A FINGERPRINT MATCHING ALGORITHM BASED ON MINUTIAE AND LOCAL RIDGE ORIENTATION

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Resumo – Este artigo apresenta um novo método de reconhecimento de impressões digitais baseado nas informações das minúcias extraídas e do campo de orientação da imagem, em que uma rede neural artificial é usada para realizar o casamento. O método proposto foi implementado em software e seu desempenho foi avaliado. O método proposto apresentou um bom desempenho para o banco de dados composto por imagens selecionadas do banco de impressões digitais de referência FVC2000.

Palavras-chave –Biometria, Impressão Digital, Extração de Minúcias, Redes Neurais.

Abstract – This paper presents a new method for fingerprint recognition based on information extracted from the minutiae and the orientation field from the image that uses an artificial neural network as a matching algorithm. The proposed method was implemented by software and its performance was evaluated.The proposed method presented a good performance for the data set used in this work which is composed by selected images from the FVC2000 database.

Keywords – Biometric, Fingerprint, Minutiae Extraction, Neural Networks.

1. Introduction

Biometric recognition refers to the use of distinctive physiological or behavioral characteristics (e.g., fingerprint, face, hand geometry, speech, iris, signature, etc.), which are called biometric identifiers or simply biometrics, for the automatic recognition of a person [1]. The biometrics has grown significantly during the last years and several commercial systems are now available on the market, the majority of them based on the fingerprint. The main reasons for that are: the increase use of digital signal processing techniques, the growing capacity of the processors and memories and the security increase of the personal identification methods.

Despite the development during the last decades, the automatic fingerprint identification is still an important and challenging problem of pattern recognition, due to the complexity of the problem and the growing need for safety on personal identification [1]. For example, varying skin and capture conditions often cause images of the same fingerprint to appear different. The automatic fingerprint identification could be divided in four stages: (1) alignment; (2) pre-processing; (3) parameter extraction; (4) fingerprint matching. The alignment of the two fingerprints is a important step to correct features extraction. The image enhancement is performed during the pre-processing envisaging the correction of the distortions and the enhancement of the image details that will be used as parameters by the matching algorithm. After the image pre-processing, the parameter extraction is performed envisaging the fingerprint matching that is performed on the fourth stage. Neural networks have been used in problems of fingerprint recognition in several ways. In [2] and [3] the parameters extraction is performed using neural networks and in [4], a comparison between several neural networks for fingerprint classification is performed. Despite that, the neural networks use for fingerprint matching is not well explored.

In this work, a multilayer feed forward neural network is used for fingerprint matching based on the minutiae extraction and local ridge orientation of the fingerprint image. The method presented here is an improvement to a previous method presented in [5], adding the information of the local ridge orientation from the image in order to increase the robustness and efficiency.

In the next section, the basic concepts of fingerprint recognition based on minutiae extraction and the estimation of the local ridge orientation field of the image are presented. Section 3 presents the proposed method for fingerprint matching. Section 4 shows the results for the proposed method. Finally, in Section 5, the conclusions are derived.

2. Fingerprint Recognition

The fingerprint is basically formed by the configuration of the epidermal ridges and furrows. The ridges are the higher lines on the epidermal while the furrows the lower lines. An example of a fingerprint image can be seen in Figure 1(a). The local ridge characteristics is called minute details and the two most important ridge characteristics, called minutiae, are the ridge termination and ridge bifurcation. A termination is defined as the ridge point where the ridge ends abruptly and a bifurcation is defined as the ridge point where a ridge forks or diverges into branch ridges. Minutiae based methods are certainly the most well-known and widely used for fingerprint matching due to its strict analogy with the forensic experts way to compare fingerprints and its acceptance as a proof of identity in the courts of law [6].

2.1 Pre-processing

The pre-processing for the minutiae based methods for fingerprint recognition envisages the enhancement of the difference between the ridges and furrows and the correction of the severe distortions that could occur during image acquisition. Usually, the first step of the pre-processing is the image normalization in order to make the image contrast more uniform. For that, the image is divided in blocks where the ridges could be considered approximately parallel straight lines. After the normalization, the orientation [7] and the frequency [8] maps should be obtained, showing the direction and the frequency of the ridges in each block, respectively. These maps are used for the image filtering [8] envisaging the image enhancement. After filtering, the image should be converted from gray-scale to black and white (binarization). Sometimes, the filtering already produces a binary output, and therefore the binarization is not needed. The binary images obtained are usually submitted to a thinning stage [9] which allows for the ridge line thickness to be reduced to one pixel. Finally, a simple image scan allows the detection of pixels that correspond to minutiae. An example of a thinned fingerprint image (binary skeleton) after all procedures of the pre-processing can be seen in Figure 1(b). The original fingerprint image is the one in Figure 1(a).

(a)

(b)

Figure 1: An example of a fingerprint image (a) and the same image after the pre-processing (b) described in Section 2.1.

In this work, the pre-processing followed the procedures described before and the details about the algorithms are described in [10].

2.2 Minutiae Extraction

A simple way to detect the minutiae is using the crossing number algorithm [11]. Once a binary skeleton of a fingerprint image has been obtained, an image scan allows the minutiae detection and the pixels corresponding to minutiae are characterized by a crossing number different from 2. The crossing number $cn(\mathbf{p})$ of a pixel $\mathbf{p}$ in a binary image is defined as half the sum of the differences between pairs of adjacent pixels in the 8-neighborhood of $\mathbf{p}$ (Equation (1)).

$$cn(\mathbf{p}) = \frac{1}{2} \sum_{i=1..8} |val(\mathbf{p}_{imod8}) - val(\mathbf{p}_{i-1})|, \tag{1}$$

where $\mathbf{p}_0$, $\mathbf{p}_1$, ... ,$\mathbf{p}_7$ are the pixels belonging to an ordered sequence of pixels defining the 8-neighborhood of $\mathbf{p}$ and $val(\mathbf{p}) \in \{0, 1\}$ is the pixel value.

There are several ways to perform the minutiae detection, but in this work, the crossing number were used for minutiae extraction.

2.3 Information Based on Minutiae

Let $\mathbf{T}$ and $\mathbf{I}$ be the representation of the template and input fingerprint, respectively. Unlike in correlation-based techniques, where the fingerprint coincides with the fingerprint image, here the representation is a feature vector whose elements are the minutiae. Each minutia may be described by a number of attributes, including its location in the fingerprint image, orientation, type (termination and bifurcation), and so on. Most minutiae matching algorithms consider each minutiae as a triplet $\mathbf{m} = \{x, y, \theta\}$ that indicates x, y the minutia location coordination and θ the minutia angle (Equation (2)).

$$\begin{aligned} &\mathbf{T} = \{\mathbf{m}_1, \mathbf{m}_2, \ldots, \mathbf{m}_m\}, \\ &\mathbf{m}_i = \{x_i, y_i, \theta_i\}, \quad i = 1, ..., m, \\ &\mathbf{I} = \{\mathbf{m'}_1, \mathbf{m'}_2, \ldots, \mathbf{m'}_n\}, \\ &\mathbf{m'}_j = \{x'_j, y'_j, \theta'_j\}, \quad j = 1, ..., n, \end{aligned} \tag{2}$$

where m and n denote the minutiae in T and I, respectively.

2.4 Estimation of Local Ridge Orientation

Let $[x, y]$ be a generic pixel in a fingerprint image. The local ridge orientation at $[x, y]$ is the angle θ_{xy} between the projection line with respect to the fingerprint ridges and the horizontal axis. Because fingerprint ridges are not oriented, θ_{xy} is an non-oriented direction lying in $[0, 180°[$. An example of image orientation can be seen in Figure 2. It is important to stress that the orientation field is extracted during the image pre-processing, therefore, its use for fingerprint matching does not increase the computational complexity of the proposed method.

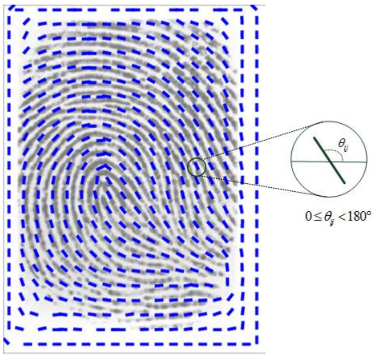


Figure 2: A fingerprint image faded into the corresponding orientation field.

3 Proposed Method for Fingerprint Matching

In this work, a neural network is used to perform the fingerprint matching aiming at the correction of the distortions which are not completely removed at the image pre-processing stage. In this way, after the system design step, the features extracted from the pair of fingerprint images should be presented to the neural network as its input parameters.

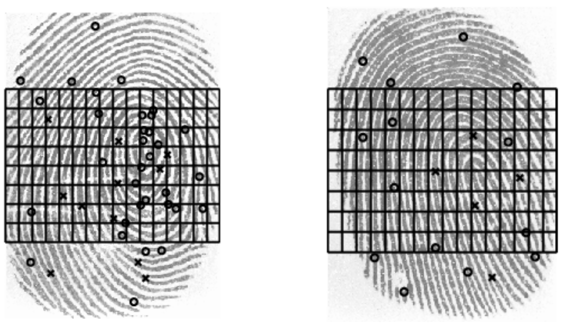
3.1 Feature Extraction for the Neural Network Matching

Two types of information are used as classifier input: based on minutiae and based on the orientation map. The feature extraction for the neural network for fingerprint matching is described in the next sections.

3.1.1 Parameters Extraction Based on Minutiae

The minutiae vector can not be directly presented to a neural network due to the variable number of minutiae extracted from image to image. Thus, in order to extract the same number of parameters for any collected fingerprint, the minutiae vector is divided in sectors. Figure 3 illustrates two fingerprint images from different fingers divided in sectors (shown as the rectangles in the figure), as well as the detected minutiae. To avoid a large number of false minutiae detected on the superior and inferior parts of the fingerprint due to the distortions occurred during the image acquisition, only the information contained in the central sectors is used on further processing.

The information from minutiae can be represented in the matrix form, where each element corresponds to a image sector and its value represents the kind of information. In this work, the bifurcation and termination ridge assigned to the sectors and its orientation angles were considered as information, resulting in 4 different matrices to each image. Once these matrices are defined, 2 types of rates are calculated, resulting in 4 parameters to each fingerprint pair.



(a) (b)

Figure 3: Image division in Sectors and the detected minutiae for the fingerprint pair selected for matching.

Let $\mathbf{M_T}$ and $\mathbf{M_I}$ be the matrices whose elements represent the number of same type of minutia and $\mathbf{A_T}$ and $\mathbf{A_I}$ the matrices whose elements represent its orientation angles, both having size $M \times N$, corresponding to template $\mathbf{T}$ and input image $\mathbf{I}$, respectively. The *Minutia Matching Rate* (MMR) is defined as the sum of the common elements of $\mathbf{M_T}$ and $\mathbf{M_I}$, where $\mathbf{M_T}(i,j)$ and $\mathbf{M_I}(i,j)$ are both different from zero, divided by total sum of $\mathbf{M_T}$ and $\mathbf{M_I}$, as it is shown in Equation (3). On the other hand, the *Angle Matching Rate* (AMR) is defined as the geometry mean of the common nonzero elements of absolute difference between $\mathbf{A_T}$ and $\mathbf{A_I}$, divided by normalized factor equal to 180 (see Equation (4)).

$$MMR = \frac{\sum \mathbf{M_T}(i,j) + \sum \mathbf{M_I}(i,j)}{\sum \mathbf{M_T} + \sum \mathbf{M_I}} \quad , \quad \begin{cases} \mathbf{M_T}(i,j) \neq 0 \\ \& \\ \mathbf{M_I}(i,j) \neq 0 \end{cases} \tag{3}$$

$$AMR = \frac{\sqrt[n]{\prod |\mathbf{A_T}(i,j) - \mathbf{A_I}(i,j)|}}{180} \quad , \quad \begin{cases} \mathbf{A_T}(i,j) \neq 0 \\ \& \\ \mathbf{A_I}(i,j) \neq 0 \end{cases} \tag{4}$$

where n is the number of common nonzero elements of $\mathbf{A_T}$ and $\mathbf{A_I}$.

3.1.2 Features Extraction Based on Fingerprint Orientation Image

Let $\mathbf{D_T}$ e $\mathbf{D_I}$ be the matrices which represents the fingerprint orientation image, corresponding to the template **T** and the input image **I**, respectively. The *Directional Image Rate* (DIR) can be defined as the absolute difference between the matrices $\mathbf{D_T}$ and $\mathbf{D_I}$, whose elements are located inside a common area, according to Equation (5). The selection of the fingerprint area is useful to avoid extraction of features in noisy areas of the fingerprint and background. In this work, the image areas for the images **T** and **I** are represented by matrices $\mathbf{ImA_T}$ e $\mathbf{ImA_I}$, respectively, whose elements have logic values: 1 for segmented area (background) and 0 for fingerprint area (see Figure (4)), where the background is removed from the processed images. Therefore, the (DIR) can be formulated by:

$$DIR = \sqrt[n]{\prod |\mathbf{D_T}(i,j) - \mathbf{D_I}(i,j)|} \quad , \quad \begin{cases} \mathbf{ImA_T}(i,j) = 0 \\ \& \\ \mathbf{ImA_I}(i,j) = 0 \end{cases} \tag{5}$$

where n is the number of elements located inside the common fingerprint area.

Figure 4: Segmentation of a fingerprint image.

3.2 The Fingerprint Matching

Once the 5 parameters are extracted from the fingerprint pair, 4 from minutiae (MMR and AMR) and 1 from local ridge orientation image (DIR), an artificial feed forward multi-layer neural network is used to perform the fingerprint matching where its input vector V_{NN} is represented by the Equation (6).

$$\mathbf{V_{NN}} = [e_1 \;\; e_2 \;\; e_3 \;\; e_4 \;\; e_5] \tag{6}$$

3.2.1 Training Methodology

The proposed method makes use of a supervised training algorithm, therefore, the first step is to generate from a known fingerprint database, several pairs of fingerprints. For each pair is known whether they come from the same fingerprint or not.

For each fingerprint pair the input parameters of the neural network should be extracted as described above. These several input vectors of the neural network are divided in two sets, the training and test sets. The training set is used for the synaptic weights update, while the test set is only used for performance evaluation. It is worth mentioning that for an efficient classification the two sets must contain similar numbers of identical and different fingerprints.

3.2.2 Application on Fingerprint Identification

In a fingerprint identification problem, a collected fingerprint is compared with the ones into the database, searching for a matching and, therefore, searching for a personal identification.

The proposed neural network matching method can be used in a fingerprint identification problem. In Section 4, the performance of the proposed method is evaluated envisaging its application into a fingerprint identification problem. For this, the trained neural network should be used for matching each fingerprint pair formed by the collected fingerprint with the database fingerprints.

4 Results

In this section, the proposed method is implemented by software. The performance of the proposed method was compared with a previous neural method based in minutiae extraction [5] .

4.1 Database

To verify the efficiency of the proposed method in a fingerprint identification problem a reference database is used [12]. This database were used on the Fingerprint Verification Competition of year 2000 (FVC2000) and is available electronically. From this database, 2756 pairs of fingerprints were selected, where 1370 correspond to pairs of image from the same fingerprints, and the others 1386 correspond to different fingerprints pairs. From the selected fingerprints, 1100 were used as training set, 756 as the test set and 900 as a validation set. The training and the test sets are used during the system design and the validation set is used to verify the system performance.

4.2 Neural Network Design

The proposed method faces the matching problem as a classification problem with two classes, one class of matched fingerprint pairs and another class of non-matched fingerprint pairs. A multilayer feed forward neural network is used for classification with the resilient back-propagation as a training algorithm.

The neural network input vector has only 5 parameters as presented in Section 3.1. The neural network activation function is the hyperbolic tangent for all neurons. The number of layers as well as the number of neurons in each layer was defined by optimizing several times the neural network with different topologies, choosing the one with best performance. The configuration which fits best the application has one hidden layer with 2 neurons, and a single neuron at the output layer. Figure (5) shows the architectural graph of the neural network used as classifier.

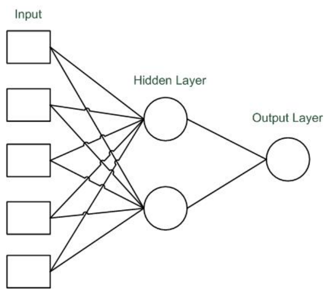


Figure 5: Architectural graph of the neural network.

The fingerprint pair at the neural network input is considered matched if the resulted neural network output is non-negative, otherwise, the fingerprint pair is considered non-matched.

4.3 Performance Evaluation

The performance evaluation of the proposed method for fingerprint identification is presented in terms of its *False Match Rate* (FMR) and *False Non-Match Rate* (FNMR) curve. These curves are often used in biometrics identification problems and show the error probability for different fingerprints (FMR) and the error probability for equal fingerprints (FNMR) when the threshold changes.

Once the neural network achieves its best performance during the learning phase, the neural network could be applied for fingerprint identification through the use of the validation data set. During the validation, the neural network parameters are fixed and the data are presented to the neural network for classification. Figure (6) shows the FMR and FNMR curves for the validation set.

A way to analyze the system performance through the FMR and FNMR curves is finding the point where both curves cross, that is, the *Equal Error Rate* (EER). In this point, the FMR and FNMR are equal and the EER is 6% (see Figure 6). For the previous method presented in [5] the ERR is 11.6% .

Moreover, the global performances (the number of the fingerprint pairs that have been correctly classified divided by total number of pairs) for the training, test and validation data sets were calculated and can be seen in Table 1.

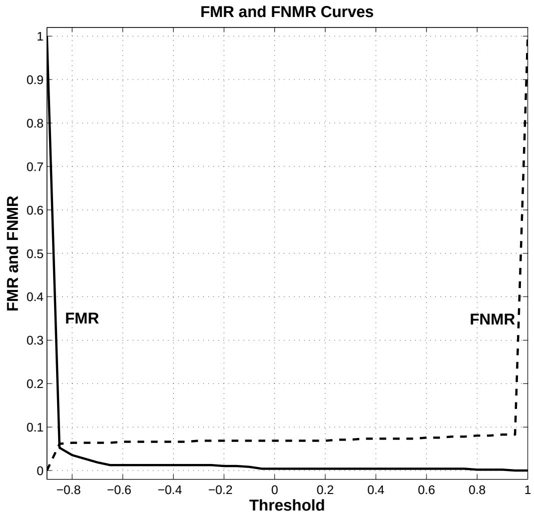


Figure 6: FMR and FNMR curves for the validation set.

Table 1: Global performances for data sets.

Method	Data Sets		
	Training	Test	Validation
Previous Method	90.80%	91.10%	89,50%
Proposed	97.27%	96.43%	96,33%

Table 1 shows that the proposed method has better performance than the previous method described in [5].

4.4 Reported Problems

After the matching process, the analysis of the misclassified fingerprint pairs was performed. Most of misclassified pairs have poor quality image. For example, Figure 7 shows a misclassified pair of the same fingerprint that had a bad extraction minutiae, once the pre-processing could not remove the distortions. Moreover, looking at this pair, it's very hard to say if these images belong to the same finger.

(a) (b)

Figure 7: A misclassified pair of the same finger.

5 Conclusions

In this work, a neural method for fingerprint matching based on minutiae extraction associate with information from local ridge orientation was presented. The neural network was used as classifier due to ability to cope nonlinear distortions that are not removed during the pre-processing. The application of neural networks for fingerprint matching is still not well explored, but this paper indicates that it is a good approach for fingerprint matching.

In order to increase the system robustness, the information combined from minutiae and the fingerprint orientation image was used as extracted parameters. With this method, even if the information from minutiae are incomplete or distorted, the system could still be able to classify correctly the pairs of images.

The results showed that the proposed method achieved good results for the data set used in this work, with a classification accuracy of 96.33% for validation data set.

It is important to stress that the principal aim of this paper is presenting the new matching method for fingerprint recognition. However, a good fingerprint recognition method based on minutiae extraction depends on the proper alignment and a good pre-processing. Therefore, studies on better methods of image pre-processing and alignment are the next steps of this work.

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