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A SYSTEM FOR FINGERPRINT *MINUTIAE* CLASSIFICATION AND RECOGNITION

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ABSTRACT

This paper shows a study about biometrics characteristics for recognition/classification and presents how it is used for individual recognition. The approach uses the automated fingerprint recognition based on minutia, which are extracted directly from the fingerprints and the methodology used to its recognition is the artificial neural networks (ANN) based system. The neocognitron model was the ANN chosen. Inasmuch as neocognitron was originally implemented for handwritten characters recognition, it is possible to verify its usefulness for another kind of pattern recognition. Finally it is presented the results for this system and the conclusions according to the number of samples and recognition rate.

Keywords: *minutia*, classification/recognition, neocognitron, artificial neural network.

1. INTRODUCTION

One of the current technologies used to identify a person is through the fingerprints. They are one of the nine biometrics characteristics used for individual recognition/classification. Fingerprints are graphical flow like ridges present on human fingers. Initially, this study had been started with some experiments based on ridges, furrows, and pores structures. After some years arose a fingerprint classification based on ridge configurations. Nowadays the studies are focused in the fingerprint recognition through *minutia* features.

The most common approach for classification and recognition is the use of artificial neural networks. The proposed recognition system uses a complex and massively parallel ANN, the neocognitron. Furthermore, the neocognitron can be efficient for *minutia* recognition since it was considered that a *minutia* is close to a ridge segment. Neocognitron was originally proposed by Fukushima [3][4][5][6][11] to handwritten character recognition, and it is inspired on the biological vision model of Hubel and Wiesel [8], which states that the first stages of the biological vision are composed of line detection neurons in different directions. On the other hand, fingerprint systems have grown significantly in both academia and industry as several research groups and companies developed new algorithms and techniques for fingerprint recognition. Otherwise, only a few benchmarks have been available for comparing the development in fingerprint verification [10]. In this way, it is presented a minutia fingerprint system for individual recognition. As it follows it is described: (a) the biometric techniques for recognition and classification; (b) the proposed system, based on neural networks (neocognitron); (c) the results obtained; and (d) conclusions.

Table 1 - Comparison of Biometric Technologies [9].

Biometrics	Universality	Uniqueness	Permanence	Collectability	Performance	Acceptability	Circumvention
Face	High	Low	Medium	High	Low	High	Low
Fingerprint	Medium	High	High	Medium	High	Medium	High
Hand Geom.	Medium	Medium	Medium	High	Medium	Medium	Medium
Hand Vein	Medium	Medium	Medium	Medium	Medium	Medium	High
Iris	High	High	High	Medium	Medium	Medium	High
Retinal Scan	High	High	Medium	Low	High	Low	High
Signature	Low	Low	Low	High	Low	High	Low
Voice Print	Medium	Low	Low	Medium	Low	High	Low
Thermogram	High	High	Low	High	Medium	High	High

2. BIOMETRIC CHARACTERISTICS FOR RECOGNITION AND CLASSIFICATION (Tab.1)

Biometrics is the technology used to identify a person based on personal characteristics. Theoretically, any human physiological/behavioral characteristic may be used for identification since it follows some requirements [2]: (a) universality, which means that every person must have the characteristic; (b) uniqueness, which indicates that two distinct people can not have the same characteristic; (c) permanence, which means that the characteristic can not change according to the time; and (d) collectability, which indicates that this characteristic can be measured quantitatively.

Otherwise, in practice, there are other requirements such as: (a) performance, where the identification process must present an acceptable result; (b) acceptability, indicating to what extent people are willing to accept the biometric system; and (c) circumvention, referring the facility to adulterate [2]

Biometric technology has been largely used in criminal's identification and prison security [9]. At present time there are nine biometric techniques: (a) face recognition; (b) fingerprint recognition; (c) hand geometry; (d) hand veins; (e) iris; (f) retinal scan; (g) signature; (h) voice print; (i) facial thermograms.

The proposed minutiae recognition based system is part of fingerprint recognition state-of-the-art, described as follows.

3. AUTOMATED FINGERPRINT RECOGNITION

Automated fingerprint recognition is a method that uses a computer aid to classify a pattern. There is two main visible characteristics found in fingerprints: (a) ending ridges; and (b) bifurcation ridges. These characteristics are usually known as *minutia* [7]. An ending ridge is defined as a point where a line ends abruptly. On the other hand, a bifurcation ridge is when it either bifurcates or diverges in two directions, Fig.1.

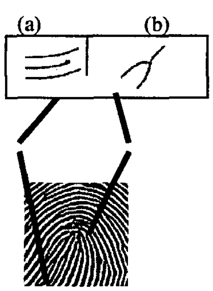

Figure 1 - *Minutia-based representation*: (a) ending ridges; (b) bifurcation ridges.

4. *MINUTIAE* CLASSIFICATION AND RECOGNITION SYSTEM

The methodology proposed for *minutia* classification and recognition is divided into four parts: (a) image acquisition; (b) pre-processing; (c) *minutia* extractor; and (d) *minutia* recognition, Fig.2.

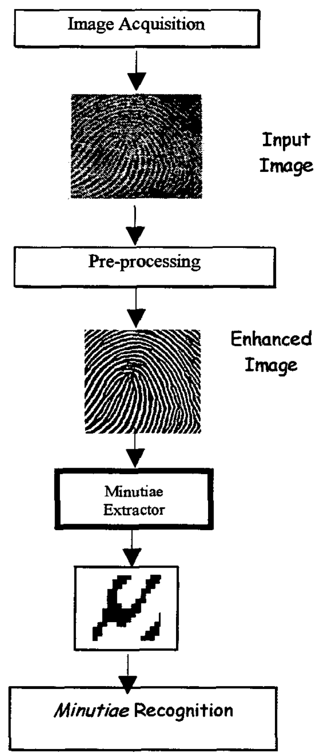

Figure 2 – *Minutia* Classification and Recognition System

4.1. Image Acquisition

The images used in the present development were acquired from two databases: (a) fingerprint database of Bolonha University [10], consisting of 20 fingerprints by an optic sensor; and (b) a database developed by the author with 100 fingerprints. All images were generated with 500dpi resolution, 256x256 gray-scale size.

4.2. Pre-Processing

In this stage all images pass through an enhancement process, Fig.3.

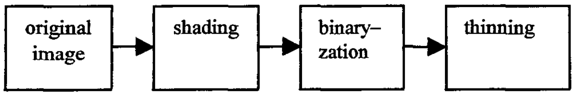

Figure 3 – Pre Processing: Image enhancement

An original image passes through an enhancement algorithm, followed by a binarization process, in order to intensify the gray-scale level of the image. Finally, it is used a thinning of the ridges in the binary image. Fig.4 shows the original image and the enhanced image.

(a) (b)

Figure 4 - (a) Original Image; (b) Enhanced Image

4.3. *Minutia* Extractor

In this phase it is extracted a 15x15 fingerprint area which contains a *minutia*, classified into 8 classes, Fig.5.

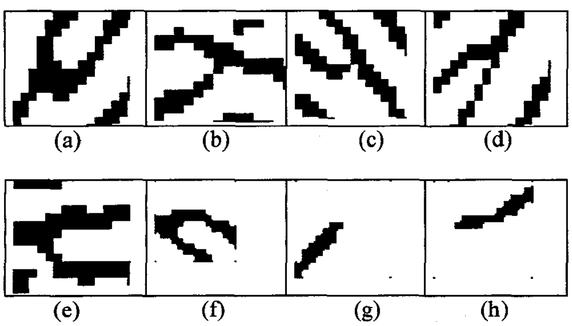

Figure 5 - *Minutia* category: (a) class 1; (b) class 2; (c) class 3; (d) class 4; (e) class 5; (f) class 6; (g) class 7; (h) class 8.

The extracted area is used as the input pattern to the neocognitron, which is previously trained to recognize the 8 categories of minutiae. It is noted that a range of 40 to 100 *minutiae* enables a high quality fingerprint. In this experiment, these *minutiae* are classified into the 8 groups by the neocognitron. Furthermore, it must be explained that on the full fingerprint image the majority of the extracted areas corresponds to the absence of *minutiae*, which corresponds to those ones non-classified by the neocognitron.

4.3.1 Minutia Classification and Recognition

The final stage of the *minutia* recognition system is its classification and recognition. An alternative neocognitron model processes this stage [1]. It is divided into two parts: (a) Control Network; and (b) Recognition Network, Fig.6. The control network is composed by a set of stages responsible by the line detection, edge detection and endpoints detection in the training phase. The results are used as input values to the recognition network. The control network does not need to be trained, since it has fixed weight values as input interconnections. The endpoints are detected and used during the training phase in order to extract the features of the input image.

The Recognition Network is composed by three layers: US_3, UC_3, US_4, UC_4, US_5 and UC_5. The training phase uses as input values the input image and the output values computed by the control network. It adopts the non-supervised learning and the features extracted by the S-cells are automatically detected by the learning process. In the end of the process, UC_5 layer, the C-cells determine final recognition result.

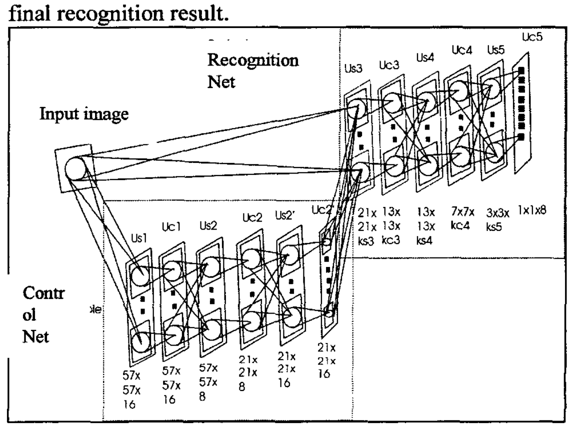

Figure 6 - Alternative neocognitron structure for minutiae extraction

Table 2 - Neocognitron Structure

	input image size	connection area (S_v)	number of cell planes
US_1	57x57	5x5	16
UC_1	57x57	3x3	16
US_2	57x57	5x5	8
UC_2	57x57	5x5	8
UC_b	57x57	5x5	16
US_3	57x57	5x5	44
UC_3	57x57	5x5	44
US_4	57x57	5x5	35
UC_4	57x57	5x5	35
US_5	57x57	5x5	8
UC_5	57x57	5x5	8

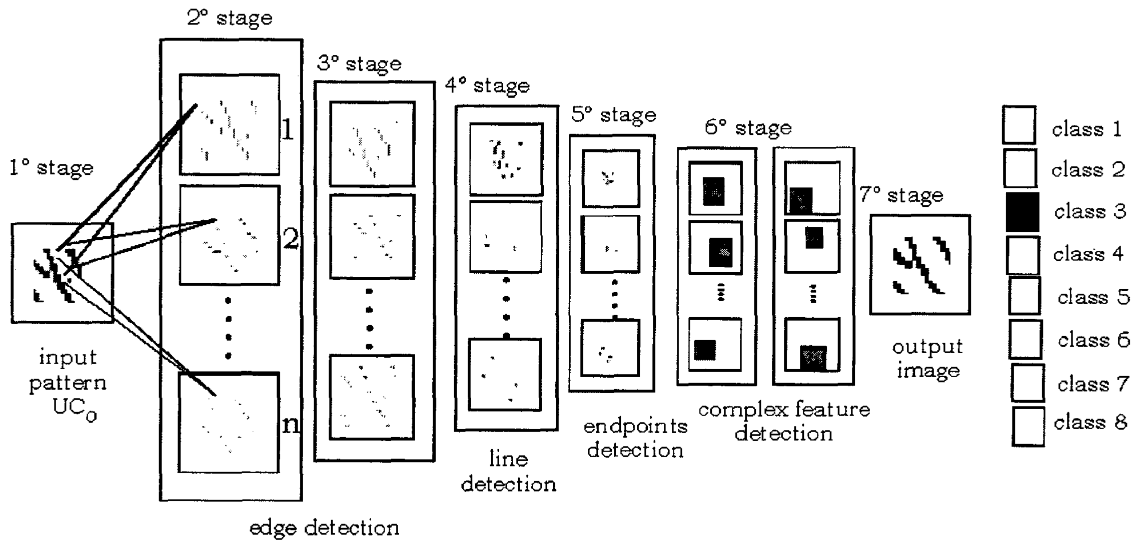

Figure 7 – Minutia recognition based system through the neocognitron model.

Fig.7 shows some aspects of the neocognitron processing results, including the control network stages and the recognition network stages (complex feature detection). It demonstrates the control points obtained with a threshold value of 0.6 for edges and ridges detection. Eight classes of *minutia*, with 20 samples of each one, were used. All these input samples are processed in the neocognitron into 3 steps: (a) the first stage shows the input pattern; (b) the next two stages show the edges of the line segment detected; (c) the fourth stage correspond to the lines detected over 8 directions; (d) the fifth stage detects the endpoints; and (e) the last stage correspond to the final image recognition.

First of all the training phase is applied to a set of minutiae samples separately. After that, the training phase is applied to the whole fingerprint image. The alternative neocognitron model is applied several times in all regions (15x15) of a 256x256 fingerprint. If one minutia is recognized in a such position, a pattern vector stores its position (x,y) and the class that it belongs.

This process is slow because the neocognitron is applied for each image position of the fingerprint. When the image has a high quality it is able to extract 25 sequences of classes. But actually, just 16 classes were used because we noticed that 12 classes were already enough for the whole fingerprint recognition.

5. RESULTS

The results were obtained by the *minutiae* recognition system using 8 distinct classes of *minutia.* Each class was composed by 20 samples. The system presented up to 95% for recognition rate and an error rate lower than 10%, Tab.3.

Table 3 - Performance Analysis

n° of classes	recognition rate (%)	error rate(%)
2	98%	2%
3	95%	5%
4	95%	5%
5	95%	5%
6	90%	10%
7	90%	10%
8	90%	10%

Fig.8 shows the variation of the recognition rate when the number of classes presented for training varies in a range of 2 to 8 classes. It is noticed that the recognition rate decreases slowly according to the number of classes. Fig. 9 shows the error rate to the same experiment.

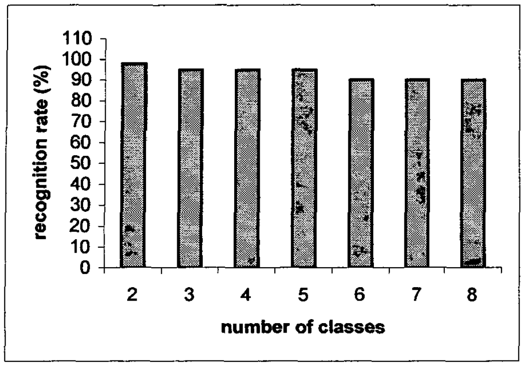

Figure 8 - Recognition Rate x Number of Classes

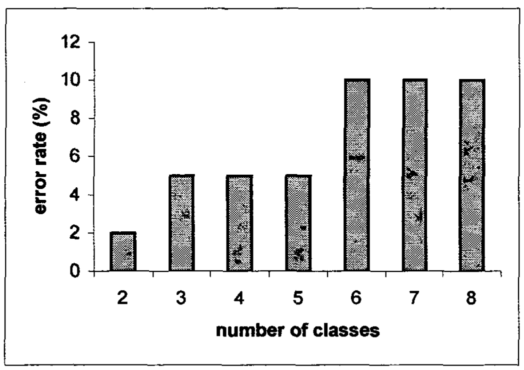

Figure 9 – Error Rate x Number of Classes

6. CONCLUSIONS

This work described a *minutia* based fingerprint recognition system through an artificial neural network, neocognitron. The neocognitron model presented a reasonable performance for *minutia* classification and recognition; although this model was proposed, initially to handwritten characters. This *minutia* recognition system is to be used by an individual fingerprint recognition system. As noted, the error rate does not exceed the 10% when the number of samples increases during the training phase. This fact validates the fingerprint recognition system. This system repeats the *minutia* recognition all over the fingerprint (256x256) image, and detects the recognized *minutia* coordinates. Future works are concerned to improve the recognition network algorithm, in order to get a better performance in the *minutiae* recognition.

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