Classification of Body Mass Index Based Face Images Using Facial Landmarks Approach and PCA plus LDA

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Abstract

Human faces contain rich information. Recent studies found that facial features have relation with human weight or body mass index (BMI). Decoding "facial information" from the face in predicting the BMI could be linked to the various health marker. This paper proposed the classification of body mass index (BMI) using facial landmark approach based on facial images. In this framework, Discriminative Response Map Fitting (DRMF) method has been used as feature extraction technique to detect and locate the facial landmark points on the facial images. About sixty-six (66) facial landmark points were identified. Only nineteen (19) of facial landmark points have been employed to extract the facial features in terms of distance and ratio features. A total of 221 facial landmark features were obtained and used as feature vector to classify the BMI classes. The rationale of using 221 facial landmark features is because these features were able to exhibit the unique characteristic of the BMI classes, which are normal, overweight and obese. Then, the extracted features were further reduced using Principal Component Analysis (PCA) plus Linear Discriminant Analysis (LDA) to map high dimension features into low dimensional feature with maximize between class scatter and minimize within class variations. Later, the reduced features were subjected to k-NN classifiers. A series of experiments has been conducted on MORPH II database using the reduced facial landmark features to classify the three BMI classes. Based on the experimental results, it shows that the reduced features using PCA plus LDA based on k-NN classifier has achieve the highest recognition rate with accuracy of 83.33 %. The obtained results show that the reduced facial landmark features were able to discriminate the three BMI classes of normal, overweight and obese, thus shows the promising results.

Keywords: Body mass index, facial images, facial landmarks, PCA plus LDA,

1 INTRODUCTION

Nowadays, humans have different way of communicating with other people, while the face is one of a human being's most impressive and special communication tools and plays an important role in visual communication [1-2]. Facial landmark is an abstraction and may have various definitions in previous studies. According to Galvánek et al. [1], the facial landmark is defined as a point that shares and has a clear biological significance for all faces. In computer science applications such as facial recognition, animation and speech analysis, facial landmarks play a prominent role. However, to automate facial landmark points such as artifacts created during 3D image acquisition, non-uniform facial expressions and positions and occlusions of facial features remains a challenging task and ongoing research[1]. In previous work, Coetzee et al.[2] have conducted the study in determining the relation between the facial cues with the body weight. They recruited two groups of Caussian and two groups of African subjects consist of both sexes with known BMI and measured their 2D facial images. They found that the width-to-height ratio, perimeter-to-area ratio, and cheek-to-jaw-width ratio are associated with BMI in males and width-to-height and cheek-to-jaw-width ratios are related to BMI in females.

In the other hand, Wen and Guo[3] developed a computational approach to predict the BMI from face images. They used an active shape model (ASM) to detect the facial fiducial points automatically. The correlation has been measured between the facial features and the BMI and it shows that all the correlation are significant based on the extremely small p-value obtained. The facial features consist of cheekbone width to jaw width ratio, width to upper facial height ratio, perimeter to area, average size of eyes, lower face to face height ratio, face width to the lower face height ratio and average distance between eyebrows and the upper edge of eyes have been extracted in predicting the BMI. The work of Wen and Guo were further extended by Jiang et al.[6] by proposing the fusion techniques by utilizing the psychology inspired geometric features (PIGF) and geometric facial representation-pointer feature (PF) defined by face shapes with a series of facial landmark points to extract a richer geometric representation. Deep learning feature representation has been used by evaluating the VGG-Face model for BMI prediction.

Recent years, a surprisingly phenomenon have been appeared in US, which is more than two-third of the adult are trend to be overweight or obese. In result, obesity have been confirming as a disease by American Medical Association due to the data show that nearly one out of every ten adult's death caused of obesity[3]. Due to the increase in weight and BMI value, in the end all this will come to a result which is getting personal health problem like diabetes, strokes and so on [4]. Thus, by take the advantage of BMI based facial images would be very crucial for us to aware the level of healthiness through BMI for each individual in order to encourage the awareness of health. Besides that, old way of detecting BMI is not convenience because of we need to calculate the BMI manually. So, detecting BMI using facial image not just another option for detecting BMI, but also a method that is non-invasive [3].

2 METHODS

Figure 1 shows the block diagram of the proposed method that consists of five main steps: original facial BMI database, facial landmark detection, feature extraction, feature reduction and BMI classification. Figure 1 shows the flowchart of the proposed method. Each of the blocks are explained in the following next subsections.

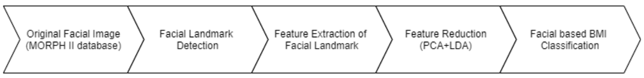

Fig 1. Block diagram of the proposed method

2.1. Image Database

In this study, a public database namely MORPH-II database has been used. It consists of 4206 facial images with measured BMI values. The database contains four categories of BMI which are underweight, normal, overweight and obese. Due to inadequate database for underweight category, we only considered three categories of facial BMI images such as normal, overweight and obese. A total number of 690 facial images (220 normal, 230 overweight and 240 obese) has been employed in the proposed method. Figure 2 shows the example of MORPH-II facial database with measured BMI for normal, overweight and obese category.

Fig 2. The example of MORPH II database for three BMI classes.

2.2. Facial Landmark Detection

In order to compute the features automatically, we used the Discriminative Response Map Fitting (DRMF) to detect facial landmark points first, and then calculate the distance and ratio features. The recently developed DRMF technique[5] can find 66 facial landmark points in a face image. We used 19 points out of 66 to produce the facial features that are related to BMI. Those points are marked as P$*$ in Figure 3 ($*$ indicates the $*$th points in the original list returned by the DRMF method). Note that even with the big number of 66 points detected by the DRMF, as shown in Figure 3 there are still some other points that are needed to compute the features.

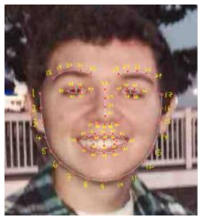

Fig 3. Illustration of facial landmark points for BMI classification

2.3. Feature Extraction

The 19 points out of 66 that define the face shape by a series of facial landmarks were extracted on facial images to produce the facial features. In this work, seven facial features were computed in terms of distance and ratio features. The rationale of using these 19 points (distance and ratio features) is because these features able to exhibits the characteristic of individual

BMI classes. They are visually shown in Figure 4. The meanings of these features are described below:

1) The landmark distance of point n to point m (n = 1, 2, 3, 4, 5, 6, 7, 8; m =10, 11, 12, 13, 14, 15, 16, 17)
2) The distance of point x to point 8 (x = 9, 10, 11, 12, 13, 14, 15, 16, 17)
3) The distance between point y to point 10 (y = 1, 2, 3, 4, 5, 6, 7, 8, 9)
4) The ratio of all of above (1, 2, 3)
5) The square root ratio of all of above (1, 2, 3)
6) Face width to height ratio (WHR)
7) Cheek to jaw width ratio (CJWR)

Fig 4. Illustration of the facial features used for BMI classification

2.4. Feature Reduction: PCA plus LDA

In this work, a total of 221 facial features was obtained and form a feature vector. Principal Component Analysis and Linear Discriminant Analysis were employed as feature reduction on the feature vector to transform the high features space into low dimensional space by maximizing between-class scatter as well as minimizing within-class scatter of the facial features. Due to these characteristic exhibit by PCA plus LDA, the intra-class and inter-class variations will be optimized.

2.5. BMI Facial Classification

In this study, k-Nearest Neighbour (k-NN) is used as classifier to classify the BMI facial classification such as normal, overweight and obese. The k-NN is one of the simplest algorithm that used in machine learning for regression and classification, but mainly used for classification. Compare to other classifier, k-NN will totally will save the time in training the data but more in predicting.

3 RESULTS AND DISCUSSIONS

3.1. Applied Facial Landmark Points on BMI Facial Images

Figure 5 shows the result of facial landmark points on facial images. A total of 66 facial landmark points has been identified. Although the DRMF technique has shown their advantages in the detecting facial landmarks, however there is also miss locating the facial landmark points that define the face shape. Figure 6 shows the example of miss locating the facial landmark points on the facial images. Thus, it may affect the accuracy of the BMI classification. Empirical studies show that only 19 points exhibit the unique features in which facial landmark points of point 1 to point 17, point 28 and point 52 are considered. From these points, distance points and distance ratio were computed to be used as facial features to classify the normal, overweight and obese. A total of 221 extracted facial landmarks features have been adopted for further investigation.

Fig 5. Results of the 66 facial landmark points

Fig 6. Miss locating the facial landmarks for obese category

3.2. Distribution of PCA plus LDA on Facial Features

In this experiment, the PCA plus LDA were conducted on original facial landmark features to map high dimension into lower dimensional and discriminate the significant features. Figure 7 presents the distribution of facial landmarks feature of three classes using PCA plus LDA in which class 1 is denoted as normal BMI (red dot), class 2 is overweight (green dot) and class 3 refers to obese (blue dot). It can be seen in Figure 7 that the distribution of three BMI classes are clearly discriminate. This can be inferred that the ratio between-class scatter of facial landmark features of the three class are maximized to that within-class scatter are minimized. However, small overlapping between the three classes still appear in the middle of the distribution.

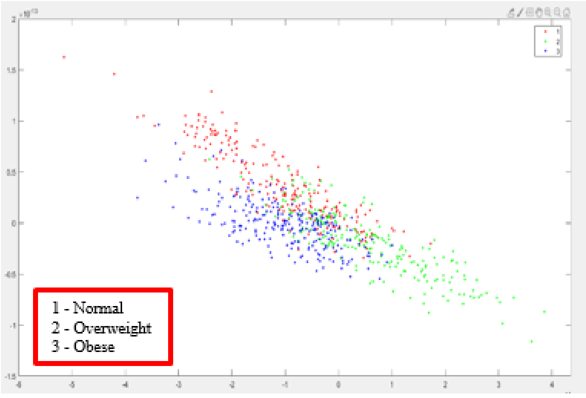

Fig 7. Distribution of reduced facial landmarks features using PCA plus LDA

3.3. Recognition Results and Discussion

To evaluate the effectiveness of the proposed method, a publicly available MORPH-II database of BMI Facial Images has been employed in this experiment. The DRMF technique has been used as feature extraction. There are 66 facial landmark points has been identified on the facial images. About 19 points out of 66 points which defines the facial shape were extracted and computed as facial features in term of distance and ratio features. A total of 221 facial features were extracted to be used as facial features. Further investigated on extracted facial features using PCA plus LDA as feature reduction before fed as input to the k-NN classifier. In this work, ten-fold cross validation has been used for training and testing the data. The nine folds of the data were used as training and the remaining ones used for testing. Each of the process was repeated for ten times at each fold and the final average accuracy was computed.

Figure 8 shows the classification rates of reduced facial feature using k-NN classifier for the BMI classification. The value of k was tuned from 1 to 12. Beyond this value, the accuracy tends to decrease.

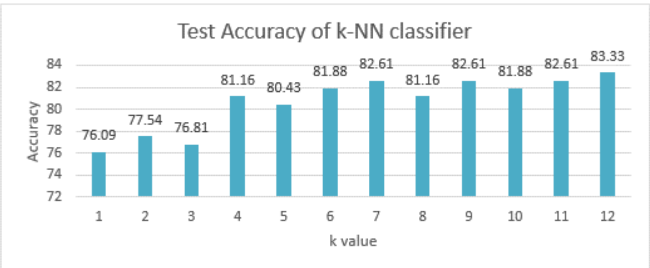

Fig 8. Classification rates of reduced facial features using k-NN classifier

As we can see from Figure 8 that the highest recognition rates was achieved when the value of k = 12 which is 83.33%. Table 1 shows the confusion matrix of using PCA plus LDA with k =12. Based on Table 1, it can be seen that the obese shows the highest recognition rate, which is 89.6%. Only 5 images were misclassified. On the other hand, the overweight gives the lowest recognition rate which is 71.7%. Thirteen out of 46 are misclassified. Seven of them were misclassified as normal and six were misclassified as obese. This can be inferred that, fiducial points of the overweight still mimicking the others BMI categories. Therefore, further study needs to be conducted to select and optimize the robust fiducial points in classifying the BMI facial images.

Table 1. Confusion matrix of reduced facial features by means PCA plus LDA using k-NN classifier (k = 12)

Status	Normal	Overweight	Obese	Average
Normal	**39**	7	2	88.6 %
Overweight	2	**33**	3	71.7 %
Obese	3	6	**43**	89.6 %
Total	44	46	48	**83.3 %**

4 CONCLUSIONS

This study has presented the classification of body-mass index based facial images using facial landmark points. It was observed that the DRMF able to identified the facial landmark points efficiently with 66 facial points. Throughout these facial points, only 19 facial points have been used to extract the facial features in terms of distance and ratio features producing 221 features. The rationale of using 221 facial features is because these features were able to exhibit the unique characteristic of the BMI classes, which are normal, overweight and obese. The used of PCA plus LDA in reducing the facial features helps to optimize the intra and inter class variation exist in BMI distribution. Based on the result obtained, it shows that the reduced features by means of PCA plus LDA with k-NN classifier has achieved the highest recognition rate with accuracy of 83.33 %. This results show that the reduced facial landmark features were able to discriminate the three BMI classes of normal, overweight and obese, thus shows the promising technique of the proposed method.

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