Feature Level Fusion using Multiple Fingerprints

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ABSTRACT
The biometric authentication is an efficient alternative for conventional authentication techniques. Researches in this field show that multi-model biometric systems perform better than single mode. The basic idea of multi-model biometrics is the integration (fusion) of the various biometric mode data. Information from multiple sources can be integrated at three distinct levels: (i) feature extraction level; (ii) match score level; and (iii) decision level. Fusions at the match score and decision levels have been studied extensively by researchers where as fusion at the feature level is a relatively understudied problem. In this paper, we present a reinvigorated technique of feature-based fusion in a special kind of multimodal system where multiple fingerprints are used. The results from the analysis of previous works indicate that the proposed technique can lead to substantial improvement in multimodal matching performance

General Terms
Biometric Security.

Keywords
Correlation; Feature level fusion; Multi-model biometric system; Multiple fingerprints.

1. INTRODUCTION
Effective security cannot be achieved just with the help of technology. Technology and people must work hand in hand as part of an overall security process. Biometrics- usage of human traits for security is considered as the most relevant security measure as it is universal, distinct, and permanent. Still there are some weakness in this area which diminishes the effectiveness of the security process. For example, some people cannot enroll in a biometrics system due to their physical retardations. Similarly, errors sometimes occur during matching process due to bugs. Studies have proved that the poor quality of biometric samples leads to a significant reduction in the accuracy of a unimodal biometric system. Due to these issues, multi modal biometric systems were developed. These systems combine the evidence presented by multiple biometric sources. Such systems are more robust to variations in the sample quality than unimodal systems due to presence of multiple pieces of evidence [2].

The multi modal biometric can be of two types:

a. Those that make use of multiple instance of the same biometric trait - eg: multiple fingers of the same person.

b. Those that make use of different biometric traits eg: facial plus hand geometry [1].

All biometric models include four basic steps:

i. Data Acquisition Module: Collecting data from users

ii. Feature Extraction Module: In this module input data get processed to extract key feature, which would be the input for matching.

iii. Matching Module: Here key features of two inputs get compared to check if they are same or not. Based on matching algorithms match score get calculated.

iv. Decision Module: At the end, based on some thresholds value, the decision is made if to accept or not.

In order to take full advantage of the multimodal approach, it is essential to implement a good method for fusing different sources of biometric information. The fusion can be done at three different levels, which are (i) feature extraction level; (ii) match score level; and (iii) decision level. Several schemes have been proposed to exploit the signal quality in fusing at the match score level and decision level. We have chosen the feature level since the feature set contain much richer information about the raw biometric data than the matching score or decision level. We also expected to get a better recognition result from this technique as this gives us a better performance/processing time. But the fusion at this level is difficult because of the following reasons (i) the feature sets of multiple modalities may be incompatible (e.g., minutiae set of fingerprints and eigen-coefficients of face); (ii) the relationship between the feature spaces of different biometric systems may not be known; and (iii) concatenating two feature vectors may result in a feature vector with very large dimensionality leading to the `curse of dimensionality problem [1]. To overcome these incompatibility problems, we have chosen multiple instance of the same trait.

The paper is organised as follows. Introduction section is followed by previous work. In the next sections we have a brief description about feature level fusion and what motivated us for this project. Next to that, we have included our design, in which we have explained about the algorithms used and how we were able to reach at our goal and finally we have concluded with the limitations of our work and chances for the future work.

2. PREVIOUS WORK
In [1] a feature level fusion using hand and face biometrics is proposed. This is a multimodal biometric system using two different traits of biometric, face and hand. They did the fusion at the feature level which included the normalization of the feature to make them compatible. After normalization, the two feature vectors were augmented. Subsequently the feature selection is performed. The criterion function to perform feature selection is defined to be the average of the Genuine Accept Rate (GAR) at four different False Accept Rate (FAR) values (0:05%, 0:1%, 1%, 10%) in the ROC (Receiver Operating Characteristics) curve pertaining to the training data [1]. The simple min-max and the median normalization techniques were used in their work. Their main aim was to highlight the importance of feature level

matching and prove that it will provide a better performance than the other two matching schemes. Through their experimentations they were able to bring forth the pros and cons of using feature level fusion. They conducted the experiment on dataset consisting of hand and face information pertaining to 50 users with each user providing 5 samples of each biometric from West Virginia University. The matching score under feature level and matching score was calculated and performance evaluation was done under 3 different scenarios (i) fusion of PCA and LDA coefficients of face; (ii) fusion of LDA coefficients corresponding to the R,G,B channels of a face image; and (iii) fusion of face and hand modalities.

In the first fusion technique in [1], the application of match level fusion is observed to degrade matching performance. But combining the feature level and match score level information neither degraded nor improved the matching performance. Therefore the significance of the proposed scheme is not borne out in this scenario. In the second method in [1], it is observed that the proposed scheme outperformed match score level fusion by a substantial margin thereby underscoring the significance of the proposed technique. The fusion of hand and face geometry also proved that the performance of the proposed fusion scheme was observed to be superior to that of match score level fusion. So to conclude, from their work, the performance of this fusion scheme was observed to be superior to that of match score level fusion.

The second paper of our reference is by Pooja, an IIT Kanpur student who did a project on multiple fingerprints [7]. Her project was on a multi-biometric system, which accepted multiple fingerprints of the same person as the input. In her project she did the fusion at the matching score level. The steps involved were getting finger print instance, image enhancement, feature extraction, finding matching score, fusion at matching score level and then decision making. For feature extraction, she considered Zernike moments around Harris corner points as key features. Here, there is no need of any normalization as she has accepted multiple instance of the same trait. In the Matching Process, the very first step is pairing of two images for getting distance between Zernike Moments of those two images. The fingers were randomly requested to increase the security. After distance calculation, two matching corner points are counted to see if they correctly matched or not. This threshold is defined as Distance-Threshold. If distance between matched corner points is less than threshold then those corner points will be counted as correctly matched. For Matching Score calculation, number of correctly matched corner points for two images are considered. Total number of correctly matched points for a pair of images is taken as matching score for that pair. In decision making there will be one more threshold for combined matching score for two fingers. If matching score is more than the threshold that pair will be chosen as matched pair and authentication was granted. She proved that there is an improvement in the security if the fingers are randomly requested. Still the result was not very good but better than the single fingers.

Our idea is to club these two papers and propose a new system on multiple fingerprints where the fusion is done at the feature level. The feature selection scheme ensures that the redundant feature values are detected and removed before invoking the matcher. This is probably one of the key benefits of performing fusion at the feature level.

3. FEATURE LEVEL FUSION

Fusion at the feature level is least explored even though they are expected to provide better recognition results and much easier to compute. The matching score level and decision level supplies less information to be exploited for personnel authentication than the feature extraction level. This is the driving force for the proposed scheme. Generally, multimodal biometric systems use different biometric, so we thought to try on multiple entries on the same biometrics. We have chosen fingerprint as the biometric trait because it is the easily and widely available sample. A feature level fusion scheme to improve multimodal matching performance has been proposed by comparing it with matching score decision making. The primary motivation of our scheme is to demonstrate the viability of such fusion and to underscoring the importance of pursuing further research in this stream.

In this paper, we are trying to prove that the system that uses the feature level fusion will offer less response time than that using matching score level, if we are using multiple instance of the same trait in our multimodal system. We provide a set of fingerprint, from which two fingerprints are randomly chosen. Randomly chosen fingerprints increase the level of security. Both the feature level decision making and matching score decision making is done and their performance is evaluated on the basis of their processing time.

We have adopted already existing algorithm for thinning of our processed sample fingerprints, like Hilditch's Algorithm [9] and Hit and Miss Algorithm [10]. The features of thinned image could be matched using an algorithm called cross correlation. No innovation is done on any of the image processing algorithm. Our aim was to prove that the feature level has better performance than matching score on the basis of their processing time. We were able to prove this just with the help of 9 samples of fingerprints.

4. DESIGN OVERVIEW

The inputs to our project are processed images. Many false minutiae can be eliminated after processing and can improve the ridge separation and continuity throughout the fingerprint image. These images will undergo thinning process twice, once using Hilditch's Algorithm and second time using Hit and Miss Algorithm, which is depicted in the Fig1 and Fig 2(Image Enhancement). The next step is feature extraction. The problem of fingerprint matching has been extensively studied and numerous algorithms have been proposed. These algorithms can be classified as correlation based, minutiae-based, and ridge feature-based approaches. Minutiae-based methods represent minutia points as a feature vector of fixed length. Minutiae based matching methods consider special points of fingerprint impressions representing ends and bifurcation points of the fingerprint ridge structure. Although the minutiae pattern of each finger is quite unique, noise and distortion during the acquisition of the fingerprint and errors in the minutia extraction process result in a number of missing and spurious minutiae. It is difficult to reliably obtain the minutiae points from a poor quality fingerprint image.

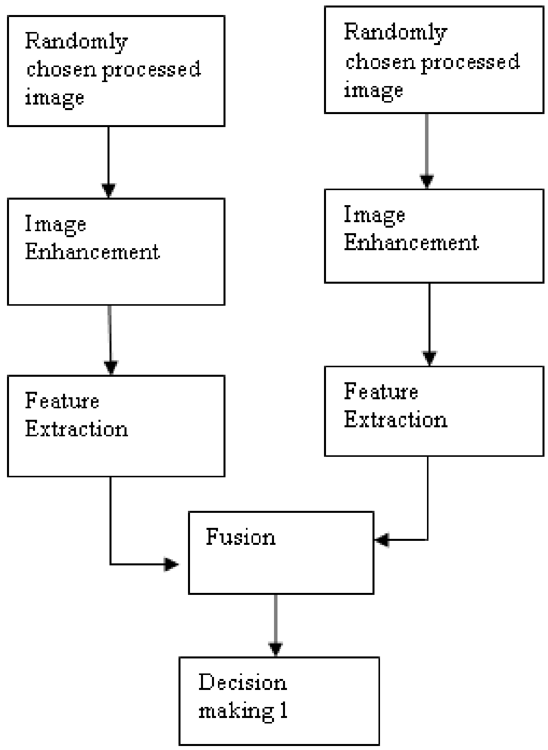

Figure 1. Fusion at Feature Extraction Level

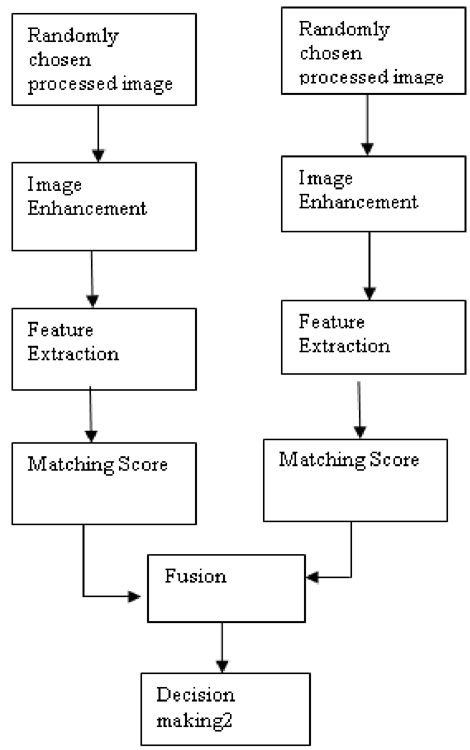

Figure 2. Fusion at Matching Score Level

However, the ridge feature-based methods suffer from their low discrimination capability. In correlation-based fingerprint matching, the template and query fingerprint images are spatially correlated to estimate the degree of similarity between them [3]. Although minutia based algorithms usually provide the best performance, they have problems matching partial or low quality fingerprint images when only a few minutiae are successfully extracted. Texture and correlation based matching methods have advantages dealing with such images as they utilize low level features not accounted for by minutia templates. So in our project we are using the correlation based feature extraction [4]. For this multimodal biometric system, fusion is introduced at the feature level and matching score level. After fusion comes the decision making step. All the above mentioned steps are well represented using the two figures Fig.1 and Fig.2.

4.1 Algorithm

Let Fi = {fi:1; fi:2, …..fi:n} and Fk = {fk:1; fk:2;…..fk:n} represent the feature vector of the finger (geometric features [5]) modalities of a user, respectively. The fused feature vector Xi = {xi;1; xi;2… xi;d} can be obtained by augmenting the feature vectors Fi and Fk, and performing feature selection on the concatenated vector. Consider feature vectors Fi and Fj obtained at two different time instances i and j. The corresponding fused matching feature vectors may be denoted as Xi and Xj, respectively. Let Si and Sj be the normalized match (distance) scores generated by comparing Fi with Fj, respectively and let $S_{fus} = S_i + S_j$ be the fused match score obtained using the simple sum rule.

4.2 Image Enhancement: Thinning Algorithm

The inputted processed image produced thick lines which in turn makes the recognition process complicated [6]. To overcome this problem, edge lines must be skeletonised, using the following edge lines thinning process; Thinning was done using Hilditch's Algorithm and Hit and Miss Algorithm. Hilditch's algorithm is a parallel-sequential algorithm. It is parallel because at one pass all pixels are checked at the same time and decisions are made whether to remove each of the checked pixels. It is sequential because this step just mentioned is repeated several times.

Hilditch's algorithm turned out to be not the perfect algorithm for skeletonization because it does not work on all patterns. In fact, there are patterns that are completely erased by the algorithm. To overcome this problem of Hiiditch, we use it in combination with Hit and Miss algorithm. Hit and Miss is an iterative process containing repeated steps to thin the shape by hit-and-miss method. For every iteration, some different structuring elements are used to identify the edge pixels to be removed, followed by the actual removal of them.

A 3x3 window is moved down throughout the image and calculations are carried out on each pixel to decide whether it needs to stay in the image or not [8]. We convert Gray tone image of fingerprints into binary edge versions in order to simplify the extraction of the features for recognition purposes and making the interpretation more reliable. This processes effectively thins the image, however, it sometimes creates undesirably artifacts. In the example of a Hilditch's thinned fingerprint, there are gaps between edges as well as regions of small area that need to be removed for proper regional analysis.

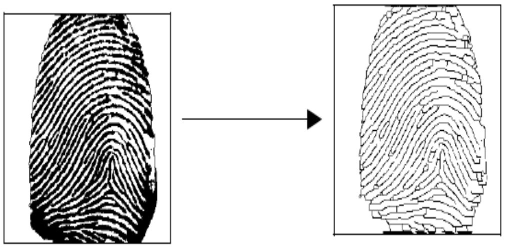

Figure 3. Hilditch's thinned fingerprint

4.3 For Fingerprint Matching: Cross Correlation

In this paper, we use normalized cross-correlation technique for fingerprint matching to minimize error rate and to reduce the computational effort .The EER (equal error rate) with minutiae matching method is 3%, while that obtained for the method proposed in this paper is approx 2% for all types of fingerprints in combined form. Two fingerprint images are superimposed and the correlation between corresponding pixels is computed for different alignments (alignments are changed by displacements and rotations).

The use of cross-correlation for template matching is motivated by the distance measure (squared Euclidean distance)

$$d^2{}_{f,t}(u,v)=\sum_{x,y}\left[f(x,y)-t(x-u,y-v)\right]^2 \text{...(1)}$$

(where, f is the image and the sum is over x, y under the window containing the feature t positioned at u, v). In the expansion of d2

$$d^2{}_{f,t}(u,v)=\sum_{x,y}\begin{bmatrix}f^2(x,y)-2F(x,y)t(x-u,y-v)+\\ t^2(x-u,y-v)\end{bmatrix}\text{....(2)}$$

the term $\sum t^2(x-u,y-v)$ is constant. If the term $\sum f^2(x,y)$ is approximately constant then the remaining cross-correlation term

$$c(u,v)=\sum_{x,y} f(x,y)t(x-u,y-v) \text{.......(3)}$$

is a measure of the similarity between the image and the feature.

4.4 Decision Making

After the fusion is done at the correlation level, the authenticity of the user is assured by checking if the fused value is more than or equal to a threshold value. The threshold value we have selected is 55. If the score value is more than 55, then they are accepted as authenticated users, in both the case. The fusion is done both at the matching score level (decision making2 from Fig.2) and at feature level (decision making1 from Fig.1), the processing time is generated in each case and which method of decision making is faster is determined. The fingers are randomly chosen to improve the performance.

5. EXPERIMENTAL SETUP AND RESULT

Our database contains 9 processed fingerprints as inputs. We collected these finger prints from internet [http://www.nist.gov] and it is of the resolution 323*352. Any of these finger prints can be randomly chosen and the output could be obtained. Our goal is to prove that the feature level fusion would be much more efficient than matching score in terms of processing time.

Table 1. Set A and Set B Contains the Same Set of Fingerprint Sample Images

Set A	Set B	Feature Level Score	Time in Milliseconds	Matching Score	Time in Milliseconds
S1.jpg S2.jpg	S1.jpg S2.jpg	99	46	99	62
S2.jpg S3.jpg	S2.jpg S3.jpg	99	31	99	63
S3.jpg S4.jpg	S3.jpg S4.jpg	99	16	99	63
S4.jpg S5.jpg	S4.jpg S5.jpg	99	32	99	62
S5.jpg S6.jpg	S5.jpg S6.jpg	99	15	99	46

Our aim is to prove that feature level fusion would be much more effective in terms of availability of raw materials and in terms of performance if we use multiple traits of the same biometric in the multimodal biometric system. We are also successful in proving the same. The processing time would be lesser because there is no need of any normalization for the features that got extracted because they are compatible with each other. Our proposed system is efficient by more than 30%.

We have plotted 3 graphs (Fig 4, 5 & 6) on basis of experimental results. The graph clearly shows that whatever be the situation, the performance of feature level is always better than the matching score. In all the three tables the processing time for feature level is lesser than that of the matching score. We have considered three various situations over here, table 1 shows the condition in which we have inputted 2 finger print sample images and those are matched with the same finger prints giving around 99 as the match score in both the cases. Table 2 depicts a condition in which the input finger print sample images are compared with totally different set of fingerprints. In table 3 also two sample finger print images are inputted and matched with two other finger prints in which one is same as the inputted image .The table 2 and 3 gave a score value less than our threshold value and they are concluded as not matching. However, whatever be the condition, the feature level time is lesser than the matching score time taken.

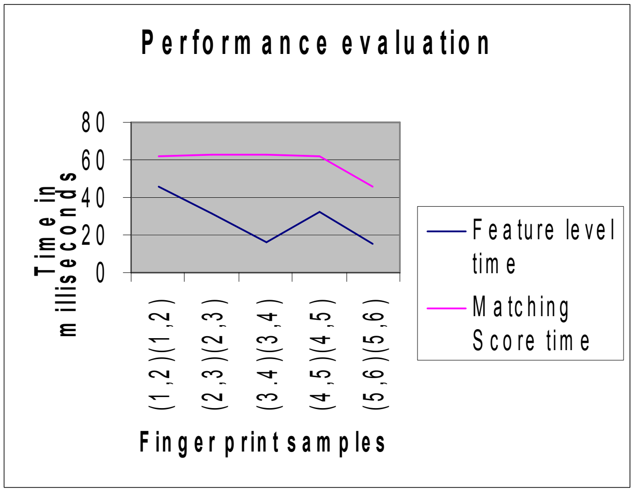

Figure 4. Graph corresponding to Table 1

Table 2. Set A and Set B Contains Different Set of Fingerprint Sample Images

Set A	Set B	Feature Level Score	Time in Millisecond	Matching Score	Time in Millisecond
S1.jpg S2.jpg	S3.jpg S4.jpg	40	31	26	78
S3.jpg S4.jpg	S5.jpg S6.jpg	24	47	17	62
S5.jpg S6.jpg	S7.jpg S8.jpg	7	31	35	46

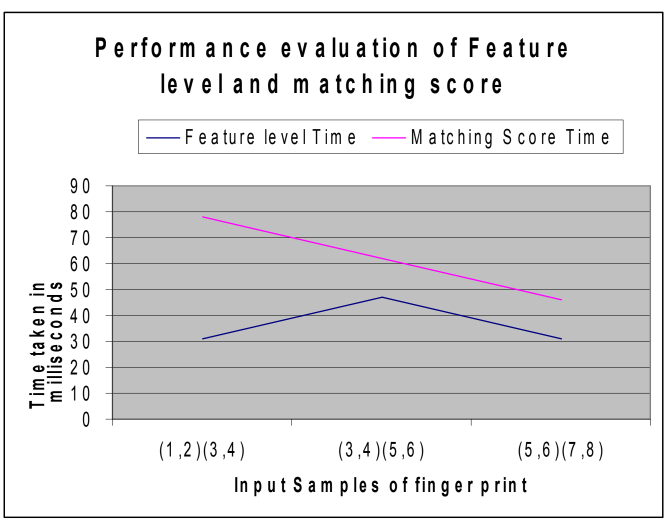

Fig.5. Graph corresponding to Table 2

Table 3. Set A and Set B Contains One of the Fingerprints Sample Images Same

Set A	Set B	Feature Level Score	Time in Millisecond	Matching Score	Time in Millisecond
S1.jpg S2.jpg	S2.jpg S3.jpg	24	31	33	78
S3.jpg S4.jpg	S4.jpg S5.jpg	16	31	13	78
S5.jpg S6.jpg	S6.jpg S7.jpg	11	31	35	48

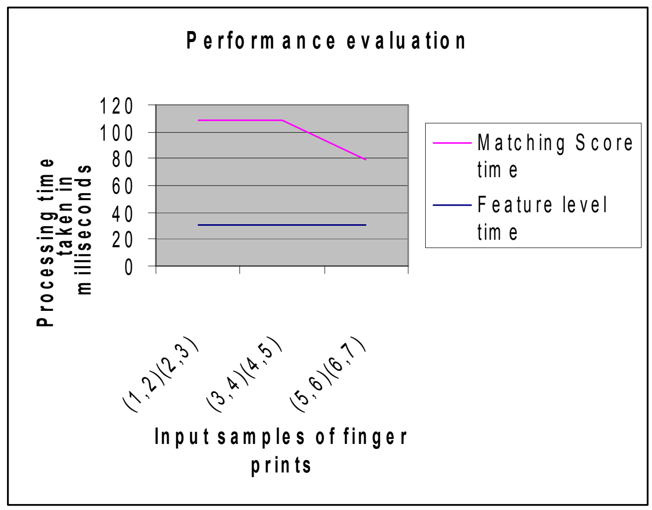

Fig.6. Graph corresponding to Table 3

6. LIMITATIONS

For the time being we have developed our system with a database of 9 fingerprints. Our database is a small one, but still with this limited amount of dataset, we could meet our goal. All the fingerprint orientations are the same. If they are a little misplaced, our system would not generate accurate results. We could only accept input of resolution 323*352. As we are using Cross correlation technique, it may sometimes cause problems in matching like:

- Non linear distortions.
- Variation in skin condition and finger pressure caused differences in brightness, contrast, ridge thickness across different fingerprints.
- Technique computationally expensive.

Algorithm presented by this system, does not allow incompatible feature set (such as minutiae points of fingerprints and Eigen-coefficients of face) to be combined.

7. CONCLUSION AND FUTURE WORK

A feature level fusion scheme to improve multimodal matching performance has been proposed. The scheme has been tested on relatively weak biometric systems, hand and face [1]. The performance gain observed has been substantial thereby indicating the importance of pursuing research in this direction. Future work will include studying the effect of noisy data on the performance of the technique and the adoption of other biometric traits in this work. The feature selection scheme ensures that redundant/correlate feature values are detected and removed before invoking the matcher. This is probably one of the key benefits of performing fusion at feature level. Therefore, it is important that biometric vendors grant access to feature level information to permit development of effective fusion strategies.

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