Multimodal Biometric Face and Fingerprint Recognition Using APEX Algorithm and Feed Forward Back Propagation

Suman Kumar Swarnkar, Asst. Prof. Amrish Tiwari Department of Computer Science and Engineering, Vindhya Institute of Technology and Science

Abstract -Biometrics is the science and technology of measuring and analyzing biological data of human body. It extracts a feature set from the acquired data, and comparing with template set in the database. In this paper we have introduced a new concept for face & fingerprint recognition by means of APEX algorithm and feed forward back propagation method by using their approach it improves the accuracy gives better performance and more reliable in terms of security and integrity of the biometric data. This approach is developed by coming ridge based & Eigen face approach. The main of their research work is to reduce the false accept rate (FAR), false reject rate (FRR) and false enroll rate (FER). After executing their approach we have compared the result of unimodal biometric system & multimodal biometric system. From the result we observed that unimodal system has many disadvantages in terms performance and accuracy. Whereas multimodal biometric system performs for better them unimodal biometric system.

Keywords - Biometric Identification, Biometric Testing, Biometric Adaptive principal component analysis, APEX algorithm, Biometrics, Feature extraction, Multilayer perception.

I. INTRODUCTION

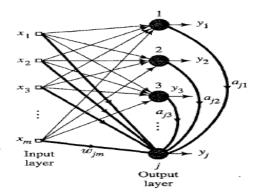
The term biometrics comes from the ancient Greek bios = "life" and metron = "measure." Biometrics refers to the entire class of technologies and techniques to uniquely identify humans. The advantage to a biometric is that it does not change or lose. Many body parts, personal characteristics and imaging methods have been used for biometric systems such as fingers, hands, feet, eyes, ears teeth, veins voices, signatures, typing styles and gaits.

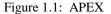
Each biometric has its own strength and limitations and accordingly each biometric is used in identification (authentication) applications. It is not difficult to steal a biometric, create a copy and use the fake trait to attack biometric systems. Multi modal biometric systems utilize

more than one physiological or behavioral characteristic for enrolment, verification or identification. The NIST report recommends a system employing multiple biometrics in a layered approach. The reason to combine different modalities is to improve recognition rate. The aim of multi biometrics is to reduce one or more of the following: False accept rate (FAR), False reject rate Failure to enroll rate (FTE) Susceptibility to (FRR), artifacts or mimics biometric systems used in real world applications are unimodal. They rely on the evidence of a single source of information for authentication. Intra-class variation: User who is incorrectly acting with the sensor typically causes these variations.Inter-class similarities: In a Biometric System where there are large no of users, there may be inter-class overlap in the feature space of multiple users.Non-Universality: The biometric System might not be able to acquire a meaningful biometric data from a subset of users. Different advanced techniques in multimodal biometric face and fingerprint recognition digital image processing, Artificial neural networks (ANN), adaptive principal component analysis multilayer perception, eigen face approach, ridge based matching, principal component analysis (PCA), feed forward back propagation Algorithm. Multimodal biometric face and fingerprint recognition. An artificial neural networks (ANN), approach was used to take advantage of neural network's ability to learn, and membership degrees and functions of neural networks.

Adaptive Principal Component Analysis -

A common method from statistics for analysing data is principal component analysis (PCA) Principal component analysis is implemented as a neural algorithm called APEX (Adaptive Principal component Extraction) developed by kung and Diamantaras (1990).Adaptive principal component Extraction (APEX) for multiple principal component extraction. All the synaptic weights of the model are trained with the normalized Hebbian learning rule. The network structure features a hierarchical set of lateral connections among the output units which serve the purpose of weight orthogonalization. This structure also allows the size of the model to grow or shrink without need for retraining the old units. The exponential convergence of the network is formally proved while there is significant performance improvement over previous methods. The APEX algorithm is also parallelizable allowing the concurrent extraction of multiple principal components. Furthermore, APEX is shown to be applicable to the constrained PCA problem where the signal variance is maximized under external orthogonality constraints.





APEX Algorithm

Step 1. Initialize the feedforward weight vector wj and the feedback weight vector aj to small random values at time n = 1, where j = 1, 2, ..., m. Assign a small positive value to the learning-rate parameter ~q.

Step 2. Set j = 1, and form = 1, 2, compute

Y1(n) = WT(n)X(n)

 $W1(n + 1) = W1(n) + \sim q [Y1(n)X(n) - Y1(Y1(n)W1(n)]$

Where x(n) is the input Vector. For large n, We have $w1(n) \rightarrow qi$, Where qi is the eigenvector associated with the largest eigenvalue A1 of the correlation matrix of x(n).

Step 3 . Set j = 2, and for n = 1, 2..., Compute

$$Y_{j-1}(n) = [Y_{1}(n), Y_{2}(n), ..., Y_{j-1}(n)]T$$

Y1(n) = WT(n)X(n) + AT(n) Yj-1(n)

 $Wj(n + 1) = Wj(n) + \sim q [Yj(n)X(n) - Yj(Yj(n)Wj(n)]$

$$Aj(n + 1) = Aj(n) - \sim q [Yj(n)X(n) - Yj(Yj(n)Aj(n)]$$

Step 4. Increment j by 1, go to step 3, and continue until j = m, where m is the desired number of principal components. (Note that j = 1 corresponds to the eigenvector associated with the largest eigenvalue, which is taken care of in step 2.) For largen we have wj(n) -> qi and aj(n) -> 0, where qj is the eigenvector associated withthe jth eigenvalue of the correlation matrix of x(n).

Multi-layer Perceptron -

A multilayer perceptron (MLP) is a feedforward artificial neural network model that maps sets of input data onto a set of appropriate output. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training the network. Several properties concerning the representational power of the feedforward MLP have been proven.- learning arbitrary functions: any function can be learned with an arbitrary accuracy by a three-layer network; learning continuous functions: every bounded continuous function can be learned with a small error by a two-layer network (the number of hidden units depends on the function to be approximated).Learning Boolean functions: every boolean function can be learned exactly by a two-layer network although the number of hidden units grows exponentially with the input dimension.

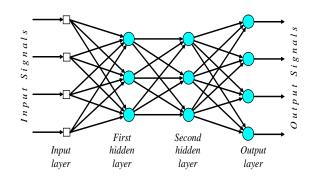


Figure 1.2: Multilayer perception (MLP)

II. . LITERATURE SURVEY

The research on multi modal biometrics started in late 90s. Face is most common biometric which is used alone or in combination with other biometrics. The earlier system based on feature extraction using principle component analysis and recognition using the feed forward back propagation. Problem in this approach we recognize the Face first and then the fingerprint in sequence it is based on unimodal biometric system. Unimodal biometric systems have variety of problems such as noisy data, intraclass variations, restricted degree of freedom, nonuniversality, spoof attack and unacceptable error rates. The system based on AND & OR Configuration this approach can not normalize the False accept rate (FAR) False reject rate (FRR) Failure to enroll rate (FTE).

In July - 2012 Dr. Shubhangi D C et al suggest that "Artificial Multi-Biometric Approaches to Face and Fingerprint Biometrics". As a part the work, an ANN is implemented. Feature extraction using principle component analysis and recognition using the feed forward back propagation neural network. Their work deals with a task where recognize the Face first and then the fingerprint in sequence. the trained ANN groups the input pixels into the different clusters which provide the results. [1].

In 2010 Sasidhar et al to him they develop multimodal biometric systems – study to improve accuracy and performance. a framework was established with assessing the performance of multimodal biometric systems. Not allowing for a common middleware layer to handle the multimodal applications with a small amount of common information. [2]

In August 2012 Hiren D. Joshi suggests that A Multimodal Biometric Authentication System for Person Identification and Verification using fingerprint and face recognition. He multimodal biometric takes the individual scores of two traits (face and fingerprint) which are combined at classifier level and trait level The logic of the multibiometric system may be implemented in an AND configuration or in an OR configuration . [3]

In 4 September, 2010 Muhammad Imran Razzak introduced an automatic method for the detection of exudates multimodal face and finger veins recognition systems in which multilevel score level fusion was performed. The imposter and genuine score are combined using Fuzzy fusion to increase the face recognition system. [5]

In August 2012 Trupti S. Indi suggests the Biometric Feature based Person Unique Identification System different image enhancement techniques such as Gaussian smoothing function, adjusting intensity values of each pixels etc. We have studied different binarization methods and selected one which gives us best results for input thumb image. We have studied some thinning algorithms like Hilditc, Rosenfeld and ZS algorithms. Based on results we have used ZS (Zhang-Suen) thinning algorithm. Problem of ANN based is difficult to understand structure of algorithm, too many attributes can result in over fitting, optimal network structure can only be determined by experimentation. [6].

III. PROPOSED METHODOLOGY

We have concentrated our implementation on adaptive principal component analysis and Multilayer perception. A proposed scheme of multimodal biometric face and fingerprint recognition using neural network is parallel the multimodal biometric takes the individual scores of two traits (face and fingerprint) which generate range approximate value for training that is in discrete interval form than system will produce good accurate result with high efficiency. Current work deals with an efficient face and fingerprint recognition algorithm combining ridge based and Eigen face approach for parallel execution. Here I am proposing a method to overcome the drawback of earlier problem, which based on combination on neural network.

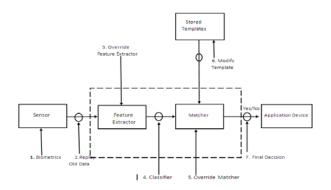


Figure 2.1: Process Logic Flow Diagram

An efficient Face and Fingerprint recognition algorithm combining ridge based and Eigen face approach. The main

purpose of the proposed system is to reduce the error rate as low as possible and improve the performance of the system by achieving good acceptable rate during identification and authentication.

Proposed implementation steps

1. Sensor level Fusion:

We combine the biometric traits taken from different sensors to form a composite biometric trait and process. Here an image of an object or a scene is captured by a digital camera or is scanned for use as the input to the system. An image is passed to the system for classification. Images vary in format, size and resolution. Face and finger Image Acquisition to collect the face images, a scanner has been used. After scanning, the image can be saved into various formats such as Bitmap, JPEG, GIF and TIFF. This FRS can process face images of any format

2 Feature level Fusion:

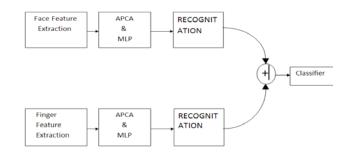
Signal coming from different biometric channels are first pre-processed, and feature vectors are extracted separately, using specific algorithm and we combine these vectors to form a composite feature vector. This is useful in classification. These are a series of steps which should be taken for making an image suitable for manipulation and interpretation by subsequent stages. The steps include removal of noise and variation of intensity recorded, sharpening, improving the contrast and stringing the texture of the image. Another important aspect is image restoration which extracts image information from a degraded form to make it suitable for subsequent processing and interpretation.

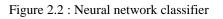
3. The Matching score level fusion:

Rather than combining the feature vector, we process them separately and individual matching score is found, then depending on the accuracy of each biometric matching scorewhich will be used for classification.

4. Decision level fusion:

Each modality is first pre-classified independently. Multimodal biometric system can implement any of these fusion strategies or combination of them to improve the performance of the system; different levels of fusion are shown in below figure.





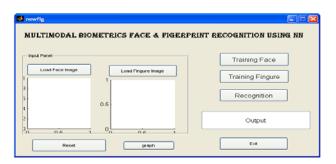
Neural network Classifier -

The classifier decides whether the image belongs to the face or the non-face class based on the information learned during training. Also know the Matching score level where testing a neural network.

IV Experimental Results

Multimodal Biometric face and Fingerprint Recognition Neural Network System based on Adaptive Using Principal Component Analysis and Multilayer perception. To improve accuracy and performance.Our implementation mainly incorporates normalize the False accept rate (FAR) False reject rate (FRR) Failure to enroll rate (FTE).Reliable method for security and integrity of the biometrics data.A system can achieve a higher recognition accuracy than uni-modal systems. A system can minimize the recognition response time. Parallel execution of both face and finger print image, so that CPU utilization is more, It produce maximum efficiency than earlier model.A key benefit of neural networks is that a model of the system can be built from theavailable data. ANN learns by adjusting the interconnections or synaptic weights between layers.multimodal biometric systems better perform than uni-modal biometric systems. Graphical user interface of Multimodal biometric face and fingerprint recognition using neural network system based on adaptive principal component analysis and multilayer are contain following-Load perception that face finger image, Button training face, Button image,Load training finger, Button recognitation, Text output, Button reset, Button graph, exit.

GUI of Multimodal Biometric face and Fingerprint Recognition Using Neural Network



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training and esting. Reduce the iteration and mean square error for face image. *Preprocessing the face image*.

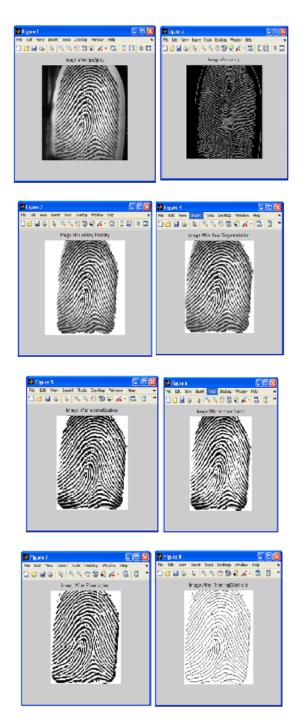
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Load face image for recognition the process of face recognition involves the examination of face features in an image, recognizing those features and matching them to one of the many faces in the database and load finger image for recognition The process of finger recognition involves the examination of finger features in an image, recognizing those features and matching them to one of the many finger image in the database

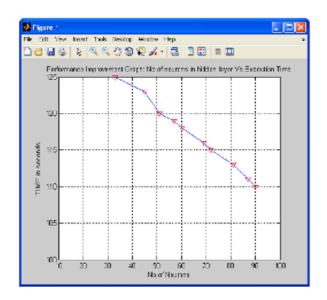


This system would try to recognize a user by reading in a face and finger and comparing it to the faces and finger of known users. The APCA and MLP algorithm for face and finger recognition was chosen for this task. This algorithm uses eigenvector analysis to compare the variance in each image, the eigenvalues and eigenvectors of a group of images were calculated correctly thus breaking down the image into mathematical coefficients. These coefficients are then used to compare the input face and finger against the faces and finger in the user database. Set a threshold level. If the distance of a detected face and finger from a vector is under this threshold then recognition.

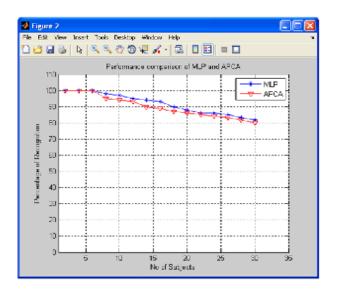


If the distance of a detected face and finger from a vector is not under this threshold value then Person is not recognition.

Performance Improvement Graph: No of neurons in hidden layer Vs Execution Time where x axis('No of Neurons') and y axis ('TIME in seconds')



Performance comparison of MLP and APCA where x aixs('No of Subjects') and y axis ('Percentage of Recognition')



VIII. CONCLUSION

Our implementation mainly incorporates normalize the False accept rate (FAR) False reject rate (FRR) Failure to enroll rate (FTE).Reliable method for security and higher recognition accuracy than uni-modal systems. A system can minimize the recognition response time. Multimodal biometric systems better perform than unimodal biometric systems As the high frequency coefficient is less sensitive to human visual systems, first few coefficients of each block is constructed. The proposed prediction models based on soft computing on the other hand are easy to implement. This has been an interesting and challenging project during which I have learned a lot about image processing, face detection, face recognition and authentication protocols. I have gained valuable experience in working with the Matlab programming which is used extensively in the computer industry. I have also gained further experience with the Neural network.We have developed a prototype biometric system which integrates faces and fingerprints in authenticating a personal identification. The proposed system overcomes the limitations of both face-recognition systems and fingerprint-verification systems.We further wish to enhance effectiveness of the system in unique identification by incorporating XOR Configuration multimodal biometric in addition to thumbprint. Together a matching score, based on ear & thumb images, will be generated to more accurate identification. The program can also be used by researchers to learn how to design highspeed face recognition systems.

integrity of the biometrics data. A system can achieve

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