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An intuitionistic fuzzy facial recognition approach by eigenvalues

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Abstract: In the present paper a facial recognition approach using a reduced set of image values as a training vector is presented. The image simplification is performed by using the calculated Eigenvector of an image to train a neural network. It results lower processing times for rough image recognition. This approach is ideal for rough facial acquisition in dynamic background where it can be used as an early detection system. The degree of coincidence is stated by an intuitionistic fuzzy estimation. To verify the approach correctness an experiment involving variety of tests over human and non-human on objects of is carried out.
Keywords: Intuitionistic fuzzy sets, Facial recognition, Image recognition, Eigenvalues, Neural networks.
AMS Classification: 03E72.

1 Introduction

Nowadays there is a growing tendency to involve computing in every human activity in order to speed up or improve the human work. An example of this is the automotive industry where a robotized labor is used to facilitate the process. Another example is in the area of security where the admission of personnel to a specific area is of the highest essence. A matter of security is also to monitor the presence of certain individuals in a crowd as a matter of prevention or early preparation required for example at the check in desk on an airport, early check of departure passengers or at certain government institution. For example this approach can also be used at the airport check-in to verify if the person ID and the subscription match, or if the waiting list at a bank desk is followed properly.

In order to address this issue a face recognition system is required. The fast recognition approach is also useful at places where there is a human flow – banks, large shopping centers and bus stops where specialized software aiding the customer service can provide in advance information about the arrived individual. Similar application for static face detection is proposed in [5], the problem with movement of the detected object is addressed in [6]. This can be used also to improve the security and service of the ATM machines and thus the customer will be expected to apply the corresponding card or ID. There are strong requirements to that system with respect to the performance and response time. To lower the response time and improve the performance, a reduction of the data processed by a neural network is required. A neural network design approach is presented in [2, 3]. Due to the fact that the neural network response to images subject of recognition is between 0 and 1 verification by intuitionistic fuzzy estimation is required. The intuitionistic fuzzy estimation approach is presented in [8].

In this work, an approach applying a method for simplification of the training process of a neural network using the Eigenvalues of an image is proposed. The main goal is a great reduction of the processed data – for example an image with size n by n pixels will result n2 values. The number of values increases by increasing the image size. While if using a vector containing only n number of values as a reference will provide tremendous increase in the efficiency even for large images. In order to test the technique a practical experiment is carried out. The results obtained by the neural network are presented as intuitionistic fuzzy sets containing the degree of membership and non-membership of the processed image.

2 Recognition approach

In many-layered networks model – Fig. 1, the exits of one layer become entries for the next one. The equations describing this operation are:

$$a^3 = f^3(w^3 f^2(w^2 f^1(w^1 p + b^1) + b^2) + b^3) \qquad (1)$$

where:

- a^m is the exit of the m-layer of the neural network for m =1, 2, 3;
- w is a matrix of the weight coefficients of the every entries;
- b is neuron's entry bias;
- f^m is the transfer function of the m-layer.

The neuron in the first layer receives outside entries p. The neurons' exits from the last layer determine the neural network's exits a. Since it belongs to the learning with teacher methods, to the algorithm are submitted couple numbers (an entry value and an achieving aim – on the network's exit):

$$\{p_1, t_1\}, \{p_2, t_2\}, ..., \{p_Q, t_Q\}, \qquad (2)$$

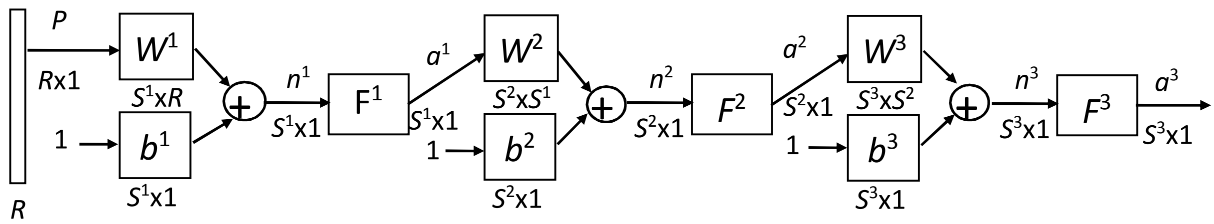

Figure1. Tree-layered neural network

where $Q \in (1...n)$, n – numbers of learning couple, where p_Q is the entry value (on the network entry), and t_Q is the exit's value replying to the aim. Every network's entry is preliminary established and constant and the exit have to reply to the aim. The difference between the entry values and the aim is the error: $e = t - a$.

The "back propagation" algorithm [4] uses least-quarter error (MSE):

$$\hat{F} = (t-a)^2 = e^2. \tag{3}$$

The conventional recognition approaches use the aforementioned neural network as recognition tool and small size images as training vectors. These methods work faster if the training vectors, respectively the images have small size. However the image size impacts the accuracy of recognition. Images under certain minimal size cannot be distinguished especially if the objects under recognition such as faces, houses and vehicles are similar to one another. A satisfactory image size is 25 × 25 pixels, a training vector that contains 625 elements. It is desirable to use square images in order to reduce the computational burden of the algorithm.

Larger images will produce better recognition, but for the price of speed. The processing speed is not a subject if the processing is not performed in real time or by high end computation hardware. In case of intense human flow, that occur on a train station or an airport for example it is of great importance to use least time for processing.

A way to solve this problem is to find the characteristic values of the image called Eigenvalues. The Eigenvalue of an image is representing if the row or column vector of the original image is changed or not in comparison to the same vector of a corresponding image. In this sense to be able to calculate an Eigenvector containing a set of Eigenvalues for a particular image it is necessary to use square image.

The number of characteristic values is a function of the image size and elements. In order to estimate and derive the Eigen vector an $n \times n$ image is required. The Eigen vector contains a number of Eigen values matching to the number of image rows/columns. The Eigenvector is a set of values that when added to the main diagonal of the image, it turns it to zeros – expression (4, 8)

$$A\mathbf{X} = \lambda\mathbf{X} \tag{4}$$

In order to obtain the Eigenvector, the determinant of the matrix defined in table 2 must be calculated by the following expression:

$$(A - \lambda I)\mathbf{X} = 0 \tag{5}$$

To calculate the determinant of $n \times n$ matrix, the following Leibniz formula must be used:

$$\left|A\right| = \sum_{[\sigma(1),\, ...,\, \sigma(n)]} (-1)^{[\sigma(1),\, ...,\, \sigma(n)]} a_{\sigma(1),1} \cdots a_{\sigma(n),n} \,, \tag{6}$$

$$|\, A - \lambda I \,| = 0 \tag{7}$$

where $[\sigma(1), ..., \sigma(n)]$ is a permutation of $[1, \ldots, n]$.

Upon the solution of (4) a vector containing the image Eigenvalues is obtained (8):

$$\alpha\lambda^{n} + \beta\lambda^{n-1} + \delta\lambda + \varphi = 0 \tag{8}$$

As a result the vector used to train the neural network is reduced by n times. In terms of facial recognition in order to localize the area where the face is located a Viola – Jones algorithm is used. The Viola Jones is the most popular algorithm [5, 6] used for face recognition in many human applications. The algorithm consists basically of four procedures that are applied to the image:

- Image features also known as Haar-like features (Fig 2) represent the human characteristics and the pixel values in white region are subtracted from the pixel values of the black region.

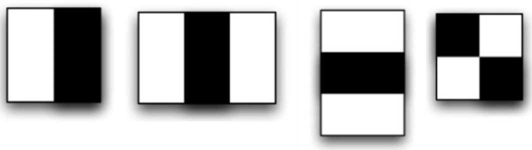

Figure 2. Haar-like features

- The integral image makes feature extraction easier and the value at pixel (x, y) is the sum of the pixel above and to the left, thus instead to compute all pixels we have one value for each rectangle and the computation process speeds up.
- All possible Haar-like features are 160,000 but not all of them are relevant so in order to decrease them the AdaBoost algorithm is applied.
- The final step is to apply Haar-like features in cascade way.

By using combination of the aforementioned methods it is possible to perform recognition over a live video stream. It can be applied to an image containing two or more individuals.

Intuitionistic fuzzy sets (IFS, [8]) are sets of elements who have degrees of belonging and not belonging. They are defined by Krassimir Atanassov (1983) as an extension of fuzzy sets of Lotfi A. Zadeh. In the classical theory, element belongs or does not belong to the summary. Zadeh defines membership in the interval [0,1]. The theory of intuitionistic fuzzy sets extends above concepts by comparing belonging and not belonging real numbers in the interval [0,1] and the sum of these numbers must also belongs to the interval [0,1].

Let the universe is E. Let A be a subset of E. Let us construct the set

$$A^* = \{\langle x,\, \mu_A(x),\, \nu_A(x)\rangle \mid x \in E\}$$

where $0 \le \mu_A(x) + \nu_A(x) \le 1$. We will call A^* an IFS.

The functions $\mu_A : E \to [0, 1]$ and $\nu_A : E \to [0, 1]$ set degree of membership and non-membership. It is defined the function $\pi_A : E \to [0, 1]$ through $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$, corresponding to the degree of uncertainty.

3 Experimental results

The experiment consists of two parts – teaching and testing the network. The first part is performed by applying the model for Eigenvalues acquisition proposed in Section 2. The images fed in the algorithm are average in size – 80 by 80 pixels – Figure 3, [7].

Figure 3. Neural network training images, [7]

The algorithm outputs a vector of image values with a size of 80 elements that are used to teach the network. The neural network is tested by applying random images of the person of interest and other persons – Figure 5. The recognition algorithm routine is as follows:

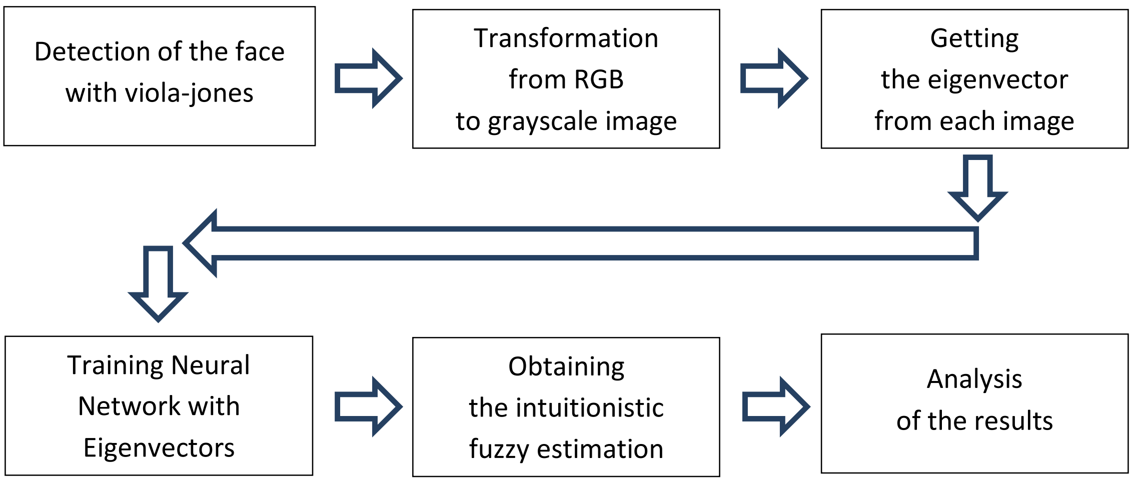

Figure 4. Recognition algorithm routine

The artificial neural network (NN) is supervised and it is trained with a set of images on the person in interest and other persons. The target for interest person is [1 0] and for other people is [0 1].

The learning trial goes through 200 epochs as shown in Figure 6, the NN consists of two layers of neurons the first one applies logsig transfer function, the second one applies linear transfer function.

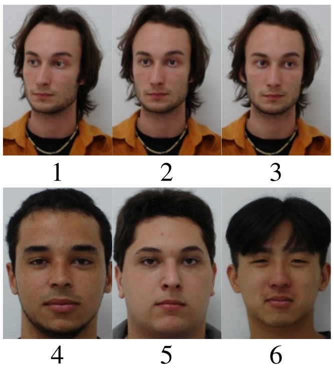

Figure 5. Neural network testing images, [7]

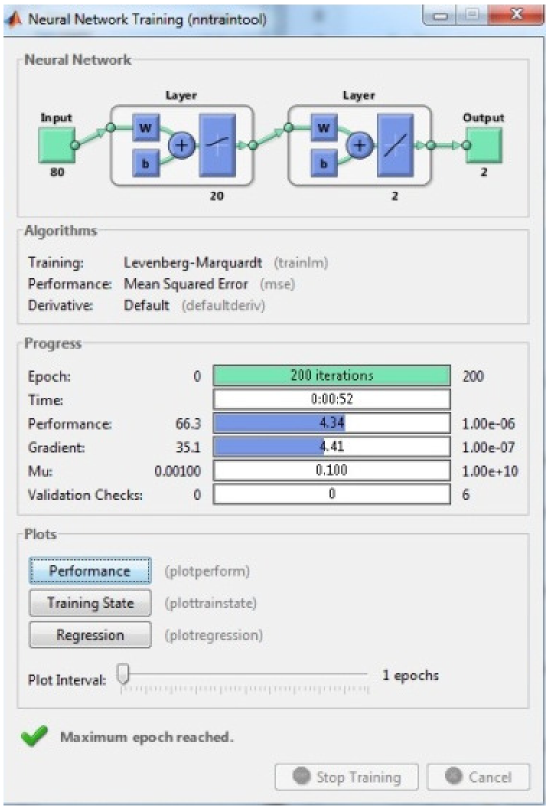

Figure 6. Learning of the Neural network

After the recognition is finished then it outputs a row vector with two values shown in Table 1 – first is the similarity percentage for the person of interest, the second value is the similarity percentage to other people used to teach the neural network.

Image	Intuitionistic fuzzy values $[\mu, \nu]$ from the output of the neural network
1	[0.70534, 0. 28434]
2	[0.65349, 0.31654]
3	[0.98250, 0.01750]
4	[0.05239, 0.94121]
5	[0.02624, 0.97326]
6	[0.21990, 0.68010]

Table 1. Testing results

The results placed at Table 1 describe the probability that the image corresponds to the person of interest. Each row corresponds to the images in Figure 4. It is obvious that images from 1 to 3 of Figure 4 are on the person subject to identification and the last three are on other individuals. For example the results for the first image show that there is 0.70534 degree of membership that the person on the image is the person of interest and 0. 28466 degree of nonmembership that this is not the person of interest. In this case, $\pi = 1 - 0.70534 - 0.28434 = 0.01032$.

The second image shows 0.65 degree of membership and 0.31 degree of nonmembership of error and 0.98 degree of membership and 0.017 degree of nonmembership for the last image. The last 3 results can be interpreted analogically. Results over 0.70 for the degree of membership confirm coincidence and results up to 0.30 coincidence are regarded as non-membership. An interesting fact is that the second result is slightly under the membership threshold and the level of uncertainty is increased. This is due to the fact that the second image has not been fed to the neural network as a training vector in Figure 3, row 3.

The results obtained by the neural network show that the individuals on the analyzed images have been correctly recognized. None of the output results show high level of uncertainty. The proper functioning of the algorithm is expressed as great improvement in terms of computation burden and memory usage as can be seen by the results.

4 Conclusion

An intuitionistic fuzzy face recognition technique using the Eigenvalues, neural networks and Viola – Jones method has been proposed in this paper. The approach used to obtain the Eigenvector is irrelevant to the image size. The efficiency of this approach increases with large images. The numerical results prove the correctness of the recognition technique. It is noticed that the overall percentage of recognized images is reasonably high, which shows that the approach is working well.

It must also be noted that the proposed technique is mainly for rough facial recognition which is ideal for the purposes of security and admittance, military applications, customer support and event management. The intuitionistic fuzzy estimation improves the neural network output by distinguishing the images level of similarity.

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