Unification of Evidence Theoretic Fusion Algorithms: A Case Study in Level-2 and Level-3 Fingerprint Features

Mayank Vatsa, Richa Singh, and Afzel Noore

Abstract—**This paper formulates an evidence theoretic multimodal fusion approach using belief functions that takes into account the variability in image characteristics. When processing non-ideal images the variation in the quality of features at different levels of abstraction may cause individual classifiers to generate conflicting genuine-impostor decisions. Existing fusion approaches are non-adaptive and do not always guarantee optimum performance improvements. We propose a contextual unification framework to dynamically select the most appropriate evidence theoretic fusion algorithm for a given scenario. The effectiveness of our approach is experimentally validated by fusing match scores from level-2 and level-3 fingerprint features. Compared to existing fusion algorithms, the proposed approach is computationally efficient, and the verification accuracy is not compromised even when conflicting decisions are encountered.**

I. INTRODUCTION

In real world applications, the performance of unimodal biometric systems may suffer due to issues such as non-universality, non-permanence, intraclass variations, poor image quality, noisy data, and matcher limitations [1]. Thus, verification based on unimodal biometric system is not always reliable. To overcome the limitations of unimodal biometrics and improve the verification performance, researchers have proposed fusing multiple biometric information. Fusion can be performed at different levels such as data fusion, feature fusion, match score fusion, and decision fusion [1], [2].

Biometric fusion algorithms yield good performance for some applications or under certain conditions but not universally for all scenarios. For instance, sum rule [1] yields good performance when the match scores are linearly separable, whereas kernel methods perform better with non-linear data. Furthermore, the performance of existing match score fusion algorithms decreases when biometric classifiers yield conflicting results. For example, if one biometric classifier generates a match score which corresponds to *accept* and another provides a match score which corresponds to *reject* for the same individual, existing fusion algorithms are not able to efficiently perform fusion and matching. The sum rule is very efficient in terms of time complexity but does not provide good performance when dealing with conflicting cases. The authors recently proposed match score fusion algorithms [3], [4] using Dezert Smarandache (DSm) theory of plausible and paradoxical reasoning [5], [6] to efficiently fuse conflicting results. DSm fusion provides better performance at the expense of higher time complexity. Veeramachaneni *et al.* [7] proposed an adaptive multimodal decision fusion algorithm in which they used particle swarm optimization for adaptively fusing the decision fusion rules to improve the recognition accuracy.

In this paper, we propose a unification framework to efficiently address both accuracy and time complexity when fusing biometric information. Our hypothesis is that unification or reconciliation of multiple fusion algorithms should satisfy most of the application requirements and yield better recognition performance. Inspired from Smarandache's theoretical concept [8], the unification framework may include a collection of fusion algorithms. Depending on the evidence obtained from the input probe data, the framework dynamically selects an appropriate fusion algorithm. Specifically in this paper, we propose a novel unification framework using two match score fusion algorithms. Existing match score fusion algorithms can be classified into three categories: statistical fusion algorithms [2], learning based fusion algorithms [9], and evidence theory based fusion algorithms [10]. Previous studies have established that augmenting the evidence obtained from representative training data with the input probe data enhances the recognition performance [3], [11], [12]. In the proposed unification framework, we therefore formulate the evidence theoretic fusion algorithms. The first match score fusion algorithm in the proposed unification framework is the evidence theoretic sum rule which is based on basic probability assignments computed from the match scores. Compared to the traditional sum rule [1], the proposed evidence theoretic sum rule incorporates prior information in terms of image quality and verification accuracy computed using the training dataset. The second fusion algorithm included in this framework is the DSm fusion algorithm [4]. This fusion algorithm is based on the theory of plausible and paradoxical reasoning and can optimally fuse the match scores even with conflicting results. The two match score fusion algorithms are then unified for improved verification performance.

To validate the proposed algorithms, we use fingerprint biometrics as the case study. Fingerprint images are chosen for this research because the level-2 minutiae features and level-3 pore features [13] obtained from fingerprint provide complementary information [14], [15] and are widely used by forensic researchers to establish or verify the identity of an individual. Fig. 1 shows an example of minutiae and pore features. Presently, there is limited research undertaken in

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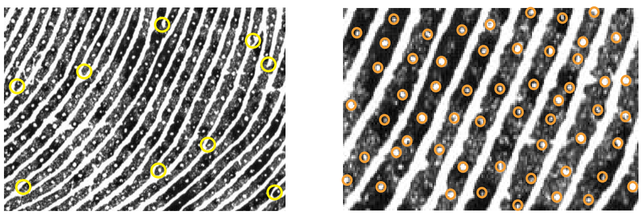
M. Vatsa, R. Singh, A. Noore are with Lane Department of Computer Science and Electrical Engineering, West Virginia University, Morgantown, WV, USA {mayankv, richas, noore}@csee.wvu.edu

fusing level-2 and level-3 fingerprint information [3], [14], [15]. Jain *et al.* [14] showed that fusing level-2 and level-3 match scores using min-max normalization and sum rule fusion improves the verification performance. Jain *et al.* [15] further proposed a hierarchical matching scheme which outperforms the sum rule fusion algorithm. Vatsa *et al.* [3] proposed DSm fusion algorithm which efficiently models the conflicting region of level-2 and level-3 match scores and yields a verification accuracy of 97.98%. A disadvantage of this algorithm is that the computational time is high compared to sum rule fusion. The unification framework adaptively selects appropriate fusion algorithm to maximize the recognition performance without significantly increasing the computational time.



(a) (b)

Fig. 1. Fingerprint images with (a) minutia features, (b) pore features.

In this paper, we first present the evidence theoretic formulation of sum rule and DSm fusion in Section II. We extend these fusion algorithms for biometric match score fusion in Section III. The proposed unification framework and adaptive fusion rules are described in Section IV. The characteristics of fingerprint database and algorithms used for validation are described in Section V. The experimental results are summarized and discussed in Section VI.

II. EVIDENCE THEORETIC FORMULATION OF SUM RULE AND DSM FUSION

In this section, we present the evidence theoretic formulation of sum rule and DSm theory using belief function models. Since biometric verification is a two class problem with the classes being *genuine* and *impostor*, both the fusion algorithms are formulated as a two class problem. Belief functions are defined on the frame of discernment which consists of a finite set of exhaustive and mutually exclusive hypothesis. Let $\Theta = \{\theta_{gen}, \theta_{imp}\}$ be the frame of discernment, and θ_{gen} and θ_{imp} be the hypothesis belonging to *genuine* and *impostor* classes respectively.

A. Formulation of Evidence Theoretic Sum Rule Fusion

In evidence theoretic sum rule, the belief function which is also known as the basic probability assignment (*bpa*) is defined as $\overline{m}(\cdot) = \Theta \rightarrow [0, 1]$, such that $\overline{m}(\theta_{gen}) + \overline{m}(\theta_{imp}) = 1$. Here $\overline{m}(\theta_{gen})$ represents the belief of data being *genuine* and $\overline{m}(\theta_{imp})$ represents the belief of data being *impostor*.

Match scores from different classifiers are transformed into basic probability assignments, $\overline{m}_1(\cdot)$ and $\overline{m}_2(\cdot)$, and fused using (1) and (2).

$$\overline{m}_{fused}(\theta_{gen}) = \frac{\overline{m}_1(\theta_{gen}) + \overline{m}_2(\theta_{gen})}{2} \tag{1}$$

$$\overline{m}_{fused}(\theta_{imp}) = \frac{\overline{m}_1(\theta_{imp}) + \overline{m}_2(\theta_{imp})}{2} \tag{2}$$

A decision to *accept* is made if $\overline{m}_{fused}(\theta_{gen}) > \overline{m}_{fused}(\theta_{imp})$, otherwise a decision to *reject* is made.

B. Formulation of Evidence Theoretic DSm Fusion

In contrast to set theory and basic probability assignment, DSm theory [5], [6] uses belief function, also known as generalized basic belief assignment (*gbba*), and operates on the hyperpower set, $D^{\Theta} = \{\emptyset, \theta_{gen}, \theta_{imp}, \theta_{gen} \cup \theta_{imp}, \theta_{gen} \cap \theta_{imp}\}$. Generalized basic belief assignment is defined as $m(\cdot) = D^{\Theta} \rightarrow [0, 1]$ so that the conditions described in (3) are satisfied.

$$\begin{aligned} & m(\emptyset) = 0 \\ & m(\theta_{gen}) + m(\theta_{imp}) + m(\theta_{gen} \cup \theta_{imp}) \\ & + m(\theta_{gen} \cap \theta_{imp}) = 1. \end{aligned} \tag{3}$$

Similar to evidence theoretic sum rule, $m(\theta_{gen})$ and $m(\theta_{imp})$ are the genuine and impostor beliefs respectively. Further, $m(\theta_{gen} \cap \theta_{imp})$ represents the belief for conflicting region and $m(\theta_{gen} \cup \theta_{imp})$ is the belief that the data belongs to the genuine-impostor feature space. In general, a match is performed with only enrolled identities and the input data belongs to the genuine-impostor feature space. Therefore the value of $m(\theta_{gen} \cup \theta_{imp})$ is set to 0.01. DSm rule of combination for fusing match scores from two classifiers is shown in (4) [5], [6].

$$m_{fused}(A) = \psi(A) \left[S_1(A) + S_2(A) + S_3(A) \right] \tag{4}$$

where, $\psi(A)$ is the characteristic non-emptiness function of A which is 1 if $A \notin \emptyset$ and 0 otherwise. $S_1(A)$, $S_2(A)$, and $S_3(A)$ are defined as,

$$\begin{aligned} S_1(A) = & \sum_{(X, Y \in D^{\Theta}, X \cap Y = A)} m_1(X)\, m_2(Y) \\ S_2(A) = & \sum_{(X, Y \in \mathbf{\Phi}, [\upsilon = A] \vee [(\upsilon \in \mathbf{\Phi}) \wedge (A = I_t)])} m_1(X)\, m_2(Y) \\ S_3(A) = & \sum_{(X, Y \in D^{\Theta}, X \cup Y = A,\ X \cap Y \in \mathbf{\Phi})} m_1(X)\, m_2(Y) \end{aligned}$$

where I_t is the total ignorance and is the union of all θ_i ($i = 1, 2$), i.e. $I_t = \theta_1 \cup \theta_2$. $\mathbf{\Phi} = \{\mathbf{\Phi}, \phi\}$ is the set of all elements of D^{Θ} which are empty under the constraints of some specific problem, and ϕ is the empty set. $\upsilon = u(X) \cup u(Y)$, where $u(X)$ is the union of all singletons θ_i that compose X and Y. Here, $S_1(A)$ corresponds to the classical DSm rule on the free DSm model [5], $S_2(A)$ represents the mass of all relatively and absolutely empty sets which is transferred to the total or relative ignorance, and $S_3(A)$ transfers the sum of relative empty sets to the non-empty sets. Detailed explanation of DSm theory is presented in [6].

After fusing the match scores using DSm theory, a decision to *accept* is made if $[m_{fused}(\theta_{gen}) + m_{fused}(\theta_{gen} \cap \theta_{imp})] > m_{fused}(\theta_{imp})$, otherwise a decision to *reject* is made.

III. BIOMETRIC MATCH SCORE FUSION

The evidence theoretic fusion rules described in Section II cannot be directly applied to biometric match score fusion. Match scores obtained from different classifiers are first converted into belief functions and then the fusion rules are applied on the belief functions. In this section, we describe the algorithm for transforming the match scores into belief functions.

A. Match Score Fusion using Evidence Theoretic Sum Rule

Let s_1 and s_2 be the two match scores to be fused. In evidence theoretic sum rule, let us assume that the distribution of match scores for every element of Θ is a Gaussian distribution.

$$p(s_i, \overline{\mu}_{ij}, \overline{\sigma}_{ij}) = \frac{1}{\overline{\sigma}_{ij}\sqrt{2\pi}} exp\left[-\frac{1}{2}\left\{\frac{s_i - \overline{\mu}_{ij}}{\overline{\sigma}_{ij}}\right\}^2\right] \quad (5)$$

where $\overline{\mu}_{ij}$ and $\overline{\sigma}_{ij}$ are the mean and standard deviation of the i^{th} classifier corresponding to the j^{th} element of Θ. The Gaussian distribution is used to compute the basic probability assignment $\overline{m}_i(j)$,

$$\overline{m}_i(j) = \frac{p(s_i, \overline{\mu}_{ij}, \overline{\sigma}_{ij})\overline{\beta}_{ij}}{\sum_{j=1}^{\Theta} p(s_i, \overline{\mu}_{ij}, \overline{\sigma}_{ij})\overline{\beta}_{ij}} \quad (6)$$

where $\overline{\beta}_{ij}$ is the weight factor of classifier i corresponding to the j^{th} element of Θ. $\overline{\beta}_{ij}$ is defined as,

$$\overline{\beta}_{ij} = Q\overline{V}_{ij} \quad (7)$$

where Q is the quality score of the input probe image and $\overline{V}_{ij}$ is the verification accuracy computed on the training database. Quality score is computed using the redundant discrete wavelet transform based quality assessment algorithm described in [3]. Values of both Q and $\overline{V}_{ij}$ lie in the range of [0, 1]. Basic probabilistic assignments, $\overline{m}_i(j)$, are fused using (1) and (2), and a decision of *accept* or *reject* is made based on the fused *bpa*.

B. Match Score Fusion using Evidence Theoretic DSm Theory

Similar to evidence theoretic sum rule, generalized basic belief assignments (gbba) of DSm fusion, $m_i(j)$, are computed using the Gaussian distribution over D^{Θ}.

$$m_i(j) = \frac{p(s_i, \mu_{ij}, \sigma_{ij})\beta_{ij}}{\sum_{j=1}^{|D^{\Theta}|-1} p(s_i, \mu_{ij}, \sigma_{ij})\beta_{ij}} \quad (8)$$

where μ_{ij}, σ_{ij}, and β_{ij} are the mean, standard deviation, and weight factor of the i^{th} classifier corresponding to the j^{th} element of D^{Θ}. β_{ij} is defined as,

$$\beta_{ij} = QV_{ij} \quad (9)$$

Here, V_{ij} is the verification accuracy computed on the training database and Q is the quality score [3] of the probe image. Finally, generalized basic belief assignments $m_i(j)$ are fused using the DSm rule of combination (4) and a decision of *accept* or *reject* is made based on the fused *gbba*.

IV. UNIFICATION OF FUSION RULES

In this section, we describe the proposed unification framework in which evidence theoretic sum rule and DSm fusion algorithms are reconciled to obtain better performance. Fig. 2 shows the steps involved in the proposed unification framework. The procedure for unification is described as follows:

1) $\overline{m}_i(j)$ is computed over $\Theta = \{\theta_{gen}, \theta_{imp}\}$ where $i = 1, 2$ and $j \in \Theta$. Thus the evidence theoretic sum rule is used if the conditions in (10) or (11) are satisfied.

$$\begin{array}{l} \overline{m}_1(\theta_{gen}) > \overline{m}_1(\theta_{imp}) + \epsilon_1 \\ \overline{m}_2(\theta_{gen}) > \overline{m}_2(\theta_{imp}) + \epsilon_2 \end{array} \quad (10)$$

$$\begin{array}{l} \overline{m}_1(\theta_{gen}) + \epsilon_1 < \overline{m}_1(\theta_{imp}) \\ \overline{m}_2(\theta_{gen}) + \epsilon_2 < \overline{m}_2(\theta_{imp}) \end{array} \quad (11)$$

   where, ϵ_1 and ϵ_2 are the error parameters of the two classifiers.

2) If the above conditions are not satisfied, i.e., when both the match scores provide conflicting results, then we apply the DSm fusion algorithm. In such cases, $m_i(j)$ is computed over $D^{\Theta} = \{\theta_{gen}, \theta_{imp}, \theta_{gen} \cup \theta_{imp}, \theta_{gen} \cap \theta_{imp}\}$. The match score fusion is performed using (4) and the identity is verified.

The proposed unification framework combines two fusion algorithms to improve the verification accuracy and decrease the computational time. The framework can be further generalized to include other fusion schemes with more than two classifiers for multimodal biometric scenarios.

V. DATABASE AND ALGORITHMS USED FOR VALIDATION

The proposed unification framework is validated using level-2 minutiae and level-3 pores based fingerprint recognition algorithm on a 1000 ppi fingerprint database. In this section, we briefly describe the database and the algorithms used for validation.

A. Fingerprint Database

To validate the proposed unification framework, a fingerprint database obtained from law enforcement agency is used. This database contains 5500 images from 550 classes. For each class, there are 10 fingerprints. The resolution of fingerprint images is 1000 ppi to facilitate the extraction of both level-2 and level-3 features. From each class, three fingerprints are selected for training and the remaining seven images per class are used as gallery and probe. We thus have 11,550 genuine matches $\left(\frac{550 \times 7 \times 6}{2}\right)$ and 7,397,775 impostor matches $\left(\frac{550 \times 7 \times 549 \times 7}{2}\right)$ using the gallery and probe database.

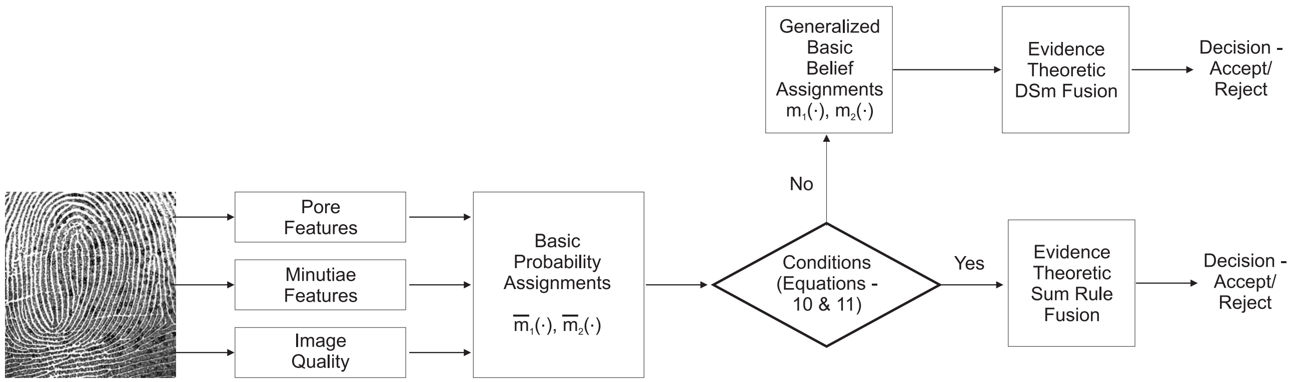


Fig. 2. The proposed unification framework to combine evidence theoretic sum rule and DSm fusion using match scores obtained from pore and minutia features.

B. Algorithms used for Validation

Fingerprint image quality and match scores corresponding to minutiae and pore features are computed using existing image quality assessment and feature extraction algorithms which are briefly described below.

Redundant Discrete Wavelet Transform based Quality Assessment Algorithm: RDWT image quality assessment algorithm [3] is used to compute the quality score, Q, of fingerprint images. The algorithm extracts the edge regions, non-edge regions and noisy regions, and assigns appropriate weights to each subband of RDWT decomposition. This information is combined to generate the composite quality score which provides both frequency and temporal content of fingerprint at different resolution levels.

Minutia-based Verification Algorithm: To extract minutiae from a fingerprint image, a ridge tracing minutiae extraction algorithm [16] is used. The extracted minutiae are matched using a dynamic bounding box based matching algorithm [17]. This algorithm generates a match score, which is normalized in the range of [0, 1] using score normalization technique [18]. If the value of the normalized match score, s_1, is 0, it represents perfect reject and if the normalized match score is 1, it represents perfect accept.

Pore-based Verification Algorithm: To extract the pore features, we use the verification algorithm described by Kryszczuk *et al.* [19], [20]. This algorithm extracts pore information from high resolution fingerprint images by applying different techniques such as correlation based alignment, Gabor filtering, binarization, morphological filtering, and tracing. The match score, s_2, obtained from this algorithm is a normalized similarity score in the range of [0, 1].

Existing Fusion Algorithms used for Comparison: To compare the performance of the proposed unification framework, we use three existing fusion algorithms namely sum rule [2], SVM fusion [9], and Dempster Shafer (DS) theory fusion algorithm [10]. Among the existing algorithms, SVM fusion by Aguilar *et al.* [9] incorporates image quality score with match scores. To evaluate the performance of the SVM fusion algorithm, we use the same quality scores computed using the RDWT quality assessment algorithm [3].

VI. EXPERIMENTAL VALIDATION OF PROPOSED UNIFICATION FRAMEWORK

The performance of the proposed unification framework is validated experimentally by computing the verification accuracy at 0.001% False Accept Rate (FAR) and statistically by computing the Half Total Error Rate (HTER) [12], [21]. We performed two experiments to validate the performance of the proposed evidence theoretic fusion algorithms and the unification framework. The first experiment computes the improvement in verification performance due to level-2 and level-3 match score fusion and the proposed unification framework. The second experiment compares the performance of the proposed evidence theoretic fusion algorithms and unification framework with existing statistical match score fusion algorithm [1], learning based match score fusion algorithm [9], and DS theory based fusion algorithm [10]. The proposed algorithms are first trained using the training database to compute the mean $(\overline{\mu}_{ij}, \mu_{ij})$, standard deviation $(\overline{\sigma}_{ij}, \sigma_{ij})$, verification accuracy $(\overline{V}_{ij}, V_{ij})$, and error parameters (ϵ_1, ϵ_2) for the evidence theoretic fusion and unification.

In the first experiment, we compute the verification performance of level-2 minutiae features, level-3 pore features, evidence theoretic sum rule, DSm fusion, and the unification framework. As shown in Fig. 3 and Table I, level-3 pore features yield a verification accuracy of 89.49% which is 0.52% less than the verification accuracy of level-2 minutiae features. This is because, there are large number of pore features in a fingerprint image and these tend to increase the false rejection. Moreover, the pore extraction algorithm [19] is not reliable when the image is of lower quality due to deformation and other noise factors. When the match scores of level-2 minutiae features and level-3 pore features are fused using the proposed evidence theoretic sum rule, verification accuracy improves by 4.69% compared to level-2 features. DSm fusion algorithm further improves the verification performance and provides an accuracy of 97.6%. The performance of evidence theoretic sum rule reduces when the minutiae-based classifier and pore-based classifier provide conflicting results. In such cases, DSm match score fusion

TABLE I

VERIFICATION PERFORMANCE OF FINGERPRINT VERIFICATION ALGORITHMS, EXISTING FUSION ALGORITHMS, EVIDENCE THEORETIC FUSION ALGORITHMS, AND THE PROPOSED UNIFICATION FRAMEWORK. VERIFICATION ACCURACY IS COMPUTED AT 0.001% FALSE ACCEPT RATE (FAR).

Algorithms	Verification Accuracy	HTER	Confidence Interval			Average Time (seconds)
			90%	95%	99%	
Level-3 Pore Features [19], [20]	89.49	5.25	0.47	0.56	0.74	12
Level-2 Minutiae Features [16], [17]	90.01	4.99	0.46	0.55	0.72	3
Sum Rule [2]	92.08	3.96	0.41	0.49	0.65	15
Evidence Sum Rule	94.70	2.65	0.34	0.41	0.54	16
SVM Fusion [9]	95.15	2.43	0.33	0.39	0.52	18
DS Theory Fusion [10]	95.82	2.09	0.31	0.37	0.48	20
DSm Fusion	97.60	1.20	0.23	0.28	0.37	23
Unification Framework	97.63	1.19	0.23	0.28	0.37	18

algorithm operates on the conflicting region ($\theta_{gen} \cap \theta_{imp}$) and makes the optimal decision using prior information of the unimodal classifiers. The DSm match score fusion algorithm thus provides better verification performance. Finally, the proposed unification framework yields the verification accuracy of 97.63% which is slightly better than the DSm fusion algorithm. We found that there are 334 instances when DSm fusion yields correct classification and evidence theoretic sum rule provides incorrect classification. Further, there are three instances when the DSm fusion produces incorrect results and the evidence theoretic sum rule provides correct results. However, in the proposed unification framework these cases are correctly classified. Another advantage of using the unified framework over the DSm theory is the computation time. As shown in Table I, the average verification time[1] taken by the DSm fusion algorithm (including feature extraction and matching) is approximately 23 seconds whereas with the unification framework, verification result is obtained in approximately 18 seconds. This result shows that the unification framework provides higher verification accuracy without significantly increasing the computational time.

We next compare the performance of the proposed unification framework with sum rule [2], SVM fusion [9], and DS theory fusion [10] algorithms. The verification accuracies in Table I and the ROC plots in Fig. 4 show the results of this experiment. Analysis of the results is summarized below:

1) Relative performance gain of 33.1% is observed with evidence theoretic sum rule compared to traditional sum rule. This improvement is because the proposed evidence theoretic sum rule operates on belief functions along with image quality and verification accuracy prior.
2) The proposed unification framework outperforms existing match score fusion algorithms by at least 1.81%. This shows that the proposed evidence theoretic approach reduces the error in match score fusion and efficiently handles cases where individual classifiers yield conflicting results.
3) In Table I, statistical evaluation using Half Total Er-

[1]Time is computed on 3.2 P-IV processor with 1GB RAM under Matlab environment.

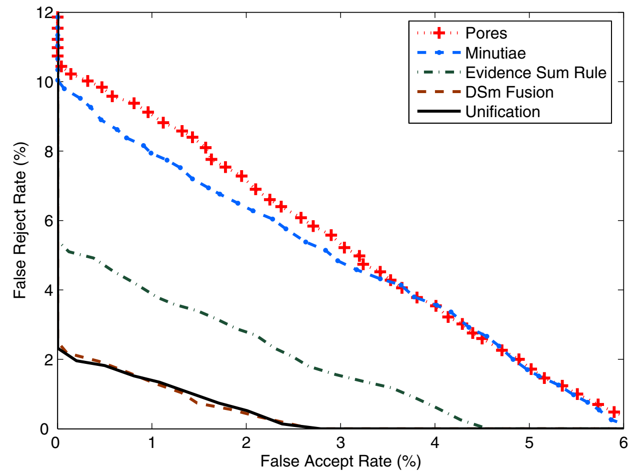


Fig. 3. ROC plot for the verification performance of level-2 minutiae [16], [17] and level-3 pore features [19], [20] along with the evidence theoretic sum rule, DSm fusion, and the proposed unification framework.

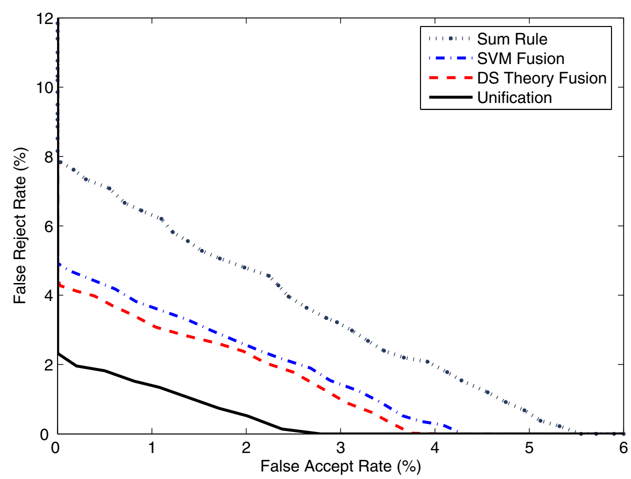


Fig. 4. ROC plot to compare the verification performance of existing sum rule [2], SVM learning based match score fusion algorithm [9], and DS theory match score fusion algorithm [10] with the proposed unification framework.

ror Rate [12], [21] shows that the proposed unification framework provides the lowest HTER and with 95% confidence, the confidence interval lies between 1.19±0.14%.

4) The computational time of the proposed unification framework is comparable to existing match score fusion algorithms.

VII. Conclusion and Future Work

The performance of existing biometric fusion algorithms is compromised when individual classifiers provide conflicting results due to non-ideal data acquisition and variation in data quality. In this paper, we proposed evidence theoretic sum rule and DSm fusion algorithms using basic probability assignments and belief functions. This formulation includes image quality and verification accuracy prior for improving the recognition performance. We further proposed a unification framework that dynamically selects the most appropriate evidence theoretic fusion algorithm. The unification framework is a case based approach in which either the evidence theoretic sum rule or DSm fusion is applied depending on the given scenario. We validated the performance of the proposed unification framework using level-2 minutiae and level-3 pore features. The experimental and statistical results show improvement in verification performance and computational time compared to individual evidence theoretic fusion algorithms and existing fusion algorithms. The unification framework can be updated to include other match score fusion algorithms. Currently, we are exploring methods to incorporate the unification framework at different levels of biometric fusion using multiple modalities.

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