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Consistency of Optimized Facial Features through the Ages

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Abstract

The evaluation and measurement of human body dimensions are achieved by physical anthropometry. The main goal of this research is to optimization of facial feature point by establishing a mathematical relationship among facial features and used optimize feature points for age classification. According to this proposes method, sixteen Euclidean distances are calculated from the eighteen selected facial feature points vertically as well as horizontally. The distances between the specified features points increase with respect the age progression of a human from his or her childhood but the ratio of the distances does not change (δ =1.618). Feature distances are used for classification of age using Support Vector Machine (SVM) - Sequential Minimal Optimization (SMO) algorithm and shown around 96% accuracy.

Keywords: *Face Anthropometrics, SVM-SMO, Facial Features Extraction, Feature distances, 3D Face Model*

1. Introduction

A detecting and tracking facial feature points from video sequences has been attracted significantly increased interests in recent years [1-10, 23-25]. Facial feature points are usually located on the corners, tips or mid points of the facial components. Identification of facial feature points plays an important role in many facial image applications like video surveillance, face detection and recognition, age grouping, expression classification, face modeling, face anthropometric, emotion expression, montage composition, and robotics [3-5]. Many approaches have already been attempted towards addressing this problem, but complexities added by circumstances like inter-personal variation (*i.e.*, gender, race), intra-personal changes (*i.e.*, pose, expression) and inconsistency of acquisition conditions (*i.e.*, lighting, image resolution) have made the task challenging. All the works that have addressed the problem of facial feature point detection so far can be grouped into several categories on the basis of their inherent techniques which will be discussed in Section 2. Since human faces provide a lot of information, and the subjects of human face are changed mainly due to three reasons viz. age, gender and ethnic group. As the age seems to be the main cause of the facial changes, it has come to the forefront. One goal of this research is to find out whether a conclusion can be arrived at as to how the appearance of a face changes subject to age levels. To achieve this goal, some objectives must be accomplished. One is to identify the facial features which are changing subject to time according to the age [2, 3].

There are lots of researches have been performed and presented in the field of facial feature extraction and analysis by this time over the world. There are many techniques are

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applied to extract the features of the face during that time [1-10, 26-42]. However, a little number of papers is discussed or discovered how the features of a face are related to each other for a specific person. Although the anthropometric measurement of faces provides useful information about the location of facial features, it has already been used in their detection and localization. In this paper, we have explored the approach of using a mathematically developed, reusable anthropometric face model for localization of the facial features as well as the selection of the 18-most important facial feature points on a face. Euclidean feature distances are calculated from the selected features. Additionally, mathematical relationships are established among calculated feature distances. Finally, we used only four feature distances for age classification that almost related to eight feature points. The main concern of this paper is to optimize of facial feature points by establishing a mathematical relationship among facial features and used optimize feature points for age classification using support vector machine (SVM)-Sequential Minimal Optimization (SMO) algorithm.

The subsequent discussion has been organized into the following six sections: Section 2 presents related works, Section 3 explains the proposed method, Section 4 discusses on age classification using optimized facial features, and finally Section 5 describes conclusions and future works of this study. The related works of this research are discussed in the next sections.

2. Related works

In [1] presented the anthropometric face model based on 18-feature points. Also automatic extraction processes of their selecting facial features points and effectiveness of points to design a face anthropometric model have been discussed. The facial appearance might have change duo to the nature of aging process is discussed in [2]. There are different types of horizontal and one vertical distance distances between the selected features like height of face, width of lips, height of forehead as horizontal distance, the length of the cornea as vertical distance are considered in this paper. Twenty selected facial feature points based on expression recognition system are proposed in the paper [3]. Thirteen horizontal and vertical distances among the selected features are considered. In [4] an expression recognition system was proposed considering 26 automatic fiducial point of human face. There are twenty selected facial feature points based facial action detection system using support vector machine is proposed in [5]. Ramanathan and Chellappa [6] proposed a modeling of age progression in young faces using 24 landmarks of facial images. This paper demonstrated on age separated face images of individual less than 24 years of age. In [7] proposed a face anthropometric model based on 57 landmarks of facial images.

Geometrical shapes of facial features have been adopted in several works for facial feature point localization and detection [8, 9]. Each feature is demonstrated as a geometrical shape; for example, the shape of the eyeball is a circle and the shape of an eyelid is ellipse. This method can detect facial features very well in neutral faces, but fails to show good performance in handling the large variation in face images occurred due to pose and expression [10]. Due to the inherent difficulties of detecting facial feature points using only a single image, spatio-temporal information captured from subsequent frames of video sequence has been used in some other work for detection and tracking facial feature points [11, 12]. Some works have also used image intensity as the most important parameter for detection and localization of facial features [13, 14]. Finally, we have considered some other's reference related to the other's relevant topics like database and software of this research work.

The research in age estimation has increase significantly since 2002 [17-21]. There huge numbers of research works are already done and still running on age classification field because of its dynamicity.

3. Proposed method

Firstly, according to this proposed method 18 facial feature points and 16 facial features distance between selected features points are calculated. Most of the selected feature points are related to the mouth, nose, eye, eye brow. The Figure 1 (a) shows the selected 18 feature points and description of the feature points of the propose method, respectively. Table 1 explains the selected 18 feature points. The proposed distance measurement among the selected facial feature points is represented in Figure 1 (b).

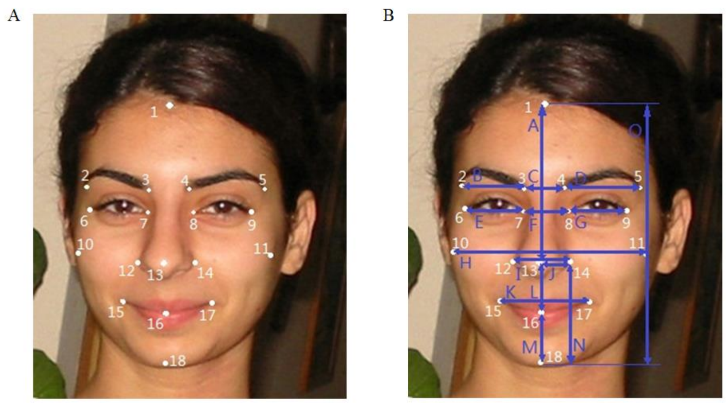


Figure 1. (A) 18 selected feature points (B) Example measurements of proposed model

There are 11 distances respect to horizontal axis and 5 distances respect to vertical axis on the facial image are represented in this section. The descriptions on horizontal and vertical distances of selected feature points are shown in Table 2, respectively.

The selected 18 feature points of a facial image from A to R are shown in Figure 1 (b). According to Figure 1 (b), we have assigned alphabet horizontally and selected horizontal points to calculate horizontal distances for establishing relationship among the distances first. The horizontal distances and their relationship according to Figure 1 (b) as follows: BC, DE, FG, HI, FI, GH, CD, LN, LM, OQ and JK are distances of the horizontal selected points on a face. Respect to the calculated distances we establish relationship among these feature distances, where

$$BC = DF \text{ and } FG = HI$$

$$BC / FG = 1.618 \text{ ,}$$

$$GH / CD = 1.618 \text{ and}$$

$$FI / OQ = OQ / LN = LN / LM = 1.618$$

On the other hand there are five vertical distances calculated from the selected feature points and relationship among the distances as follows: AR, AM, MP, PR, and MR are distances between selected vertical feature points, where all four ratios show equality, such as $AR / AM = AM / MR = MR / PR = PR / MR = 1.618$.

Table 1. Descriptions of selected feature points

Point No.	Points Description
1	Top of the head
2	Left eyebrow outer corner
3	Left eyebrow inner corner
4	Right eyebrow inner corner
5	Right eyebrow outer corner
6	Left eye outer corner
7	Left eye inner corner
8	Right eye inner corner
9	Right eye outer corner
10	Left most point of face
11	Right most point of face
12	Left nose corner
13	Top of the nose
14	Right nose corner
15	Left corner of the mouth
16	Middle of the mouth
17	Right corner of the mouth
18	Tip of the chin

Table 2. Horizontal and Vertical distances between the feature points

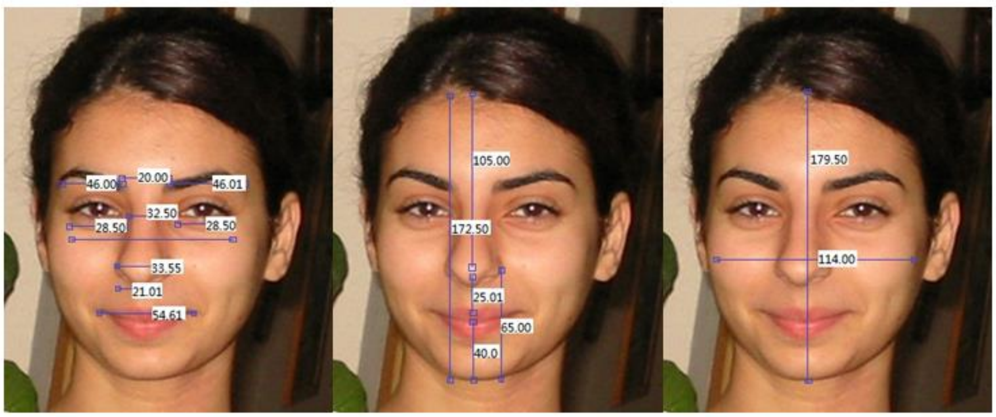
Direction	No.	Features	Definition
Horizontal	1	Width of left eyebrow	$wleb = x_C - x_B$
	2	Width of right eyebrow	$wreb = x_E - x_D$
	3	Width of left eye	$wle = x_G - x_F$
	4	Width of right eye	$wre = x_I - x_H$
	5	Eye outer cornet distance	$eoc = x_I - x_F$
	6	Eye inner cornet distance	$eic = x_H - x_G$
	7	Eyebrow inner cornet distance	$ebc = x_D - x_C$
	8	Nose corner distance	$ncd = x_N - x_L$
	9	Nose corner and middle points distance	$ncmpd = x_M - x_L$
	10	Width of mouth	$wom = x_Q - x_O$
	11	Width of the face	$wof = x_K - x_J$
Vertical	1	Top of head and chin points distance	$thcd = y_R - y_A$
	2	Top of head and nose middle points distance	$thnmd = y_M - y_A$
	3	Nose and mouth middle points distance	$nmmd = y_P - y_M$
	4	Mouth middle and chin points distance	$mmcd = y_R - y_P$
	5	Nose middle and chin points distance	$nmcd = y_R - y_M$

The final considered vertical desistance is PR . We have also discovered that the relationship between height and width of face exist as follows:

$$AR / JK = 1.618$$

Among the five vertical distances only one distance is calculated between middle mouth points to chin point. Other's distances are calculated from the represented mathematical relationships among the selected vertical feature points. Among the selected 16 distances and from established relationships among the selected feature points, we optimized feature points and finally used only 8 points instead of 16 points. As the selected facial features distance are follows a mathematical relationship. Finally, only four feature distances FG, GH, OQ , and PR are used to classify of age in this study. Figure 2 (a) and (b) show horizontal and vertical distances, and face height and width relationships of two different ages for 14 years and 9 years old in the same person, respectively.

A



B

Figure 2. Measured Horizontal and Vertical distance, Height and width of face of a boy in (A) age 14 and (B) 9 years old

According to the relationship mentioned above, it is clear that four feature distances are enough to calculate all the others distances for facial image to extract the desired features according to this proposed method. Finally, Instead of 18 feature points we used only 8 feature points in this study. The main concern of this paper is to three optimization of facial feature point by establishing a mathematical relationship among facial feature and used optimize feature point for age classification. We have used only four feature distance for age classification. The next paragraph represents effective experimental study of this proposed feature optimization method.

4. Age classification using optimized facial features

Matlab-7.9 and WEKA 3.6.3 are used in this study under Windows-7 environment on Intel® Core™ 2Duo CPU E7200 @ 2.53GHz (2CPUs) desktop with 4096MB RAM. In this section age classification method is discussed in details respect to above mathematical facial features relationship method as an effective application of this proposed optimize facial feature reduction system. We have collected final facial datasets from FG-NET Aging Database [22], which contains 1,002 face images from 82 subjects.

For this case study, around 150 faces for 50 persons are considered, whose age ranges are from 3 to 45 years. Class 1 represents age range 1 - 10. Class 2 represents age range 11 - 23. And class 3 represents ages above 24. Firstly, selected 8 facial feature points are marked with green points in final facial image database. We have marked with selected eight green points with identity due to calculate the distances perfectly. Secondly, calculated four feature distances for individual person are stored in a excel file as csv format. The excel file contains around 600 calculated facial feature distances. Individual distance is considered as an attributes of final excel file. Finally, SVM-SMO algorithm is applied to the final data set to classify data according to age using WEKA machine learning tools.

All experiments have been made using SVM-SMO algorithm from WEKA machine learning tool developed in the JAVA language. The results for age classification using WEKA of this propose system is show in Figure 3.

```
=== Summary ===
Correctly Classified Instances         143               95.9732 %
Incorrectly Classified Instances         6                4.0268 %
Kappa statistic                          0.9384
Mean absolute error                      0.2312
Root mean squared error                  0.2881
Relative absolute error                 53.305  %
Root relative squared error             61.88   %
Total Number of Instances              149

=== Detailed Accuracy By Class ===
         TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
           0.935     0          1         0.935     0.967      0.995    Class1
           1         0.021      0.963     1         0.981      0.99     Class3
           0.943     0.035      0.892     0.943     0.917      0.954    Class2
Wght Avg.  0.96      0.015      0.962     0.96      0.96       0.983

=== Confusion Matrix ===
  a  b  c   <-- classified as
 58  0  4 |  a = Class1
  0 52  0 |  b = Class3
  0  2 33 |  c = Class2
```

Figure 3. WEKA outputs for age classifications

As important parameters, the number of instances, test-mode, and time to build a model are 149, 10-fold cross-validation, and 0.02 seconds, respectively.

According to the result it represents around 96% accuracy with correct classification and 4% incorrect classification. From the confusion matrix it can be seen that around 58 belongs to class1 and four are miss-classified. Around 52 classified as class2, 33 classified as class3 and miss-classified 2. The main advantage of this proposed method is reduction of time complexity and also it is required less memory with respect to other proposed methods.

6. Conclusion and Future Works

In this paper, we have proposed optimized facial features based on the age classification model by establishing mathematical relationships among selected feature points in order to reduce a lengthy computational time. It is also discovered that four distances calculation among selected facial feature points are enough to calculate other twelve horizontal and vertical distances among 18 feature points, which represent common characteristics of faces. As selected features points are related to a mouth, eyes, eyebrows, and a chin so it is easier to detect from facial images. The relationship between height and width of a face is also important in the model proposed. The main goal of this research is find out whether a conclusion can be arrived at as to how the appearance of a face changes due to age progression of a human. Therefore, in order to accomplish this target, this research used an approach of classified the exacted facial feature distances using SVM- SMO algorithm. Finally, the classifier has shown around 96% accuracy. The experimental results show that the proposed system is robust and accurate to an age classification.

This research was conducted only for the FG-NET database for age classification. However, this methodology which happens in a similar way can be applied to draw conclusions on the aging process in the facial images for each and every ethnic group based on the different age, and various facial expressions. The technique of the automatic facial feature point's detection and extraction will be applied to make proposed system more defection-free and automatic processing in the future. Finally, we are going to apply this proposed facial feature measurement system to design 2D or 3D facial model perfectly and robustly in the near future.

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