Personalized Fingerprint Segmentation

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Abstract. Fingerprint segmentation is an important pre-processing step in automatic fingerprint identification system. Traditional fingerprint segmentation methods either highly depend on empirical thresholds sophistically chosen by experts or a learned model trained by elements generated from manually segmented fingerprints. It is manpower and time consuming. They always try their best to tune their fingerprint segmentation methods to be universal to all unseen fingerprints. However, one fingerprint may have a significantly distinct distribution from another in feature space because fingerprint acquisition is affected by several factors, such as pressure, the types of sensors, finger tip condition (dry, wet etc.). As a result, the delicate threshold and the well trained model may not be suitable to the new input fingerprints from a new finger or a new person. And it makes worse when automatic fingerprint identification systems meet sensor interoperability. To solve the problem, we propose a personalized fingerprint segmentation method: Automatic Labeling based Linear Neighborhood Propagation (ALLNP), which learns a segmentation model special for each input fingerprint image based on the input image only. The proposed method is tested with typical fingerprint images from four heterogeneous data bases of FVC2000. Experimental results show its effectiveness and encouraging strength when fingerprint segmentation meets sensor interoperability.

Keywords: Fingerprint recognition, Fingerprint segmentation, Semi-supervised learning, Label propagation, Linear Neighborhood Propagation.

1 Introduction

Owning to uniqueness and immutability of fingerprint [1], it has been used as one of the biometrics features for a very long time. An automatic fingerprint identification system (AFIS) consists of several steps, such as fingerprint segmentation, image enhancement and filtering, binarization, thinning, gaining minutiae of fingerprint matching, and so on. Fingerprint segmentation is important as a pre-processing step in AFIS. A captured fingerprint image mainly consists of two components: foreground and background. The foreground is the component that originates from the contact of the fingertip with the sensor, and the background is the noisy area at the border of the image. The purpose of fingerprint segmentation is separating foreground of high quality from background and

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foreground of low quality or unrecoverable. Effective fingerprint segmentation not only decreases the computational cost in the subsequent steps but also improves the system performance.

Fingerprint segmentation typically extracts features (or single feature) for every element first, which can be a pixel or an un-overlapped block of the input fingerprint image. Then what segmentation methods need to do is to decide the type (foreground or background) of each element. Statistical features of grey level, e.g., mean and variance of pixel intensity, directional image, ridge projection signal and Gaussian-Hermite moments are often used in fingerprint segmentation. Mehtre [2] proposed a segmentation method based on directional image. To overcome the limitations of [2] when the input image has perfectly uniform regions, a composite segmentation method [3] is suggested using the variance criterion wherever the directional method fails. Bazen [4] proposes a completely different solution based on pixel-wise direction and coherence. Bazen [5] trains an optimal linear classifier based on three pixel features: coherence, mean and variance (CMV). Yin [6] trains a quadric surface model based on pixel-wise CMV features. Ratha [7] computes the variance of the projection signal on different directions with the prior knowledge that the foreground block is of large variance along the direction orthogonal to the ridges and is of small variance along the direction parallel to the ridges, and background is usually of small variance along all directions. Wang [8] proposes to segment fingerprint based on Gaussian-Hermite moments. Jain [9] takes texture energy of each pixel and their spatial locations as input to a squared-error clustering algorithm. Helfroush [10] proposes a modified method based on Jain [9], but uses dominant ridge score of each block instead of coherence, and takes median filtering as a post processing step to improve the performance of the fingerprint segmentation. Yin [11] proposes a segmentation method consisting of two steps: in the primary segmentation, non-ridge regions and unrecoverable low quality ridge regions are removed as background by a well trained neural network, and the secondary segmentation, the remaining ridges are identified and removed according to the two typical differences between the remaining ridges and the true ridges. Bernard [12] proposes a multiscale Gabor wavelet filter bank using the Phase of Multiscale Gabor Wavelets for a robust and efficient fingerprint segmentation. Ross [13] apply convex hull algorithm to Fingerprint segmentation. Klein [14] uses a hidden Markov model (HMM) to solve the problem of fragmented segmentation.

Although there are lots of researches on fingerprint segmentation, they either highly depend on empirical thresholds sophistically chosen by experts or a learned model trained by samples generated from manually segmented fingerprints. It is manpower and time consuming. They always try their best to tune their fingerprint segmentation methods to be universal to all unseen fingerprints. However, one fingerprint may have a significantly distinct distribution from another in the feature space, as shown in Section 2, because fingerprint acquisition is affected by several factors, such as pressure, the types of sensors, finger tip condition (dry, wet etc.). As a result, the delicate thresholds and the well trained models may not be suitable to the new input fingerprint from a new finger or a new person. And it makes worse when fingerprint verification meets sensor interoperability [15]. To the best of our knowledge, there is no research on how to segment a fingerprint image based on the input fingerprint image only. Thus we argue that personalized fingerprint segmentation makes more sense. Here, *personalized* means fingerprint segmentation result for one fingerprint relies only on the input fingerprint image. The contribution of the paper is two folds. For one, to realize personalized fingerprint segmentation, we propose Automatic Labeling based Linear Neighborhood Propagation (ALLNP) method, which learns from the input fingerprint image only instead of a set of fingerprints, and segments the input fingerprint image specifically. For another, to avoid fragmented blocks in segmented fingerprints to some extent, we take position information of elements, i.e., block row index and block column index in the paper, as new segmentation features. Experiments show encouraging strength of the proposed method in sensor interoperability.

The remainder of the paper is organized as follows. Section 2 presents a new formulation of fingerprint segmentation in transductive view. Our method ALLNP is proposed in section 3. Section 4 contains the experimental results. And section 5 concludes the paper.

2 Formulation of Fingerprint Segmentation in Transductive View

Traditional fingerprint segmentation methods are analyzed in this section theoretically and empirically, followed by a new formulation formulated in the paper. As we stated in Section 1, almost each of previous fingerprint segmentation methods either chooses an empirical threshold sophistically according to experience of experts or learns a model by samples generating from manually segmented fingerprints by experts. However, it is unreasonable to learn a fingerprint segmentation model in such a way, especially when the fingerprint images, on which the model is trained, have distinct distribution in feature space. For instance, they are captured via sensors of different types.

Fig.1 shows the scenario when traditional fingerprint segmentation methods do not work. For one input fingerprint image denoted by elliptic dots, Hyperplane1 can easily separate it. And for another input fingerprint image, Hyperplane1 can easily separate it. However, when a segmentation model is trained by a mixture of samples generated from the two input fingerprint images, it seems difficult to find an exact hyperplane suitable for the two and subsequent numerous input fingerprints.

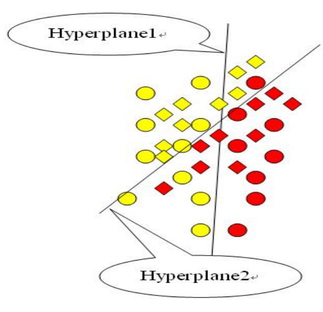


Fig. 1. Illustration of traditional fingerprint methods. Elliptic dots represent samples (elements) from one fingerprint image, while diamondoid ones represent samples from another fingerprint image. Dots in yellow color represent foreground samples, while ones in red color represent background samples.

Formally, we assume the input fingerprint image can be divided into n un-overlapped blocks denoted by $\chi=\{x_1,x_2,\cdots,x_l,x_{l+1},\cdots,x_n\}$, where $x_i \in R^d$, and let $\{y_1,y_2,\cdots y_l,y_{l+1},\cdots y_n\}$ represents the class (foreground or background) of blocks in the fingerprint image, where $y_i \in \{1,-1\}$, 1 for foreground and -1 for background. The fingerprint segmentation task is to learn a hypothesis $f \in F$. And it is unsupervised learning. However, if we can get some prior knowledge of what blocks are most likely foreground and background ones. In other word, if we can get the first l labels $\{y_1,y_2,\cdots y_l\}$ corresponding to $\{x_1,x_2,\cdots,x_l\}$, we can transfer the knowledge from the labeled data to unlabeled data. The learning task will become a transductive learning [16], since we only anticipant its generalization ability on a definite and closed data set. In the next section, we exhibit an oracle how to partially label blocks in a fingerprint image.

To validate the rationality of the new formulation in fingerprint segmentation preliminarily, we select two typical fingerprints from NIST-4 [17], and project them to CMV space the most commonly used in fingerprint segmentation, as shown in Fig.2. The original fingerprint images are listed in the top left, and their histograms in individual dimension of CMV space are aligned in the top right and the second row correspondingly. It can be seen that the two fingerprints have significantly different distribution in CMV feature space.

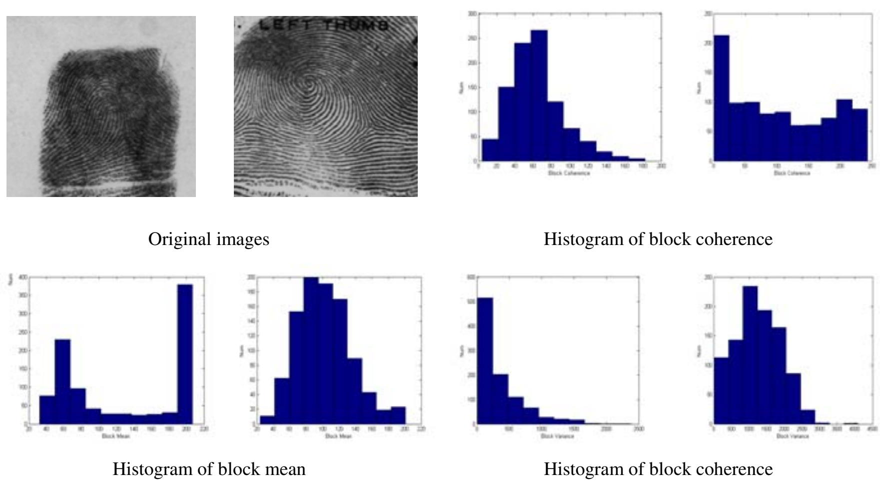


Fig. 2. Distribution of typical fingerprint images in CMV space

3 The Proposed Method: ALLNP

In the section, an Automatic Labeling based Linear Neighborhood Propagation (ALLNP) is proposed, which in fact is a self-help semi-supervised fingerprint segmentation method.

Before conducting semi-supervised learning on the dataset generated from the input image, an oracle is used to label some unlabeled data automatically. ALLNP works as in Fig. 3. An input fingerprint image to be segmented is first divided into un-overlapped blocks[1]. Then a feature vector is extracted for each block. Subsequently, some definitely foreground and background blocks are automatically by an oracle. Provided with these labeled data (blocks) L and the remaining unlabeled data U in the image, a graph-based semi-supervised method called linear neighborhood propagation (LNP) is adopted to do the transductive learning on D, resulting in the segmented fingerprint. Some readers may be confused and argue why we conduct an oracle to label only some data points instead of all. Selectively labeling some data points is a much easier task than labeling all, so we take the easier task as a mediate step of the more complex task.

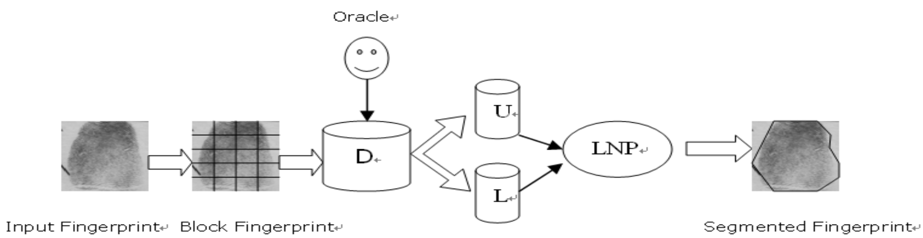


Fig. 3. Flow diagram of the proposed method ALLNP

3.1 Block Contrast as an Oracle

We have investigated several commonly used image features. And block contrast seems to be a more discriminative feature. Suppose an input fingerprint image is divided into a set of $w \times w$ blocks. For one block B, block contrast is defined to be the quotient of block variance and block mean, as shown

$$Block\ Contrast_B = \frac{Block\ Variance_B}{Block\ Mean_B} \tag{1}$$

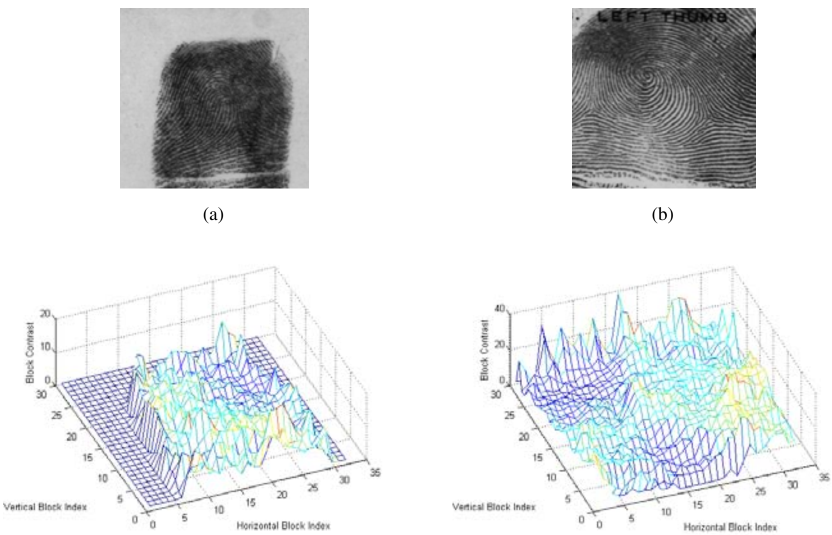
The block mean for block B is defined to be

$$\text{Block Mean}_B = \frac{1}{w \times w} \sum_{(x,y)\in B} I_{(x,y)} \tag{2}$$

where $I_{(x,y)}$ is the intensity of the pixel (x, y). And the block variance for block B is defined as the variance of intensity of each pixel in the block B, represented by .

[1] In the paper, we segment fingerprint images in a block-wise way.

$$Block\ Variance_B = \frac{1}{w \times w} \sum_{(x,y) \in B} (I_{(x,y)} - Block\ Mean_B)^2 \tag{3}$$



(a) (b) (c) (d)

Fig. 4. The example plots of block contrast

Fig.4 shows two example plots of block contrast for two fingerprints, where both images are represented by 16×16 blocks. (a) and (b) in Fig.4 represent the two fingerprints, while (c) and (d) are their plots of block contrast respectively. In the two block contrast plots, x-axis and y-axis represent block indices in horizontal and vertical directions of the original fingerprint images respectively, and the z-axis stands for block contrast value of each block.

In the paper, block contrast is taken as an oracle to automatically label some foreground and background blocks for an input image. For each block, block contrast, as defined in (1), is extracted first. Then, each block is sorted into a list according to its block contrast in ascending order. Blocks in the top of the list have larger probabilities to be background blocks than those in the bottom, while these in the bottom have larger probabilities to be foreground ones than those in the top.

3.2 Label Propagation by LNP Algorithm

The graph-based semi-supervised learning methods have received considerable attraction in recent years, which model the whole dataset as a graph. The construction of the graph is at the heart of these graph-based methods. And most of these methods [18, 19] adopt a Gaussian function to calculate the edge weights of the graph but the variance of the Gaussian function will affect the classification results significantly. To address the above limitation of graph-based semi-supervised learning, Linear Neighborhood Propagation [20] is proposed.

The reason why we select LNP as our solution is twofold. First, the number of the nearest neighbors k in LNP is easier to tune since it is selected from only positive integers in a small range. Some other semi-supervised learners, such as S3VM and co-training, need to explicitly specify the ratio of two classes[2], or implicitly assume the unlabeled data has the same ratio with labeled data. That may be improper for fingerprint segmentation problem. Because fingerprint images captured by different sensors actually have different proportions of foreground owing to various resolutions of sensors. The proportions of foreground for the same finger acquired by the same sensor may distinctly differ if with different pressures. Every fingerprint can be seen as a manifold embedded in a high space. The parameter k may be inherently affected by fingerprints, and insensitive. Second, LNP has been shown of the capability to automatically erase the noise in labeled data. So even we injected some noise in the automatic labeling the first step of our algorithm, LNP still works.

The LNP algorithm consists of two steps. In the first step, it approximates the whole graph by a series of overlapped linear neighborhood patches, and the edge weights in each patch can be constructed by solving the following standard quadratic programming problem

$$\begin{aligned} &\min_{w_{i,j}} \sum_{j,k:x_j,x_k \in \mathrm{N}(x_i)} w_{ij} G^i_{jk} w_{ik} \\ &s.t. \quad \sum_j w_{ij} = 1, w_{ij} \geq 0 \end{aligned} \tag{4}$$

Where $\mathrm{N}(x_i)$ represents the neighborhoods of x_i, w_{ij} is the contribution of x_j to x_i, and G^i_{jk} represents the $(j,k)-th$ entry of the local Gram matrix $(\dot{\mathrm{G}})_{j,k} = (x_i - x_j)^T (x_i - x_k)$ at point x_i, where $(.)_{j,k}$ represents the $(j,k)-th$ entry of a matrix. Then all the edge weights will be aggregated together to form the weight matrix of the whole graph. In the second step, the labels of the labeled data to the remaining unlabeled data using the constructed graph in the first step. In detail, (5) is used to update the labels of each data object until convergence.

$$\mathrm{f}^{t+1} = \alpha \mathrm{W} \mathrm{f}^{\mathrm{t}} + (1-\alpha) y \tag{5}$$

Where $0 < \alpha < 1$ is the fraction of label information that x_i receives from its neighborhoods. Let $y = (y_1, y_2, \ldots y_n)^T$ with $y_i = L_i (i \leq l)$, $y_u = 0 \ (l+1 \leq u \leq n)$, $\mathrm{f}^t = (f_1^t, f_2^t, \ldots, f_n^t)^T$ is the prediction label vector at

[2] Unless otherwise specified, the paper talks about two class problem.

iteration t and $f^0 = y$. And LNP has been derived from a regularization framework to provide a theoretical guarantee of its feasibility [20].

4 Experiments

In this section, we present some experimental results of our personalized fingerprint segmentation algorithm ALLNP. In order to validate the strength of ALLNP in segmenting fingerprints of sensor interoperability, it is tested with typical fingerprints from 4 heterogeneous databases of the Fingerprint Verification Competition 2000 (FVC2000) [21]. For the reason that the fingerprint segmentation result needs human inspection, we select 10 typical fingerprints of different quality from each fingerprint database. So there are 40 images in all in our test set. We divided each input fingerprint image into a set of 16 by 16 blocks, then a feature vector consisting of block mean, block variance, block contrast and block coherence is extracted for each block. Besides, to avoid fragmented blocks in the segmented fingerprints to some extent, we take position feature of each block, i.e., block row index and block column index, as new features. In all the experiments, the parameter α is set to 0.99, which stands for the fraction of label information that a block receives from its neighbors in feature space in each iteration. The number of neighbors calculated for each block seems insensitive in fingerprint segmentation, and it is set to be 7 in the experiment for all input fingerprint images.

Some segmentation results by our method without any post-processing are shown in the Fig.5. Two fingerprints are selected from each data set. Images in the first column are input fingerprints. And the second column shows corresponding partially automatically labeled fingerprints of the first column. For each input fingerprint 20 foreground and 10 background blocks are automatically labeled. To distinguish the automatically labeled foreground and background blocks we deal with them as follows. Labeled foreground blocks are displayed the same intensity as these in the input image, and labeled foreground ones are displayed as black, while unlabeled blocks are displayed as white. Some fingerprints in the second column have black margin, because the sizes of their input images can not divide by the block size. And we simply segment the margin to be background. Segmented fingerprints by ALLNP are shown in the last column. It can be seen that the proposed personalized fingerprint method ALLNP achieves favorable segmentation results on almost all the fingerprints, which indicates its strength in sensor interoperability.

Some statistical experiment results of previous fingerprint segmentation methods available are listed in Table.1 for comparison. It is worth noting that these figures were quoted simply from their papers, and we did not realize these methods. It can be observed that our method ALLNP is better than all the other methods except Yin 2005 [6]. With human inspection our personalized fingerprint segmentation method ALLNP achieves an encouraging fingerprint segmentation performance with an error rate of only 2.89% in block-wise segmentation. And post-processing will reduce the error rate of our method further.

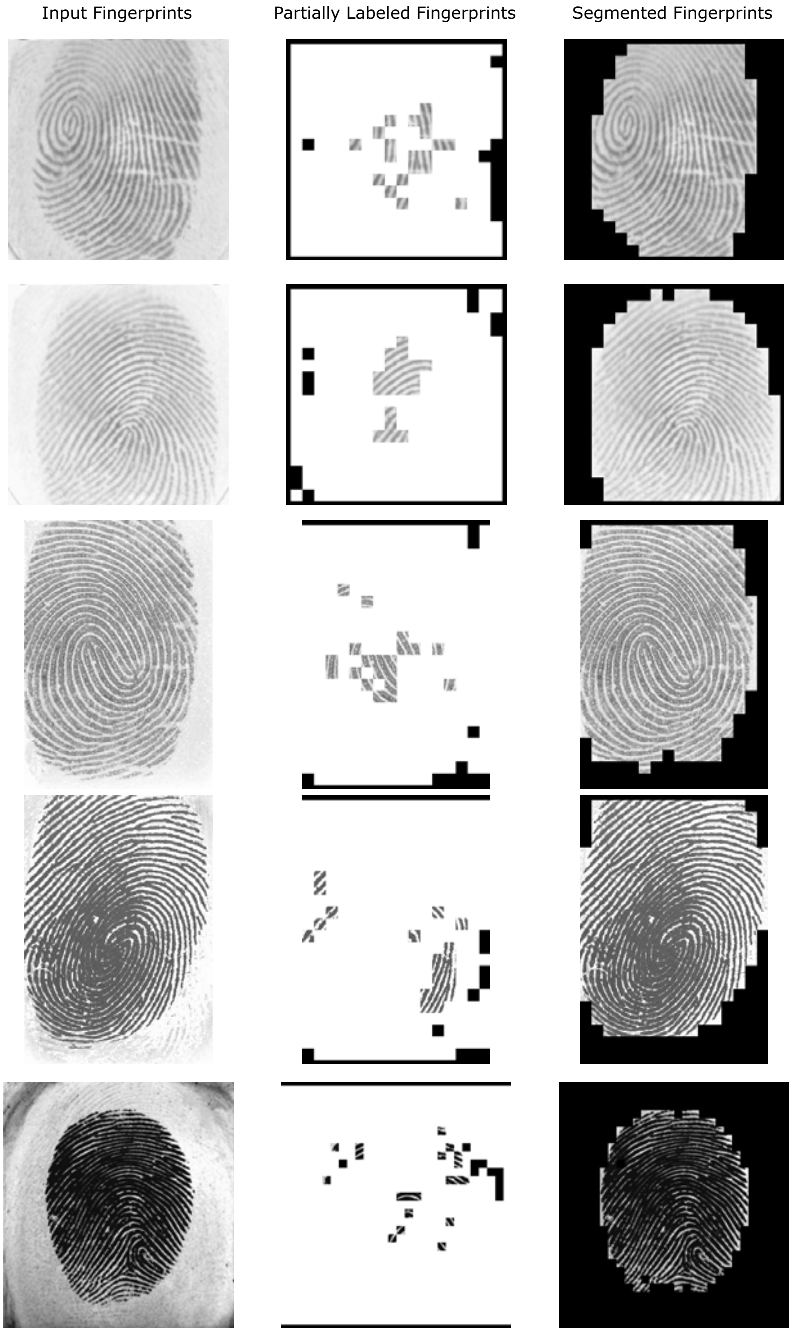


Fig. 5. Segmentation results of ALLNP on some typical fingerprints of FVC2000

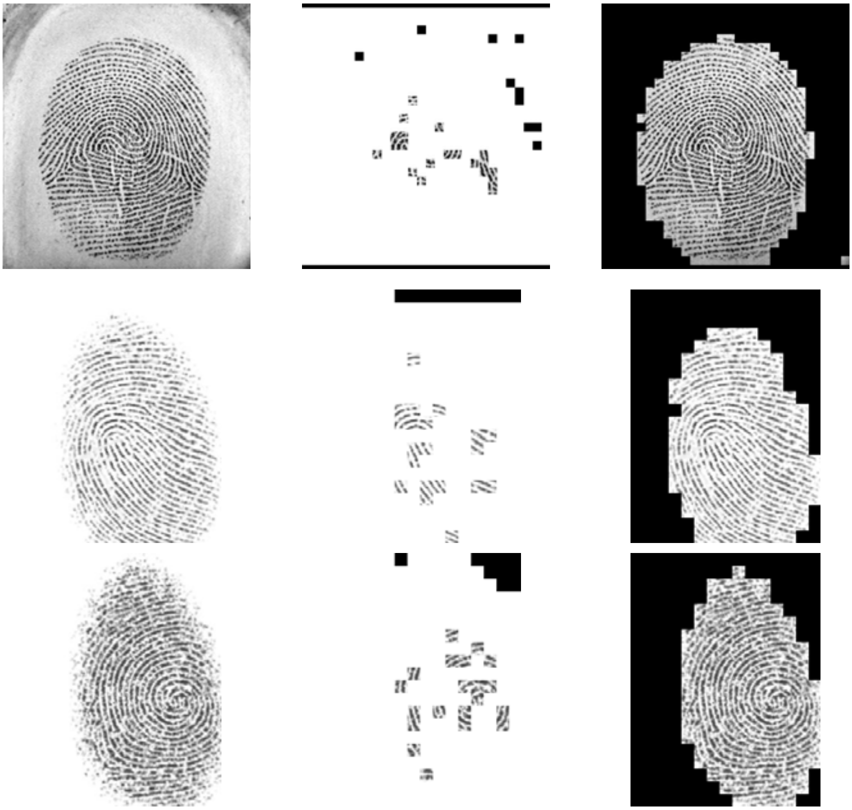


Fig. 5. (*Continued*)

Table 1. Comparison of fingerprint segmentation methods. In the third and the fourth columns, “Y” denotes yes, “N” denotes no, while “-” represents unknown from the paper.

Methods	Block-wise/Pixel-wise	Pre-processing	Post-processing	Error Rate
Bazen 2001 [5]	Pixel-wise	Y	Y	6.8%
Klein 2002 [14]	Block-wise	-	N	6.5%
Yin 2007 [11]	Block-wise	-	-	>10.6%
Yin 2005 [6]	Pixel-wise	-	Y	0.53%
Bernard 2002 [12]	Pixel-wise	Y	-	> 1.85%
ALLNP	Block-wise	N	N	2.89%

Although our algorithm has achieved above advantage, it is worthy to mention that almost all the experiments of previous fingerprint segmentation methods are carried out on single homogeneous fingerprint data set, in which all the fingerprints are obtained via the same sensor. When the trained models by these fingerprint segmentation methods are tested on several heterogeneous fingerprint data sets, their performance will significantly drop.

5 Conclusion

Traditional fingerprint segmentation methods always try their best to tune their fingerprint segmentation methods to be universal to all unseen fingerprints. However, one fingerprint may have a significantly distinct distribution from another in the feature space because fingerprint acquisition is affected by several factors. As a result, the delicate threshold and the well trained model may not be suitable to the new input fingerprints from a new finger or a new person. And it makes worse when automatic fingerprint identification systems meet sensor interoperability. In the paper, we propose a personalized fingerprint segmentation method ALLNP, which learns a fingerprint segmentation model specially for an input fingerprint image based on the input image only. The proposed method is tested with representative fingerprints from four heterogeneous databases of FVC2000. The experiments show encouraging performance of the proposed method when fingerprint segmentation meets sensor interoperability. However, in Section 3, some foreground and background blocks are automatically labeled by a simple oracle based on block contrast before learning. And the block numbers automatically labeled for each input fingerprint are small. We may wish more labeled data, for the more exactly labeled data provided the better segmentation performance it achieves. However, some noise may be injected as the number of automatically labeling blocks increases. In the future work, we will investigate robust automatically labeling mechanics.

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