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***Abstract*—Due to the advantages in privacy and efficiency requirements, minutiae template based matching is the dominant technique among the authentication approaches of fingerprint image and its performance fully relies on the quality of the input fingerprint image. In this case, it is reasonable to consider qualifying fingerprint with fingerprint minutiae template information extracted from fingerprint image, particularly when using for embedded applications due the limited memory. In fact, the speed of fingerprint recognition increases with the decrease of the size of database. For these reasons, a new confidence measure called Minutia Confidence Index (MiCI) for each minutia of the template is proposed. This index predicts the importance and the usefulness of each minutia with respect to the others in the template. It takes into account only minutiae template information (i.e., x and y coordinates, the type and the orientation). MiCI score is a value between 0 and 1, where highest values are for the mostly relevant minutiae in the template whereas lowest values are for less important ones. This measure has been applied in the template reduction use case on Fingerprint Verification Competition (FVC) and SFINGE0 databases and demonstrated its capability to reach high performance.**

I. Introduction

Nowadays, the ubiquity of electronic devices such as smartphones, tablets, and so on necessitates means to easily access data or applications whatever the used device. One of solutions deployed is based on the use of one biometric modality, such as face or fingerprint most of the time. Even if fingerprint based-biometrics recognition systems reach high level of confidence, some question relying on fingerprint quality assessment are still challenging. The various stages of the pipeline through which a fingerprint image passes before the system granted or refused the individual who attempts to access the system are: 1) the minutiae extractor stage which generates a new minutiae template and 2) the minutiae matching stage which consists of finding alignment [7] of minutiae between the fingerprint reference template and the new one, and figures out the number of matched or correctly aligned minutiae.

From the last decade, many investigations have been performed to assess the impact of the image quality on the performance of fingerprint recognition systems and now, it is commonly accepted by the community, that the accuracy of any fingerprint recognition process without using the quality may be affected. Thus, once the acquired image is considered as of sufficient quality, a minutiae extractor is applied, and the obtained template is also considered of equivalent quality to facilitate the matching process.

The extracted template is composed of a set of specific points called minutiae. Each minutia follows the ISO Compact Card standard [1] and is encoded over three octets with 4 values $(x_i, y_i, T_i, \theta_i)$, where (x_i, y_i) is the location of the minutia in the image, T_i the type (bifurcation, ridge, ending,...) and θ_i the orientation (related to the ridge). There are many types of minutiae but since the focus when matching is only on the two main minutiae (ridge ending and ridge bifurcation), minutiae are clustered into three types [1]: 1) Type 0 corresponding to the ridge ending, 2) Type 1 for a ridge bifurcation and 3) Type 2 concerning all remaining minutiae. Fig. 1 displays the description of an extracted minutia.

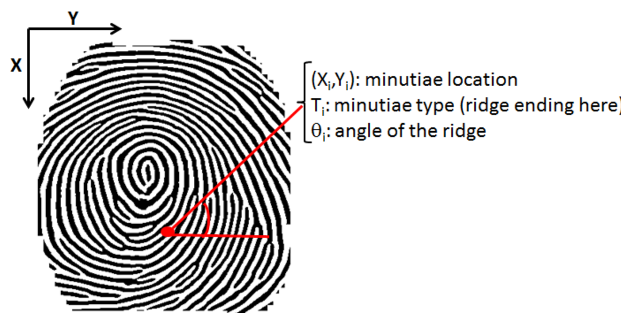

Fig. 1: Description of an extracted fingerprint minutia following the ISO Compact Card standard [1].

Nevertheless, one question remains: when considering a fingerprint template (usually obtained using a minutiae extractor), can one considered all extracted minutiae having the same level of quality? In other words, have the extracted minutiae the same level of importance? We can reformulate this question addressing the question of the confidence we can have in a minutiae, including the concept of its usefulness. Some remarks can then be formulated:

1) Only few works based on the quality of a fingerprint template can be found in the literature [2], [16]. However, system performance fully relies on the matching approach such as minutiae-based system which is most employed for actual deployments. In this case, it is reasonable to consider qualifying fingerprint with only minutiae information, particularly when using for embedded applications due to the limited memory.
2) In most cases, implementations compute an image-based quality score for each minutia, such as MINDTCT [10]. Moreover, none of the state-of-the-art approaches qualifies a fingerprint minutia from the minutiae tem-

plate alone. Once all minutiae template extracted from fingerprint image, it is more convenient to speak about confidence index and not quality of each minutia. This confidence index represents the importance and usefulness of each minutia with regard to the others in the template.

These remarks motivated us to propose a new framework to compute the confidence of any minutia of the fingerprint template. This yields us to predict the importance and usefulness of each minutia with respect to the others in the template. This confidence score results from the computation of a new Minutia Confidence Index (MiCI) which we proposed. This scoring is a non-image based value and aims to associate a confidence index to each minutia in template. The index computation only depends on fingerprint template information. Surveying research works in the literature, this index is the first one proposed which is only based on fingerprint template data and not on fingerprint image.

The paper is organized as follows: section II presents research works which are related to the fingerprint quality assessment domain. Major existing metrics scoring image-based quality of minutiae are investigated. Section III describes the new concept of Minutia Confidence Index as well as its associated MiCI index computation. Section IV is dedicated to the comparative study of the introduced template-based MiCI scores with two other template-based methods which are the truncation and the centroid and one image based metric namely MINDTCT. Experimental results on five databases for the template reduction problem is depicted. We finally conclude and give some perspectives.

II. Related works

Fingerprint quality assessment aims to improve and guarantee the performance of a biometric system [6] by eliminating bad quality fingerprint samples, especially during the enrollment session. In another terms, it works as a toll-gate to ensure that poor quality samples could be rejected before sending them to next stage. Therefore, this limitation has attracted attentions from both academic and industrial area, and a lot of studies had been made [2] [16].

There are very few quality assessment approaches that take into account minutiae information. One can cite NFIQ [15] and MINDTCT [10]. On the one hand, MINDTCT provides a reliability metric which computes a quality score depending on the Quality Map [15] and the pixels neighbouring statistics. On the other hand, NFIQ, which is an open source quality assessment algorithm for fingerprint images [14], computes a set of quality features and uses them to predict the fingerprint image quality. It employs a customized version of FingerJet FX OSE minutia extractor for determining the amount of minutiae detected in the whole image (Minutiae cnt) and an average minutiae quality. It expresses the average (*i.e.*, arithmetic mean) quality of all returned minutiae by the open source edition of Digital Personas FingerJet FX algorithm. Two different methods for computing the quality of the minutiae are used. The first method calculates the quality using an arithmetic mean of pixel values in the input image (FJFXPos_Mu_MinutiaeQuality_2). The second method of minutiae quality assessment computes the quality as the Orientation Certainty Level of blocks of pixels centred at the minutia location (FJFXPos_OCL_MinutiaeQuality_80).

Unfortunately, NFIQ provides minutiae count at different minutiae quality levels and not a quality score for each minutia.

III. Minutia Confidence Index

A biometric system essentially tends to process samples of good quality which are beneficial for matching operations and can efficiently improve system performance [6]. Among fingerprint matching approaches, minutiae-based approach is the mostly used [9] due to low computation cost and good performance. It depends on minutiae points extracted from fingerprint images and stored in minutiae template.

In this section, our first contribution consists of proposing a new framework to score the minutia confidence. The obtained value reflects the importance and usefulness of each minutia in the template. In another word, it describes the closest density and distribution of minutiae with each minutia present in the template. In addition, it depends essentially of the fingerprint template information (*i.e.*, template features). More specifically, it uses two template features which are the x and y coordinates and the minutia type T. For the second contribution, we propose a new MiCI index which follows three important steps as illustrated in Figure 2:

1) One of the minutiae is selected as a reference minutia. The fingerprint region is decomposed into s sectors of equal angular with respect to this reference minutia.
2) Next, we compute a confidence index for each sector, namely Sector-Based Confidence Index (SBCI). This index depends on the probability of minutiae points of the same type with regard to the inverse of the square of the distance between the reference minutia and the centroid of minutiae points in a this sector.
3) The final confidence index of the reference minutia is computed as the sum of all SBCIs of all sectors s.

A. Sector decomposition

Given a minutiae template T_i of a fingerprint that contains the set of raw minutiae V_{up} extracted from the input fingerprint image

$$V_{up} = \{m_i\}_{i=1}^{n} \tag{1}$$

where n is the total number of minutiae points in V_{up}.

$$m_i = \{(x_i, y_i), \theta_i, T_i\} \tag{2}$$

The i^{th} minutia is denoted by m_i where (x_i, y_i) , θ_i and T_i are the coordinate positions, orientation and type respectively.

During this step, one of the minutiae point m_i from V_{up} is selected as a reference minutia m_{ref}. Further, the fingerprint template is split into s sectors of equal angular width around the reference minutia in an anti-clockwise direction where V_{s_j} represents the set of minutiae in the sector s_j.

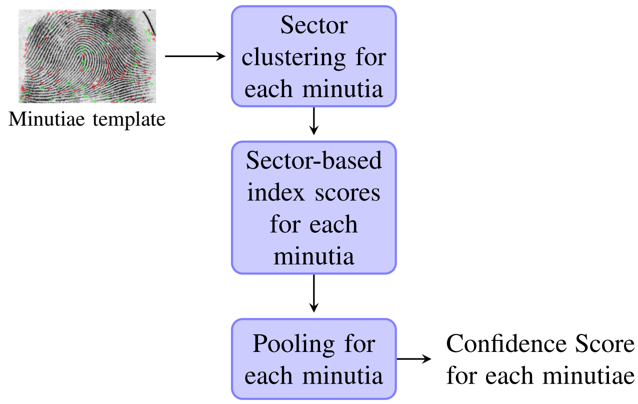

Fig. 2: Overall synopsis of the minutiae confidence index scoring.

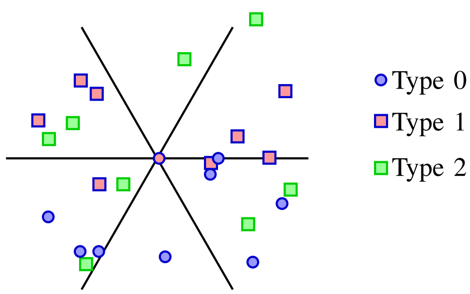

Fig. 3: Illustration of the distribution of the minutia types (as defined in [1]) around a given minutia (red disk) for a sector decomposition into six sectors of equal angular (60°)

For each set V_{s_j}, one subset V_{T_i,s_j} is designed per type T_i of minutiae. Finally, at the end of this stage, three subsets are generated by angular sector (one per type).

Figure 3 illustrates the applied sector decomposition around a centered minutia into six sectors. Within each sector, one observes the three different types of minutia encountered, yielding us to generate subset of minutiae per type.

This sector decomposition is applied for each minutia of V_{up}.

B. Sector-based Confidence Index

In this section, a confidence index per angular sector is computed. The main idea is to quantify the usefulness of a minutia. In order to perform such a measure, we need to take into account the influence of each subset on the minutia m_{ref} which the confidence is computed for. It is commonly admitted that the influence of a subset is decreasing if the distance to the minutia m_{ref} increases. In addition, the size of the subset has an influence on the usefulness: the smaller the subset, the lesser influence is. From those two assumptions, a sector-based confidence index (SBCI) is developed and is defined as:

$$\mathrm{SBCI}_{m_{ref},s} = \sum_{k=1}^{3} p(T_k, s) * 1/\sqrt{d(m_{ref}, c(T_k, s))} \quad (3)$$

where

- $p(T_k, s)$ is the probability of appearance of minutiae of type T_k within the sector s:
$$p(T_k, s) = \frac{V_{T_k,s}}{V_s} \quad (4)$$
where $V_{T_k,s}$ is the set of minutiae of type T_k within the sector s, and V_s represents the number of minutiae contained within the sector s
- $d(m_{ref}, c(T_k, s))$ is the Euclidean distance between the centroid $c(T_k, s)$ of minutiae of type T_k within the sector s and the reference minutia m_{ref}.

SBCI determines a useful information for the distribution of minutiae in the sector as well as the importance of the sector. In addition, the *inverse* of the distance of the centroid of this distribution with regard to the reference minutia determines the locality of the distribution of features. The nearest the minutiae distribution could have a high value of SBCI.

C. Minutia Confidence Index

Finally, a pooling strategy of SBCIs is applied to compute the final Minutia Confidence Index (MiCI) of each reference minutiae:

$$\mathrm{MiCI}_{m_{ref}} = \sum_{i=1}^{s} \mathrm{SBCI}_{m_{ref},i} \quad (5)$$

where s represents the number of angular sectors obtained from the sector decomposition process.

IV. Performance Evaluation

In order to evaluate the performance of the proposed method, we will address the template reduction problem. The aim of such a problem is to reduce the number of minutiae of the reference template while preserving high performance of biometric systems.

To perform such an evaluation, we compare our index with two template selection methods from the literature which are 1) the truncation and the centroid selection methods and 2) an image based minutia score which is the MINDTCT algorithm.

A. Experimental setup

1) Fingerprint databases: In this study, experiments are conducted with the four FVC databases with different resolutions [11] :

- FVC 2002: DB1 and DB2
- FVC 2004: DB1 and DB2

All FVC Fingerprint images are captured using an optical sensor. Each database contains 100 fingerprints, and 8 samples for each fingerprint. The intra-class scores contain $7 \times 100 = 700$ genuine scores, and the inter-class scores consist of $7 \times 99 \times 100 = 69300$ impostor scores for the whole database.

Five synthesized fingerprint image databases will be used to evaluate the performance of the MiCI index:

- SFINGE0 with different quality images randomly ranging from low quality to very high quality,
- SFINGEA where images are of very high quality,

TABLE I: Databases details.

Database	Sensor	Resolution	Image dimension
FVC2002DB1	Optical	500dpi	388 × 374
FVC2002DB2	Optical	569dpi	296 × 560
FVC2004DB1	Optical	500dpi	480 × 640
FVC2004DB2	Optical	500dpi	328 × 364
SFINGE0	Optical	500dpi	328 × 364
SFINGEA	Optical	500dpi	328 × 364
SFINGEB	Optical	500dpi	328 × 364
SFINGEC	Optical	500dpi	328 × 364
SFINGED	Optical	500dpi	328 × 364

(a) FVC2002DB1 ex. (b) FVC2002DB2 ex. (c) FVC2004DB1 ex.

(d) FVC2004DB2 ex. (e) SFINGEA ex. (f) SFINGED ex.

Fig. 4: Examples of fingerprint images from both FVC and SFINGE datasets

- SFINGEB with high quality images,
- SFINGEC where images are of medium quality,
- SFINGED containing low quality images

Table I describes all databases.

Figure 4 displays some digital fingerprints from the above mentioned datasets.

2) Minutiae extractor and comparison: Minutiae templates used in the experiment were extracted using the NBIS tool, MINDTCT [10] . This software generates a quadruple representation of minutia point, $m = (x, y), o, t, q$, where (x, y) is the location of minutia point, θ indicates orientation, t is the minutia type and q is a quality score of minutia point.

Furthermore, the MINDTCT extractor provides a reliability metric assigned to each detected minutia in the input image. This metric computes a quality score with regard to: 1) the quality level associated with the position of the minutia from the so called Quality Map [15] and 2) the quality level with simple neighborhood pixel statistics neighbouring the minutia point. MINDTCT produces for each minutia in the image a quality score in the range [0, 1], where 0 represents the lowest minutia quality whereas 1 represents the highest minutia quality.

Yet, this extractor provides only the two first types of minutiae: 1) Type 0 (end ridge) and 2) Type 1 (ridge bifurcation). Fig. 5 illustrates some such obtained fingerprint templates from two fingerprint images.

Fig. 5: Examples of extracted minutiae using MINDTCTC from FVC2002DB1 and SFINGE0 databases. Violet squares corresponds to minutiae of Type 0 and green squares are associated to minutiae of Type 1

Two fingerprint comparison algorithms have also been used. The first one is the Bozorth3 algorithm proposed by the NIST [**?**]. The MCC algorithm [**?**] is the second comparison one.

3) State-of-the-art template reduction methods:

a) Truncation method: This method is based on a simple truncation by only keeping a certain number of minutiae from the initial template. The efficiency of this simple approach depends on the method used to generate the fingerprint template. For many commercial biometric systems, a fingerprint template is generated with a specific method. It can be generated considering minutiae with the ascending locations Y as for example.

b) Centroid method: This method based on a pruning mechanism is simple. It has been proposed by the NIST for minutiae selection in [5]. It has been shown that minutiae located near the core of a fingerprint minutiae are the most useful ones for the matching process [8]. Given a fingerprint template, the core location is usually unknown. However, the centroid of minutiae can be a good estimate (when no other information is available). This minutiae selection approach tends to only keep minutiae near to the centroid. For this reason, we have four steps for its computation process:

- Compute the centroid of the minutiae from the fingerprint template (containing N minutiae);
- Compute the distance of each minutiae to the centroid;

$$centroid = \frac{1}{N} \times (\sum_{i=1}^{N} X_i, \sum_{i=1}^{N} Y_i) = (X_{cent}, Y_{cent}) \quad (6)$$

- Sort in ascending order minutiae according to the distance d_i, $i = 1 : N$

$$d_i = \sqrt{(X_i - X_{cent})^2 + (Y_i - Y_{cent})^2} \quad (7)$$

- Select minutiae having the lowest distance to the centroid.

4) Measure of performance: Many measures exist to evaluate the performance of a biometric system. Along all of them, the AUC (Area-under-Curve) of ROC (Receiver Operating Characteristics) is used to assess the performance of the proposed method. The AUC value is a quantitative index derived from the ROC curve [8]. ROC curve is a plot between FAR (False Acceptance Rate) and FRR (False Rejection Rate) for different values of the threshold t.
FAR indicates that two biometric samples from two different individuals are regarded as the samples from the same person. It is the fraction of impostor fingerprints which are accepted and is calculated as follows:

$$\text{FAR} = \frac{\text{Number of impostor fingerprints accepted}}{\text{Total number of impostor tests}} \quad (8)$$

Whereas, FRR indicates that biometric samples from one person are measured as two different samples from different users. It is the fraction of genuine fingerprints which are rejected and is calculated as follows:

$$\text{FRR} = \frac{\text{Number of genuine fingerprints rejected}}{\text{Total number of genuine tests}} \quad (9)$$

The AUC value can be viewed as a measure ranking which is very useful and is based on pairwise comparisons between classifications of two classes. In other words, the AUC value is equal to the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one. That way, AUC can be considered as a global criterion of the performance.

Finally, considering two algorithms and their associated AUC values, the better algorithm is one whose AUC value is lower than others AUC value over a suitably large range of threshold values t.

B. Optimal number of sector

In order to determine the optimal number of sectors needed to obtain the best performance, the MiCI index is appplied using 4, 6, 8 and 10 sectors. We reduce fingerprint template by discarding the 5, 10 and 15 minutiae having the lowest MiCI scores. Then, we perform the matching using reduced fingerprint templates and we compute its associated AUC value for the two trial matchers: Bozorth3 and MCC.

Tables II and III represent AUC values for all trail databases. From those tables, one can observe that the number of sectors minimizing the AUC values is reach when 8 sectors are used to compute the minutiae confidence index MiCI. One observes that the used database does not influence the number of sectors to perform the decomposition, since whatever the used database, the decomposition into 8 sectors always provides the best results.

C. Results

In this section, the performance of the MiCI-based template reduction algorithm is compared to the performance of two state-of-the-art truncation algorithms, namely tuncation and centroid and of one MINDTCT quality-based template reduction technique.

			#Minutiae removing		
		# Sectors	5	10	15
Real databases	FVC2002DB1	4	0.022	0.030	0.051
		6	0.022	0.030	0.048
		8	**0.020**	**0.026**	**0.047**
		10	0.024	0.031	0.050
	FVC2002DB2	4	0.024	0.030	0.049
		6	0.022	0.030	0.048
		8	**0.020**	**0.025**	**0.045**
		10	0.024	0.030	0.048
	FVC2004DB1	4	0.042	0.061	0.089
		6	0.043	0.055	0.081
		8	**0.039**	**0.048**	**0.078**
		10	0.041	0.055	0.086
	FVC2004DB2	4	0.041	0.050	0.066
		6	0.043	0.052	0.061
		8	**0.037**	**0.042**	**0.051**
		10	0.040	0.048	0.062
Synthesized databases	SFINGE0	4	0.047	0.076	0.130
		6	0.046	0.070	0.125
		8	**0.040**	**0.065**	**0.113**
		10	0.045	0.081	0.14
	SFINGEA	4	0.035	0.061	0.102
		6	0.032	0.058	0.099
		8	**0.029**	**0.048**	**0.093**
		10	0.033	0.059	0.118
	SFINGEB	4	0.040	0.064	0.105
		6	0.038	0.062	0.101
		8	**0.025**	**0.052**	**0.095**
		10	0.039	0.063	0.119
	SFINGEC	4	0.049	0.078	0.134
		6	0.048	0.076	0.131
		8	**0.041**	**0.067**	**0.116**
		10	0.049	0.085	0.141
	SFINGED	4	0.061	0.096	0.154
		6	0.059	0.082	0.142
		8	**0.051**	**0.075**	**0.140**
		10	0.061	0.088	0.149

TABLE II: Evolution of the AUC value on the trail databases with respect to both the number of sectors and the number of selected minutiae, using Bozorth3.

Considering the MiCI-based template reduction algorithm, minutiae with the lowest MiCI scores are removed form the template. We proceed to eliminate minutiae by step of 5 in three times. As a result, we obtain three reduced templates for each initial one. The first reduced template encompasses minutiae except 5 minutiae having the lowest MiCI scores. Each resulted reduced template follows the same process two times. In the end, we obtain three reduced fingerprint templates by 5, 10 and 15 minutiae respectively.

The same strategy is applied for the MINDTCT quality-based template reduction technique. The removing process of minutias is driven by the lowest MINDTCT quality scores.

Finally, AUC values are computed for all generated templates. Obtained results are displayed in tables IV and V for all trial database and using the Bozorth3 matcher and MMC algorithm respectively.

At least, two global remarks can be formulated, whatever the considered matcher algorithm:

1) the AUC values obtained from the reduction template algorithm based on the proposed MiCI values performs best than all the three trail schemes. This yields us

			#Minutiae removing		
		# Sectors	5	10	15
Real databases	FVC2002DB1	4	0.018	0.026	0.044
		6	0.012	0.020	0.038
		8	**0.018**	**0.024**	**0.047**
		10	0.014	0.021	0.049
	FVC2002DB2	4	0.014	0.020	0.040
		6	0.012	0.018	0.028
		8	**0.010**	**0.021**	**0.025**
		10	0.013	0.020	0.029
	FVC2004DB1	4	0.039	0.058	0.078
		6	0.034	0.050	0.074
		8	**0.029**	**0.044**	**0.070**
		10	0.035	0.048	0.076
	FVC2004DB2	4	0.023	0.030	0.046
		6	0.021	0.025	0.043
		8	**0.018**	**0.019**	**0.031**
		10	0.022	0.027	0.044
Synthesized databases	SFINGE0	4	0.031	0.064	0.112
		6	0.026	0.054	0.089
		8	**0.024**	**0.050**	**0.082**
		10	0.025	0.061	0.093
	SFINGEA	4	0.025	0.042	0.080
		6	0.022	0.038	0.067
		8	**0.019**	**0.024**	**0.060**
		10	0.024	0.039	0.078
	SFINGEB	4	0.030	0.049	0.098
		6	0.027	0.044	0.078
		8	**0.024**	**0.033**	**0.066**
		10	0.029	0.044	0.089
	SFINGEC	4	0.033	0.070	0.121
		6	0.030	0.067	0.118
		8	**0.029**	**0.054**	**0.110**
		10	0.032	0.066	0.119
	SFINGED	4	0.039	0.075	0.134
		6	0.036	0.070	0.124
		8	**0.032**	**0.067**	**0.118**
		10	0.035	0.071	0.130

TABLE III: Evolution of the AUC value on the trail databases with respect to both the number of sectors and the number of selected minutiae, using MCC.

			#Minutiae removing		
		# Sectors	5	10	15
Real databases	FVC2002DB1	No-reduction	0.015	0.015	0.015
		Trucation	0.024	0.038	0.066
		Centroid	0.021	0.032	0.050
		MINDTCT	0.022	0.029	0.050
		MiCI	**0.020**	**0.026**	**0.047**
	FVC2002DB2	No-reduction	0.018	0.018	0.018
		Trucation	0.024	0.033	0.055
		Centroid	0.022	0.029	0.053
		MINDTCT	0.022	0.027	0.047
		MiCI	**0.010**	**0.021**	**0.025**
	FVC2004DB1	No-reduction	0.034	0.034	0.034
		Trucation	0.041	0.055	0.096
		Centroid	0.045	0.061	0.089
		MINDTCT	0.040	0.056	0.080
		MiCI	**0.039**	**0.048**	**0.078**
	FVC2004DB2	No-reduction	0.036	0.036	0.036
		Trucation	**0.036**	0.044	0.058
		Centroid	0.042	0.057	0.082
		MINDTCT	0.039	0.048	0.061
		MiCI	0.037	**0.042**	**0.051**
Synthesized databases	SFINGE0	No-reduction	0.027	0.027	0.027
		Trucation	0.048	0.093	0.161
		Centroid	0.041	0.074	0.130
		MINDTCT	0.044	0.078	0.141
		MiCI	**0.040**	**0.065**	**0.113**
	SFINGEA	No-reduction	0.017	0.017	0.017
		Trucation	0.032	0.069	0.118
		Centroid	0.030	0.064	0.097
		MINDTCT	0.031	0.067	0.101
		MiCI	**0.029**	**0.048**	**0.093**
	SFINGEB	No-reduction	0.020	0.020	0.020
		Trucation	0.036	0.072	0.121
		Centroid	0.028	0.060	0.101
		MINDTCT	0.032	0.065	0.109
		MiCI	**0.024**	**0.033**	**0.066**
	SFINGEC	No-reduction	0.023	0.023	0.023
		Trucation	0.044	0.076	0.121
		Centroid	0.042	0.070	0.117
		MINDTCT	0.041	0.069	0.117
		MiCI	**0.041**	**0.067**	**0.116**
	SFINGED	No-reduction	0.038	0.038	0.038
		Trucation	0.057	0.089	0.153
		Centroid	0.056	0.077	0.147
		MINDTCT	0.055	0.080	0.151
		MiCI	**0.051**	**0.075**	**0.140**

TABLE IV: AUC values of the trial minutiae template reduction methods and the proposed scheme MiCI for all databases, using the Bozorth3 matcher.

to argue that the proposed framework to score the confidence of a minutia is valid and promising.

2) Reducing the minutiae templates by 5 minutiae not have such a great impact on the matching performance since AUC values of different methods approximately equal to the AUC obtained when no reduction is computed on the template. This is an interesting results since we can consider a lower storage of fingerprint templates database, since we can consider less minutiae.

From Table IV, one can observe that when considering a reduction step by five minutiae for the FCV2004DB2 database, the truncation scheme provides the lowest AUC value. Yet, the result obtained for the MiCI-based reduction template method is very close. Thus, it makes sense to consider the performance of the two algorithms of the same level.

This observation is not valid when the MCC matcher is considered (Table V) since the template reduction process based on the use of the proposed MiCI index provides the lowest AUC values for both real and synthesized databases.

Two kind of fingerprint image databases are considered to perform the comparison: 1) fingerprint captured from real fingers and 2) synthetic fingerprint.

From Table IV, results obtained from the real fingerprints and considering the Bozrth3 matcher, one can observe that the difference of AUC values between MiCI-based approach and the second best approach is tiny and varies in mean between 0.001 (for a 5 minutiae reduction step) and 0.004 (for a 15 minutiae reduction step). When synthetsized fingerprints are considered, theses differences globally increase and varie between 0.0025 and 0.0158. We observe a slight drop of performance when synthesized database are used with Bozorth3.

Considering the MCC matcher (Table V), the difference of AUC values between MiCI-based approach and the second best approach is tiny and varies in mean between 0.001 (for a 5 minutiae reduction step) and 0.002 (for a 15 minutiae reduction step) for real databases. For synthesized databases,

			#Minutiae removing		
		# Sectors	5	10	15
Real databases	FVC2002DB1	No-reduction	0.015	0.015	0.015
		Trucation	0.021	0.028	0.056
		Centroid	0.019	0.028	0.050
		MINDTCT	0.019	0.025	0.049
		MiCI	**0.018**	**0.024**	**0.047**
	FVC2002DB2	No-reduction	0.012	0.012	0.012
		Trucation	0.016	0.028	0.048
		Centroid	0.015	0.023	0.044
		MINDTCT	0.015	0.021	0.043
		MiCI	**0.014**	**0.020**	**0.041**
	FVC2004DB1	No-reduction	0.025	0.025	0.025
		Trucation	0.031	0.047	0.088
		Centroid	0.029	0.056	0.080
		MINDTCT	0.029	0.045	0.073
		MiCI	**0.029**	**0.044**	**0.070**
	FVC2004DB2	No-reduction	0.021	0.021	0.021
		Trucation	0.028	0.034	0.059
		Centroid	0.026	0.033	0.054
		MINDTCT	0.025	0.031	0.051
		MiCI	**0.024**	**0.029**	**0.050**
Synthesized databases	SFINGE0	No-reduction	0.018	0.018	0.018
		Trucation	0.038	0.061	0.091
		Centroid	0.030	0.058	0.087
		MINDTCT	0.026	0.058	0.085
		MiCI	**0.024**	**0.050**	**0.082**
	SFINGEA	No-reduction	0.013	0.013	0.013
		Trucation	0.022	0.029	0.068
		Centroid	0.020	0.026	0.067
		MINDTCT	0.021	0.026	0.064
		MiCI	**0.019**	**0.024**	**0.060**
	SFINGEB	No-reduction	0.017	0.017	0.017
		Trucation	0.036	0.062	0.121
		Centroid	0.028	0.056	0.101
		MINDTCT	0.27	0.055	0.099
		MiCI	**0.025**	**0.052**	**0.095**
	SFINGEC	No-reduction	0.022	0.022	0.022
		Trucation	0.030	0.056	0.114
		Centroid	0.030	0.056	0.112
		MINDTCT	0.029	0.055	0.111
		MiCI	**0.029**	**0.054**	**0.110**
	SFINGED	No-reduction	0.026	0.026	0.026
		Trucation	0.037	0.072	0.127
		Centroid	0.036	0.070	0.126
		MINDTCT	0.033	0.068	0.120
		MiCI	**0.032**	**0.067**	**0.118**

TABLE V: AUC values of the trial minutiae template reduction methods and the proposed scheme MiCI for all databases, using the MCC matcher.

the difference globally increases and varies between 0.0014 and 0.024. In that, case, the behavior of MCC is the same for both real and synthesized databases. This is not really surprising since Fierrez *et al.* [3], [11] have shown in that synthetic fingerprint databases generated from SFinGe have the same behavior and similar performance than those obtained from real fingerprint databases since the main inter-class and intra-class variations of fingerprints in nature are very well captured by SFinGe.

Some remarks can be formulated :

- the performances obtained when the MCC matcher algorithm is used is better than performance measures obtained with the Bozorth3 matcher for both real and synthesized databases,
- For the Bozorth3 matcher, one may consider that the confidence computed for a minutiae obtained from synthetic data is not as relevant than the confidencec computed for a minutiae extracted from real data. Since this is not confirmed bu results obtained with MCC, we may hypothesized that Bozorth3 is more sensitive to synthesized data and, by the way, may be quite easily faulted with synthesized data. This matcher does not be necessarily suitable for presentation attack detection process.
- The performance measure has been computed on 1) the FVC2004DB2 which contains distorted images since images are acquired with a slight plan projection, emphi.e. the acquired images are not perpendicular to the optical sensor and 2) two SFINGE databases, SFINGEC and SFINGED, contains fingerprint images whose the quality is ranking from medium to low. From the obtained results, whatever the matcher algorithm considered, one observes that the AUC values do not drastically inscrease with respect to the computed values on all remaining fingerpeint databases. This demonstrated that the proposed approach to mesaure the minutia confidence is robust to tested distortions.

The obtained results shows that the proposed strategy is a new promising way to investigate the usefulness of any minutia.

V. Conclusion and future works

Recently, biometric techniques have been widely deployed and will be very soon primordial in the constitution of information security as well as in other social service. Fingerprint has been one of the most important means of biometric applications and will still be a leading role in this domain. Minutiae template based matching is the dominant technique among the authentication approaches of fingerprint image and its performance fully relies on the quality of the input fingerprint image. In this case, it is reasonable to consider qualifying fingerprint with fingerprint minutiae template information extracted from fingerprint image, particularly when using for embedded applications due the limited memory.
The contributions of this paper are:

- a new framework to compute a the usefulness and the importance of a minutia in the fingerprint template taking into account the distribution of other minutiae in its neighborhood.
- a new Minutiae Confidence Index (MiCI) which is a non-image based value and aims to attribute a confidence index to each minutia in template. In fact, it depend only on fingerprint template information which are the location of the minutia with respect to a 2D plane of the corresponding fingerprint image and its type.
- the validation of this new index in the case of template reduction for embedded applications.

In the future, we plan to:

- improve the MiCI index by taking into account more features obtained for the ISO Compact Card Standard.

- investigate the robustness of MiCI for different type and strength of fingerprint distortions, such as blur, crop, rotation, and wrinkled in order to simulate realistic situations.
- apply the MiCI index for the indexation of fingerprint features.

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