Integrating minutiae based fingerprint matching with local mutual information

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Abstract

Minutiae based fingerprint matching algorithms are wildly used in fingerprint identification and verification applications. However,they may suffer from spurious matches because they do not use the rich local image information. In this paper, we extend minutiae based methods to incorporate such local image information. Our method uses local mutual information, a proven similarity measure in various applications, to improve the matching rate. The overall minutiae distribution pattern between two fingerprints is represented by the initial minutiae matching result, while the mutual information measures the similarity between neighborhoods of matched minutiae, thus enhancing the final matching decision. FVC2002 DB1 and DB3 databases are used to test the proposed approach. Experimental result shows the improvement when combining minutiae matching scores with mutual information scores.

1. Introduction

Fingerprint is the most common biometric modality in use today for various civilian and security applications of access control. Fingerprint verification is the process of matching a pair (test and enrolled) of finger-skin ridge impressions to determine if the impressions are from the same finger. The non-linear stretching of the finger-skin makes any two instances of impressions of the same finger (quite) different. Other challenges are due to the varying contrast levels (moist fingers tend to give smudged impressions and dry fingers tend to give impressions with broken ridge contours), the rotation of the finger, the pressure applied on the sensor, and the partial nature of most fingerprints captured by commercial sensors.

Fingerprint matching algorithms reported in the literature are of three types based on: (i) minutiae (discontinuities in the ridge contour) (ii) texture, and (iii) image correlation. Minutiae based matching methods consider special points of fingerprint impressions representing ends and bifurcation points of the fingerprint ridge structure. In texture matching, spatial relationship and geometrical attributes of the fingerprint ridges are used. Correlation scores from the intensities of corresponding pixels are used in the third approach. Various matching systems have been developed based minutiae [1] [2], on texture [3] [4] [5], and on image correlation [6]. Also, different matching algorithms are combined to seek better performance [7] [8] [9].

Although minutia based algorithms usually provide good performance, they have problems matching partial or low quality fingerprint images when only a few minutiae are successfully extracted. Texture and correlation based matching methods have advantages dealing with such images as they utilize low level features not accounted for by minutia templates. On the other hand, minutia based approaches are faster and can take into consideration the non-linear deformations of fingerprint impressions.

In this paper, we propose to incorporate a local image similarity measure based on mutual information to improve the robustness when matching a pair of minutia. Using mutual information(MI) to measure the similarity between the corresponding areas in the fingerprint image, our experiments show that MI delivers useful scores. When used along with minutiae matching score such MI score reduce the ambiguity between matched minutia pairs in genuine and impostor fingerprint matches.

In the following section we will first cover the minutia based matching method that we used to get the matching minutia pairs and fingerprints alignment. Then we introduce the proposed method to improve robust matching using mutual information. After that we describe score combination method, followed by the experiment and result section. Finally, conclusion is given in the last section.

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2. Minutiae based fingerprint matching

Most of the current fingerprint matching systems are based on minutiae extraction and minutiae matching. A standard minutiae matching system is composed of fingerprint image preprocessing, fingerprint image enhancement, minutiae feature extraction and matching. The preprocessing and enhancement steps reduce image noise and enhance the ridge information, partitioning the given image into regions that are composed of the fingerprint ridges and background area. Minutiae can be extracted from binarized fingerprint image or from gray-scale image directly.

Jea et al.[10] proposed a multi-path matching system based on the secondary features, which are the five element tuples extracted from each minutiae and its two nearest neighbors. Heuristic rules are used to get the matching score for final decision. Based on this work, we will introduce our correlation methods in next section, and show the improvement made in result section when it is combined with this minutia matching system.

3. Improving match robustness with local mutual information

Since mutual information was first introduced, it has become one of the most used similarity measure in many researches, over other measures like SAD, SSD, NCC etc. It is empirically found by various researchers to be more robust when there can be deformations in the region and varying lighting conditions across the images.

3.1 Mutual information

Based on the research that has been done for image registration dates back to 1990's [11] [12], mutual information was first introduced for medical image registration by Collignon et al.[13] and Viola et al.[14]. Given two images A and B, the mutual information between A and B can be defined as follows:

$$I(A,B) = H(B) - H(B|A) \tag{1}$$

$$I(A,B) = H(A) - H(A|B) \tag{2}$$

$$I(A,B) = H(A) + H(B) - H(A,B) \tag{3}$$

where $H(A)$ and $H(B)$ are the Shannon entropy of image A and B, $H(B|A)$ is the conditional entropy of B given A, it is based on the conditional probability $p(b|a)$, represents the chance of grey value b in image B given that the corresponding pixel in A has grey value a. Given the marginal probability distributions $p(a)$ $p(b)$ of A and B, and the joint probability distribution $p(a,b)$ of A and B, according to the Kullback-Leibler distance that is defined between two distributions, the mutual information between A and B can be defined as :

$$I(A,B) = \sum_{a,b} p(a,b) \log \frac{p(a,b)}{p(a)p(b)} \tag{4}$$

Many studies use the normalized measure of mutual information, which is proposed by Studholme et al. [15], it is less sensitive to changes in overlap.

$$NMI(A,B) = \frac{H(A) + H(B)}{H(A,B)} \tag{5}$$

3.2 Mutual information as a local similarity measure

The matched pair minutia neighborhood mutual information is used to measure the local similarity between the matched pair of minutiae of the two fingerprint images. According to the definition, maximizing mutual information is correspond to matching verification, assuming that the images have to be aligned in such way that the amount of information they contain about each other is maximal.

Compute the mutual information between the two regions using Eq. 4 and Eq. 5, get the neighborhood NMI score for each pair of matched minutiae. The joint probability distributions is estimated by using the joint histogram of two neighborhood regions as showed in figure 1. The probability distributions for each region can be estimated by summing over rows or columns of the joint histogram (marginal probability distribution).

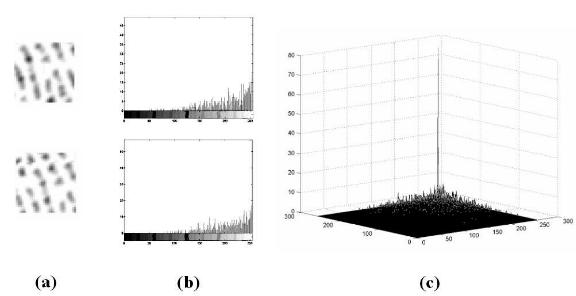

Figure 1. Joint probability distribution estimation (a) two neighborhood regions (b) histogram for each region (c) joint histogram

The appropriate window size should be selected for calculating mutual information such that it is large enough to contain statistical information to measure similarity between two regions, while it should be small enough to avoid including too much local deformation. By experimenting on some training data, we select a neighborhood of 31*31 region around the minutiae.

Due the the various minutia extraction processes, the exact location of the minutiae point will not always be extracted, therefor, the exact alignment between two matched minutia points at pixel level will not always hold. To achieve a more reliable mutual information based on such minutia pairs, we implement a local search for maximizing local mutual information. For each pair of matched minutiae, we get described neighborhood region mutual information scores and the median of these scores is taken as final minutia neighborhood similarity.

4. Score combination

Data fusion is necessary for decision making. When the minutia based matching result and the local mutual information are considered, we will have a better evaluation of how well two fingerprints match with each other. There are various rules for combining scores, in this study, we use simple product rule to generate final matching scores. As mentioned before, minutia based matching considers the match of global minutia distribution pattern, mutual information score gives a measure of how well the match is in the local and semi-global level of the similarity between two fingerprints. Different combination methods will give us different explanation at certain level. For example, when the number of matched minutiae pairs (minutiae score) is multiplied with neighborhood mutual information, it gives the simple sum of correlations of matching minutiae pairs, this sum represents a composite of evidences collected for all matching minutiae pairs.

5. Experiments and results

FVC2002 DB1 and DB3 are used as experimental set for the algorithm we proposed, the general image qualities are quite different. Each database contains 8 impressions is 110 fingers(880 fingerprints in all). For genuine match tests, each sample is matched against the remaining samples of the same finger to compute the false rejection rate - FRR. If the matching g against h is performed, the symmetric one (i.e., h against g) is not executed to avoid correlation. The total number of genuine tests (in case no enrollment rejections occur) is: ((8*7) /2) * 100 = 2,800. For impostor match tests, the first sample of each finger is matched against the first sample of the remaining fingers to compute the false acceptance rate - FAR. If the matching g against h is performed, the symmetric one (i.e., h against g) is not executed to avoid correlation. The total number of false acceptance tests (in case no enrollment rejections occur) is: ((100*99) /2) = 4,950. In the experiment, we randomly choose 1000 genuine matches and 1000 impostor matches from above test set from each database. Note that the scores are computed only for hypothesized matched and aligned minutiae.

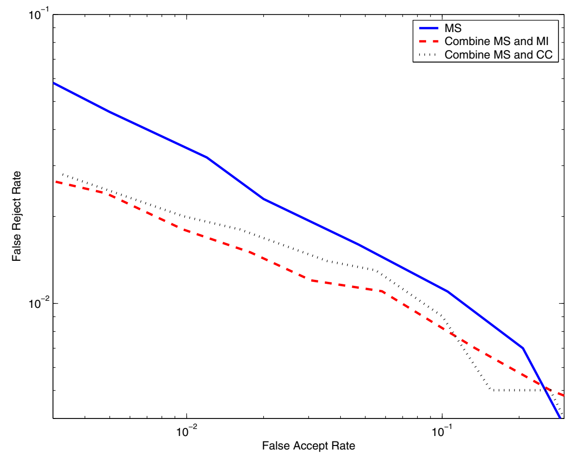

Figure 2. ROC curves of different score combinations of DB1 data set. MS: Minutiae score. MI: neighborhood mutual information score. NH: Neighborhood correlation score. Combining rule: product rule.

The ROC curves for both DB1 and DB3 and for product combination rule are showed in Figures 2 and 3. Note that we also included correlation coefficient as another similarity measure for the neighborhood matching from previous work [9]. The figures show that, when the minutiae matching score and neighborhood similarity score are combined, it gives improvement for the final matching decisions. Notice that although the FVC database is using same type of fingerprint enrollment sensor, mutual information should be more robust with respect to variations of illumination if different type of sensors are used for fingerprint enrollment.

6 Conclusion

This paper proposed a fingerprint matching algorithm that incorporates minutia based matching method

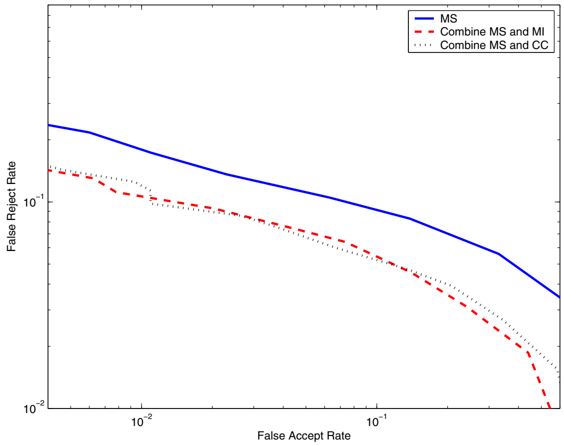

Figure 3. ROC curves of different score combinations of DB3 data set. MS: Minutiae score. MI: neighborhood mutual information score. NH: Neighborhood correlation score. Combining rule: product rule.

with local mutual information.It proves that mutual information can be used as a similarity measure in fingerprints matching process. It seems possible to expand MI and implement EMMA(empirical entropy manipulation and analysis) technique with deformation models for more advanced fingerprint matching algorithms.

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