High-Resolution Mobile Fingerprint Matching via Deep Joint KNN-Triplet Embedding

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Abstract

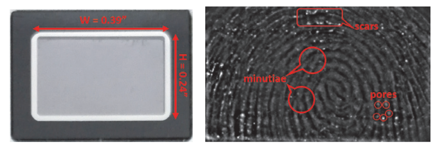
In mobile devices, the limited area of fingerprint sensors brings demand of partial fingerprint matching. Existing fingerprint authentication algorithms are mainly based on minutiae matching. However, their accuracy degrades significantly for partial-to-partial matching due to the lack of minutiae. Optical fingerprint sensor can capture very high-resolution fingerprints ($2000dpi$) with rich details as pores, scars, etc. These details can cover the shortage of minutiae insufficiency. In this paper, we propose a novel matching algorithm for such fingerprints, namely Deep Joint KNN-Triplet Embedding, by making good use of these subtle features. Our model employs a deep convolutional neural network (CNN) with a well-designed joint loss to project raw fingerprint images into an Euclidean space. Then we can use L_2-distance to measure the similarity of two fingerprints. Experiments indicate that our model outperforms several state-of-the-art approaches.

Introduction

Nowadays, fingerprint authentication in mobile devices becomes increasingly popular. Limited by space, the fingerprint sensors are miniaturized, which leads to partial fingerprints. Mobile fingerprint sensors are mainly capacitive, capturing images of resolution around $500dpi$. Partial fingerprint matching is challenging under such resolution because local features are relatively insufficient. Accuracy of minutiae-based fingerprint matching algorithms (Fu et al. 2012) degrades significantly with inadequate number of minutiae. Some other texture descriptors such as AKAZE (Alcantarilla and Solutions 2011) can increase the number of local matching (Mathur et al. 2016), but they are not designed to make full use of fingerprint structures.

Optical fingerprint sensor can capture fingerprints with resolution as high as $2000dpi$, providing very rich details such as pores, scars and so on (Fig. 1). These features can make up for the insufficiency of minutiae. Moreover, with these details, fingerprint authentication system is much harder to crack. However, making use of these subtle features is challenging, since they are unstable and irregular. It is tedious to detect and match these details one by one.

In this paper, we propose a novel model named Deep Joint KNN-Triplet Embedding (Fig. 2) to address the above challenges. We have two major contributions. First, instead of using handcrafted features, we employ a deep CNN with triplet loss to learn features from scratch in an end-to-end manner. It embeds fingerprint images into an Euclidean space. Moreover, we carefully design a K-Nearest-Neighbor policy to select proper triplets for training. Second, by exploiting the advantages of triplet loss and softmax loss, we joint both losses to make our model converge fast and stably.



(a) (b)

Figure 1: (a) Optical fingerprint sensor, (b) Minutiae, pores and scars on a partial high-resolution fingerprint.

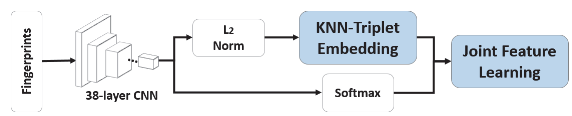


Figure 2: Model structure.

Experiments on our in-house database show that the proposed model achieves true accept rate of 89.17% where false accept rate is under 0.1%, and equal error rate of 1.94%, which outperforms several state-of-the-art approaches.

Deep Joint KNN-Triplet Embedding

We design a 38-layer CNN[1]. Let $f(x) \in R^d$ denote the feature embedding. It embeds a fingerprint image x into a d-dimension Euclidean space. In addition, we constrain $\|f(x)\|^2 = 1$ suggested by (Schroff, Kalenichenko, and Philbin 2015). The following sections describe how we employ KNN-Triplet Embedding and Joint Feature Learning.

KNN-Triplet Embedding

We first briefly review the standard triplet loss. For each triplet of images $< x_i^a, x_i^p, x_i^n >$, where x_i^a (*anchor*) and x_i^p

[1]Details of our network and more complementary materials are available in https://zhangfd.github.io/fp/djkte/

(*positive*) come from the same identity while x_i^n (*negative*) comes from another identity, we want the feature embedding of them to satisfy the following constraint:

$$J_i = \|f(x_i^a) - f(x_i^p)\|^2 + \alpha - \|f(x_i^a) - f(x_i^n)\|^2 \leq 0, \quad (1)$$

where α is a given constant representing the margin enforced between positive and negative pairs. The loss function of N triplets is defined as,

$$J_{triplet} = \sum_{i}^{N} max\{0, J_i\} \quad (2)$$

Triplet selection policy is quite crucial. Random sampling may result in slow convergence, since most triplets easily satisfy Eq.(1). Online hard example mining can accelerate convergence (Schroff, Kalenichenko, and Philbin 2015). However, a pair of partial fingerprints from the same identity may be captured from different regions of a finger. It's not reasonable to force them to be close in feature space. Triplets containing these couples should be ignored.

We employ KNN policy to address such a problem. To create one mini-batch, we firstly sample N^c identities and N^p fingerprints per identity as anchors. Then we randomly sample N^n negative fingerprints to select hard negatives. For a given anchor, we only select k nearest positives to generate *anchor-positive* (*a-p*) pairs. For each *a-p* pair, we select the nearest negative sample to the anchor to form a triplet. Therefore we have $N^c \times N^p \times k$ triplets in one mini-batch.

Joint Feature Learning

Triplet loss can constrain features in Euclidean space. However, it has a relatively slow convergence speed. Here are two possible reasons. First, triplet loss measures relative distances. The optimization objective is relative and uncertain. Gradients of different batches may conflict to each other. Second, inter-class gradient (Eq. (3)) of triplet loss is small when $f(x_i^a)$ and $f(x_i^n)$ are close, which makes harder negative samples separate from other more slowly. Besides, bad parameter initialization or undesirable triplets may lead to a collapsed model $f(x) = \mathbf{C}$, where $\mathbf{C}$ is a constant vector.

$$\frac{\partial J_i}{\partial x_i^n} = f(x_i^a) - f(x_i^n) \quad (3)$$

Softmax loss doesn't have the above problems, but it can't promise the features extracted from the same identity to be close in Euclidean space, since dissimilar vectors could have same outputs of softmax.

$$J = J_{triplet} + \lambda J_{softmax} \quad (4)$$

Therefore, we joint triplet loss and softmax loss (Eq. (4)) to take both advantages, providing not only a constraint in Euclidean space, but a fast and stable convergence.

Experiments

Due to lack of publicly available partial high-resolution fingerprint database, we collected an in-house database. We used an optical fingerprint sensor with area 0.24" $\times$ 0.39". Size of captured images is 480×800. We collected the database of 1800 identities in two steps. In first step, 20 scans on different finger regions were registered as templates for each person. In the second step, same volunteers gave 40 scans with varying finger regions and orientations as test images during matching. Then we randomly sampled 180 identities for testing and remaining 1620 for training.

Table 1: TAR@FAR$\leq$ 0.1% on in-house database ($\%$)

M	A	OurST	OurS	OurKT	Proposed
28.83	11.11	80.78	76.17	71.33	**89.17**

Table 2: EER on in-house database ($\%$)

M	A	OurST	OurS	OurKT	Proposed
20.48	41.16	2.83	3.81	6.78	**1.94**

We compared accuracy of the proposed model against minutiae-based algorithm (Fu et al. 2012) (denoted as M) and AKAZE-based algorithm (Mathur et al. 2016) (denoted as A). We also compared accuracy of 3 variants of the proposed model by removing KNN (denoted as OurST), KNN-Triplet (denoted as OurS) and Softmax (denoted as OurKT). Table 1 shows the TAR (True Accept Rate) with FAR (False Accept Rate) under 0.1% and Table 2 lists EER (Equal Error Rate) for above algorithms.

As shown in Table 1 and Table 2, all deep models outperform both algorithms based on minutiae and A-KAZE feature, showing great power of deep convolutional network. Removing any of the joint components in loss, or KNN sampling policy will make the accuracy degrade, proving the effectiveness of proposed method.

Acknowledgments

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Conclusions and Future Work

In this paper, we propose a novel model to solve partial high-resolution fingerprint matching problem. Experimental results show that proposed model performs better than several existing methods. In future, we decide to investigate some pre-processing such as rough alignment, denoising, enhancing, etc. We also want to consider minutiae topology which proposed model can't take fully advantage of.

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