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Quality-augmented fusion of level-2 and level-3 fingerprint information using DSm theory

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Abstract

Existing algorithms that fuse level-2 and level-3 fingerprint match scores perform well when the number of features are adequate and the quality of images are acceptable. In practice, fingerprints collected under unconstrained environment neither guarantee the requisite image quality nor the minimum number of features required. This paper presents a novel fusion algorithm that combines fingerprint match scores to provide high accuracy under non-ideal conditions. The match scores obtained from level-2 and level-3 classifiers are first augmented with a quality score that is quantitatively determined by applying redundant discrete wavelet transform to a fingerprint image. We next apply the generalized belief functions of Dezert–Smarandache theory to effectively fuse the quality-augmented match scores obtained from level-2 and level-3 classifiers. Unlike statistical and learning based fusion techniques, the proposed plausible and paradoxical reasoning approach effectively mitigates conflicting decisions obtained from classifiers especially when the evidences are imprecise due to poor image quality or limited fingerprint features. The proposed quality-augmented fusion algorithm is validated using a comprehensive database which comprises of rolled and partial fingerprint images of varying quality with arbitrary number of features. The performance is compared with existing fusion approaches for different challenging realistic scenarios.

Keywords: Fingerprint recognition; Quality assessment; Redundant discrete wavelet transform; Information fusion; Dezert–Smarandache theory

1. Introduction

Biometrics is one of the most widely used approaches for identification and authentication of individuals. It uses a person's physiological or behavioral characteristics such as fingerprint, face, iris, gait, and signature for authentication [1]. Most of the biometric systems use fingerprint for authentication as it is unique for every

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individual, easy to capture, and is universal. Law enforcement applications also involve identification using rolled and partial fingerprints obtained from different surfaces [2].

Fingerprint features are divided into three categories: level-1, level-2, and level-3 features [2]. Level-1 features represent the ridge-flow pattern and general morphological information. These features are not unique for establishing identity but are used for broad classification of fingerprints into different classes such as left loop, right loop, whorl, arch, and tented arch. Level-2 features represent the minutiae information such as ridge endings and bifurcations. Level-3 features are obtained from the sweat pores and ridges present in fingerprints [3,4]. These features represent the intricate details of a fingerprint such as the dimensional attributes and structure of pores and ridges which are the most discriminating among all three levels of features. Despite their discriminating property, current automatic fingerprint identification systems (AFIS) focus on determining the similarity or dissimilarity between fingerprints using level-1 and level-2 features and do not use level-3 for establishing identity. This is because level-1 and level-2 features can be extracted from a 500 pixels per inch (ppi) image but extracting level-3 features requires high resolution images such as a 1000 ppi fingerprint image. Fig. 1a shows a 500 ppi fingerprint image, from which level-1 and level-2 features can be extracted but the quality is not adequate to extract level-3 information reliably. Fig. 1b shows a partial fingerprint with level-3 features such as pores and ridge structure. In this case, level-1 and level-2 features cannot be used for recognition. Matching is performed using only level-3 features. Fig. 1c shows a 1000 ppi fingerprint image containing both level-2 and level-3 features.

Researchers have proposed fingerprint recognition algorithms which use level-3 features such as ridge counts and sweat pores for matching [5–8] but very limited research has been undertaken to scientifically analyze the effectiveness of combining level-2 and level-3 features [9]. Another challenge with fingerprint recognition is the quality of images [10,11]. Fingerprint images shown in Fig. 1 are of varying quality and these non-ideal, partial, and low quality fingerprints can affect the overall performance of the system.

In this research, we propose a fusion algorithm to efficiently combine level-2 and level-3 fingerprint features by incorporating image quality. We first compute the quality score of fingerprint image using the proposed redundant discrete wavelet transform (RDWT) based quality assessment algorithm [11]. This quality score provides the degree of imprecision for the extracted information. We then extract the level-2 and level-3 features from fingerprint image using existing minutiae [12,13] and pores [7,8] based recognition algorithms. These algorithms provide matching scores for both level-2 and level-3 features which are further normalized using quality scores to generate the quality-augmented match scores. There are several fusion algorithms in literature that fuse two or more biometric information. These algorithms are generally based on statistical rules such as sum rule [10,14,15], min–max rule [14,15], product rule [14,15], or learning techniques [16]. Both the existing statistical and learning based rules can not efficiently handle the imprecise and incomplete information. The performance deteriorates if information on any of the features is missing or highly conflicting. In our approach, we efficiently fuse the imprecise and incomplete information for fingerprint recognition by applying the Dezert–Smarandache (DSm) theory of paradoxical reasoning [17,18] to the quality-augmented match scores. DSm theory based match score fusion algorithm computes the final match score and determines the verification accuracy. To validate the proposed algorithms, we use a database of 500 classes obtained from

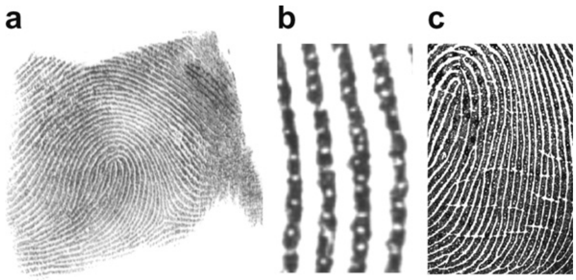

Fig. 1. (a) A poor quality fingerprint image which cannot be used for level-3 feature extraction; (b) a partial fingerprint image containing pores and ridges (level-3 features) but no minutiae (level-2 features); and (c) a fingerprint image containing both level-2 and level-3 features.

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law enforcement agencies. The performance of the proposed algorithms is evaluated on fingerprint images with varying amount of level-2 and level-3 features. We also show the effectiveness of the proposed reasoning theory based match score fusion algorithm by comparing with other existing fusion algorithms.

Section 2 presents the proposed fingerprint image quality assessment algorithm using RDWT. In Section 3, we describe the proposed match score fusion algorithm for level-2 and level-3 features using DSm theory. Section 4 presents the algorithms and the database used for validation and the experimental results are summarized in Section 5.

2. Image quality assessment using RDWT

The performance of a fingerprint recognition system depends on the quality of images. For example, poor quality images may lead to spurious minutiae and thus lower the recognition performance. Image quality may be degraded due to several factors, such as noise in sensor, wetness, and dryness. To determine the fingerprint image quality, we need to determine the edge information, along with smoothness and noise present in the image. Further, in biometric image quality assessment, unlike the standard image quality assessment techniques, we do not have the flexibility of having a reference image to compute the degree of irregularity present in the image. To address these challenges, we use our previously proposed quality assessment algorithm [11] for fingerprint images using redundant discrete wavelet transform (RDWT) [19,20].

RDWT can be considered as an approximation to DWT that removes the downsampling operation from DWT. The transform captures both the frequency content of the input image by examining it at different scales and the temporal content. Further, in RDWT subband, coefficients in the subbands are large for edges, and zero or close to zero for non-edge regions. This property is helpful in determining the edge and non-edge regions present in the image. Another property of RDWT is that the distortion in the original image from noise in a single RDWT subband depends only on the decomposition scale at which the subband resides and is independent of other subbands. This property is known as *per-subband noise relationship* [20].

Let I be the input fingerprint image of size $n \times n$. This image is decomposed to l levels of RDWT using db9/7 mother wavelet [21]. Eq. (1) represents the l level decomposition of image I

$$[I_{Aj}, I_{Hj}, I_{Vj}, I_{Dj}] = \mathrm{RDWT}(I) \tag{1}$$

where $j = 1, 2, \ldots, l$ represents the level of decomposition and $i = A, H, V, D$ denotes the approximation, horizontal, vertical, and diagonal subbands at l levels of decomposition. Quality factor of the approximation and detailed subbands, q_i, are computed using the following equation:

$$q_i = \sum_{j=1}^{l} \sum_{x,y=1}^{n} I_{ij}(x, y) \tag{2}$$

We then compute the weight factor, w_i, of each subband using the following equation:

$$w_i = \sum_{j=1}^{l} \frac{1}{1 + \sum_{x,y=1}^{n} \nabla I_{ij}(x, y)} \tag{3}$$

where j represents the level of decomposition and ∇ represents the gradient operation. The quality factors, q_i, of each subband augmented with the corresponding weight factors, w_i, are combined to compute the final weighted quality score Q.

$$Q = \frac{\sum_i w_i q_i}{\sum_i w_i} \tag{4}$$

This weighted quality score ensures proper weight to the four subbands at each level depending on the information contained in each of the bands. The quality score is then normalized using tanh normalization method [22]

$$Q_{\mathrm{norm}} = \frac{1}{2}\left[\tanh\left(\frac{Q - \mu}{\sigma}\right) + 1\right] \tag{5}$$

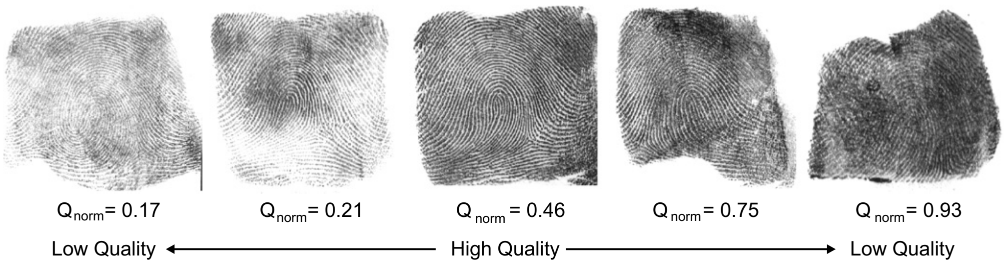

Fig. 2. Images with quality scores computed using the proposed RDWT based quality assessment algorithm.

where μ and σ are mean and standard deviations of quality scores obtained from good quality training fingerprint images. Normalized quality score Q_{norm} lies in the range of $[0,1]$, where 0.5 represents the best quality image and 0 & 1 represent worst quality image. Fig. 2 shows fingerprint images of different quality and their quality scores computed using the proposed RDWT quality assessment algorithm with 3-levels of RDWT decomposition.

3. Biometric information fusion using Dezert–Smarandache (DSm) theory

Due to the presence of multiple evidences or information, fusion from two different biometric evidences provides higher accuracy [15]. However, researchers have shown that fusion of two or more biometric evidences does not necessarily give better performance in comparison to a uni-modal biometric system [23,24]. The performance in this case is highly dependent upon the fusion algorithms and the biometric sources. Further, in multimodal biometric fusion, individual biometric information can sometimes be highly conflicting or imprecise, thereby affecting the overall decision and performance. For example, in multiple classifier fingerprint recognition, one classifier may generate a match score which yields the decision of perfect accept, whereas another classifier may generate a match score which yields the decision of perfect reject. In this situation, both the information are highly conflicting. Imprecision can occur during match score generation due to the noise present in the images, non-ideal imaging, or inherent limitations of recognition algorithms. In such cases, fusion algorithms have to deal with imprecise and conflicting information. Considering these factors, we propose a multimodal biometric fusion algorithm which is based on the DSm theory [17,18]. DSm theory is a mathematical tool that can be applied to efficiently fuse conflicting and imprecise information. In this section, we first present a brief mathematical overview of the DSm theory followed by the proposed quality-augmented multimodal biometric match score fusion algorithm.

3.1. Overview of Dezert–Smarandache theory

Dezert–Smarandache (DSm) theory is a powerful approach for representing and fusing uncertain knowledge. DSm theory is an extension of the Dempster–Shafer theory of evidence [25]. It can solve complex static or dynamic fusion problems using plausible and paradoxical reasoning [17,18]. Since biometric verification is a two-class problem with the classes being *genuine* and *impostor*, DSm theory is explained on a two class problem.

DSm theory is based on Dedekind's lattice, D^Θ, also known as hyperpower set of the frame of discernment Θ. It is defined as a finite set of exhaustive and exclusive elements, θ_i. Let $\Theta = \{\theta_1, \theta_2\}$ consists of a finite set of hypothesis, then $D^\Theta = \{\emptyset, \theta_1, \theta_2, \theta_1 \cup \theta_2, \theta_1 \cap \theta_2\}$. D^Θ is closed under $\cup$ and $\cap$, and $\theta_1 \cap \theta_2 \neq \emptyset$. A mapping, $m(\cdot)$ is defined on Θ, $m(\cdot) = D^\Theta \to [0,1]$, such that $m(\emptyset) = 0$ and $\sum_{A \in D^\Theta} m(A) = 1$. $m(A)$ is called generalized basic belief assignment (gbba) of A. A generalized belief function, Bel, is a mapping function Bel: $D^\Theta \to [0,1]$ such that

$$\text{Bel}(A) = \sum_{X \subseteq A, X \in D^\Theta} m(X) \tag{6}$$

More specifically,

$$\mathrm{Bel}(A)_{y,t}^{\Theta,D^{\Theta}}[E_{y,t}](w_0 \in A) = x \tag{7}$$

This equation denotes the degree of belief x of the classifier y at time t when w_0 belongs to A, where $A \in D^{\Theta}$. Belief is based on evidential corpus $E_{y,t}$ held by y at time t where $E_{y,t}$ represents all what y knows at time t. To simplify, generalized belief function can also be written as $\mathrm{Bel}(A)$. Further, generalized belief function Bel uniquely corresponds to generalized basic belief assignment m and vice versa.

Fusion in DSm theory starts with the notion of free DSm model $M^f(\Theta)$, and considers Θ as a frame of exhaustive elements θ_i that can potentially overlap. This model is free because no other assumption is made on the hypothesis. Given two independent sources of evidence over the same frame Θ and belief functions associated with generalized basic belief assignment $m_1(\cdot)$ and $m_2(\cdot)$, classical DSm rule of combination is operated on $M^f(\Theta)$ and is written as

$$m_{M^f(\Theta)}(A) \equiv m(A) = \sum_{X,Y \in D^{\Theta}, X \cap Y = A} m_1(X)m_2(Y) \tag{8}$$

This combination rule ensures that $m(\cdot)$ is a proper generalized belief assignment. The rule is commutative and associative, and can always be used for fusion of different sources. However, it is possible that the free model does not hold depending on the intrinsic nature of elements of the fusion problem under consideration. This happens when some subsets of Θ contain elements known to be truly exclusive but also actually non-existing at a given time. Therefore, some constraints are introduced explicitly and formally in $M^f(\Theta)$ in order to adapt as close as possible with reality. The new model $M(\Theta)$ is thus constructed on which the combination can be efficiently performed and $M(\Theta) \neq M^f(\Theta)$. In such cases, the hybrid DSm rule of combination [17,18] is defined as

$$m_{M(\Theta)}(A) = \psi(A)[S_1(A) + S_2(A) + S_3(A)] \tag{9}$$

where $\psi(A)$ is the characteristic non-emptiness function of A defined as

$$\psi(A) = \begin{cases} 1 & \text{if } A \notin \emptyset \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

and $S_1(A), S_2(A), S_3(A)$ are defined as

$$\begin{aligned} S_1(A) &= \sum_{(X,Y \in D^{\Theta} X \cap Y = A)} m_1(X)m_2(Y) \\ S_2(A) &= \sum_{(X,Y \in \mathbf{\Phi}, [\upsilon = A] \vee [(\upsilon \in \mathbf{\Phi}) \wedge (A = I_t)])} m_1(X)m_2(Y) \\ S_3(A) &= \sum_{(X,Y \in D^{\Theta}, X \cup Y = A, X \cap Y \in \mathbf{\Phi})} m_1(X)m_2(Y) \end{aligned} \tag{11}$$

where I_t is total ignorance on Θ and is the union of all θ_i, i.e. $I_t = \theta_1 \cup \theta_2$. $\mathbf{\Phi} = \{\mathbf{\Phi}, \phi\}$, $\mathbf{\Phi}$ is the set of all elements of D^{Θ} which are empty under the constraints of some specific problem, and ϕ is 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 $M^f(\Theta), S_2(A)$ 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. Further, hybrid DSm rule of combination holds the property

$$\sum_{A \in D^{\Theta}} m_{M(\Theta)}(A) = 1 \tag{12}$$

Comparing DSm theory with probability theory and Dempster–Shafer theory over $\Theta = \{\theta_1, \theta_2\}$, probability theory deals with basic probability assignment $m(\cdot) \in [0,1]$ such that

$$m(\theta_1) + m(\theta_2) = 1 \tag{13}$$

while Dempster–Shafer theory [25] deals with basic belief assignment $m(\cdot) \in [0,1]$ such that

$$m(\theta_1) + m(\theta_2) + m(\theta_1 \cup \theta_2) = 1 \tag{14}$$

In contrast, the DSm theory is capable of dealing with imprecise, conflicting, and uncontrolled evidences arising from different sources of information which do not have access to the absolute and same interpretation of the element of Θ. DSm theory deals with belief function associated with the generalized basic belief assignment $m(\cdot)$ such that

$$m(\theta_1) + m(\theta_2) + m(\theta_1 \cup \theta_2) + m(\theta_1 \cap \theta_2) = 1 \tag{15}$$

In biometrics, $\theta_1 \cap \theta_2$ belongs to the genuine–impostor region of overlap which is very critical in ensuring the robustness of the system. Both probability theory and Dempster–Shafer theory do not incorporate the belief induced by the region of overlap. Hence DSm theory is more useful than probability theory or Dempster–Shafer theory.

3.2. Proposed multimodal biometric fusion algorithm

One of the major problems with multimodal biometrics is unbalanced systems where two different classifiers have uncertain and highly conflicting results. In such cases, the performance of fixed-rule biometric fusion algorithms such as sum rule, product rule and min–max rule degrades drastically. However, the performance can be enhanced if the fusion algorithm is capable of fusing information correctly even when discrepancy between sources exist. We propose to apply plausible and paradoxical reasoning of DSm theory for fusing biometric information. Furthermore, we associate quality score of input image to increase robustness of the proposed fusion algorithm. In this section, we describe the proposed DSm theory based multimodal biometric fusion algorithm using image quality scores.

Fig. 3 shows the proposed match score fusion algorithm using DSm theory [17,18] to combine the outputs of minutia-based and pore-based fingerprint verification algorithms. Minutia-based fingerprint verification algorithm [12,13] and pore-based verification algorithm [7,8] are used as the primary classifiers. Both the classifiers generate similarity based matching scores which are normalized in the range of 0–1, where 0 represents perfect reject and 1 represents perfect accept. Let the matching score generated by the classifiers be S_j, where $j = 1, 2$ represents the fingerprint classifiers. The quality score Q_{norm} computed in Section 2 is augmented with the matching score S_j of both the fingerprint verification algorithms to generate the quality-augmented match score Sq_j.

$$Sq_j = \begin{cases} \frac{Q_{\text{norm}} S_j}{0.5} & \text{if } 0 \leqslant Q_{\text{norm}} \leqslant 0.5 \\ \frac{(1-Q_{\text{norm}}) S_j}{0.5} & \text{if } 0.5 < Q_{\text{norm}} \leqslant 1 \end{cases} \tag{16}$$

In the proposed DSm theory based match score fusion algorithm, we define the frame of discernment, $\Theta = \{\theta_{\text{genuine}}, \theta_{\text{impostor}}\}$ and Dedekind lattice, $D^\Theta = \{\theta_{\text{genuine}}, \theta_{\text{impostor}}, \theta_{\text{genuine}} \cup \theta_{\text{impostor}}, \theta_{\text{genuine}} \cap \theta_{\text{impostor}}\}$. Further, for every input fingerprint image, each classifier assigns a label *true* or 1 to proposition $a, a \in \Theta$ and the remaining classes are labeled as *false* or 0. Thus, there are two focal elements for each fingerprint verifi-

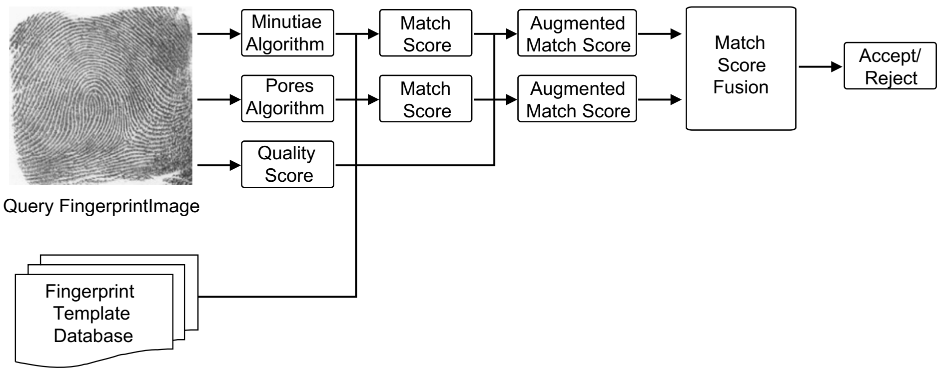

Fig. 3. DSm theory based fusion of quality-augmented match scores obtained from the two fingerprint verification algorithms.

cation algorithm, a and $\neg a$ ($\neg a = \Theta - a$). a is for confirming and $\neg a$ is for denying a proposition for mass assignment in the DSm theory. For every verification algorithm or classifier, we compute the respective predictive rates which are used to assign their gbba. Let an input pattern belonging to class $i(i \in D^{\Theta})$ be classified as one of the $k(k \in D^{\Theta})$ classes. Then, the predictive rate [26] of a classifier P_k for an output class k is the ratio of the number of input patterns classified correctly to the total number of patterns classified as class k where input patterns belonging to all classes is presented to the classifier.

In the proposed reasoning based approach, when the jth fingerprint verification algorithm classifies the result $k \in D^{\Theta}$ over the normalized matching score Sq_j, it is considered that for all instances the likelihood of k being the actual class is P_{kj} and the likelihood of k not being the correct class is $(1 - P_{kj})$ [26]. For the jth fingerprint verification algorithm, the generalized basic belief assignment or mass $m_j(k)$ is computed using Eq. (17) by multiplying P_{kj} with the quality-augmented normalized match score Sq_j

$$m_j(k) = P_{kj} \cdot Sq_j \tag{17}$$

Here $j = 1, 2$ corresponds to the two fingerprint verification algorithms. Similarly, the disbelief is assigned to $m_j(\neg k)$ with $m(\Theta) = 1$. Further, the mass of each evidence or classifier is combined to generate the generalized basic belief assignment of the fused information, m_{final} using the following equation:

$$m_{\text{final}} = m_1 \oplus m_2 \tag{18}$$

where $\oplus$ represents the hybrid DSm rule of combination defined in Eq. (9). The final verification result is obtained by applying the threshold $\mathbf{t}$ to pignistic probability, $B\text{et}P(m_{\text{final}})$

$$\text{Decision} = \begin{cases} \text{Accept} & \text{if } \text{Bet}P(m_{\text{final}}) \geqslant \mathbf{t} \\ \text{Reject} & \text{otherwise} \end{cases} \tag{19}$$

4. Algorithms and database used for validation

The proposed quality-augmented match score fusion algorithm is validated using existing fingerprint verification algorithms and fingerprint database obtained from the law enforcement agencies. In this section, we briefly describe the verification algorithms and the database used for validation.

4.1. Fingerprint verification and fusion algorithms

Two fingerprint verification algorithms are used as primary classifiers in the proposed DSm theory based fusion algorithm. These are minutia-based (level-2 features) and pore-based (level-3 features) algorithms.

4.1.1. Minutia-based verification algorithm

To extract minutiae from a fingerprint image, a ridge tracing minutiae extraction algorithm [13] is used. The extracted minutiae are then matched using a dynamic bounding box based matching algorithm [12]. This algorithm generates a match score which is then normalized in the range of $[0, 1]$ using score normalization technique [22]. The score 0 represents perfect reject and 1 represents perfect accept.

4.1.2. Pore-based verification algorithm

To extract the level-3 features, we use the pore-based verification algorithm described by Kryszczuk et al. [7,8]. This algorithm extracts pore information from the high resolution fingerprint images using different techniques such as correlation based alignment, Gabor filtering, binarization, morphological filtering and tracing. The match score obtained from this algorithm is a similarity score in the range of $[0, 1]$.

4.1.3. Existing fusion algorithms used for comparison

To compare the performance of the proposed quality-augmented DSm fusion algorithm, we use six existing fusion algorithms namely min–max rule [14,15] product rule [14,15] sum rule [14,15], quality based sum rule [10], quality based SVM fusion [16], and Dempster–Shafer theory fusion algorithm [27]. Min–max rule, product rule, sum rule, and quality based sum rule are fusion algorithms based on statistical rules. Quality based

SVM fusion algorithm is learning based fusion algorithm and Dempster–Shafer theory fusion algorithm is based on theory of evidence.

4.2. Fingerprint database

To validate the proposed quality-augmented fusion algorithm, a fingerprint database obtained from law enforcement agencies is used. This database contains images from 500 different classes. For each class, there are five rolled and five slap fingerprints. The resolution of fingerprint images is 1000 ppi to facilitate the extraction of both level-2 and level-3 features. From each class, two rolled fingerprints are selected as training and gallery data and the rest of the images are used as the test or probe data. Further, to highlight the advantages of the proposed DSm theory based fusion algorithm with limited evidence, we generated partial fingerprint databases by cropping rolled and slap fingerprint images with respect to the center of images. In this manner, we created two partial fingerprint datasets, one with fingerprints having 5–10 minutiae and another with fingerprints having no minutia, with the constraint that the size of the cropped image is at least 64×64. Thus we have four sets of probe dataset:

(1) Rolled fingerprint images from 500 classes with three images for each class.
(2) Slap fingerprint images from 500 classes with five images for each class.
(3) Partial fingerprints with 5–10 minutiae from 500 classes with eight images for each class.
(4) Partial fingerprints with 0 minutia from 500 classes with eight images for each class.

5. Experimental results

Performance of the proposed quality-augmented DSm fusion algorithm is validated using fingerprint verification algorithms and the databases described in Section 4. In the experiments, we compute the verification accuracy of all the algorithms at 0.01% false accept rate (FAR). Experimental results are divided into three parts. In the first part, we compute verification accuracy when the test images are rolled fingerprints, i.e. for matching rolled fingerprint with a rolled fingerprint. The results for this experiment are summarized in Section 5.1. In the next experiment explained in Section 5.2, we compute the verification accuracy for test images containing reduced information or evidences, i.e. verification accuracy for matching rolled fingerprint with slap fingerprint. The last experiment described in Section 5.3 evaluates the effectiveness of the proposed algorithm when the number of minutia features is relatively very small, i.e. verification accuracy of matching rolled fingerprints with partial fingerprints.

5.1. Matching rolled fingerprints

For matching rolled fingerprints, minutia-based verification algorithm [12,13] gives an accuracy of 90.04% and pore-based algorithm [7,8] gives an accuracy of 88.45%. Receiver operating curve (ROC) in Fig. 4 shows that the proposed quality-augmented DSm fusion algorithm provides a significant improvement of 7.94% in the verification accuracy compared to the best performance obtained when either minutiae or pores are used. We study the performance when the match scores obtained from minutia and pore features are fused. ROC in Fig. 5 shows that the existing statistical fusion rules such as min–max rule, product rule and sum rule [14,15] increase the verification performance by 1–3%. Quality based sum rule [10] and quality based SVM rule [16] show an improvement of around 6% and the Dempster–Shafer theory based fusion algorithm [27] improves the performance by 6.43% compared to the performance of minutia-based verification algorithm. Among the fusion algorithms, the proposed quality-augmented DSm fusion algorithm outperforms other existing algorithms by at least 1.6%.

5.2. Matching rolled fingerprints with slap fingerprints

The matching of slap fingerprints with rolled fingerprints is challenging because of the limited features available. In this experiment, the gallery database comprises of rolled fingerprints and the probe dataset is

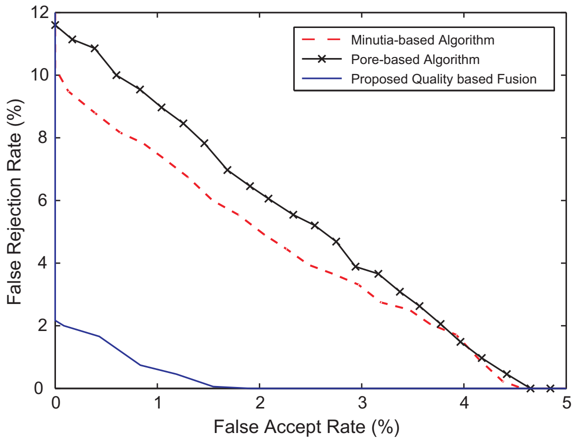

Fig. 4. ROC plots for verification performance of minutia-based recognition algorithm, pore-based recognition algorithm, and the proposed DSm theory based match score fusion algorithm.

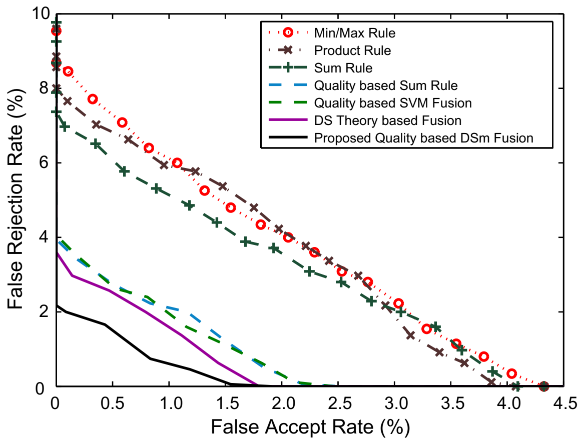

Fig. 5. ROC plots comparing existing fusion algorithms with the proposed quality-augmented DSm fusion algorithm for level-2 and level-3 features.

the slap fingerprint dataset. Experimental results summarized in Table 1 show that on matching rolled fingerprints with slap fingerprints, a marginal decrease in the verification accuracy is observed. Statistical rule based fusion algorithms yield verification accuracies in the range of 90–92%, whereas quality based sum rule and quality based SVM rule improve the accuracy to 95.31% and 95.28%, respectively. Further, Dempster–Shafer theory based fusion algorithm gives an accuracy of 95.85%. The existing fusion algorithms show a decrease in verification accuracy compared to the accuracy of matching rolled fingerprints. The decrease in verification accuracy using existing algorithms is in the range of 0.38–0.73%, whereas the decrease in accuracy of the proposed quality based DSm fusion algorithm is only 0.02%. This indicates that even with partial information, the verification accuracy is not compromised.

5.3. Matching rolled fingerprints with partial fingerprints

The effectiveness of the proposed quality-augmented DSm fusion algorithm is further studied when the number of minutia features is small. This is likely to be the case with latent fingerprints collected at a crime scene. Specifically, the performance of the fusion algorithm is studied when the number of minutiae is between 5 and 10. Experimental results show that while the performance of existing fusion algorithm decreases by 1.31% to 1.9% compared to the performance of using complete rolled fingerprints, the proposed DSm fusion

Table 1
Comparison of verification accuracies of the proposed quality-augmented DSm fusion algorithm with existing fusion algorithms using fingerprints with varying number of features

Algorithm	Rolled to rolled fingerprint (%)	Rolled to slap fingerprint (%)	Rolled to partial print with 5–10 minutiae (%)	Rolled to partial print with 0 minutia (%)
Level-2 minutiae [12,13]	90.04	89.91	65.52	0.00
Level-3 pores [7,8]	88.45	88.30	88.21	87.93
Min–max fusion rule [14,15]	91.17	90.79	89.47	51.64
Product fusion rule [14,15]	92.01	91.56	90.69	0.00
Sum fusion rule [14,15]	92.76	92.07	91.38	52.40
Quality – sum fusion rule [10]	96.03	95.31	94.14	55.29
Quality – SVM fusion rule [16]	96.01	95.28	94.13	55.27
Dempster–Shafer theory based fusion [27]	96.43	95.85	95.52	87.93
Proposed quality-augmented DSm fusion	97.98	97.96	97.89	91.35

Verification accuracy is computed with FAR = 0.01%.

algorithm is able to compensate for the limited partial information with superior performance. A drop of only 0.09% in verification accuracy is observed.

In the worst case when no minutia exists, level-2 features are non-existent. The algorithm depends on only the level-3 features related to pore information. Clearly, minutia-based algorithm fails to perform a match. However, pore-based matching algorithm yields an accuracy of 87.93%. Table 1 summarizes the results of this experiment. Existing statistical and learning based fusion algorithms perform poorly with accuracy ranging from 0% to 55%. Dempster–Shafer theory fusion performs similar to pore-based algorithm because it is based on the theory of evidence. In contrast, the proposed DSm fusion with image quality assessment performs the best with further improvement in accuracy of around 3% compared to the pore-based recognition algorithm.

6. Conclusion

Current automatic fingerprint identification systems (AFIS) use only level-2 fingerprint features to perform recognition. However, these systems fail when the number of level-2 features falls below a certain threshold or the quality of image is poor. Fingerprints that are collected in an uncontrolled environment such as crime scenes, do not guarantee the quality or the minimum number of level-2 features needed for an AFIS to perform matching. To address this issue, we proposed a quality-augmented match score fusion algorithm which fuses match scores obtained from matching level-2 and level-3 features. We used redundant discrete wavelet transform to assess the image quality by determining the presence of noise, smoothness, and edge information in a fingerprint image and compute a quality score. The quality-augmented match scores of level-2 and level-3 feature matching algorithms were fused using Dezert–Smarandache theory. The proposed algorithm was validated experimentally using a comprehensive fingerprint database containing rolled, slap, and partial fingerprints with varying quality and varying number of features. We compared the performance of our approach with existing statistical and learning based fusion algorithms. The results showed that the proposed quality-augmented DSm fusion algorithm enhanced the performance of rolled and slap fingerprints by approximately 8% whereas existing algorithms only increased the performance by 6%. For partial fingerprints, the performance of level-2 feature based verification algorithm significantly reduced with decreasing number of minutiae. This also decreased the performance of fusion using statistical and learning algorithms. The performance of fusion algorithm using Dempster–Shafer theory was similar to the performance of level-3 feature based recognition algorithm. However, the proposed quality-augmented DSm fusion algorithm further enhanced the performance by 3% even when no minutia was present in the image and only level-3 features were present. Thus, the proposed quality-augmented fusion algorithm was able to perform well even in the presence of imprecise, inconsistent, and incomplete fingerprint information.

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