A Novel Verification Criterion for Distortion-Free Fingerprints

Neil Yager and Adnan Amin

School of Computer Science and Engineering,
University of New South Wales, Sydney, NSW 2052, Australia
{nyager, amin}@cse.unsw.edu.au

Abstract. An important aspect of fingerprint verification systems is the method used to quantify the similarity between two fingerprints. This involves two key components: choosing fingerprint features that will be used for comparison and selecting a match score function to calculate the degree of correspondence. The choice of features and a match score function can have a significant impact on the performance of a system. This paper presents a novel fingerprint verification criterion based on tabulating ridge intersections between distortion free fingerprints. Several alternative matching criteria have been implemented, and their performance is compared using a publicly available FVC2002 dataset. The novel ridge based approach proves to be highly discriminative, and a strong result is obtained by a hybrid system using a combination of minutiae and ridge based features.

1 Introduction

Biometrics is the automatic identification of an individual based on his or her physiological or behavioural characteristics. Fingerprints have emerged as one of the most researched and trusted biometrics. However, despite decades of study there remains several challenges for the developers of automated fingerprint verification systems. These challenges include the enhancement of noisy fingerprint images, dealing with the nonlinear deformations present in fingerprints, and exploiting the full, rich structure of fingerprints for verification. This last point involves selecting appropriate fingerprint features for comparison and deriving a method to calculate the degree of correspondence. This is an important (and often overlooked) aspect of designing a fingerprint verification system and can have a significant effect on a system's performance.

As fingerprint databases increase in size, it is becoming increasingly important to choose features that are highly discriminative. The majority of algorithms in the literature rely heavily on minutiae information [1]. Minutiae do embody much of a fingerprint's individuality, yet when used in isolation useful discriminatory information is inevitably lost. Therefore, for systems requiring a high degree of accuracy it is important to supplement minutiae information with non-minutiae features.

A. Gagalowicz and W. Philips (Eds.): CAIP 2005, LNCS 3691, pp. 65–72, 2005.

Several approaches to fingerprint deformation modelling are available in the literature [2,3]. As these techniques become more mature and robust, fingerprint verification algorithms should begin to exploit the discriminative information from the entire fingerprint ridge map. Two approaches to this are explored in this paper. In one approach, correlation techniques are used to compare the pixel intensities between the images. For the second approach, a novel method of fingerprint verification based on tabulating ridge intersections is developed.

Section 2 contains a review of existing approaches to fingerprint verification, and Section 3 presents the proposed ridge based method. The results of the experimental validation can be found in Section 4. Finally, the paper concludes with a discussion of the results in Section 5.

2 Fingerprint Verification

The output of a fingerprint verification systems is a score that quantifies the degree of similarity between two prints. Without loss of generality, we will assume the score is between 0 and 100, with 100 indicating a very strong match. A threshold is determined for verification, above which two prints are labelled a match and below which they are labelled a non-match. Fingerprint verification systems can be broadly categorized by the features they use for matching. The most common feature is minutiae points, however systems incorporation non-minutiae features are becoming more common.

2.1 Minutiae Based Verification

Minutiae are local ridge discontinuities that come in two varieties: ridge endings occur when a ridge terminates, and bifurcations are locations where a single ridge separates into two. Each minutiae has a type, location, and orientation. Match score functions using minutiae features typically involve tabulating minutiae correspondences. A minutiae correspondences is two minutiae (one from each print) that are in close proximity after registration and have similar attributes. The ratio of minutiae correspondences to the total number of minutiae gives a score for the match. An example score function is [4]:

$$\text{Match Score} = \frac{100 N_{\text{pair}}}{\max\{M, N\}} \tag{1}$$

where N_{pair} is the number of correspondences, M is the number of minutiae in the reference set, and N is the number of minutiae in the test set.

There are three main drawbacks of minutiae based matching: (i) Minutiae detection is a very difficult task (especially for low qualities images). This often leads to missing and spurious minutiae, having a detrimental effect on the robustness of the system. (ii) Many of the scanning devices currently being used for biometric systems have a very small capture surface, so the amount of overlap between two prints may be very small. Consequently, there may be few (or even 0) minutiae correspondences. (iii) Finally, minutiae information is only a subset of the information contained by a fingerprint's ridge structure. By using only this information, much of a fingerprint's discriminatory information is lost.

2.2 Non-minutiae Based Verification

One approach to non-minutiae verification is the correlation of fingerprint images. At first glance, this seems like an obvious and powerful approach to fingerprint verification as it uses all of the information from the images. However, there are several obstacles that prevent this from being a common approach. In particular, the presence of nonlinear distortions and varying skin conditions can cause captures of the same fingerprint to appear very different [5]. One approach to overcome the problem of fingerprint deformations is to perform correlation locally rather than globally [6,7].

Other non-minutiae features that can be used for verification can be derived from local textural analysis. In these systems, filters are applied to extract frequency and orientation information from the ridges in a local area [8,9,10]. The main disadvantage of these approaches is that they do not take fingerprint deformations into consideration.

3 A Ridge Based Matching Criterion

Assume that the distortion has been mostly removed from a query fingerprint with respect to a reference print. This deformation modelling can be accomplished using any of the available methods in the literature [2,3]. After aligning the ridge maps, the ridges patterns will appear very similar for genuine matches (assuming the deformations have been modelled accurately). This can be illustrated with an example. In Fig. 1 (a), the alignment of a genuine match pair is shown. Although not all ridges align exactly, it is obvious that their patterns are the same. However in Fig. 1 (b), two prints from different fingers are shown. In this case, although the overall curvature and ridge spacing is very similar, it is obvious that the ridge patterns are different. It is this intuitive notion of ridge map similarity that should be captured and quantified.

(a) A Genuine Match (b) An Imposter Match

Fig. 1. Ridge map alignment examples

The approach proposed in this paper is to count ridge crossings between the aligned ridge maps. A crossing is defined as any contact between two ridges.

For each ridge in the query ridge map, it is traced and the number of distinct ridges (after the first) in the reference ridge map that are crossed is tallied. A score for each ridge is computed as $100 - (r \times 100)$, where r is the number of ridge crossings. A global score for the entire match is calculated by averaging the individual ridge scores. Negative global match scores are set to 0. This is a very simple algorithm, but it elegantly captures the notion of ridge map similarity.

There are a few implementation points that should be made. First of all, very short ridges should be ignored. Due to their short length, they are unlikely to cross any other ridges, and therefore give the overall print an artificially high score. Secondly, dealing with bifurcations is a little bit troublesome. We have found that the best approach is to break bifurcations, and treat all of the branches as individual ridges. Finally, there are a few situations in which ridges end prematurely, leading to spurious crossings. Ridges may be broken due to noise or when part of the fingerprint leaves the capture area. When tracing a ridge, if the ridge it last crossed has ended before a new ridge is reached, it should not be counted as a new crossing. For example, in Fig. 2 the upper portion of

Fig. 2. In the reference ridge map, many ridges are broken due to the upper region of the fingerprint not being captured

the reference print has not been captured. Therefore, when tracing ridges in the query print, the ridge will make contact with a reference ridge, the query ridge will loop around above and eventually make contact with a new ridge. This "new" ridge is not actually a new ridge: it is the same reference ridge as before, but has been broken because part of the print was not captured. Therefore, this should not be counted as a new ridge crossing. The best way to handle this situation is to record the remaining length of the reference ridge at each crossing. When a new ridge is reached, it will not be counted as a new crossing if the previous ridge has ended.

There are several advantages of this approach over both minutiae and correlation based methods. One advantage over minutiae based methods is that missing and spurious minutiae will have little effect on the match score. This is because their effect is local and will not cause additional ridge intersections. Furthermore, this method has the potential to be much more discriminative as it is based on information from the entire ridge map. The primary advantage over correlation techniques is that it does not require perfect alignment of the ridge maps. For correlation techniques to be successful it is necessary for the ridges to align exactly, and this is very difficult to achieve. The ridge counting method has some tolerance for misaligned ridges; even if the ridges are not aligned exactly, they will not create false ridge crossings as long as they stay within the boundaries created by the neighbouring ridges. Therefore, the method is robust even if the deformation modelling is not exact.

4 Experimental Results

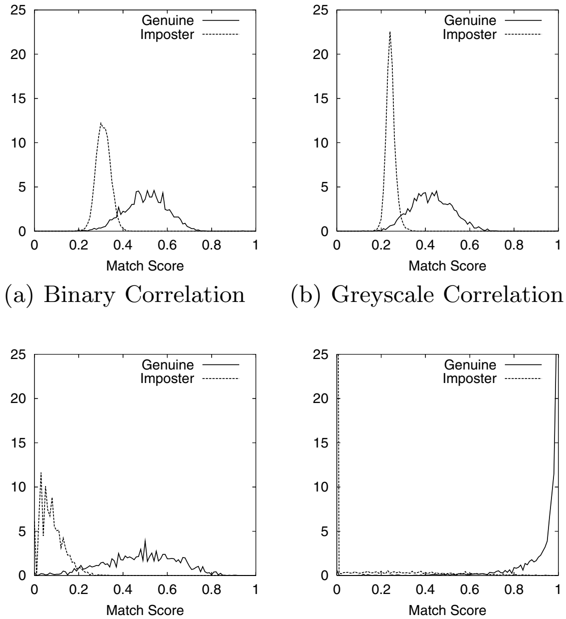
Several verification methods have been implemented for comparison. All methods use the same preprocessing, registration and deformation modelling. For registration, we have used a two stage optimization algorithm that first finds a coarse registration using orientation field, curvature and frequency information, and then fine tunes this registration using minutiae features [11]. Fingerprint deformation modelling is accomplished using a nonparametric elastic modelling algorithm [3].

The following five verification methods have been implemented for evaluation. (i) Minutiae matching based on the ratio of minutiae correspondences to the maximum number of minutiae from the reference or query fingerprint (see Eq. 1). (ii) The correlation of greyscale fingerprint pixel intensities. The score is based on finding the average absolute difference of corresponding pixel intensities between the registered images. This value is normalized and subtracted from 100 to give a match score. (iii) The correlation of binary ridge maps. Before correlation, the images are processed to extract binary ridge maps with a standard ridge width. These binary ridge maps are then compared using cross-correlation. (iv) The ridge based method presented in Section 3. (v) A hybrid method using both minutiae and ridge crossing information. Assume that a minutiae score s_m and ridge score s_r have been obtained for a given pair of fingerprints. The match score S is defined as follows:

$$S = \begin{cases} 0 & \text{if } s_r < t_1, \\ 100 & \text{if } s_r > t_2, \\ s_m & \text{otherwise.} \end{cases} \tag{2}$$

where t_1 and t_2 are determined empirically. Intuitively, when prints have a very similar (different) ridge map, they are automatically accepted (rejected). When the ridge based match score is midrange, the minutiae matching score is used to discriminate them.

The dataset used for evaluation is the publicly available FVC 2002 database DB1 [12]. The fingerprint images were captured using fingerprint scanners and contain a wide variety of fingerprint image qualities. The database contains 880 fingerprints from 110 different fingers. The competition organizers have selected a set of 2,800 genuinely matching pairs and 4,950 non-matching pairs from the databases for evaluation. A variety of performance measures are calculated, the



(a) Binary Correlation (b) Greyscale Correlation

(c) Minutiae Matching (d) Ridge Crossings

Fig. 3. Match score distributions

Table 1. Match Score EERs

Match Score Method	EER	Run Time (ms)
Binary Correlation	6.21 %	21
Greyscale Correlation	4.52 %	35
Minutiae Matching	4.51 %	6
Ridge Crossing	3.46 %	21
Combination	2.09 %	27

details of which can be found in [12]. One measure in particular is often used to summarize a system's performance. The equal error rate (EER) is the point at which a system's false match rate (FMR) equals its false non-match rate (FNMR).

The EER's and run times for the various match score functions can be found in Table 1, and the match score distributions can be found in Fig. 3. The running times do not include the time taken for preprocessing, registration, and deformation modelling (which is constant for all algorithms).

The error rate for greyscale correlation is lower than for binary correlation. This is surprising as it was expected that the preprocessing applied for binary correlation would remove much of the noise, making correlation more reliable. However, it appears that using the full range of pixel intensities is advantageous despite the presence of noise. The results of both correlation algorithms are not very impressive. There are two main reasons for this. First of all, highly accurate deformation modelling is necessary to obtain high scores for genuine matches. Secondly, there tends to be a lot of ridge overlap between imposter matches with similar ridge patterns. This can lead to relatively high scores. These two factors lead to many midrange genuine and imposter scores. These midrange scores lead to greater overlap of the score distributions, and consequently a higher error rate.

The proposed ridge based method has a lower error rate than both the minutiae and correlation algorithms. Furthermore, there is a significant reduction in error by using a combination of ridge and minutiae information. Using combinations of multiple features has been investigated by several researchers, and shows promise for powerful algorithms [13].

In terms of running time, all methods are roughly in the same range. These running times are almost insignificant compared to the other stages of verification (e.g. preprocessing and deformation modelling).

The match score distributions in Fig. 3 illustrate an important advantage of the ridge based approach developed in this paper. The genuine and imposter distributions are extremely well separated compared to the other distributions. Specifically, over 90% of genuine matches receive a score greater than 80, and almost 80% of imposter matches receive a score of 0. This is highly discriminative. Approximately 2% of genuine matches receive a score below 50, and virtually the only reason for this is when the nonlinear distortions have not been modelled accurately. If improvements to the deformation modelling algorithm are made, it is expected that the EER for the ridge based approach will drop dramatically.

5 Conclusion

The results in this paper show that the choice of features for verification makes a dramatic difference on the accuracy of a system. In our experiments, the exact same registration and deformation modelling was used, yet the EER's varied from 6.21% down to 2.09%.

Traditionally fingerprint deformation algorithms have not been common in verification systems due to the additional computational costs they demand. However, as computational resources increase and become more readily available this will cease to be as much of an issue. Therefore, it is expected that deformation modelling algorithms will be increasingly researched, and become more common and robust in the coming years. As this happens, it will be important for verification systems to select fingerprint features that are able to exploit the full, rich discriminatory power from a fingerprint's ridge pattern. In particular, it will be important to no longer rely strictly on minutiae information. Correlation is one approach that has been explored, but its results are comparatively poor. The novel ridge based approach presented in this paper is very discriminative, and has the potential to be a powerful addition to future verification systems.

References

1. Yager, N., Amin, A.: Fingerprint verification based on minutiae features: a review. Pattern Analysis and Applications **7** (2004) 94-113
2. Bazen A., Gerez, S.: Fingerprint matching by thin-plate spline modelling deformations. Pattern Recognition **36** (2003) 1859-1867
3. Yager, N., Amin, A.: Nonparametric fingerprint deformation modelling. Proceedings of CAIP 2005.
4. Jain, A., Hong, L., Bolle, R.: On-line fingerprint verification. IEEE Trans. Pattern Analysis and Machine Intelligence **19** (1997) 302-314
5. Maltoni, D., Mario, D., Jain, A., Prabhakar, S.: Handbook of Fingerprint Recognition. Springer-Verlag, New York (2003)
6. Bazen, A., Verwaaijen, G., Gerez, S., Veelenturf, L., Zwaag, B.: A correlation-based fingerprint verification system. Proceedings of the Workshop on Circuits Systems and Signal Processing. Veldhoven, The Netherlands (2000) 205-213
7. Kovacs-Vajna, Z.: A fingerprint verification system based on triangular matching and dynamic time warpipng. IEEE Trans. Pattern Analysis and Machine Intelligence **22** (2000) 1266-2000
8. Jain, A., Prabhakar, S., Hong, L., Pankanti, S.: Filterbank-based fingerprint matching. IEEE Trans. Image Processing **9** (2000) 846-859
9. Ross, A., Reisman, J., Jain, A.: Fingerprint matching using feature space correlation. Proceedings of Post-ECCV Workshop in Biometric Authentication. Lecture Notes in Computer Science, Vol. 2359. Springer-Verlag, Berlin Heidelberg New York (2002) 48-57
10. Park, C., Lee, J., Smith, M., Park, S., Park, K.: Directional filter bank-based fingerprint feature extraction and matching. IEEE Trans. Circuits and Systems for Video Technology **14** (2004) 74-85
11. Yager, N., Amin, A.: Fingerprint verification using two stage optimization. Pattern Recognition Letters. In Press.
12. FVC2002: Second International Fingerprint Verification Competition. http://bias.csr.unibo.it/fvc2002/.
13. Prabhakar, S., Jain, A.: Decision-level fusion in fingerprint verification. Pattern Recognition **35** (2002) 861-874