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Extraction of Fingerprint Pore Using Convolutional Neural Networks

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ABSTRACT

Sweat pores have been recently employed for automated fingerprint recognition, in which the pores are usually extracted by using a convolutional neural networks. In this paper, however, we show that real pores are not always isotropic. To accurately and robustly extract pores, we propose an adaptive anisotropic pore model, whose parameters are adjusted adaptively according to the fingerprint ridge direction and period. The fingerprint image is partitioned into blocks and a local pore model is determined for each block. With the local pore model, a matched filter is used to extract the pores within each block. Experiments on a high resolution fingerprint dataset are performed and the results demonstrate that the proposed pore model and pore extraction method can locate pores more accurately and robustly in comparison with other state-of the-art pore extractors.

Keywords: Biometrics, Convolutional Neural Network (CNN), Fingerprint, Pore Extraction

I. INTRODUCTION

Most existing automated fingerprint recognition systems (AFRS) utilize only level one and level two fingerprint features (e.g. orientation field and minutiae) for personal identification. Level-three fingerprint features like pores, though seldom used by existing AFRS, are also very distinctive. Thanks to the advancement of imaging techniques, more and more researchers are now exploring how to extract and use level-three features in AFRS. Proposed a high resolution AFRS using features from level 1 to level 3 (i.e. orientation fields, minutiae, pores and ridge contours A common challenge to the pore-based fingerprint recognition systems is how to accurately and robustly extract pores from fingerprint images. In this paper, we present an adaptive pore model based on our investigation in real pore profiles. The model can adjust its parameters adaptively according to the local ridge direction and period. A novel pore extraction method is then proposed based on this model.

II. METHODS AND MATERIAL

Pore intensity extraction using CNN and postprocessing using PIR as presented in Fig. 1. In this section, we describe the CNN architecture for pore intensity extraction and then explain how to train the CNN. Finally, we introduce PIR, the postprocessing process.

A. Proposed Network

We use a convolutional network inspired by CNN visual geometry group (VGG) [10] and train the CNN of Pore in a supervised learning manner. The goal of training to estimate a pore intensity map where the pores are enhanced and other patterns are reduced. We design the ground truth of a pore intensity map using soft labels. That is, the closer the distance to the pore, the higher the value of the label. Let l i,j and di,j n p denote the label value at a pixel coordinate (i, j), and the Euclidean distance between (i, j) and its nearest pore from (i, j) in the fingerprint image. If di,j n p is less than dτ , l i,j = 1 − di,j n p /dτ where dτ is the pore distance threshold. Otherwise (i, j) is a non-pore pixel.

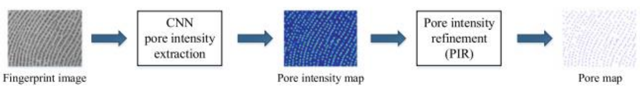

Figure 1. CNN Architecture for Pore Detection

B. Training

We now describe the process of training CNN. Let x and y denote the fingerprint image and the label of its pore intensity map, respectively. Given a training dataset {xi, yi}N i=1 , our goal is to train model f to predict y =ˆ f(x), where yˆ is the estimate of the pore intensity map and N is the batch size.

C. Pore Intensity Refinement (PIR)

The pore pixels appear as peaks in the pore intensity map. The intensity of each pore peak varies depending on the thickness of the ridge to which it belongs and its type (open or closed pore). Therefore, it is difficult to accurately detect the pores with BT over the entire pore intensity map.

We manually marked and cropped hundreds of pores in several fingerprint images, including both open and closed pores. Based on the appearance of these real pores, we summarized three types of representative pore structures as shown in Fig. 3. Among them, the last two types correspond to open pores and they are not isotropic. With more observation of the pore appearance, we found that along the ridge direction, all the three types of pores appears.

III. RESULTS AND DISCUSSION

We have presented an automated fingerprint matching system that utilizes fingerprint features in 1,000 ppi images at all three levels. To obtain discriminatory information at Level 3, we introduced algorithms based on convolutional neural networks. Our experimental results demonstrate that Level 3 features should be examined to refine the establishment of minutia correspondences provided at Level 2. More importantly, consistent performance gains were also observed in both high quality and low quality images, suggesting that automatically extracted Level 3 features can be informative and robust, especially when the fingerprint region, or the number of Level 2 features, is small. The potential of improving AFIS matching by utilizing Level 3 features at 1,000 ppi is promising and should be further investigated.

IV. CONCLUSION

Adaptive pore extraction is a difficult problem because the pore information depends on the person, region, and pore type. To solve the problem, we have presented a pore extraction method using CNN and pore intensity refinement. We have demonstrated that our CNN outperforms the state-of the-art methods by a large margin on the benchmark database. In the future, we will research various biometric systems based on pores.

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