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Face Recognition with Image Rotation Detection, Correction and Reinforced Decision using ANN

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Abstract—Rotation or tilt present in an image capture by digital means can be detected and corrected using Artificial Neural Network (ANN) for application with a Face Recognition System (FRS). Principal Component Analysis (PCA) features of faces at different angles are used to train an ANN which detects the rotation for an input image and corrected using a set of operations implemented using another system based on ANN. The work also deals with the recognition of human faces with features from the foreheads, eyes, nose and mouths as decision support entities of the system configured using a Generalized Feed Forward Artificial Neural Network (GFFANN). These features are combined to provide a reinforced decision for verification of a person's identity despite illumination variations. The complete system performing facial image rotation detection, correction and recognition using re-enforced decision support provides a success rate in the higher 90s.

Keywords—Rotation, Face, Recognition, ANN.

I. Introduction

As one of the most successful application of image analysis and understanding, Face Recognition System (FRS)s have recently received significant attention. A FRS is a computer application for automatically identifying or verifying a person from a digital image or a video clip captured by a camera. One of the ways to do this is by comparing selected facial features from the image and a related database. It is typically used in security systems and can be compared to other biometrics such as finger print or eye iris recognition system. A face recognition system recognizes an individual by matching the input image against images of all users in a database and finding the best match. FRSs, however, suffer if input images are rotated and have tilt. The success rate of an FRS considerably is dependent on the ability of the system to detect and correct the rotation. This is because most of the time FRSs are designed to handle faces oriented in one direction only. Digital cameras also can record images in one angle but the view required can be in another. Therefore, image rotation detection and correction always have certain role to play in any image processing system. Rotation correction is used in image mosaic, image registration etc. For applications such as radiology, high quality rotation is required [1]. Some of the relevant work in this regard are [1] to [8].

This work attempts to use a multi-level decision making process to detect image rotation and carry out subsequent correction, and use it to accomplish the recognition task using a Generalized Feed Forward Artificial Neural Network (GFFANN) which has multiple decision making. One stage of recognizing a face is to figure out how the foreheads, eyes, nose and mouth are placed in the facial structure which are used as decision support entities of the system configured GFFANN. A specially designed features set extracted from the forehead, eyes, nose and mouth are fed to a GFFANN which provides a recognition decision. The other flow of the system takes the entire face and extracts its features which are applied to another GFFANN. The decision from these two GFFANNs are combined to provide a reinforced decision for verification of a person's identity. The work includes images with light condition variations.

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II. A brief description of the proposed image rotation detection and correction system

The proposed image rotation detection and correction system consists of the following blocks-

- **Input:** Samples to the system is provided by the input block. A preprocessed digital image is given as the input to the system..
- **Rotation:** The input image is then rotated for use as test samples. The input images are rotated the entire cycle with gaps of 22.5^o which gives a total of 16 orientations.
- **Feature extraction:** The rotated images are next passed through the feature extraction system which is a PCA block that provides the best set of relevant details. Principal Component Analysis is a mathematical procedure for variable reduction where a number of possibly correlated variables are transformed into a smaller number of uncorrelated variables called principal components [3].
- **Rotation Classifier:** This is a GFFANN block designed to detect rotation angle of an input image. The PCA feature of each rotated image is applied to the GFFANN with an associated class code. The GFFANN is subjected to extensive training using (error) back propagation algorithm. At the end of the training the GFFANN is able to correctly recognize the angle of rotation of an image and generates the response by producing a class code appropriate for the specific rotation.
- **Correction:** This provides the correction algorithm applied to the rotated image to recover the original image. The correction block is constituted by a set of 16 GFFANNs each trained to correct the rotated image. Figure 1 shows the correction setup where each ANN block handles the specific rotation correction depending upon the decision generated by the preceding rotation detection ANN. Image rotation is corrected by using the relation

given by eq. 1, called the three pass shear rotation. It is a separable image rotation technique which decomposes the rotation into operations which only involve rows or columns of the image [1]. A three step decomposition is used in this approach which is quiet tedious hence requires a method which is faster. A ANN based method can be a solution which is attempted in this work as summarized by the block diagram shown in Figure 1.

$$R(\theta) = \begin{pmatrix} cos(\theta) & -sin(\theta) \\ sin(\theta) & cos(\theta) \end{pmatrix} \quad (1)$$

Each GFFANN is trained to implementation the image rotation correction using eq. 1 for specific rotation detected by the previous ANN block. During training each GFFANN is configured to handle the image rotation correction. For a decided angle, the GFFANN receives the rotation corrected image as its reference for training. The reference image is generated using the eq. 1 and the training carried out. At the end of the training, the rotation corrected image is generated.

The image rotation detection is performed by generating a set of outputs by the GFFANNs as below (Figure 1):

$$y_{1p} = f[\sum_k \sum_j f\{\sum \sum x[i,j] \times w[i,j] + b_{ij}\} \times w[j,k]] \quad (2)$$

where f(.) is the activation function associated with the ANNs, w[.] are the inter-layer connectionist weights, b[.] are the bias values and p is the number of rotation decision states. For each of the p rotation states image correction is carried out using eq. 1 which is implemented using 16 ANNs one each for the detected states. The output of these ANN blocks are governed by the following output expression:

$$y_{2p} = f[\sum_{jk} f\{\sum_i \sum_j x[i,j] \times w[i,j] + b[i,j] \times w[j,k]\}] \quad (3)$$

where b[.] are bias values required for the GFFANN training. The training of the GFFANNs are carried out by following the considerations as described in Section IV.

III. Re-enforced decision support in a Face Recognition System (FRS)

Re-enforced recision support is an essential component in verification and security systems to avoid duplication or faking. It tries to provide a recognition decision by deriving multi-level decision support as proposed in this work. The system is considered to be an integral part of a FRS. A generic face recognition system comprises of the following blocks:

- **Facial Feature Extraction**: Facial feature extraction is a special form of dimensionality reduction. When the input data is too large and it can contain redundancy. In that situation the input data is transformed into a reduced representation set of extracts that forms the feature vector. Transforming the input data into the set of features is called features extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. The input for a FRS is a digitized pre-processed image of which features are extracted.
- **Classifier**: The classifier is designed to the input samples. It is first trained with the feature set and next tasked with finding the best match. In this case several classifiers are available which includes Statistical Classifiers, Artificial Neural Network (ANN)s, Genetic Algorithm (GA)s etc. The present work considers the GFFANN as a classifier.
- **Output**: The output block gives the decision based on the classification result. It transforms the classifier output to a presentation domain.

Given still or video images of a scene, identify or verify one or more persons in the scene using a stored database of faces. Available collateral information such as race, age, gender, facial expression and speech may be used in narrowing the search (enhancing recognition). The solution of the problem involves segmentation of faces (face detection) from cluttered scenes, feature extraction from the face region, recognition or verification. In identification problems, the input to the system is an unknown face and the system reports back the decided identity from a database of known individuals, whereas in verification problems, the system needs to confirm or reject the claimed identity of the input face [3].

The FRS only uses a singular decision support mechanism provided by a classifier. It can provide satisfactory levels of success with few failures for which multi-level decision making is essential. The multi-level decision support can prevent loop-holes in a security system formed by such a verification and recognition system.

A. *FRS with multi-level decision support*

TABLE I
FACIAL REGION SELECTION FOR FEATURE EXTRACTION

Sl Num	Facial Region	Size N x M
1	Fore-head	$0.62N$ x $0.25M$
2	Eyes	$0.62N$ x $0.125M$
3	Nose	$0.25N$ x $0.125M$
4	Mouth	$0.375N$ x $0.125M$

The block diagram of a FRS with multi-level decision support is as in Figure 3 named Multi-Level Decision Support FRS (MDSFRS) architecture. The system considers forehead, eyes, nose and face to be essential facial sections from which features are extracted to re-enforce a decision given by an FRS. A face may be subdivided into these four sections as shown in Figure 4. To extract features from the forehead, eyes, nose and mouth rectangles as shown in Figure 4 are fixed statically immediately after pre-processing. For a 400 x 400 image, the forehead is considered to be of dimension 250 x 100, while the eyes are taken to have a size of 250 x 50. For the nose and the mouth the corresponding values are 100 x 50 and 150 x 50. For a sample set of 50 faces each of size N x M, this static segmentation of the four regions are carried out by taking into account the considerations as shown in Table I, with 0.0125N pixel difference in-between the regions.

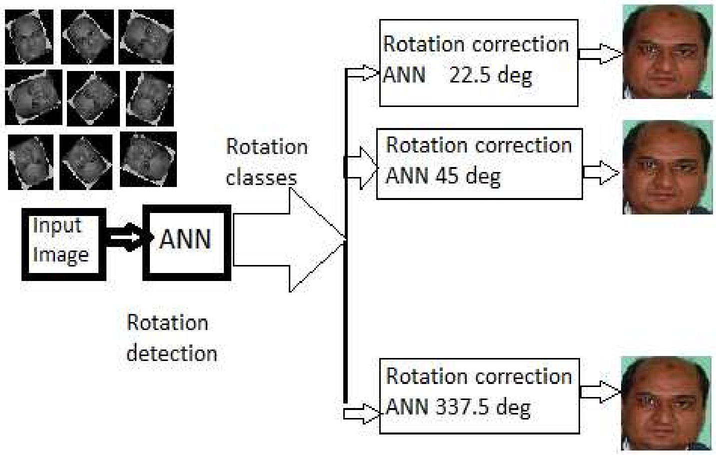

Fig. 1. Block Diagram

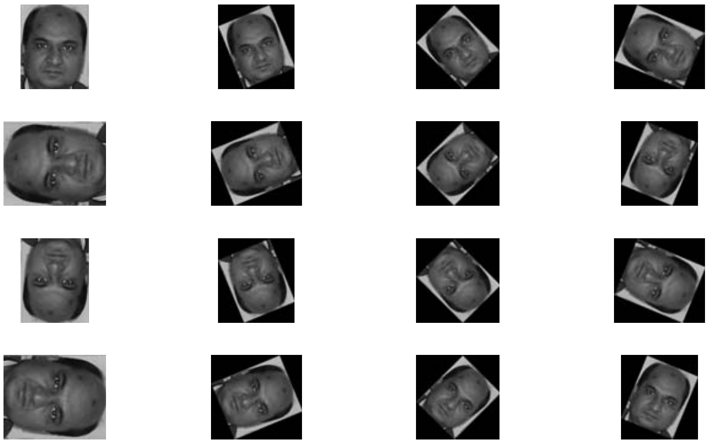

Fig. 2. Rotated image samples

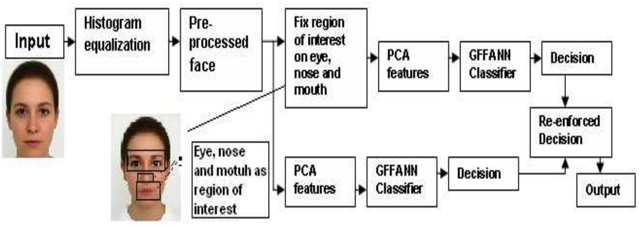

Fig. 3. Block diagram of Multi-Level Decision Support Face Recognition System (MDSFRS)

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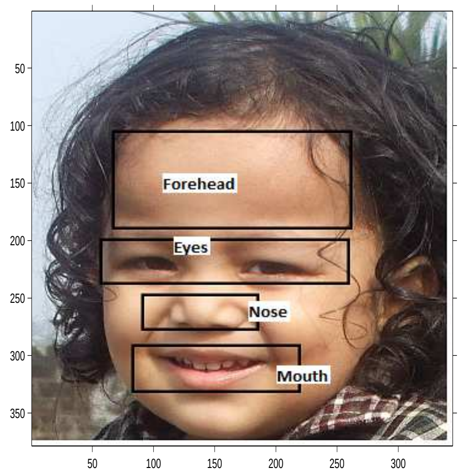

Fig. 4. Sample face with four different facial sections for re-enforced decision making

B. Pre- Processing

The input face may contain several deficiencies including the presence of noise, variation in illumination etc. These can be corrected by several preprocessing operations like histogram equalization, noise- removal etc.

C. Feature Extraction

Feature is a set of values that best describe an object. Therefore, selection of features play a very significant part in any pattern recognition application development. Feature extraction involves transforming the input data into the set of values that best describes the input under consideration [9]. The Principal Component Analysis (PCA) is a subspace projection technique widely used for face recognition [2]. PCA deals with second order statistics and finds a set of representative projection vectors such that the projected samples retain most information about original samples [9]. Two separate sets of features are considered.
First, for the four selected facial regions, four separate PCA feature sets are extracted. For a 400 x 400 image these four sections produce a feature set of size 750. The image size is critical. Hence, the input image is considered in four forms: 32 x 32, 64 x 64, 64 x 32, 64 x 50. All input images are resized to one of these four groups depending upon the closeness they share with respect to size. As such, from each of these image sizes the feature sets derived from the four different facial segments will also vary. Table II shows the facial segment feature lengths for the four different image sizes. For the four different image sizes the feature length varies as shown by Table III. A section of the samples used for the work is shown in Figure 5. The proposed system is formed by four blocks each of which are similar to the MDSFRS block shown in Figure 3. The four blocks are taken to deal with four image size variations. The block diagram of the proposed system constituted by four MDSFRS is shown in Figure 6. Each of

TABLE II
FACIAL REGION FEATURE LENGTHS FOR FOUR DIFFERENT IMAGE SIZES

Sl Num	Facial Region	Size of Image	Length of Feature
1	Fore-head	32 x 32	8
		64 x 64	16
		64 x 32	8
		64 x 50	13
2	Eyes	32 x 32	4
		64 x 64	8
		64 x 32	4
		64 x 50	7
3	Nose	32 x 32	4
		64 x 64	8
		64 x 32	7
		64 x 50	8
4	Mouth	32 x 32	4
		64 x 64	8
		64 x 32	4
		64 x 50	7

TABLE III
FACIAL REGION FEATURE LENGTH WITH IMAGE SIZE VARIATION

Sl Num	Image Size	Feature Length
1	32 x 32	20
2	64 x 64	40
3	64 x 32	20
4	64 x 50	34

Fig. 5. Some of the samples used

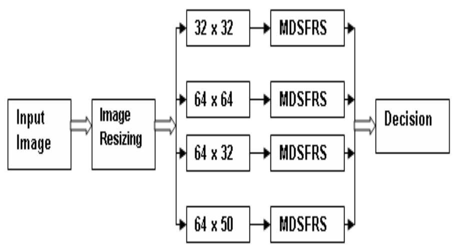

Fig. 6. Block diagram of the multi-level decision support face recognition system

the MDSFRS blocks are formed by two Generalized Feed Forward Artificial Neural Network (GFFANN). The output decision depends upon the responses of the MDSFRS formed by two GFFANNs the outputs of which can be expressed as below:
Let x(i,j) be a rotation corrected image which after pre-processing is taken as xp(i,j).

- **Block 1**: This block receives the PCA features of a pre-processed and rotation corrected image which is represented as $xp_p(i,j)$. The output of the GFFANN is given as below:

$$y_{B1} = f[\sum_j \sum_k f\{\sum_i \sum_j xp_p(i,j) \times w(i,j) + b_{ij}\} \times w(j,k)] \quad (4)$$

- **Block 2**: Let $\sum_{m=1}^{4} xp_{pm}$ be the four sections namely forehead, eyes, nose and mouth for decision making. The PCA features of the four sections are generated and represented as $\sum_{m=1}^{4} xpp_m$ which forms a feature set for training and testing the GFFANN. The sample set created is subdivided into two parts with 40% of the data used for training while 60% are used for testing. The output of the GFFANN can be expressed as

$$y_{B2} = f[\sum \sum f\{\sum_{i,j} \sum_m xpp_m \times w[i,j] + b_{ij}\} \times w(j,k)] \quad (5)$$

  Re-enforced decision is made by considering the best decision resulting between eq.s 4 and 4 or their combinations.

IV. Prediction and Classification using Artificial Neural Network (ANN)s

Accuracy of a prediction and estimation process depends to a large extent on a higher value of proper classification. ANNs have been one of the preferred classifiers for their ability to provide optimal solution to a wide class of arbitrary classification problems [10]. GFFANNs trained with (error) Back Propagation (BP) in particular has found wide spread acceptance in several classification, recogntion and estimation applications. The reason is that the GFFANNs implement linear discriminants but in a space where inputs are mapped nonlinearly. The strength of this classification is derived from the fact that GFFANNs admit fairly simple algorithms where the form of nonlinearity can be learned from training data [10]. The classification process involves defining a decision rule so as to provide boundaries to separate one class of data from another. It means placing the j^{th} input of the input vector **x(j)** in the proper class among M outputs of a classifier.
Classification by a ANN involves training it so as to provide an optimum decision rule for classifying all the outputs of the network. The training should minimize the risk functional [10] :

$$R = \frac{1}{2N} \sum (d_j - F(x_j))^2 \quad (6)$$

where d_j is the desired output pattern for the prototype vector x_j, $((.))$ is the Euclidean norm of the enclosed vector and N is the total number of samples presented to the network in training. The decision rule therefore can be given by the output of the network:

$$y_{kj} = F_k(x_j) \quad (7)$$

for the j_{th} input vector x_j.
The GFFANNs provide global approximations to non-linear mapping from the input to the output layers. As a result, GFFANNs are able to generalize in the regions of the input space where little or no data are available [10]. The size of the network is an important consideration from both the performance and computational points of view.

A. GFFANN Configuration and Training Considerations

The fundamental unit of the ANNs is the McCulloch-Pitts Neuron (1943). The GFFANN is the product of several researchers: Frank Rosenblatt (1958), H. D. Block (1962) and M. L. Minsky with S. A. Papart (1988). Backpropagation, the training algorithm , was discovered independently by several researchers (Rumelhart et. al.(1986) and also McClelland and Rumelhart (1988)).
A simple perceptron is a single McCulloch-Pitts neuron trained by the perceptron algorithm is given as:

$$O_x = g(([w].[x] + b) \quad (8)$$

where [x] is the input vector, [w] is the associated weight vector, b is a bias value and g(x) is the activation function. Such a setup, namely the perceptron will be able to classify only linearly separable data. A GFFANN, in contrast, consists of several layers of neurons. The equation for output in a GFFANN with one hidden layer is given as:

$$O_x = \sum_{i=1}^{N} \beta_i g[w]_i.[x] + b_i \quad (9)$$

where β_i is the weight value between the i^{th} hidden neuron. The process of adjusting the weights and biases of a perceptron or GFFANN is known as *training*. The perceptron algorithm (for training simple perceptrons consists of comparing the output of the perceptron with an associated target value. The most common training algorithm for GFFANNs is error backpropagation. This algorithm entails a back propagation of the error correction through each neuron in the network.

B. Application of Error Back Propagation for GFFANN training:

The GFFANN is trained using (error) Back Propagation (BP) depending upon which the connecting weights between the layers are updated. This adaptive updating of the GFFANN is continued till the performance goal is met.Training the GFFANN is done in two broad passes -one a forward pass and the other a backward calculation with error determination and connecting weight updating in between. Batch training method is adopted as it accelerates the speed of training and the rate of convergence of the MSE to the desired value [10]. A few methods used for GFFANN training includes:

- Gradient Descent (GDBP)
- Gradient Descent with Momentum BP (GDMBP)
- Gradient Descent with Adaptive Learning Rate BP (GDALRBP) and
- Gradient Descent with Adaptive Learning Rate and Momentum BP (GDALMBP).

Training continues till the error between the actual output and the desired output, $\overline{e}$ approaches the desired goal. Several configurations of the GFFANN can be utilize for training. The ANN configurations used have one input layer, one hidden layer and one output layer. A single hidden layered GFFANN is found to be computationally efficient for the work as 2-hidden layered or a 3-hidden layered GFFANNs are found to be showing no significant performance improvement at the cost of slowing down training. The choice of the length of the hidden layers have been fixed by not following any definite reasoning but by using trial and error method. For this case several sizes of the hidden layer have been considered. Table IV shows the performance obtained during training by varying the size of the hidden layer.

TABLE IV
PERFORMANCE VARIATION AFTER 1000 EPOCHS DURING TRAINING OF AN ANN WITH VARIATION OF SIZE OF THE HIDDEN LAYER

Case	Size of hidden layer (x input layer)	MSE Attained	Precision attained in %
1	0.75	1.2×10^{-3}	87.1
2	1.0	0.56×10^{-3}	87.8
3	1.25	0.8×10^{-4}	87.1
4	1.5	0.3×10^{-4}	90.1
5	1.75	0.6×10^{-4}	89.2
6	2	0.7×10^{-4}	89.8

The case where the size of the hidden layer taken to be 1.5 times to that of the input layer is found to be computationally efficient. Its MSE convergence rate and learning ability is found to be superior to the rest of the cases. Hence, the size of the hidden layer of the ANNs considered is 1.5 times to that of the input layer. The size of the input layer depends upon the length of the input vector and the output layer represents the number of parameters. Noise free and noised data were used for the training.
The selection of the activation functions of the input, hidden and output layers plays another important part in the performance of the system. A common practice can be to use a similar type of activation function in all layers. But certain combinations and alterations of activation function types carried out during training provide certain different directions and show a way to attain better performance. Two types of GFFANN configurations are considered- the first type constituted by a set of similar activation functions in all layers of the ANNs and the other with a varied combination of activation functions in different layers. Both these two configurations are trained with GDMALBP as a measure of training performance standardization.

The back-propagation algorithm used for training often suffers from more than one problems leading to difficulties in mean square error (MSE) convergence. Hence, varied AWGN considerations are used in the inputs to make the correlation between adjacent samples of the training data as low as possible. The training continues till the MSE convergence attains the desired goal and the accuracy of generating the output by the ANN reaches the required precision level.

TABLE V
EFFECT ON AVERAGE MSE CONVERGENCE AFTER 1000 EPOCHS WITH VARIATION OF ACTIVATION FUNCTIONS AT INPUT, HIDDEN AND OUTPUT LAYERS

Case	Input layer	Hidden Layer	Output Layer	MSE x 10^{-4}
1	log-sig	log-sig	log-sig	1.45
2	tan-sig	tan-sig	tan-sig	1.32
3	tan-sig	log-sig	tan-sig	1.01
4	log-sig	tan-sig	log-sig	1.08
5	log-sig	log-sig	tan-sig	1.15
6	log-sig	tan-sig	log-sig	1.19

TABLE VI
PROCESSING SPEED VARIATION OF ANN BASED AND MANUAL IMAGE ROTATION CORRECTION

Sl Num	Image Size	Time in sec.s taken by ANN based system	Time in sec.s taken by manual system
1	32 x 32	8.5	15
2	64 x 64	10.1	18.2
3	64 x 32	9.5	14.3
4	64 x 50	10.1	17.5

V. EXPERIMENTAL RESULTS AND DISCUSSION

The experiments are carried out separately for the image rotation - correction and recognition system, hence the results are shown separately.

A. Image Rotation Detection and Correction:

A set of 50 images each with 16 rotations were used to carry out the experiment. These samples were used to train the GFFANN blocks. The success rate achieved are in high 90s. Another set of samples were created by mixing AWGN noise to ascertain the effectiveness of the system under varied conditions during testing. The time taken by the GFFANNs during training is a major factor. But after training the GFFANN blocks when used for rotation correction are found to be atleast 1.5 times faster than the corresponding manual system for four different image sizes (Table VI). This contributes towards speeding up of the image rotation process and automates the entire approach.

B. Image Recognition with re-enforced decision support:

The outcome of the GFFANN blocks vary depending upon the number of training sessions and the data used. Mean Square Error (MSE) convergence and prediction precision are used to ascertain the performance of the GFFANN blocks. Samples used for training includes images with several types of noise between 1 to 30 dB. Also twelve contrast and illumination conditions are generated for the samples mixed with different levels of noise. The results show that the GFFANN blocks are robust enough in handling the image variations. Some of the samples taken during training are as shown in

Fig. 7. Samples with contrast and illumination variation

Fig. 8. Samples with contrast and illumination variation with salt and pepper noise

Fig. 9. Samples with contrast and illumination variation with Gaussian noise

Fig. 10. Samples with contrast and illumination variation with speckle noise

Figures 7 to 10. The training is carried out using three such variations of twelve contrast and illumination conditions for eleven sample faces. It constitutes a total of around 400 faces. Ten noise variations between 1 and 30 dB are also considered which results in around 4000 faces. The testing set is formed by another 5000 such faces created with minor to sudden variations compared to the training samples.

The system performance is considered first, with respect to, the time taken by each of the MDSFRS block and the composite unit as a whole. The training time and the success rate achieved at the end of 3000 session by taking the facial section features only for the four input image size variations are shown in Table VII. These results are the average values considered for about 3000 images with contrast, illumination and noise variations. Similarly, a set of results derived after training upto 3000 session by taking the images of four different sizes and considering the PCA feature inputs with contrast, illumination and noise variations are generated. Success rates are better but the training time required is more. These are shown in Table VIII. When the two trained GFFANN blocks are taken and the recognition performed with re-enforced decision making, the training is carried out in a cooperative manner until a global MSE is attained and the expected success rate generated. The average success rate for the MDSFRS system for four different image sizes derived for about 5000 images

TABLE VII
AVERAGE PERFORMANCE OF A GFFANN AFTER 3000 EPOCHS CONSIDERING ONLY FACIAL SECTION FEATURES.

Sl Num	Image Size	Feature Length	Time in sec.s	Success rate in %
1	32 x 32	20	12.1	92
2	64 x 64	40	22.3	94
3	64 x 32	20	13.1	92
4	64 x 50	34	20.2	93

TABLE VIII
AVERAGE PERFORMANCE OF A GFFANN AFTER 3000 EPOCHS CONSIDERING COMPLETE IMAGE FEATURES.

Sl Num	Image Size	Time in sec.s	Success rate in %
1	32 x 32	155.9	93
2	64 x 64	215.3	95
3	64 x 32	201.6	94
4	64 x 50	189.8	95

from blocks formed by two configurations of GFFANNs is as in Table IX. These results constitute an average of 2 to 3 % improvement compared to the case when the re-enforced decision making is not used with the FRS. This validates the importance of the MDSFRS architecture.

VI. CONCLUSION

The ANN based image rotation detection and correction system speeds up the process of removing orientation in faces which is vital in a FRS. The ANN approach is accurate as well and has the ability to control precision because of the fact that the training phase of the ANNs can make it robust enough to handle variations. The only difficulty faced in the approach is the time spent in training the ANN. When used as part of a FRS, the system can contribute towards making face resonation more effective using ANNs. The work also shows the importance of multi-level decision support in face recognition and verification applications. The work provides a way to deal with face recognition and verification despite a wide range of contrast, illumination and noise variations using GFFANNs configured in a cooperative set-up. The system together with image rotation detection and correction provides improved performance as part of an extended FRS.

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TABLE IX
AVERAGE PERFORMANCE OF THE MDSFRS CONSIDERING FACIAL SECTION AND COMPLETE IMAGE FEATURES.

Sl Num	Image Size	Success rate in %
1	32 x 32	94
2	64 x 64	96
3	64 x 32	95
4	64 x 50	96

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