Dense Fingerprint Registration via Displacement Regression Network

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Abstract

Dense registration of fingerprints provides pixel-wise correspondences between two fingerprints, which is beneficial for fingerprint mosaicking and matching. However, this problem is very challenging due to large distortion, low fingerprint quality and lack of distinctive features. The performance of existing dense registration approaches, such as image correlation and phase demodulation, are limited by manually designed features and similarity measures. To overcome the limitations of these approaches, we propose a dense fingerprint registration algorithm through convolutional neural network. The key component is a displacement regression network (DRN) that can regress pixel-wise displacement field directly from coarsely aligned fingerprint images. Training ground-truth data is automatically generated by an existing dense registration algorithm without tedious manual labelling. We also propose a multi-scale matching score fusion method to show the application of the proposed registration algorithm in improving fingerprint matching accuracy. Experimental results on FVC2004 DB1_A and DB2_A, and Tsinghua Distorted Fingerprint (TDF) database show that our method reaches state-of-the-art registration performances.

1. Introduction

Dense registration of fingerprints builds a pixel-level correspondenc between two fingerprints of the same finger. It is a relatively new issue and is barely discussed, as most previous registration algorithms build only sparse correspondences by minutiae or other features [21][5][17][22]. Due to nonlinear distortion inhere in fingerprint acquisition, dense registration of fingerprints is essential for accurate fingerprint mosaicing, and it can improve fingerprint matching accuracy [16].

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Recently, two dense fingerprint registration methods have been introduced. Image correlation method [19] proposed by Si *et al*., which is based on block-based image correlation and global energy minimization, provides denser and more precise registration results than previous methods. Phase demodulation method [10] proposed by Cui *et al.* makes use of fingerprint phase features to compute dense displacement field for alignment. However, these algorithms suffer from highly distorted fingerprints and poor fingerprint quality, thus the registration performance is limited.

Deep learning method has developed prosperously during the last decade, and has made promising success in image classification [13]. A number of papers in stereo matching and medical image registration have already utilized deep learning method [23][8], which shows the ability of deep learning in image registration. Some researchers have already come up with deep learning architecture to solve problems in fingerprint area [7][20][15][18][11]. These applications show that deep learning has the ability to learn features better than handcrafted features, and inspire us to explore its application in fingerprint registration.

To overcome limitations of handcrafted features, we propose a dense fingerprint registration algorithm via deep learning. As shown in Figure 1, the input fingerprints are first coarsely registered by minutiae-based initial registration as in [10], and then they are sent into the proposed displacement regression network (DRN) to obtain a pixel-wise displacement field for fine registration. We use Siamese network architecture to simultaneously extract features from input and reference fingerprint patches. Different from [23] which computes similarity between 0 and 1, we train the network to directly regress the displacement vector between input and reference fingerprint patches.

A large number of densely registered fingerprints are required for network training. We implement a state-of-the-art dense registration algorithm [10] and run the algorithm on FVC2002 [1] DB1_A to generate displacement field ground-truth, which does not need exhausting man-

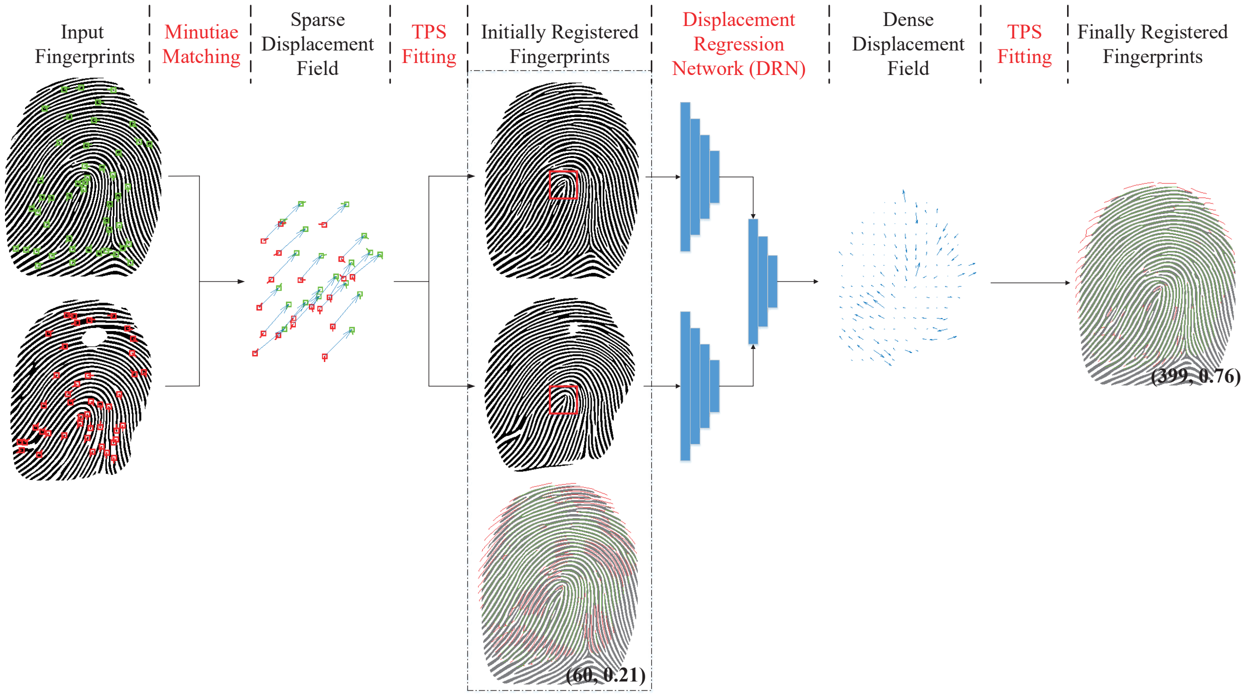


Figure 1. Flowchart of the whole fingerprint registration algorithm (the focus of this paper is the Displacement Regression Network). Red lines in registration results correspond to misalignment of ridges or non-overlap region, and green lines correspond to well-registered regions. The increase of matching scores by VeriFinger and image correlation from (60, 0.21) to (399, 0.76) indicates better registration result.

ual labelling. With data augmentation, we have up to 1M training pairs to train our network well.

An important application of dense registration is to improve matching accuracy. We found that the scale or resolution of the displacement field has major impact on matching accuracy. Displacement field of higher resolution dramatically increases matching scores of mated fingerprints, but it also increases matching scores of non-mated fingerprints at the same time. Meanwhile, although displacement field of lower resolution has minor impact on improving matching scores of genuine matches, but also barely increases matching scores of impostor matches. To combine advantages of different scales, we come up with a multi-scale matching score fusion method which merges matching scores from registration results using different scales of displacement fields.

In summary, our work has three main contributions:

1) We are the first to introduce deep learning approach into dense fingerprint registration, and we utilize Siamese network as a regressor to directly compute displacement from input fingerprint patches.

2) The ground-truth data for training are generated automatically, and don't require manual labelling. We use equalized sampling strategy to make distribution of the training data suitable for training network.

3) We propose a multi-scale matching score fusion technique to improve matching performances.

Extensive experiments on DB1_A and DB2_A of FVC2004 [2], and Tsinghua Distorted Fingerprint (TDF) database [19] show that the proposed method has better registration performance than state-of-the-art dense registration algorithms.

2. Proposed Dense Registration Method

2.1. Algorithm Overview

The proposed dense fingerprint registration algorithm mainly consists of three modules: (1) a minutiae-based initial registration algorithm which finds minutiae correspondences and coarsely aligns the input fingerprints, as in [19] and [10]; (2) a displacement regression network (DRN) which takes coarsely aligned fingerprints as inputs and outputs a displacement field corresponding to each pixel, which is further described below; (3) a TPS fitting algorithm [6] which transforms the input fingerprint according to the displacement field.

2.2. Initial Registration

In initial registration step, the two fingerprints are coarsely aligned by minutiae correspondences. First, the minutiae of two fingerprints are extracted by commercial

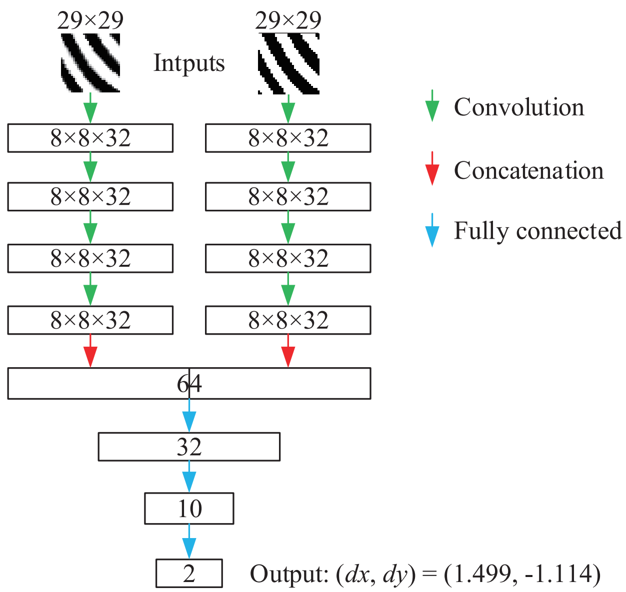


Figure 2. Architecture of the proposed displacement regression network (DRN).

software VeriFinger SDK 6.2 [4]. Then, MCC minutia descriptor [9] is adopted to compute minutiae similarity between all minutiae pairs among two fingerprints. Next, we use spectral clustering method [14] to select the correct minutiae pairs from all possible matches. Finally, a thin-plate spline (TPS) model [6] is fitted to transform input fingerprint to align with reference fingerprint, using minutiae pairs as landmark points.

2.3. Displacement Regression Network

As showed in Figure 2, the proposed displacement regression network (DRN) is a typical Siamese network, similar to the MC-CNN architecture in [23]. During training, the input patches are of size 29×29, cropped from binarized fingerprint images. The output is a displacement vector $d = (dx, dy)$. Each Siamese network brunch consists of 4 convolution layers of filter size 8×8×32, so that the extracted features are just of size 1×1×32, and doesn't need extra flatten layer. Batch normalization and ReLU activation are used after each convolution layer. Then the two features of length 32 are concatenated to be one feature vector of length 64, which passes through 3 fully connected layers to finally become a 2 dimensional output d. ReLU activation is used in each FC layer except for the last one.

Because our network has no flattening or any other reshaping layers, it can be generalized to any input size. Once trained, the network is directly used for testing, only needing to pad input images from size $(height, width)$ to $(height + 28, width + 28)$. And it directly outputs a dense displacement field of size $(height, width)$.

2.4. Training Data

To train the network, we need a large number of fingerprint patch pairs and their displacement vectors. We select 156 pairs of genuine matching fingerprints from FVC2002 DB1_A. These fingerprint pairs are first registered by minutiae-based registration, which is described as *Initial Registration* in [19]. Then they are registered by phase-based fingerprint registration, which was shown to provide state-of-the-art fingerprint registration performance [10]. We use the displacement field outputted by phase registration as ground-truth. Although we use phase registration results to train the network, but our method can learn more effective feature representation and obtain better registration performances, as shown in the following experimental results.

We choose FVC2002 DB1_A for two reasons since fingerprints in this database are of high quality. We can make sure the registered results are of high confidence level. We further select 156 pairs out of total 2800 genuine matches because their matching scores by VeriFinger [4] after phase registration are larger than 1200. Therefore, the selected 156 training pairs are registered very well, and their displacement fields can be used as ground-truth data.

As pointed out in [8], direct uniform or random sampling from images causes an uneven distribution of distortion level. Most pixels in image pairs are of small displacement, thus a large proportion of the sampled image patches are very close to zero displacement, which is bad for training network. As shown in Figure 3(a), most displacements are of small value, the standard deviation of displacement $d = \sqrt{dx^2 + dy^2}$ is 1.98, which is relatively a small number. Therefore, sampling strategy is needed.

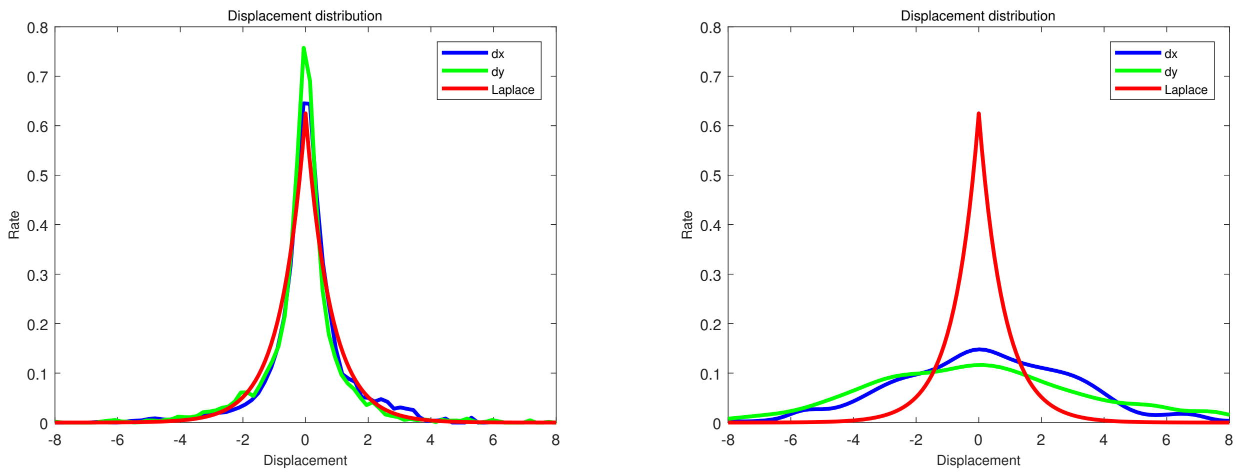
We can clearly see from Figure 3(a) that the distribution curves of dx (blue line) and dy (green line) are very similar to a zero-centered Laplace distribution (red line):

$$f(x, \lambda) = \frac{1}{2\lambda} e^{-\frac{|x|}{\lambda}}. \quad (1)$$

We also assume that dx and dy are independent, so that they can be sampled according to Equation 1 separately. As shown in Figure 3(b), the distribution curves of dx and dy are much flatter after sampling. And the standard deviation of displacement d increases to 4.96.

2.5. Data Augmentation

We sample 500 pairs of patches and corresponding displacements dx and dy from each pair of selected 156 fingerprint pairs, up to total 78k pairs of training patches. They are augmented through flipping horizontally and vertically (×2); rotating by 0°, 90°, 180°, and 270° (×4); and swapping two input patches (×2), as shown in Figure 4. Therefore, we expand training data by $2 \times 4 \times 2 = 16$ times, up to 1.248M training pairs.



(a) Before sampling (b) After sampling

Figure 3. Displacement distribution before and after sampling.

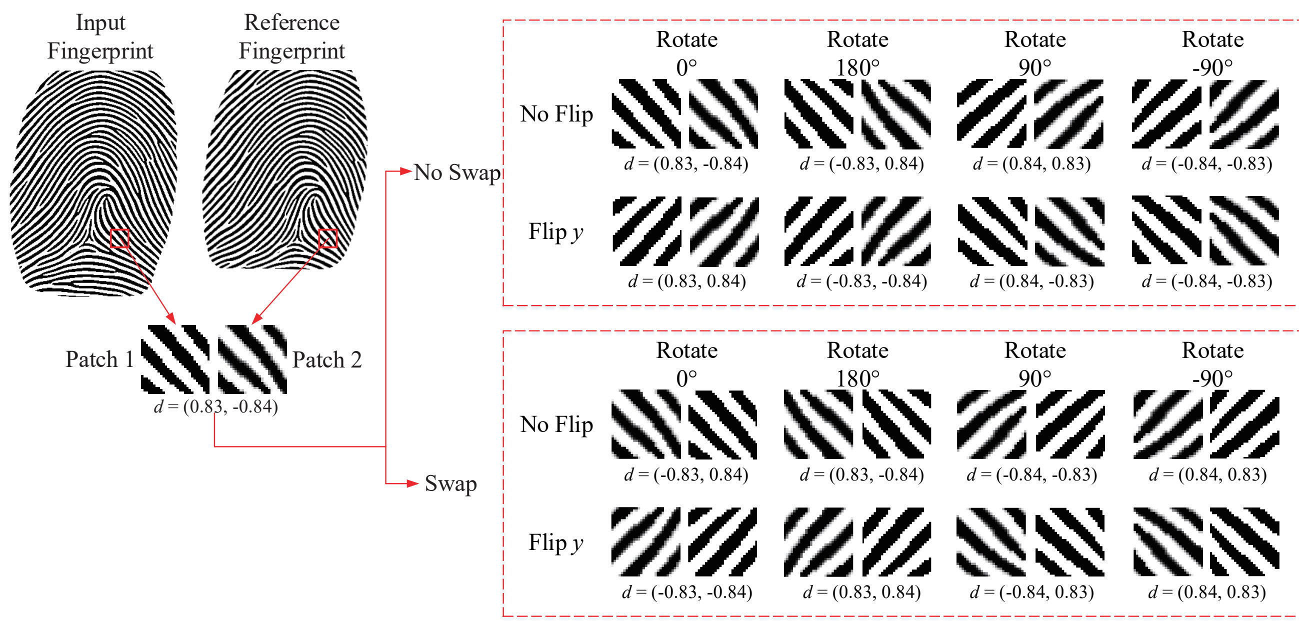


Figure 4. Data augmentation for training the proposed displacement regression network (DRN).

When augmenting training patches, their corresponding displacement vectors $d = (dx, dy)$ are changed simultaneously. For example, if the input two patches are flipped upside down, d changes to $(dx, -dy)$; if the input two patches are rotated 90° counterclockwise, d changes to $(-dy, dx)$; if the input two patches are swapped, d changes to $(-dx, -dy)$.

3. Application in Fingerprint Matching

A major application of dense registration is to increase matching accuracy, because it can reduce geometric variation between mated fingerprints. However, as registration algorithm is designed to align mated fingerprints, it also tends to register non-mated fingerprints well, thus increases matching scores of impostor matching. We found that the resolution of displacement filed is essential to registration accuracy and matching score.

An example is given in Figure 5. During testing, we first down-sample the output displacement field by 20 and 10, and we get three different levels of displacement field including the original one with no down-sampling. Then the input fingerprint is registered by TPS transformation [6]

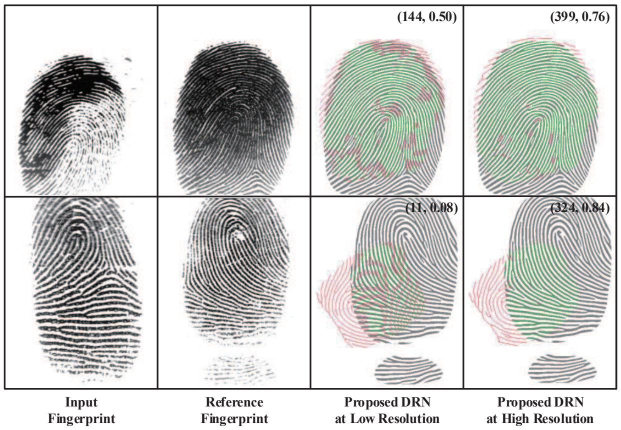


Figure 5. Registration results of genuine and impostor matching examples (from FVC2004 DB1_A) by the proposed registration algorithm at low resolution and high resolution. Row 1 is a genuine example, and row 2 is an impostor example.

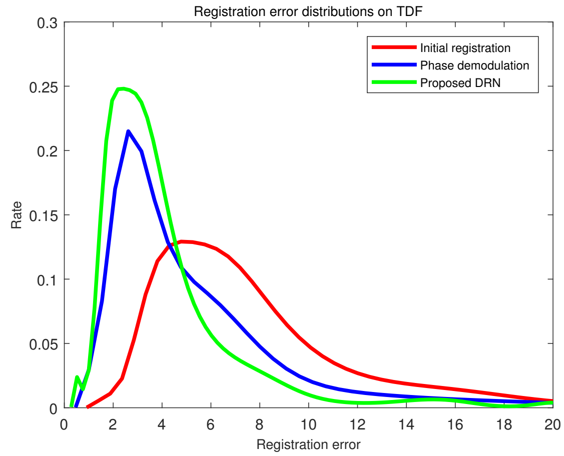


Figure 6. Registration error distribution on TDF database of three registration algorithms: initial (red), phase (blue), and the proposed DRN registration (green).

whose landmark points are provided by different displacement fields. Thus we obtain three registration results, and we can compute their matching scores.

Registration based on high resolution displacement field also increases impostor matching scores when having good registration results on genuine matches, but registration based on low resolution displacement field provides more robust result on genuine and impostor matches. That is to say, the high resolution displacement field tries its best to register input fingerprints, regardless of genuine matches or impostor matches. Therefore, it reaches excellent genuine matching performances at the cost of increasing impostor matching. This result is not surprising, as we feed the network with all genuine matching fingerprint patches. So the network treats any input fingerprint pairs as genuine matches, and computes a most probable displacement field.

Therefore, a multi-scale score fusion is necessary. Registration with larger scale performs more robustly on genuine and impostor matches, but it cannot achieve the best registration performances. Meanwhile, registration with smaller scale registers fingerprints better, but is not good at distinguishing genuine and impostor matches. Therefore, we combine matching scores from multi-scale registration results, to avoid confusing genuine and impostor matches and reaching good matching performances.

Two approaches of score fusion are used. The first approach is a simple linear combination of three scores:

$$score_{fusion} = \sum_i w_i score_i. \tag{2}$$

The coefficients w_i are off-line learned by a linear regression, which is trained to regress genuine matches as 1, impostor matches as 0. The second approach is a back-propagation (BP) network with two hidden layers. It takes all matching scores as an input vector, and outputs fusion result. It's also trained off-line with genuine matches as 1, impostor matches as 0. Both fusion methods are trained from matching scores on FVC2002 DB1_A.

4. Experiments

4.1. Implementation Details

We train the proposed network on the augmented training patches on 2 Nvidia 1080Ti by Keras [3]. We use Adam [12] optimizer with default parameters: learning rate $= 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, decay rate $= 0$. We use mean square error as loss function. The network converges after 50 iterations for about 2 hours with batch size 512. The loss drops to 0.37 pixel, which is far smaller than training data variation $4.96^2 = 24.6$.

We run test on FVC2004 DB1_A, FVC2004 DB2_A, and Tsinghua Distorted Fingerprint (TDF) database. FVC2004 DB1_A and DB2_A both contain 800 fingerprints from 100 fingers, many of which are of larger distortion and lower quality, therefore more challenging to register. TDF consists of 320 pairs of fingerprints, half of which are highly distorted. 120 pairs of fingerprints in TDF have manually marked corresponding points, and are used to compute registration error.

We compare the proposed fingerprint registration method with image correlation method proposed by Si *et al*. [19], and phase demodulation method by Cui *et al*. [10]. Consistent with [19] and [10], we use VeriFinger and image correlation to generate matching scores.

4.2. Registration Accuracy

Figure 6 shows the registration error distribution curves on TDF database by initial registration (red), phase demod-

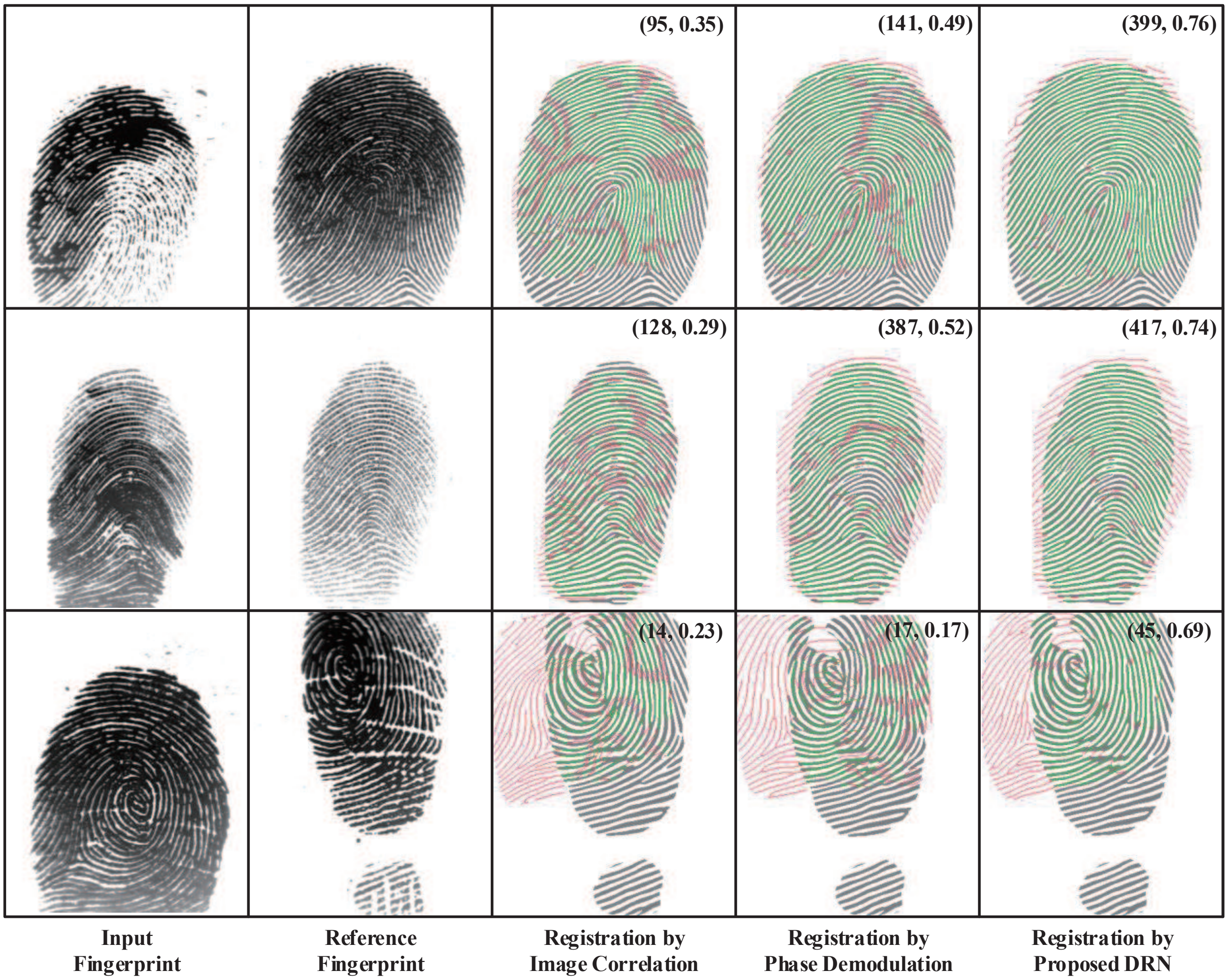


Figure 7. Registration results of genuine matching examples (from FVC2004 DB1_A) by different registration methods.

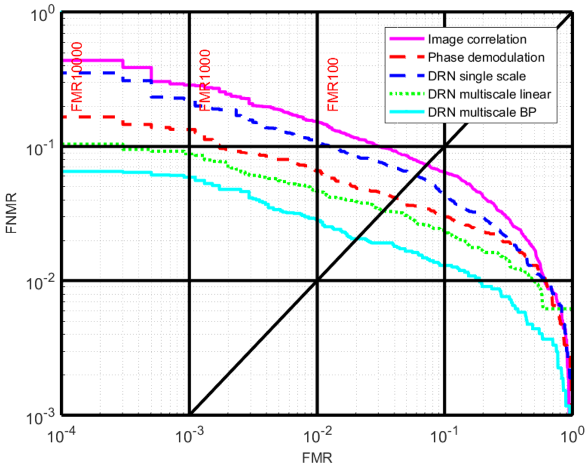
ulation (blue), and the proposed DRN registration (green). Hereby we use the pixel-wise DRN registration result since it has the most precise registration result, which is explained more thoroughly in the following sections. And the average registration errors of initial registration, phase registration, and DRN registration are 8.99, 5.95, 4.33 pixels respectively, which proves our method has the lowest registration error.

Figure 7 shows registration results by different registration algorithms for three examples in FVC2004 DB1_A. Each row corresponds to a genuine matching example, and column 3-5 correspond to registration results by different algorithms. Red lines on registration results mean misalignment of ridges or non-overlapping regions, and green lines correspond to well-registered regions. Numbers on northeast corners refer to matching scores by VeriFinger and image correlation respectively. These examples show that the proposed DRN registration outperforms other methods and registers fingerprints well.

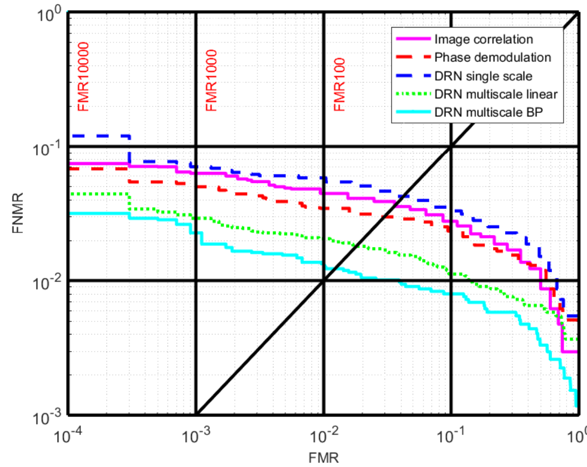
4.3. Matching Accuracy

Figure 8 shows the Detection Error Tradeoff (DET) curves on FVC2004 DB1_A by VeriFinger matcher and image correlator. DRN single scale refers to the matching scores by transforming input fingerprints using the sampled displacement field every 20 points. Comparing with [19] and [10], the performance of DRN single scale is between image correlation and phase demodulation algorithms. But with our multi-scale score fusion, the performance of linear fusion is almost as good as phase demodulation result. And with BP network fusion, our method outperforms phase demodulation algorithm.

The DET curves on FVC2004 DB2_A by VeriFinger matcher and image correlator are shown in Figure 9. We

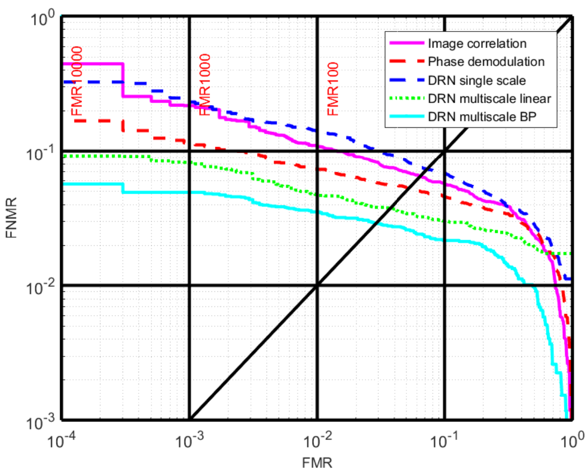


(a) Image correlator on FVC2004 DB1_A

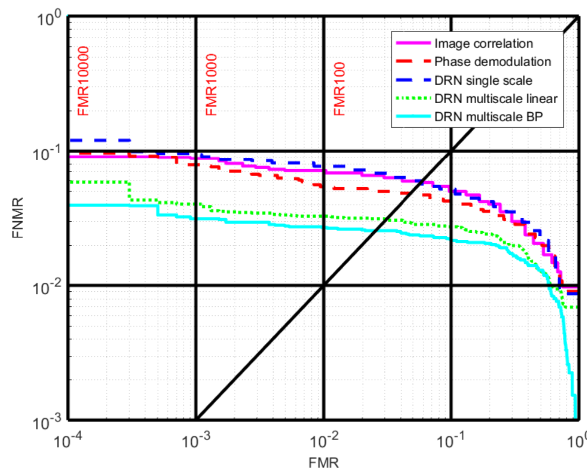


(b) VeriFinger matcher on FVC2004 DB1_A

Figure 8. DET curves of image correlator and VeriFinger matcher on FVC2004 DB1_A.



(a) Image correlator on FVC2004 DB2_A



(b) VeriFinger matcher on FVC2004 DB2_A

Figure 9. DET curves of image correlator and VeriFinger matcher on FVC2004 DB2_A.

can see from Figure 9 that DRN single scale results are no better than phase demodulation. But with linear score fusion, the results are comparable with phase demodulation results. Further with BP network fusion, the results can exceed phase demodulation. Therefore, the multi-scale score fusion is very useful.

4.4. Effeciency

It takes about 2 hours to train the proposed network on 2 Nvidia 1080Ti by Keras, and costs about 0.32s to run on a full fingerprint image from FVC2004 DB1_A of size 480×640. With larger input image size, the network needs more time. For example, it takes 0.44s to run a fingerprint from TDF of size 750×800. Other dense registration algorithms are conducted on CPU, so it may not be fair to compare our algorithm's time on GPU with other methods.

Meanwhile, multi-scale fusion method would spend much more time on TPS transformation, because it needs to compute three transformations of different scales. The time cost of TPS transformation increases with denser displacement field, as more points are used in computation. As for scale 1 situation, we already get a pixel-wise displacement field, so that a direct interpolation to transform fingerprint is applied instead of TPS fitting, which costs much less time. Therefore, the order of time cost would be scale 10>scale 20>scale 1.

5. Conclusion

Dense registration of fingerprints is beneficial to image mosaicking and improving matching accuracy. Although several dense registration algorithms have been published, their performance is not satisfactory on fingerprints with large distortion and low image quality.

In this paper, we propose a dense fingerprint registration method using displacement regression network (DRN) to directly regress displacement from fingerprint ridge patches. To train the network, we collect more than a million fingerprint ridge patches and corresponding displacements. We use equalized sampling strategy to balance the data over displacement values.

To our knowledge, this is the first work that uses deep learning in dense fingerprint registration. Through fusion of matching scores generated by registered fingerprints with multi-scale displacement fields, our method outperforms other fingerprint registration algorithms in terms of matching accuracy on FVC2004 DB1_A, FVC2004 DB2_A and TDF database.

6. Acknowledgement

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