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***Abstract*— Recently, palmprint recognition in forensic domain has gained considerable attention since 30% of evidence left in crime scene originate from palms. Like most of recognition systems, palmprint one is composed of three steps: preprocessing, features extraction and representation and finally features matching. Minutiae are the most reliable and discriminating features used in these systems. Minutiae matching is then very critical. Quantifying the similarity between two sets of extracted minutiae and assigning a score is particularly important in this step. In this paper, we designed similarity scores for a minutiae based recognition system using a minimum of extracted information. Our proposed scores are based on the score of [1], used in point pattern matching. They are tested and compared on the database used in [2]. The best one is tested and compared to the one presented in the same work[2]. Obtained results are very interesting.**

Keywords—Palmprint, High-Resolution, Point Pattern Matching, Similarity, Score.

I. INTRODUCTION

Palmprint has gained an interest as a biometric modality due to its universality, uniqueness, acceptability, stability and large amount of information that it contains. Like most of biometric traits, Palmprint has been used for different applications and domains and in different forms : complete low resolution form for civil and commercial applications and complete or latent high resolution form for forensic cases.

The early works on palmprint recognition appeared in the late 90's. They dealt with high resolution full to full comparison and tried to exploit specific features of palms, such as principal lines [3], and creases [4]. [5] reinforced principal lines using singular points for a first classification phase. [6] introduced global texture energy feature for a coarse level classification in an hierarchical approach. The Plessey operator to detect interesting points as features on the fine level was used. Feature points along the prominent palm lines were introduced in [7].

This research axis has been quickly abandoned with the current trend of adopting biometric recognition in civil and commercial applications. This is mainly due to the market which privileges low-resolution for a less expensive acquisition and a faster processing. High resolution is left to the forensic field which does not exploit a complete palmprint but a partial latent one. Since 2007, many researchers started working on latent palmprint recognition. It has become an important field of study [8-13].

These works are based mainly on minutiae as main feature. Minutiae are represented only by their locations and directions [8-10] or by local descriptors. These can be based on *the neighbouring minutiae information* such as the n-nearest neighbourhood minutiae eigenvector [11][12], the Minutia Cylinder-Code (MCC) descriptor [13] and the fixed radius based local minutiae structure descriptor [14]. They can also be based on *texture information* such as for ridge orientation descriptor and ridge period descriptor [14]. This texture can be captured using the Scale Invariant Feature Transformation (SIFT), the case in the Invariant Local Minutiae Descriptors (ILMD) [2]. A *combination of texture information and the neighbouring minutiae* is the base of The MinutiaCode descriptor [15].

Minutiae can be organized in local structures based on radial triangulation [16][17] or in an expanded triangle set based on minutia triplets obtained from Delaunay triangulation[18] or they can be represented in spectral domain such as in [19].

Some multifeatured works try to reinforce the minutiae by using other features such as principal lines[9] density map[9][10], directional map [9] [10] [15] and SIFT features [8]

Only few works, such as [20] [21], exploit the fourier transform domain. SIFT features are used in[22].

As we can see, minutia is the most used feature in recent works on high resolution palmprint recognition dealing with latent prints. Moreover, it was proven that minutia point feature has higher discriminability than other features [23].

In many cases, features extraction is performed manually by forensic experts since latent palmprint images are of very poor quality. Therefore, methods, using only features that can reliably be extracted by those experts such us minutiae position and direction information, gain great importance.

Minutiae extraction is followed by a matching step in the general process of biometric recognition. This step of minutiae matching is very difficult and critical in latent recognition. This is mainly due to the partiality of the prints that have no reference points to be used for alignment. Thus, the search for best alignment is implicitly performed during the matching process. This last can be *global* [8][9] where general hough transform is applied to find the optimal alignment transformation parameters. The global similarity score between minutiae sets is measured to guide this search. The matching process can also be *local* where similarity between minutiae descriptors is designed and computed in order to decide a set of best matched minutiae [11-13][15-18]. According to this set, a number of candidate transformations is delimited for a further phase of *consolidation.* In this consolidation step a global matching based on browsing all this candidate transformation is performed. A global similarity score is also measured to guide this search. We note that the best descriptor similarity is considered as the final similarity score between prints only in one work [2] where we talk about local matching without consolidation .

As we can see, the global similarity score measurement seems very important to guide the minutiae matching process. It consists of quantifying the similarity between two aligned sets of minutiae (after applying a transformation on the query set). It is generally based on the number of mated and unmated minutiae. It represents alone the final similarity score between minutiae feature in the global matching [8][9] or reinforced with the local descriptors similarity score in the local matching with consolidation [11] [13-17].

In this work, we propose global matching scores based on the distance between mated minutiae instead of just their number where no local structure construction is needed. To do so, we will represent the minutiae set as a point pattern, and reduce the problem to a minutiae point pattern matching problem. Thus, our proposed scores will be based on the similarity calculation in the point pattern matching problem presented in [1]. They will be analysed, tested and compared. We will test the best score on the palmprint database used in [2] and compare our approach to [2]. This will prove the efficacity of our score especially on the partial prints.

The rest of the paper is organized as follows. Section II presents a matching similarity scores state of art in palmprint recognition and some similarity scores that inspired us in point pattern matching. Section III introduces the different proposed matching scores in a progressive way. Section IV is dedicated to the test and results. It presents the implementation of the palmprint recognition system, the database used, compares and discusses the results of the different matching scores. Finally, Section V draws some conclusions.

II. RELATED WORK IN GLOBAL SIMILARITY SCORE :

As mentioned before, measuring the similarity between two aligned sets of minutiae plays an important role in minutiae matching. In this section, we will present the different global similarity scores used in palmprint recognition based on minutiae matching. Moreover, and since minutiae matching can be seen as a special case of point pattern matching, we will present some interesting similarity scores, especially the one presented in [1] (that we will name Tico's score in this paper) and on which are based our new scores.

A. *Similarity score in Minutiae Matching based palmprint recognition*

Given two sets of minutiae, a reference one A and a query one B, where minutiae are represented by their locations and directions m_i (x_i,y_i, θi) and a transformation T. The similarity between A and T(B) is generally based on the number of mated minutiae. Two minutiae m_i, m_j are considered mated if differences between their location and direction are less than a given threshold:

$$\begin{pmatrix} | x_i - x_j \ | < th_x \\ | y_i - y_j \ | < th_y \\ | \theta_i - \theta_j \ | < th_\theta \end{pmatrix} \tag{1}$$

The traditional way to compute the matching scores for a minutiae point pattern matching system in fingerprint recognition is [24]:

$$S = \frac{n^2}{size_r * size_q} \tag{2}$$

where $size_r$ and $size_q$ represent the numbers of minutiae in reference and query minutiae sets, respectively, and n is the number of mated minutiae. However, Bazen and Gerez [25] claim that using the following alternative will give better results [24].

$$S = \frac{2n}{size_r + size_q} \tag{3}$$

In works on palmprint recognition, researchers try to improve this quantitative score by adding qualitative information. The similarity score is computed in [9] as product of matching quantity and quality score :

$$S = S_{mq} * S_{mn} = \frac{C_p}{C_p + N_0} * \frac{{C_p}^2}{C_r C_q} \tag{4}$$

Where C_r and C_q are respectively the amount of minutiae in common area for reference and query palmprints. This amount is defined as the sum of the minutiae's confidence level (based on the image quality) estimated on minutiae extraction.

In [10] authors use the formula (4) but confine the amount of minutiae to be only their numbers. This is because minutia is not the main feature used in this work.

In [14-17] this score is reinforced by the local descriptors (structures) similarity without taking the confidence level into account:

$$S = \left(\frac{N_M}{N_M + N_0}\right) * \left(S_D * \frac{N_M}{N_M + N_L} * \frac{N_M}{N_M + N_F}\right) \tag{5}$$

where S_D is the average similarity of local descriptors or structures for all mated minutiae, N_L and N_F denote the number of unmatched minutiae in query latent and reference full palmprints. N_M denotes the number of mated minutiae.

N_0 is an estimation of the minimum number of matching minutiae for genuine matches. It is set to 5 in [10], 10 in [14] and to 20 in all other works [9][15][16][17] .

In [11] the authors combine the number of mated minutiae, the distance between them M_g, and the distance between their local structures. The similarity score is the weighted sum of the three information. Where M_g is defined as follow:

$$Mg(i,j) = |xi - xj| + |yi - yj| + \mu 3|\theta i - \theta j| \tag{6}$$

As we can see, all similarity scores for the minutiae matching approaches are based on the concept of mated and unmated minutiae. Some of them take into account the reliability and the confidence of the minutiae. Others involve the local similarity.

B. *Similarity score in Point Pattern matching*

Similarity scores in PPM are not based on the number of mated points but on the global distance between point sets. This gives more accuracy for the global matching.

A minutiae set matching can be seen as a point pattern matching problem (PPM) formulated as follows[26]:

Given two sets of point patterns P={p_i / $p_i \in R^N$, i=1…m} and O= ={o_j / $o_j \in R^N$, j=1…n} we want to find an assignment

P'→O' where P'⊆ P and O'⊆ O such that the match error between T(P') and O' is minimized.

We note that PPM can be a complete or uncomplete matching. In the first, we have a one to one mapping between the two point sets to be matched. In the second some points may not be matched. However we talk about a labelled PPM matching when using additional information (such as color, intensity, etc.) other than 2-D image coordinates [27].

In [27] the authors propose a genetic algorithm (GA) as a global matching solution for incomplete unlabelled point pattern. They consider the partial bidirectional Hausdorff distance H_{LK} as similarity score (in this case it represents also the fitness of the GA) since it can measure the degree of match between two point sets without explicitly pairing points:

$$fitness = \frac{1}{1+ H_{LK}(T(P'), O')} \tag{7}$$

In [26] the authors claim that using the *squared error* alone quantifies how well a portion of the model P matches the corresponding portion of the observed O. That is why they design a heuristic measure that penalizes incomplete matching and thus takes into account the overall quality of the match as follows:

$$\varepsilon = \sum_{i=1}^{k}((u_i - u'_i)^2 + (v_i - v'_i)^2) \tag{8}$$

$$\varepsilon' = \begin{cases} \frac{\varepsilon}{s}\left(1 + \left(\frac{m-2}{k-2}\right)\log\left(\frac{m-2}{k-2}\right)\right) & for\ k \geq 3 \\ \infty & for\ k = 0,1\ and\ 2 \end{cases} \tag{9}$$

Where m is the number of model points, s is the scale factor and k is the number of matching point.

In [1], authors develop a genetic algorithm that aims to solve the incomplete point pattern matching. They use the voronoi tessellation to speed the process. Authors propose an objective function claimed to be with one global maximum. It tries to avoid the implosion cases and takes inexact matching situation into account in order to obtain more continuous objective function. It allows all points to contribute into this function even non corresponding ones.

Given two point sets P and Q, a transformation T, r (p_i^T) denotes the minimum euclidean distance between the point $p_i^T \in P^T$ and a point $q \in Q$

$$r(p_i^T) = \min\{d(p_i^T, q) | q \in Q\} \tag{10}$$

And R_j denotes the set of all $p_i^T \in P^T$ which occurs in the neighborhood of the point $q_j \in Q$

$$R_j = \{p_i^T | r(p_i^T) = d(p_i^T, q_j)\} \tag{11}$$

Each point q_j contributes in the objective function by its minimum distance to its nearest neighbourhood $e(q_j)$ which is defined as:

$$e(q_j) = \begin{cases} \min\{r(p_i^T) | p_i^T \in R_j\}, & if\ |R_j| > 0 \\ \infty & if\ |R_j| = 0 \end{cases} \tag{12}$$

Finally the objective function is defined as:

$$F(T) = \frac{\sum_{j=1}^{|Q|} exp^{\left(-\frac{e(q_j)}{\alpha}\right)}}{|Q|} \tag{13}$$

F (T) takes real values between 0 and 1. This score that we will mention as Tico's score will be the base of our work.

III. PROPOSED SCORES

Palmprint recognition system is composed of three steps : pre-processing, features extraction and representation and finally features matching. In our case, we choose to extract minutiae and each one is represented by its location, orientation and type (bifurcation/ end) such as m (x,y,θ,type).

Thus, we are interested in the global similarity score between two minutiae sets R={m_1, m_2, …m_p}, Q={n_1, n_2, …n_q} We will adapt the Tico's score to our problem through four main modifications: adding a simple condition to the euclidean distance, changing the euclidean distance by a fusion of euclidean and orientation distance, improving the matching process, taking into account the concept of mated minutiae. These modifications resulted in five different scores (Atico_v1, Atico_v2, Atico_v3, Atico_v4, Atico_v5)

We first simplify the formulation of the Tico's solution [1] as follows:

Let r(m_i) be the closest minutiae to m_i defined as

$$r(m_i) = \{ n \in Q \mid \min(d_1(m_i, n))\} \tag{14}$$

We define R(n_j) as the set of all minutiae in the neighbourhood of n_j that are candidate to be assigned to n_j:

$$R(n_j) = \{ m_i \in R \mid n_j \in r(m_i)\} \tag{15}$$

Let e(n_i) be the assigned minutia to n_j chosen from R(n_j)

$$e(n_j) = \{ m \in R(n_j) \mid \min(d_2(n_j, m))\} \tag{16}$$

The final score is defined as

$$Tico_{Score} = \frac{\sum_{j=1, e(n_j)\neq\emptyset}^{|Q|} exp^{\left(-\frac{d_3(n_j, e(n_j))}{\alpha}\right)}}{\min(|Q|, |R|) + 1} \tag{17}$$

The distances d_1, d_2 ,d_3 used are the euclidean distance.

A. *Adding simple conditions:*

We adapted the Tico's score to our problem by taking orientation and minutia type in consideration through conditions added to the Euclidian distance d_1 to identify the assigned minutia r(m_i). d_1 is defined as:

$$d_1(m,n) < d_1(m,n') \\ \left(if\ eucl_{distance}(m,n) < eucl_{distance}(m,n')\right)\ and \\ \left(or_{dist}(m,n) - or_{dist}(m,n') < th_{diff.or}\right) \tag{18}$$

This means that the minutia n' is closer to m than n only if it is nearer in term of Euclidean distance and not farther than an accepted threshold $thr_{or.diff}$ in term of orientation distance.

On the other hand, we define d_2 to be :

$$d_2(n,m) < d_2(n,m') \\ \left(if\ eucl_{distance}(n,m') - eucl_{distance}(n,m)\right) > th_{diff.euc} \\ or(or_{dist}(n,m) < or_{dist}(n,m')\ and\ eucl_{distance}(n,m') \\ < eucl_{distance}(n,m)) \tag{19}$$

This means that minutia m is closer to n than m' only if it is closer in term of euclidean distance and orientation distance or is closer enough in term of euclidean distance to ignore the difference of orientation distance. This gives more importance to the location of minutiae.

The similarity score, *Atico_v1* is then defined based on the distance d_3

$$d_3(n,m) = 0.5eucl_{dist}(n,m) + 0.5\, or_{dist}(n,m) \quad (21)$$

A second variant of this similarity score, *Atico_v2*, is defined based on the distance d_3 :

$$d_3(n,m) = 1.5\frac{eucl_{dist}(n,m)}{1024} + 0.05\frac{or_{dist}(n,m)}{3.14} \quad (22)$$

Where we take into account the proportion to the max Euclidean distance which is the image size and the max orientation distance which is 3.14.

B. Distance based on Eucledian distance and orientation distance fusion

In this variant, *Atico_v3,* the euclidean distance between two minutiae used in Tico's d_1, d_2 ,d_3 is modified to be a fusion of location and orientation distance. This takes into account the importance of the minutia orientation as feature. We consider the following distance:

$$d_1(n,m) = d_2(n,m) = d_3(n,m) = Score(m,n) = 1.5\frac{eucl_{dist}(n,m)}{image_{size}} + 0.05\frac{or_{dist}(n,m)}{3.14} \quad (23)$$

C. Reinforcing one-to-one asignement

Atico_v4 is an improvement of *Atico_v3* where we try to reinforce the one-to-one correspondence by allowing a minutia to be linked to its second nearest neighbor if the first one is already assigned to another minutia.

We defined $s(m_i)$ as

$$s(m_i) = \{\, n \epsilon Q \text{ and } n \notin r(m_i) |\min(Score(m_i,n))\} \quad (24)$$

Where Score(m,n) is defined in (23).

We compute $e(n_i)$ after sorting minutiae in descending order according to the size of $R(n_j)$. Thus when $e(n_i)$ is calculated all $R(n_l)$ l>j are updated :

$$\begin{aligned} &for\ all\ m_i \ \epsilon \{R(n_j) - q(n_j)\} \\ &if\ n \in s\ (m_i)\ \ R(n) \leftarrow R(n) \cup m_i \end{aligned} \quad (25)$$

D. Considering minutiae matching conditions

In palmprint recognition, two minutiae are considered mated only if they are of same type and having locations and orientation close enough. So we consider this condition in *Atico_v5* when constructing $r(m_i)$

$$r(m_i) = \left\{ \begin{matrix} n \epsilon Q |\ eucl_{dist}(m_i,n) < th_{edist} \ and \\ or_{dist}(m_i,n) < th_{ordist} \end{matrix} \right| \min(Score(m_i,n))\} \quad (26)$$

IV. Test And Results

In order to test Tico and the proposed scores, evaluate and compare them, we implemented the whole process of palmprint recognition. All implemented techniques are classical ones. First, Palmprints are enhanced using the Hong technique [28]. It consists of five steps: normalization, orientation image estimation, ridge-frequency image estimation, region mask generation, and Gabor-based filtering. Then, palmprints are binarized using simple fixe thresholding. Palmprint image is then segmented using morphological operators and finally the fast parallel algorithm [29] is used to thin the prints.

After this preprocessing step, we use the classical technique based on Crossing Number and Direction Number for minutiae extraction. We use two rules to eliminate false minutiae: eliminate minutiae on the border of the palmprint and those whose distance is below than a certain threshold.

The result of this process is a vector of minutiae where each is characterized by its coordinates x, y, orientation and type (termination or bifurcation). Fig. 1 describes an example of the minutiae extraction process step by step.The database used in our tests is the one described in [2]. It is composed of scanned palmprints from 100 persons. Each one provided his left and right palmprints to build a database of 200 full palmprints (FP). Each full image was divided into 4 Half palmprint (HP), 4 Quarters palmprint (QP) and 4 Random palmprint (RP). Fig. 2 present an example. The images are of various quality impressions, ranging from poor to good [2]. Images used in these experiments are reduced to 1024 ×1024. They were recorded at 500 dpi. The RP part was not used in our experiments since our aim is not to test translated and rotated parts of palms.

Tests were performed in three phases: first, Tico and the five proposed scores were tested and evaluated on a part of the database [2]. Then, strategies and parameters used in the best one were confirmed. Finally the best obtained score (with best parameters) was tested on the whole database and compared to the results obtained in [2]. These tests will be presented in the next three sections.

A. Similarity scores evaluation and comparaison:

Using the whole database to evaluate and compare the different proposed variants is time consuming. Thus, we use a part of our database only. This part is composed of 4 full prints, 16 half prints and 16 quarter prints.

Every print is compared to 9 full reference prints including its own reference (the genuine comparison). This adds up to

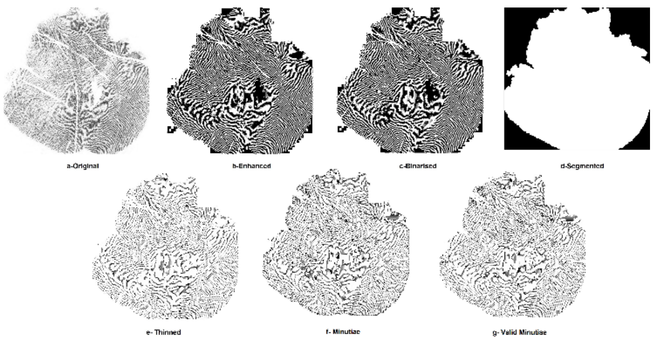

Fig 1 Minutiae extraction process

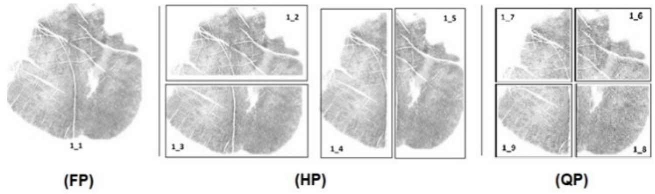

Fig. 2 Example of database used in experiments

36 genuine comparisons and 288 imposter comparisons. The details of these comparisons are given in Table. I. In Table. II we summarize the different used parameters.

All the proposed score are compared to the Tico's one. We consider the difference between Average genuine scores and average imposter scores as an evaluation index. The larger this difference is, the more genuine and imposter classes are distinct. It is important to have large genuine score but this will have no mean if the imposter one is large too. This average is computed for the whole used database and for each part alone (FP, HP, QP).We summarize the results obtained for every score in Table. III.

For all scores, the averages of the genuine and imposter classes are well separated. As one can note, adding simple conditions on the location and orientation differences in Atico_v1 and Atico_v2 does not improve the difference between the average genuine and imposter scores. However it decreases the number of assigned minutiae (decrease the number of nj with e(nj)= ∅).Therefore, this added condition decreases the imposter score which is requested in our case. The hybridization of Euclidean and orientation distance used in Atico_v3 has also the same effect. On the other hand, trying to improve the matching process in Atico_v3 by giving more chances to minutiae to be mated to its second best nearest minutiae in Atico_v4 improves the genuine scores. In Atico_v5, we try to combine these three ideas, used in the variants presented before, and reinforce the first one by adding strong conditions on matting minutiae to decrease the imposter scores and increase the genuine one. Number of comparisons for the scores evaluation. This score gives the best results with a difference of 0.61 between the two classes in total and 0.99 in the full prints case.

TABLE I. NUMBER OF COMPARAISON FOR THE SCORES EVALUATION

	Genuine	Imposter
FP	4	32
HP	16	128
QP	16	128

TABLE II. DIFFERENT PARAMETERS IN SCORE IMPLEMENTATION

parameters	values	parameters	Values
th_{edist}	5	$th_{diff.or}$	30
th_{or}	5	$th_{diff.or}$	7

B. Parameters and stratigies confirmation:

In order to confirm the utility of adding a minutia in the matching process (the use of s(mi)) we implement four more scores:

1) Atico_v3': where we add the minutiae mating conditions used in Atico_v5 without using s(mi) (used in Atico_v4) to the Atico_v3.

2) Atico_v5': where we increase the threshold th_{or} and th_{eucl} to be (10,10)

3) Atico_v5'': where we test inversing the sets of minutiae by using the reference (resp. query) minutiae set as Q set (resp. R) instead of the query one in Atico_v5

4) Atico_v3'': where we test inversing the sets of minutiae on Atico_v3'

The results are summarized in Table. IV. As we can see, Atico_v5 out is slightly better than Atico_v3'. This confirms the utility of s(mi). The performance degradation in Atico_v5' confirms the utility of using (5,5) as threshold. Contrariwise inversing sets, in Atico_v5'', proofs its efficiency. This can be explained by the fact that our first comparison is based on the smallest set instead of the largest. This reduces the conflict in the minutiae matching process and increases the chance for minutiae to be mated. This has the same effect as using s(mi). This is why this improvement is more obvious in Atico_v3''.

C. Palmprint recognition evaluation:

To confirm the performance of Atico_v5'', we tested the process on the whole database. This implies 1800 genuine comparisons (200 FP, 800 HP, 800 QP) and 385200 imposter comparisons (39800 FP, 159200 HP, 159200 QP). We computed the Equal Error Rate (EER) for each set of palmprints and compare it to the results in [2].

To compute the EER, we proceed as following: if a Genuine score is lower than certain threshold, a False rejection error is marked and if an Imposter score exceeds it, a false acceptance error is marked. The false rejection rate (FRR) and the false acceptance rate (FAR) are computed separately and this by given threshold until finding the EER point where FAR=FRR= EER.

Another important measure especially in identification problems is the rank-r which can be defined as the probability that the user's identity is among the first r identities returned.

TABLE III. SCORE SIMILARITY EVALUATION AND COMPARAISON

	Tico	Atico_v1	Atico_v2	Atico_v3	Atico_v4	Atico_v5
Total						
Avg Genuine	0.765911791	0.734620864	0.748208488	0.737220708	0.773186356	**0.664076921**
Avg Imposter	0.398661299	0.375166065	0.413444278	0.377222366	0.452023519	**0.050176526**
Difference	0.367250492	0.3594548	0.33476421	0.359998343	0.321162837	**0.613900395**
FP						
Avg Genuine	0.999240223	0.999240223	0.999240223	0.999240223	0.999240223	**0.999240223**
Avg Imposter	0.453408183	0.422019537	0.457126266	0.424051004	0.51866895	**0.059901706**
Difference	0.545832039	0.577220686	0.542113957	0.575189218	0.480571272	**0.939338517**
HP						
Avg Genuine	0.763395358	0.731681809	0.743169966	0.733912913	0.770819884	**0.675882415**
Avg Imposter	0.387216189	0.363084254	0.398734137	0.365075709	0.437908684	**0.050075926**
Difference	0.376179169	0.368597555	0.344435829	0.368837204	0.3329112	**0.625806489**
QP						
Avg Genuine	0.710096115	0.671405081	0.690489076	0.675023625	0.719039363	**0.568480601**
Avg Imposter	0.396419687	0.375534508	0.417233922	0.377661863	0.449476997	**0.047845832**
Difference	0.313676428	0.295870573	0.273255154	0.297361762	0.269562365	**0.520634769**

TABLE IV. - SCORE ATICOV5 AMELIORATION

	Atico_v3'	Atico_v3''	Atico_v5	Atico_v5'	Atico_v5''
Total					
Genuine	0.661878955	0.663235946	**0.666301719**	0.703046009	**0.666393399**
Imposter	0.050586285	0.050451557	**0.051116752**	0.151567015	**0.051093564**
Difference	0.61129267	0.612784389	**0.615184967**	0.551478994	**0.615299834**
FP					
Genuine	0.999240223	0.999240223	**0.999240223**	0.999240223	**0.999240223**
Imposter	0.060288807	0.060160145	**0.061015973**	0.18022937	**0.060907973**
Difference	0.938951415	0.939080078	**0.93822425**	0.819010853	**0.938332250**
HP					
Genuine	0.672750496	0.673740653	**0.678350946**	0.712753009	**0.678048284**
Imposter	0.050424785	0.050243951	**0.051007935**	0.149330878	**0.050997629**
Difference	0.622325712	0.623496702	**0.62734301**	0.56342213	**0.627050655**
QP					
Genuine	0.566667097	0.568730171	**0.571017866**	0.619290455	**0.571526807**
Imposter	0.048322156	0.048232016	**0.048750764**	0.146637562	**0.048735897**
Difference	0.518344941	0.520498155	**0.522267102**	0.472652893	**0.522790910**

So, we computed Rank1,Rank10 and Rank20 for each set. While we were interested by having the most distinctive classes we computed for each palmprint set the average of the difference between the genuine score and the highest imposter score for each print. The results are summarizing in Table. V. Fig. 3 represents the different Receiver Operating Characteristic (ROC) curves for the sets FP, HP, QP (global and zoomed ones) which is the curve used to compute the EER. Fig.4 represents the Cumulative Match Characteristic (CMC) for the QP set of palmprints.

The proposed score achieve a high distinctiveness on the three sets and best performance among the proposed method in [2] on the HP set. On the other hand, it presents a good EER results on the QP set but does not exceed the one in [2]. This is mainly due to the 0 genuine score recorded for three of the QP images that belong to two degraded palmprint images shown in fig. 4. By analysing the process we found that this bad score is due to bad segmentation process (the result of their segmentation is a black image). Removing this two prints from the database improves the EER for the HP and the QP sets to become EER-HP = 0% and EER-QP= 0.5102%. It improves the Rank-1-QP and Rank-10-QP to become 99.36% and 99.74% respectively.

We note that all the implemented scores (including the Tico one), consider only minutiae of same types. Accepting minutiae from different types to be mated with small probability (0.05) does not influence the EER on the different parts of the database. However, accepting them (with probability 1) deteriorates the performance of the system. We got in this case, EER-HP = 0.12% and EER-QP= 1.51%. This is due to the increase of the mated minutiae number in the imposter case. The average imposter score increases to reach 0.09055019 and 0.087689852 in the HP and QP part respectively. The maximum imposter score also increases significatively and reach 0.32424496 and 0.40062619 in the HP and QP part respectively.

V. CONCLUSION

In this work, we designed new similarity scores for minutiae matching in palmprint recognition systems. Our aim was to reach a similarity score that can be used to guide a global matching in an efficient way. We did not limit our score to the number of mated and unmated minutiae but extended it to take into account the global distance between mated minutiae. We based our work on the Tico score [1] and proposes different adaptations and scores that we evaluated and compared. We can conclude that taking the minutiae orientation distance into account, improves the matching process. Moreover, accepting only close minutiae (considering mated minutiae condition) improves the efficacity of the score significantly. However, ignoring the type of minutiae claimed to be without influence on the matching process for the fingerprint case [24] deteriorates significantly the performance of our palmprint system.

The best reached score is normalised in [0,1]. It has the force of combining the distances between the minutiae sets (in term of location and orientation) with the particularity of the minutiae (through penalising false mated minutiae). The results outperform the ones in [2] for the HP part. Promising results are obtained for further global matching process especially for better segmentation techniques.

REFERENCES

[1] Tico, M., & Rusu, C. (1998, September). Point pattern matching using a genetic algorithm and Voronoi tessellation. In 9th European Signal processing Conference (EUSIPCO 1998) (pp. 1-4). IEEE.

[2] Laadjel, M., Bouridane, A., Kurugollu, F., Nibouche, O., & Yan, W. (2010). Partial palmprint matching using invariant local minutiae descriptors. In Transactions on data hiding and multimedia security V (pp. 1-17). Springer, Berlin, Heidelberg.

[3] Zhang, D., & Shu, W. (1999). Two novel characteristics in palmprint verification: datum point invariance and line feature matching. Pattern recognition, 32(4), 691-702.

[4] Chen, J., Zhang, C., & Rong, G. (2001). Palmprint recognition using crease. In Proceedings 2001 International Conference on Image Processing (Cat. No. 01CH37205) (Vol. 3, pp. 234-237). IEEE.. *(references)*

[5] Shu, W., Rong, G., Bian, Z., & Zhang, D. (2001). Automatic palmprint verification. International Journal of Image and Graphics, 1(01), 135-151.

[6] You, J., Li, W., & Zhang, D. (2002). Hierarchical palmprint identification via multiple feature extraction. Pattern recognition, 35(4), 847-859.

[7] Duta, N., Jain, A. K., & Mardia, K. V. (2002). Matching of palmprints. Pattern Recognition Letters, 23(4), 477-485.

[8] A. K. Jain and M. Demirkus, "On Latent Palmprint Matching," Michigan State University, Tech. Rep., 2008, http://biometrics.cse.msu.edu/Publications/Palmprints/OnLatentPalmprintMatchingJainDemirkus08.pdf.

[9] Dai, J., & Zhou, J. (2011). Multifeature-based high-resolution palmprint recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 33(5), 945-957.

[10] Dai, J., Feng, J., & Zhou, J. (2012). Robust and efficient ridge-based palmprint matching. IEEE transactions on pattern analysis and machine intelligence, 34(8), 1618-1632.

[11] Li, J., Shi, G., Feng, Q., & Wan, H. (2007, July). A New Point Pattern Matching Method for Palmprint. In Artificial Intelligence and Pattern Recognition (pp. 302-306).

[12] Tan, Z., Yang, J., Shang, Z., Shi, G., & Chang, S. (2009, May). Minutiae-based offline palmprint identification system. In 2009 WRI Global Congress on Intelligent Systems (Vol. 4, pp. 466-471). IEEE.

[13] Cappelli, R., Ferrara, M., & Maio, D. (2012). A fast and accurate palmprint recognition system based on minutiae. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 42(3), 956-962

[14] Liu, E., Jain, A. K., & Tian, J. (2013). A coarse to fine minutiae-based latent palmprint matching. IEEE Transactions on Pattern Analysis and Machine Intelligence, 35(10), 2307-2322.

[15] Jain, A. K., & Feng, J. (2009). Latent palmprint matching. IEEE Transactions on pattern analysis and machine intelligence, 31(6), 1032-1047.

[16] Wang, R., Ramos, D., & Fierrez, J. (2011, October). Latent-to-full palmprint comparison based on radial triangulation under forensic conditions. In 2011 International Joint Conference on Biometrics (IJCB) (pp. 1-6). IEEE.

[17] Wang, R., Ramos, D., & Fierrez, J. (2012, March). Improving radial triangulation-based forensic palmprint recognition according to point pattern comparison by relaxation. In 2012 5th IAPR International Conference on Biometrics (ICB) (pp. 427-432). IEEE.

[18] Hernández-Palancar, J., Muñoz-Briseño, A., & Gago-Alonso, A. (2013, November). A new triangular matching approach for latent palmprint identification. In Iberoamerican Congress on Pattern Recognition (pp. 294-301). Springer, Berlin, Heidelberg

[19] Wang, R., Veldhuis, R., Ramos, D., Spreeuwers, L., Fierrez, J., & Xu, H. (2013, April). On the use of spectral minutiae in high-resolution palmprint recognition. In 2013 International Workshop on Biometrics and Forensics (IWBF) (pp. 1-4). IEEE.

[20] Laadjel, M., Kurugollu, F., Bouridane, A., & Boussakta, S. (2009, November). Degraded partial palmprint recognition for forensic investigations. In 2009 16th IEEE International Conference on Image Processing (ICIP) (pp. 1513-1516). IEEE.

[21] Singh, S., Ramalho, M., Correia, P. L., & Soares, L. D. (2012, August). PP-RIDER: A Rotation-Invariant degraded partial palmprint recognition technique. In 2012 Proceedings of the 20th European Signal Processing Conference (EUSIPCO) (pp. 1499-1503). IEEE.

[22] Carreira, L., Correia, P.L., Soares, L.D.: 'On high resolution palmprint matching'. Int. Workshop Biometrics Forensics, Valletta, Malta, March 2014, pp. 1–6

[23] Fei, L., Lu, G., Jia, W., Teng, S., & Zhang, D. (2018). Feature extraction methods for palmprint recognition: A survey and evaluation. IEEE Transactions on Systems, Man, and Cybernetics: Systems, (99), 1-18

[24] Sheng, W., Howells, G., Fairhurst, M., & Deravi, F. (2007). A memetic fingerprint matching algorithm. IEEE Transactions on Information Forensics and Security, 2(3), 402-412.

[25] Bazen, A. M., & Gerez, S. H. (2003). Fingerprint matching by thin-plate spline modelling of elastic deformations. Pattern Recognition, 36(8), 1859-1867.

[26] Ansari, N., Chen, M. H., & Hou, E. S. (1990, November). Point pattern matching by a genetic algorithm. In [Proceedings] IECON'90: 16th Annual Conference of IEEE Industrial Electronics Society (pp. 1233-1238). IEEE.

[27] Zhang, L., Xu, W., & Chang, C. (2003). Genetic algorithm for affine point pattern matching. Pattern Recognition Letters, 24(1-3), 9-19.

[28] Hong, L., Wan, Y., & Jain, A. (1998). Fingerprint image enhancement: algorithm and performance evaluation. IEEE transactions on pattern analysis and machine intelligence, 20(8), 777-789.

[29] Zhang, T. Y., & Suen, C. Y. (1984). A fast parallel algorithm for thinning digital patterns. Communications of the ACM, 27(3), 236-239.

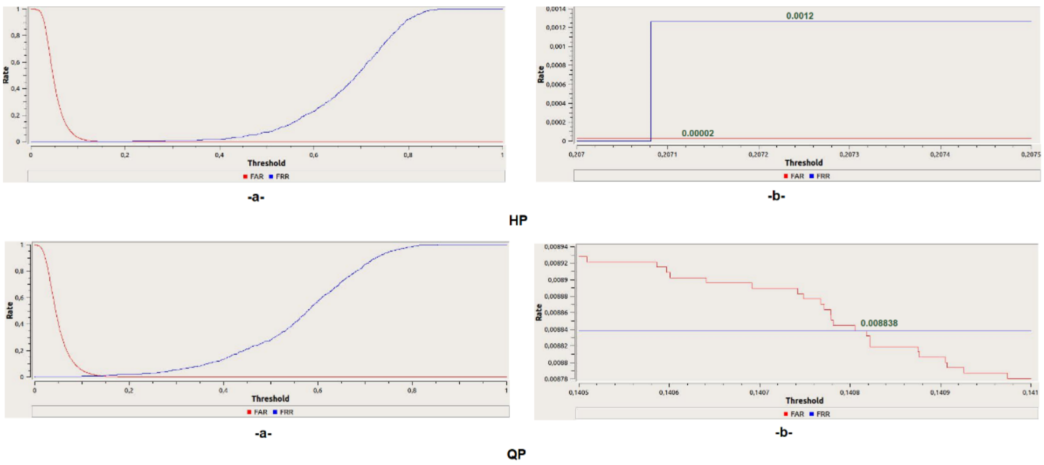

Fig 3 ROC curves for the different set of palmprint in the database (a- without zooming- with zooming)

TABLE V. T- EVALUATION OF ATICOV5'' ON THE DATABASE[2]

	FP	HP	QP
Avg genuine	0.99924615	0.67159771	0.559172463
Avg imposter	0.059676718	0.050871455	0.04953633
Min genuine	0.99827586	0.20708124	0
Max imposter	0.15640487	0.21999152	0.28493154
avg Diff	0.888110902	0.5466228847	0.4179718841
Rank-1	100%	100%	98.7373%
Rank-10	100%	100%	99.3686%
Rank-12	100%	100%	99.49494%
EER	0	0.002	0.88
EER[2]	/	0.19	0.62

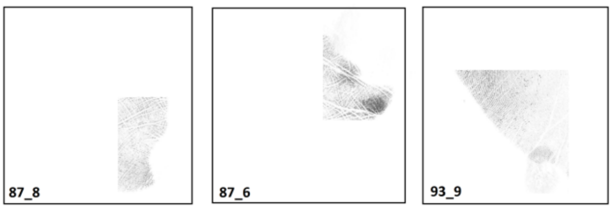

Fig 4 Palmprints of bad quality with genuine score=0