Fast Minutia-based Palmprint Matching Using CNN and Generalized Hough Transform

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Abstract

Due to the large number of minutiae in a palmprint, the matching process between two palm images is time consuming. One way to address this issue is aligning all palmprint images to a reference image. In this paper, using convolutional neural network (CNN) and generalized Hough transform (GHT), we propose a new method to find the corresponding rotation and displacement between any palmprint and the reference palm image. Furthermore, the proposed method is capable of distinguishing between left and right palmprint automatically which helps to speed up the matching process. The proposed registration method followed by minutiacylinder code (MCC) matching algorithm has been evaluated on the THUPALMLAB database, and the results show the superiority of our algorithm over most of the state-of-the-art.

1 Introduction

Biometrics is used to recognize or verify human identity based on physical or behavioral characteristics. Biometric features such as face, iris, fingerprint, hand geometry, palmprint and signature have been used for human identification and recognition. Among all these features, recently, palmprint recognition has gained considerable attention as a reliable personal identification technique. In palmprint recognition systems mainly two different types of images: 1) low and 2) high resolution images are used . Features in the low resolution palmprints includes principal lines, wrinkles and ridges. Features obtained from high resolution images are minutiae (specific plot points on a palmprint, e.g. ridge bifurcation or a ridge ending) and the orientation image. In this paper, our focus will be on minutia-based palmprint matching.

In literature, a lot of effort has been made regarding minutiabased palmprint matching in order to reduce the matching time. Palmprint Registration has been used to address the problem of large number of minutia comparison [1], [2]. By registration, we apply the matching algorithm only to the same parts of the two palmprints. To increase the matching speed, we developed a new palmprint registration method. We combined CNN and GHT to register palmprint images with a reference image. Two new criteria are used to measure the confidence of the registration. Using these two criteria our method is capable of recognizing left palm from right palm which can double the matching speed.

2 Palmprint Registration and Matching

To align all palmprint images to a reference image, we first roughly find the rotation (around *z* axis) of images by CNN. After that, the exact values of registration parameters is obtained by use of GHT. We formulated the task of finding rotation of each image as a classification problem, i.e., the rotation of input palmprint will be classified to one of the 24 existing classes. These classes are 0° , 15° , ..., 345° . To build a training set, we used palm images in THUPALMLAB and rotate them with different angles around *z* axis. A CNN was trained to classify the rotation of each un-seen image to one those 24 classes and find θ . Rotation $-\theta$ is applied to images to remove the rotation (rough registration by CNN).

To find exact values of rotation, we apply GHT. We used orientation field of each palmprint image to find the registration parameters. The average orientation field of palmprints is used as the reference image, and other palmprint are aligned with this image. All possible pairs of 16×16 blocks between the input (unregistered) palmprint orientation and the reference orientation field vote for corresponding rotation and the displacement. To measure the reliability of registration results, we define two new parameters: $q_1 = \frac{\#of all blocks in foreground}{\#of all blocks in image}$ and $q_2 = \frac{\#blocks vote for best candidate(\theta, d_x, d_y)}{\#of all blocks in foreground}$. A larger value of q_1 shows the higher quality of registration. Larger values of q_2 guarantees the registration accuracy. The

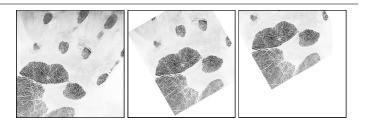


Fig. 1: Sample registration result. From left to right: original image, registered by CNN and registered by GHT

reference orientation palmprint which we use for refining the registration, belongs to left hand. GHT is applied to do exact registration for both original and flipped version of the input palmprint. Now, two q_2 s are in hand, resulted from registration of reference image with orientation of input palmprint and its flipped version (q_{2L} and q_{2R}). If q_{2L} is larger than q_{2R} , then input palmprint is left hand and vice versa. Fig. 1 shows a sample registration result.

After registration, minutiae are extracted and the matching process is applied. In the local minutia matching stage, the similarity of a minutia pairs is computed with the MCC descriptor and in the second stage, overall similarity of two palmprints is calculated [2]. All steps before matching are offline pre-processing, and take around 4 second per image (which is in the same order of other methods).

3 Experiments

The only publicly available high-resolution palmprint database, Tsinghua Palmprint Database, is used as the main database. A typical palmprint contains 1000 minutiae on average; then the original MCC algorithm needs to do $1000 \times 1000 = 10^6$ MCC local similarity computations. By our proposed registration technique, only 12 percent of all computations, i.e. 1.2×10^5 local MCC similarity computation needs to be done. As it is seen in in table 1, by the proposed system, 166 palmprint matches per second can be done whereas the feasible number of matches per second for algorithm in [3] (the fastest CPU-based algorithm to the best of our knowledge) is 26. Note that, we can double the matching speed by applying proposed left-right palm detector, i.e. average matching time is 3 milliseconds (332 matches per seconds). Our method is six times faster than the state-of-the-art, and the matching accuracy is still very high. It does 166 matches per second while keeps the EER at level of 0.04%.

Table 1: Average matching time (second) and Accuracy

Method	Time	EER	FNMR at FMR = 0
Tariq et.al(GPU) [4]	0.4	> 0.4	> 0.4
Capelli and Ferrara [3]	0.038	0.01	0.48
Proposed method	0.006	0.04	0.24

References

- J. Dai, J. Feng, and J. Zhou, "Robust and efficient ridgebased palmprint matching," *IEEE Trans Pattern Anal Mach Intell*, vol. 34, pp. 1618–1632, 2012.
- [2] H. Soleimani and M. Ahmadi, "Fast and efficient minutia-based palmprint matching," *IET Biometrics*, vol. 7, no. 6, pp. 573–580, 2018.
- [3] R. Cappelli, M. Ferrara, and D. Maio, "A fast and accurate palmprint recognition system based on minutiae," *IEEE Trans Syst Man Cybern B Cybern*, vol. 42, pp. 956–962, 2012.
- [4] S. A. Tariq, S. Iqbal, M. Ghafoor, I. A. Taj, N. M. Jafri, S. Razzaq, and T. Zia, "Massively parallel palmprint identification system using gpu," *Cluster Computing*, pp. 1–16, 2017.