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A Multimodal SVM Approach for Fused Biometric Recognition

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***Abstract*— With the advent of most modern electronic sophisticated applications automatic person identification has become a very important topic. Traditional based person identification techniques had several drawbacks since they are easy for spoofing and performing fraudulent operations. In this aspect we are developing a fused biometric person recognition using support vector machine in a multimodal approach for an efficient identification in several security aspects. A biometric trait is his/her unique behavioural and physiological trait which is used for identification aspects. Almost all systems use the application of unimodal biometric identification but they are vulnerable for spoofing. So a multimodal identification process has evolved which integrates information from multiple biometric sources. For the fusion we are using score level fusion approach and clustering using k means clustering. The classification is done by a multi svm machine which is an efficient classification.**

***Keywords*— Biometric, k-means clustering, multimodal biometric, score level fusion, support vector machine, multi svm .**

I. INTRODUCTION

Accurate personal identification is becoming more and more important to the operation of our increasingly electronically interconnected information society. Reliability in the personal authentication is key to the security in the networked society. Many physiological characteristics of humans *i.e.;* biometrics are typically time invariant, easy to acquire, and unique for every individual. Biometric features such as face, iris, fingerprint, hand geometry, palm print, signature, *etc*. have been suggested for the security in access control. Biometrics is a rapidly evolving technology that has been widely used in forensics, such as criminal identification and prison security, and has the potential to be widely adopted in a very broad range of civilian applications [2].

Unimodal biometric systems which use single trait for recognition are often affected by various practical for example, the deaf cannot provide sound information, the man who often engaged in manual work may not provide clear fingerprint texture. Hence each biometric cannot have a true sense of universality. Multibiometrics is a relatively new approach to biometric knowledge representation that strives to overcome the problems by consolidating the evidence presented by multiple biometric traits/sources [4]. Multimodal biometric system combines multiple biometric samples, or characteristics derived from samples, have been developed. A multimodal approach uses a fusion technology called score level fusion where information from various unimodal approaches is combined. Mainly fusion occur at three levels; fusion at the feature extraction level, fusion at the confidence level and fusion at the abstract level.

In the final result accuracy process we are using a classifier called multi support vector machine. A support vector machine (SVM) is a computer algorithm that learns by example to assign labels to objects. Support vector machines (SVMs) are primarily designed for 2-class classification problems. Here we are using the combination of combination of k SVMs can be used to solve a k-class classification problem , such a procedure requires some care.

II. PROPOSED METHOD

Multibiometrics is a relatively new approach to biometric knowledge representation that strives to overcome the problems by consolidating the evidence presented by multiple biometric traits/sources. Multibiometric systems can significantly improve the recognition performance in addition to improving population coverage, deterring spoof attacks, increasing the degrees of freedom, and reducing the failure-to-enrol rate. Although the storage requirements, processing time, and computational demands of a multibiometric system can be higher than that for a unimodal biometric system, the aforementioned advantages present a compelling case for deploying multibiometric systems in real-world large-scale authentication systems [1].

The key to successful multibiometric system is in an effective fusion scheme. The goal of fusion is to determine the best set of experts in a given problem domain and devise an appropriate function that can optimally combine the decisions rendered by the individual experts. So we employ an efficient fusion of two biometric traits; iris and fingerprint since they are the two unique biometric trait of any individual. Even though each of the traits is unique we are accepting the fusion of two because in order to overcome the fraudulent attack we need an efficient system. The pattern of fingerprint is unique but as the age progress it is difficult to trace the pattern since it is vulnerable for erasing some minutiae points and similar is the case of iris, the pattern of conical cells [5].

A. *Feature Extraction*

Fingerprints are graphical flow-like ridges present on human fingers. Their formations depend on the initial conditions of the embryonic mesoderm from which they develop. The unique features of fingerprint which separates each individual from others are the minutiae points and they comprises of ridge bifurcation points and ridge end points. So by extracting these minutiae points we can obtain the unique feature points.

Similar is the case for iris. The iris contains several conical cells which have a unique orientation and these orientations of cells differ for each individual. And the optical cells have branching similar as in the case of fingerprint images. So by a single feature extraction method we can extract the features of iris and fingerprint.

The feature extraction algorithm is described below which has following steps:

- Orientation estimation
- Ridge/optical cell detection
- Minutiae/optical cell extraction

1) Orientation Estimation

The orientation estimation algorithm initially divides the input image into blocks of size W X W, then the gradient values along x and y directions are obtained. After that we are estimating the local orientation at each pixel by specifying a window of size W and doing convolution. Next the consistency level of orientation field in local neighbourhood of block (i, j) is obtained and if consistency is above a threshold then local orientation is re estimated at a lower level until C (i, j) is below a certain level.

2) Ridge / conical cell Detection

An important property of the ridges in a fingerprint image is that the gray-level values on ridges/optical cell attain their local maxima along a direction normal to the local ridge/optical cell orientation. First the input image is convolved with two masks, then we get local maximum gray level value along a direction normal to local ridge direction / conical cell direction. If the gray level value of convolved image is greater than threshold then it is labelled as ridge/conical cell.

3) Minutiae /optical cell extraction

The extracted image is thinned and we get all the values as zeros or ones. Then we apply connectivity for pixels let (x,y) denote a pixel on thinned edge then N0,N1,...N7 denotes its 8 neighbours. A pixel (x, y) is a ridge ending if $\sum Ni = 1$ and ridge bifurcation if $\sum Ni > 2$.

In the similar way we obtain the conical pattern which is a unique trait using the very same algorithm.

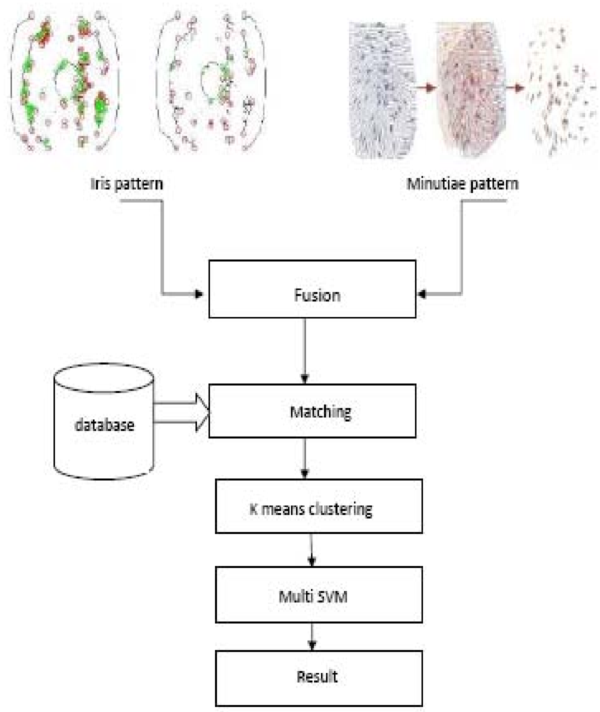

Fig. 1 Block Diagram

B. *Score level Fusion*

Score level fusion is the fusion in matching score level. For this reason, it is also called matching level fusion. Different matching scores got by different classifiers or from different biometrics can be fused to match at this level. Fusion at matching level can be approached in two distinct ways. One is viewed as a classification problem; the other is viewed as an information combination problem. In the classification approach, a feature vector is reconstructed using matching scores output by individual matchers. Then these feature vectors are classified into “Accept” or “Reject”[6]. In the information combination approach, individual matching scores are fused to generate a single scalar score that is used to make final decision.

A multimodal biometric system integrates information from multiple biometric sources to compensate for the limitations in performance of each individual biometric system. Matching score level fusion is commonly preferred because matching scores are easily available and contain sufficient information to distinguish between a genuine and an impostor case. Given a number of biometric systems, one can generate matching scores for a pre-specified number of users even without knowing the underlying feature extraction and matching algorithms of each biometric system. Thus, combining information contained in the matching scores seems both feasible and practical. Here we are considering the scores as similarity scores.

C. Classification

K-means clustering

A matching score fusion obtain a partial matching on the template database in order to select the most closely related traits we are using k means clustering. Thus k means clustering gives the most similar four or five traits which closely match with the input query. The main idea is to define k centroids, one for each cluster. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early groupage is done. At this point we need to re-calculate k new centroids as barycentre of the clusters resulting from the previous step [1]. After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop we may notice that the k centroids change their location step by step until no more changes are done. In other words centroids do not move any more. Finally, this algorithm aims at minimizing an *objective function*, in this case a squared error function. The objective function

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left| x_i^{(j)} - c_j \right|^2$$

where |xi - Cj|^2 is a chosen distance measure between a data point and the cluster centre Cj, is an indicator of the distance of the *n* data points from their respective cluster centre.

Support Vector Machine in Multi Approach

In essence, an SVM is a mathematical entity an algorithm (or recipe) for maximizing a particular mathematical function with respect to a given collection of data. To understand the essence of SVM classification, one needs only to grasp four basic concepts: (i) the separating hyperplane, (ii) the maximum-margin hyperplane, (iii) the soft margin and (iv) the kernel function. The concept of treating the objects to be classified as points in a high-dimensional space and finding a line that separates them is not unique to the SVM. The SVM, however, is different from other hyperplane-based classifiers by virtue of how the hyperplane is selected. With some thought, one may come up with the simple idea of selecting the line that is, roughly speaking, 'in the middle'. In other words, one would select the line that separates the two classes but adopts the maximal distance from any one of the given expression profiles.

We can create a non linear classifiers by applying the kernel tricks. In essence, the kernel function is a mathematical trick that allows the SVM to perform a 'two-dimensional' classification of a set of originally one-dimensional data. In general, a kernel function projects data from a low-dimensional space to a space of higher dimension. If one is lucky (or smart) and chooses a good kernel function, the data will become separable in the resulting higher dimensional space. A multi SVM uses a radial basis kernel function for efficient classification.

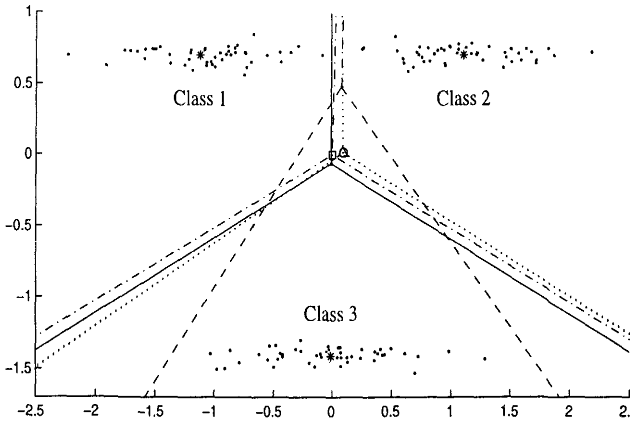

Fig 2 A 3-class example.

III. EXPERIMENTAL RESULTS

The new multimodal approach using fingerprint and iris based on score level fusion has been evaluated. Experimental results indicate that a multimodal biometric system, which combines multiple biometric data, can achieve significantly better performance compared to a single biometric system. Here by implementing a single feature extraction technique for two biometric modalities the classification time has reduced to some extend compared to other multimodal approaches and for the same using two different feature extraction techniques. The performance graph is shown below

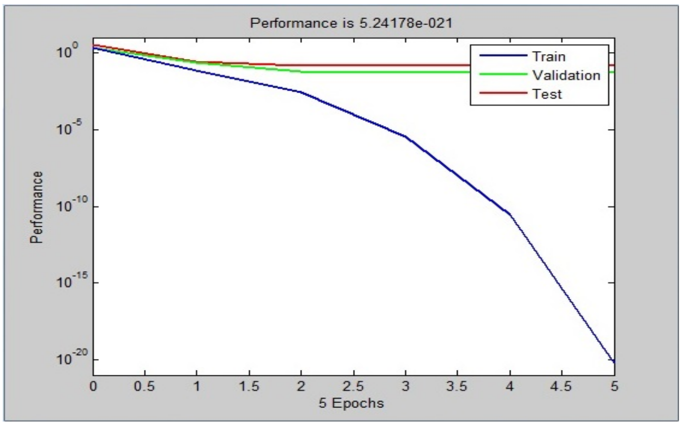

Fig. 3 Performance Evaluation Graph of Proposed System

In enrolment process enrol the fourty users with iris image and Fingerprint image of each person. After the processing of input images (feature extraction) in enrolment and create the template database. In identification process enter the iris and fingerprint image of person. After that processing and get the correct output that is enter person recognized correctly. Same way if it is enter the different iris and fingerprint images of different person from the database, get the output as Not Recognized. If it is taking the iris and fingerprint images which are not from the databases then it get the output as Unknown Person.

The classification technique which separates the feature values and classifies the accurate person features is shown below. For an accurate classification the similar feature values aligns close to the hyperplane.

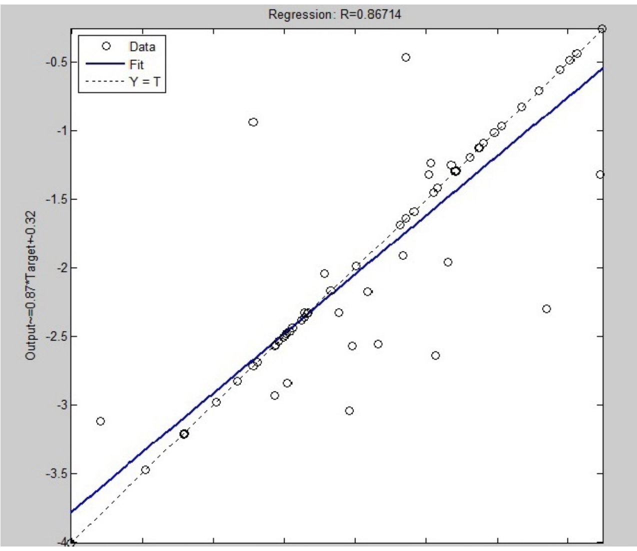

Fig.4 Regression Plot Showing Classification

IV. CONCLUSION

Biometric systems offer several advantages over traditional based methods. This work focuses on using the multimodal biometrics. A New framework for fingerprint and iris recognition using support vector machine based score level fusion. The individual scores of two traits, iris and fingerprint are combined at the matching score level to develop a multimodal biometric authentication system. K-mean clustering is used to search the database. Comparison of Support vector machine and Extreme learning machine will decrease the recognition time. The experiments are conducted to evaluate the performance of support vector machine and extreme learning machine. In future work the method try to employ PCA spaces separately modelling face texture, intrinsic geometry and expression information by fitting a generic mask and warping the texture for iris recognition. Based on a combination of texture and appropriately defined geometric attributes, superior recognition performance can be achieved.

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