International Journal of Current Research and Modern Education (IJCRME)
ISSN (Online): 2455 - 5428
(www.rdmodernresearch.com) Volume I, Issue II, 2016

FINGER PRINT ANALYSIS USING MULTIMODAL FUSION APPROACH

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Abstract:

With the increasing emphasis on the automatic personal identification applications, biometrics especially fingerprint identification is the most reliable and widely accepted technique. So, the idea is to investigate the effects of varying image quality on a multialgorithm approach based on minutiae-based and pore-based matchers. These two matchers provide complementary information commonly exploited by score-level fusion. The idea of quality-based score fusion has been incorporated into this multiple algorithm approach. This paper formulates an evidence theoretic multimodal fusion approach using belief functions that takes into account the variability in image characteristics. 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.

Index Terms: Fusion, Minutiae, Pore, Multialgorithm & Score-Level

1. Introduction:

The convenience confidence in fingerprints has been demonstrated through long-term research, and fingerprints have intrinsic features that they do not change for whole life and are personally different. And they are easy to use, cheap and the most suitable for miniaturization. So fingerprint verification is an efficient personal verification method that has been the most widely used in comparison with other biometric information [1- 5]. But, 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 [6], [7]. Biometric fusion algorithms yield good performance for some applications or under certain conditions but not universally for all scenarios. For instance, sum rule [6] 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.

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.

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 [9] obtained from fingerprint provide complementary information [10], [11] 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 fusing level-2 and level-3 fingerprint information [10], [11]. Jain et al. [10] 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. [11] further proposed a hierarchical matching scheme which outperforms the sum rule fusion algorithm. Vatsa et al. 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.

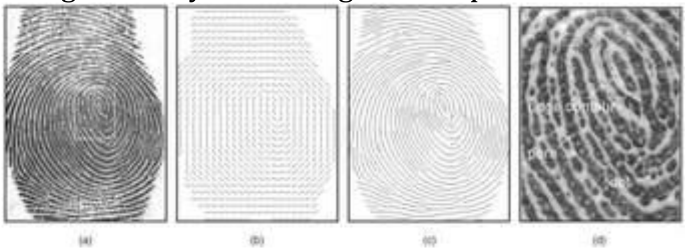


Figure 1: Fingerprint images with minutiae and pore features

2. Fingerprint Recognition:

Fingerprint recognition refers to the automated method of identifying or confirming the identity of an individual based on the comparison of two fingerprints. Fingerprint recognition is one of the most well known biometrics, and it is by far the most used biometric solution for authentication on computerized systems. The reasons for fingerprint recognition being so popular are the ease of acquisition, established use and acceptance when compared to other biometrics, and the fact that there are numerous (ten) sources of this biometric on each individual.

The important steps involved in fingerprint recognition using minutiae matching approach are:

- ✓ Image Enhancement
- ✓ Minutiae Extraction
- ✓ Minutiae Matching
- ✓ Image Enhancement

(i) Image Enhancement: A fingerprint image is corrupted by various kind of noise such as creases, smudges and holes. It is impossible to recover the true ridge/valley structures in the unrecoverable regions; any effort to improve the quality of the fingerprint image in these regions is futile. Therefore, the reasonable enhancement algorithm is used to improve the clarity of ridges/valley structures of fingerprint images in recoverable regions and to mask out the unrecoverable regions.

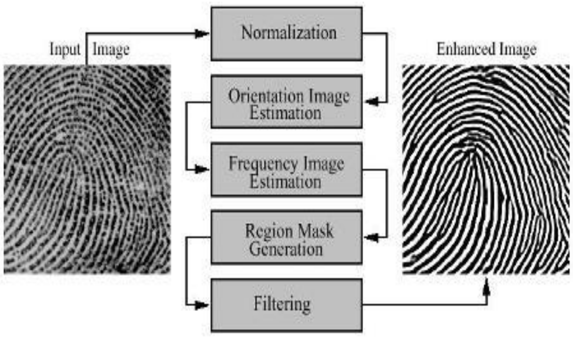


Figure 1: Different Steps of Image Enhancement

The main steps of the algorithm include (shown in Figure 1):

a) Normalization: An input fingerprint image is normalized so that it has a pre-specified mean and variance.

b) Local orientation estimation: The orientation image is estimated from the normalized input fingerprint image.

c) Local frequency estimation: The frequency image is computed from the normalized input fingerprint image and the estimated orientation image.

d) Region mask estimation: The region mask is obtained by classifying each block in the normalized input fingerprint image into a recoverable or unrecoverable block.

e) Filtering: A bank of Gabor filters which is tuned to local ridge orientation and ridge frequency is applied to the ridge-and-valley pixels in the normalized input fingerprint image to obtain an enhanced fingerprint image.

(ii) Minutiae Extraction: The enhanced fingerprint image is binarized and submitted to the thinning algorithm which reduces the ridge thickness to one pixel wide. The skeleton image is used to extract minutiae points which are the points of ridge endings and bifurcations. The most commonly employed method of minutiae extraction is the Crossing Number (CN) concept. This method involves the use of the skeleton image where the ridge flow pattern is eight-connected. The minutiae are extracted by scanning the local neighborhood of each ridge pixel in the image using a 3x3 window. The CN value is then computed, which is defined as half the sum of the differences between pairs of adjacent pixels in the eight-neighborhood. Using the properties of the CN the ridge pixel can then be classified as a ridge ending, bifurcation or non-minutiae point. For example, a ridge pixel with a CN of one corresponds to a ridge ending, and a CN of three corresponds to a bifurcation.

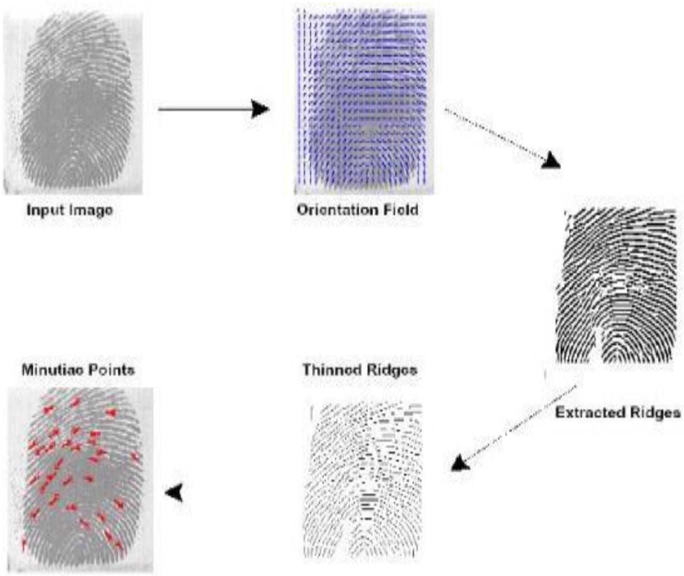


Figure 2: Steps involved in Minutiae Matching

The points are matched between database and query images using Elastic Matching approach.

3. Level of Fusion:

The important issue to designing multibiometric system is to determine the sources of information and combination strategies. Depending on the type of information to be fused, the fusion scheme can be classified into different levels. According to Sanderson and Paliwal [12], the level of fusion can be classified into two categories, fusion before matching (pre classification) and fusion after matching (post classification) as shown in Figure 2.

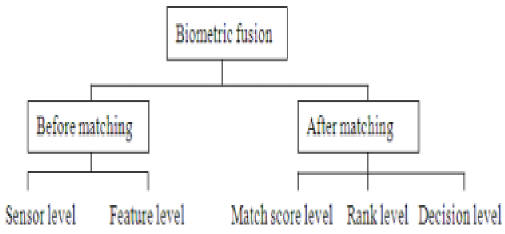


Figure 2. Level of fusion

For fusion before matching, the integration of information from multibiometric sources in this scheme includes fusion at the sensor level and fusion at the feature level. Meanwhile, fusion after matching can be divided into two categories which are fusion at the match score level and fusion at the decision level. A. Fusion before Matching Sensor Level Fusion. In this level, the raw data from the sensor are combined together as shown in Fig. 3. However, the source of information is expected to be contaminated by noise such as non-uniform illumination, background clutter and other [13]. Sensor level fusion can be performed in two conditions i.e. data of the same biometric trait is obtained using multiple sensors; or data from multiple snapshot of the same biometric traits using a single sensor [14, 15].

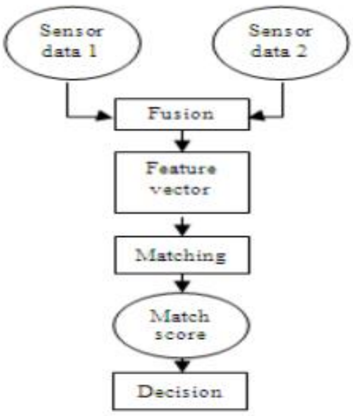


Figure 3. Sensor level fusion process flow

Feature Level Fusion: In feature level fusion, different feature vectors extracted from multiple biometric sources are combined together into a single feature vector as depicted in Fig. 4. This process undergoes two stages which are feature normalization and feature selection. The feature normalization is used to modify the location and scale of feature values via a transformation function and this modification can be done by using appropriate normalization schemes [16]. For instance, the min-max technique and median scheming have been used for hand and face [17] and the mean score from the speech signal and lipreading images scores have been employed in the feature level fusion [18]. Another research has implemented Scale Invariant Feature Transform (SIFT) to obtain features from the normalized fingerprint and ear [19]. Consequently, feature selection is executed to reduce the dimensionality of a new feature vector in order to improve the matching performance of the feature vector by accepting more authentic as true accept. There are several feature selection algorithms have been applied in the literature for instances Sequential Forward Selection (SFS), Sequential Backward Selection (SBS) and Partition about Medoids [20]. The advantage of the feature level fusion is the detection of correlated feature values generated by different biometric algorithms, and, in the process, identifying a salient set of features that can improve recognition accuracy [21]. However, in practice, fusion at this level is hard to accomplish due to the following reasons i.e. the feature sets to be joined might be incompatible and the relationship between the joint feature set of different biometric sources may not be linear [22]. Moreover, concatenating two feature vectors yield a new feature vector which gives larger dimensionality compared to the original once thus leads to the dimensionality problem. Large feature variance affects the system accuracy and also increases the processing time. Hence, only few researchers have focused on the feature level scheme compared to the other levels of fusions such as score level and decision level.

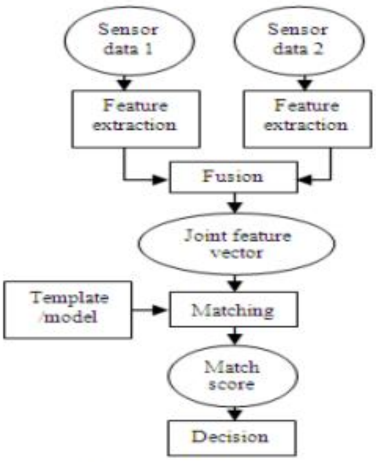


Figure 4. Feature level fusion process flo

Score Level Fusion: In score level fusion, the match outputs from multiple biometrics are combined together to improve the matching performance in order to verify or identify individual as shown in Fig. 5 [23].

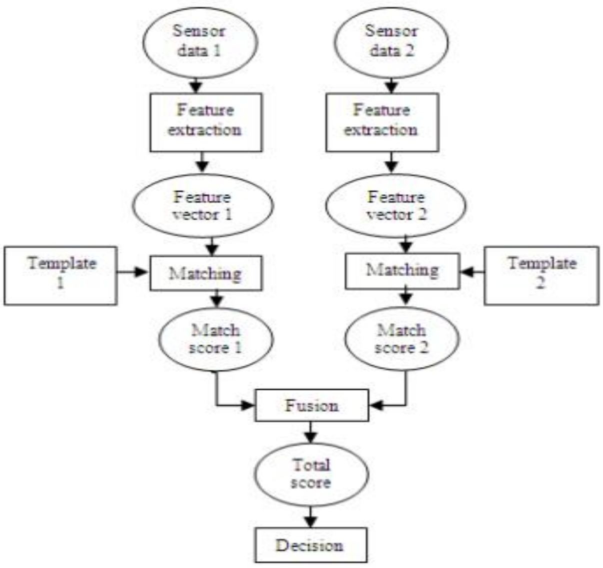


Figure 5. Score level fusion process flow

The fusion of this level is the most popular approach in the biometric literature due to its simple process of score collection and it is also practical to be applied in multibiometric system. Moreover, the matching scores contain sufficient information to make authentic and imposter case distinguishable [26]. However, there are some factors that can affect the combination process hence degrades the biometric performance. For example, the matching scores generated by the individual matchers may not be homogenous due to be in the different scale/range or in different probability distribution. In order to overcome this limitation, three fusion schemes have been introduced i.e. density-based schemes; transformation-based scheme; and classifier-based scheme [27]. The density-based scheme is based on score distribution estimation and has been applied in well-known density estimation models such as Naive Bayesian and Gaussian Mixture Model (GMM) [24]. This scheme usually achieves optimal performance at any desired operation point and estimate the score density function accurately. However, this scheme requires a large number of training samples in order to perfectly approximate the density functions. Moreover, it requires more time and effort for the operational setting compared to the other schemes. On the other hand, the transformation-based scheme is commonly applied for the score normalization process. This process is essential to change the location and scale parameters of the underlying match score distributions in order to ensure compatibility between multiple score variables [27]. This scheme can be applied using various techniques such as sum rule, product rule, min rule and max rule techniques [25]. In the classifier-based scheme, the scores from multiple matchers are treated as a feature vector and a classifier is constructed to discriminate authentic and imposter score [24]. From the literatures, various types of classifiers such as SVM, neural network and multi-layer perceptron (MLP) [25] have been implemented to classify the match vector in this scheme. However, this scheme has some drawbacks such as unbalanced training set and misclassification problems.

Decision Level Fusion:

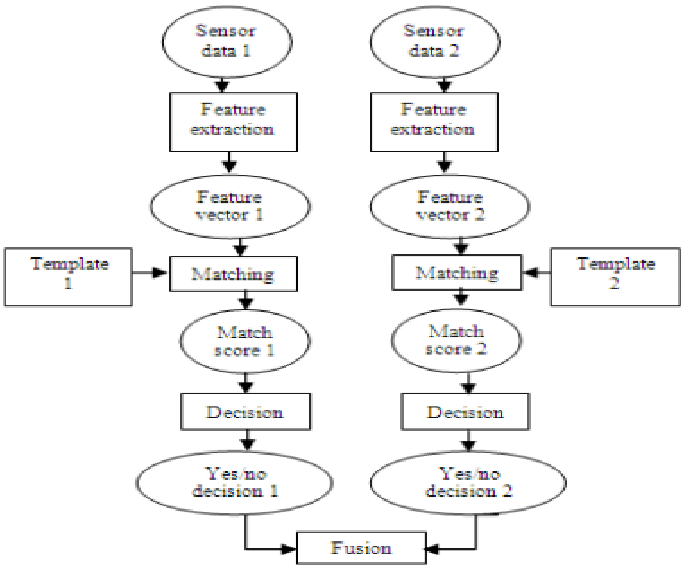


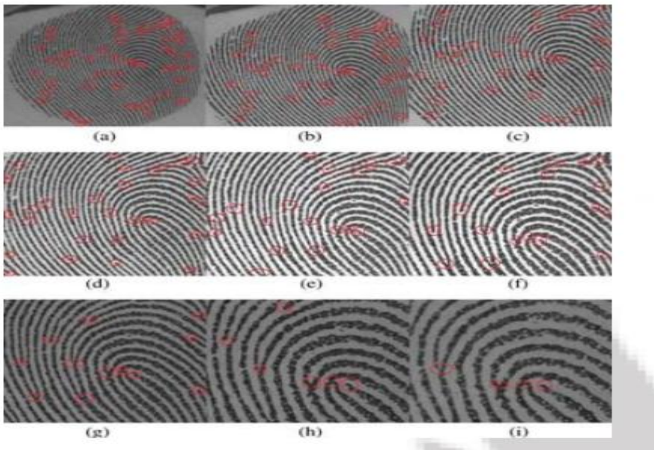
Figure 6. Decision level fusion process flow

Fusion at the decision level is executed after a match decision has been made by the individual biometric source as depicted in Fig. 6. So far, there are many different methods have been applied to join the distinct decision into a final decision such as

"AND" and "OR" rules [18], majority voting, weighted majority voting, Bayesian decision fusion, Dempster-Shafer theory of evidence and behaviour knowledge space [27]. On the other hands, Ramli et al., [25] implemented the proposed decision fusion by using the spectrographic and cepstrumgraphic as features extraction and UMACE filters as classifiers in the system to reduce the error due to the variation of data.

4. Fusion of Finger Print Pore Information and Minutia Information:

Pore to pore distance is computed using the following distance formula: D = √(x1-x2)2 + (y1-y2)2 Where (x1,y1) and (x2,y2) are the pore's coordinates/locations. Similarly minutia location and minutia to minutia distance is computed using above formula for query image as well as the data base images. The finger print matching score is computed based on the fusion of pore's and minutia information using the following formula: Score = α * ED(Pore) + β * ED(Minutia) Where ED is the Euclidean distance between the pores and minutia distance vectors. As the resolution increases, the constant α increases and β decreases and vice versa. This is on the fact that as the resolution increases or improves, the pore becomes significant and minutia count reduces and the problem becomes finger print matching based on pores. And as the resolution decreases, the pore becomes less significant and minutia count increases and the problem becomes minutia based finger print matching. Therefore, there is a tradeoff between the resolution and the finger print matching based on pores and minutia.



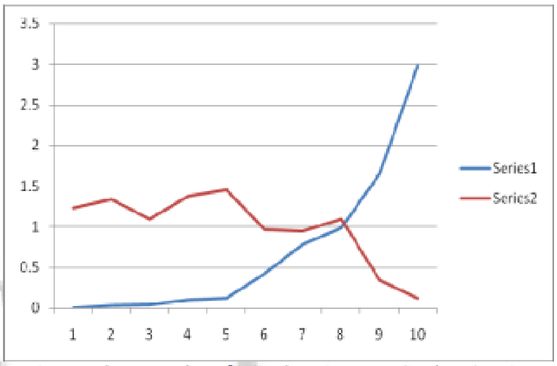
Two indexes are well accepted to determine the performance of a fingerprint recognition system: one is FRR (false rejection rate) and the other is FAR (false acceptance rate). For an image database, each sample is matched against the remaining samples of the same finger to compute the False Rejection Rate. If the matching g against h is performed, the symmetric one (i.e., h against g) is not executed to avoid correlation. All the scores for such matches are composed into a series of Correct Score. Also the first sample of each finger in the database is matched against the first sample of the remaining fingers to compute the False Acceptance Rate. If the matching g against h is performed, the symmetric one (i.e., h against g) is not executed to avoid correlation. All the scores from such matches are composed into a series of Incorrect Score

Image No.	*Data Base Image*	*SD*
a	12	0.023
b	105	0.221
c	13	0.301
d	45	0.334
e	32	0.212
f	17	0.254

In the proposed work, a pore based finger print identification system is proposed. The proposed system works better in comparison to minutia based as the pore density is much higher than the minutia. It may be observed that pore to minutia density may be in the ratio of 10:1. i.e. for one minutia, there are ten no.pf pores in a finger print image. In the presented approach, pore to pore distance network has been generated and that has been used for finger print based person identification. As more complex is the distance fabric network, more it is difficult to break the identity. Also, the minutia based finger print identification again uses the inter minutia distances. But, as the minutia based distances are dependent upon the no. of minutiae. The pore based finger print identification gives more repeatable results for the same finger matching even if the query finger print is cut from any side or any partial finger print is provided for its match from the data base.

False Acceptance and False Rejection Rate Plot

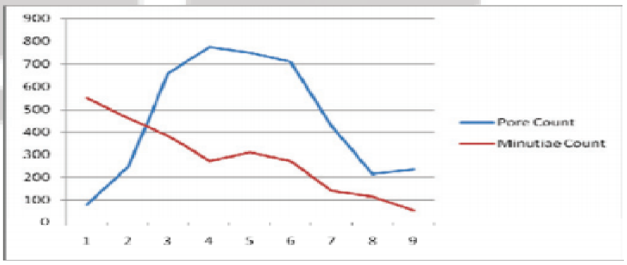
Finger	*FAR*	*FRR*
a	0.003	1.234
b	0.034	1.344
c	0.043	1.098
d	0.099	1.376
e	0.123	1.456
f	0.421	0.973



FAR and FRR Plot → Series-1 FRR, Series-2 FAR

As the resolution improves/increases, rate of finger print identification decreases based on minutia and increases based on error based on pores and vice versa. This is due to the fact that at higher resolution pores becomes significant and minutia count reduces. Some results are compiled on finger print images given in previous section. Following tables shows the results: Pores and Minutia Counts at Different Resolutions

Resolution	*Minutia Based FP Identification (Minutia Count)*	*Pores Based FP Identification (Pore Count)*
500	79	550
600	246	462
700	659	382
800	775	271
900	751	309
1000	709	272
1200	425	139
1600	215	113
2000	234	53



5. Conclusion:

In the presented work, it has been observed that the finger print identification based on minutia and pores at different resolutions gives a break even, beyond which either of the two methods survives. It has observed that at higher resolution, pores based finger print identification gives better results as the pores become more significant as compared to minutia or it can be said that the minutia count reduces. The accuracy of the finger print identification depends upon how much minutia or pores are available for feature extraction. Similarly, as the resolution is decreased, minutia becomes significant in numbers and pores become invisible. At that time, accuracy due to minutia is better. However, when the resolution is varied over a range, there is point at which accuracy becomes almost equal based on pores and minutia. This may be observed from the graphical representation of the results given in result section. The complete algorithm has been developed in Matlab software. A finger print data base of more than 100 persons is generated using the Futronic make finger print scanner with variable resolution adjustment.

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