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MULTIMODAL BIOMETRIC FACE AND FINGERPRINT RECOGNITION USING K-NEAREST NEIGHBOR ALGORITHM

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Abstract - Biometrics is the science and machinery of measuring and analyzing biological data of human carcass. 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 K-Nearest Neighbor 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 loom we have compared the result of unimodal biometric system & multimodal biometric system. From the effect 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, K-NN 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. several body parts, personal uniqueness and imaging methods have been used for biometric systems such as fingers, hands, feet, eyes, ears teeth, veins voices, signatures, typing styles and gaits. Apiece biometric has its possess 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 exploit 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 rationale to combine different modalities is to advance recognition rate. The aim of multi biometrics is to reduce one or more of the following: False accept rate (FAR), False reject rate (FRR), Failure to enroll rate (FTE) Susceptibility to objects or mimics biometric systems used in actual world appliances 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 feeler typically causes these variations. Inter-class similarities: In a Biometric System where there are large no of users, there may be inter-class be related 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.

K-Nearest Neighbor (KNN) Algorithm

KNN is an non parametric lazy learning algorithm. That is a pretty concise statement. When you say a technique is non parametric , it means that it does not make any assumptions on the underlying data distribution. This is pretty useful , as in the real world , most of the practical data does not obey the typical theoretical assumptions made (eggaussian mixtures, linearly separable etc) . Non parametric algorithms like KNN come to the rescue here. It is also a lazy algorithm. What this means is that it does not use the training data points to do any generalization. In other words, there is no explicit training phase or it is very minimal. This means the training phase is pretty fast .Lack of generalization means that KNN keeps all the training data. More exactly, all the training data is needed during the testing phase. (Well this is an exaggeration, but not far from truth). This is in contrast to other techniques like SVM where you can discard all non support vectors without any problem. Most of the lazy algorithms – especially KNN – makes decision based on the entire training data set (in the best case a subset of them).The dichotomy is pretty obvious here – There is a non existent or minimal training phase but a costly testing phase. The cost is in terms of both time and memory. More time might be needed as in the worst case, all data points might take point in decision. More memory is needed as we need to store all training data.

KNN for Density Estimation

while classification remains the main application of KNN, we can use it to do density evaluation also. Since KNN is non parametric, it can do estimation for arbitrary distributions. The idea is very similar to use of Parzenwindow . Instead of using hypercube and kernel functions, here we do the estimation as follows – For estimating the density at a point x, place a hypercube centered at x and keep increasing its size till k neighbors are captured. Now approximate the density using the formula,Where n is the total number of V is the volume of the hypercube. Notice that the numerator is essentially a constant and the density is influenced by the volume. The intuition is this :Lets say density at x is very high. Now, we can find k points near x very quickly . These points are also very close to x (by definition of high density). This means the amount of hypercube is small and the resultant density is high. Lets declare the density around x is very low. Then the amount of the hypercube needed to encompass k nearest neighbors is large and consequently, the ratio is low.The amount performs a job similar to the bandwidth parameter in kernel density estimation. In fact , KNN is one of common methods to approximate the bandwidth (eg adaptive mean shift).

KNN for Classification

Lets see how to use KNN for classification. In this case, we are given a few data points for training and also a new unlabelled data for testing. Our aim is to find the class label for the new point. The algorithm has different behavior based on k.

Case 1 : k = 1 or Nearest Neighbor Rule

This is the simplest scenario. Let x be the point to be labeled . Find the point closest to x . Let it be y. Now nearest neighbor rule asks to assign the label of y to x. This seems too simplistic and some times even counter intuitive. If you feel that this procedure will result a huge error , you are right – but there is a catch. This reasoning holds only when the number of data points is not very large. If the number of data points is very large, then there is a very high chance that label of x and y are same. An example might help – Lets say you have a (potentially) biased coin. You toss it for 1 million time and you have got head 900,000 times. Then most likely your next call will be head. We can use a similar argument here.

Let me try an informal argument here- Assume all points are in a D dimensional plane. The number of points is reasonably large. This means that the density of the plane at any point is fairly high. In other words, within any subspace there is adequate number of points. Consider a point x in the subspace which also has a lot of neighbors. Now let y be the nearest neighbor. If x and y are sufficiently close, then we can assume that probability that x and y belong to same class is fairly same – Then by decision theory, x and y have the same class. The book "Pattern Classification" by Duda and Hart has an excellent discussion about this Nearest

Neighbor rule. One of their striking results is to obtain a fairly tight error bound to the Nearest Neighbor rule. The bound is

 $P^* \le P \le P^* \left(2 - \frac{c}{c-1}P^*\right)$

Where is the Bayes error rate, c is the number of classes and P is the error rate of Nearest Neighbor. The result is indeed very striking (atleast to me) because it says that if the number of points is fairly large then the error rate of Nearest Neighbor is less that twice the Bayes error rate. Pretty cool for a simple algorithm like KNN. Do read the book for all the juicy details.

Case 2 : k = K or k-Nearest Neighbor Rule

This is a straightforward extension of 1NN. Basically what we do is that we try to find the k nearest neighbor and do a majority voting. Typically k is odd when the number of classes is 2. Lets say k = 5 and there are 3 instances of C1 and 2 instances of C2. In this case, KNN says that new point has to labeled as C1 as it forms the majority. We follow a similar argument when there are multiple classes.One of the straight forward extension is not to give 1 vote to all the neighbors. A very common thing to do is weighted kNN where each point has a weight which is typically calculated using its distance. For eg under inverse distance weighting, each point has a weight equal to the inverse of its distance to the point to be classified. This means that neighboring points have a higher vote than the farther points.It is quite obvious that the accuracy *might* increase when you increase k but the computation cost also increases.

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, intra-class variations, restricted degree of freedom, non-universality, 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 multi-biometric 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 2.2: 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.



Figure 2.2 : Neural network classifier 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 Using Neural Network System based on Adaptive 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 perception that are contain following- Load face image,Load finger image, Button training face, Button training finger, Button recognitation ,Text output, Button reset, Button graph, exit. GUI of Multimodal Biometric face and Fingerprint Recognition Using Neural Network Select face image from folder test database for Training face image.

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Select finger image from folder test database for Training finger image.

Training of finger image include preprocessing finger image , minutia extractor and minutia matcher and then computed scores and feature value is then passed through a simple classifier. The classifier will respond with either +1, meaning the feature passed or with -1 meaning the feature does not satisfy the criteria of the classifier. Fig. show the Preprocessing of finger image - Image after rgb2gray,Image after canny, Image after whiting boundary ,Image after final segmentation Image after normalization , Image after remove noise , Image after binarization ,Image after thinning(skelton)

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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

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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.



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')

V. 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 integrity of the biometrics data. A system can achieve higher recognition accuracy than uni-modal systems. A system can minimize the recognition response time. Multimodal biometric systems better perform than uni-modal 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 facerecognition 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 high-speed face recognition systems.

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