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A Multi-Biometric System Based on Feature and Score Level Fusions

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ABSTRACT In general, the information of multiple biometric modalities is fused at a single level, for example, score level or feature level. The recognition accuracy of a multimodal biometric system may not be improved by carrying fusion at a single level, since one matcher may provide a performance lower than that provided by other matchers. In view of this, we propose a new fusion scheme, referred to as the *matcher performance-based (MPb)* fusion scheme, in which the fusion is carried out at two levels, feature level, and score level, to improve the overall recognition accuracy. First, we consider the performance of the individual matchers in order to find out which of the modalities should be used for fusion at the feature level. Then, the selected modalities are fused at this level by utilizing their encoded features. Next, we fuse the score obtained from the feature-level fusion with that of the modality for which the performance is the highest. In order to carry out this fusion, a new normalization technique referred to as the *overlap extrema-variation-based anchored min–max (OEVBAMM)* normalization technique, is also proposed. By considering three modalities, namely, fingerprint, palmprint, and earprint, the performance of the proposed fusion scheme as well as that of the single level fusion scheme, both with various normalization and weighting techniques are evaluated in terms of a number of metrics. It is shown that the multi-biometric system based on the proposed fusion scheme provides the best performance when it employs the new normalization technique and the confidence-based weighting (CBW) method.

INDEX TERMS Biometrics, feature level fusion, multi-biometric system, normalization, score level fusion.

I. INTRODUCTION

Person authentication has become an essential task for providing security to access restricted resources and systems. Unimodal and multimodal biometric-based authentication systems have been used for this purpose [1]. A unimodal biometric system utilizes single source of information for identifying a person. A general block diagram of such a system is shown in Fig. 1. There are five modules in a unimodal biometric system as described below. 1) *Sensor module*: it acquires biometric data of a person. For example, image of a person's palm is acquired by a palmprint sensor as shown in the figure. 2) *Feature extraction module*: it extracts features from a biometric data. For example, the orientations of line and vein patterns in a palm are extracted as features for the palmprint image as shown in the figure. 3) *Matching module*: it compares the feature values against those stored in a system database as templates, and generates a score value. For example, the score for the palmprint image is 100 as shown in the figure. 4) *Ranking module*: it produces a rank value based on the score value. For example, the rank value for the score value of 100 of the palmprint image is 10 as shown in the figure. 5) *Decision module*: it makes a decision based on the rank value for accepting or rejecting a person. It is to be noted that a decision module can accept or reject a person based on the score value obtained from a matching module when the ranking module is not available. Multimodal biometric systems utilize multiple information that are obtained from multiple sensor, multiple feature extraction, multiple matching, multiple ranking, and/or multiple decision modules for identifying a person. In recent years, multimodal biometric systems have drawn more attention than unimodal systems,

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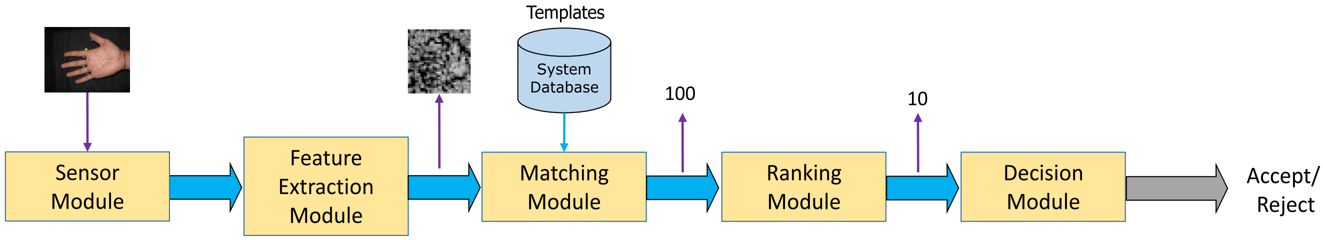


FIGURE 1. General block diagram of a unimodal biometric system.

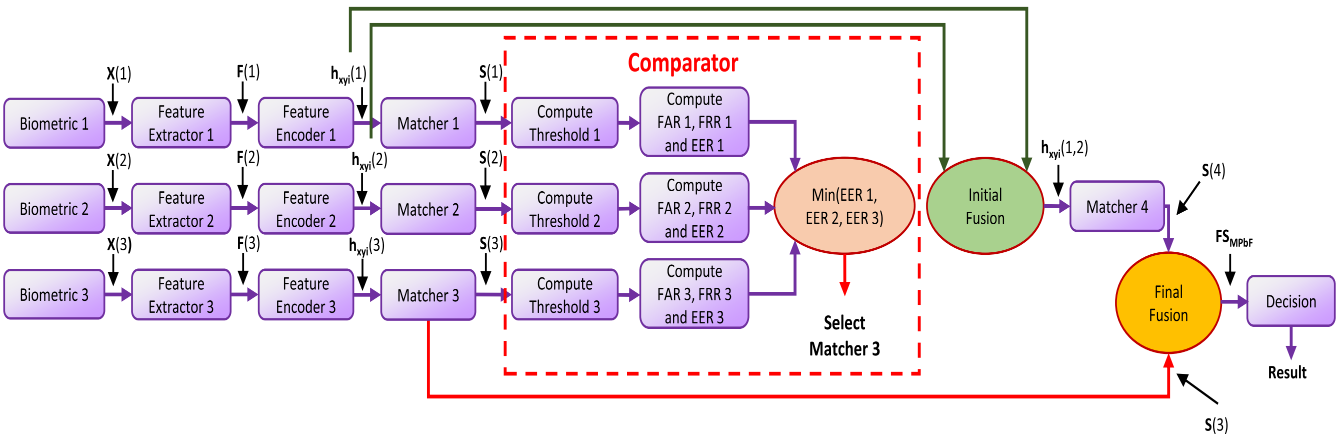


FIGURE 2. Block diagram of the proposed matcher performance-based (MPb) fusion scheme using three biometric sources.

since they can increase security level as well as improve the overall recognition rate by consolidating multiple biometric sources.

Fusion is an essential task that plays an important role for improving the recognition accuracy of a multimodal biometric system. In a multimodal biometric system, fusion can be carried out at five levels: sensor level [2], [3], rank level [4]–[7], decision level [8]–[10], feature level [11]–[25], or score level [26]–[42]. In sensor-level fusion, images obtained from multiple sensors are fused, and this fused image is passed through the feature extraction, matching and/or ranking, and decision modules for identifying a person. Very little work has been done in sensor-level fusion, since multisensor data may be incompatible and high processing time may be required to fuse them. In rank-level fusion, ranks obtained from multiple ranking modules are fused, and this fused rank is passed through the decision module for identifying a person. Very few rank-level fusion techniques have been developed for multimodal biometric systems, since they are not applicable for the verification problem of a person, and thus has not received much attention. In decision-level fusion, decisions obtained from multiple decision modules are combined to make the final decision for the identification of a person. Decision-level fusion has not drawn much attention, since the information is too abstract at this level to improve the recognition accuracy of a multimodal biometric system. In feature-level fusion, feature sets obtained from multiple feature extraction modules are fused, and this fused feature set is passed through the matching and/or ranking, and decision modules for identifying a person. Feature-level fusion is expected to provide better recognition rate, since features contain richer information about the biometric data than the matching scores or the decision of a matcher. Considerable work has been done in feature-level fusion based on transformation of features [11]–[18], shapes of features [19]–[22], or encoded features [23], [24]. Limitations of the existing feature-level fusion techniques are that they require ranking information of feature sets, transformation function, or iterations in order to improve the recognition rate. Moreover, the performance of the matchers has not been considered in the existing techniques of feature-level fusion that may lead to an improved recognition rate. In score-level fusion, scores obtained from multiple matching modules are fused, and this fused score set is passed through the ranking and/or decision modules for the identification of a person. Score-level fusion has drawn much attention, since the matching scores obtained from multiple matchers are easy to access and easy to fuse. Many score-level fusion techniques have been developed based on arithmetic operations, such as addition, subtraction, maximum, minimum, or median [26]–[41]. However, scores are required to be weighted and/or brought to a common scale for improving the overall recognition rate of a multimodal biometric system. Moreover, the existing score-level fusion techniques have not considered the performance of individual matchers for fusing multiple scores. Our methodology focuses on fusion at the feature-level and score-level for a multimodal biometric system in view of their above mentioned advantages over fusion at other levels.

Normalization is an essential task for improving the overall recognition rate of a multimodal biometric system under score-level fusion, since multiple scores may be on different numerical scales, or may not be homogeneous, or may have different statistical distributions. Many normalization techniques have appeared in the literature for multimodal biometric systems to improve the recognition rate [32]–[41], [43]. Based on the raw matching scores, several normalization techniques, such as Min-max (MM), Median and median absolute deviation (MAD), decimal scaling (DS), z-score (ZS) [38], and improved anchored min-max (IAMM) [41], have been developed. Limitations of these techniques are that they are sensitive to outliers, or require scores to be on a logarithmic scale, or require repeated score values or cannot transform scores into a common range. Based on the genuine score, TanH normalization technique has been developed to overcome the limitations of raw matching score-based normalization techniques [38]. However, it requires Hampel influence function to estimate the parameters for normalizing the scores. Based on both the genuine and imposter scores, few normalization techniques, such as the performance anchored min-max (PAN-MM) [36], overlap extrema-based anchored min-max (OEBAMM) [33], and mean-to-overlap extrema-based anchored min-max (MOEBAMM) [33], have been developed for improving the recognition rate of a multimodal biometric system. However, these techniques require errors of individual matchers, or neighboring scores of the overlap region between the genuine and impostor scores. It should be noted that in almost all the existing schemes, fusion is carried out using the information of the multiple modalities at a given level, for example, score level or feature level.

Unlike the existing multimodal biometric systems in which the fusion is carried out at a single level, this paper is concerned with the problem of fusing multiple modalities at more than one level. In particular, the fusion scheme proposed here is one in which three modalities are fused at two levels, feature level and score level. We first consider the performance of the individual matchers in order to find out as to which of the two modalities should be used for the feature-level fusion, and choose those two modalities for which the EER is not the least. The idea behind choosing such two modalities is that they need to be improved the most in order to enhance the recognition capacity through their feature-level fusion. We fuse the encoded features rather than the raw ones of these two modalities. The reason behind using encoded values of features is to reduce the processing time for the matchers to identify a person as well as to utilize useful information from each of these two modalities. Next, we fuse at the score-level the score obtained from the feature-level fusion with that of the modality for which the EER is the lowest. In order to carry out this fusion we consider not only the extrema, but also the amount of variation of the overlap scores between the

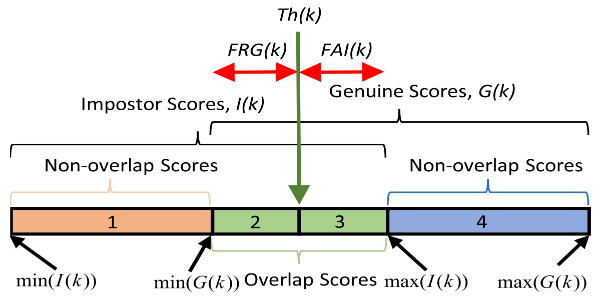


FIGURE 3. Genuine and impostor scores of a biometric system with falsely rejected genuine (FRG(k)) and falsely accepted impostor (FAI(k)) based on the threshold value $Th(k)$.

genuine and impostor scores for the proposed normalization technique, since they provide the information on the recognition error of a multimodal biometric system. Finally, these normalized scores are fused under the weighted-sum (WS) rule to improve the overall recognition rate of the multimodal biometric system.

The paper is organized as follows. In Section II, the proposed fusion scheme based on the performance of individual matchers and the encoded features for a multimodal biometric system is discussed. A new normalization technique based on the extrema and the variations of the genuine and impostor scores is proposed in Section III. Experimental results obtained by a multi-biometric system using the proposed fusion scheme and the single level fusion scheme with various normalization and weighting techniques are presented in Section IV. Finally, conclusions are given in Section V.

II. PROPOSED FUSION SCHEME BASED ON THE PERFORMANCE OF MATCHERS

In this section, we explain in detail the proposed fusion scheme, referred to as the *matcher performance-based (MPb)* fusion scheme, for a multimodal biometric system.

A block diagram of the proposed fusion scheme is shown in Fig. 2 using three biometric sources. Let the biometric and feature images for the modality k ($k = 1, 2, 3$) be denoted by $X(k)$, and $F(k)$, respectively. Let the feature value at the position (x, y) of $F(k)$ be denoted by $f_{xy}(k)$, $h_{xyi}(k)$ being the encoded form of $f_{xy}(k)$, and i is the bit position. $F(k)$, $f_{xy}(k)$, and $h_{xyi}(k)$ are obtained using the technique in [44]. Next, the matching, genuine and impostor score sets for the modality k are obtained using the method in [30], and denoted by $S(k)$, $G(k)$ and $I(k)$, respectively.

The proposed MPb fusion scheme consists of two steps, and is described in detail below.

Step 1: In a multimodal biometric system, equal error rate (EER) is the value at which the acceptance and rejection rates are equal. We utilize the genuine score set, $G(k)$ and the impostor score set, $I(k)$ for the modality k in order to select the matcher that provides the lowest EER in comparison with others in a multimodal biometric system using the comparator. The region of the genuine and impostor scores can be divided into four parts [30], as shown in Fig.3.

In order to compute the threshold value for the modality k, two parameters of the genuine and impostor scores, namely, $\min(I(k))$, and $\max(G(k))$, which are the minimum value of impostor scores, and maximum value of genuine scores, respectively, are utilized. The threshold value is computed for the modality k as follows.

$$Th(k) = [min(I(k)) : step\_size : max(G(k))] \tag{1}$$

where

$$step\_size = \frac{max(G(k)) - min(I(k))}{p} \tag{2}$$

p being an empirical parameter. The parameter p controls the step size for the variable $Th(k)$ that is utilized to compute the number of falsely rejected genuine and falsely accepted impostor. The higher the value of p, the smaller is the step size for $Th(k)$. In this paper, we have found that $p = 10^3$ is the best value for the step size by running several experiments. Next, we count the number of rejected genuine scores accepted falsely as impostor scores for $G(k)<Th(k)$, and accepted impostor scores accepted falsely as genuine scores for $I(k) \geq Th(k)$, and refer to them as *falsely rejected genuine (FRG(k))* and *falsely accepted impostor (FAI(k))* for the modality k, respectively, as shown in Fig. 3. Now, false acceptance rate (FAR), false rejection rate (FRR) and EER for the modality k are computed as follows

$$FAR(k) = \frac{100 * FRG(k)}{length(G(k))} \tag{3}$$

$$FRR(k) = \frac{100 * FAI(k)}{length(I(k))} \tag{4}$$

$$EER(k) = \frac{FAR(k) + FRR(k)}{2} \tag{5}$$

The EER of the matcher that provides the lowest value is given by

$$EER_{lowest} = min(EER(k, k = 1, 2, 3)) \tag{6}$$

We assume, without loss of generality, that it is matcher 3 that provides the lowest EER. Based on this assumption, we propose to perform the first fusion between the modalities 1 and 2, and refer to this fusion as *initial fusion* (see Fig. 2). In other words, the initial fusion is done between the encoded features obtained from the modalities 1 and 2. It is to be noted that the encoded features $h_{xyi}(k)$ for the modality k are binary numbers in which '1' provides more information about the feature than '0' does. Therefore, the initial fusion can be done using the logical operators, such as XOR, AND, and OR in order to obtain the fused encoded feature. We utilize the logical OR operator for the initial fusion, since it considers encoded feature value of '1' at the position (x, y, i) available from the modality 1 or 2. The fused encoded feature, $h_{xyi}(1, 2)$ can be computed as [24]

$$h_{xyi}(1, 2) = h_{xyi}(1) \oplus h_{xyi}(2) \tag{7}$$

at the position (x, y, i), and the sign $\oplus$ indicates the logical OR operation. Next, following the method in [30], the matching score $S(4)$ is obtained from matcher 4 (see Fig. 2).

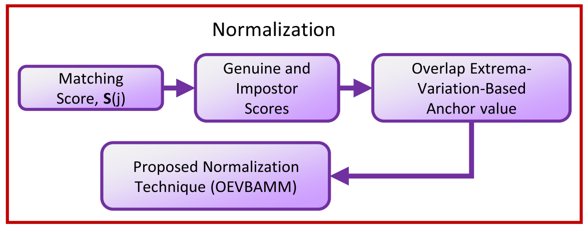


FIGURE 4. Block diagram of the proposed normalization technique.

Step 2: The matching score $S(4)$ obtained from Step 1 and the score $S(3)$ from matcher 3 are fused using the weighted-sum (WS) fusion rule. The fused score FS_{MPbF}, is obtained as

$$FS_{MPbF} = w(3)\ \boldsymbol{S}_N(3) + w(4)\ \boldsymbol{S}_N(4) \tag{8}$$

where $w(j)$ represents the weight attached to the score from matcher j and $\boldsymbol{S}_N(j)$ denotes the normalized value of $\boldsymbol{S}(j)$.

In [30], the authors have reported that the matching scores from multiple matchers may be non-homogeneous, or may be on different numerical scales or may have different statistical distributions, and therefore, normalization of scores is an essential task under WS rule for the score-level (SL) fusion. In view of this, we introduce a new normalization technique for the proposed multimodal biometric system in the following section.

III. PROPOSED NORMALIZATION TECHNIQUE

In the existing normalization techniques, the variations of the genuine and impostor score sets are not taken into consideration. One can expect to improve the performance of a multimodal biometric system by including this additional information in the normalization technique. Hence, we propose a normalization technique that takes into account this information and investigate its effect on the performance provided by the multimodal biometric system using the SL fusion and the proposed fusion scheme. The proposed normalization technique does not require Hampel influence function, EER or repeated score sets, unlike the TanH [38], performance anchored min-max (PAN-MM) [36] and anchored min-max (AMM) [40] or improved anchored min-max (IAMM) [41] normalization methods, respectively. Also, it does not require the information of neighboring scores of the overlap region between the genuine and impostor scores as required by the mean-to-overlap extrema-based anchored min-max (MOEBAMM) [33] method. A block diagram of the proposed normalization technique is shown in Fig. 4.

An anchor value, the value that aligns the scores of a matcher, referred to as the *overlap extrema-variation-based anchor (OEVBA)* value, is computed for the proposed normalization technique. In order to obtain this anchor value, we utilize the genuine and impostor scores obtained from the matcher $j (j = 3, 4)$ (see Fig. 2) using the method in [30], and denote them by $\bar{G}(j)$ and $\bar{I}(j)$, respectively. Four parameters of the genuine and impostor scores, namely, $\min(\bar{G}(j))$, std($\bar{G}(j)$), max($\bar{I}(j)$) and std($\bar{I}(j)$), the former two being the minimum and standard deviation values of genuine scores, and the latter two being the maximum and standard deviation values of the impostor scores, for the score $S(j)$, are utilized for computing the anchor value for the proposed normalization technique.

A. OVERLAP EXTREMA-VARIATION-BASED ANCHOR (OEVBA)

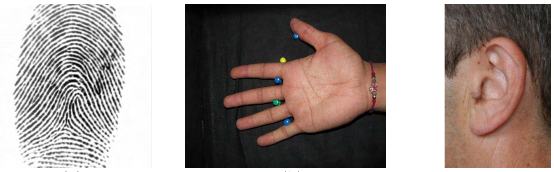
In this case, the anchor value is computed from the extrema and the standard deviations of the genuine and impostor score sets. The lowest correct score values in the genuine and impostor score sets are represented by the minimum and maximum values of the corresponding sets [30]. The standard deviation of the genuine and impostor scores represent the variations of the scores in their corresponding sets. A high performance biometric matcher is expected to produce a small overlap area between the genuine and impostor scores; further, the value of the standard deviations of these scores are smaller than the minimum value of the genuine scores. Based on these two considerations, the ratio of the width of the overlap area and the difference between the standard deviations of the impostor and genuine scores would provide a smaller value than the minimum value of the genuine scores. We consider this ratio as the anchor value for our proposed normalization technique; more specifically, we compute the ratio of the difference between the maximum of the impostor scores and the minimum of the genuine scores, and the difference between the standard deviations of the impostor and genuine scores. The overlap extrema-variation-based anchor (OEVBA) value, $A(j)$, in a multimodal biometric system is formulated as

$$A(j) = \frac{max(\bar{I}(j)) - min(\bar{G}(j))}{std(\bar{I}(j)) - std(\bar{G}(j))} \quad (9)$$

We utilize the above anchor value as an operating point in the MM normalization technique; more precisely, it is an extension of the MM normalization technique based on the proposed OEVBA anchor value, and we refer to it as the *overlap extrema-variation-based anchored min-max (OEVBAMM)* normalization technique. Since the OEVBA anchor value is smaller than the minimum value of the genuine scores for a high performance biometric matcher, the number of normalized scores with high values would be more than the number of normalized scores with low values. In view of this, one can expect to improve the recognition rate of a multimodal biometric system using the OEVBA anchor value for the normalization of scores. The normalized scores for the score set $S(j)$ using $A(j)$ is computed as

$$\boldsymbol{S}_N(j) = \begin{cases} \dfrac{\boldsymbol{S}(j) - min\{\bar{G}(j), \bar{I}(j)\}}{2(A(j) - min\{\bar{G}(j), \bar{I}(j)\})}, & if\ \boldsymbol{S}(j) \leq A(j) \\ 0.5 + \dfrac{\boldsymbol{S}(j) - A(j)}{max\{\bar{G}(j), \bar{I}(j)\} - A(j)}, & if\ \boldsymbol{S}(j) > A(j) \end{cases} \quad (10)$$

where $\boldsymbol{S}_N(j)$ denotes the normalized value of $\boldsymbol{S}(j)$.



(a) (b) (c)

FIGURE 5. Sample images of (a) fingerprint, (b) palmprint, and (c) earprint.

IV. EXPERIMENTAL RESULTS

In order to study the performance of the proposed multimodal biometric system, we consider three modalities, namely, fingerprint (FP), palmprint (PP), and earprint (EP).

A. DATABASES

The images for earprint, fingerprint, and palmprint are obtained from the multi-biometric database [30]. This database was constructed using three unimodal databases, namely, FVC2002-DB1-A fingerprint database [45], COEP palmprint database [46] and AMI earprint database [47], respectively. This multi-biometric database contains 150 images for each of the modalities, more specifically, 25 subjects and 6 samples per individual from FVC2002-DB1-A, COEP and AMI databases. Sample images for the three modalities are shown in Fig. 5.

B. PERFORMANCE RESULTS

Features and matching scores are generated for the three modalities using the techniques presented in [44], [48]. In a biometric system, genuine acceptance rate (GAR) and false rejection rate (FRR) are the ratios of the number of genuine subjects accepted and false subjects rejected, respectively, for a predefined threshold to the total number of enrolled subjects [4]. The lower the value of EER, higher the value of GAR and lower the value of FRR at a lower FAR, the better is the biometric system. The performance of a multi-biometric system is measured in terms of EER, GAR @0.5% FAR and FRR @0.5% FAR. Receiver operating characteristics (ROCs) and detection error tradeoff (DET) curves [49] are generated in terms of the false acceptance rate as a function of the genuine acceptance rate and the false rejection rate, respectively.

We now study the performance of the proposed MPb fusion scheme and compare it with that of the score level (SL) fusion scheme. For this purpose, we employ the various existing weighting techniques and various normalization techniques, including the one proposed in this paper. Table 1 gives EER, GAR @0.5% FAR and FRR @0.5% FAR provided by the two fusion schemes. The various weighting techniques employed are equal error rate weighted (EERW) [34], d-prime weighted (DPW) [34], fisher discriminant ratio weighted (FDRW) [50], score reliability based weighted (SRBW) [51], confidence based weighted (CBW) [33]) techniques, while the various normalization methods employed are min-max (MM) [38], z-score [38], performance anchored min-max (PAN-MM) [36], TanH [38], improved anchored min-max

TABLE 1. EER(%), GAR @0.5% FAR, and FRR @0.5% FAR provided by the proposed MPb fusion scheme and SL fusion scheme with various weighting and normalization techniques for the multi-biometric database.

Normalization techniques \ Weighting methods		EERW	DPW	FDRW	SRBW	CBW
	SL Fusion					
MM	EER(%)	**0.54**	1.34	2.66	0.79	**0.54**
	GAR @0.5% FAR	**99.47**	98.4	94.93	98.67	**99.47**
	FRR @0.5% FAR	**0.53**	1.6	5.07	1.33	**0.53**
OEBAMM	EER(%)	0.56	**0.54**	1.33	1.33	**0.54**
	GAR @0.5% FAR	99.2	**99.47**	98.67	97.6	**99.47**
	FRR @0.5% FAR	0.8	**0.53**	1.33	2.4	**0.53**
MOEBAMM	EER(%)	0.56	**0.54**	1.34	1.07	**0.54**
	GAR @0.5% FAR	99.2	**99.47**	98.67	97.33	**99.47**
	FRR @0.5% FAR	0.8	**0.53**	1.33	2.67	**0.53**
OEVBAMM (proposed)	EER(%)	**0.54**	3.41	4.53	1.6	1.06
	GAR @0.5% FAR	**99.47**	94.67	92.8	97.07	98.4
	FRR @0.5% FAR	**0.53**	5.33	7.2	2.93	1.6
	Proposed MPb Fusion Scheme					
MM	EER(%)	3.15	1.07	1.34	2.39	0.83
	GAR @0.5% FAR	92.8	96.53	96.27	96	98.67
	FRR @0.5% FAR	7.2	3.47	3.73	4	1.33
Z-score	EER(%)	3.47	3.2	3.2	3.2	2.93
	GAR @0.5% FAR	90.13	92.53	92.53	91.2	93.33
	FRR @0.5% FAR	9.87	7.47	7.47	8.8	6.67
PAN-MM	EER(%)	3.2	1.08	1.39	2.39	0.8
	GAR @0.5% FAR	92.8	96.53	96.53	95.47	98.67
	FRR @0.5% FAR	7.2	3.47	3.73	4.53	1.33
TanH	EER(%)	3.2	1.86	2.12	2.66	1.34
	GAR @0.5% FAR	92.27	95.47	95.2	94.4	97.6
	FRR @0.5% FAR	7.73	4.53	4.8	5.6	2.4
IAMM	EER(%)	3.2	2.13	2.39	2.93	1.08
	GAR @0.5% FAR	92.53	96	95.47	93.87	96.53
	FRR @0.5% FAR	8	4	4.53	6.13	3.47
OEBAMM	EER(%)	3.2	2.4	2.67	2.94	1.33
	GAR @0.5% FAR	92	96	95.2	93.87	96.27
	FRR @0.5% FAR	8.27	4	4.8	6.13	3.73
MOEBAMM	EER(%)	3.2	2.67	2.87	2.96	1.89
	GAR @0.5% FAR	91.47	95.2	94.4	93.07	96
	FRR @0.5% FAR	9.07	4.8	5.6	6.93	4
OEVBAMM (proposed)	EER(%)	2.67	1.03	0.8	1.11	**0.47**
	GAR @0.5% FAR	94.93	98.67	98.67	96.53	**99.73**
	FRR @0.5% FAR	5.07	1.33	1.33	3.47	**0.27**

(IAMM) [41], overlap extrema-based anchored min-max (OEBAMM) [33], mean-to-overlap extrema-based anchored min-max (MOEBAMM) [33]) as well as the proposed overlap extrema-variation based anchored min-max (OEVBAMM) normalization technique. In this table, the best results corresponding to the lowest EER, the highest GAR @0.5% FAR, and the lowest FRR @0.5% FAR, for each of the fusion schemes are indicated by boldfaced fonts. It is seen from this table that there are 7 combinations of normalization and weighting techniques that offer the same best performance for the SL fusion scheme. It is also seen from Table 1 that, for a given weighting technique (except for the EERW), the MPb fusion scheme with the proposed OEVBAMM normalization technique provides a performance superior to that provided

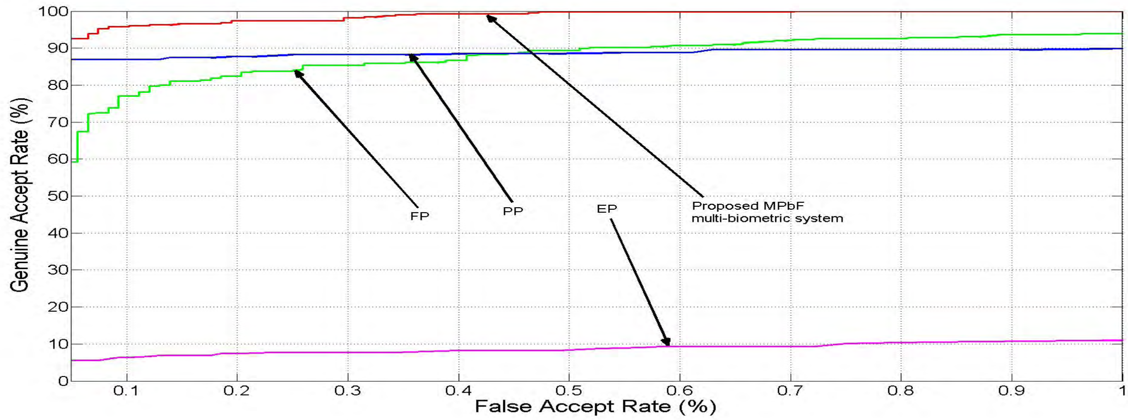


FIGURE 6. ROC performance of the unimodal (namely, FP, PP, and EP) biometric systems and the proposed MPbF multi-biometric system.

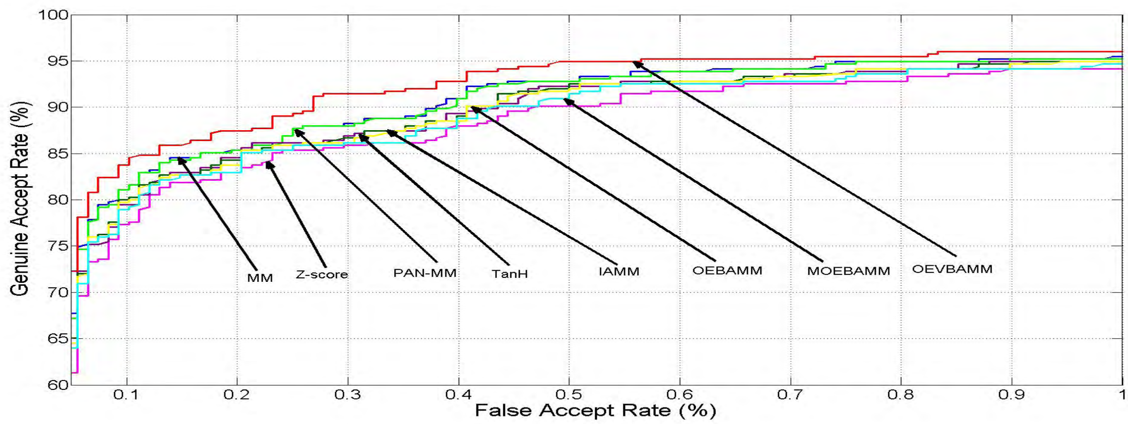


FIGURE 7. ROC performance of the proposed MPb fusion scheme employing various normalization techniques and the EERW weighting method.

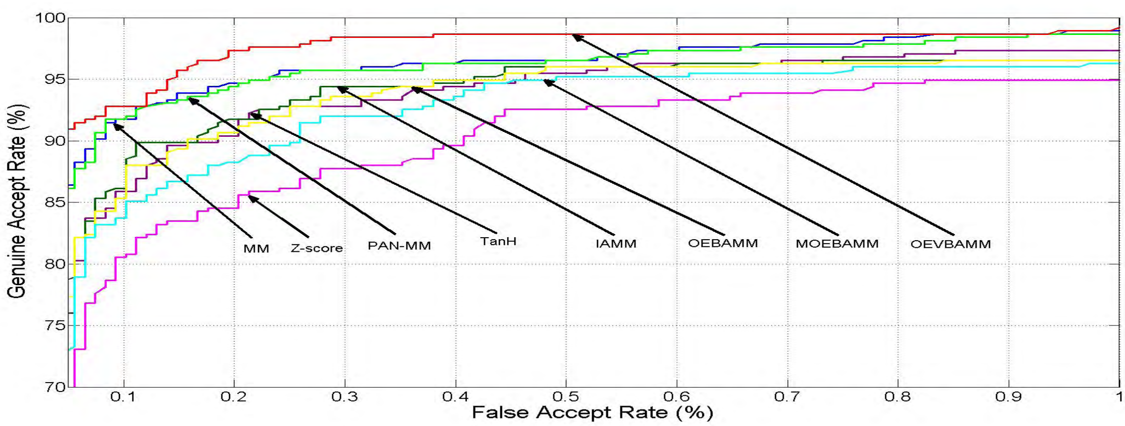


FIGURE 8. ROC performance of the proposed MPb fusion scheme employing various normalization techniques and the DPW weighting method.

by the SL fusion scheme using any of the normalization techniques. Further, the best performance is provided by the proposed MPb fusion scheme using the OEVBAMM normalization technique proposed in this paper along with the CBW weighting technique that was previously proposed by the authors in [30]. We refer to this system with this combination as the MPbF multi-biometric system.

We now measure the processing time per image required by the SL fusion scheme with normalization and weighting techniques for the 7 cases that provide the lowest EER value

TABLE 2. Processing time (in seconds) required by the proposed MPb fusion scheme and SL fusion scheme with various weighting and normalization techniques for the multi-biometric database.

Normalization techniques \ Weighting methods	EERW	DPW	FDRW	SRBW	CBW
			SL Fusion		
MM	11.2	-	-	-	11.2
OEBAMM	-	11.2	-	-	11.2
MOEBAMM	-	11.2	-	-	11.2
OEVBAMM (proposed)	11.2	-	-	-	-
			Proposed MPb Fusion Scheme		
OEVBAMM (proposed)	1.1	1.1	1.1	1.1	1.1

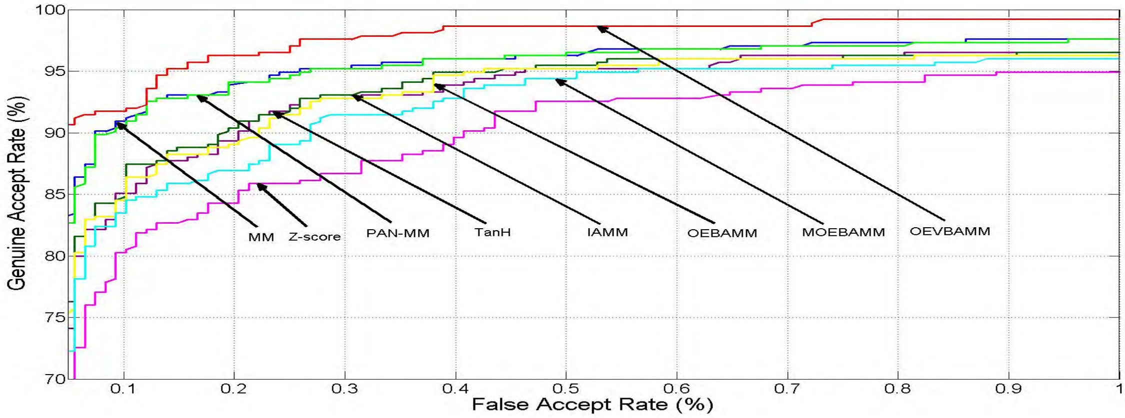


FIGURE 9. ROC performance of the proposed MPb fusion scheme employing various normalization techniques and the FDRW weighting method.

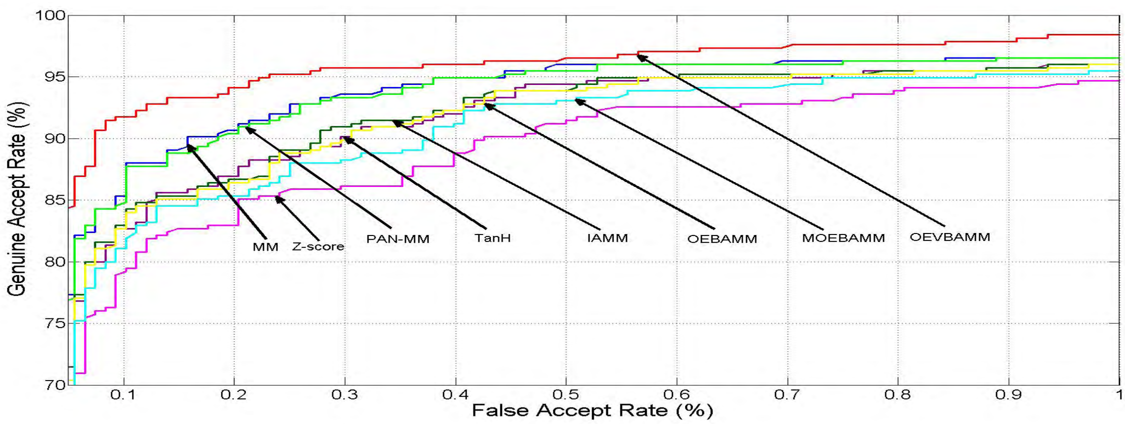


FIGURE 10. ROC performance of the proposed MPb fusion scheme employing various normalization techniques and the SRBW weighting method.

of 0.54%, highest GAR value of 99.47% @0.5 FAR, lowest FRR value of 0.53% @0.5 FAR, as well as for the proposed MPb fusion scheme with the proposed OEVBAMM normalization technique and various weighting techniques. These measured processing times are given in Table 2. It is to be noted that the processing time is measured including the time taken for feature extraction, feature encoding, matching, normalization and weighting of scores. We have run the experiment using MATLAB 2014 in the environment of Windows PC platform with a 2.93 GHz Intel(R) Core(TM) i7 CPU and 8 GB RAM. It can be seen from Table 2 that the SL fusion scheme requires the same processing time of 11.2 (seconds) per image for the 7 cases. In other words, if SL fusion scheme is used in a multi-biometric system, then any one of the 7 combinations of normalization and weighting techniques would offer the best performance with the same computational load. Table 2 also shows that the proposed MPb fusion scheme with the proposed OEVBAMM

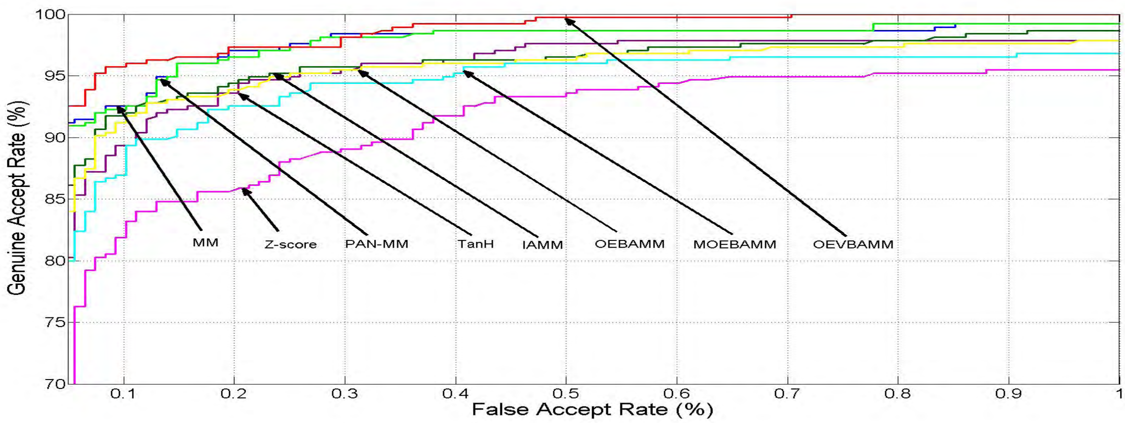


FIGURE 11. ROC performance of the proposed MPb fusion scheme employing various normalization techniques and the CBW weighting method.

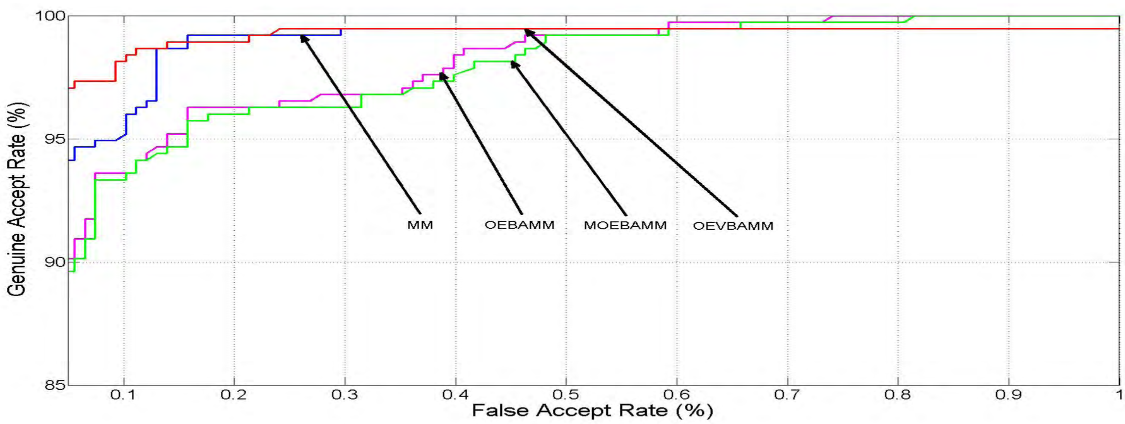


FIGURE 12. ROC performance of the SL fusion scheme employing various normalization techniques and the EERW weighting method.

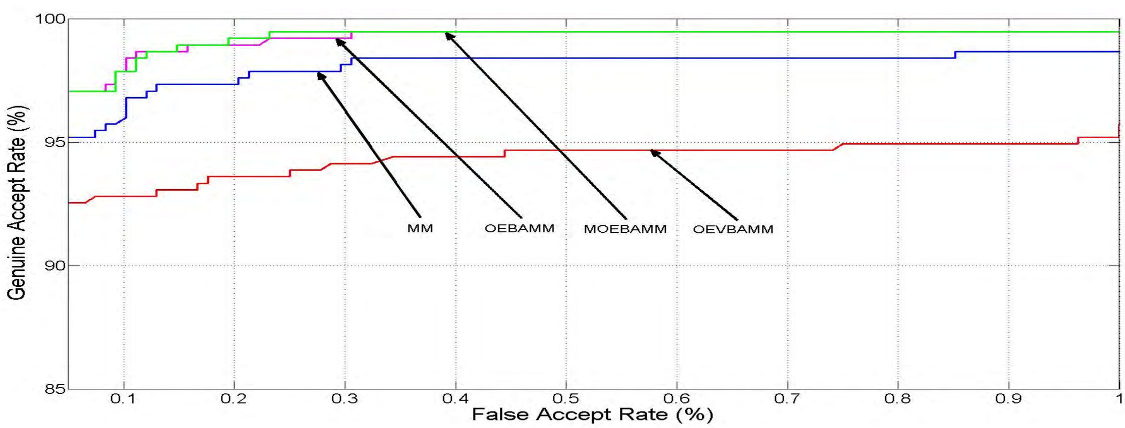


FIGURE 13. ROC performance of the SL fusion scheme employing various normalization techniques and the DPW weighting method.

normalization technique and various weighting techniques requires a processing time of 1.1 (seconds) per image irrespective of the weighting method used, which is about one-tenth of that required by the SL fusion scheme. Therefore, the proposed MPb fusion scheme is a better choice than the SL fusion scheme in terms of the processing time per image. Hence, it can be concluded that the proposed MPbF multi-biometric system is the best choice in terms of not only EER,

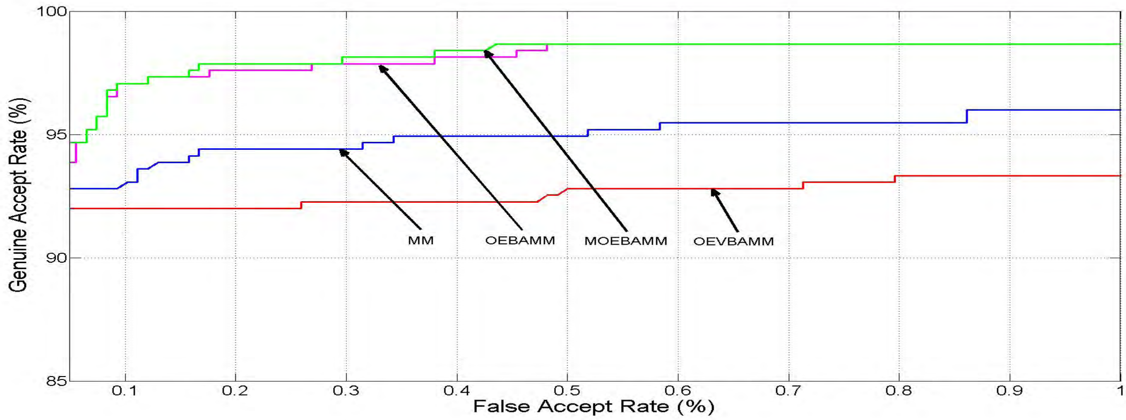


FIGURE 14. ROC performance of the SL fusion scheme employing various normalization techniques and the FDRW weighting method.

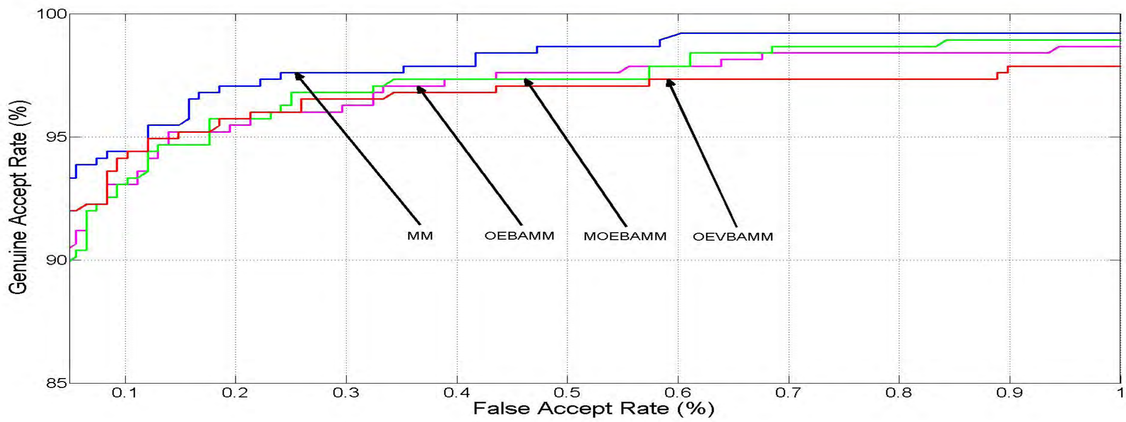


FIGURE 15. ROC performance of the SL fusion scheme employing various normalization techniques and the SRBW weighting method.

GAR @0.5% FAR, and FRR @0.5% FAR, but also in terms of the processing time.

Fig. 6 shows the ROC curves of the unimodal biometric systems (namely, FP, PP and EP), and for the proposed MPbF multi-biometric system. It can be seen from this figure that the proposed MPbF multi-biometric system provides a performance superior to that provided by any of the uni-biometric systems in terms of GAR irrespective of the value of FAR.

Figs. 7-11 show the ROC curves for a multi-biometric system using the proposed MPb fusion scheme with various normalization methods for a given weighting technique. As seen from these figures, the performance of the proposed MPb fusion scheme using the proposed OEVBAMM normalization technique is superior to that using the existing normalization techniques with any of the weighting techniques.

Figs. 12-16 show the ROC curves for a multi-biometric system using the SL fusion scheme with various normalization methods for a given weighting technique. It can be seen from Fig. 12 that the SL fusion scheme using the OEBAMM normalization technique provides a GAR value of 100% at a lower FAR than that provided at a higher FAR using the existing normalization techniques with the EERW weighting technique. Figs. 13 and 14 show that the SL fusion scheme using the MOEBAMM normalization technique provides a GAR value, which is higher than that provided using the existing normalization techniques with the DPW and FDRW weighting techniques, respectively. Fig. 15 shows that the SL fusion scheme using the MM normalization technique provides a GAR value, which is higher than that provided using the existing normalization techniques with the SRBW weighting technique. It is seen from Fig. 16 that the SL fusion scheme using the MOEBAMM normalization technique provides a GAR value of 100% at a lower FAR than that provided at a higher FAR using the existing normalization techniques with the CBW weighting technique.

Fig. 17 shows the best ROC curves for a multi-biometric system using the proposed MPb fusion scheme with the proposed OEVBAMM normalization technique and with various weighting techniques, taken from Figs. 7, 8, 9, 10 and 11. It is seen from Fig. 17 that the proposed MPbF multi-biometric system provides a GAR value of 100% at a lower FAR than

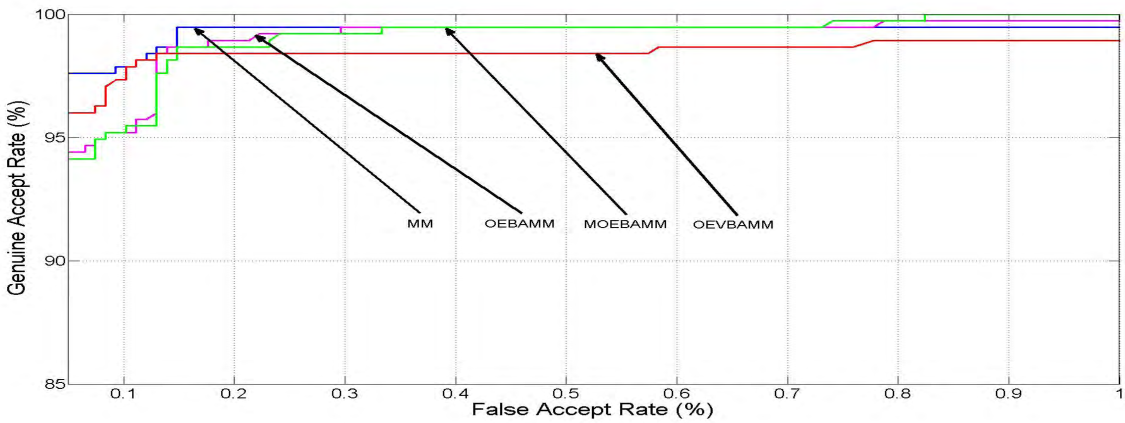


FIGURE 16. ROC performance of the SL fusion scheme employing various normalization techniques and the CBW weighting method.

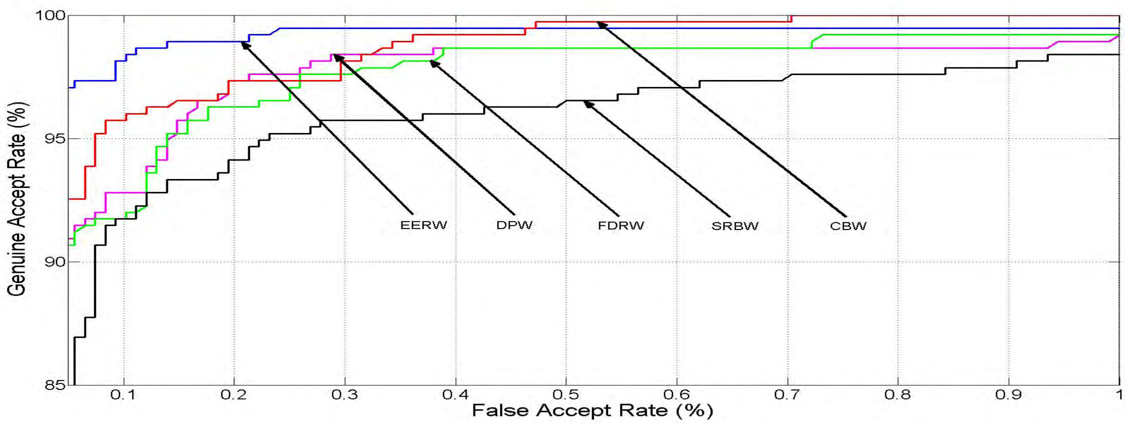


FIGURE 17. ROC performance of the MPb fusion scheme with OEVBAMM normalization technique and various weighting techniques.

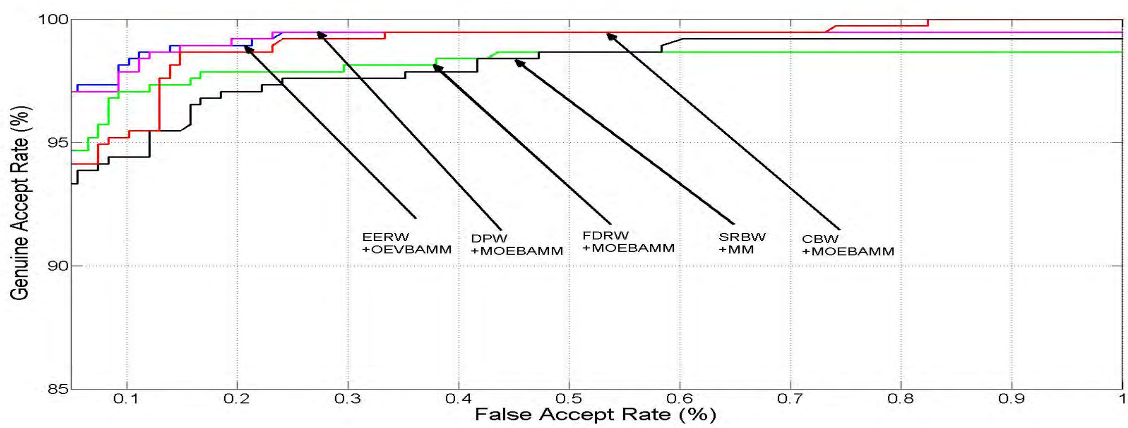


FIGURE 18. ROC performance of the SL fusion scheme using OEVBAMM with EERW, MOEBAMM with DPW, FDRW and CBW, and MM with SRBW.

that provided at a higher FAR by the MPb fusion scheme using the proposed normalization technique with the other weighting techniques.

Fig. 18 shows the best ROC curves for the SL fusion scheme taken from Figs. 12, 13, 14, 15 and 16. It is seen from this figure that the SL fusion scheme using the MOEBAMM normalization technique and the CBW weighting method provides a GAR value of 100% at a lower FAR than that provided at a higher FAR using the other normalization and weighting techniques.

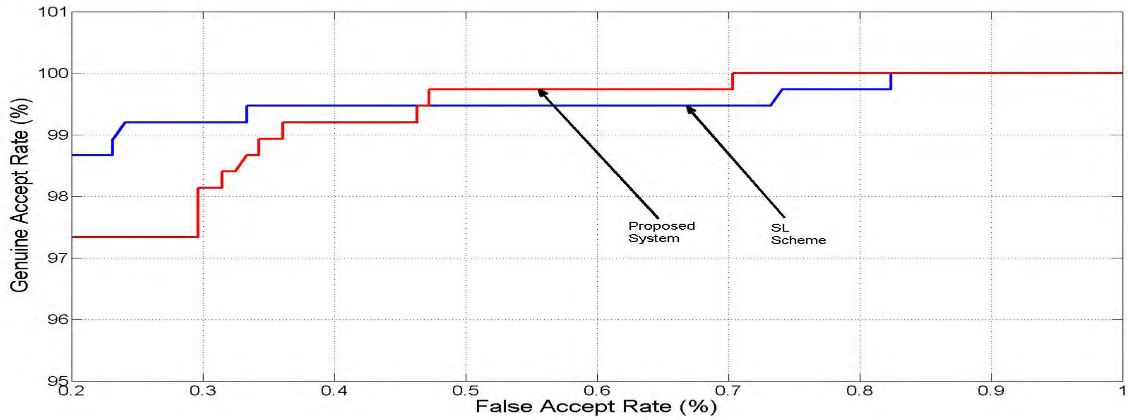


FIGURE 19. ROC performance of the proposed MPbF multi-biometric system and that of the best SL fusion scheme.

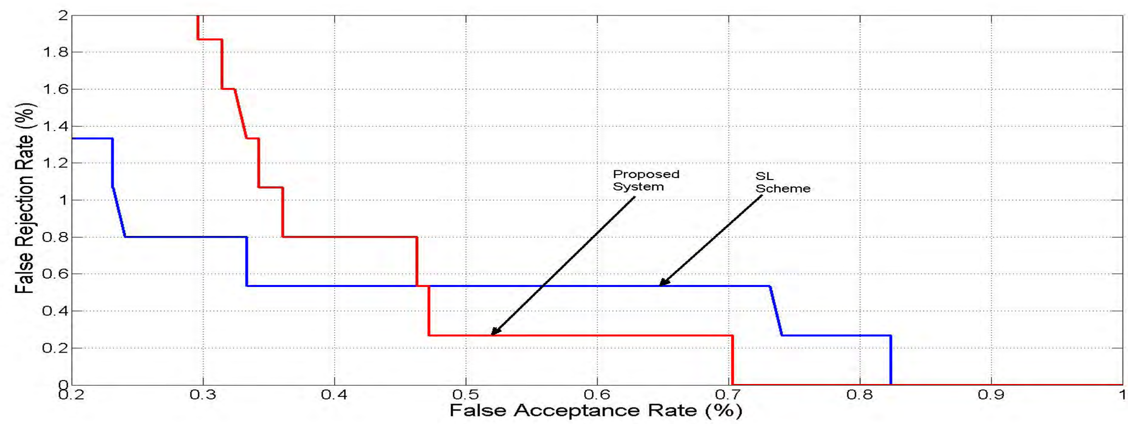


FIGURE 20. DET performance of the proposed MPbF multi-biometric system and that of the best SL fusion scheme.

Fig. 19 shows the ROC curves for the proposed MPbF multi-biometric system and for the best multi-biometric system using the SL fusion scheme, taken from Figs. 17 and 18. This figure shows that the proposed MPbF multi-biometric system provides a value of GAR, which is higher than that provided by the best SL fusion scheme. Hence, the former provides a performance superior to that provided by the latter.

Fig. 20 shows the DET curves for the proposed MPbF multi-biometric system and for the multi-biometric system using the SL fusion scheme with the MOEBAMM normalization technique and CBW weighting method, which has been shown to have the best ROC performance. It is seen from this figure that the proposed MPbF multi-biometric system provides a value of FRR lower than that provided by the SL fusion scheme with the MOEBAMM normalization technique and CBW weighting method. Thus, the former provides a DET performance superior to that provided by the latter.

V. CONCLUSION

In this paper, we have presented a new scheme for fusion that is carried out at two levels, feature and score levels. Three modalities have been fused using the proposed fusion scheme, referred to as the *matcher performance-based (MPb)* fusion scheme. The fusion is carried out in two stages, for the feature and score level fusions, respectively. The two of the modalities for which the EER is not the least are first fused using their encoded features. In the second stage of fusion, the score obtained from the feature-level fusion and that from the modality that provides the lowest EER are fused by employing various normalization and weighting techniques, including a proposed normalization technique, referred to as the *overlap extrema-variation-based anchored min-max (OEVBAMM)* normalization technique, that utilizes the extrema and the variations of the genuine and impostor score sets.

The performance of the proposed MPb fusion scheme has been evaluated using three traits, fingerprint, palmprint and earprint. The experimental results have shown that the proposed MPbF multi-biometric system comprising the MPb fusion scheme along with the OEVBAMM normalization technique and the CBW weighting technique provides values of EER, GAR @0.5% FAR, and FRR @0.5% FAR superior to that provided by the score level fusion scheme irrespective of the normalization method or of the weighting technique used. Further, it has been shown that the proposed MPbF multi-biometric system requires a much lower processing time than that required by the score level fusion scheme. The ROC curves have shown that the proposed multi-biometric system provides a value of GAR that is higher than that provided by the score level fusion scheme, and the DET curves have shown that the former provides a value of FRR that is lower than that provided by the latter.

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