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Fingerprint – Iris Fusion based Identification System using a Single Hamming Distance Matcher

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Abstract

Conventional multimodal biometric identification systems tend to have larger memory footprint, slower processing speeds and a higher implementation and operational cost. In this paper we propose a state of the art framework for multimodal biometric identification system which can be adapted for any type of biometrics to provide smaller memory footprint and faster implementation than the conventional multimodal biometrics systems. The proposed framework is verified by development of a fingerprint and iris based fusion system which utilizes a single Hamming Distance matcher. Extensive testing is performed on the system running in identification mode and the results show that the system not only provides higher accuracy than the individual unimodal system but also the results are comparable to the conventional system.

1. Introduction

The effectiveness of a biometric authentication system can be gauged by not only the accuracy of the system but also the error rates. The most critical error rates are considered to be the False Accept Rate (FAR) and the False Reject Rate (FRR). False Accept Rate identifies the number of times an imposter is classified as a genuine user by the system and False Reject Rate pertains to misidentification of a genuine user as an imposter. Although ideally both FAR and FRR should be as close to zero as possible in real systems, however, this is not the case.

For biometric applications that demand robustness and accuracy higher than that provided by any single biometric trait, multimodal biometric approaches often provide promising results. Multimodal Biometric Authentication or Multimodal Biometrics is the approach of using multiple biometric traits from a single user in an effort to improve the results of the authentication process and to reduce error rates i.e. FAR and FRR. In addition to the reduction in error rates one of the major advantages of a multimodal approach is that it is harder to circumvent or forge. The reason being, that it is harder to obtain and replicate multiple traits as compared to a single trait. In fact, even if the accuracy and performance of the multimodal system is on par with t unimodal system the overall security of the whole system is improved. Therefore, the development of Multimodal Biometric System was considered to be a logical extension to the unimodal approach.

Traditionally, multimodal biometric systems are always considered to be the combination of two or more complete unimodal biometric systems. In fact, almost all of the multimodal biometric systems developed to date have been based on this traditional framework. Some of the more well-known multimodal biometric systems proposed thus far are outlined below.

Hong et al in [1] empirically proved that multimodal biometrics can improve performance in respect to increasing accuracy and decreasing False Accept Rates. Jain et al in [2] provide a fingerprint; face and speech based multimodal authentication system. They use minutiae based approach to detect fingerprint, Eigen face-based approach to detect faces and text dependent speaker recognition system using Hidden Markov Model (HMM) to detect Voice. The fusion is carried out in a parallel mode using rank level fusion at post-matching stage. Wang et al in [3] provide comparison between multiple fusion techniques at rank level by fusing face and iris to identify users and they also use an Eigen face-based approach to detect faces and employ an algorithm that characterizes local variations in iris for matching. The fusion techniques used for comparison include weighted sum, a Fisher discriminant analysis and neural network based classifier. Middendorff, Bowyer and Yan in [4] detail different approaches used in combining ear and face for identification.

The approach of applying multiple algorithms to single sample is described in [5] and [6]. In [5] three different minutiae based fingerprint matching approaches i.e. Hough transform based matching, String distance based matching and 2D dynamic programming based matching are integrated using a logistic regression transform to reduce False Rejection Rate (FRR) for a given False Acceptance Rate (FAR). In [6] the authors perform a decision level fusion based on Sum, Support Vector Machine and Dempster-Shafer theory on multiple fingerprint matching algorithms submitted to FVC 2004 competition with a view to evaluate which biometrics to fuse and which technique to use for fusion. In [7] an experimental comparison of decision level fusion of face and voice modalities using various classifiers is described. The authors evaluate the use of sum, majority vote, three different order statistical operators, Behavior Knowledge Space and weighted averaging of classifier output as potential fusion techniques. In [8] Prabhakar and Jain explore a scheme to combine multiple classifiers at the decision level stage in an optimal fashion for a multimodal biometrics. They select two or more of the four selected classifiers for fusion based on evaluation of predicted ranking of the multimodal system evaluated from the two dimensional genuine and impostor probability distributions of the selected classifiers.

Bowyer et al [9] worked with multiple samples of face from same and different sources to create a multimodal system using 2D and 3D face images. The approach uses 4 different 2D images and a single 3D image from each user for verification and fusion takes place in parallel at matching score level using sum, product or the minimum value rule.

In [10] Lumini and Nanni fuse Fingerprint and Iris using the mean rule (MEAN) and three Machine Learning approaches: linear support vector machines (LSVM), radial-basis- function support vector machines (RSVM) and the Dempster-Shafer model (DS) to combine similarity scores. They use multiple fingerprint detection algorithms from the FVC2004 competition and the phase code using Gabor filters based Iris Recognition approach for fusion to show that multimodal approach reduces the EER and FAR errors.

In his PhD thesis Karthik [11] proposes a fusion strategy based likelihood ratio used in the Neyman-Pearson theorem for combination of match score. He shows that this approach consistently achieves high recognition rates over multiple databases without any parameter tuning. He uses NIST-BSSR1 and XM2VTS (public domain score databases) to test the fusion algorithms.

It is clear that the traditional multimodal biometric approach improves the accuracy and stability of the system over its individual unimodal components but this improvement comes at a cost. In most cases it requires either installation of multiple sensors or multiple algorithms or both. This translates into a higher installation and operational cost and a larger memory footprint.

In this paper we propose a framework for multimodal biometric fusion based on utilization of a single matcher implementation for both modalities. The proposed framework is designed to not only provide improved performance over the unimodal systems but also to provide a comparable performance to the traditional approach based systems. The major advantage of the framework over the traditional approach is that since both modalities utilized the same matcher module the memory footprint of the system is reduced. This is desirable for applications designed for low power consumption, small memory footprint devices like mobile phones etc. The framework is demonstrated through the development of a fingerprint and iris based multimodal biometric identification system with score level fusion that utilizes a single hamming distance based matcher.

The rest of the paper is organized as follows Section 2 outlines the proposed framework. Section 3 summarizes the experimental test system with Section 4 providing the details of the experimental results and analyzing them whereas conclusions and future research directions are furnished in Section 5.

2. Proposed framework

One of the major driving forces behind the development of the proposed framework was to demonstrate that it is possible to design an effective deployable multimodal biometric system without the availability of two complete unimodal systems.

Traditional approach, although effective, causes considerable implementation issues that limit its effectiveness as a deployable solution e.g. each unimodal system contains its own unique set of feature extractor and matcher thus fusing their scores require an additional score normalization setup and a complex fusion approach. Another issue that arises is of memory footprint as two complete unimodal systems are to be implemented before the multimodal system can be designed which restricts the utilization of these systems in low memory and low power devices. A traditional score level fusion based multimodal biometric identification system is shown in figure 1. Conventionally, multimodal systems work in sequential mode i.e. both biometric inputs are acquired one at a time. The workflow is as follows. First one input is acquired and passed on to the first unimodal system and then the other input is acquired and forwarded to the second unimodal system. The fusion takes place when the results from both systems are available and properly normalized.

Figure 2 shows the proposed framework, where one can observe that the complexity of the system is reduced since the additional matcher and consequently the normalization algorithms are removed. This framework is also designed to operate in sequential mode. The workflow for this framework is as follows: First one biometric input is acquired and passed to the first feature extractor. The processed reference is compared with the templates in the database using the provided matcher. In the mean time, the second input is acquired and forwarded to the second feature extractor. In the time that the matcher completes the processing of the first biometric and generate the matching output, the second biometric input is processed and ready for matching. The same matcher is now used to compare the second biometric reference with the template and generate the output. The fusion takes place once both matching scores are available.

One of the major advantages of using the single matcher for both modalities is that both output scores will be in same format thus eliminating the need for any additional normalization functions. This not only improves the processing speed and reduces the memory footprint of the system it also simplifies the design process.

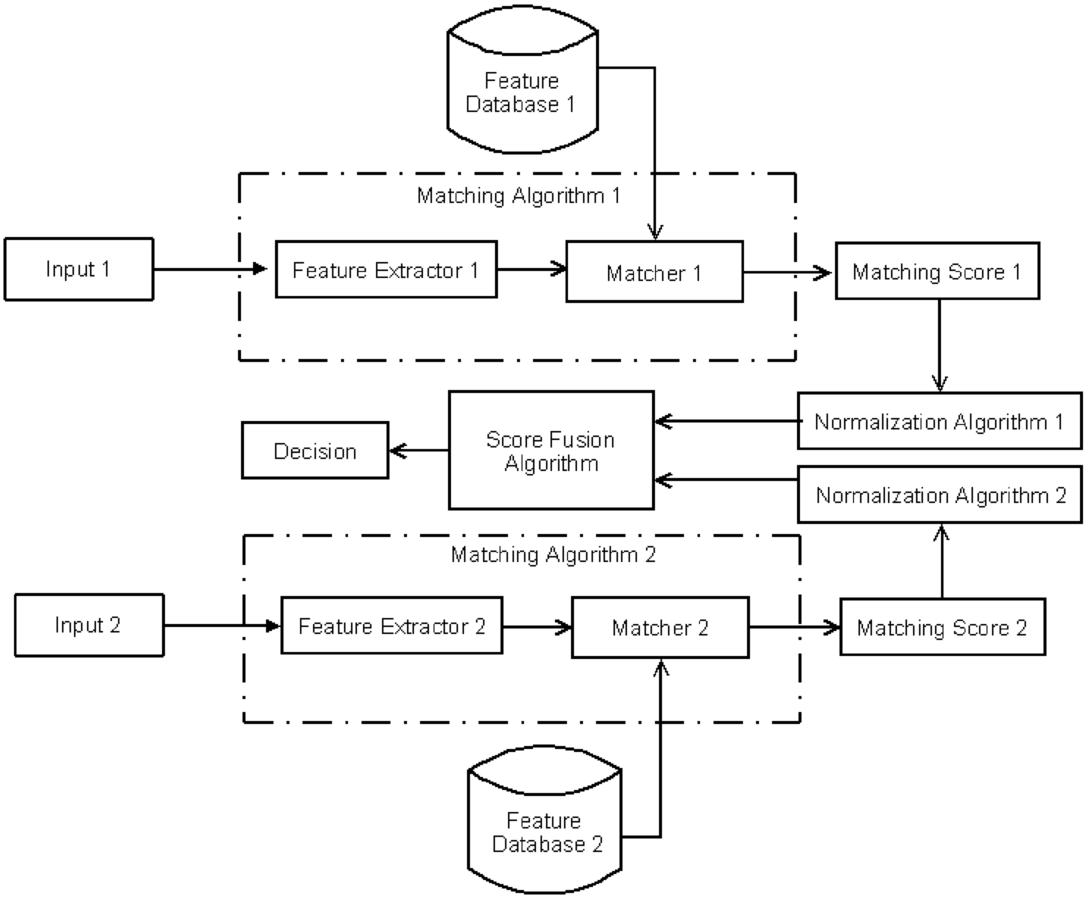

Figure 1. Score fusion based multimodal biometric system

This framework is designed to be flexible in that any set of biometrics, any matcher and any fusion approach can be used in the implementation of the framework. It should be noted that the actual gain in performance and the reduction in memory footprint and consequently the redcution in complexity will be dependent on the selection of the matcher and fusion algorithm. Selection of matcher and fusion approach is therefore the key element of the propose framework. We briefly describe the three major components of this framework namely the feature extractors, the matcher and the fusion algorithm.

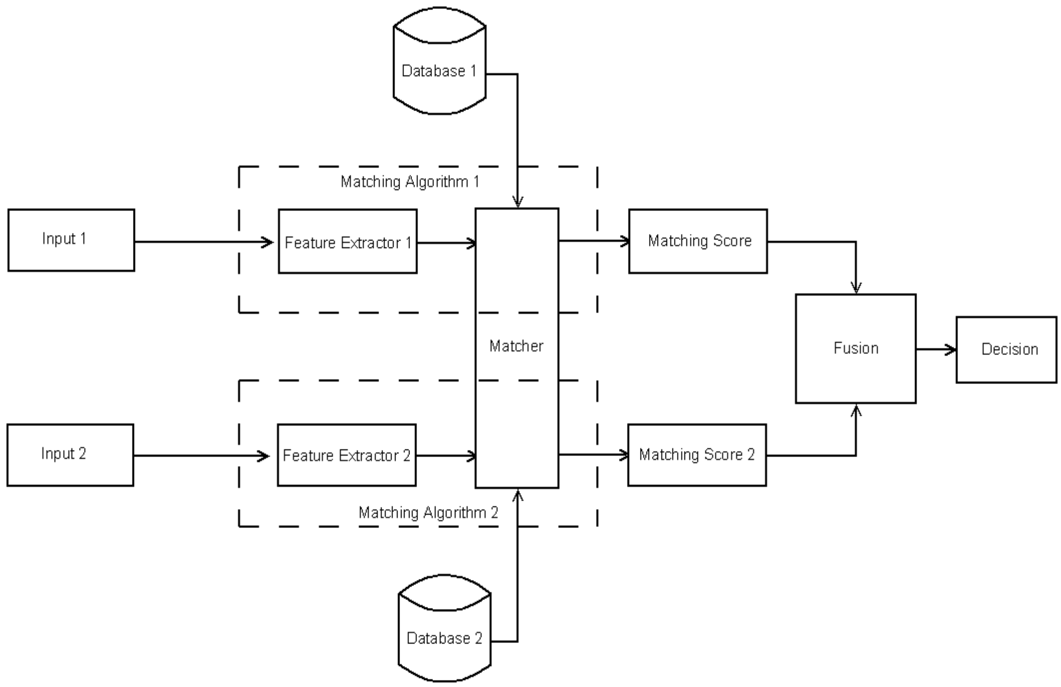

Figure 2. The proposed system

2.1. Feature extractor

The proposed framework does not put any particular restriction on the type of modality or the feature extractor utilized. It should however be kept in mind during the design of the feature extractors that their output must conform with the input requirements of the selected matcher.

2.2. Matcher

The proposed framework is not restrictive to the selection of the matcher. The only consideration is that the selected matcher should be a strong matcher.

A matcher is considered to be a strong one if it consistently provides high score for genuine matchers and considerably lower scores for imposter matches. Even if it fails to identify the correct match, a strong matcher will almost always produce significantly high score, in other words, the genuine target will have higher rank than almost all imposters, as illustrated in figure 3. This figure shows the matching result of an iris input against 80 templates. Although the actual input template is the 26^{th} the best match score is provided for the 54^{th} template, even then, the genuine match still yields a high score.

2.3. Fusion algorithm

Although just like the other components of the framework there is no restriction on the type of fusion algorithm/approach to use. We have, however, for the purpose of this paper utilized a summation based fusion algorithm.

3. Experimental System

One of the most effective ways of demonstrating the usefulness of a framework is to utilize reasonably weak components in the development of the test system and testing it on the standard datasets. The rational being, if the framework performs comparably with weaker components its performance will definitely be better with state of the art elements. Keeping this in mind the following components were utilized in the creation of the test system.

The feature extractor employed for Iris modality is based on Daugman's approach [12] and was implemented by Libor Masek as described in [13]. This feature extractor generates an Iris code which comprises of bit streams called Iriscode by Daugman that are used by the hamming distance based matcher to provide the matching score.

Two different feature extractors are used for Fingerprint modality and are fused individually with the Iris modality to further evaluate the fusion results. The first feature extractor utilized for Fingerprint modality was developed by the Center of Unified Biometrics and Sensors (CUBS) at University of New York at Buffalo. This approach contains a Chain code based feature extractor with contour following to detect minutiae as elucidated in [14]. The second feature extractor is a simple binarization and thinning based minutia extractor consisting of a segmentation stage [15], an enhancement stage utilizing High-Boosting filtering, a binarization stage using Niblack approach, an 8-connected minutiae detector and a line tracing approach to remove spurious minutiae [16].

The extracted minutiae are then converted to a minutiae code. The minutiae code is developed by converting the location, angle and type data of the minutiae into bit stream and concatenating them together. The complete minutiae code comprises of 100 blocks and each block is 49 bit long divided into 16 bits for each of the row position, column position and the angle and 1 bit for the type of minutiae as shown below in Table 1. The bit for type of minutiae is set to 0 for a Bifurcation and 1 for a Ridge.

Table 1. Minutiae code description

16 bit *Row Position*	16 bit *Column Position*	16 bit *Minutiae Angle*	1 bit *Minutiae Type*

The extracted minutiae code and the iris code are then matched with the template database via a simple hamming distance based matcher to provide a matching result between 0 and 1. A simple accumulator based fusion approach is employed here. The reason for the effectiveness of such a simple approach is based on the fact that since a single matcher is utilized by both modalities the resulting matching scores are in similar format and thus easy to accumulate. The reason this simplistic accumulator is able to provide results comparable to the traditional approach is because it exploits the property of the strong matcher detailed above. Figure 3 shows the matching scores for Iris modality and figure 4 shows the matching score for Fingerprint modality. It can be seen that although individually both modalities provide inaccurate results and give the highest score for different templates but the genuine match score is still considerably high. It follows that if we add the matching scores of two separate modalities the correct match score will be higher. Figure 5 shows the accumulated scores and it can be observed that the actual template generates the highest score.

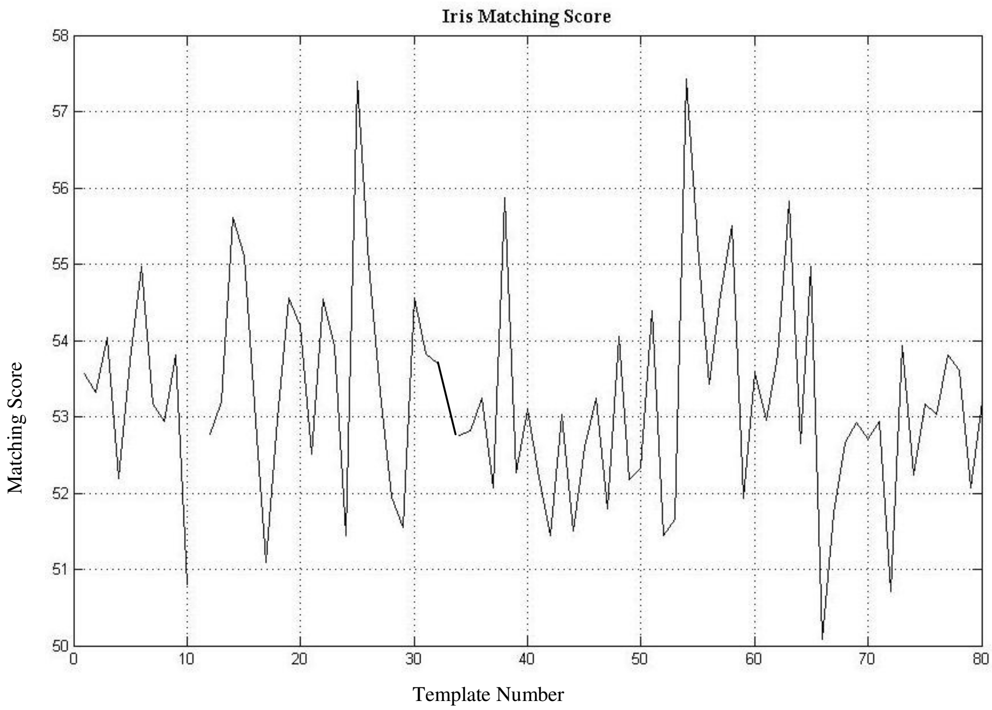

Figure 3. Iris matching scores

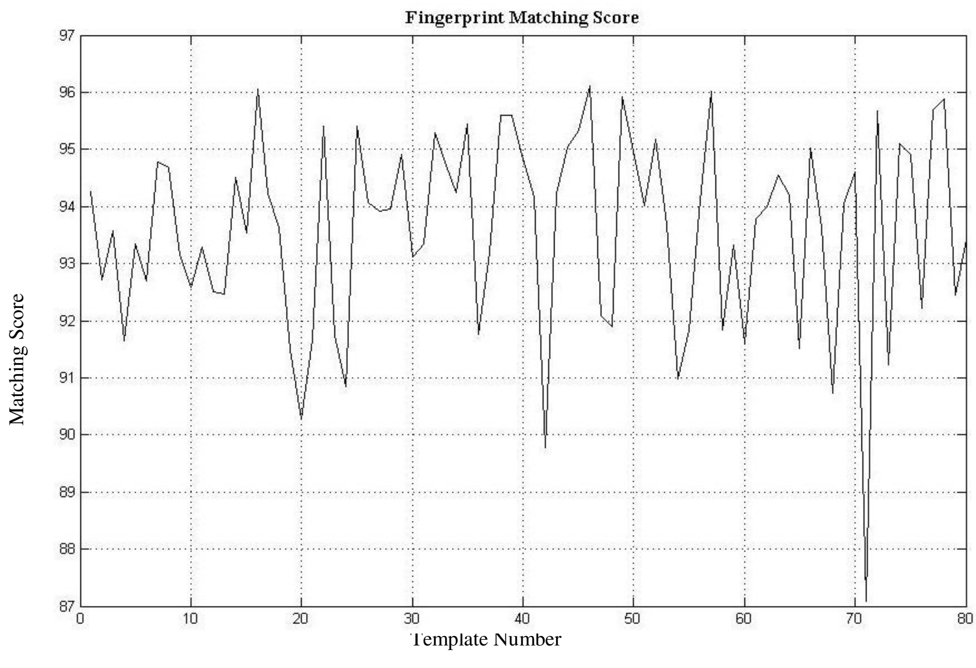

Figure 4. Fingerprint matching scores

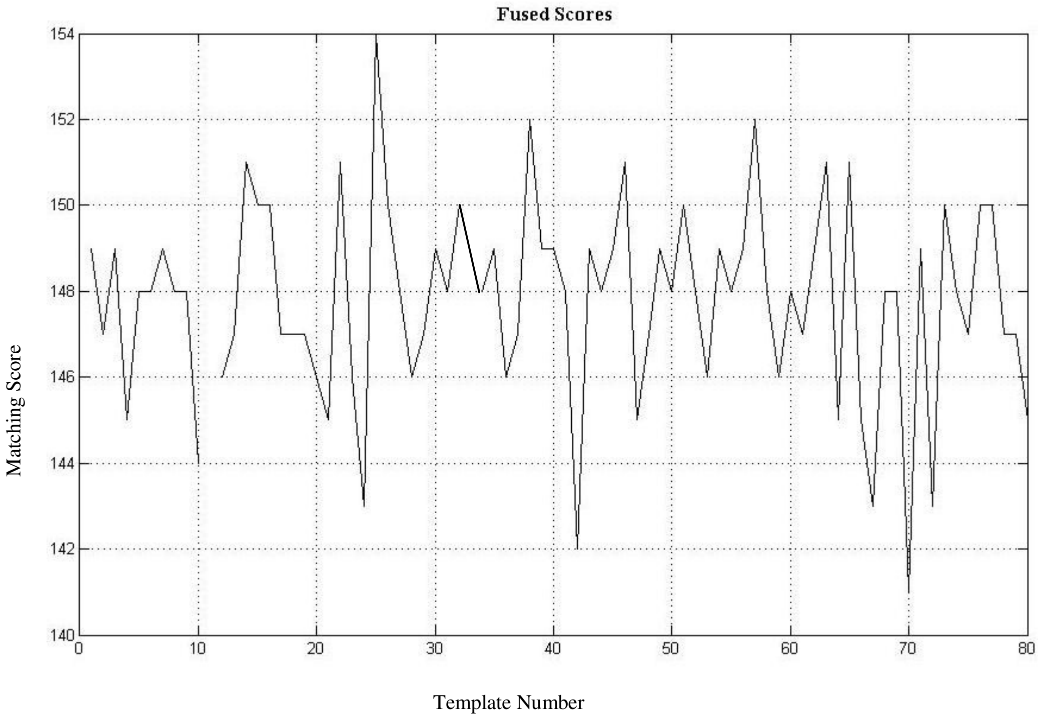

Figure 5. Fused scores

The framework is designed to be highly flexible, giving the implementer the choice not only of selecting the desired biometric trait but also of allowing freedom in the selection of feature extractors and the matcher. Another feature of this framework is that it provides highly comparable results to the conventional approach even with such a simple fusion approach (i.e. addition operation) and simpler feature extractors and matcher.

4. Experimental results and analysis

The experiment is setup in "Verification Mode" and is preformed to try and compare the result for a real world situation. For this experiment the West Virginia University's multimodal database is utilized. The details regarding the acquisition and storage of this database are provided in [17]. In this test 100 individuals are randomly selected from the database and for each of these 100 individuals one fingerprint image is selected as the verification template or input image and 4 unique images taken at different times are selected as enrollment images. Each input image is matched against the entire enrollment image database i.e. against 400 images (4 Enrollment Images * 100 Users).

To evaluate the genuine vs. imposter decision the maximum matching scores of all four enrollment images for each person is selected and then threshold. The threshold is set at the Equal Error Rate (ERR). If the matching score is above the threshold the user is identified as genuine. If the matching score is under the threshold or if more than one enrollment set provides the highest score, then the user is identified at imposter. The same decision scheme is used to evaluate the results for both unimodal as well as the fused system.

Two different multimodal fusion systems are tested on this dataset each with a different Fingerprint feature extractor (detailed above) and same Iris feature extractor. The raw results from both are compared with the corresponding raw individual unimodal scores. This comparison is done to illustrate the fact that the proposed system provides improved results as compared to the results from the individual constituting unimodal system. Table 1 provides the results for this experiment. The results show a marked improvement in the accuracy as well as a considerable decrease in the Equal Error Rate.

Table 2. Raw experimental results

	Correct Match	False Accept	False Reject	Incorrect Match
System 1 with Chain code based Minutiae Extractor				
Fingerprint	60	15	15	10
Iris	65	13	13	9
Fused	**72**	**9**	**9**	**10**
System 2 with Binarization based Minutiae Extractor				
Fingerprint	64	13	13	10
Iris	65	13	13	9
Fused	**75**	**8**	**8**	**9**

As mentioned above, although these results show a marked improvement in accuracy over the individual unimodal systems, to truly demonstrate the advantage of the proposed framework the experimental system should be evaluated against a traditional fingerprint and iris fusion based multimodal system.

To facilitate this analysis the results obtained from the experimental system are compared against two different traditional multimodal fusion systems. The first traditional system used for comparison is based on the unimodal Iris system detailed in [13] and fused using accumulator based fusion with a unimodal fingerprint system based on feature extractor detailed in [14] and the matcher detailed in [18]. The reason this traditional system is used for comparison is because it contains almost all the same components as the experimental system except for the matcher. The results are also compared against the ones provided in [10].

Table 3. Comparison between % improvement in ERR

ERR	Fingerprint	Iris	Fused	% improvement
Experimental System 1	15	13	9	**40.00%**
Experimental System 2	17	13	10	**41.17%**
Traditional System	8	13	4	**50.00%**
Results in [10] For P075	5.61	3.2	2.86	**49.01%**

An important point to note here is that in [10] the best algorithms from FVC2004 (Fingerprint Verification Competition 2004) were selected and fused with a very strong Iris based matcher. In addition to this, [10] utilizes some very complex fusion approaches (mean, Dempster-Shafer, Radial Support Vector Machine and Linear Support Vector Machine). For sake of keeping the comparison as realistic as possible we compare the experimental results with the results obtained in [10] via mean based fusion of a middle-ranking competitor algorithm (P075) and Iris scores. It should also be noted that the hamming distance based matcher is a considerably weaker fingerprint matcher as compared to the one used in the implemented traditional system. Therefore the comparison is being made in terms of percentage improvement in ERR rather than the ERR values themselves. Table 2 shows the individual ERR values, the ERR value for the fused score and the percentage improvement in ERR along with the results provided in [10] and by the implemented traditional system.

The results clearly show that the proposed framework provides comparable results to the fusion of two best of breed unimodal system using conventional approach.

5. Conclusions

This paper presents a proof of concept for a single matcher based multimodal biometric identification framework. The framework is verified by utilizing fingerprint and iris modalities. The proposed framework is low cost with a small memory footprint and easier hardware implementation. It is interesting to note that the flexibility and openness of this framework, which allows for easy interchangeability of various feature extractors and matcher helps to spawns the plug and play nature of the system. This approach also has an additional advantage in that it is easier to implement, with low memory footprint and cost. One of the major impacts of applying this framework is on system design in that it forces the designer to think about fusion from the start and pay special attention to the design of the feature extractors. It should, however, be noted that the proposed system is in no way presented as a replacement to the traditional approach, it is, in fact, presented as an alternative option when using two complete unimodal biometric systems may not possible or viable.

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