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Deep convolutional neural network for latent fingerprint enhancement

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ABSTRACT

In this work, we propose a novel latent fingerprint enhancement method based on FingerNet inspired by recent development of Convolutional Neural Network (CNN). Although CNN is achieving superior performance in many computer vision tasks from low-level image processing to high-level semantic understanding, limited attention has been paid in fingerprint community. The proposed FingerNet has three major parts: one common convolution part shared by two different deconvolution parts, which are the enhancement branch and the orientation branch. The convolution part is to extract fingerprint features particularly for enhancement purpose. The enhancement deconvolution branch is employed to remove structured noise and enhance fingerprints as its task. The orientation deconvolution branch performs the task of guiding enhancement through a multi-task learning strategy. The network is trained in the manner of pixels-to-pixels and end-to-end learning, that can directly enhance latent fingerprint as the output. We also study some implementation details such as single-task learning, multi-task learning, and the residual learning. Experimental results of the FingerNet system on latent fingerprint dataset NIST SD27 demonstrate effectiveness and robustness of the proposed method.

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1. Introduction

As one of the most important biometric information in last decades, fingerprints have been widely applied in many aspects such as access control, security checking, mobile identification, and criminal investigation. Automated Fingerprint Identification System (AFIS) has been proved very successful with high rank-1 identification rate, especially for plain and rolled fingerprints [1,2]. Different from these conventional fingerprint images that acquired professionally, latent fingerprints are left in criminal scene unintentionally as shown in Fig. 1. Therefore, latent fingerprints often encounter very poor quality due to unclear ridge structure, uneven ridge/valley contrast, and the structured noise (lines, letters, stains, and so on) [3,4]. Then, feature extraction (*e.g.*, minutiae detection and orientation field estimation) for latent fingerprints is unreliable. This results in low rank-1 identification rate for latent fingerprints, which is far from actual usage in supporting law enforcement.

In order to increase identification rate for latent fingerprints, enhancement is employed to improve latent fingerprint quality before feeding into the AFIS. Latent fingerprint enhancement can help improve the clarity of ridge structure, recover corrupted regions, remove structured noise, and increase ridge/valley contrast in some degree. These tasks are not only similar with image deblurring, denoising and super-resolution, but also including the special aspect of latent fingerprints such as removing structured noise. After enhancement, more reliable feature extraction, and then higher identification rate can be obtained for latent fingerprint identification [5].

Fingerprint enhancement has been actively studied in the past decades. As one classical pre-processing technique in fingerprint recognition, many conventional methods have been proposed and studied in the fingerprint community. The earlier algorithms are related to contextual filtering [6–11], that applied directional filtering with the estimated local orientation and frequency from fingerprint images. Then, orientation field (OF) estimation became a significant role and attracted much attention [5,12–16]. In order to have better estimation on orientation field, researchers started from local orientation estimation and then applied varieties of smoothing techniques with adding more constraints from fingerprint property. Representative algorithms include the global OF dictionary method and its extended localized OF dictionary method [5,12]. With the help of texture component extraction using total variation (TV) and adaptive directional TV (ADTV) [4,17–19], ridge structure dictionary methods could estimate OF from a coarse-to-fine manner [20] or in a multi-scale manner [21].

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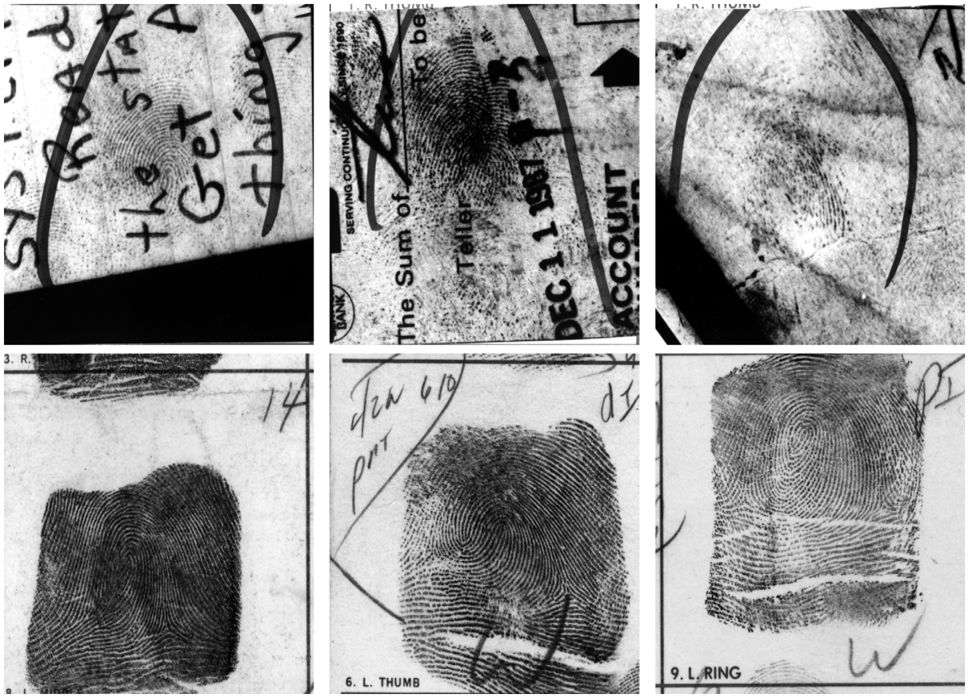

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Fig. 1. Three examples of latent fingerprints and their corresponding rolled fingerprints as true mates from NIST SD27, shown in top row and bottom row respectively.

Nowadays, deep learning technique particularly convolutional neural network (CNN) has been proved to be successful on both low-level and high-level vision applications [22–27]. Recently, Cao et al. proposed a CNN based OF estimation method, that treated it as a classification problem [28].

Our work is inspired by the recent development of CNN on image processing applications, particularly using the pixels-to-pixels and end-to-end learning manner [26,29–34]. We propose a deep network architecture (FingerNet) directly targeting on fingerprint enhancement in the aforementioned pixels-to-pixels and end-to-end fashion. FingerNet is able to predict the enhancement resulting pixels as output directly from the input pixels of fingerprint texture component (pixels-to-pixels). This process is from the input end to the output end, without the need of estimating actual orientation to perform enhancement (end-to-end). Different from [28] that applied CNN only on orientation classification and then enhanced fingerprints with the predicted orientation (not from fingerprint end to enhancement end in direct), our method is a solution in new angle to solve enhancement more directly. In this work, training data is firstly generated via distorting clear fingerprint patches by adding structured noise such as lines and characters. Texture component of the distorted fingerprint patch is then used as training input, which has similar structured noise with latent fingerprint. The Gradient-based method is then applied to the clear fingerprint patch to have its orientation field and enhancement result. The corresponding orientation field is quantized as ground truth for orientation branch of FingerNet, and the enhancement result is used as ground truth for the enhancement branch of FingerNet. Our network architecture is consist of multiple convolutional layers and their corresponding symmetrical deconvolutional (or, transposed convolutional) layers. This is also within the framework of encoder–decoder network. Instead of increasing depth of the network to enlarge the receptive field [31–34], we apply pooling the first time for image processing applications. Two branches of orientation classification and fingerprint enhancement are involved via multi-task learning. In order to compensate the possible image details lost caused by pooling during recovering, skip connections are introduced to pass image details of different resolution.

The major contribution of this work include five folds: First, to our best knowledge, we are the first one to apply pixels-to-pixels and end-to-end learning for latent fingerprint enhancement; Second, we propose a better data preparation/augmentation strategy to include both characters and lines as structured noise; third, we successfully train the encoder–decoder network with pooling and striding included. This is different from all other image processing networks without pooling layers involved; Fourth, the multi-task learning combining orientation and enhancement branches is proved to be effective and successful; Fifth, the residual learning strategy is studied thoroughly in this work.

The rest of this paper is organized as follows. Related work in the literature is introduced in Section 2. Then, our proposed method including several implementation details is introduced in Section 3. Experimental results are shown and analyzed in Section 4. Finally, we summarize this work and point out possible future work in last section.

2. Related work

2.1. Latent fingerprint enhancement

As a very traditional computer vision application, many researchers have applied classical image processing techniques on fingerprint enhancement. In this section, we introduce some representative methods in the literature.

Contextual or directional filtering was first applied locally on fingerprint enhancement. Hong et al. modeled local fingerprint as the sinusoidal waves with a specified orientation and frequency [8]. Local orientation in a 16 × 16 block is estimated by gradient-based analysis and ridge frequency is estimated by the sinusoidal-shaped wave modeling. Then, the Gabor filter-banks tuned with the estimated local orientation and frequency are applied as to enhance fingerprint. Instead of spatial domain, Chikkerur et al. estimated local orientation and ridge frequency via the 2-D Short Time Fourier Transform (STFT) in a probabilistic manner [11]. STFT method also conducts the enhancement in the Fourier domain by contextual filtering.

Then, researchers started to study how to have better orientation field estimation. Since local estimation of orientation is sensitive to

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