IOP Conf. Series: Materials Science and Engineering **420** (2018) 012095 doi:10.1088/1757-899X/420/1/012095

Probabilistic neural network and invariant moments for men face shape classification

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Abstract. Face shape classification is useful for grooming personalities, such as the selection of haircut, the selection of facial makeup, the selection of glasses frames or even the selection of appropriate shirts. The face shape in men is divided into six forms, namely: oval, round, diamond, rectangle, triangle and square. Facial shape determination has been introduced by many beauty experts, but for society, in general, is still a little difficult to classify it because the form of each face is almost the same and manual measurement requires a long process. That's why it needs a method to classify face shape quickly and precisely. A proposed method in this research is Probability Neural Network and Invariant Moments. Men face images are used as input for image processing. The stages before classification are image pre-processing (Gray scaling, Scaling, and Gabor Filter). Then feature extraction using Invariant Moments. The final step is classification using Probability Neural Network. After testing is done to 90 data training and 30 data testing, it was concluded that the proposed method has the capability to classify men face shape with accuracy 80%.

1. Introduction

The classification of facial shape is especially useful for grooming personalities, such as the selection of haircut shape, the selection of facial makeup, the selection of sunglasses or even the selection of appropriate shapes [5][6]. The process of determining facial shape can be done in several stages such as taking pictures with the camera, outlining the face, counting the length and width of the face, cheekbones, jaw, and forehead then done determination type face shape. The face shape in men is divided into six forms, namely: oval, round, diamond, rectangle, triangle and square [4]. Facial shape identification has been introduced by many experts beauty, but for the community, in general, is still a little difficult to classify it because the shape of each face is almost the same and the measurement manually requires a long process and must be done carefully to get accurate results.

Research on the classification of facial shape has been done in previous studies. Classifies face shape in women to get haircut recommendations using AAM (Active Appearance Model) algorithm and facial segmentation based on the color region [1]. From the research, the researchers get the highest accuracy with the classifier SVM-RBF of 72% in the test set and 70,67% in the training set. The issue surfaced in the research is the existence of the misclassification between round and square facial shapes, while oval is the most difficult facial shape to identify.

Other research conducted on face recognition using invariant moment and backpropagation neural network. The researcher does engineering the image object by changing the size and lighting of the same image. The research used 50 facial data and processed them through the processes of rotation, scaling, and translation which resulted in 400 facial images. The conclusion of this research is Invariant Moment, and Backpropagation Neural Network can produce high enough accuracy, with an accuracy of the introduction of 50 face images by 98.22% [2].

Further research is a study conducted by Qiakai, et al. In this study, the researchers conducted a comparison of classification for face recognition by comparing three classifiers namely PNN, LVQ, and BPNN and using Discrete Cosine Transform and Wavelet Decomposition as its feature extraction. Of the three classifiers, PNN ranks the highest-accurate classifier with an accuracy of 93% [3].

In our study, the author will do the classification using Probabilistic Neural Network (PNN) and Invariant Moments as its feature extraction to determine the effectiveness and accuracy of the method in the classification of faces in men. Generally, PNN is widely uses as neural classifier with good accuracy [7]. Several other researches has been conducted regarding face recognition such as, mobile based face recognition using fisher face method [8] and face recognition using eigen face in cloud environment [9] and the use of other classifier such as SVM and Random Forest for face recognition [10].

With the selection of this method is expected to authors can classify the face shape in men with more accurate and in a shorter time.

The limitations set for the research, among which are:

1. The input system is a clear facial image with the hair does not cover the forehead, with no glasses and hats, mustache and beard are not so dense, and manual editing had been performed on the face image.
2. The app only detects six types of men facial shapes, namely oval, round, diamond, oblong, triangular and square.
3. System output is in the form of facial shape label.
4. The inputted images were using the front face perspective.
5. File extension applied in this research are jpeg (.jpg) and png (.png)

2. Methodology

2.1. Face Shape Determination Rules

Every human face has its characteristics. Furthermore, according to the beauty experts, human face has been classified following the size of the jaw, the length, and width of the face, forehead and size of the cheekbones.It will be easier to determine the suitable hair style, eyebrows, make-up even selection of glasses that fit with the face if the facial shape has been identified.The process of measuring the facial shape consists of several stages, such as taking pictures with the camera, outlining the face, calculating the length and width of the face, cheekbones, jaw, and forehead, then determining the type of face based on the results of the previous calculation.The face can be classified into six shapes: round, square, oblong, heart, oval, and diamond [4]. Each shape can be identified by the following rules:

- Oval: The forehead is wider than the chin. The face length is one and a half times more than the width of the face.
- Round: The length and width of the face are almost the same, and the cheekbones are the most prominent part.
- Oblong: Almost the same as the oval shape, but longer and not so wide. The shape of the chin is also more pointed.

- Square: All face sizes are almost the same width (forehead, cheekbones, and jaw), while the jaw angle is sharper.
- Triangular: The jaw is the widest part and slowly narrows to the forehead.
- Diamond: the cheekbone is the most dominant part bigger than the forehead and jaw.

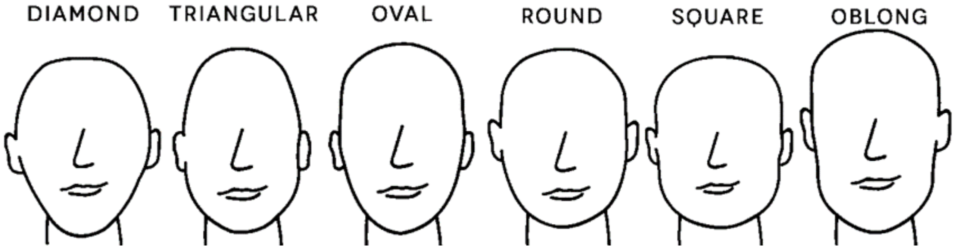

Figure 1. Types of human face based on shape

2.2. *Dataset*
The data used for the research consisted of 90 facial images of male obtained from the search site of http://www.google.com and direct retrieval using a mobile camera consisting of 120 images of male faces. 90 pictures were used for training consisting of 15 images for each facial type and 30 images used for the test consisting of 5 images for eachtype.

2.3. *General Architecture*
The method proposed to classify the face shape of men is composed of several stages. These stages start from the image acquisition and data grouping of the male facial images of oval, round, oblong, rectangle, square and triangle shapes that will be used for training data and testing data. The process continues to preprocessing step of gray-scaling to convert the image into a grayscale image. The next step is CLAHE that aims to add more contrast to the image [12], then followed by facial segmentation by converting the image into a binary image to bring up the facial feature using Gabor filter. Extraction feature will be performed after facial segmentation to obtain seven moment values using invariant moments. Following the feature extraction, the system will proceed to classification process using probabilistic neural network to get the nearest classification value to the existing data in the database. After these steps were executed, the system will generate the classification output of male facial shapes. The general architecture of this research is shown in Figure 2.

2.4. *Invariant Moments*
Two-dimensional $(p+q)^{th}$ order moment are defined as follows:

$$m_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^p\, y^q f(x,y)\,dxdy \tag{1}$$

$$p,q = 0, 1, 2, \ldots$$

If the image function f(x,y) is a piecewise continuous bounded function, the moments of all orders exist and the moment sequence $\{m_{pq}\}$ is uniquely determined by f(x,y), and correspondingly, f(x,y) is also uniquely determined by the moment sequence $\{m_{pq}\}$.One should note that the moments in (1) may be not invariant when f(x,y) changes by translating, rotating or scaling. The invariant features can be achieved using central moments, which are defined as follows:

$$\mu_{pq} = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1}(x - \bar{x})^p (y - \bar{y})^q f(x,y) \tag{2}$$

where

$$\bar{x} = \frac{m_{10}}{m_{00}} \qquad \bar{y} = \frac{m_{01}}{m_{00}}$$

The pixel point (x , y) is the centroid of the image f(x,y). The centroid moments μpq computed using the centroid of the image f(x,y) is equivalent to the mpq whose center has been shifted to the centroid of the image. Therefore, the central moments are invariant to image translations. Scale invariance can be obtained by normalization. The normalized central moments are defined as follows:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}{}^{\gamma}}; \gamma = \frac{p+q}{2} + 1 \tag{3}$$

Based on normalized central moments, the seven moment invariants are as follows:

$$\emptyset_1 = \eta_{20} + \eta_{02} \tag{4}$$
$$\emptyset_2 = (\eta_{20} + \eta_{02})^2 + 4\eta_{11}{}^2 \tag{5}$$
$$\emptyset_3 = (\eta_{30} + 3\eta_{22})^2 + (3\eta_{21} + \eta_{03})^2 \tag{6}$$
$$\emptyset_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \tag{7}$$
$$\emptyset_5 = (\eta_{30} + 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} - \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \tag{8}$$
$$\emptyset_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} - \eta_{12})(\eta_{21} - \eta_{03}) \tag{9}$$
$$\emptyset_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \tag{10}$$

The seven moment invariants are useful properties of being unchanged under image scaling, translation, and rotation.

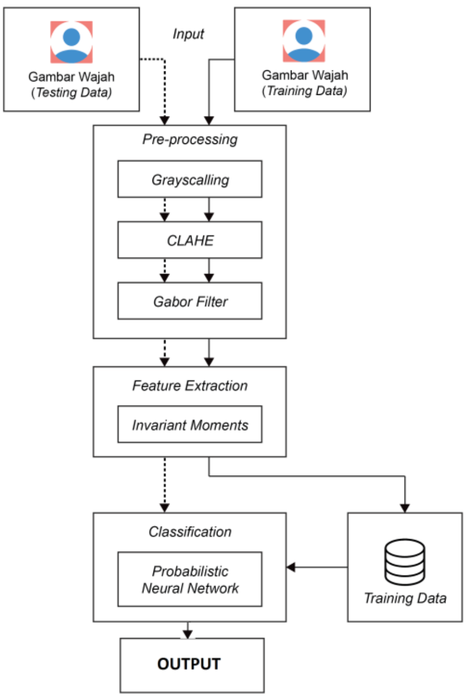

Figure 2. General Architecture

2.5. Probabilistic Neural Network
Probabilistic neural network is a kind of feed-forward neural networks evolved from the radial basis function networks. Its theoretical basis is the Bayesian minimum risk criteria. In pattern classification, its advantage is to substitute nonlinear learning algorithm with a linear learning algorithm. Meanwhile, it maintains the characteristics of high precision compared with a nonlinear algorithm. PNN includes the input layer, pattern layer, summation layer and output layer. The input layer receives the value of the training sample.

2.6. Feature Extraction
We obtained a discriminative feature set by extracting the valid dataset with Invariant Moments algorithm. This method selected seven unique features value that invariant to rotation, translation, and scalation. This system doesn't have face landmarking feature, so this research using a picture that has been cropped with 3rd part software. The image will be processed by Gabor filter to remove skin and unnecessary part of a face and make line art picture. Those line art will be extracted with invariant moments and generate seven unique features value.

(a) **(b)** **(c)**

Figure 3. Output images processed by different pre-processing; (a) Original picture; (b) CLAHE; (c) Gabor kernel

3. Result and Discussion
In this section we described our testing and result. The data entered into the system is a male face image taken from the search site http://www.google.com and manual retrieval. The data is selected and divided into six classes: diamond, oblong, oval, round, square and triangular. Each category has 15 training data and 5 test data, so the total training data is 90 images and 30 image test data.Classification testing in PNN uses different smoothing parameter values (σ) to determine which values have the highest accuracy. The value of σ used is 0.1, 0.3, 0.5, 0.7 and 0.9. Testing with σ different from the 5 test data for each face class can be seen in Figure 4.

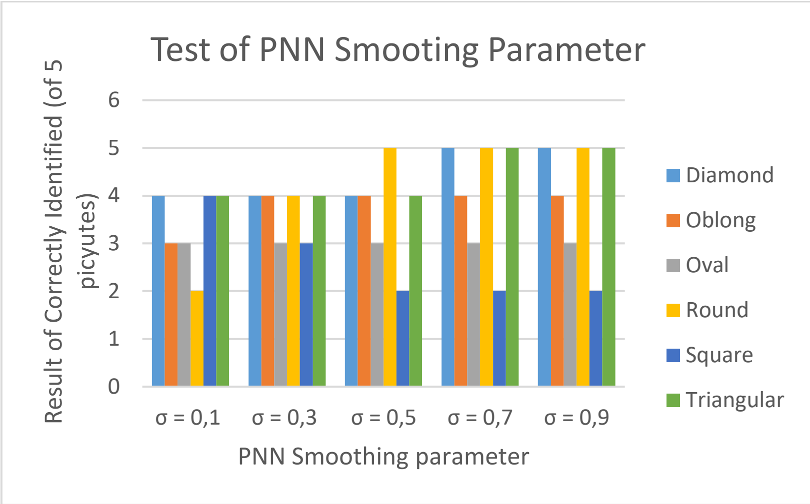

Figure 4. Smoothing Parameter Experiment

Based on Figure 4, we can see that $\sigma = 0.1$ has the lowest accuracy values. While if we start from $\sigma = 0.7$ the bar has risen up consistently until it reaches $\sigma = 0.9$. To make it clear, the confusion matrices for the test sets are shown in Table 1. These matrices reveal that square-shaped faces were often predicted as round-shaped. Square-shaped faces tended to be most difficult to classify correctly as the classifier was the least accurate when applied to this face shape. Diamond-shape and Round-shape tended to be most easy to classify correctly. Overall, the PNN algorithm achieved 80% accuracies for predicting the test sets. 80% is below our expectation this is mainly because of the un-optimal image processing process that has been conducted.

Table 1. The Confusion Matrix On Test Data

True Label	Predicted Label						
	Diamond	Oblong	Oval	Round	Square	Triangular	Accuracy(%)
Diamond	5	0	0	0	0	0	100.00
Oblong	0	4	0	1	0	0	80.00
Oval	0	1	3	0	0	1	60.00
Round	0	0	0	5	0	0	100.00
Square	0	0	0	2	2	1	40.00
Triangular	0	0	0	0	0	5	100.00

4. Conclusion

Probabilistic neural network and invariant moments method is able to classify face shape in men with high accuracy with 80% accuracy and 20% error rate. Noise, background, and image resolution are very influential on the results of classification because the IM method will calculate the entire area of the image, including the remnants of pixels after the filter. The skin detection will be implemented in the next research [11].

Smoothing parameter values used in the calculation of PNN greatly affect the level of accuracy due to the smaller value of σ then the accuracy will be lower. The value of $\sigma \geq 7$ is the best value to get fairly high accuracy. The square face has the lowest accuracy than other facial types and often misclassification because square face shape is almost similar to round face.

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