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Multimodal Image Fusion Biometric System

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***Abstract*— In the real world applications, unimodal biometric systems often face limitations because of sensitivity to noise, intra class invariability, data quality, and other factors. Improving the performance of individual matchers in the aforementioned situation may not be effective. Multi biometric systems are used to overcome this problem by providing multiple pieces of evidence of the same identity. This system provides effective fusion scheme that combines information presented by the multiple domain experts based on the Rank level fusion integration method, thereby increasing the efficiency of the system which is not possible by the unimodal biometric system. The proposed multimodal biometric system has a number of unique qualities, starting from utilizing principal component analysis and fisher's linear discriminant methods for individual matchers authentication and the novel rank level fusion method is used in order to consolidate the results obtained from different biometric matchers. The ranks of the individual matchers are combined using highest rank, borda count, and logistic regression method. From the results it can be concluded that the overall performances of the multi biometric systems are very good even in the presence of poor quality of data.**

***Index-term*—Singular value decomposition (SVD), Pattern recognition, Multi biometric system, Rank level fusion, Principal Component Analysis (PCA).**

I. INTRODUCTION

In many real-world applications, Unimodal Biometric Systems often face significant limitations due to sensitivity to noise, intra class variability, data quality, non universality, and other factors. Attempting to improve the performance of individual matchers in such situations may not prove to be highly effective. So to overcome these problems, the Multimodal Biometric System is used, which is relatively a new approach that improves the recognition performance in addition to improving population coverage, deterring spoof attacks, increasing the degrees of freedom, and reducing the failure to enroll-rate. The key to successful Multi biometric system is in an effective fusion scheme, which is necessary to combine the information presented by multiple domain experts. Multimodal biometric system seeks to alleviate some of the problems by providing multiple pieces of evidence of the same identity. The developed multimodal biometric system possesses a number of unique qualities, starting from utilizing principal component analysis and Fisher's linear discriminant methods for individual matchers identity authentication and utilizing the novel rank-level fusion method in order to consolidate the results obtained from different biometric matchers. The ranks of individual matchers are combined using the highest rank, Borda count, and logistic regression approaches. The results indicate that fusion of individual modalities can improve the overall performance of the biometric system. Along with the Highest rank level method, the Borda count method and the Logistic regression method , the principal component analysis is also used. Face , iris and thumb impression are used and the analysis is performed. Hence for authentication purpose the efficiency of the Multimodal Biometric System is improved when compared to that of the existing system.

1.1 System Analysis

The analysis of the system starts from the enrollment stage in which the features are enrolled after Pre processing and they are projected on to the respective Eigen space and Fisher face, followed by the storage process in which they are stored in the system data base and their respective codes are obtained. Next is the identification stage, in which the image to be identified is pre processed similar to that of the enrollment stage. Then the feature matching process is done, in which the input image is compared with the database available and they are ranked accordingly with respect to the data available. Each feature is ranked separately. Followed by the ranking process, rank level fusion is done and the final output is obtained.

1.1.1 Existing system

In the existing system, three different features such as face, ear and signature are taken into account. Firstly, the features are extracted by integrating the acquired raw data, by using eigen image feature extraction based on the K-L transforms and the most important features from the face, ear and signature sub images are obtained. These features are obtained by projecting the original sub images into the corresponding sub spaces. By using this, the three image sub spaces are obtained for face, ear and signature. The system is first initialized with the set of training images. Eigen vectors and eigen values are computed on the covariance matrix of these images. After defining the eigen space, any test image is projected into the eigen space. An acceptance (the two images match) or rejection (the two images do not match) is determined by applying a threshold .Any comparison producing a distance below the threshold is a match .

The key to successful multibiometric system is in an effective fusion scheme, which is necessary to combine the information presented by multiple domain experts. 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 [4]. Pieces of evidence in a multibiometric system can be integrated in several different levels, but we can subdivide them in the following two main categories.

1) Prior to matching fusion.
2) After matching fusion

For fusion to achieve the claimed performance enhancement, fusion rules must be chosen based on the type of application, biometric traits, and level of fusion.

1.1.2 Biometric systems

A biometric identification (matching) system is an automatic pattern recognition system that helps in recognizing a person by determining his/her behavioral and/or physiological characteristics for the purpose of authentication. As a result, a decision made by a biometric system is either a genuine individual type of decision or an impostor type of decision. For each type of decision, there are two possible outcomes, namely, true or false. Therefore there are a total of four possible outcomes, a genuine individual is accepted, a genuine individual is rejected, an impostor is rejected, and an impostor is accepted. Outcomes 1 and 3 are correct, whereas outcomes 2 and 4 are incorrect. This is characterized by the genuine distributed and the impostor distribution, which are used to establish the following two error rate

1. **False Acceptance Rate** (FAR), which is defined as the probability of an imposter being accepted as a genuine individual. It is defined as the fraction of the impostor score exceeding the predefined threshold.
2. **False Rejection Rate** (FRR), which is defined as the probability of a genuine individual being rejected as an impostor. It is measured as the fraction of the genuine score below the predefined threshold.

FAR and FRR are dual of each other. A small FAR usually leads to a larger FRR and vice versa. There are also other reasons like data quality, non universality, intra class invariability, etc…which results in the reduced efficiency of these systems. Generally, the system performance requirement is specified in terms of FAR. A FAR of zero means that no impostor is accepted as a genuine individual. Sometimes, another term, genuine accept rate (GAR), is used to measure the accuracy of a biometric system. It is measured as the fraction of genuine score exceeding the predefined threshold. The equation(1) is used to find out the GAR of a system.

$$GAR = 1 - FRR \qquad (1)$$

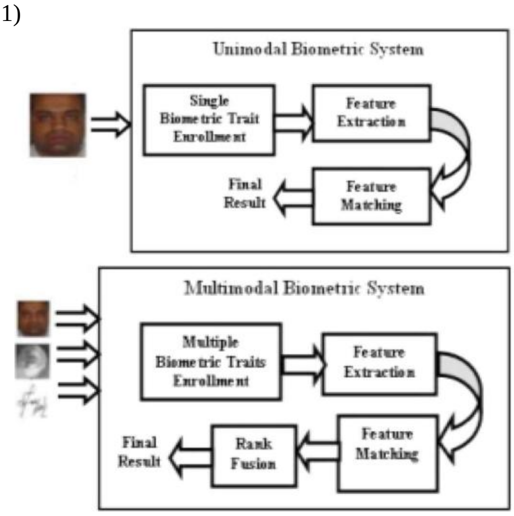

Figure.1. Block Diagram of Unimodal and Multimodal Biometric System.

The figure 1 shows the block diagram of unimodal and multimodal biometric system with different stages in the system.

The steps for the recognition process can be summarized as follows.

1. Project the test image into the eigen space, and measure the distance between the unknown image's position in the eigen space and all the known image's positions in the eigen space.
2. Select the image closest to the unknown image in the eigen space as the match.
3. In order to apply the rank-level fusion method, the output of matched images are ranked. For this, the image with the lowest distance as rank-1 image, the image with the second lowest distance as rank-2 image, and so on.

In the existing system, only the first ten ranked images are considered because images with ranks beyond 10 have little effect on the fusion result. This same technique is applied for ranking of face, ear, and signature. Then it is stored in the data base. This is the enrollment stage.

Secondly, it is the identification stage, in which the image that is to be tested is projected on to the eigen sub space and it is compared with the data base.

Followed by it, the fusion matching is done using rank level fusion method, which consists of three steps namely,

1) Highest Rank Level Method
2) Borda Count Method
3) Logistic Regression Method.

II. PRINCIPAL COMPONENT ANALYSIS (PCA)

Principal component analysis (PCA) is one of the statistical techniques frequently used in signal processing to the data dimension reduction or to the data de correlation. PCA takes the advantage of eigenvectors properties for determination of selected object orientation. Principal component analysis (Karhunen-Loeve or Hotelling transform) - PCA belongs to linear transforms based on the statistical techniques. This method provides a powerful tool for data analysis and pattern recognition which is often used in signal and image processing as a technique for data compression, data dimension reduction or their de correlation as well.PCA is a statistical method which involves analysis of *n*-dimensional data.The basis dimensions or vectors computed by PCA are in the direction of the largest variance of the training vectors. These basis vectors are computed by solution of an "eigen" problem, and as such, the basis vectors are eigenvectors. These eigenvectors are defined in the image space. They can be viewed as images. Hence, they are usually referred to as eigen images. Eigen image recognition derives its name from the German prefix eigen, meaning own or individual.In Averaging Method,the first eigen image is the average image, while the rest of the eigen images represent variations from this average image. Each eigen image can be viewed as a feature. When a particular image is projected onto the image space, its vector (made up of its weight values with respect to each eigen image) into the image space describes the importance of each of those features in the image. In Representation the context of personal identification, the background, transformations, and illumination can be controlled, and the eigen image approach has a compact representation of an image of a face, ear, or signature can be concisely represented by a feature vector with a few elements. Also, it is feasible to index an eigen image-based template database using different indexing techniques such that retrieval can be conducted efficiently. Moreover, the eigen image approach is a generalized template-matching approach which was demonstrated to be more accurate than the attribute-based approach. The eigen image technique has some limitations too. This method is very sensitive to image conditions such as background noise, image shift, occlusion of objects, scaling of the image, and illumination change. When substantial changes in illumination and expression are present in the face image, much of the variation in the data is due to these changes. The eigen image technique, in this case, cannot give the highly reliable results.

2.1. Problem Solving Technique

For the aforementioned reasons, we also use the Fisher face Approach in order to achieve higher recognition rate. Due to certain illumination changes in the images of the face database used in this work, a fisher face-based face recognition method is developed to compare it with the eigen face technique. The fisher face method uses both PCA and LDA to produce a subspace projection matrix, similar to that used in the eigen face method. However, the fisher face method is able to take advantage of within-class information, minimizing variation within each class, yet still maximizing class separation .

2.2 Recognition Using Fisher face

Eigen space representation is very sensitive to image conditions such as background noise, image shift, occlusion of objects, scaling of the image, and illumination change. When substantial changes in illumination and expression are present in any image, much of the variation in data is due to these changes, and the eigen image technique, in this case, cannot give highly reliable results. Due to certain illumination changes in the face images of the database used in this work, a Fisher face based face recognition method is developed to compare with the eigen face technique. The fisher face method uses both PCA and LDA to produce a sub space projection matrix, similar to that used in the eigen face method.

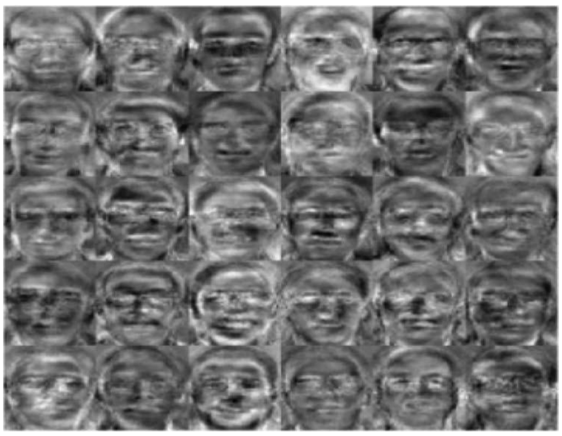

Figure.2 Fisher faces generated from the Training sets

III. RANK LEVEL FUSION APPROACH

Large multimodal biometric systems with various methods and strategies have been proposed over the last decade to achieve higher accuracy performance. In this context, it is also observed that, although the PCA-based multimodal biometric system has been developed by some researchers, the application of PCA for face, ear, and signature in the context of multimodal system has not been investigated. Also, according to literature review on this topic, practically, no research has concentrated on investigating the FLD method's performance in multibiometric systems. Moreover, fusion for the multibiometric system is a relatively new area, and fusion at the rank level is understudied problem. Thus, aiming at the same issue, i.e., to reduce FARs and FRRs, we fill the niche and develop a multibiometric system incorporating three unimodal experts for face, ear, and signature. The system is based on PCA and FLD methods and the rank-level fusion approach to obtain the consensus rank of individuals by consolidating the ranking outputs produced by three unimodal experts. To the best of our knowledge, this is the first time that the rank-level fusion approach is combined with PCA and FLD methods to produce higher and more reliable. Rank-level fusion is a relatively new fusion approach and is not a well-studied research problem. When the output of each biometric matcher is a subset of possible matches sorted in decreasing order of confidence, fusion can be done at the rank level. The goal of rank-level fusion is to consolidate the rank output by individual biometric subsystems (matchers) in order to derive a consensus rank for each identity using three methods to combine the ranks assigned by different matchers. They are the Highest Rank Method, the Borda Count Method and the logistic regression method. Figure 3 shows the Block Diagram of Multi biometric System.

In the highest rank method, each possible match is assigned the highest (minimum) rank, as computed by different matchers. Ties are broken randomly to arrive at a strict ranking order, and the final decision is made based on the combined ranks.The Borda count method uses the sum of the ranks assigned by individual matchers to calculate the final rank. This method assumes that the ranks assigned to the users by the matchers are statistically independent and that the performances of all the modules are equally well.Logistic Regression Method on the other hand, in the logistic regression method, a weighted sum of the individual ranks is calculated. The weight to be assigned to different matchers is determined by logistic regression .This method is very efficient when different matching modules have significant differences in their accuracies but requires a training phase to determine the weights.However, these methods have one drawback.

In multibiometric systems, it is most likely that there will be four or five different identities that will come out from two or three matching modules which are designed to show the first three identities.That means that some identities can appear in the result of only one matcher. In this case, there will be a possibility of wrong results after rank-level fusion. To deal with this problem, we have modified these methods of rank-level fusion. We propose to use all three matchers (face, iris, and thumb impression) and have considered only those identities which appear in the results of at least two matchers. The identities which appear in the result of only one matcher have been discarded or not considered for the final rank in this system.

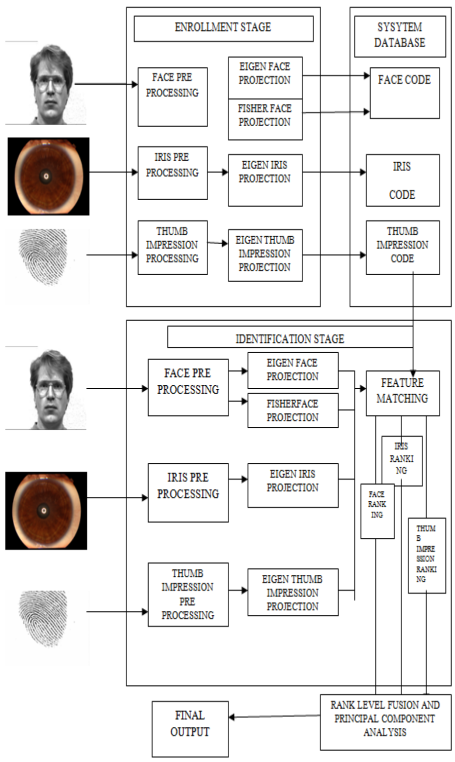

Figure .3. **Block Diagram of Multi biometric System**

In order to apply the rank-level fusion method, we need the output of matched images which are ranked. For this, we define the image with the lowest distance as rank-1 image, the image with the second lowest distance as rank-2 image, and so on. In the proposed system, we consider only the first ten ranked images because images with ranks beyond 10 have little effect on the fusion result. This same technique is applied for ranking of face, iris, and thumb impression.

The capacity of a biometric system (how many persons can be enrolled in a system at a time) is an important issue for biometric system design. As we consider only the top ten matched images for fusion (ten images whose matching distances are the lowest), the system faces no problem to work for a large database. No matter what the number of images considered into the training set, the system will output only the first ten ranked images from those training images. Only the training and recognition times will be larger in the case.

3.1 . Test Data Base for Face

Different persons are considered. Each persons different face expressions (smile, ironical, anger, etc) under different conditions (eg: in the absence and presence of light) are obtained.

Figure .4 Virtual Multimodal Databases for Face

3.2. Test Database for Iris

Different person’s IRIS is considered. Each person’s IRIS is obtained under different conditions similar to that of Face.

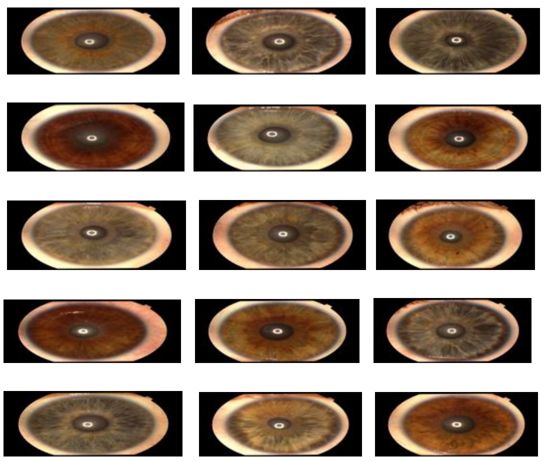

Figure .5 Sample of the virtual multimodal database for Iris

3.3 . Test Data Base for Thumb Impression

Different person’s thumb impressions are considered. Each person’s thumb impression under different conditions is obtained similar to that of Face and Iris.

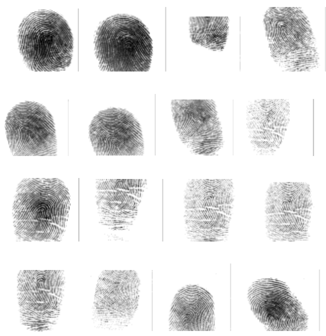

Figure.6 Sample of the virtual multimodal database for Thumb Impression

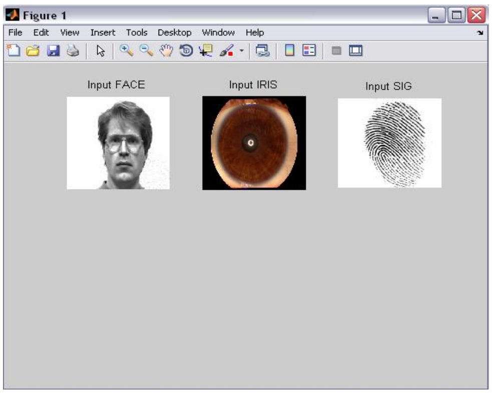

Figure 7: Input image to be recognized

Fig 7 is the input image or the query image that is to be tested. This image is otherwise called the image from the test database, to which no preprocessing is done. The domain of multibiometrics is a new and exciting area of information science research directed toward understanding of traits and methods for accurate and reliable personal information representation for subsequent decision making and matching. Recent years have seen a significant increase in research activity directed at understanding all aspects of biometric information system representation and utilization for decision-making support, for use by public and security services, and for understanding the complex processes behind biometric matching and recognition. This paper is specifically focused on understanding the complex mechanisms employed to find a good combination of multiple biometric traits and various fusion methods to get the optimal identification results.

Test data bases are obtained and they are stored in the system data base. In future the Eigen image of the Training database is formed followed by the normalized training set. Finally the mean image is produced. The query image uses only this mean image to compare and find out the result whether it is recognized or not.

REFERENCES

[1]. Md.Maruf Monwar ,and Marina L. Gavrilova, “Multimodal biometric system using Rank Level Fusion approach” IEEE Transactions On System, Man and Cybernetics – Part B: Cybernetics, Vol.39,No.4,August 2009.

[2]. Y. Wang, “The theoretical framework of cognitive informatics,” *Int. J. Cognit. Informat. Nat. Intell.*, vol. 1, no. 1, pp. 10–22, 2007.

[3]. U. M. Bubeck and D. Sanchez, “Biometric authentication: Technology and evaluation,” San Diego State Univ., San Diego, CA, 2003. Tech. Rep.

[4]. M. P. Down and R. J. Sands, “Biometrics: An overview of the technology, challenges and control considerations,” *Inf. Syst. Control J.*, vol. 4, pp. 53– 56, 2004.

[5]. A.Ross, K. Nandakumar, and A. K. Jain, *Handbook of Multibiometrics*. New York: Springer-Verlag, 2006.

[6]. K. Chang, K. W. Bower, S. Sarkar, and B. Victor, “Comparison and combination of ear and face images in appearance-based biometrics,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 9, pp. 1160–1165, Sep. 2003.

[7]. G. L. Marcialis and F. Roli, “Fingerprint verification by fusion of optical and capacitive sensors,” *Pattern Recogn. Lett.*, vol. 25, no. 11, pp. 1315– 1322, Aug. 2004.

[8]. A. Ross and A. K. Jain, “Information fusion in biometrics,” *Pattern Recogn. Lett.*, vol. 24, no. 13, pp. 2115–2125, Sep. 2003.

[9]. T. Kinnunen, V. Hautamäki, and P. Fränti, “Fusion of spectral feature sets for accurate speaker identification,” in *Proc. 9th Conf. Speech Comput.*, St. Petersburg, Russia, 2004, pp. 361–365.

[10]. J. Bhatnagar, A. Kumar, and N. Saggar, “A novel approach to improve biometric recognition using rank level fusion,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recog.*, Minneapolis, MN, 2007, pp. 1–6.

[11]. L. Hong and A. K. Jain, “Integrating faces and fingerprints for personal identification,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 20, no. 12, pp. 1295–1307, Dec. 1998.

[12]. R. Frischholz and U. Dieckmann, “BiolD: A multimodal biometric identification system,” *Computer*, vol. 33, no. 2, pp. 64–68, Feb. 2000.

[13]. J. Fierrez-Aguilar, J. Ortega-Garcia, D. Garcia-Romero, and J. Gonzalez- Rodriguez, “A comparative evaluation of fusion strategies for multimodal biometric verification,” in *Proc. 4th Int. Conf. Audio- Video-Based Biometric Person Authentication*, J. Kittler and M. Nixon, Eds., 2003, vol. LNCS 2688, pp. 830–837.

[14]. T. Wang, T. Tan, and A. K. Jain, “Combining face and iris biometrics for identity verification,” in *Proc. 4th Int. Conf. Audio-Video-Based Biometric Person Authentication*, J. Kittler and M. Nixon, Eds., 2003, vol. LNCS 2688, pp. 805–813.

[15]. K. A. Toh, X. D. Jiang, and W. Y. Yau, “Exploiting global and local decisions for multi-modal biometrics verification,” *IEEE Trans. Signal Process.*, vol. 52, no. 10, pp. 3059–3072, Oct. 2004.

[16]. R. Snelick, U. Uludag, A. Mink, M. Indovina, and A. K. Jain, “Large scale evaluation of multimodal biometric authentication using state-of the-art systems,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 27, no. 3, pp. 450– 455, Mar. 2005.

[17]. M. V. Erp and L. Schomaker, “Variants of the Borda Count method for combining ranked classifier hypotheses,” in *Proc. 7th Int. Workshop Frontiers Handwriting Recog.*, Amsterdam, The Netherlands, 2000, pp. 443–452.

[18]. G. L. Marcialis and F. Roli, “Fusion of appearance-based face recognition algorithms,” *Pattern Anal. Appl.*, vol. 7, no. 2, pp. 151–163, Jul. 2004.

[19]. M. Turk and A. Pentland, “Eigenfaces for recognition,” *J. Cogn. Neurosci.*, vol. 3, no. 1, pp. 71–86, 1991.

[20]. M. M. Rahman and S. Ishikawa, “A robust recognition method for partially occluded/destroyed objects,” in *Proc. 6th Asian Conf. Comput. Vis.*, Jeju, Korea, 2004, pp. 984–988.