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Facial Recognition on the Basis of Facial Fragments

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***Abstract*—**There are many articles that attempt to establish the role of different facial fragments in face recognition. Various approaches are used to estimate this role. Frequently, authors calculate the entropy corresponding to the fragment. This approach can only give approximate estimation. In this paper, we propose to use a more direct measure of the importance of different fragments for face recognition. We propose to select a recognition method and a face database and experimentally investigate the recognition rate using different fragments of faces. We present two such experiments in the paper. We selected the PCNC neural classifier as a method for face recognition and parts of the LFW (Labeled Faces in the Wild*)* face database as training and testing sets. The recognition rate of the best experiment is comparable with the recognition rate obtained using the whole face.

***Keywords*—**Face recognition, Labeled Faces in the Wild (LFW) database, Random Local Descriptor (RLD), random features.

I. Introduction

THERE is an old discussion of whether face recognition is a feature-based or holistic process [1]. In experiments with fragments of images, authors usually calculate a measure of the importance of a fragment for face recognition. This measure is frequently based on entropy. In experiments with humans, authors measure the time spent for face identification [2]. These measures only provide indirect information about the importance of a fragment for face recognition. To obtain direct information, it is possible to conduct two parallel lines of experiments. One line employs experiments in face identification using a whole face, and another line uses a selected fragment of the face. Calculating the recognition rates for the first and second lines of experiments, it is possible to obtain a measure of the importance of the fragment for face recognition. For example, it is possible to calculate the relationship of the recognition rate in the second line of experiments to the recognition rate in the first line of experiments and use this relationship as a measure of fragment importance for face recognition. For this purpose, it is necessary to select a classifier for face recognition and an image database for training and testing the selected classifier. For this work, we selected the PCNC classifier and the Labeled Faces in the Wild database that are described below.

The recognition of human faces is an important research topic in the field of computer vision and is one of the most important tasks in the area of image recognition [3]-[12]. This technology is used in various fields, such as security, administration, industry, authentication and labeling of images in social networks, to name a few. To recognize human faces, different methods are used, such as the Support Vector Machine (SVM) method, statistical methods, neural networks etc. [13]. In this study, for the recognition of human faces, we use the Permutation Coding Neural Classifier (PCNC) method applied to images extracted from the natural environment without controlled conditions (Labeled Face in the Wild (LFW) image database). An algorithm has been developed to implement the PCNC [14], [15] on different face image databases. The LFW database contains 13,233 face images with a size of (250 x 250) pixels in JPG format. To carry out our experiments with PCNC, we have selected subjects that have more than 10 images. The complexity of this base is that these images are obtained from natural environments without any preliminary preparation to identify the faces, so some images contain more than one face, have different types of lighting, positions, facial expressions, etc.; hence, identifying the target faces may be difficult [16]. There are different methods of applying facial recognition to different databases of images [17]-[19]. Face recognition has benefited greatly from the various databases that have been produced for studies. Most of these databases were created under controlled conditions to facilitate the study of specific parameters in the problem of face recognition. Examples of face image bases include the FEI and FRAV image databases [20]-[23].

The FEI image database is a database of Brazilian faces containing a set of images taken between June 2005 and March 2006 in the Artificial Intelligence Laboratory of the Educational Foundation of Ignatius in São Bernardo do Campo, São Paulo, Brazil [20], [21]. This base is made up of 2800 images corresponding to 200 different individuals with 14 images of each person. All images were taken in full color against a uniform white background, in front position with a rotation to profile of approximately 180°. The original size of each image is (640 x 480) pixels. This image database was created mainly of students and FEI staff, aged between 19 to 40 years, with different appearances, hairstyles and accessories. The number of male and female subjects is exactly the same for a total of 100. Fig. 1 shows some examples of variations in the position of the persons in the FEI database [21]. The FRAV2D database and FRAV3D database were developed at the King Juan Carlos University in Madrid, Spain. The main feature of these databases is that images of each person are presented with different inclinations, facial expressions and lighting conditions [23].

Fig. 1 Example of variations in the face position in the FEI database

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The FRAV2D database is composed of 109 subjects (75 men and 34 women) with 32 color images per person. Every image has a resolution of (320 x 240) pixels; most of the images are of front positions. In all cases, the images have a dark blue background. The 32 images were classified into groups according to the pose and lighting conditions and with different angles. Examples of the images that form FRAV2D are shown in Fig. 2.

Fig. 2 Example of images from database FRAV2D

To carry out face recognition, we developed different neural classifiers, such as a Random Thresholds Classifier (RTC), a Random Subspace Neural Classifier (RSC), a Limited Receptive Area (LIRA) Neural Classifier and a Permutative Coding Neural Classifier (PCNC), which due to its characteristics, was chosen to carry out the fragment evaluation task. Section II describes the PCNC.

II. Methods of PCNC

The PCNC was developed for image classification and has been used in different tasks such as handwritten digit recognition, texture recognition, etc. The PCNC structure is shown in Fig. 3 [24]-[26].

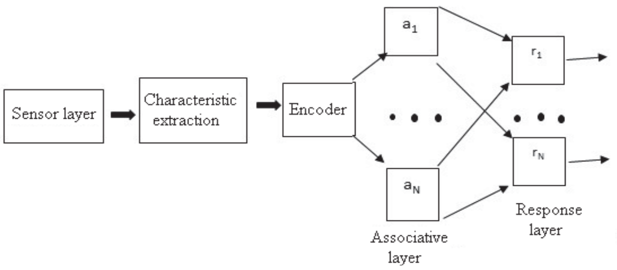

Fig. 3 Structure of PCNC

The PCNC neural classifier chosen for this work is based on the concept of local descriptors (Random Local Descriptor (RLD)). The RLD functions were used as a general feature extractor, establishing connections between random points in the input image and neurons in the associative layer, calculating the brightness depending on the selected point [24]. The general scheme of a system based on neural networks for the recognition of faces is shown in Fig. 4.

The PCNC starts working when a grayscale image is presented to the input feature extractor; the extracted features are presented to the encoder, which in turn transforms them into a binary vector of great dimension. This vector is processed by the associative layer, either for training or for testing recognition if previously trained.

The PCNC classifier contains some hundreds of RLDs, each full image scanning; if it detects a characteristic corresponding to an RLD (the output of the neuron is equal to 1), it introduces a special coding binary vector V in the associative layer. To test the PCNC we selected the LFW image database. In Section III, we describe this image database.

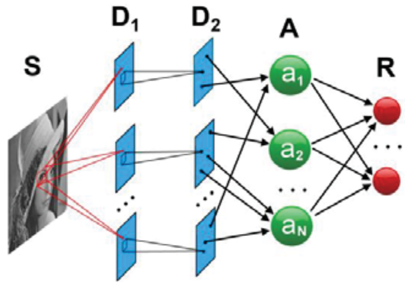

Fig. 4 General scheme of PCNC for face recognition

III. LWF Image Database

The Labeled Faces in the Wild (LFW) database of images was collected from the internet to study face recognition and is free of licensing or copyright concerns [27]. It consists of 13,233 images of 5,749 different people, with variations in pose, with occlusions and expressions organized in folders. The images are identified by the name of the person and are in JPG format with a dimension of 10.0 KB (10,263 bytes) per image.

In Fig. 5 some examples of the images from this database are shown without any preliminary treatment. We can see that some of these images have the subject face with other faces, so there may be more than one subject in the image, shadows, different angles of image capture, different facial expressions, etc.

The complexity of the characteristics of the images from an uncontrolled environment makes identification of faces difficult. For our investigation of face recognition with neural networks, we decided to select archives (folders) containing at least 10 images of the same subject. Therefore, we reviewed the images on this basis and selected only those folders containing at least 10 images of the same subject. An example of this selection is shown in Fig. 6.

To select folders to be used in our experiments, it was desired that they contain more than 100 Kb. However, in analyzing the image database we found that some folders are duplicates of the same subject and despite having the same data volume, some folders contain fewer images than others. For example, 121 KB (124,193 bytes) corresponded to 8 images and 187 KB (192,253 bytes) corresponded to 13 images. Hence, it was not possible to implement any selection algorithm to speed the task of image selection. Several errors were reported in the distribution of some folders of images, such as Janica_Kostelic_0001, etc.

Once the folders and images were identified, we proceeded to convert their JPG format to BMP format for treatment with the program designed for analysis in visual C ++.

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Fig. 5 Original images from LFW image database

Fig. 6 Image examples selected for our experiments

The image of a person in BMP format had the dimension of 183 KB (188,054 bytes). Once images were converted to BMP, we renamed the database for uniform naming with each folder as a subject with a serial number, and similarly identified images of the same subject with a serial number within each folder; therefore, it was possible to identify each image uniquely. Fig. 7 shows the organization of the images.

Fig. 7 Current organization of image database

We trained the PCNC system and tested it with images of subjects with the goal of identifying the most robust features to allow us to identify the test subjects regardless of condition of heterogeneity [13]. Fig. 8 shows the organization within the folders.

Fig. 8 The image organization within the folders

IV. Experiments and Results

For our experiment, we used 20 persons from the LFW database, each of whom had more than 10 images. We used only the 10 initial images of each person. We used odd-numbered images for classifier training and even-numbered images for testing the recognition rate. The training and testing sets each contained 100 images. For both training and recognition, we manually masked all of the images with rectangles that contained only the area of the face. The examples of masked images are shown in Fig. 9.

Fig. 9 Masked images of whole face

The images within the masked rectangle were transformed to a gray scale image of 100 x 100 pixels. Examples of transformed images are shown in Fig. 10.

Fig. 10 Transformed images

For experiments with a fragment of the face, we masked the initial images with a rectangle encompassing the selected fragment. In the first case, it was the “eye-eyebrow” fragment. In the second case, it was “mouse-chin” fragment. Examples of masked images are shown in Figs. 11 and 13.

Fig. 11 Eye-eyebrow fragment masked images

The image in the masked rectangle was transformed to a gray scale image 30 x 30 pixels. Examples of transformed images are shown in Figs. 12 and 14.

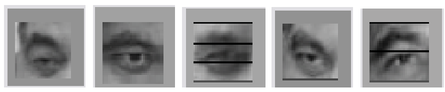

Fig. 12 Fragmented eye images

Each experiment began by training the PCNC classifier using transformed face or fragment database images with odd numbers, 5 such images for each person.

Fig. 13 Mouth-chin fragment masked images

Fig. 14 Fragmented mouth-chin images

After training, the PCNC classifier was used to recognize the even numbered transformed face or fragment images, also 5 such images per person. In total, we used 100 images to obtain the recognition rate. To obtain reliable results we performed 5 runs for each experiment because the structure of the PCNC classifier depends on aleatory numbers. We took the mean value of recognition rates as our final result. The experimental results for whole-face recognition are shown in Table I.

TABLE I
EXPERIMENT RESULTS FOR WHOLE FACE RECOGNITION

Run	1	2	3	4	5	Mean	Error rate %	Recognition rate %
Errors	58	59	58	56	53	56.8	56.8	43.2

The results of face recognition using face eye-eyebrow fragments are shown in Table II.

TABLE II
EXPERIMENT RESULTS FOR EYE- EYEBROW FACE FRAGMENT RECOGNITION

Run	1	2	3	4	5	Mean	Error rate %	Recognition rate %
Errors	59	56	54	51	53	54.6	54.6	45.4

The results of face recognition using face mouth-chin fragments are shown in Table III.

TABLE III
EXPERIMENT RESULTS FOR MOUTH-CHIN FACE FRAGMENT RECOGNITION

Run	1	2	3	4	5	Mean	Error rate %	Recognition rate %
Errors	69	67	59	60	62	63.4	63.4	36.6

The rate of whole face recognition was 43.2%. The rate of eye-eyebrow fragment recognition was 45.4% and the rate mouth-chin fragment recognition was 36.6%. Computation time for 100 images was 18 sec. in the whole face recognition and 3 sec. in the fragment recognition. To obtain more reliable results it is needed to perform additional experiments with other fragments, other databases and other classifiers.

V. CONCLUSION

The face recognition rate was investigated experimentally for three different cases. In the first, the recognition process was based on images of the whole faces. In the second case, the recognition process was based on fragment (eye-eyebrow) images. In the third case, the recognition process was based on fragment (mouth-chin) images. The results of the first experiment demonstrated that recognition using a eye-eyebrow fragment of a face can give a recognition rate comparable to the recognition rate of using a whole face. Additional experiments are needed to verify this conclusion.

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