# Fingerprint Indexing Based on Singular Point Correlation

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***Abstract*—Fingerprint indexing is an efficient technique that greatly improves the performance of Automated Fingerprint Identification Systems. We propose a continuous fingerprint indexing method based on location, direction estimation and correlation of fingerprint singular points. Location and direction estimation are achieved simultaneously by applying a T-shape model to directional field of fingerprint images. The T-shape model analyzes homocentric sectors around the candidate singular points to find lateral-axes and further main-axes. Then a distortion-tolerant filter of Minimum Average Correlation Energy is utilized to obtain a correlation-based similarity measure which gives the evidence of searching priority. The experiment is performed by 400-fingerprint retrieval from 10,000 templates and the mean search space is only 3.46% of the whole dataset.**

***Keywords-fingerprint indexing, singular point, MACE filter, T-shape model, directional field.***

## I. INTRODUCTION

The huge amount of data in large fingerprint databases (e.g. several million fingerprints) seriously compromises the efficiency of the fingerprint identification task in Automated Fingerprint Identification Systems (AFIS) for both forensic and civil applications. There are two technical choices to reduce the number of comparisons during fingerprint retrieval and consequently to reduce the response time of the identification process: one is classification and the other is indexing.

Traditional classification techniques [1-3] attempt to classify fingerprints into five classes: Right Loop (R), Left Loop (L), Whorl (W), Arch (A), and Tented Arch (T). Due to the uneven natural distribution, comparatively large inter-class similarity and intra-class difference, the workload reduction resulted from classification is not gratifying.

Fingerprint indexing algorithms select most probable candidates and sort them by the similarity to the input one [4]. For indexing technique performs better than exclusive classification considering the size of space that need to be searched [5]. Many indexing algorithms have been proposed recently. In [4] and [6], the triplets of minutiae are used in the indexing procedure. These methods focus on the detailed information of fingerprints and ignore the macro information which is more robust to local noise. A.K. Jain et al [7] use the features around a core point of a Gabor filtered image to realize indexing. Although this approach makes use of the core point information but the discrimination power of just one core is limited. We also can see the efforts on combining methods, such as [8] and [9].

As a sort of prominent and global feature, singular points (SPs) in fingerprint images can be robustly identified and contain fingerprint intrinsic features. According to this fact, we propose an indexing approach based on SP correlation. SP detection and direction estimation are achieved simultaneously by applying a T-shape model to directional field (DF). The T-shape model reveals the intrinsic nature of SPs including cores and deltas which broadly exist in fingerprint images but are seldom utilized in fingerprint indexing. Then the Minimum Average Correlation Energy (MACE) filter [10], a kind of distortion-tolerant filter, is used to synthesize templates and perform correlation computation to give the similarity measurement. Further indexing is obtained by sorting the similarity between the query image and all stored templates.

This paper is organized as follows. In Section II, a so-called T-shape model is introduced and utilized to detect SPs and to estimate their directions. Then the MACE filter is introduced in Section III. In Section IV, some experimental results are presented. Finally, the conclusion is drawn in Section V.

## II. DETECTION OF SPS AND ESTIMATION OF THEIR DIRECTIONS

As a global feature of fingerprints, DF is very important to automatic fingerprint recognition. It also contributes to our detection of SPs. Before calculating it, we use an approach based on transition-number minimization in [11] to segment the original fingerprint image in order to get rid of disturbance of the background, which often brings in a number of spurious SPs. Then Pixel-wise DF (PDF) and Block-wise DF (BDF) are estimated by using gradient-based approach proposed in [12]. To obtain more precise resulting SPs' locations, we choose the side length of the square blocks to be 2.

Poincaré index (PI), which was first introduced in [13], is a kind of widely exploited feature in detection of SPs. By following a counterclockwise closed contour, which is often chosen as a 2x2 square, around a possible SP in the DF, and by adding up the difference between the subsequent angles, the resulting cumulative change of orientation is PI. Because of the presence of noise in original BDF, we use Gaussian filter to

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denoise the BDF before calculating PI. By choosing $\sigma$ (standard deviation) as 3.5, this operation can eliminate the spurious SPs significantly while preserving true ones. Then we obtain a relatively smaller number of candidate SPs for further analysis.

To analyze a potential SP finely, a direction that can be robustly detected and precisely expressed must be identified. Here we define a main-axis (direction) of an SP as the direction in which ridges in SP's neighborhood tend to leave the SP. Obviously a delta has three main-axes according to this definition. Some examples of SPs' main-axes are shown in Fig 1.

Considering an SP as a starting point, ridges that are passed by while following the radius along SP's main-axis are flowing away from SP, namely parallel to the radial direction. And following the radius in the opposite direction, crossed ridges are flowing around the SP, i.e. perpendicular to radial direction. We believe this fact is an intrinsic nature of all SPs and is invariant to translation and rotation. We visually name this pattern "T-shape model". Then how well a region matches this model can measure the confidence of the center being an SP.

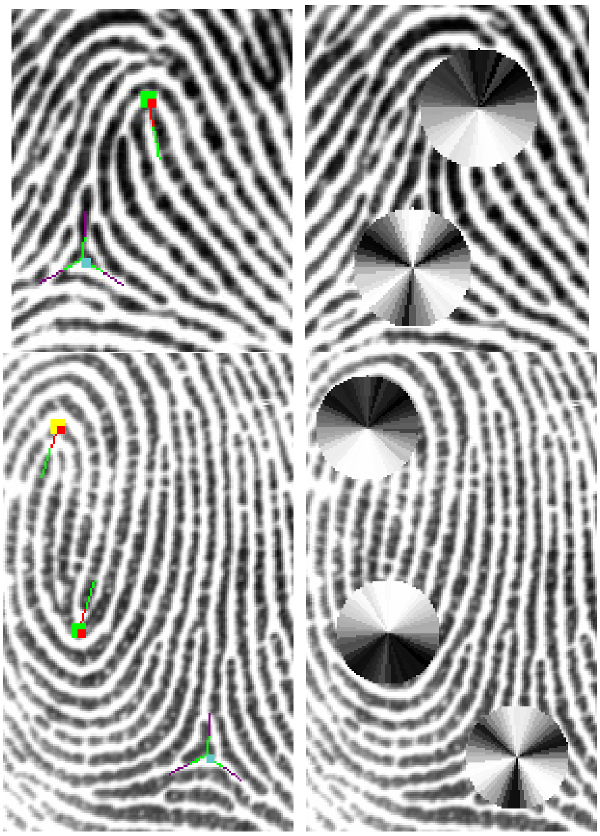

**Fig. 1.** Illumination of the T-shape model: grayscale of each sector in the circles expresses parallelism of its AOS and the radial orientation

To apply this idea on a candidate SP acquired above, we first cut out a circle in PDF centered at it with certain radius, which is decided empirically in relation to the resolution of fingerprint images, as the region of interest. Then the circle is divided into homocentric sectors with a series of equally distributed radius so that all sectors' central angles are equal. The average orientation of every sector, namely AOS, is calculated in a similar way to BDF except for the set of average.

Now we are about to detect the candidate SP's main-axis with AOS. First, we pick out lateral-axes whose corresponding sector fulfill (1), where k' is the opposite sector of k, $(S_x(i), S_y(i))'$ represent the i-th sector's orientation, $\theta_i$ is i-th radial angle, $\lambda$ is the weight of parallelism and *TH* is a predefined threshold. Each lateral-axis is probable main-axis or almost parallel to it on the whole. Then we make use of the value of *f(k)* to measure each lateral-axis' confidence of being true main-axis or parallelism to it.

$$f(k) = \frac{\lambda T_{//} + T_{\perp}}{\lambda + 1} - TH > 0 \tag{1}$$

where $T_{//} = |\cos(\frac{1}{2}\mathrm{tg}^{-1}(S_y(k)/S_x(k)) - \theta_k)|$

$$T_{\perp} = |\sin(\frac{1}{2}\mathrm{tg}^{-1}(S_y(k')/S_x(k')) - \theta_{k'})|$$

To avoid accidental peak values of *f(k)* badly affecting the result of main-axis detection, which are usually caused by noise, we consider connecting sets that consist of consecutive lateral-axes. We select the set(s) with the largest one (for core) or three (for delta) total summation(s) of *f(k)* as winner(s) for further processing and use $C(\phi) = \sum_{k \in \phi} f(k)$ to represent the confidence of corresponding winning set $\phi$. Next, in each $\phi$ we calculate a weighted average direction with all candidate lateral-axes as main-axis, where the weights are corresponding *f(k)*. Finally, one main-axis with corresponding confidence is obtained to a core, and three main-axes to a delta. As a part of T-shape model, we use the summation of all main-axes to measure the candidate SP's confidence. With this confidence, the determination of a candidate SP's authenticity can be realized by a simple thresholding. In practice, the thresholds for a core and a delta are different.

In dataset made up of every finger's first prints (count up to 100) in FVC2002 DB1 set A, FAR and FRR of our detection are 4.52% and 1.13%, respectively. 92.40% of SPs' direction estimation errors are within 10 degrees. Two resulting images are shown in Fig 2. For more details of T-shape model, refer to our another paper [14].

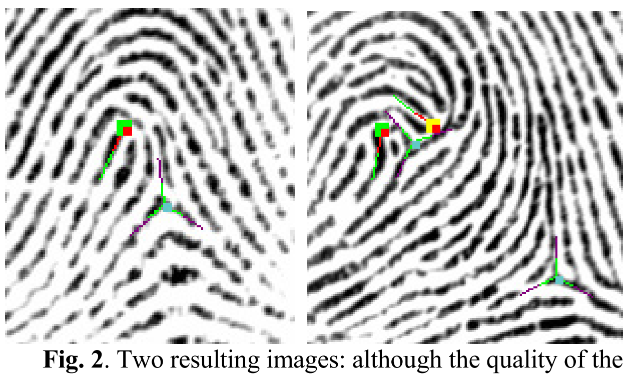

**Fig. 2**. Two resulting images: although the quality of the left image is not very good and the right is an unusual type of fingerprint, our T-shape model works well on them.

## III. MACE FILTER

In this paper, we use the MACE filter to synthesize templates and perform correlation computation. The filter has been used widely in various applications because of its notable advantages. Likewise, it also had been employed to accomplish tasks in biometric recognition and good experimental results had been achieved [15] [16].

The MACE filter is a type of composite filters (also known as Synthetic Discriminant Function or SDF filters), which use a set of training images to synthesize a template that is expected to not only yield pre-specified correlation outputs in response to training images (Equation (2) describes the constraints on the correlation peaks), but also minimize the average correlation energy defined by equation (3)

$$\boldsymbol{X}^T \boldsymbol{h} = \boldsymbol{u} \tag{2}$$

$$E_{ave} = \frac{1}{N}\sum_{i=1}^{N}\sum_{k}\sum_{l}|H(k,l)|^2|X_i(k,l)|^2 = \boldsymbol{h}^+\boldsymbol{D}\boldsymbol{h} \tag{3}$$

where **h** is the filter vector, $\boldsymbol{X} = [\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots, \boldsymbol{x}_N]$ is a $d \times N$ matrix with the $N$ training image vectors (each with $d$ pixels) as its columns, and $\boldsymbol{u} = [u_1, u_2, \cdots, u_N]^T$ is a $N \times 1$ vector containing the desired peak values for the training images that are set to 1 in this paper, **D** is a diagonal matrix containing power spectrum of the average training image on its diagonal. So the MACE filter is then given by

$$\boldsymbol{h} = \boldsymbol{D}^{-1}\boldsymbol{X}(\boldsymbol{X}^+\boldsymbol{D}^{-1}\boldsymbol{X})^{-1}\boldsymbol{u} \tag{4}$$

The MACE filter solution in equation (4) is in the frequency domain and **h** in equation (4) is therefore the vector representation of the Fourier transform of the filter *H(k, l)*. In order to make it robust to noise and intra-class variations, the MACE filter used in this paper has the following formulation finally (it is also mentioned as Optimal Tradeoff SDF):

$$\boldsymbol{h}_{\text{MACE}} = (\alpha\boldsymbol{D} + (1-\alpha)\boldsymbol{C})^{-1}\boldsymbol{X}[\boldsymbol{X}(\alpha\boldsymbol{D} + (1-\alpha)\boldsymbol{C})^{-1}\boldsymbol{X}]^{-1}\boldsymbol{u} \tag{5}$$

where **C** is the diagonal matrix of noise PSD in which the PSD of the noise is represented along the diagonal of **C**, and **C** is the identity matrix if the noise is white; and the parameter $\alpha$ is varied over a range of acceptable values (0.0-1.0) and is selected by the user to give the optimal performance. Especially, the value 0.997 is set to it for our experiments.

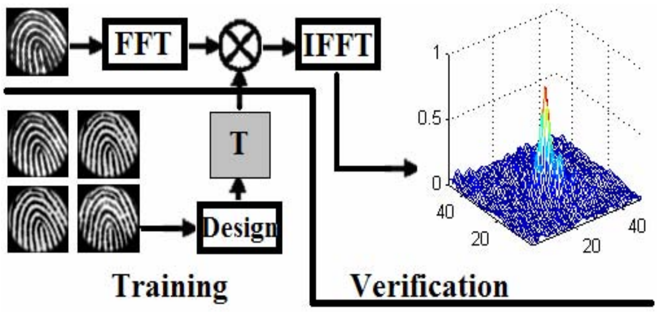


**Fig. 3**. MACE filter working flow chart on the same sub-type SP correlation.

## IV. EXPERIMENTAL RESULTS

The indexing experiments are performed mainly on FVC2002 DB1 set A, where images are all of 256 grayscales, 388x374 size and 500 dpi resolution. It is established with 100 fingers, 8 impressions per finger (800 impressions). To test the indexing power of the proposed method, other 9900 images (one finger one impression) are captured by an optical fingerprint scanner with the same resolution.

First, every SPs' locations and directions are determined by T-shape model for each fingerprint. Authenticities (true or spurious), sub-type (upper or lower to core and left or right to delta) of detected SPs and main direction of delta (for it has three axes) are determined by analyzing their confidences, directions, spatial relationships and angles between them. After this operation, each detected SP is partitioned to one and only one sub-type and each sub-type occurs at most once in a fingerprint.

Then, in the enrollment process, to each sub-type of SP if it occurs in the former 4 impressions of a finger in FVC2002, we use its all occurrence to build a template with the MACE filter. For the other 9900 images, the same process is applied except that the impression numbers of them are one, so each sub-type's occurrence is one at most. To each occurrence, we cut a small square image centered at the SP with a side length of 96-pixel out of the fingerprint image.

Finally, we set the grayscales of the pixels, which distances from SP are more than 48-pixel or stand out of the foreground border, to 0 and perform rotation normalization by rotating the image according to direction of corresponding SP.

Now our goal is to retrieve the latter 4 impressions of each finger in FVC2002 (total number is 400) from above 10,000 finger data (including 100 corresponding fingers and 9900 subsidiary fingers). For each query fingerprint, if certain sub-type occurs, we extract its corresponding area as above and perform FFT on the area. Then the transformation result is multiplied by each finger's template from same sub-type (if exists). The product is transformed back to spatial space to find correlation plane. Flow chart of this process is illustrated in Fig 3. The magnitude of peak value of it is used for the measurement of similarity. Then we choose the maximum peak value among the existing SP sub-type pairs to represent the similarity of two images (query and enrolled).

Due to SPs lost in collection (e.g. no SP appears in fingerprint image) or detection process (Missing mainly occurs to the SPs on near-border), there are only 376 from 400 images being retrieved. The Correct Index Power (CIP) of our indexing approach and approach in [7] ("FingerCode") is shown in Fig 4. Mean rank of query image's corresponding finger is 346 in our approach and 592 in [7] respectively. It can also be seen that our CIP curve approximates 100% horizontal line better than [7]'s does especially in condition of bigger number of hypotheses.

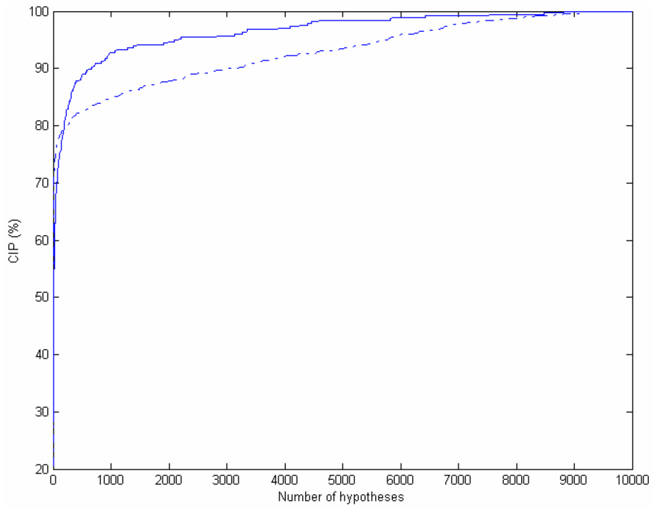


**Fig. 4**. CIP of our proposed approach (solid line) and FingerCode (dash-dot line)

Indexing based on the ordering according to our similarity measure gives a priority strategy on fingerprint identification. Matching is performed in decreasing order of indexing rank of the query one. The number of comparisons is significantly reduced and average search space is only 346/10000=3.46%. 1% Top rank enrolled fingers cover 73.9% counterpart of query images and 10% enrolled cover 92.8% query ones. A comparison of indexing performance between the two approaches is shown in Table I.

TABLE I. COMPARISON OF INDEXING PERFORMANCE

| | **Mean Rank** | **1% Top rank coverage** | **10% Top rank coverage** |
|---|---|---|---|
| Our approach | 346 | 73.9% | 92.8% |
| FingerCode | 592 | 77.8% | 84.5% |

Not like some published experiments in the literature, ours are completely carried out automatically. However, due to the feature detection process is SP-based, our approach can't deal with the fingerprints that have no SPs such as arch type ones. A possible solution may be found in [17] which proposed a method for locating reference points in all types of fingerprints.

## V. CONCLUSION

Fingerprint identification in a large dataset is a very time consuming task. Fingerprint indexing can evidently reduce the number of comparisons. SPs can be robustly identified and contain fingerprint intrinsic features. We present a continuous retrieval approach based on information of all detected SPs including not only cores but also deltas which were omitted traditionally. For having fully utilized the locational and directional information of SPs in fingerprint images and distortion-tolerance of the MACE filter, our experimental results with a large testing data set are satisfactory.

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