FACE RECOGNITION USING FUZZY NEURAL NETWORK

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ABSTRACT:

Face recognition is a biometric tool for authentication and verification, has great emphasis in both research and practical applications. Increased requirement on security, fully automated biometrics on personal identification and verification has received extensive attention over the past few years. In this paper we propose a novel face recognition using Fuzzy Neural network, which is used to extract features from face images by dividing the images into two phase one is of training phase by neural network second is extracting phase done by fuzzy inference system. At first the Complex Wavelet Transform is a tool applied here that uses a dual tree of wavelet filters to find the real and imaginary parts of complex wavelet coefficients. The DT-CWT is, however, less redundant and computationally efficient. Dual Tree methods are based on image at different resolution. Here the DT-CWT is used to convert the entire image into 2-D form and also here Principal Component Analysis which is a linear dimensionality reduction technique is used, that attempt to represent data in lower dimensions, i.e., used to perform the face recognition which means simply it reduces the 2-D form to 1-D form. Finally we have to extract face by comparing features using fuzzy neural networks. At present many methods for image recognition are available but most of them include feature to any type of images. The proposal is divided into two phases: the training phase and the extraction or processing related to type of image. In this paper these two parts of the network one is neural network for training, second is fuzzy inference system which helps us improve the performance result in face recognition. Fuzzy logic has proved to be a tool that can improve the performance of the existing system.

Keywords: *Face recognition. Dual Tree Complex Wavelet Transform, Principal Component Analysis,, Fuzzy network, Neural network.*

I INTRODUCTION

FACE recognition is a biometric approach that employs automated methods to verify or recognize the identity of a person based on his/her physiological characteristics. Machine Recognition of faces from still and video images is emerging as an active research area spanning several disciplines such as image processing, pattern recognition, computer vision, neural networks etc. Face recognition technology has numerous commercial and law enforcement applications. Applications range from static matching of controlled format photographs such as passports, credit cards, photo IDs, driver's licenses to real time matching of surveillance video images.

In recent years face recognition received more attention in the field of biometric authentication. Biometrics refers to the automatic identification of a person based on his/her physiological or behavioural characteristics. This method of identification offers several advantages over traditional methods involving such as security systems, credit card verification, scene Surveillance including commercial and law enforcement applications for various reasons: 1.The person to be identified is required to be physically present at the point-of-identification. Face recognition problem has become one of the most relevant research areas in pattern recognition. There is several recognition algorithms transform the original image into critically sampled domain such as Discrete Real Wavelet Transform (DWT), principal components analysis, Discrete Cosine Transform (DCT) or Discrete Fourier Transform (DFT) Dual Tree Complex Wavelet Transform (DTCWT).

The combining of the techniques of fuzzy logic and neural networks suggests the novel idea of transforming the burden of designing fuzzy logic systems to the training and learning of connectionist structure and learning to the fuzzy logic systems and the fuzzy logic systems provide the neural networks with a structural framework with high-level fuzzy IF-THEN rule thinking and reasoning. These benefits can be witnessed by the success in applying neuro-fuzzy system in areas like pattern recognition and control.

Fuzzy logic [1, 2, 3] and artificial neural networks [4, 5] are complementary technologies in the design of intelligent system. The combination of these two technologies into an integrated system appears to be a promising path toward the development of intelligent systems capable of capturing qualities characterizing the human brain. However, fuzzy logic and neural networks generally approach the design of intelligent systems from quite different angles. Neural networks are essentially low-level, computational algorithms that sometimes offer a good performance in pattern recognition tasks. On the other hand, fuzzy logic provides a structural framework that uses and exploits those low-level capabilities of neural networks. Both neural networks and fuzzy logic are powerful design techniques that have their strengths and weaknesses. Neural networks can learn from data sets while fuzzy logic solutions are easy to verify and optimize. Table 1 shows a comparison of the properties of these two technologies. In analyzing this table, it becomes obvious that a clever combination of the two technologies delivers the best of both worlds. Evolutionary Artificial Neural Networks have been widely studied in the last few decades. The main power of artificial neural networks lies in their ability to correctly learn the underlying function or distribution in a data set from a number of samples. This ability can be expressed in terms of minimizing the estimation error of the neural network, on previously unseen data. As discussed in the comprehensive review[6],, variety of methods has been applied on different issues of ANNs, such as the architecture and the connection weights to improve their performance. There are several published works in the literature that have shown an ensemble of neural networks demonstrates improved generalization ability in comparison with individual networks [7,8,9,10,11,12]. Most real world problems are too complicated for a single individual network to solve. Divide-and-Conquer approach, which tries to solve a complex problem by dividing it into simple problems, has proved to be efficient in many of such complex situations.

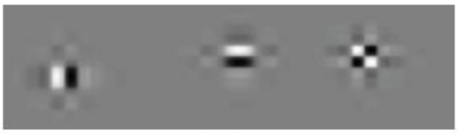
Table 1: Properties of neural networks and fuzzy logic

	Neural Networks	*Fuzzy Logic*
Knowledge Representation	Implicit, the system cannot be easily interpreted or modified	Explicit, verification and optimization are very easy and efficient
Trainability	Trains itself by learning from data sets	None, everything must be defined explicitly

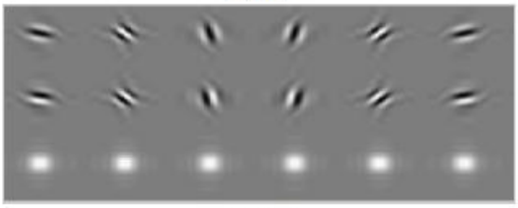
The remainder of the paper is organized as follows Section 2 introduces an overview of the Dual Tree Complex Wavelet Transform (DTCWT), Principal Component Analysis (PCA) Section 3 presents proposed fuzzy neuro network. Section 4 provides the conclusion.

II Dual Tree Complex Wavelet Transform (DTCWT), Principal Component Analysis (PCA)

Dual Tree Complex Wavelet Transform (DTCWT). DTCWT gives better directional selectivity in 2-D with Gabor like filters. Standard DWT offers the feature selectivity in only 3 directions with poor selectivity for diagonal features, where as DT-CWT has 12 directional wavelets (6 for each of real and imaginary trees) oriented at angles of ±15°, ±45°, ±75° in 2-D as shown in following Fig. 1. The improved directionality with more orientations suggests the advantage of DT-CWT in a vide rage of directional image processing applications, e.g. texture analysis. Approximate Shift Invariance, Good Directional Selectivity in 2-Dimensions, Perfect Reconstruction, Limited Redundancy and Efficient order - N Computations are the major properties of DTCWT. The filter bank structure of the CWT has CWT filters which have complex coefficients and generate complex output samples. This is shown in Fig. 2, in which each block is a complex filter and includes down sampling by 2 (not shown) at its outputs. Since the output sampling rates are unchanged from the DWT, but each sample contains a real and imaginary part, a redundancy of 2:1 is introduced. The complex filters may be designed such that the magnitudes of their step responses vary slowly with input shift only the phases vary rapidly. The real part is an odd function while the imaginary part is even. The level 1 filters, Lop and Hip in Fig. 2, include an additional pre filter, which has a zero at $z = -j$, in order to simulate the effect of a filter tree extending further levels to the left of level 1.



a) DWT



b) DTCWT

Fig 1: Directionality

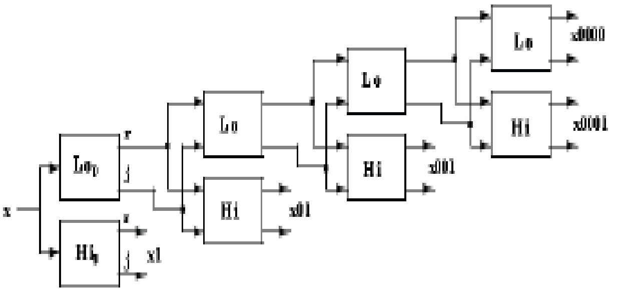


Fig 2 Four levels of Complex Wavelet Tree for real 1-D input signal x.

Extension of complex wavelets to 2-D is achieved by separable filtering along rows and then columns. However, if row and column filters both suppress negative frequencies, then only the first quadrant of the 2-D signal spectrum is retained. Two adjacent quadrants of the spectrum are required to represent fully a real 2-D signal, so we also need to filter with complex conjugates of either the row or column filters.

This gives 4:1 redundancy in the transformed 2-D signal. If the signal exists in $m - d$ ($m > 2$), then further conjugate pairs of filters are needed for each dimension leading to redundancy of $2m$: 1.

The most computationally efficient way to achieve the pairs of conjugate filters is to maintain separate imaginary operators, $j1$ and $j2$, for the row and column processing, as shown in Fig. 3.

This produces 4-element `complex' vectors: {r, $j1$, $j2$, $j1j2$} (where r means 'real'). Each 4-vector can be converted into a pair of conventional complex 2-vectors, by letting $j1 = j2 = j$ in one case and $j1 = -j2 = -j$ in the other case. This corresponds to sum and difference operations on the {r, $j1j2$} and {$j1$, $j2$} pairs in the summation blocks in Fig. 3 and produces two complex outputs, corresponding to first and second quadrant directional filters respectively.

Complex filters in multiple dimensions provide true directional selectivity, despite being implemented separable, because they are still able to separate all parts of the m – D frequency space. For example a 2-D CWT produces six band pass sub-images of complex coefficients at each level, which are strongly oriented at angles of ±15°, ±45°, and ±75 °, shown by the double-headed arrows in Fig. 3.

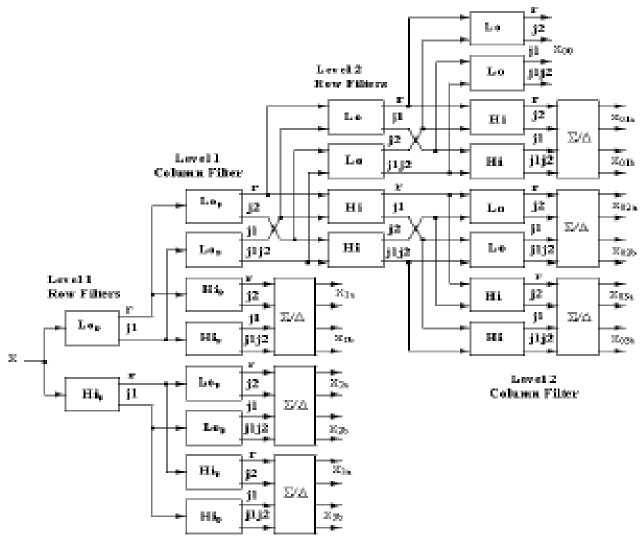


Fig. 3 – Two levels of the Complex Wavelet tree for a real 2-D

Input image x giving 6 directional bands at each level.

Principal Component Analysis

PCA is a useful statistical technique that has found applications in fields such as face recognition and image compression it is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. Since patterns in high dimensional data are hard to find due to the 61 unavailability of graphical representation, PCA is a powerful tool for analyzing the data. PCA is applied to normalized vector which transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called principal components. Normally covariance matrix is calculated by, C= X X‟. Covariance matrix C is difficult to calculate due to its large size, which may leads to memory problem. Hence it can be calculated by indirect method. First, the matrix L is formed by, L=X „ X. Even vectors v for L is calculated. Eigen vectors v is sorted according to the Eigen values. Eigen vectors for C is calculated from v,(i.e.)u= Xv, where „u‟ is the eigenvectors of C.

III. Proposed Fuzzy Neuro Network:

At present many methods for image recognition are available but most of them include feature to any type of images. The proposal is divided into two phases: the training phase and the extraction or processing related to type of image.

The method proposed in this paper can be applied recognition phase.

3.1. Training of the Neural Network:

The training of neural network consists of following steps as shown in Figure 1.

• The first step for training is to provide the network with data set. For this purpose identical row from the image matrix is considered as input for designing the structure.

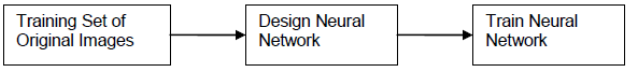


Fig 4 – Training of neural network

The dataset obtained from step 1 is now used to design the neural network architecture as shown in Figure 2. The network designed has number of input equals to number of columns in the dataset matrix. Here, BPNN is working in feed forward mode. This network has a layered structure. The basic layers are input, hidden and output layer. This is different from others based on the way the weights are calculated during learning. When the numbers of hidden layers are increased, training becomes more complex. There can be more than one hidden layer in the network, but one layer is sufficient to solve our purpose. The training of BPNN is done in three stages:

* Feed-forward of input
* Calculation of weights and error

Input layer consists of units which receives external input. There are no connections within a layer. This input is fed to the first layer of hidden units. Hidden unit apply activation function and receives weighted bias, the output of the hidden units is distributed over the next layer of hidden units. This process continues until the last layer of hidden units. The outputs are fed into a layer of output units. Though training of BPNN is very slow, once the network is trained it produce results rapidly.

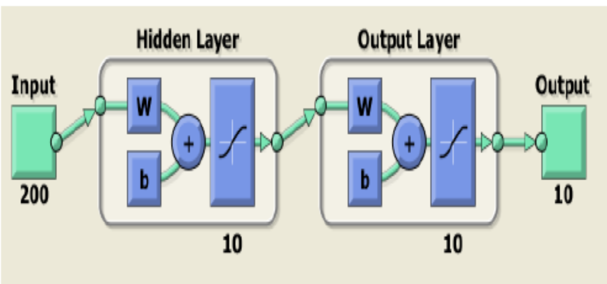


Fig 5 – Designed neural network

In the final step training of neural network is performed, after the database is created target is set corresponding to the images we want to store in our database. The above designed network is then trained such that output of the network well matches with the target values. Much closer the trained value, accuracy comes out to be more. Thus, for this purpose network can be trained up to 4 to 5 times. This step completes the first phase.

Recognition of the data using Fuzzy Logic:

Accuracy of the neural network is calculated on the two parameters namely

Epochs- Fewer epochs mean network learns in small repetitions. Less time means network achieved goal easily and shortly. Lower value of epochs is associated with higher network accuracy.

Gradient- Low value of gradient plot indicates that the network is learning up to a large extent which means finer adjustments in the weights and bias. This in turn makes network more accurate and reliable, avoiding chances of *false predictions.*

Figure 6 depicts two output parameters of neural network on basis of which accuracy is calculated is given to Fuzzy Inference System as inputs. The two input blocks in the figure shows the same.

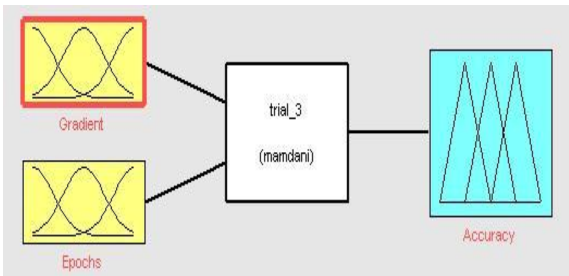


Fig 6 Designed FIS

The input to the FIS is defined by the membership function which is defined between the ranges in which the two input values lies. Here range is selected as 0 to 50. We can select from any membership function which are already defined or customize our own membership.

Figure 7 shows the membership function selected for inputs Gradient & Epochs.

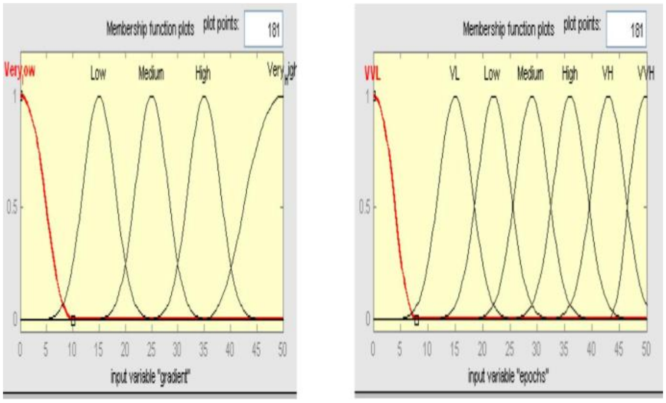


Figure 7 (a)Membership Function for Input Gradient and Epochs

The central block consists of the rules for the network which are based on the combination of two input parameters to provide the desired output. The fuzzy rules are redundant for each input; we must repeat the set of rules for input parameter.

The third and final block in recognition phase is the output membership function which is defined in the range of recognition rate from [0 100]. When the two inputs are low in range accuracy is calculated to be more as defined by the rules. Figure 8 shows the output membership.

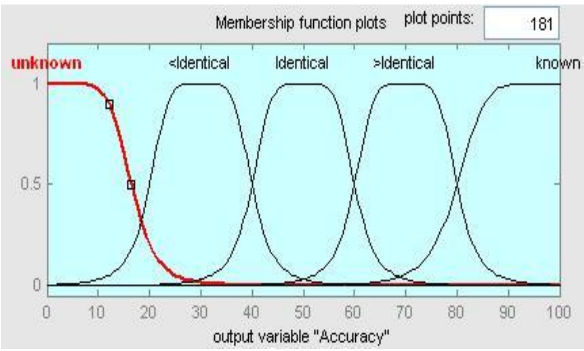


Figure 8. Membership Function

The combined algorithm of both the phases is shown in Figure 9

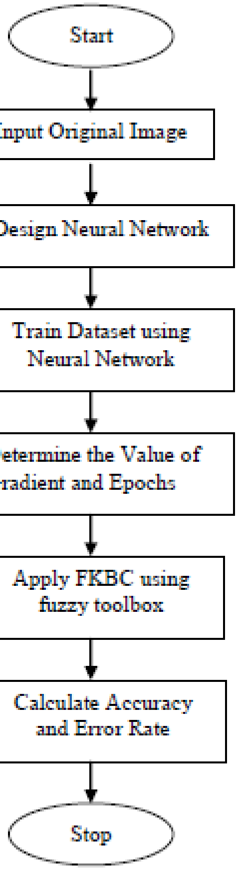


Fig 9: Algorithm for the proposed method.

V.CONCLUSION

In this paper we propose a novel face recognition using Fuzzy Neural network, which is used to extract features from face images by dividing the images into two phases one is of training phase by neural network second is extracting phase done by fuzzy inference system. At first the Complex Wavelet Transform is a tool applied here that uses a dual tree of wavelet filters to find the real and imaginary parts of complex wavelet coefficients. The DT-CWT is, however, less redundant and computationally efficient. Dual Tree methods are based on image at different resolution. Here the DT-CWT is used to convert the entire image into 2-D form and also here Principal Component Analysis which is a linear dimensionality reduction technique is used, that attempt to represent data in lower dimensions, i.e., used to perform the face recognition which means simply it reduces the 2-D form to 1-D form. Finally we have to extract face by comparing features using fuzzy neural networks. At present many methods for image recognition are available but most of them include feature to any type of images. The proposal is divided into two phases: the training phase and the extraction or processing related to type of image. In this paper these two parts of the network one is neural network for training, second is fuzzy inference system which helps us improve the performance result in face recognition. Fuzzy logic has proved to be a tool that can improve the performance of the existing system. Experimental result confirms the importance of combining these two technologies (neural networks and fuzzy logic) in face recognition.

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