Deep Convolutional neural network for Fingerprint Recognition

Elham Tabassi Xiao Zeng

1. Introduction

Fingerprints are ridge and valley patterns presented on the surface of human fingertips. Fingerprints recognition techniques are applied in many areas such as authentication, suspects identification and privacy protection. Typically, to query a fingerprint, the system needs to search and match thousands of fingerprints that are stored in the database. This is a time-consuming process due to huge amount of computation. To mitigate this problem, we can first classify a fingerprint into a basic type and then perform fingerprint matching within fingerprints of that type.

Most of fingerprint classification problems adopts GaltonHenry classification scheme.[3] which divide fingerprints into five groups: arch, left Loop, right Loop, tented arch and whorl. Because arch and tented arch only accounts for a small portion(around 6%) in human, in some automatic fingerprint identification systems, they combine these two classes into one class. Fig.1 shows the five classes of fingerprints. We can see that tented and tented arch are similar.

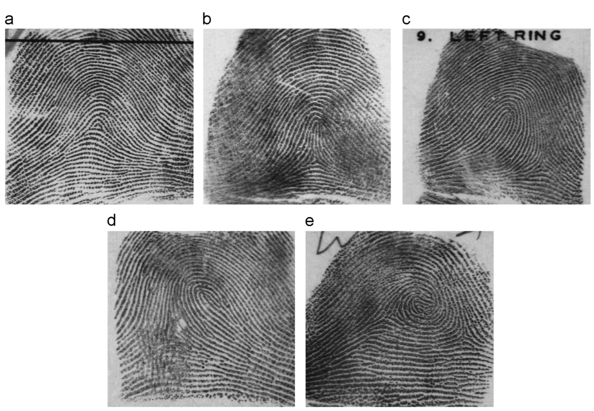

Figure 1. Examples of fingerprint classes: (a) Arch (b) Tented Arch (c) Left Loop (d) Right Loop (e) Whorl [2]

2. Motivation

The challenge of classifying fingerprint includes: 1) the quality of some fingerprints images are poor; 2) the inter-class dissimilarity is small and the intra-class similarity is small; 3) There are ambiguities in some labels. Some fingerprints can be classified into multiple classes, or different classes by different fingerprint experts.

To solve these problems, many researchers propose to use handcrafted features instead of raw fingerprint images for classification and many methods have been proposed, including ridge, orientation field, singular point. Kai Cao *et al.*[2] propose a novel method to extract fingerprint orientation feature and use a hierarchical classifier for classification. Ruxin Wang *et al.* [7] also use orientation filed as features. By adopting a stacked autoencoder , they achieve 93.1% in four-class classification.

Using accurate handcrafted features can improve performance. However, due to the existence of noise and poor image quality, the accuracy of handcrafted features cannot be guaranteed. Convolutional neural network (CNN) has the capability of learning features and it can be directly applied on raw images. CNN also exhibits powerful classification capability in many areas[5][6].

3. Plan

In this project, we aim to develop and implement a deep learning algorithm for addressing fingerprint classification problem.

3.1. Feature Extraction

To explore possible features, we will first apply raw fingerprint images to train a CNN for classification. The outputs of some intermediate layer of CNN will be used as features. We will also use traditional handcrafted features (*e.g.*,orientation filed) as inputs for CNN training. In the end, we plan to combine raw images and handcrafted features as input to train CNN.

For CNN architecture, we will first use canonical architecture (such as 5 *convolutional* + 3 *fully-connected* in *AlexNet*[4]). We will then modify the CNN architecture to improve the performance.

3.2. Classifier

We will consider two classifiers. The first one is the prediction layer of CNN. The values in last layer indicates the predicted probabilities of each class. The second one is support vector machine (SVM).

3.3. Data Augmentation

For further improve the performance, we will use data augmentation technique to generate more train samples in order to increase the generalization ability of our model.

4. Dataset

In this project, we will use NIST Special Database 4 [1] for our experiments. Some samples can be seen in Fig.1. The NIST database of fingerprint images contains 2000 8-bit gray scale fingerprint image pairs, totally 4000 images. Each image is 512-by-512 pixels with 32 rows of white space at the bottom and classified using one of the five following classes: Arch, Left and Right Loops, Tented Arch, Whorl. Each of the five classes has 400 pairs Each of the fingerprint pairs are two completely different rollings of the same fingerprint.

References

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