

Hybrid Algorithm for Fingerprint Matching Using Delaunay Triangulation and Local Binary Patterns

Alejandro Chau Chau and Carlos Pon Soto

Departamento de Ingeniería de Sistemas y Computación
Universidad Católica del Norte, Chile
{achau2, cpon}@ucn.cl

Abstract. This paper proposes a hybrid algorithm for fingerprint matching using geometric structures with Delaunay triangle's based formed by the minutiae. For those minutiae triangles candidates for fingerprint matching, the texture information is extracted from the original raw image localized inside the triangle using Local Binary Patterns techniques (LBP). The preliminary results have shown that the merging technique is fairly robust for genuine fingerprint matching discrimination, reducing thus the error rate for FRR and FAR and the time comparison between fingerprint in the verification and/or identification process. The experimental results have shown that the proposed algorithm is effective and reliable. Tests were conducted from the database BD1 and BD2 of FVC2002 competition, obtaining an EER of 6.18% and 3.17% respectively.

Keywords: Fingerprint Matching, Delaunay Triangles, Local Binary Pattern.

1 Introduction

Fingerprint matching provides a matching score that quantifies the similarity between the recognition feature set and the enrollment template. Fingerprint matching applications are concerned with two types of systems: the verification and identification systems. A verification system authenticates a person's identity by comparing the captured fingerprint characteristics with her enrolled template fingerprint. It conducts a one-to-one comparison to confirm whether the claim of identity by the individual is true. In a identification system this recognizes an individual by searching the entire enrollment template database for a match. It conducts one-to-many comparisons to establish if the individual is present in the database.

A categorization of fingerprints matching approaches are divided in three groups [1]: Correlation-based-matching, is the superposition of two fingerprint images and the correlation between corresponding pixels is computed for different alignments (e.g., various displacements and rotations). Minutiae-based-matching, is based on the minutiae extraction on both fingerprints and stored as sets of points in the two-dimensional plane. This type of matching can be classified as local and global matching. The global matching consists of finding the alignment between the template and the input minutiae sets that result in the maximum number of minutiae pairings. The local matching algorithms try to match a subset of minutiae that are

closed related based on geometric structures formed by local minutiae neighborhood. The attributes of these geometric structures provides a matching invariant to rotation and displacement of fingerprints. The Delaunay triangulation has been used in the last few years as an approach of geometrical structures [3-5]. One problem with Delaunay triangulation is its sensitivity to the false minutiae, producing different local structures. However, the inclusion of a new point in the triangulation only affect the topology around the new point, keeping the other areas of the topology undisturbed [5]. The third category of fingerprint matching is a non-minutiae feature-based. The approach belonging to this family compare fingerprints in terms of features extracted from the ridge pattern. The most popular technique for comparing fingerprint texture is based on the method used by FingerCode [6], obtaining information using a Gabor filterbank around the core of the fingerprint. The most critical approach is to align the FingerCode using the area around the core. Some fingerprints do not have a core or are very difficult to determine their position accurately. In other case, the core is very close to the edges of the image, which cause the FingerCode to be incomplete or incompatible with the image of the fingerprint. In [7, 8] they propose a hybrid variant in which the images are aligned using information from the minutiae and then extract the information based on the texture of the fingerprint using Gabor filters on the entire image. In [9] it is presented another hybrid approach where the fingerprints are aligned using the minutiae and then the texture-based features are extracted from the full image using the local binary patterns (LBP) operator [10] with Gabor filters. A problem with methods based on comparison of fingerprint features is a high computational cost to calculate the vectors [7-9].

This paper propose a hybrid approach combining fingerprint triangle structures, where the minutiae are vertices of the triangle using Delaunay triangulation techniques, merged with textural characteristics of the fingerprint extracted locally on the center of each triangle candidate for matching using the LBP operator. For each pair of feature vectors obtained from the Delaunay triangle candidates for matching, a difference of the LBP histogram is calculated from the center of the triangle which offer better discrimination between fingerprints.

Section 2 describes the implementation details of the hybrid algorithm. Section 3 shows the experiments and results. Finally, in section 4 presents conclusions and future work.

2 Comparison of Fingerprints

The system is to compare fingerprints with Delaunay minutiae triangles structures. For each triangle, geometric features invariant to rotation and translation are obtained to avoid a previous step of alignment. Once the similarity between triangles are calculated, they are confirmed by comparing the LBP operator histogram obtained locally on the center of the structures, which contain information about the texture of the triangle image.

2.1 Delaunay Triangulation

By applying the Delaunay triangulation on the set of minutiae, each fingerprint is represented as a set of triangles. The Delaunay triangles have certain properties that

are desirable for the application [5, 11, 12]: 1) The Delaunay triangulation of a non-degenerated set of N minutiae is unique and can be computed in $O(N \log N)$, producing $O(N)$ triangles. 2) The inclusion or absence of a triangulation point only affects the neighboring triangles, keeping the topology in unaffected areas. 3) The Delaunay triangulation guarantees the connectivity of each point, with about 2.6 segments per point. This representation of the minutiae triangle structures is used to find similarity between fingerprints.

2.2 Local Binary Patterns

The LBP operator is a descriptor of texture images and has been used widely in face recognition applications [13, 14]. It has been proven to be highly discriminative and its main advantage is its invariance to changes to the gray scale and computational efficiency. The basic idea for the calculation of LBP is that the binary code is described using a pattern of local texture, constructed by the central value pixel used as a threshold and its neighbour pixels (Fig. 1).

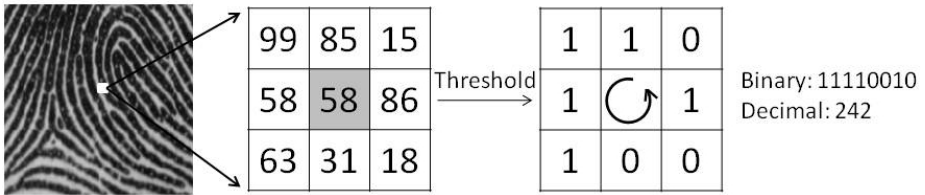


Fig. 1. Calculation of the LBP operator

Then a histogram formed by the values obtained for each pixel of the image is used as a texture descriptor. To deal with textures at different sizes, the LBP operator defines the local neighborhood as a set of equally spaced sampled points on a circle centered at the tagged pixel, allowing the LBP define any kind of radio r and p sample points, whose notation is $LBP_{(p,r)}$. Another extension for the LBP is the definition of uniform patterns, whose notation is $LBP_{(p,r)}^{u2}$. A LBP is called uniform if the binary pattern contains at most two transitions 0 to 1 or viceversa. To calculate the LBP histogram, each uniform pattern is stored in a separated bin and all non-uniform patterns are assigned to a single common bin [10].

2.3 Algorithm

The proposed method uses two different types of information in the fingerprint image: The minutiae and texture based features on the image of the fingerprint. The minutiae extraction stage is performed by applying the NFIS Mindtct [15]. Thus, there are two sets of minutiae, one for the input fingerprint and another for the template fingerprint. By applying the Delaunay triangulation on both minutiae sets, it obtaining two sets of triangles, computed for both the feature vector set invariant to rotation and translation, used for comparing the structures between the two fingerprints. The vector of local characteristics of a triangle is given by $V_i = [dij, djk, dki, ang\alpha, ang\beta, ang\gamma, difiSij,$

$diffS_{ij}$, $diffS_{jk}$, $diffS_{jk}$, $diffS_{ki}$, $diffS_{ki}$], where d_{ij} represents the distance between the minutiae i and j , α correspond to the inner angle of the triangle with respect to the minutiae i , $diffS_{ij}$ is the angle between the direction of the minutiae i with respect to the segment formed between the minutiae i and j in clockwise direction. (Fig. 2).

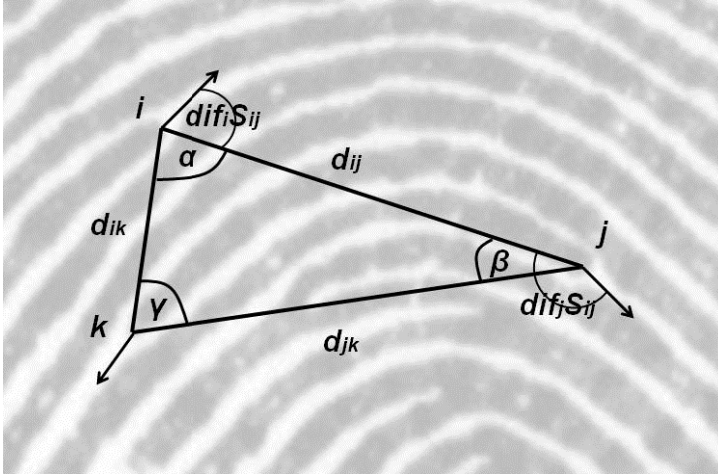


Fig. 2. Delaunay minutiae triangle and their features

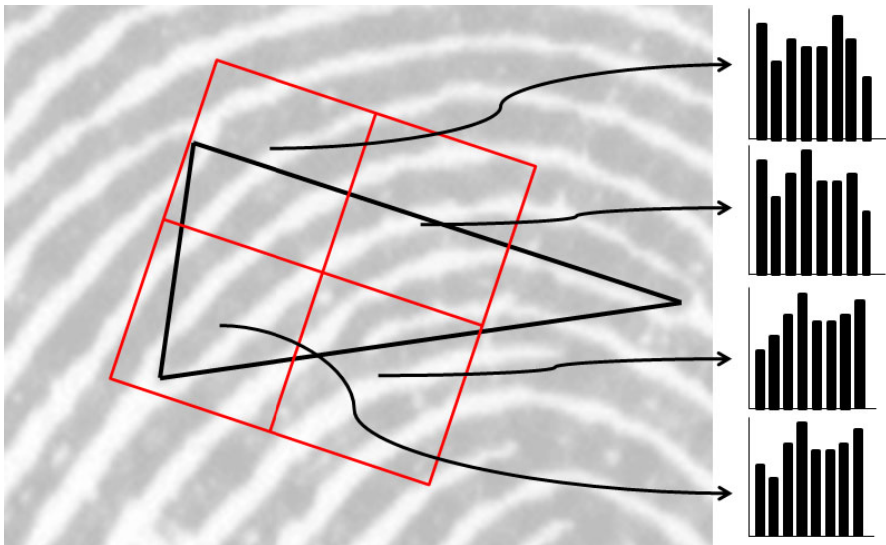


Fig. 3. LBP operator applied on a Delaunay minutiae triangle

The Delaunay triangulation tends to avoid triangles with obtuse angles, but this is not guaranteed. To avoid these triangles, the system rejects those who have interior angles greater than 168° and below 10° . The comparison is to find matches between vectors of the triangles of the input fingerprint and the template fingerprint. For each of the comparisons between the feature vectors of fingerprints, the feature vector of the input fingerprint is rotated three times, one for each side of the triangle, using the smallest difference between the vectors, this being the best similarity to be found. If the difference of these vectors is below a define threshold, the two vectors are considered a possible match, being marked and stored as candidate matched triangles. Following, for each pair of candidates, a comparison is made by the LBP operator. This approach uses the operator $LBP_{(8,2)}^{u2}$ which is used by [13, 14] for face recognition. The way of applying the LBP operator is through a window $w \times w$ whose midpoint coincides with the centroid of the structure analyzed. The window is divided into 4 sub-windows, by computing the LBP histograms independently in each. The four histograms are concatenated into a single vector (Fig. 3). Before applying the LBP operator, the window of the input fingerprint is rotated by the angular difference with one side common of the triangle of the template fingerprint. Thus, the LBP is applied in both windows with the same orientation.

To measure the difference between both histograms, it uses the chi-square distance χ^2 [13]:

$$\chi^2(T, E) = \sum_{i=1}^n \frac{(T_i - E_i)^2}{(T_i + E_i)} \quad (1)$$

where T and E are histograms of the template fingerprint and input fingerprint, respectively, n is the length of the histogram. If the difference between the two histograms does not exceed a defined threshold, the LBP histograms are similar, confirming the similarity of the triangle at the level of minutiae and texture of the fingerprint image. Finally, to determine whether these sets of triangles have a similar spatial distribution, it determines the Euclidean distance between each centroid structure, removing those triangles that vary in distance. Figure 4 shows two fingerprints of the same finger, which shows triangles that match (in white) and triangles that does not complied with the LBP operator neither in the spatial distribution (in segmented lines). We define the score of comparison between the input fingerprint and the template fingerprint as:

$$sc = \frac{e}{\min(e1, e2)} \quad (2)$$

where e is the number of structure pairs that match, $e1$ and $e2$ corresponds to the structure numbers that are formed by Delaunay triangulation of the input fingerprint and the template fingerprint respectively.

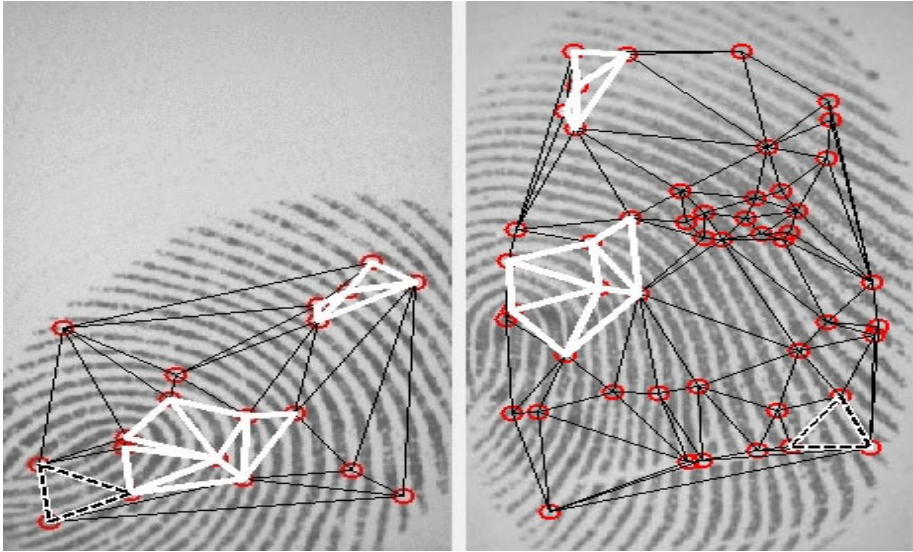


Fig. 4. Delaunay triangle structures for two fingerprints of the same finger taken from DB2 for the FVC2002 competition

3 Experiments and Results

3.1 Data Set and Evaluation Methodology

To obtain the results and determine the performance of the algorithm, it used fingerprint database DB1 and DB2 from FVC2002 competition [16]. Each database contains 800 images, 8 prints of the same finger for each of 100 individuals. The images of DB1 are 388x374 acquired with an optical sensor "TouchView II" by Identix. The images of DB2 are 296x560 using an optical sensor "FX2000" by Biometrika.

The performance of the algorithm is measured by the Equal Error Rate (EER), parameter given by [16]. The EER occurs when the FRR (percent of comparisons when there is a false rejection) and FAR (percent of comparisons when there is a false acceptance) have the same value. The lower EER, the better is the comparison system.

The algorithm was implemented in Matlab. The implementation of the algorithms was done in a laptop with Windows 7, Intel Core i5 (2.27 GHz), under normal working session.

3.2 Experimental Results

The first experiment is to estimate the parameters to be used in the LBP operator $LBP_{(8,2)}^{u2}$. We use two configurations and two sizes of windows. One configuration use a single window of $w \times w$ and the other configuration use the same window size divided en four sub-windows, to obtain four LBP histograms that are concatenated to

get a single histogram. The purpose of the last configuration arises from the fact that you can get better results by dividing a window into sub-windows for greater discrimination. A histogram with four sub-windows contain more texture information locally than one with a single window. Table 1 and Table 2 show the results obtained with DB1 and DB2 respectively. It is observed that the execution time between a complete window and four sub-windows of the same size (1 of 80x80 and 4 of 40x40) shows no difference between the execution times. The best results of EER are obtained when it uses a set of 4 sub-windows in an area. In the LBP of DB1 4 sub-windows of 20x20, performs better with respect to other configurations due to the size of the image being used. When larger windows size is used (80x80), the performance drops, because it captures areas that fall outside the zone of interest. By contrast, DB2 obtain better performance with bigger window size because the images are larger (4 sub-windows of 40x40) and these windows capture more texture information.

Table 1. EER and times associated with different parameters for LBP in DB1

N° of windows	window size	EER	Avg. FAR	Avg. FRR
1	80x80	9.19%	0.18seg	0.39seg
4	40x40	7.48%	0.19seg	0.47seg
1	40x40	6.67%	0.17seg	0.32seg
4	20x20	6.18%	0.19seg	0.39seg

Table 2. EER and times associated with different parameters for LBP in DB2

N° of windows	window size	EER	Avg. FAR	Avg. FRR
1	80x80	4.59%	0.28seg	0.71seg
4	40x40	3.27%	0.32seg	0.75seg
1	40x40	5.58%	0.25seg	0.43seg
4	20x20	5.24%	0.28seg	0.51seg

Table 3. EER and times associated with different configurations for LBP in DB1

Configuration	EER	AVG
(+LBP +DIST)	6.18%	0.26seg
(+LBP -DIST)	7.17%	0.22seg
(-LBP +DIST)	7.33%	0.14seg
(-LBP -DIST)	8.39%	0.12seg

The second experiment is to validate the behavior of the hybrid algorithm. Different tests are performed using the LBP operator in different configurations with the Euclidan distance between structures. The EER and time associated with each of the configurations are shown in Table 3 and Table 4 for DB1 and DB2 respectively. The lowest EER is obtained when combining the comparison of Delaunay triangles in conjunction with the LBP operator and the Euclidan distance between structures (+LBP + DIST). The highest execution times were obtained for those configurations where EER was less, mainly because of the increased number of calculations of LBP operator when fingerprints have more common structures.

Table 4. EER and times associated with different configurations for LBP in DB2

Configuration	EER	AVG
(+LBP +DIST)	3.27%	0.47seg
(+LBP -DIST)	4.07%	0.40seg
(-LBP +DIST)	4.30%	0.36seg
(-LBP -DIST)	7.30%	0.33seg

4 Conclusions and Future Work

This paper presents a hybrid approach using Delaunay triangulation in conjunction with the LBP texture based operator. The triangle structures proved to have sufficient discriminatory features for comparison. The execution times are relatively low because the LBP operator is calculated only on those triangles that are candidate for comparison. The fusion of the Delaunay and LBP operator generates a structure with additional discriminatory features in the comparison for fingerprint matching. As future work we intend to use the ridge count between minutiae as another parameter for discrimination in the triangles, and generate more tests with the new addition to the algorithm with other databases. One problem with Delaunay triangulation is its sensitivity to false minutiae, affecting the formation of false structures, thus worsening the system performance. For this problem it is proposed the use of another minutia extractor and use enhanced fingerprint images.

References

1. Maltoni, D., Maio, D., Jain, A.K., Prabhakar, S.: Handbook of Fingerprint Recognition, 2nd edn. Springer, New York (2009)
2. Bazen, A., Verwaaijen, G., Gerez, S., Veelenturf, L., Zwaag, B.: A correlation-based fingerprint verification system. In: Proceedings of the Program for Research on Integrated Systems and Circuits, pp. 205–213 (2000)
3. Wang, C., Gavrilova, M.L.: Delaunay triangulation algorithm for fingerprint matching. In: Proceedings of the 3rd IEEE International Symposium on Voronoi Diagrams in Science and Engineering (ISVD 2006), pp. 208–216 (2006)
4. Parziale, G., Niel, A.: A Fingerprint Matching Using Minutiae Triangulation. In: Zhang, D., Jain, A.K. (eds.) ICBA 2004. LNCS, vol. 3072, pp. 241–248. Springer, Heidelberg (2004)
5. Bebis, G., Deaconu, T., Georgiopoulos, M.: Fingerprint Identification Using Delaunay Triangulation. In: Proc. IEEE International Conference on Intelligence, Information, and Systems (ICIIS), pp. 452–459 (1999)
6. Jain, A.K., Prabhakar, S., Hong, L., Pankanti, S.: Filterbank-based fingerprint matching. IEEE Transactions on Image Processing 9, 846–859 (2000)
7. Ross, A., Jain, A.K., Reisman, J.: A hybrid fingerprint matcher. Pattern Recognition 36, 1661–1673 (2003)
8. Jain, A.K., Ross, A., Prabhakar, S.: Fingerprint Matching Using Minutiae and Texture Features. In: Proc. Int. Conf. on Image Processing, pp. 282–285 (2001)
9. Nanni, L., Lumini, A.: Local Binary Patterns for a Hybrid Fingerprint Matcher. Pattern Recognition 41(11), 3461–3466 (2008)

10. Ojala, T., Pietikäinen, M., Mäenpää, T.: Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 24(7), 971–987 (2002)
11. Deng, H., Huo, Q.: Minutiae Matching Based Fingerprint Verification Using Delaunay Triangulation and Aligned-Edge-Guided Triangle Matching. In: Kanade, T., Jain, A., Ratha, N.K. (eds.) AVBPA 2005. LNCS, vol. 3546, pp. 270–278. Springer, Heidelberg (2005)
12. Ham, M.I., Pereira, Y.B., Reyes, E.B.G.: A Multiple Substructure Matching Algorithm for Fingerprint Verification. In: Rueda, L., Mery, D., Kittler, J. (eds.) CIARP 2007. LNCS, vol. 4756, pp. 172–181. Springer, Heidelberg (2007)
13. Ahonen, T., Hadid, A., Pietikäinen, M.: Face description with local binary patterns: Application to face recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 28(12), 2037–2041 (2006)
14. Maturana, D., Mery, D., Soto, A.: Face Recognition with Local Binary Patterns, Spatial Pyramid Histograms and Naive Bayes Nearest Neighbor classification. In: I Workshop Chileno Sobre Reconocimiento de Patrones: Teoría y Aplicaciones, pp. 125–132 (2009)
15. User's Guide to NIST Fingerprint Image Software (NFIS), NISTIR 6813, National Institute of Standards and Technology
16. Maio, D., Maltoni, D., Capelli, R., Wayman, J.L., Jain, A.K.: FVC 2002: Second Fingerprint Verification Competition. In: 16th International Conference on Pattern Recognition, Quebec City, QC, Canada, pp. 30811–30814 (2002)