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OPTIMIZATION OF FINGERPRINT SIZE FOR REGISTRATION

Abstract

The propose algorithm finds the optimal reduced size of latent fingerprint. The algorithm accelerates the correlation methods of fingerprint registration. The Algorithm is based on decomposition and reduction of fingerprint to one dimension form by using the adoptive method of empirical modes. We choose the most appropriate internal mode to determine the minimum distance between the extremes of empirical modes. We can estimate how many times the fingerprint in the first step of the comparison can be reduced so as not to lose the accuracy of registration. This algorithm shows best results as compared to conventional fingerprint matching techniques that strongly depends on local features for registration. The algorithm was tested on latent fingerprints using FVC2002, FVC2004 and FVC2006 databases.

1. INTRODUCTION

Identification of a person using fingerprints has been used for many years. Traditionally, the people that act as driving force behind the promotion of fingerprint technologies have become law enforcement agencies and forensic professionals. The use of fingerprints taken at the scene of crime to identify suspects can be a decisive stage in the criminal examination; Figure 1 shows fingerprints taken from crime scene. Massive fingerprint databases have been collected by law enforcement agencies around the world. These large databases

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encourage research work to towards development of Identification systems by fingerprints. The latent fingerprints collected from crime scene are noisy, low resolution and contain little information. Matching latent fingerprints is a challenge.

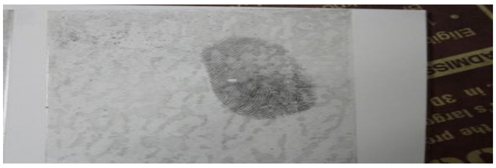

Fig. 1. Latent Finger Print [source: database of Indraprastha Institute of Information Technology]

Many fingerprint matching algorithms are based on a comparison of small fingerprints features known as minutiae (Yager & Amin, 2004). These features are of many types. During the minutiae extraction phase, any errors will extend to the stages of alignment and verification, which are dependent on the quality of minutiae information. Some researcher took interest in matching techniques, not dependent on minutiae, like pixel intensities (Bazen, Verwaaijen, Gerez, Veelenturf & Zwaag, 2000) or filter banks which are based on orientation information (Park, Lee, Smith, Park & Park, 2004).

2. RELATED WORK

In this section, we identify some studies conducted on fingerprint registration. Transformation by Hough for fingerprint registration was proposed (Ratha, Karu, Chen & Jain, 1996). The volume is converted into a discrete set of values of all possible transformations. The rotation and translation to register them is computed for each pair of significant matching minutiae. Proof of this transformation is collected in the parameter space. To select the most likely transformation parameters, the minutiae space is used. The main disadvantage of this method is that it is computationally expensive. However it will work properly, since the performance of method is a very broad search of the parameters volume. This approach is based on minutiae and can be compared with minutiae based registration algorithms.

The main disadvantage of transformation of Hough is its execution time. Several attempts have been made to develop more efficient matching algorithms. A commonly used technique is to provide additional information that leads to leveling and decreasing the number of dependent values (Bazen, Verwaaijen, Gerez, Veelenturf & Zwaag, 2000; Jain, Hong & Bolle, 1997; Park, Lee, Smith, Park & Park, 2004; Ratha, Karu, Chen & Jain, 1996; Yager & Amin, 2004) uses ridge information as an registration help and this approach has been implemented. During the extraction of minutiae, the form of its associated ridge is also stored.

In the case of a possible pair of details, if the corresponding ridges are the same, the minutia pairs are in the same place. Then they are rotated to even the projections. This rule applies to all possible minutiae pairs and alignment, which leads to the most global match.

Structural approaches utilize local fingerprint feature mechanisms to quickly find possible matching items. An algorithm of structural matching proposed by Jiang (Jiang & Yau, 2000) has been developed. The data used in this approach is the distance between fingerprint local features, the relative differences between the radial angles and the directions of minutiae, the types of details and the size of the ridges. This information is used to search for possible curiosities. Then, the registration parameters are calculated to register this match.

The only approach of non-minutiae for registration is based on the alignment of checkpoints. Maes, Vandermeulen & Suetens (2003) define a reference point (or base point) as the point of maximum curvature of concave ridges in the fingerprint. The authors create a way to identify the main points that use the mask to integrate sine components of local orientations. This method was used to determine the position of the reference point. After extracting the control point from each fingerprint, the registration is done by searching for parameters that align them. It should be noted that this includes only translation parameters (no rotation).

3. METHODOLOGY

The approach presented in this paper is based on normalization for fingerprint registration by non-minutiae correlation methods.

3.1. Correlation Methods

The most sustainable to various types and modalities of images are correlation methods. In such methods, the concept of similarity of images is introduced (this is how the correlation methods differ from each other). And further for the registered fingerprint image, the best transformation option is selected in such way that the transformed and target fingerprint images are the most similar. In this paper, we use mutual information (Maes, Vandermeulen & Suetens, 2003) as a similarity metrics. Method Maximizing Mutual Information (MMI) is one of the most common entropy correlation methods. Entropy methods do not depend on the nature of the image, since they work mainly with image histograms.

MMI use some optimized version of the search for the maximum value of the (Zhao et al., 2014). One of the most obvious and effective ways to optimize is to look for an approximate maximum on the grid, and then refine the meaning with a full search or reduce the image several times and apply the algorithm to them, and after registering the reduced copies, refine the result on the original images.

Similar optimizations can be made, since the mutual information increases smoothly when it approaches the desired point (Maes, Vandermeulen & Suetens, 2003). An example of the change in MI, when the image is shifted along the x and y axes, is shown in Fig. 2.

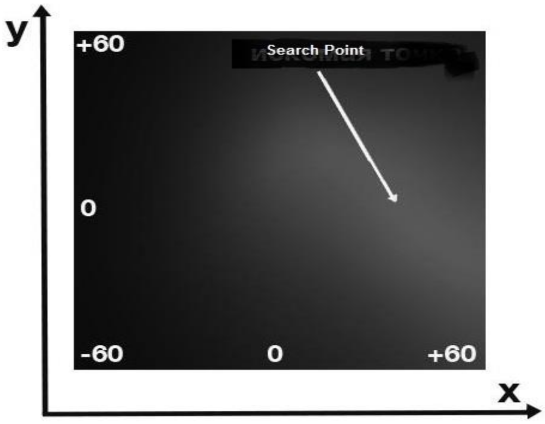

Fig. 2. Graph dependent on mutual information on the displacement of the fingerprint along the x and y axes

Thus, it is possible to make such optimization if the following question is answered. How many times the image can be reduced without losing the accuracy of registration? This paper answers the questions of such estimates by using the method of empirical modes.

3.2. The Method of Empirical Modes

Empirical Mode Decomposition (EMD) was developed in 1998 and its application can be find in many studies (Bhuiyan, Adhami & Khan, 2008; Guryanov & Krylov, 2017). It allows you to analyze nonlinear and non-stationary data and obtain a frequency distribution of data over time for one-dimensional signals by decomposing the signal into functions of different frequencies. An empirical mode is a function with the following properties:

1. For the considered interval, the number of extrema does not differ by more than one, from the number of intersections of zero.
2. The Half-Sum of the upper and lower envelopes of a given function is close to zero.

As a result of signal *f(t)* into empirical modes, we get the following sum:

$$f(t) = r(t)\sum_{i}^{N}\phi_i(t), \tag{1}$$

where $\varphi_i(t)$ are empirical modes, and $r(t)$ is the remainder. The first modes contain high frequency characteristics of the signal, and the latter and the remainder are low-frequency characteristics.

3.2.1. Fast decomposition algorithm

There are different methods of decomposing the signal into empirical modes. In this paper, we use the fast adaptive decomposition method for empirical modes (Bhuiyan, Adhami & Khan, 2008). The decomposition algorithm for the one-dimensional signal *I*, consists of the following steps:

1. We set the initial window size to $w = 3$.
2. We find the signal *I* local extremes by search window of size equal to *w*. The local Maxima *p* must satisfy the following conditions:

$$I(p) > I(q), \forall q \in W_w(p), \tag{2}$$

   where $W_w(p)$ denotes the window centered at *p* and *w*. Then the local Minima *q* must satisfy the following conditions:

$$I(p) < I(q), \forall q \in W_w(p). \tag{3}$$

3. For each local Maxima, we find the distance to the next nearest maximum and denote this distance by $d_{\max}$. Then for each local Minima, we find the distance to nearest mnimum and denote it by $d_{\min}$. Find the minimum of these values $d = \min(d_{\max}, d_{\min})$.
4. Update the window size $w = 2 + [{}^{d}/_{2}] + 1$.
5. Compute the upper U and the lower L envelope with updated window size *w*:

$$U(p) = \max_{q \in W_w(p)} I(q), L(p) = \min_{q \in W_w(p)} I(q), \tag{4}$$

6. We calculate the average envelope arithmetic mean R for the upper and lower envelopes with blur window size w:

$$R(p) = \frac{1}{w}\sum_{q \in W_w(p)} \frac{U(q) + L(q)}{2}. \tag{5}$$

7. For signal I, calculate the empirical mode $M = I - R$. We get high-frequency empirical mode M and the low-frequency residual R.
8. Next, we assume $I = R$ and repeat steps 2–7 (each time we get the next internal mode) until R becomes impossible (i.e. when R has less than two maxima or minima).

3.2.2. Window Size

In the decomposition algorithm described above, the size of the window w plays an important role. The window size at each step is the distance between extremes of the same type (Minima or Maxima). The higher the number of empirical mode, low is the frequency. This means that for each next internal mode, the number of extrema will decrease, and the distance between them will increase. The window size for each empirical mode will also increase. Moreover, w is an important characteristic of the signal, since by reducing the signal frequency by a factor of w, we do not lose local extrema.

4. THE METHOD OF MAXIMIZATION OF MUTUAL INFORMATION

The method of maximizing mutual information is a correlation method of recording images, which is described by the following formula:

$$t^* = \arg\max_t \sum_{u,v} H_{I_t J}(u,v) \log \frac{H_{I_t J}(u,v)}{H_I(u) H_J(v)}, \tag{6}$$

Where H_I and H_J are the normalized histograms of the signals I and J, respectively:

$$H_I(u) = \frac{\left|\{ p \in domI : I(p) = u \}\right|}{N_I}, \tag{7}$$

$$H_J(u) = \frac{\left|\{ p \in domJ : J(p) = v \}\right|}{N_J}, \tag{8}$$

And H_{ItJ} the normalized joint histogram of the signals I_t and J:

$$H_{I_t J}(u,v) = \frac{\left|\{ p \in domJ : I_t(p) = u, J(p) = v \}\right|}{N_J}, \tag{9}$$

This method is widely used for combining images.

5. OPTIMIZATION OF MMI METHOD

We will consider the example using the above described approach of signal decomposition by the method of empirical modes. It is possible to optimize the correlation methods for registering the fingerprint images.

5.1. Reduction to a one-dimensional signal and its decomposition

It can be seen from the examples of fingerprints (Figure 3) that the important characteristics of the fingerprints under consideration are its orientation field.

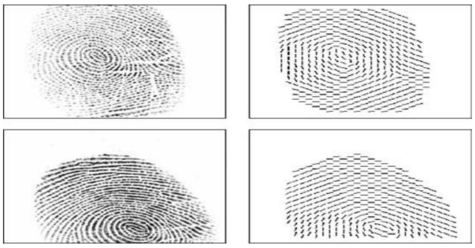

Fig. 3. Shows the orientation filed of two same fingerprint images.

Select orientation field of fingerprints and based on the characteristics of the orientation field, we will draw a conclusion about how many times we can reduce the size of fingerprints without losing the accuracy of registration. First, we construct a binary mask of the fingerprint from the image of the fingerprint. The mask is constructed using a luminance thresholding with complementary morphological analysis to remove the gaps inside the mask and the extra elements outside the fingerprint. The data were taken from (Sharat, 2005). An example of a mask and its fingerprint for this fingerprint is shown in Figure. 4.

(a) (b)

Fig. 4. Mask of Fingerprint(a) and Fingerprint (b)

Further, we translate these masks into a polar coordinate system with a reference to core of the fingerprint and move from 2D picture to one-dimensional signal. The result of such a transition is shown in Figure 4. Now we decompose the resulting one-dimensional signal using the fast adaptive method of empirical modes.

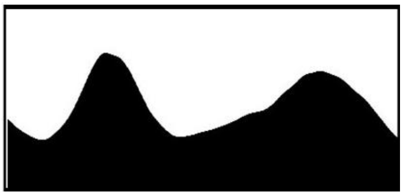

Fig. 5. The inverted Mask

The result of decomposition of fingerprints in Figure 6, can be seen in Figure 7. We are interested in the size of the window *w*, obtained after each Empirical Mode.

(a) (b) (c)

Fig. 6. Fingerprints from Database FVC2002

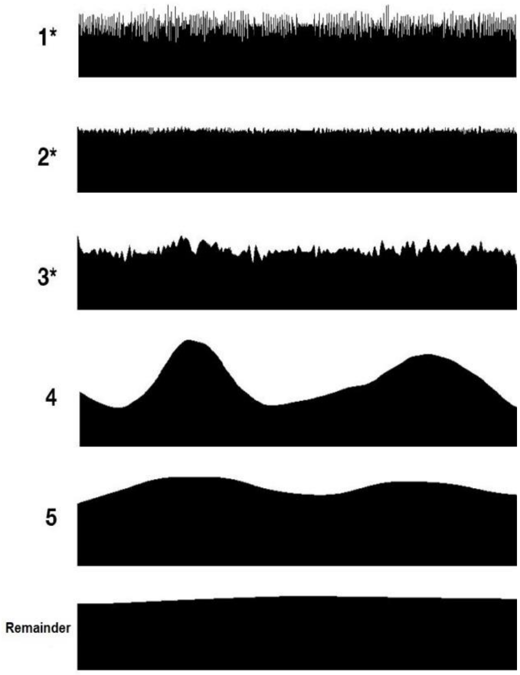

Fig. 7. The result of decomposition by the method of Empirical Signal Modes (modes marked with an asterisk (*) are scaled for clarity)

5.2. Computing the Reduction Ratio of a Fingerprint

Table 1 reflects the important properties of the algorithm (Guryanov & Krylov, 2017). The Jump in Window size is determined by the following formula:

$$k \to \min : \frac{\ln(w_{k+1})}{\ln(w_k)} \geq \frac{\ln(w_{i+1})}{\ln(w_i)}, \forall i. \tag{10}$$

Tab. 1. Dependence of the window size on the internal mode number for the three test images

Modes / Images	1	2	3	4	5	6	7
a	3	3	**10**	220	262	5	3
b	3	3	7	**9**	51	180	300
c	3	3	3	**10**	72	240	312

Further, internal modes after the jump in the window size contain the lowest-frequency characteristics of the fingerprint. For the purpose of reducing the size of registered images, we will choose an Empirical Mode directly before the jump in the size of window. This Empirical Mode contains the most important high-frequency characteristics, since noise and other random extremes are eliminated in the calculation from the first Empirical Mode. Therefore, the main parameter for calculating the image reduction factor, we take the window size w corresponding to this Empirical Mode. Now using the window size w, we calculate the image reduction factor k as follows:

$$k = \frac{\pi w(width + height)}{4N}. \tag{11}$$

Where width and height are respectively the width and height of the fingerprint, and N is the number of steps by angle parameter, while passing to a one-dimensional signal from the polar coordinate system. We translate w from the polar coordinate system, back to the Cartesian coordinate system and into pixels. Therefore, the value depends on the image dimensions and on the number of steps by angle parameter. The obtained parameter k is used to optimize the selection of transformation to Maximize Mutual Information.

6. RESULTS OF OPTIMIZATION STAGE

We tested the proposed method on a set of images. To estimate the acceleration coefficient of the Algorithm instead of a full search for transforming the angle and shifts along the x and y, we looked first for a maximum of mutual information on the grid with step k. The computation time is reduced to k^3 times. The results of the algorithm for different pairs of images are shown in Table 2.

Tab. 2. The fingerprints marked with (*) were computed on the proposed algorithm of Normalization

	X	Y	Angle	Scale	Coef.	Time (s)
Fingerprint 1	40	-10	-25	1.15	–	5100
Fingerprint 1*	40	-10	-25	1.15	8	20
Fingerprint 2	4	18	-8	1	–	4900
Fingerprint 2*	4	18	-8	1	8	26
Fingerprint 3	-40	-11	25	0.85	–	4780
Fingerprint 3*	-40	-11	25	0.85	9	21

It can be seen that while applying the optimization, the images registration result do not change. This significantly reduces the running time of the algorithm. It can be seen that our estimate of the acceleration coefficient was adequate. Thus, it can be argued that the resulting estimation of the optimization factor is successful, since we significantly speed up the registration process and do not degrade the quality of the method of Maximizing Mutual Information.

Further the normalized fingerprints were tested on matching Algorithms. Three correlation matching algorithms were considered. Table 3 contains the details of these algorithms.

Tab. 3. The Matching Algorithms

Author	Technique	Feature
Jain, Hong & Bolle, 1997	Correlate **(Correlation Matching)**	Finger codes
Sharat, 2005	Chain code **(Correlation Matching)**	Binary image
Bansal, Sehgal, & Bedi, 2011	Flow ridge **(Correlation Matching)**	Ridge uses flow

The performance of these algorithms on quality fingerprint images was very good but when tested on fingerprints of poor quality in databases FVC2002, FVC2004 and FVC2006, their Equal Error Rate (EER) were more than 50%. EER is the spot where False Match Rate (FMR) becomes equal to False Non-Match Rate (FMNR).

The same poor quality images when optimized by our algorithm and again tested on these algorithms, their performance improves a lot. Table 4 shows the result of these experiments.

Tab. 4. The Results of poor quality/Latent images when the proposed algorithm is applied

Algorithm	Results %	Average Run Time (ms)
Correlate **(Correlation Matching)**	EER = 45%	586
Chain code **(Correlation Matching)**	EER = 42%	168
Flow ridge **(Correlation Matching)**	EER = 46%	135

7. CONCLUSION

The algorithm proposed in this paper for optimization of fingerprint size is very powerful, and solve many problems of conventional fingerprint verification techniques. Specially the techniques performs strongly for latent fingerprint. By using orientation information for registration, the alignment is not strictly based on trying to maximize the number of minutiae correspondences.

The algorithm for estimating the possible reduced size of registered images, accelerate the correlation methods of image registration. The algorithm was tested to optimize the method of maximizing mutual information.

The experiments showed good results on a set of poor quality fingerprints. We were able to substantially improve the speed of the comparison algorithms without degrading the quality of registration.

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