometric measures and body volume data to conduct body composition classification without body fat percentage estimation improves the accuracy of classifying obesity level . Ng, et al. [24] indicated that 476 anthropometric measures enable to obtain from 3DPS. In this study, only 8 anthropometric measures (body mass, height, upper leg length, calf circumference, upper arm length, arm circumference, waist circumference, and thigh circumference) were selected to use. Additional anthropometric measures should be extracted for the new mathematical modelling in further development to improve the accuracy of obesity classification.

The specificity of the developed model was higher than the specificity of the traditional model. However, the sensitivity of the developed model was lower than the traditional model. The possible reason might be that the traditional models usually overestimate body fat percentages. This interpretation is supported by the results reported in a previous study [25]. The body fat percentages calculated by the equations presented by Siri [12] and Brožek, et al. [13] should be calibrated to eliminate the systematic errors to improve the accuracy in obesity classification. By contrast, the error for body fat percentage estimation can be ignored while applying new models. To optimize body composition classification for obesity quantification, further development should concentrate on the improvement of new models.

This study shows that the new models enable accurate body composition classification using only the anthropometric measures and body volume data. Nevertheless, the anthropometric measures and body volume data were collected from manual measurement and estimated from DXA scanning output instead of obtaining from 3DPS. Glock, et al. [9] indicated that the anthropometric measures obtained from 3DPS are highly correlated to the manual measurement results. Adler, et al. [18] and Wilson, et al. [21] indicated that the difference between the body volume data obtained from 3DPS and air displacement plethysmography, DXA and air displacement plethysmography were very small. The small difference in anthropometric measures and body volume data between 3DPS and other measurements might still cause some error in body composition classification for obesity quantification. This study showed the new model can deliver a more accurate body composition classification than the traditional model. Further studies should investigate the different effect and build the new models for the anthropometric measures and body volume data acquired from 3DPS.

The main limitation of this study is that the developed model could not be applied to the participants in different genders or age groups since the differences of body shapes and sizes. Apart from binary obesity classification, some advanced classification for obesity quantification has been developed. For example, World Health Organization [26] categorized obese levels in four classes: normal range, grade 1 overweight, grade 2 overweight, and grade 3 overweight. This kind of advanced classification enables users to understand their obese level precisely. Thus, further study should extend the developed model for quantifying advanced obesity levels for people in different genders and age groups.

V. Conclusion

Traditionally, researchers have estimated body fat percentages and then complete the body composition classification to determine whether a subject is obese or not obese. The error in body fat percentage estimation usually causes body composition misclassification. In this study, a new model was developed for improving the accuracy of body composition classification. The new model used a combination input of anthropometric measures and body volume data to obtain more useful information for body composition classification. Furthermore, the pattern recognition techniques were applied to develop a new model without the traditional procedure of body fat percentage acquisition to avoid the effect of estimation error. The results showed that the accuracy and specificity of the developed model were better than the traditional models. Therefore, the developed model improves the accuracy of results in body composition classification.

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