Analysis and Improvements of Fingerprint Enhancement From Gabor Iterative Filtering

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***Abstract*—The quality of the input fingerprint has a big impact on the performance of the Automatic Fingerprint Identification System (AFIS). So, the fingerprint enhancement is an important and necessary step to refine the quality of images. Over the past few years, fingerprint enhancement approaches have been proposed to investigate and test technologies in an attempt to find improvements. One of the most common methods in the literature to achieve that is the convolution with Gabor filters. By using coherent parameters and successive iterations, it is possible to highlight clearly the lines present in the images. This paper analyzes and presents improvements in a renowned algorithm that uses a contextual iterative filtering. Experimental results show that the proposed upgrades developed in this research obtained gains of 21% over the baseline.**

I. Introduction

Biometrics provides a reliable authentication mechanism using physical or behavioral traits to identify users based on their natural characteristics. Fingerprint recognition is one of the most used biometrics approaches since its high accuracy and low cost make the system more affordable and acquire satisfactory results. The reliability and the performance of minutiae extraction algorithms and other fingerprint recognition techniques rely heavily on the quality of the input fingerprint images [1]. If the quality of the fingerprint is good, the fingerprint lines flow, known as ridges and valleys, is evident and a reliable set of minutiae can be extracted. Otherwise, if the fingerprint is very noisy, the minutiae extraction algorithm may detect a large number of spurious minutiae and miss several genuine, thus making the error rates increase in the matching [2].

Usually, for a given fingerprint image, the fingerprint regions resulting from the segmentation step may be assigned to one of the following three categories [1]:

- **well-defined region**: the ridge-valley flow is extremely defined, the ridges can be clearly differentiated from each other.
- **recoverable region**: ridges are corrupted by some kind of noise but are still visible and the neighboring regions provide information to assist in the recovery of genuine structures.
- **unrecoverable region**: the noise is so high that the ridge-valley flow are corrupted and cannot be reconstructed.

Therefore, an enhancement algorithm has a high importance for preparing a fingerprint image for later processing stage, improving the clarity of the ridge and valley structures in the recoverable regions and marking the unrecoverable regions as too noisy.

According to Gottschlich [3], a fingerprint enhancement method should have three important properties:

- *Reconnect broken ridges, e.g., caused by dryness of the finger or scars.*
- *Separate falsely conglutinate ridges, e.g., caused by the wetness of the finger or smudges.*
- *Preserve ridges endings and bifurcations*

Many types of enhancement algorithms have been proposed with the contextual filtering approach standing out. Therefore, in this paper, after an analysis of fingerprint enhancement algorithms that use contextual filtering, some improvements have been proposed. The work presented by Turroni et al. [2] uses iterative contextual filtering on the enhancement process and is considered the state-of-the-art in the area. The flaws pointed by the authors in [2] were the high processing time and the attempt of enhancing the background and unrecoverable regions. The main contributions of this work are to overcome the flaws mentioned by Turroni et al. and decreasing the EER by improving the method. These achievements were accomplished by the following changes: the obtention of a region of interest during the enhancement process, the generation of the adaptive Gabor masks based on the signal frequency and optimization of the o algorithm.

This paper is organized as follows. In Section II the related works are reviewed and discussed; in Section III the proposed improvements to fingerprint enhancement method are described in detail, and in Section IV, the experiments and results are shown and a discussion about them is made. Finally, in Section V are presented the conclusions obtained from this research and the future works are introduced.

II. Related Work

Recently, Schuch, Schulz and Busch [4] presented a survey about the impact of fingerprint image enhancement, where a set of representative methods of image enhancement was evaluated. The authors identified six groups of models: Signal domain models, energy models, noise statistics model, frequency-domain models, fingerprint models and compositional models. The contextual filtering is a fingerprint model that includes specific knowledge about the domain of fingerprints. This approach is the base for numerous variants methods and it is considered the most widely used technique for fingerprint image enhancement. The context is often defined by the local ridge orientation, local ridge frequency, and local quality being used to adapt filter characteristics for each region of the fingerprint.

One of the most used contextual filterings is based on Gabor filters, as proposed by Hong, Wan, and Jain [5] which shows that the Gabor filters have both frequency-selective and orientation-selective properties and have an optimal joint resolution in both spatial and frequency domains.

Zhang and Xinsheng [6] proposed an algorithm based on the first derivative matrix method and uses Gabor filters as a bandpass filter to remove the noise and preserve genuine ridge and valley structures. The first derivative of each pixel is enhanced for each $w \times w$ block of a fingerprint image, and a histogram analysis is performed in a specific orientation. Afterward, the contrast is defined in that orientation. Lastly, Gabor filtering is applied to eliminate undesired noise and preserve true ridge patterns.

A contextual iterative filtering that does not need prior local information is described by authors in Turroni, Capelli and Maltoni [2]. Aiming to achieve better results at the border of low-quality regions, a strategy of several iterations of Gabor filters is used, starting from high-quality regions and then iteratively expanding to low-quality regions. Initially, the fingerprint image is convolved with a bank of Gabor filters with 8 orientations and 3 frequencies to produce a set of 24 response images. The responses are combined according to the max filter response in an image C. In order to remove discontinuities in the input image, a homogeneity image H is defined by encoding the local ridge flow homogeneity. The homogeneity image is normalized in the range [0,1] and varies during the iterative process. The combined image C and homogeneity image H are used to select the set of candidate pixels, according to a top-ranking criterion. The idea is to select a percentage of good quality pixels with strong (positive or negative) response to the filtering and possibly belonging to highly-homogeneous regions. The candidate pixels are then sorted in two sets corresponding to ridges and valleys. Finally, the $n\%$ of pixels will be enhanced, where n is a constant, and the algorithm continues iterating until a convergence criterion is satisfied. However, the authors mention some points to be improved, like the high processing time (about 10 seconds to enhance a fingerprint image) and the enhancement of low-quality regions of the fingerprint, leading to spurious minutiae, being necessary a Region of Interest (ROI) that removes unrecoverable regions from the original image.

Baig, Huqqani and Khurshid [7] proposed a method based on the conventional Gabor filter integrated with a new segmentation scheme. The methodology comprises of four core phases: Image Segmentation, Ridge Orientation, Estimation, Ridge Frequency Estimation, and Filtering. In the first phase is used the Factorized Directional Band-pass (FDB) to demarcate the region of interest (ROI). The ridge orientation is computed using the least mean square method and is rectified by low-pass filtering. To calculate the ridge frequency is used the X-Signature method cited in [1]. In the last phase, a conventional Gabor filter is applied to get the enhancement version.

One of the most recent enhancement technique is proposed in [8]. The process combines Gabor filter and classification dictionaries learning. To construct the classification dictionary, the fingerprint is enhanced using Gabor filtering and is divided into patches where the orientation and quality of each fingerprint patch are estimated. The training patches are classified into eight groups based on their own ridge orientation pattern, and the training samples of each class are selected from candidate patches by their own quality. After sampling, the patches with high quality in each class are selected to build the corresponding classification dictionary training set. Then each patch is transformed to the frequency domain, and the classification spectrum training sets are built. The classification dictionaries are constructed based on the corresponding classification spectrum training set. The fingerprint image is enhanced based on spectra diffusion using classification dictionaries learning.

More recently, Li, Feng and Kuo [9] proposed a latent fingerprint enhancement using Convolutional Neural Network (CNN) with three different parts: a convolutional part, that extract fingerprint features; and two deconvolutional parts, the enhancement deconvolution branch, responsible to recover image details using the extracted CNN features; and the orientation deconvolution branch, which guides enhancement through a multi-task learning strategy.

III. Methodology

The fingerprint enhancement proposed by Turroni, Cappelli and Maltoni [2] that uses an iterative contextual filtering instead of classical Gabor was very promising and showed its efficacy achieving a higher matching accuracy. However, the own authors cite some points of possible improvements. This section aims to analyze and propose some changes to solve some of these flaws.

The diagram of the proposed approach overview is shown in Figure 1. The flow-chart is composed of six main steps: filter-bank convolution, combined image computation, homogeneity image computation, selection of the candidates, generation of the ROI and the enhancement of the candidates. The step which generates the ROI is performed only in the first iteration. The details of each step are explained later in this section.

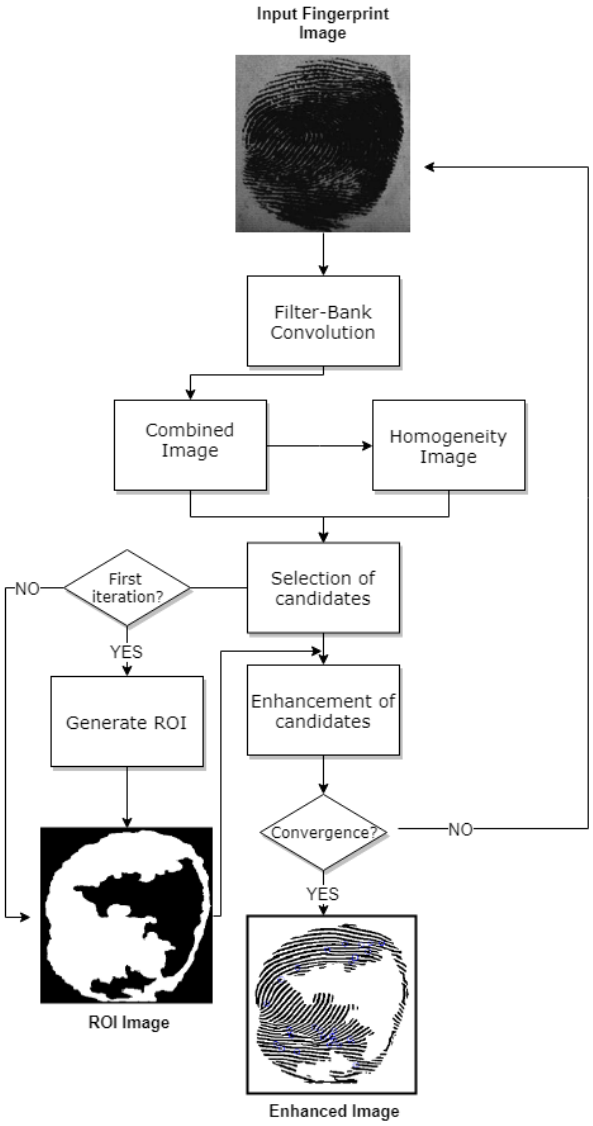


Fig. 1. Flow-chart of the proposed method.

An important step in [2] is the creation of Gabor filter-bank. A Gabor filter is defined by a sinusoidal plane wave tapered by a Gaussian, according to the following equation:

$$g(x, y : \theta, f) = \exp\left\{ -\frac{1}{2}\left[\frac{x_\theta^2}{\sigma_x^2} + \frac{y_\theta^2}{\sigma_y^2}\right]\right\} \cdot \cos(2\pi f \cdot x_\theta) \quad (1)$$

where θ is the orientation of the filter and [x_θ,y_θ] are the coordinates of [x, y] after a clockwise rotation of the Cartesian axes by an angle of (90°-θ), and, σ_x and σ_y are the standard deviations of the Gaussian along the x and y axes, respectively. Such filter depends on four parameters ($\theta, f, \sigma_x, \sigma_y$).

A Gabor filter-bank is defined as a set $G = \{g_{i,j}(x, y)|i = 1..n_o, j = 1..n_f\}$ of Gabor filters, where n_o is the number of discrete orientations $\{\theta_i|i = 1..n_o\}$ and n_f is the number of discrete frequencies $\{\theta_j|j = 1..n_f\}$.

To select the values σ_x and σ_y is necessary to understand that the larger the values, the more robust the filters are to noise, however, may create spurious ridges and valleys. In this work we propose a new method of building the Gabor filter-bank where dynamically define values to σ_x and σ_y according to the frequency f of each mask, instead of using a fixed value as in [5] and [2]. Figure 2a shows Gabor signal with different frequencies and a fixed σ, and Figure 2b shows the Gabor signal using different frequencies and dynamic σ for each frequency.

In our approach, σ is dynamically calculated, based on the signal frequency. Thus, the higher the signal frequency, the narrower the Gaussian function is (see Figure 2b). The resulting Gabor filter presents similar behavior for all frequencies: one prominent peak, instead of what can be observed in Figure 1a, with a fixed σ and a different number of peaks from each mask. As a result of this modification, the filter has become more robust to noise, making easier the pattern recognition, especially in high-frequency signals.

Aiming to increase the variation of generated filters and making the bank more effective, 4 frequencies and 12 orientations were used (varying the orientation in the range [0, π]), totaling 48 filters, where each filter highlights a different orientation and frequency in a fingerprint image. Figure 3 shows an illustrative Gabor filter-bank with 6 orientations and 3 frequencies.

All the 48 filters are computed previously in order to avoid unnecessary computations during the enhancement process. In the following iterations, we just access the filters.

A problem cited in [2] is that the algorithm enhances the whole fingerprint image, including background and unrecoverable regions. This approach may create a large number of spurious minutiae, impairing other steps like minutiae extraction and matching. To make the algorithm more effective, it is necessary to define a Region Of Interest (ROI) segmentation.

Aiming to solve the previous issue, an ROI is defined from the first iteration of the enhancement process with some subtle changes. The set of response images is used to compute a single combined image C where the combination is performed according to the max filter response:

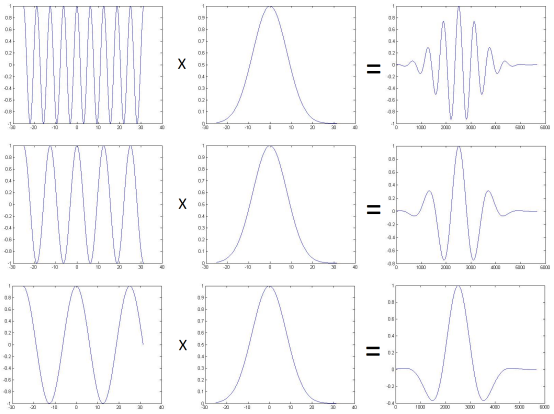
$$C_{i,j} = v_{i,j}^{l\ t} \quad (2)$$

where $l, t = argmax_{i,j}\{|v_{x,y}^{i,j}|\} i = 1..n_o, j = 1..n_f, x = 1..w, y = 1..h$.

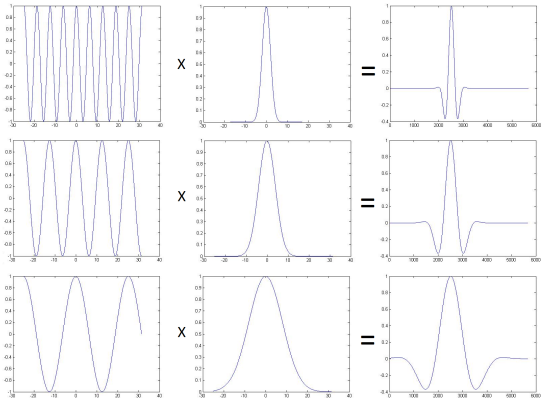
The ridges run smoothly across the fingerprint pattern, abrupt discontinuities in the ridge flow can indicate the presence of improper regions, except for singularity regions. The homogeneity image H is computed to find such discontinuities and is defined as follows:

$$h_{x,y} = \frac{\sum_{(p,k)} |C_{p,k}| \cdot S_{p,k}}{\sum_{(p,k)} |C_{p,k}|} \quad (3)$$

where $p, k = -\frac{m}{2}, .., \frac{m}{2}$ and $S_{p,k}$ is an orientation homogeneity measure defined as:



(a) Signal with different frequencies and fixed σ to each frequency.



(b) Signal with different frequencies and dynamic σ to each frequency.

Fig. 2. Effect of σ in the gabor signal.

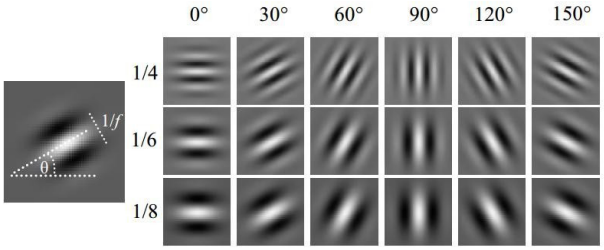


Fig. 3. A Gabor filter-bank with six orientations (columns) and three frequencies (rows) [2].

$$S_{p,k} = \frac{\pi}{2} - |d\phi(O_{x,y}, O_{p,k})| \tag{4}$$

$$d\phi(\theta_1, \theta_2) = \begin{cases} \theta_1 - \theta_2 & \text{if } -\frac{\pi}{2} \leq \theta_1 - \theta_2 < \frac{\pi}{2} \\ \pi + \theta_1 - \theta_2 & \text{if } \theta_1 - \theta_2 < -\frac{\pi}{2} \\ \pi - \theta_1 - \theta_2 & \text{if } \theta_1 - \theta_2 \geq -\frac{\pi}{2} \end{cases} \tag{5}$$

Then, H is normalized to fit values in the range [0,1]. Lower values denote a lower homogeneity, and vice-versa.

After calculating the combined image C and the homogeneity image H, the pixels with strong (positives or negatives) responses in C and belonging to highly-homogeneous regions in H are considered pixels of interest. The equation below describes this process.

$$p_{x,y} = c_{x,y} \cdot h_{x,y} \tag{6}$$

Let $P = \{p_{x,y} | x = 1..w, y = 1..h\}$. P is the resulting image of a pixel-wise multiplication between the C and H. The higher the absolute pixel value, the higher the confidence that is a well defined and good-quality region. The signal of the pixel value determines whether it corresponds to a ridge or a valley, negative and positive values, respectively. The elements in P are then classified as pixels of interest by:

$$ROI(x,y) = \begin{cases} 1, & \text{if } |p_{x,y}| \geq t \\ 0, & \text{if } |p_{x,y}| < t \end{cases} \tag{7}$$

where t is a threshold value. The value of t used in the experiments is 6.0.This value was defined after analyzing the experiments, and it was, on average, the best threshold value for all datasets, regarding EER. It is a very sensitive parameter, and a variation of one unit is enough to make substantial changes.

After thresholding, the ROI image may present some noise. Therefore, the image must be processed by some filters to find the best region and remove the possible noise. Firstly, a median filter is applied, and then the largest white connected region is defined in order to exclude small regions outside the foreground. Figure 4 shows the ROI segmentation process.

At the end of the process, the background region and the unrecoverable regions are removed (see Figure 4). Then, the enhancement algorithm will be applied only in the pixels of the ROI. By using ROI, at the end of the enhancement process, the false minutiae present in the unrecoverable regions no longer will be present, improving the extraction process. Figure 5 and Figure 6 show the effect of the proposed ROI on minutia extraction, low-quality and high-quality fingerprint images, respectively.

Another important factor of the iterative method approach analyzed by this work is the γ variable which defines a percentage of good quality pixels to be improved in the respective iteration. Turroni, Capelli and Maltoni [2] use a fixed γ value. In this approach, the smaller the value of γ is, the larger is the number of iterations and the longer the time is to finish the enhancement process. Although a higher value of γ performs the enhancement faster, probably will lead to mistakes in the process. In this work, we update γ according to iteration index. Before the first iteration, the fingerprint image has no enhanced pixel. The variable γ is initialized

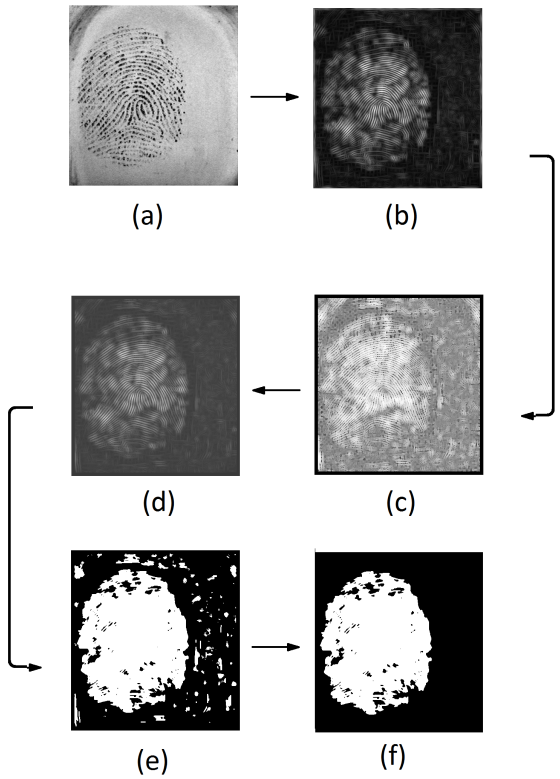


Fig. 4. The ROI segmentation process. (a) original image, (b) combined image C, (c) homogeneity image H, (d) C and H combination, (e) ROI image with noise, (f) final ROI image.

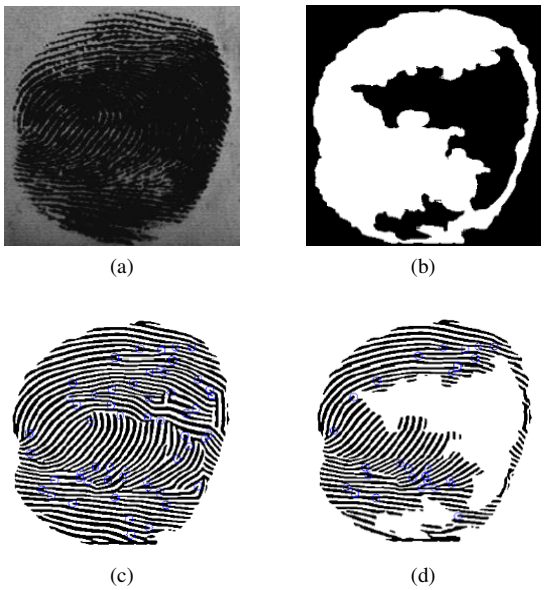


Fig. 5. Effect of ROI segmentation on low-quality fingerprint image. (a) original image, (b) ROI image, (c) minutia extraction without ROI, (d) minutia extraction with ROI.

with a default value, and before each iteration, it is updated by incrementing its value according to the following equation:

$$\gamma = \gamma + (\beta \cdot i) \tag{8}$$

where β is a multiplicative constant and i is the iteration index, started from zero.

From Equation 8, at each iteration the enhancement iterative method becomes more aggressive, resulting in a smaller number of iterations required to fully enhance the image. The algorithm continues iterating until a convergence criterion is satisfied: the maximum number of iterations is reached or no more low-quality regions exist in the image.

IV. Experimental Results

The goal of an enhancement algorithm is to improve the clarity of the ridge and valleys in the recoverable regions and mark the unrecoverable regions as too noisy to perform a more reliable minutia extraction process and so, improving the matching accuracy. Public fingerprint images from six databases from the last editions of Fingerprint Verification Competition (FVC) were used to measure the effectiveness of enhancement methods. We used 6 databases, the Database3 from 2000 edition [10], Database1 from 2002 edition [11], Database1, Database2 e Database3 from 2004 edition [12] and Database2 from 2006 edition [13]. These datasets were

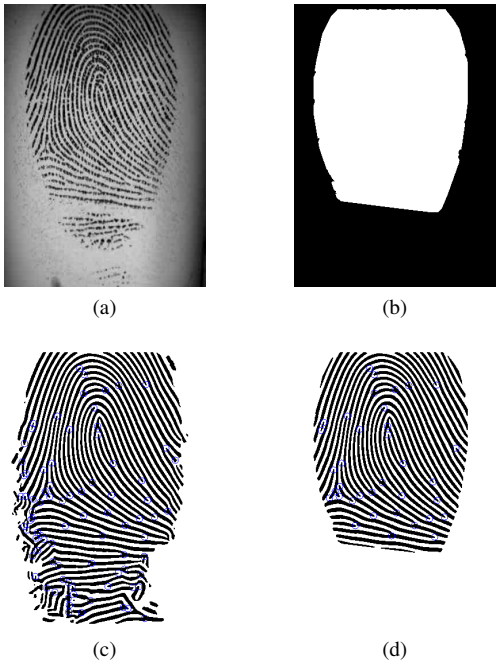


Fig. 6. Effect of ROI segmentation on high-quality fingerprint image. (a) original image, (b) ROI image, (c) minutia extraction without ROI (d) minutia extraction with ROI

chosen because they are the ones used by the most authors in the literature, including the work presented by Turroni et al. [2]. Thus, making possible a fair comparison between the methods. These databases have a set of diversified samples, with different sizes, quality and resolution that generate a higher heterogeneity. In total, our experiments used 5680 fingerprint images.

A good fingerprint enhancement is very important for minutiae-based fingerprint matchers. We made the tests using a common fingerprint matcher to assess the fingerprint enhancement algorithms. In order to compare the proposed improvements with respect to the work proposed in [2], the Minutia Cylinder-Code (MCC) matcher [14] was used.

The final performance of this matcher algorithm will determine the best fingerprint enhancement. In this work, the performance is measured by using the False Acceptance Rate (FAR), False Rejection Rate (FRR) and Equal Error Rate (EER). These metrics were chosen due to their high adoption in the literature, being also considered the main metrics of several international competitions to evaluate AFIS, like the FVC.

Our experiments were compared using four fingerprint enhancement algorithms: the baseline Gabor [5], the contextual iterative method [2], the proposed method, and an open source fingerprint enhancement present in SourceAFIS [15]. All matching experiments were conducted following the FVC protocol [16]. Other methods found in the literature were not used in the experiments due to their limitations, such as matching algorithm unmentioned, usage of different matching algorithms and incompatible approaches to measuring the algorithms' efficiency. Figure 7 shows a visual comparative analysis of the four algorithms applied in a fingerprint image.

In Figure 7, it can be noticed that the reconstruction of fingerprint regions by our algorithm was well performed preserving well-defined regions, reconstructing recoverable regions and removing unrecoverable regions. In addition, it is important to observe that other algorithms removed some recoverable regions at the edges of fingerprint image, failing to extract possible genuine minutiae. The main differences between the proposed enhancement method (Figure 7d) and the enhancement proposed by Turroni et al. [2] (Figure 7d) are indicated by green and red circles, where the red circles are the regions of the fingerprint image that Turroni et al. [2] algorithm made some mistakes, creating spurious minutiae, whereas green circles are the same regions with our proposed enhancement method.

A quantitative analysis of our improvements in fingerprint enhancement can be shown in Table I that presents the Equal Error Rate (EER) results of the above algorithms over the datasets.

The experiments in Table I show that the proposed enhancement improvements, got better results than the Gabor baseline and the method proposed by Turroni, Capelli and Maltoni [2]. The gains were 14.6%, 22.7% and 42.4% in FVC2004 Database2, FVC2004 Database3 and FVC2006 Database2, respectively, thus, having an improvement of 21% in average, regarding to Turroni et al. [2]. It is observed that the proposed method also overcome the rates of fingerprint enhancement algorithm available in the SourceAFIS [15].

TABLE I
FINGERPRINT VERIFICATION ERR ACCURACY

DB	Gabor [5]	Turroni et al. [2]	Source AFIS [15]	Proposed Method
FVC2000 Database3	-	-	6.74%	2.40%
FVC2002 Database1	-	-	1.22%	0.71%
FVC2004 Database1	-	-	6.24%	4.22%
FVC2004 Database2	6.569%	5.678%	7.40%	4.85%
FVC2004 Database3	3.640%	3.175%	3.90%	2.45%
FVC2006 Database2	2.325%	0.659%	0.64%	0.38%
Mean	4,18%	3.17%	4.35%	2.50%

The fingerprint in Figure 8 is characterized by a wide unrecoverable region in the central part. Turroni, Capelli and Maltoni showed the enhancement result is poor, once it recovers the whole fingerprint foreground area, creating a high number of spurious minutiae. Our reconstruction in such image is better because the unrecoverable region is discarded and the enhancement is performed only in the region of interest.

The processing time of the enhancement process was evaluated as well. Turroni, Capelli, and Maltoni [2] cite in their work that the mean processing time of their proposed fingerprint enhancement method was around 10 seconds for each image. However, the authors did not specify the machine configuration they used. After applying our improvements, the number of iterations has been reduced in comparison with the research of Turroni, Capelli, and Maltoni [2], once we acquire good quality enhancement with just 3 or 4 iterations, mainly from the change of γ. The mean processing time obtained in the experiments is 1.9 seconds, by using an Intel Core I5, 4GB RAM. This result represents an improvement of 81% in the processing time.

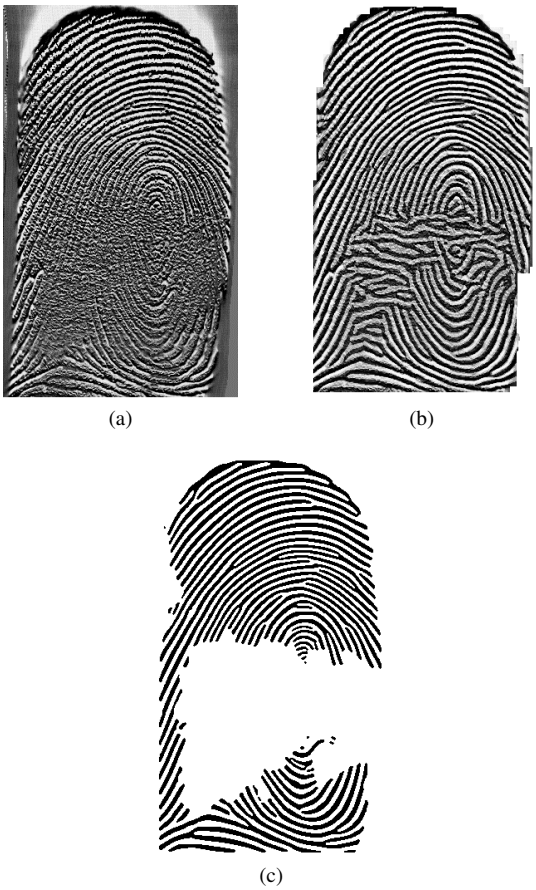
V. CONCLUSIONS

The development of a fingerprint enhancement to improve the quality of fingerprint images is extremely necessary to increase the reliability of further steps. This paper has explored and suggested many improvements to the fingerprint enhancement method proposed in [2].

For evaluation of the proposed improvements, fingerprint enhancement on available databases of Fingerprint Verification Competition (FVC) was performed. The method proposed by this paper was compared to other methods using a common matching algorithm, the MCC matcher [14], and used the EER metric to evaluate each algorithm.

(a) (b) (c) (d)

Fig. 7. Enhancement of fingerprints with various algorithms. (a) original image present in FVC2006 database, (b) Enhanced using the baseline Gabor [5], (c) Enhanced using the contextual iterative method [2], (d) Enhanced using the proposed method. Green circles indicate the regions that were correct enhanced using the proposed method, whereas the red circles are the same regions, but incorrectly enhanced by Turroni, Cappelli and Maltoni [2].



(a) (b)

(c)

Fig. 8. Enhancement of bad fingerprint with unrecoverable regions. (a) original image present in FVC2004 database, (b) Enhanced using the contextual iterative method [2], (c) Enhanced using the proposed method.

The results obtained from the experiments suggest that the proposed work achieved success in its objective of improving the algorithm proposed by Turroni, Campelli and Maltoni [2], correcting some of their failures and consequently decreasing the error rates and the processing time. Furthermore, this work can report promising results, with error rates near of the best algorithms in the literature.

For future works, we intend to study different approaches to turn our approach more competitive in the international scenario, by decreasing the error rates and the processing time. The amount of Gabor filters may also be reduced by using information of only frequencies and angles presented in the image. We may also try learning dictionaries as in [8] and convolutional neural networks (CNN) as in [9] to enhance a fingerprint image. The idea is to let the network learn the best possible filters to enhance an image, even if it is slow to generate these results, and before the training, be able to reproduce the enhancement in other images faster.

We also intent to compute others image quality metrics to achieve better evaluation of our method. In addition, we may also compare our method with other matching algorithms presented in the literature, such as BOZORTH [17], M3gl [18] and the Neurotechnology VeriFinger, to allow more comparisons with other enhancement approaches.

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