Fingerprint local analysis for high-performance Minutiae extraction

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***Abstract*— The paper presents a novel approach to identify the minutiae present in a fingerprint image based on the analysis of the local properties. The typical patterns of minutiae called *ridge termination* and *bifurcation* are identified by studying the intensity along squared paths in the image. The presented algorithm works both on grey-level image and binarized image and, despite its simplicity, it achieves good accuracy and it can be a good candidate to be implemented in hardware or executed on simple hardware architectures, for example in biometric systems embedded in portable applications such as cellular phones and smart cards.**

I. INTRODUCTION

A fingerprint as been defined by as a smoothly flowing pattern of alternating valleys and ridges [1]. In order to reliably establish whether two prints came from the same finger or different fingers, it is necessary to capture some invariant representations (features) of the fingerprints: the features which over a lifetime should continue to remain relatively unaltered irrespective of the cuts and bruises, the orientation of the finger placement with respect to the medium of the capture, the imaging technology used to acquire the fingerprint from the finger, or the elastic distortion of the finger during the acquisition of the print.

Fingerprint representations can be broadly categorized into two types: *global* and *local* [1]. Global representation is an overall attribute of the finger and a single representation is valid for the entire fingerprint and is typically determined by an examination of the entire finger. A local representation consists of several components, each component typically derived from a spatially restricted region of the fingerprint. Major representations of the local information in fingerprints are based on finger ridges, pores on the ridges, or salient features derived from the ridges.

The most widely used local features are based on minute details called minutiae of the ridges (figure 1).

The localization of the minutiae in a fingerprint forms a valid and compact representation of the fingerprint. Very often in automatic fingerprint matching, only the two most relevant types of minutia are used for identification. For example, the USA Federal Bureau of Investigation and most of the Automatic Fingerprint Identification Systems (AFIS) use only *ridge ending* and *ridge bifurcation* [1]. Several approaches to local automatic minutiae extraction have been proposed in the literature. Although rather different from one other, most of these methods transform fingerprint images into binary images through an ad-hoc filtering algorithm. The images obtained are submitted to a thinning process which allows for the ridge line thickness to be reduced to one pixel width. Finally, a simple image scan allows for locating the pixels that correspond to minutiae [1, 5]. In the following we refer to these methods as *classical methods*.

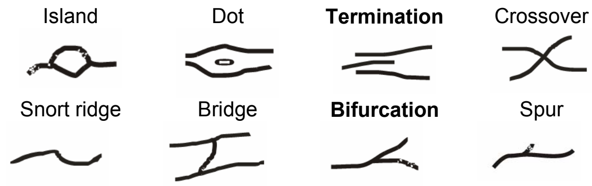

Figure 1: The most important minutiae types

Other approaches uses detect the minutiae directly by processing the gray scale image [2]. The basic idea of this method is to follow the ridge lines on the gray scale image, by "sailing" according to the fingerprint directional image. A set of starting points is determined by superimposing a square-meshed grid on the gray scale image. For each starting point, the algorithm keeps following the ridge lines until they terminate or intersect other ridge lines (minutiae detection). A labelling strategy is adopted to examine each ridge line only once and locate the intersections between ridge lines [2, 3]. In the following we refer to these methods as *direct gray scale* (DGS) methods.

Last group of local methods identifies the minutiae by analyzing the intensity patterns nearby a pixel with different techniques. For example, in [4] neural and neuro-fuzzy systems identify the presence of ridge ends and bifurcations using as input the pixels nearby the processed point sub-partitioned in 4 small quadrants.

In this paper we propose an algorithm belonging to the last group of algorithms. It solved the problem of local identification of ridge ends and bifurcations by analyzing the intensity patterns along squared paths centred on the processed pixel. The proposed method shows low computation complexity with respect to the methods presented in the literature [6], it requires small amount of memory, it performs a good accuracy of minutiae identification and it is suitable to

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parallel implementation. Nowadays, the attention on such a kind of issues is growing, aiming to host biometric systems onto cheap, small, portable and low-power hardware architectures [9]. Such architectures are characterized by low computing capabilities, limited memory and small biometric template size [9].

The paper is structured as follow: section 2 presents the proposed method and section 3 provides the accuracy indices necessary to correctly evaluate the accuracy of the system. Finally, section 4 describes the experimental results and the accuracy of the presented methods in terms of the presented quality indices.

II. The Method of Squares

In our paper the minutia point M can be defined as a 4-uple, $M(x, y, t, \alpha)$ where, x and y are the coordinates of the minutia point in the image, t is the type of the minutia (a *bifurcation* minutia or a *termination* minutia) and α corresponds to the angle made by the tangent to the corresponding ridge at the point (x,y). Our goal is to identify the elements of the 4-uple for each minutia present in the image provided in input to the algorithm.

The proposed algorithm is based on an image analysis method based on squared paths. The basic idea of the method of squares is sketched in figure 2. Each pixel in the image has to be classified as bifurcation point, edge-termination point, or no-minutia point. The intensity pattern nearby the candidate pixel is studied along a squared path. The upper left subplot of figure 2 shows the case of ridge termination, while the others subplots show the case of bifurcation with different orientations. The extracted intensities along the squared path have standard patterns when the candidate point is a *true* minutia. In particular, the number of pattern transitions between the mean dark and white levels is fixed. The presence of two transitions if the related to the presence of a minutia.

We notice that a choice of the square path as path of analysis is related just to implementative aspects: the *circular* path can be considered as an ideal path. On the other hand, processing an image along rows and columns can be faster than following different shaped scanning paths (i.e., circular).

Interestingly, even if the squared path can not be considered as adapt as the circular one, the presented method still works, and it maintains its peculiar rotational independence. That is because the presence of the two transitions is almost guaranteed in case of presence of minutiae, whatever their orientation, as shown in the figure 2 (the two bottom subplots).

In the following of the paper we will consider binarized images as input, but the present method is suitable also with gray-scale image. Binary images represent the lowest quality image for a biometric fingerprint system since we have the maximum loss of information.

Conversely, in the binary case, the identification of the transitions along the path is trivial. The binary case is reasonable considering biometric system working with cheap sensors or with low computational hardware/low memory architecture (i.e a smart card or cellular phone).

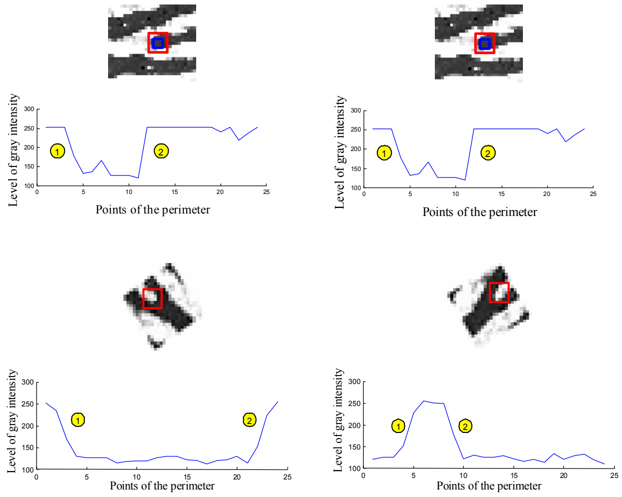

Figure 2: The pattern intensities along a square path around a ridge termination (top left) and a bifurcation minutia (top right). The bottom row shows the patterns of rotated sub-images.

Without lack of generality, the following methods is adapt to binary image. In fact, high quality gray-scale images can be pre-filtered and binarized by adaptive algorithms well-known in the biometric literature [5,7]. In addition, the proposed method can be easily adapted to proper directly work on gray-scale image.

The presented method is composed by the following steps repeated for each pixel of the input image.

1) Create a 3x3 square mask around the (x,y) pixel and compute the average of the pixels (0 and 1 in the binarized images). If the average is lesser than 0.25 the pixel is preliminary identified as a ridge *termination* minutia, otherwise if the average is greater than 0.75 the pixel is treated like a *bifurcation* minutia.

2) Create a square perimeter P around the (x,y) pixel of size WxW, where W is twice the mean ridge size in that point. Many algorithms are available in the literature to estimate the mean ridge size [7].

3) Compute the number of the logic commutations present in the perimeter P without considering isolated pixels as shows in figure 3.

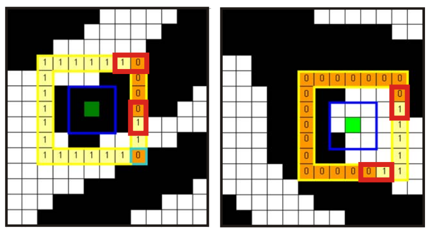

Figure 3: Processing the commutations.

4) The algorithm continues if there are two logic commutation, otherwise it jump to step 1 processing another pixel.

5) Compute the average of the pixels in the perimeter P. If the pixel has been defined as a termination minutia in step 1, we check if the average is greater than the threshold K. (in bifurcation minutia, the average must be lesser than 1-K) otherwise it jump to step 1 processing another pixel.

6) Estimate the orientation angle α in the minutia point. The orientation angle estimation can simply obtained by a proportion between the position of the ridge mean point along the perimeter P and the 2π angle. (figure 4, left) The mean point of the ridge is identified by considering the mean point of the segment along the perimeter P with zero/one values in the termination/ bifurcation case.

7) False detection removal: create a square path P_2 twice larger than P. If P_2 intersects another ridge at $\alpha + \pi$ angle the minutia is rejected as spurious, otherwise is accepted as correct (figure 4, right).

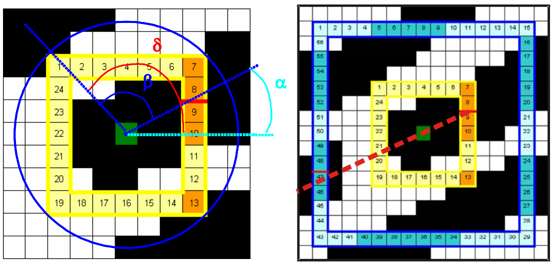

Figure 4: Estimating the orientation angle (left) and removing the false terminations detections (right).

III. Indices of Accuracy

In this section we describe the indexes of accuracy used to compare automatic methods of minutiae's identification. In the literature it is not present a standard set of indices that directly measures the accuracy of a system that identifies minutiae in images. The main problem is the reference: how it is possible to determine where exactly the minutiae are located in a fingerprint image? We solved this problem by assuming as correct the minutiae coordinates provided by a supervisor. In our case, the supervisor (an experienced operator) used a graphical interface to identify the coordinates, the type and the orientation of each minutia present in a database of images.

A minutia extracted by an automatic method is *correct* if the supervisor identified a minutia of the same type in its neighbourhood [8]. The **positional correctness** is also considered, and it refers to the correctness of a minutia without considering the minutia's type (bifurcation or ridge). The **index of minutiae revelation** $I_{revealed}$ is the ratio between the minutiae *positionally correct* extracted by an automatic method ($N_{CorrectAuto}$) and the minutiae *positionally correct* extracted by the supervisor (N_{Man}). It is defined as follows:

$$I_{Revealed} = \frac{N_{CorrectAuto}}{N_{Man}} \quad (1)$$

The **index of positional correctness** $I_{PositionCorrect}$ is the ratio between the minutiae *positionally correct* extracted by an automatic method and the minutiae *correctly* extracted by the automatic method (N_{Auto}). It is defined as follows:

$$I_{PositionCorrect} = \frac{N_{CorrectAuto}}{N_{Auto}} \quad (2)$$

The **index of correctness** $I_{Correct}$ is the ratio of the minutiae *correctly* extracted by an automatic method and is defined as:

$$I_{Correct} = \frac{N_{CorrectAuto} - N_{Exchanged}}{N_{Auto}} \quad (3)$$

where $N_{Exchanged}$ represents the number of minutiae whose type has been wrongly determined, i.e. a ridge has been extracted as a bifurcation and vice versa.

It is worth noting that the index $I_{Correct}$ is the most valuable one among the other indexes: an automatic method which provides an index $I_{Correct}$ close to 1 but an index $I_{revealed}$ near to 0 is better than an second method characterized by a small value of index $I_{Correct}$ and an index $I_{revealed}$ close to 1. As such, it is most valuable that an automatic method extracts a large number of *correct* minutiae with respect to only a large number of minutiae, eventually miss-classified in type.

IV. Experimental Results

The proposed method has one threshold parameter that has to be fixed: the threshold K required to classify the type of the located minutia. After trials on tens of images different in qualities and definition it has been fixed to the value of 0.7.

The positional accuracy of the presented method can be qualitatively evaluated in Figure 6 where it is plot a sample fingerprint image. The circles (radius = 10 pixels) point out the positions of the minutiae chosen by a human supervisor and the dots indicate the positions of the minutiae chosen by the proposed method.

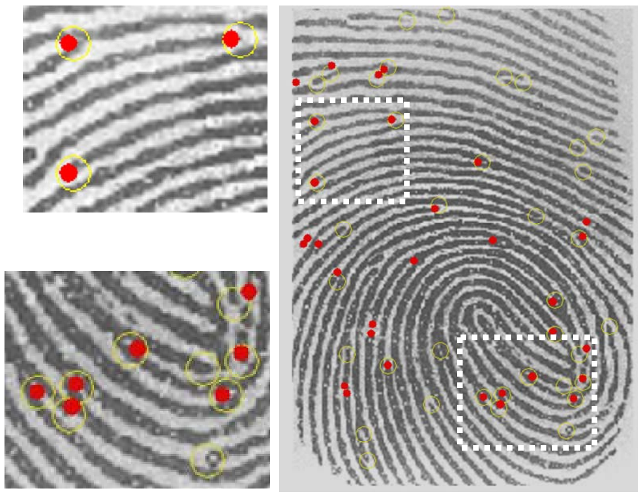

Figure 6: Evaluation of the positional accuracy of the proposed method. The minutiae chosen by the human supervisor (circles) are compared with the ones chosen by the proposed method. The two left subplots are zooms of the bigger image corresponding to the dashed areas.

In order to quantitatively test the method, a reference dataset of 40 images has been produced from the dataset available in [9]. The images have been binarized by using the well-known Otsu method [10].

A human supervisor identified for each image a list of minutiae and its attributes (coordinates and type). At this stage, we applied the proposed method on the reference dataset. Results show that the 58% of the identified minutiae are located within less of 4 pixels from the minutiae identified by the supervisor. That can be considered as a good result since typically only a fraction of the minutiae identified by the supervisor are identified also by the algorithms (the $I_{revealed}$ index).

In addition, the accuracy of the algorithm has been tested by *directly* comparing the presented algorithm with respect to the classical approach described in [1] and with respect to the DSG method described in [2]. Figure 5 shows the minutiae selected by the supervisor, by the classical methods and by the DSG method respectively applied to a sample image. Table 1 shows the indexes of accuracy based on the sample image plotted in figure 5.

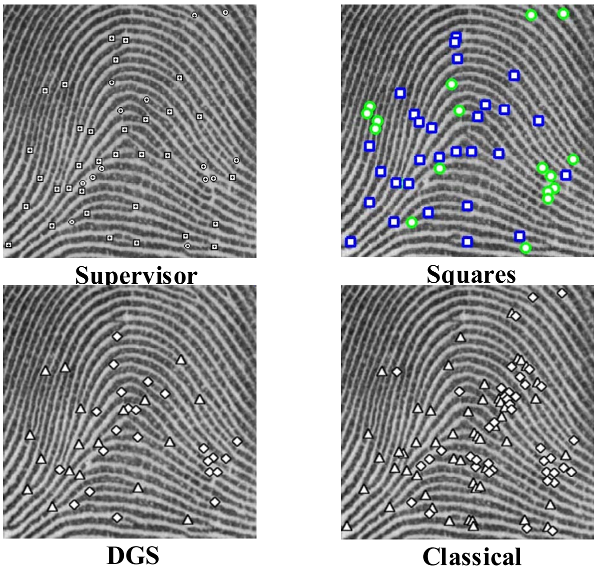

Figure 5: Example of identified minutiae for a sample image with the *method of squares*, *DSG* and *classical* algorithms

TABLE I

RESULTS FOR THE *METHOD OF SQUARES*, *DSG* AND *CLASSICAL* ALGORITHMS

Method	N_{man}	N_{auto}	$N_{corr.Auto}$	$N_{exch.}$	$I_{Rilevated}$	$I_{Position\ Correct}$	$I_{Correct}$
Classic	47	95	45	2	**96%**	47%	45%
DGS	47	41	37	10	79%	**90%**	66%
Square	47	47	38	1	81%	81%	**79%**

TABLE II

RESULTS WITH RESPECT TO THE NEURAL AND NEURO-FUZZY CLASSIFICATION SYSTEMS

Method	N_{man}	N_{auto}	$N_{corr.Auto}$	$N_{exch.}$	$I_{Rilevated}$	$I_{Position\ Correct}$	$I_{Correct}$
Fuzzy	19	47	6	N.A.	32%	13%	Max 13%
NeuroF.	19	41	8	N.A.	42%	20%	Max 20%
Square	19	65	19	0	**100%**	**29%**	**29%**

The proposed algorithm has been also compared with respect to the neural and neuro-fuzzy system proposed in [3]. Since the dataset images and the related extracted minutiae of the cited papers is not available in order to execute a direct comparison, we used as input of our method the original image scanned from the document. Results are given in table 1 and table 2. In these experiments we consider a minutia as position-correct if it is far less than 10 pixels with respect to the closest minutia identified by the supervisor.

The proposed method shows a good capability to correctly locate the minutiae without confusing the type since the index $I_{Correct}$ has the highest value in both tables. In addition, the presented method shows high values of the three indexes in both tables.

V. CONCLUSIONS

This paper presented a method for the identification of minutiae in a fingerprint image based on the analysis of local properties. The typical patterns of minutiae called ridge termination and bifurcation are identified by studying the intensity along squared paths in the image. Results indicate that the proposed method is achievable and it offers remarkable identification accuracy. The method can be considered as good candidate to be implemented in hardware (i.e. FPGA or VLSI circuits) or executed on processes with low computational power, for example in biometric systems hosted on cellular phones and smart cards. Further studies will be focused in order to validate the algorithm on larger datasets and to make the method fully adaptive with respect all parameters.

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