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A Novel Approach for Face Recognition based on ANN and ANFIS

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***Abstract*— With the progression of information technology combined with the need for high security, the application of biometric as identification and recognition method has received special attention. Face recognition is one of biometric methods, to identify given face image using main features of face. In this paper, an algorithm based on ANN (Artificial Neural Networks) and ANFIS (Adaptive Neuro-Fuzzy Inference System) is presented combining the computational capability of ANN and IF-THEN rules of ANN. ANN, ANFIS, and proposed method were applied to 200 face images from faces96 dataset. While ANN and ANFIS had very good results, the proposed method yields 97.1 % of classification accuracy, which indicates efficiency of the algorithm.**

***Index Terms*— Face Recognition, ANN, ANFIS, Eigenfaces.**

I. INTRODUCTION

The face is the main focus of attention and plays a key role in identification and establishing the distinctiveness of a specific person from the rest of the human society, as well as expressing identity and emotion. A human can distinguish hundreds of thousands of faces learned throughout the lifetime and distinguish familiar faces at a glimpse even after years apart.

While it is clear that people are good at recognizing a face, but it's not at all obvious how faces are encrypted or decrypted by the human brain. Human face recognition has been explored for more than twenty years. Developing a proper program which can be used digitally in identifying a face is a somewhat challenging task, since human faces are complex and differ from each other in every feature.

Investigations by numerous researchers [1] [2] [3] over the past several decades have indicated that certain facial characteristics are used by human beings to identifying faces. PCA eigenfaces is one of the basic methods of feature extraction based on the information theory concepts, which is also known as the principal component analysis method. M. Kirby and L. Sirovich [4] [5] have shown that any particular face could be economically represented in terms of a best coordinate system that they termed "eigenfaces". Later, M. Turk and A. Pentland [6] have proposed a face recognition method based on the eigenfaces approach.

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Artificial neural networks were successfully applied for solving signal processing problems in 20 years [7]. Neural Network concept is used because of its ability to learn ' from observed data. Since ANN is quite powerful classification method, there have been many different approaches using ANN [8] [9] [10].

An adaptive neuro-fuzzy inference system (ANFIS) is a type of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. The method was developed in the early 1990s [11]. As it combines both neural networks and fuzzy logic rules, it has the ability to capture the benefits of both in a single framework [12]. ANFIS concept is used for its IF-THEN rules that have learning ability to estimate nonlinear functions [13]. While ANFIS is a powerful for classification as well, there has not been as many approaches to face recognition as with ANN, mainly for its lack of possible input arguments. Previous works mainly concentrated on facial expressions [14] [15], and some on face recognition [16] [17].

This paper presents a novel approach to face based on ANN and ANFIS algorithms. The method uses PCA-based eigenfaces to extract features of a face, ANN to reduce the number of input attributes, and ANFIS for face recognition. The strategy of the Eigenfaces method consists of extracting the characteristic features on the face and representing the face in question as a linear combination of the so called "eigenfaces" obtained from the feature extraction process.

II. MATERIALS AND METHODS

There are many methods such as security purpose, credit card authentication, criminal detection etc. where the identification of a face plays a crucial role. Recent cases of identity theft have heightened the need for methods to prove that someone is truly who he/she claims to be. Face recognition technology may solve this problem since a face is undeniably connected to its owner expect in the case of identical twins. It is nontransferable. The system can then compare scans to records stored in a central or local database or even on a smart card.

The first step of human face recognition is to obtain the important features from facial images. The issue naturally arises as to how good facial features can be quantified. If such a quantification if possible then a computer should be capable of recognizing a face from a given of features.

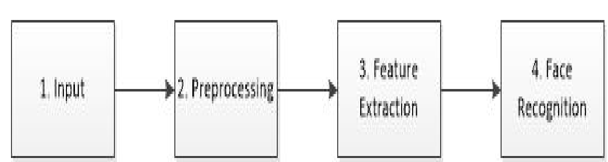

Figure 1 - Face Recognition Process

2.1 Dataset

The dataset used to test the algorithm is faces96 [18].

Acquisition conditions:

Using a fixed camera, a sequence of 20 images per individual was taken. During the sequence the subject takes one step forward towards the camera. This movement is used to introduce significant head variations between images of same individual. There is about 0.5 seconds between successive frames in the sequence.

Database Description:

- Number of individuals: 152
- Image resolution: 196x196 pixels (square format)
- Contains images of male and female subjects
- Variation of individual's images:
- Backgrounds: the background is complex (glossy posters)
- Head Scale: large head scale variation
- Head turn, tilt and slant: the images contain minor variation in these attributes
- Position of face in image: some translation
- Image lighting variation: as subject moves forward, significant lighting changes occur due to the artificial lighting arrangement
- Expression Variation: some expression variation
- Additional comment: there is no hairstyle variation as the images were taken in a single session.

2.2 Preprocessing

Image size resizing, conversion into gray scale, and double-precision conversion are applied for preprocessing the images.

Initial dataset images were 196x196 pixels. Size is reduced in half (98x98) in order to preserve the size and to increase the speed of eigenfaces feature extraction. Next step was converting images from truecolor (RGB) to grayscale intensity images by eliminating the hue and saturation information while retaining the luminance [19]. Last part of preprocessing was used for converting the intensity of the image to double precision, rescaling the data if necessary.

2.3 PCA Eigenfaces

The foundation of the eigenfaces technique is the Principal Component Analysis (PCA). Eigenfaces and PCA have been used by Sirovich and Kirby to represent the face images effectively [5]. They have started with a set of initial face images, and calculated the best vector method for image compression. Then Turk and Pentland utilized the Eigenfaces to face recognition system [6].

Eigenfaces are set of features that together characterize the variation between face images. Often, its operation can be thought of as revealing the internal structure of the image in the way which best explains the major features of the data [20]. Each image location contributes more or less to each eigenvector, so eigenvectors can be displayed as a sort of ghostly face called an eigenface. Each eigenface differs from uniform gray where some facial feature differs among the set of training faces [6]. Each face can be represented accurately in terms of a linear combination of the eigenfaces. Every face can also be estimated using only "best" eigenfaces – those that have the biggest eigenvalues, and which hence account for the most discrepancy within the collection of face images. The best M eigenfaces span an M-dimensional subspace – "face space" of all possible images. [21]

2.3.1 Eigenface Algorithm

Step 1: Prepare the data

In this step, the faces constituting the training set (Γi) should be prepared for processing.

Step 2: Subtract the mean

The average matrix (Ψ) has to be calculated, then subtracted from the original faces (Γi) and the result stored in the variable Φi

$$\psi = \frac{1}{M}\sum_{n-1}^{M} \Gamma_n$$

$$\phi_i = \Gamma_i - \psi$$

Step 3: Calculate the covariance matrix

In the next step the covariance matrix C is calculated according to

$$C = \frac{1}{M}\sum_{n-1}^{M} \phi_n \phi_n^T$$

Step 4: Calculate the eigenvectors and eigenvalues of the covariance matrix

The covariance matrix C in step 3 (see equation 2) has a dimensionality of $N^2 \times N^2$, so one would have N^2 eigenfaces and eigenvalues. For a 256 × 256 image that means that one must compute a 65, 536 × 65, 536 matrix and calculate 65, 536 eigenfaces. Computationally, this is not very efficient as most of those eigenfaces are not useful for our task [22]. PCA tells us that since there is only M images, there is only M non-trivial eigenvectors. To solve for these eigenvectors, the eigenvectors of a new M x M matrix have to be taken:

$$L = A^T A$$

Because of the following math trick:

$$A^T A\, V_i = \mu_i V_i$$

$$A\, A^T A\, V_i = \mu_i\, A_{V_i}$$

where V_i is an eigenvector of L. From this simple proof, A_{V_i} is an eigenvector of C. The M eigenvectors of L are finally used to form the M eigenvectors u_i of C that form the eigenface basis:

$$u_i = \sum_{k=1}^{M} v_{lk} \phi_k$$

where u are the eigenfaces. Usually, only a subset of M eigenfaces is used, the M^l eigenfaces with the largest eigenvalues. Eigenfaces with low eigenvalues can be omitted, as they explain only a small part of characteristic features of the faces.

2.4 ANN

An Artificial Neural Network (ANN) is a data processing model that is inspired by the way biological nervous systems, like brain, process data. The main element of this model is the unique structure of the data processing system. It is comprised of a large number of highly organized and connected processing elements (neurons) functioning in unison to solve particular problems. ANNs, similar to people, learn by example [23].

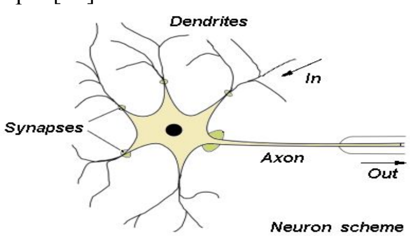

Figure 2 - Neuron Scheme

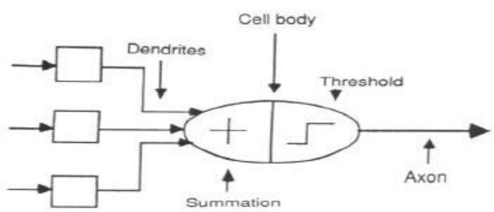

Figure 3 - Neuron Model

An ANN is designed for a particular application, such as pattern recognition or data classification, throughout a learning progression. Learning in biological systems includes modifications to the synaptic links that exist amongst neurons. Neural networks are usually arranged in layers. Layers are made up of a number of interconnected 'nodes' which hold an 'activation function' [24]. Patterns are presented to the network via the 'input layer', which communicates to one or more 'hidden layers' where the actual processing is done via a system of weighted 'connections'. The hidden layers then link to an 'output layer' where the answer is output as shown in the graphic below: [25]

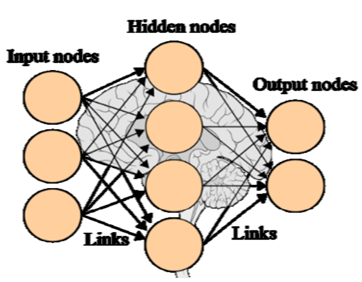

Figure 4 - ANN Model

There are different kinds of neural networks, which can be differentiated on the basis of their configuration and directions of signal flow. Every type of neural network has its own way of training. Usually, neural networks may be distinguished as follows

- feedforward networks
  - one-layer networks
  - multi-layer networks
- recurrent networks
- cellular networks

2.5 ANFIS

ANFIS (Adaptive network-based fuzzy inference system) is a fuzzy inference system applied in the framework of adaptive networks. By using a hybrid learning procedure, the ANFIS can construct an input-output mapping based on both human knowledge (in the form of fuzzy if-then rules) and stipulated input-output data pairs [26].

ANFIS's network is organized in two parts, much like fuzzy systems. The first part is the antecedent part, while the second part is the conclusion part. These two parts are connected to each other by rules in network form [27]. The ANFIS network structure can be demonstrated in five layers, as shown in Figure 5 for the simplest case of two inputs. The first layer executes a fuzzification process, the second layer executes the fuzzy AND of the antecedent part of the fuzzy rules, the third layer normalizes the Membership Functions (MFs), the fourth layer executes the consequent part of the fuzzy rules, and finally the last layer computes the output of fuzzy system by summing up the outputs of the 4th layer [26].

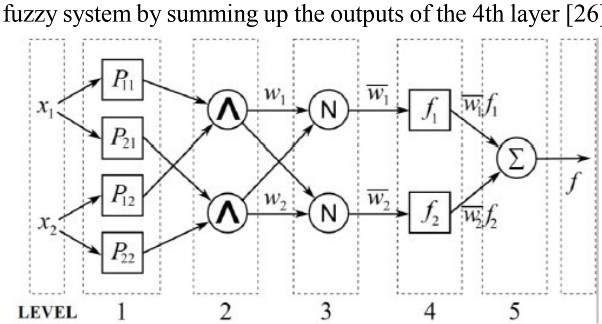

Figure 5 - The structure of the ANFIS.

The feed forward equations of ANFIS are as follows:

$$w_i = \mu_{p_{i1}}(x_1) \times \mu_{p_{i2}}(x_2)$$
$$\overline{w}_i = \frac{w_i}{w_1 + w_2}$$
$$f_1 = p_1x_1 + q_1x_2 + r_1$$
$$f_2 = p_2x_1 + q_2x_2 + r_2$$
$$f = \overline{w_1}f_1 + \overline{w_2}f_2$$

In order to model complex nonlinear systems, the ANFIS model carries out input space partitioning that splits the input space into many local regions from which simple local models (linear functions or even adjustable coefficients) are employed. The ANFIS uses fuzzy MFs for splitting each input dimension; the input space is covered by MFs with overlapping that means several local regions can be activated simultaneously by a single input. As simple local models are adopted in ANFIS model, the ANFIS approximation ability will depend on the resolution of the input space partitioning, which is determined by the number of MFs in ANFIS and the number of layers [28].

2.6 Proposed Method

Basic problem with ANFIS application to problem of classification in whole and face classification/recognition in particular is its inability to process a large number of features (inputs) as it generates rules exponentially. On the other hand, ANN faces no such issues and processes multiple inputs easily. Hence, a structure reducing inputs for ANFIS processing is needed, and ANN appears to be a logical solution. This idea leads to the structure presented in Fig. 6.

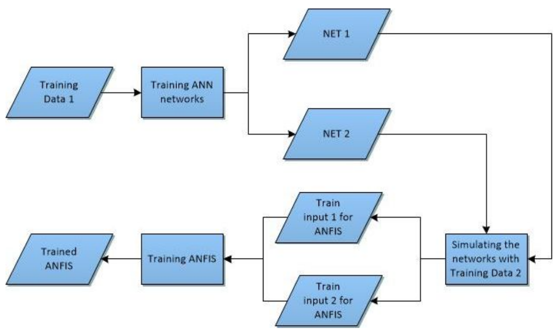

Figure 6 - Proposed Method

ANN in the structure can be trained on an arbitrary number of attributes and instances, whereas this particular implementation used 160 instances with 20 attributes each for initial training data. The same data is used for training of two separate ANNs (NET 1 and NET 2), which are then simulated on the same data. This would be bad practice for classification, but take note that this is still not classification: it is feature reduction. Output of simulation for the two networks is fed into ANFIS as its two inputs. ANFIS trained on these inputs works as a variant of a voting machine. With ANFIS trained, the system can start validation on the testing data, which is performed in the same way.

III. RESULTS AND DISCUSSION

The aim of the experiment was to find the proper way to classify the face images by trying to combine properties of ANN and ANFIS. Both ANN and ANFIS algorithms were tested, as well as the combined version.

20 attributes were extracted for every image using eigenfaces.

A standard 5-fold cross-validation was integrated into the evaluation of ANN, ANFIS, and combined algorithm, having the dataset being randomly partitioned into 5 subsets. The training was implemented for a series of 5 times, engaging only 4 subsets for each training while retaining the remaining 5th for testing. As a result, 5 models were established during the cross-validation. Additionally, a final prediction performance was carried out on the subsets evaluating the average results from the experiment.

Dataset was imported into spreadsheet file, which will be used for reading the input and corresponding output vectors in order to train our ANN and ANFIS. Spreadsheet was also used for reading the input vector so that the performance of our ANN and ANFIS could be tested after the training. Afterward, the accuracy performance of our ANN and ANFIS classifier in MATLAB was calculated. These input and output vectors required for training and testing of our ANN and ANFIS were stored in separated sheets under the same Excel file. Both training and testing of ANN ANFIS is carried out in MATLAB.

This spreadsheet was prepared in such a way that the percentage of instances used for training and testing were (tr, te) = (80%, 20%). It is important to note that 80% of instances of each class were stored in the training set, while the remaining 20% was reserved for the testing purposes.

200 images were used, 20 per person.

3.1 ANN Results

Learning algorithm that was used for this experiment was 'trainscg'. Maximum number of epochs was 3000, and training goal was 0.00001

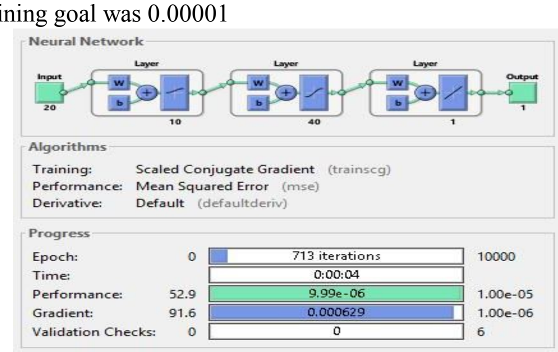

Figure 7 – ANN in MATLAB

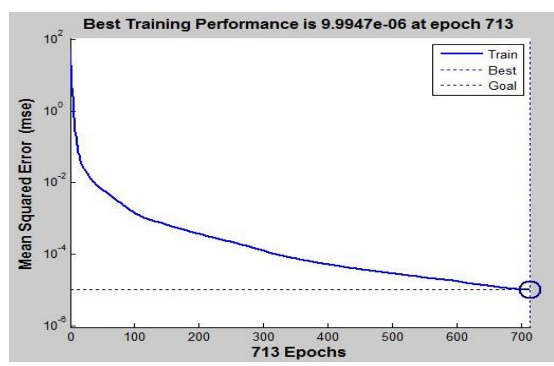

Figure 8 - ANN Training Performance

The results are shown in the table below:

ANN	
Hidden layer (number of neurons)	Correct instances
10-1	94%
40-1	95%
75-1	**95,5%**

Table 1 - ANN Results

ANN overall showed very good results. As it is shown in the table, performance slightly increased with the larger number of neurons in a hidden layer. The best result was achieved with 75 neurons in a hidden layer, where it had only 9 incorrect instances.

3.2 ANFIS Results

Two different ANFIS structures were used, one with 2, and one with 3 membership functions (MF).

The first problem encountered with the number of input attributes. Since, ANFIS creates huge number of IF-THEN rules, the number of input attributes had to be cut down from 20 to maximum 5.

ANFIS info:

Number of nodes: 524
Number of linear parameters: 1458
Number of nonlinear parameters: 45
Total number of parameters: 1503
Number of training data pairs: 160
Number of checking data pairs: 0
Number of fuzzy rules: 243

The results are shown in the table below:

ANFIS	
Membership Functions	Correct instances
2	70,5%
3	**84,5%**

Table 2 - ANFIS Results

ANFIS didn't show as good results, especially with 2 MFs. When the number of MFs is increased to 3, it showed improvement and attained 84,5% accuracy. Slight increase in performance was achieved, but it largely suffered from speed, since it took the program 5:15 minutes to run.

3.3 Combined Method Results

The proposed method had better results than ANN and ANFIS, with 98% correctly classified instances. This method also solved the speed issues that ANFIS had, running the same data in just 29 seconds.¸

3.3.1 Training

2 training sets of the same data were made (tr1, tr2), both of the equal size and equal number of the same faces (160,160). Two feed-forward networks were applied to tr1 (net1, net2). Afterwards, the simulation was made based on the inputs, rather than the test data, which is usually done. This method resulted in two input attributes, instead of 20, that initial input data had.

3.3.2 Testing

In the testing part, 20% of our dataset was used (40 instances). To test the data, the same procedure was implemented as in the training part

The results are shown in the table below:

Combined Method		
Hidden layer (number of neurons)	Membership Function	Correct instances
10-1	3	98%
40-1	3	94%
75-1	3	94%

Table 3 - Combined Method Results

CONCLUSION

The paper deals with face recognition and classification problem. Three methods were implemented, one of them being the novel approach to classification. ANN had good results (95,5%), while ANFIS suffered from speed (5:15 minutes) and performance problems (84,5%). The proposed method was designed as a fusion between computational capabilities of ANN and IF-THEN rules of ANFIS. The experimental had better results than ANN and ANFIS with 98% correctly classified instances, which indicates the effectiveness and usefulness of the proposed method.

In the future work, the novel approach and its superiority will be compared to similar classification methods such as Random Forest, Support Vector Machine and Random Tree, as well as different datasets of faces. Furthermore, the plan is to extend this method to problems of prediction as well, trying to prove the effectiveness of the approach on different types of datasets.

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