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MINIMUM SET OF GEOMETRIC FEATURES IN FACE RECOGNITION

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ABSTRACT

Biometric technology is often used for verification and identification of individuals and objects. Face recognition requires feature processing and analysis of a particular face. Amongst the most used is the feature – based method. It includes detection of the face region from the digital image, then component detection with feature-selection and finally face identification.

This paper develops the idea of a system which identifies a face based on a minimum number of selected features. Predefined number of features was extracted from the basic face components where solely geometrical distances were taken into consideration. Implementing proper analysis and research we showed that minimum 7-feature set is needed for proper face recognition on a small-to-medium face database.

Keywords: face recognition, feature-based, geometric features, Euclidean distance, variable expression

I. INTRODUCTION

The need for passive[1] identification in face recognition has increased with the Fourth generation of technologies and devices including the so-called "smart environments" that need to be aware of the entities and people in their surroundings. Nowadays, only a PIN number is necessary to get money from an ATM, a password for computer access, and other similar for Internet access. Although there are more reliable and accurate identity authentication methods, such as iris identification and finger print, face recognition does not require the presence of the participant who is identified and presents more economical way of implementation.

Commercial and law technology applications for face recognition go from static images in controlled environment to uncontrolled video frames, which results in augmenting number of challenges and issues in this area. For the above mentioned one needs techniques for image processing and analysis as well as for pattern recognition. Generally, problems may be classified into two groups: static and dynamic (video) matching. Differences come in sense of quality image, background complexity, carefully defined matching techniques, etc.

[1] No need of human interaction and unobtrusive

II. PROBLEM DESCRIPTION

The chosen feature-set which would define i.e. represent unique definition of a face, still presents an existing challenge in the area of face recognition. The features included in the set are supposed to have a property of distinctiveness for each face in everyday circumstances: variable lighting, background, facial expression, poses, occlusion, etc. The idea of feature selection which would represent a face comes from solving a problem in pattern recognition with N features. The following question is always present: Is it possible to obtain the same performance with less number of features?

The use of old existing methods, dating from the early years of research in the field of face recognition based on local feature selection hides the possibility to improve their disadvantages and performance. Re-election of face features could improve the basic methods and contribute to more efficient and faster identification.
This paper will present research for designing minimum feature set to be used by a system to identify an individual. First we determined which features are to be taken into account. This selection of features is next used to define the minimum number of features that is sufficient to identify a face. Thus, the feature choice would be crucial for the system's performance and recognition rate. In future a fully automatic algorithm will be designed that will use this feature set to identify faces, which would fully implement every phase of the process of face recognition.

III. LIMITATIONS

In this section the limitations of the research are stated.

Methods of image compression and improvement of the performance of the image database was not considered.
Images of people with variable expression were taken in a controlled environment. Lighting issues, pose variation and occlusion are left as future replenishment and improvement of the idea.
We worked with 2D face model, 3D face model requires proper understanding of the 2D model before it could be used to explore and improve the process of face identification.
Only geometric features are considered through predefined components and fiduciary points on the face. Automatic definition of face shape through template-matching is still challenge and was not fully implemented in the research. The information on the face shape was manually defined from a predefined 4 template face shapes.

IV. Related work

One of the earliest feature-based attempts was by Kanade [1], who used simple image processing methods to extract 16 facial parameters - which were ratios of distances, areas and angles - and used a simple Euclidean distance measure for matching to achieve a performance of 75% on a database of 20 different people using 2 images per person.
Brunelli and Poggio [2], building upon Kanade's research, computed a vector of 35 geometric features from a database of 47 people (4 images per person) and reported a 90% recognition rate. However, they also reported 100% recognition efficiency for the same database using a simple template-matching approach.
In the 90's Cox [3] reported a recognition performance of 95% on a database of 685 images (a single image for each individual) using a 30-dimensional feature vector from 35 facial features. However, the facial features were manually extracted, so one can assume that the recognition performance would have been much lower if an automated feature extraction method had been used.
In 2009, K. Selvam and Dr. B. Poorna [4] detected significant discriminatory properties of the nasal bone which he set as a possible model that yet needs to be explored and tested.
One of the latest researches in the field of face recognition with feature-based methods belongs to researchers Ramesha K., K. B. Raja, Venugopal K. R. and L. M Patnaik [5] who actually showed the importance of reviewing older feature-based methods. Their research includes determining the minimum number of features but in terms of age and sex recognition.

V. Databases of faces

Personal database of faces was used as training set to obtain preliminary results. The minimum feature sets were defined through analysis of the images of faces in this database.

The other databases of faces in this section were used as test dataset in order to evaluate the chosen feature combinations.

1) Faces94, Faces95, Faces96, Grimace

These face databases [6] consist of 395 different faces, each having 20 different samples, in total of 7900 face images. The databases contain samples of male and female faces, all from different race. Most of the images are from 18-20 year old students, while there are also images from elderly people included. The images represent portrait faces with different backgrounds as well as complex and significant variations in face expressions and small pose variation.

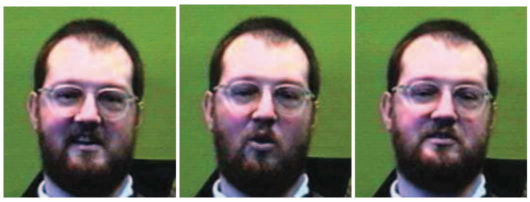

Figure 1.Sample images from face database faces94

Figure 2.Sample images from face database grimace

Link to face databases faces94, faces95, faces 96, grimace: http://cswww.essex.ac.uk/mv/allfaces

2) IMM face database

IMM face database was created in 2001 in the Mathematics and Informatics Department in the Technical University of Denmark. The database contains images of 40 people; 33 male and 7 female individuals. The images were taken in single session with 7 images per person, for total of 280 face images. For each individual there are images with variable facial expression, pose and lighting. Most are color images, while the rest are gray nuances with resolution of 640x480 pixels.

Figure 3.Sample images from IMM face database

Link to face database:
http://www2.imm.dtu.dk/~aam/datasets/datasets.html

3) *Personal face database*

In order to obtain preliminary results as well as to include family-related entities, a personal small face database of portrait images with variable facial expressions, in a controlled environment was created.

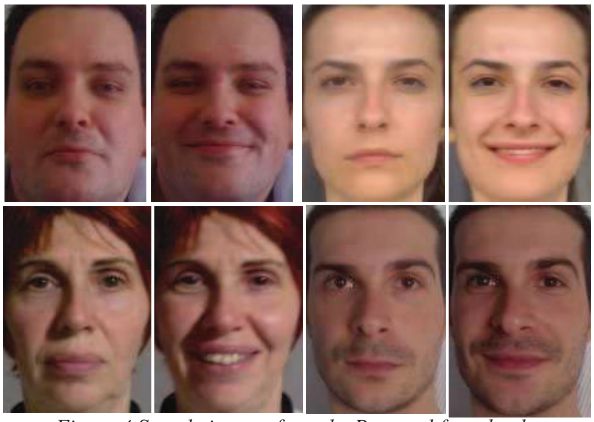

Figure 4.Sample images from the Personal face database

The faces are with variable expression in order to choose a combination of features which would be invariant to the facial expression of the face being identified, as well as to be able with the same combination to obtain family-related entities to be classified as most similar to the face being identified in relation to the other faces in the database.

VI. MODEL

Traditionally, the problem of face recognition can be implemented with two different approaches [7]: Image-based and feature-based method.

The image-based method [8] uses all the information the image contains, color ranges and intensities. The feature-based method [8] uses the information obtained as a set of features specific for the image being identified, for example edges, relative pixel-to-pixel position, pixel distance, etc. [8] Mainly, the face recognition algorithms [9] use images in the gray color range, in this way the problem of face recognition comes to problem in pattern recognition. The method used in this paper is feature-based with the usage of strait portrait images with variable facial expression. Proper analysis and research resulted in accurate choice of the more significant and discerning facial features which eventually led to satisfactory recognition. The chosen minimum feature sets were evaluated over a larger public collection of faces (Section V) in order to obtain its rate of identification.

The features were defined by predefined face components, geometric distances and positions (Figure 5). Discussing the issue with an expert[2] in the area of drawing techniques of face portraits as well as according to the research in [10], the following distances were marked as significant even from the time of Ancient Rome [11]:

i. *Left eye - Right eye:* The distance from the inner edge of the left to the inner edge of the right eye

ii. *Left eye – mouth:* The distance from the inner edge of the left eye to the midpoint of the top part of the mouth.

iii. *Right eye – mouth:* The distance from the inner edge of the right eye to the midpoint of the top part of the mouth.

iv. *Left eye – nose:* The distance from the inner edge of the left eye to the midpoint of the nose.

v. *Right eye – nose:* The distance from the inner edge of the right eye to the midpoint of the nose.

vi. *Left eye – nose:* The distance from the outer edge of the left eye to the midpoint of the nose.

vii. *Right eye – nose:* The distance from the outer edge of the right eye to the midpoint of the nose.

viii. *Left eye – mouth:* The distance from the outer edge of the left eye to the midpoint of the top part of the mouth.

ix. *Right eye – mouth:* The distance from the outer edge of the right eye to the midpoint of the top part of the mouth.

x. *Nose – mouth:* The distance from the midpoint of the nose to the midpoint of the top part of the mouth

xi. *Nose length:* The distance from the midpoint of the nose to the midpoint of the distance between the eyes.

xii. *Nose width:* Horizontal distance between the two sides of the nose in its lowest part.

xiii. *Face shape:* The shape of the face from previously given face templates.

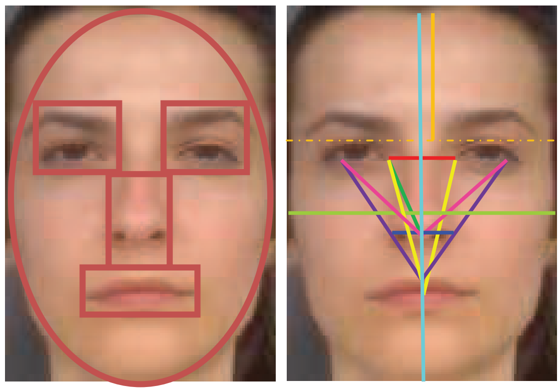

Figure 5.Face components and geometrical face distances

[2] Goran Boev – Faculty of Art and Design, EURM

i. *Face length:* Vertical distance from the top of the forehead to the bottom of the beard.

ii. *Forehead:* Distance from the top of the forehead to the midpoint of the distance between the eyes.

iii. *Face width:* Horizontal distance between the cheeks. (This distance is used solely to obtain the 15 predefined feature distances).

A set of 15 features was defined which preliminary represent every face in the personal face database. Every feature is defined as ratio of *Face width/*Distance. The face width was chosen as a constant since it showed minimum variance in comparison to the other distances mentioned above in relation to the two images per face in the personal face database. The distance *Face width* (Distance no.16) resulted in least variable in images with variable expression. Consequently, the feature-set was defined as 15 ratios of the Face width with all the rest of the distances listed above.

A. Minimum feature set

All 15 features were included in the research. The research used hierarchical clustering technique for face identification to obtain preliminary results.

Hierarchical clustering [12] uses the distances or differences between the objects being clustered. Similarities represent a set of rules which serve as grouping criteria or for object separation. These distances are based on multiple dimensions, where each dimension presents a rule or grouping condition. In this paper, the differences between the faces in multidimensional space were determined through calculation of the Euclidean distance between every pair of face images in the face database (Figure 6). The Euclidean distance [12] is the most frequently used method for geometrical distance in multidimensional space.

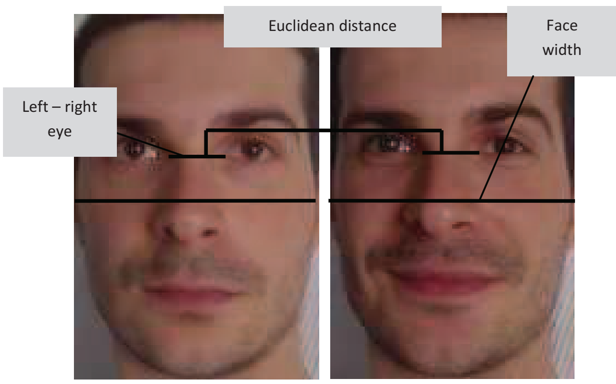

Figure 6. Image 7 and 8 from the personal database. Euclidean distance of feature ***Face width/left eye-Right eye*** *on two images with variable facial expression*

For connecting the cluster Ward's method was used. This method was chosen since it is the best combination with Euclidean distance as a similarity measure of the objects being analyzed.

1) Preliminary results

Analyzing the feature set which would give complete identification of the personal preliminary face database included all the possible feature combinations and results comparison. In order to test all the possible combinations, a personal Matlab code was used which listed and tested all the possible combinations with different element sets of features mentioned in Section V. For each feature combination the number of accurately identified faces was recorded (faces in the same cluster in the lowest level of the hierarchical tree below the chosen threshold). Since the number of faces in the personal face database was 15, each combination which contributed to complete identification of all faces in the database was marked and recorded.

It was noted that even with as many as 4 features complete face identification was obtained over the personal preliminary face database. However, since it is expected to work with a larger face database, the number of features needed in the minimum feature set would definitely increase.

Additionally, the feature combinations were tested if they identify the family-related faces in the personal database. From 9 existing family relations, the system was able to successfully identify 5 of the relations while keeping 100% identification on the preliminary face database. However because of the lack of public face databases which contain records of family related faces in the database, the combinations were not able to be evaluated on a larger face database to confirm the preliminary results.

VII. Evaluation

The type of identification in this research represents a general case i.e. open-set identification [13]. In the open-set identification a system determines whether a test sample p_j belongs to a face from the gallery G and further more it determines its identity. In this case, the 3 most similar faces form the database are shown, based on the similarity score generated by the hierarchical clustering tree.

Evaluation of an open-set identification method characterizes with two typed of statistical measures:

- Rate of detection and identification
- Rate of false alarm

In this research, the chosen feature combinations were evaluated for their rate of detection and identification. The rate of detection and identification is a fraction of the accurately detected and identified test samples P_G. The detection and identification rate for a given threshold τ is given with the following equation:

$$P_{DI}(\tau,1) = \frac{|\{p_j : rank(p_j) = 1, и\ s_{*j} \geq \tau\}|}{|P_G|} \quad (1)$$

In the paper the threshold τ =1 represents the largest value that the similarity score could be between two face images, while P_G= {25, 30, 35, 40, 45, 55, 60} faces on which the previously chosen combinations were evaluated. The individual performance was recorded of each of the feature combinations when the face database was increased. It was also recorded as to which of the combinations was most efficient per set of features where {6, 7, 8, 9, 10, 11} is the number of features per set. The set of features with {5, 12, 13, 14, 15} set elements were not included since during the evaluation they did not achieve complete identification over a face database of 25 faces.

A. Feature sets

All the feature combinations which recorded 100% face identification on the preliminary face database of 15 faces were included in the evaluation stage. Figure 7 shows the rate of identification for each of the possible feature sets over the test dataset of faces.

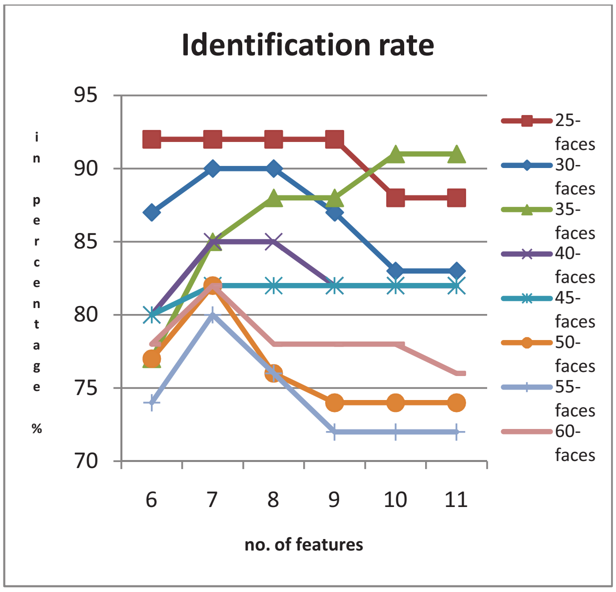

Figure 7. Identification and detection rate when face test dataset was increased. On x-axis are the different element feature sets, while y-axis shows the rate in percents.

For every considered feature-set the most frequently occurring feature combination when the face database was increased and which obtained most efficient identification of the faces in the test dataset are listed. Every combination is given by its ordinal number in the list of combinations in the given feature set:

- 6-element feature set = {27,29}
- 7-element feature set {78}
- 8- element feature set = {62}
- 9- element feature set = {65}
- 10- element feature set = {44}
- 11- element feature set = {12}

In order to obtain the feature combination which gives the most efficient identification of face database the average and the standard deviation were calculated of the combinations in a given element feature set. These are shown in Figure 8 and Figure 9.

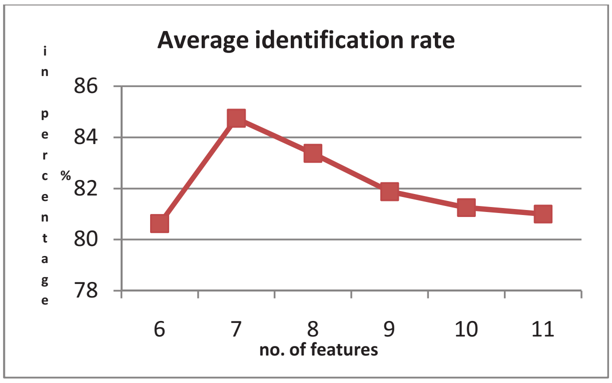

Figure 8.Average on identification rate in percents (%)

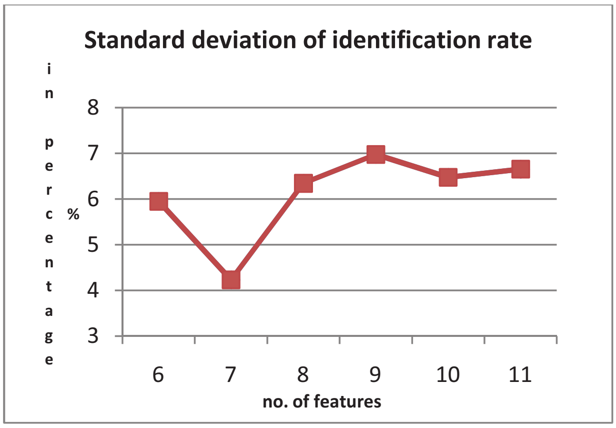

Figure 9. Standard deviation on identification rate in percents (%)

VIII. RESULTS AND CONCLUSION

From the results obtained in VII, the average rate of identification of faces in the test dataset over all the different element feature sets was = 82% while the minimum standard deviation was 4.

The most efficient feature combination, which was to be used by the application, was chosen based on the occurring frequency of each feature combination as well as its efficacy in the identification of the faces in the test dataset. Therefore, it was noted that the 7-element feature set continuously expressed most efficient identification of the faces in the test dataset (Figure 7) even when the number of the faces in the test dataset increased (Figure 8 and Figure 9). From the 7-element feature set it was found that the most frequent feature combination was the combination with ordinal number 78. This combination is represented with the features with their ordinal numbers from VI shown in Table 1 and visually on Figure 10.

Table 1.Feature combination 78

1	7	8	9	13	14	15

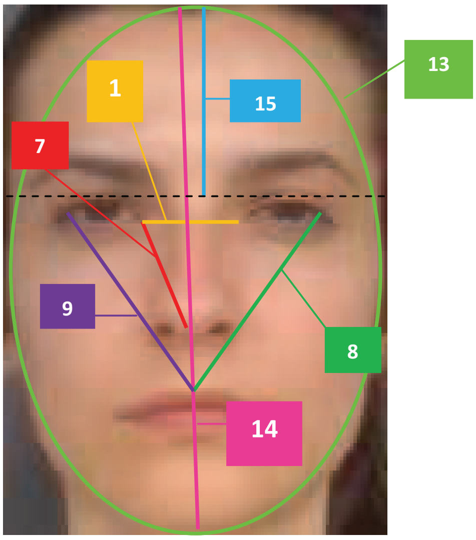

Figure 10. Visual representation of the features in the feature combination 78

IX. FUTURE WORK

In future the chosen feature combination will be integrated in a fully automatic face recognition algorithm. Face features detection will be automated as well as face shape detection with template matching.

The system will be evaluated over a larger database (>300 faces) which would include more diverse facial expression images. The system would perform better as a part of a hybrid system which incorporates a holistic approach as well.

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