On the Segmentation of Fingerprint Images

How to Select the Parameters of a Block-wise Variance Method

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***Abstract*—Fingerprint image segmentation is the process of separating the fingerprint ridge area – that is, the foreground – from the background of the captured image. It is an important process because it prevents a fingerprint recognition system from analysing the unnecessary fragments of the captured image. This is the reason why segmentation should be executed during the initial stages of the fingerprint analysis process. This manuscript presents a method based on the gray-level variance of the captured image, where this variance is calculated per block of image pixels, instead of doing it for each image pixel. This then necessitates careful and informed choices for the values of – both – the gray-level variance threshold, and the pixel-block size. This manuscript solely focuses on studying the effects of these two variable parameters, and the results indicate that the choice of their respective values should be well-informed.**

Keywords*—*fingerprint segmentation, gray-level variance, pixel-block size, variance threshold

Figure 1. A fingerprint image showing the background area (set B) which is just a surface, and the foreground area (set F) which is composed of fingerprint ridges and furrows

I. Introduction

In its crude form, a fingerprint image – or perhaps any image – is a matrix with pixels that contain intensity values that range from 0 to 255 (gray-level values). There is a number of ways in which a fingerprint image can be looked at. However, one way that is of particular interest in this manuscript is the one where a fingerprint image is considered as a set, say I, that encompasses two subsets, B and F, and the two sets do not intersect. This can be mathematically expressed as follows:

A fingerprint image is a set, I, *such that –*:
$B \subset I$ *and* $F \subset I$, *but*
if there exists $b \in B$, *then* $b \notin F$, *and*
if there exists $f \in F$, *then* $f \notin B$.

The process of extracting subset F from set I is called fingerprint image segmentation, and it is neccesary because F is a subset whose elements, known as fingerprint ridges and fingerprint furrows, represent all the important characteristics of a given fingerprint. The subset B contains no fingerprint ridges and fingerprint furrows, hence contains very little information about a given fingerprint. That is why it is important to extract the fingerprint image foreground from the rest of the image. Figure 1 depicts a fingerprint image with the background, set B, and the foreground, set F, clearly marked.

The sole purpose of this work is to conduct a formal study of the two non-constant parameters – the variance threshold (T) and the pixel-block size (W) – involved in a block-wise, variance-based segmentation technique. A block-wise computation is preferred because of its ability to counter-balance the effects of the computational costs generated by executing the more conventional pixel-wise computation. Even though it has the advantage of speeding up the process, a block-wise computation might introduce the disadvantage of reduced segmentation accuracy. This essentially implies that, when measured against its pixel-wise counterpart, a block-wise computation is more fast and less accurate, however that has not reduced its popularity.

An inspection of existing literature reveals that there is a number of instances where block-wise algorithms have been used to successfully segment fingerprint images. In the year 1995, Ratha *et al* [1] presented a method that used gray-level variance in a direction perpendicular to the orientation of the ridges. In their study, the image was split into 16×16 blocks, however there is no formal account of how the pixel-block size was arrived at.

Another interesting study was conducted by Maio and Maltoni [2] in 1997, where they computed the average gradient of each block and used it to separate the image foreground from the background. The idea was that the fingerprint foreground area has a high gradient response, while the background area has a very low gradient response. Again, there is no formal account of how the pixel-block size was arrived at. In 2001, Shen *et al* [3] introduced the idea of convolution to separate the image foreground from the background. Each pixel-block was convolved with a series of Gabor filters and the variance of the responses of these filters was used for the separation, but then again, there is no formal account of how the pixel-block size was arrived at. Other implementations that failed to give an account of the pixel-block size, include the works of Mehtre and Chatterjee [4], Naji *et al* [5], and Mehtre *et al* [6].

The formal study of parameters proposed in this manuscript, is executed through a set of carefully chosen experiments, with speed and accuracy taken into consideration. The first key constraint accompanying this study is that, literature has not yet revealed a formal tool or measure that can be employed to quantify the accuracy of a fingerprint image segmentation algorithm. The effects of this constraint can be counterbalanced by having an image segmentation practitioner acting as an expert, and having to visually inspect the output image from the segmentation algorithm. Based on the expert's observation, a decision can be made on whether, or not, the image is properly segmented. In order to minimize the effects of individual subjectivity, this manuscript introduces the idea of having inspection guidelines.

II. Inspection Guidelines

Because there is no formal measure of image segmentation accuracy, it is important for the practitioner to have guidelines to adhere to when inspecting the output from a segmentation algorithm. These guidelines assist in arriving at a decision as to whether, or not, the segmentation is satisfactory. The two major guidelines for the practitioner to follow are listed as:

- No element of subset F may be removed, and
- All elements of subset B should be removed.

The first guideline is important because the removal of any part of the fingerprint area could translate to the removal of an important fingerprint feature which, ultimately, affects other fingerprint processing stages such as the matching or the classification problem. The second part is important because, depending on the quality of the image at hand, there could be some isolated areas outside the fingerprint foreground that are included for further processing. An improved way of determining segmentation accuracy would be to come up with a more formal measure, preferably mathematical, to do so. The chosen fingerprint image segmentation technique is described in the following section.

III. Algorithm Description

The chosen approach is summarized as algorithm 1, where steps 2 – 4 serve as the initialization of the segmentation system. This is where the practitioner, after image acquisition, specifies the pixel-block size together with the gray-level variance threshold. The pre-processing stage is made up of both step 5 and step 6. These steps are focused on normalizing the image and, thereafter, dividing it into non-overlapping blocks with dimensions specified during initialization.

Image normalization is an operation that goes through all the pixels of the image, however, experiment shows that it is not a computationally expensive exercise. Fingerprint image normalization is an important step because it serves to ensure that the intensity variations along ridges and furrows are removed, that is, it enhances the contrast between the ridges (blacks) and the furrows (white). A normalized image is given by the following equation [8]:

$$G(i,j) = \begin{cases} M_0 + \sqrt{\frac{V_0(I(i,j)-M)^2}{V}}, & if\ I(i,j) > M \\ M_0 - \sqrt{\frac{V_0(I(i,j)-M)^2}{V}}, & otherwise \end{cases} \tag{1}$$

where $G(i,j)$ is the intensity value of the normalized image at the i^{th} row and j^{th} column, M_0 and V_0 are, respectively, the desired mean and variance, $I(i,j)$ is the intensity of the pixel at the i^{th} row and j^{th} column, and M and V are, respectively, the estimated mean and variance of $I(i,j)$.

Algorithm 1: A fingerprint image segmentation algorithm that uses the gray-level variance of the image to separate the foreground from the rest of the image

Input : Gray-level Fingerprint Image, I
Output : Segmented Fingerprint Image, S
Variables: Pixel-block Size, W, and
Variance Threshold, T

1 **begin**
2 Acquire: a gray-level fingerprint image, I;
3 Specify: the pixel-block size, W;
4 Specify: the gray-level variance threshold, T;
5 Normalize I to get a normalized image, N;
6 Divide N into non-overlapping $W \times W$ blocks;
7 Compute the gray-level variance, V, of each block;
8 **if** $V < T$ **then**
9 assign the block a value of 0 (black);
10 **else**
11 assign the block a value of 255 (white);
12 **end**
13 Matrix containing 1's and 0's is the mask image, L;
14 The segmented image is given by, $S = N \times L$;
15 **end**

Steps 6 – 12 form the central part of the image segmentation algorithm, where step 7 computes the gray-level variance of each block. The gray-level variance of a $W \times W$ block is given by the following equation [8]:

$$V = \frac{1}{W^2} \sum_{i=0}^{W-1} \sum_{j=0}^{W-1} \left[I(i,j) - M \right]^2 \tag{2}$$

where V is the gray-level variance of the block, and M is the mean gray-level value of the block, where this mean gray-level value is defined as [8]:

$$M = \frac{1}{W^2} \sum_{i=0}^{W-1} \sum_{j=0}^{W-1} I(i,j) \tag{3}$$

Steps 8 – 12 perform the discrimination task, where a low-variance block is assigned to the background (gray-level 0) and a high-variance block is assigned to the foreground (gray-level 255). These 0's and 255's are stored in a matrix called the mask image. Step 14 serves as the final step, where the image is segmented. The segmented image is the product of the mask image and the normalized image. It is important to note that the segmented image, S, is a set that encompasses two subsets, F and B', where F is the required subset and B' is an empty subset – that is, its elements have been eradicated (blacked-out).

IV. Critical Algorithm Analysis

In his work, Thai [9] recommends the use of a pixel-block size of 16 and a gray-level variance threshold of anything between 100 and 200. This recommendation is based on the assumption that the images are 8-bit gray-level images scanned at a resolution of about 500 dots per inch (dpi), a standard recommended by the Federal Bureau of Investigation (FBI). In spite of this recommendation, there is a need to experimentally estimate the most optimum pixel-block size, W, and variance threshold, T. A total of three experiments are identified, and they are summarized in the table below. Experiments A1 and A2 are useful in determining the boundaries of W, while experiment A3 plays a useful role in determining the boundaries of T. It is easy for any practitioner to fall for the trap of studying the relationship between the processing time and the gray-level variance threshold. The processing time is a variable that is independent of the said threshold, hence, the results from such a study bear very little information.

TABLE I
List of experiments to optimize variable parameters T and W

Experiment ID	Description
Experiment A1	Processing Time Versus W
Experiment A2	Segmentation Accuracy Versus W
Experiment A3	Segmentation Accuracy Versus T

A. Experiment A1

The aim of this experiment is to determine boundary values of the pixel-block size, W, measured against the processing time. This is done by increasing W, from 1 to the smaller dimension of the image, while observing the time. For an image of height H and breadth B, where $B < H$, W is varied from 1 to B; however if $H < B$, W is varied from 1 to H. For smaller values of W, a high value of T is expected; while a small value of T is expected for larger values of W. The outcome of this experiment is depicted in figure 2, and it satisfies both of these expectations.

Looking at figure 2, it can be observed that the processing time is extremely high for smaller values of W and consistently remains low after an exponential drop at around $W = 14$. This, therefore, implies that the boundary condition obtained from experiment A1 is:

$$W \geq 14 \tag{4}$$

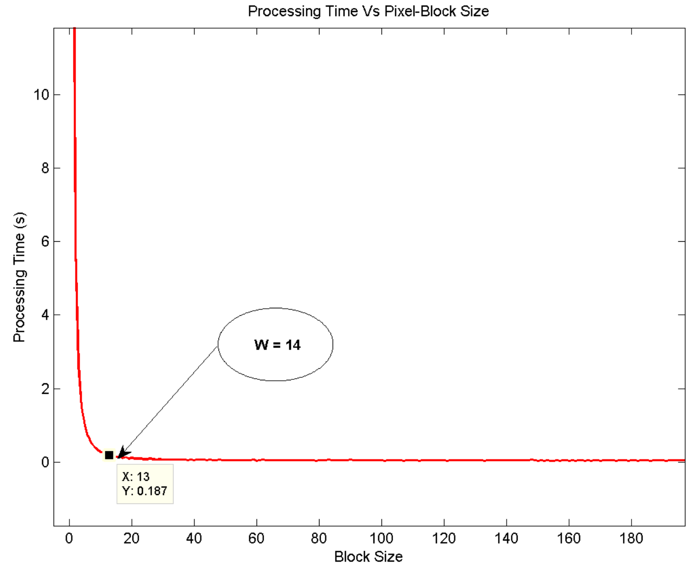

Figure 2. Processing time vs the pixel-block size

B. Experiment A2

The aim of this experiment is to determine the boundary conditions for W measured against the segmentation accuracy. Because there is no formal measure for accuracy, it is therefore modeled as a binary variable. If an image is deemed to be properly segmented, as observed by the expert practitioner, then it is assigned a score of 1, otherwise it is assigned a score of 0. Similarly, the procedure for this experiment is to, accordingly, vary W while observing the accuracy. For very small values of W, a small accuracy value is expected. This is because the chosen algorithm tends to discriminate some parts of the image foreground area, and regard them as part of the background, as depicted in figure 3 (a).

Very large values of W are expected to lead to a small accuracy value because there is a possibility of an overlap between the foreground and the background blocks, hence leading to some parts of the background being regarded as the foreground, as depicted in figure 3 (c). A fairly medium value of W is expected to do the trick, as depicted in figure 3 (b). The effect of a range of W values on segmentation accuracy is summarized in figure 4. Looking at figure 4, it is observable that the segmentation accuracy is satisfactory in the region where W has a value between 10 and 35. The boundary condition obtained from this observation is, therefore, given by the following:

$$35 \geq W \geq 10 \tag{5}$$

C. Experiment A3

The aim of this experiment is to determine the boundary conditions for the gray-level variance threshold, T, measured against the segmentation accuracy, where T is varied from 0 to 300. Very small values of T are expected to lead to some, if not most, fragments of the background area being regarded as part of the foreground, as depicted in figure 5 (a). Very

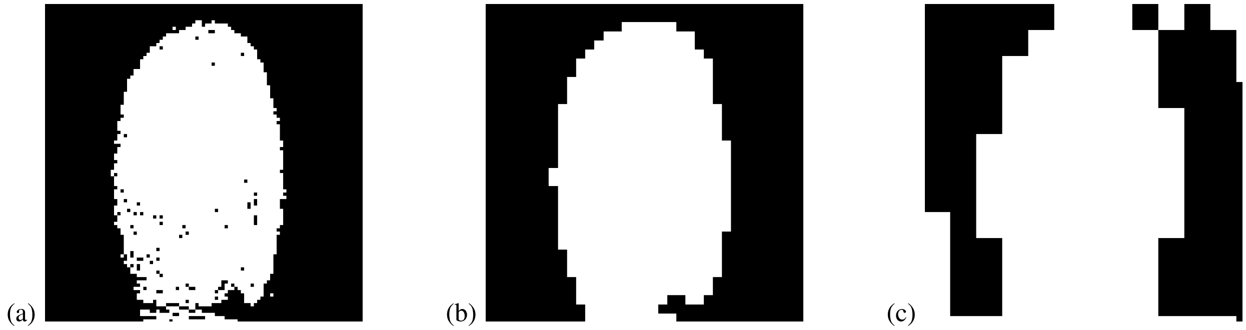

Figure 3. Mask image obtained through at (a) $W = 5$ (very small value), (b) $W = 14$ (fairly medium value), and (c) $W = 40$ (very large value). For this experiment the value of T is constantly kept at 200

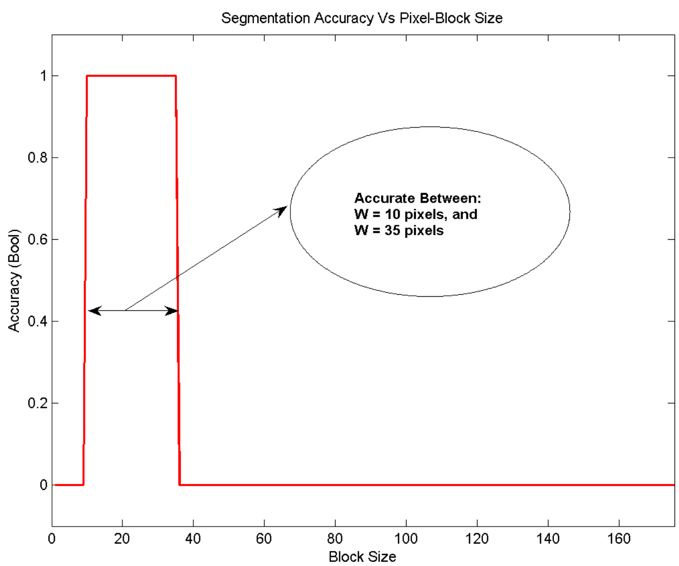

Figure 4. Segmentation accuracy vs the pixel-block size (W)

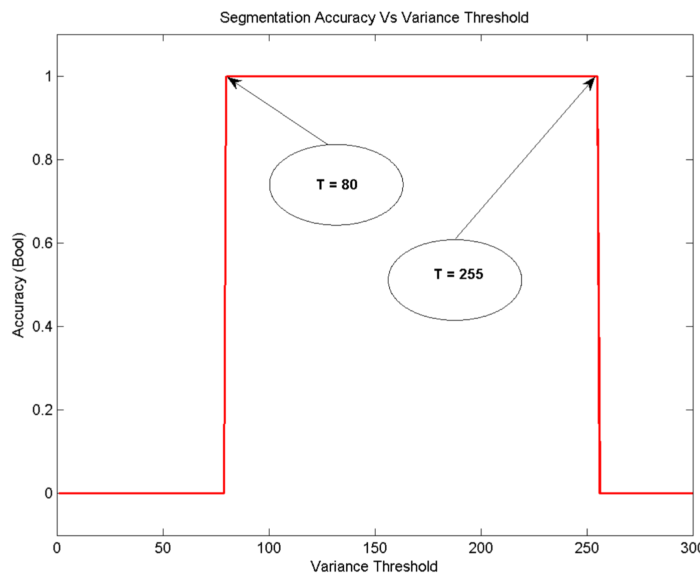

Figure 6. Segmentation accuracy vs the variance threshold

large values of T are expected to do the opposite, that is, some fragments of the foreground are classified as forming part of the background, as depicted in figure 5 (c). A fairly medium value of T is expected to do the trick, as depicted in figure 5 (b). The effect of a range of T values on segmentation accuracy is summarized in figure 6. Looking at figure 6, it is observable that the segmentation accuracy is acceptable in the region where T is anything between 80 and 255. This gives the boundary condition as:

$$255 \geq T \geq 80 \tag{6}$$

D. Recommended Parameters

Considering boundary conditions (4) and (5), it can immediately be inferred that an optimum value for the pixel-block size is in the region given by $35 \geq W \geq 14$. However, because the segmentation accuracy value is expected to be higher at a lower value for the pixel-block size, a value of $W = 14$ is likely to be chosen by most practitioners. Boundary condition (6) begins to suggest that the segmentation accuracy will not be compromised for any value of T between 80 and 255. This therefore implies that, with regard to the gray-level variance threshold, any value in the region of $255 \geq T \geq 80$ is recommended.

V. Algorithm Testing

In order to test the chosen algorithm, fingerprint images from database Db1_a of the 2002 Fingerprint Verification Competition (FVC2002) are used. Based on the experimental outcomes presented above, the testing is done with a gray-level variance threshold, $T = 210$ and pixel-block size, $W = 14$.

A. Normalization Results

The results of the normalization module of the segmentation algorithm prove successful on all the images in the test space. All the images are normalized to have zero mean and unity variance. Figure 7 is an example of an original image and its normalized version.

B. Gray-level Variance Results

The results of the gray-level variance computation module show that this algorithm correctly identifies the variance at the

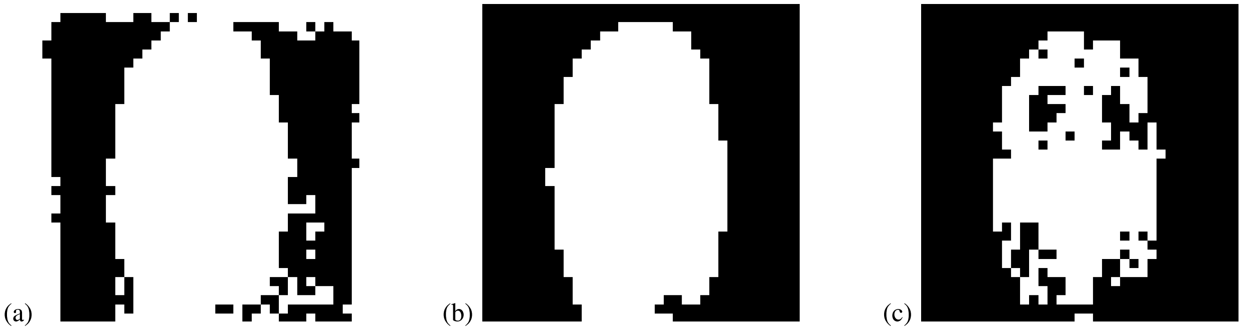

Figure 5. Mask image obtained at (a) $T = 70$ (very small value), (b) $T = 200$ (fairly medium value), and (c) $T = 300$ (very large value). For this experiment, the value of W is constantly kept at 14

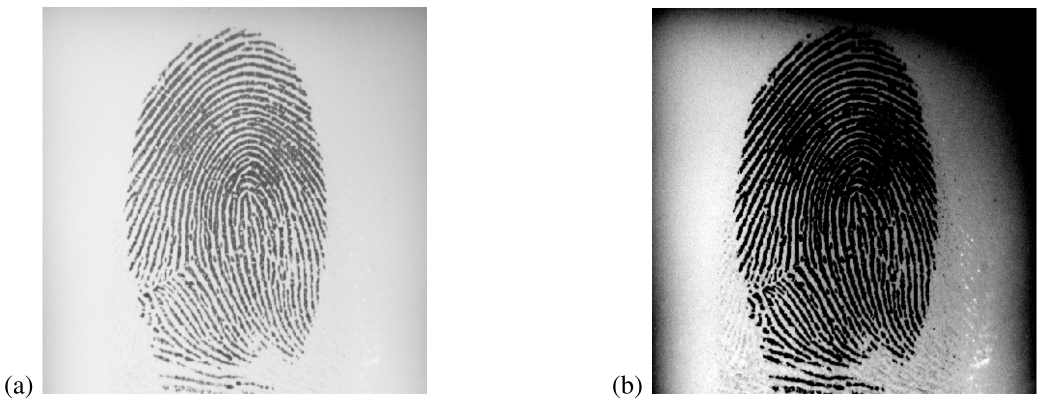

Figure 7. Normalization results: (a) original image, (b) normalized image

right regions of the image. Figure 8 shows an original image, together with the variance image.

C. Masking Results

Figure 9 shows the original image, together with its mask image. The mask image contains only two colors; black and white. The black region is the image background, which should not be further processed during all the subsequent image manipulation stages. It is only the white region that should be included in subsequent processes.

D. Segmentation Results

The ultimate end result of the algorithm is for it to be able to produce a segmented image. This is an image that only contains the fingerprint area itself, as depicted in figure 10 (b). This outcome is indicative of the fact that the proposed algorithm does achieve its initially intended task.

VI. Possible Improvements

This part of the document serves to present ideas that can further improve the functionality of the chosen segmentation algorithm. The functionality of this algorithm can be improved by including a module that can be employed to compute the gray-level variance threshold at a local level. This implies that, instead of having a global threshold for the use of all the images presented to the system, a threshold will be dynamically computed for each image based on the quality of that image. This module can be implemented through the use of computational intelligence techniques such as neural networks [10]. One advantage of having such a module is an improved segmentation accuracy value, while a possible disadvantage is that it might reduce the performance of the system. Another advantage of this module is that it can be used as a way of preventing bad-quality, irrecoverable images from being processed. This can be done because the variance threshold value of any acceptable-quality image should fall within a certain range of values. If the dynamically computed variance threshold falls outside that range, it then implies that the image is of poor, irrecoverable quality, hence the system should request a re-capture of that image. This will ensure that the system does not waste computing resources on poor quality images.

VII. Conclusion

Image segmentation was introduced as an important process that serves to separate the fingerprint area from the rest of the fingerprint image. Given its importance, it should form part of the early fingerprint processing stages. In this study, the computational cost is identified as one of the important drivers. One of the existing challenges was identified as the lack of an objective measure to quantify the accuracy of a segmentation algorithm, hence the idea of having inspection guidelines was introduced.

The chosen algorithm uses the idea of gray-level variance to separate the image foreground from the background. The

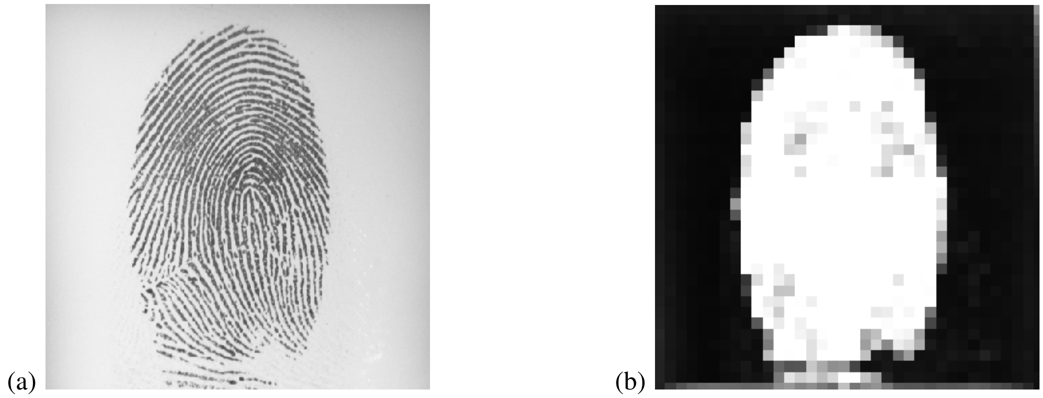

Figure 8. Variance results: (a) original image, (b) variance image

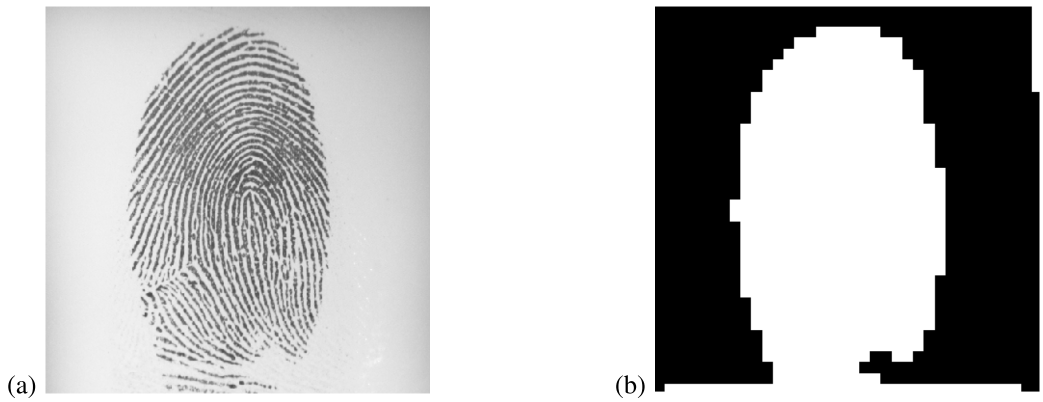

Figure 9. Masking results: (a) original image, (b) mask image

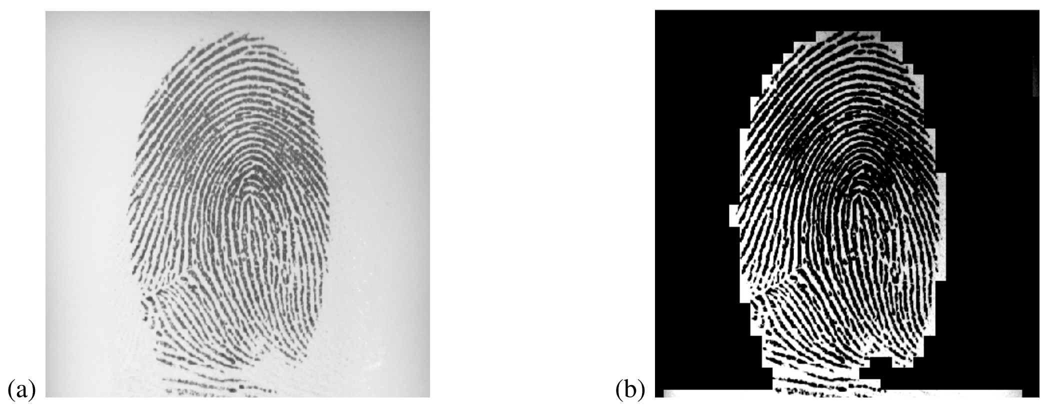

Figure 10. Segmentation results: (a) original image, (b) segmented image

foreground has a high variance value, while the background has a lower value. Critical analysis of the algorithm suggested a pixel-block size of 14 and a threshold of anything between 80 and 255. Fingerprint images in database Db1_a of the FVC2002 were used to test the algorithm and it proved and demonstrated that the choice of the two variable parameters should be well-informed and carefully chosen. A module for the local, dynamic computation of the variance threshold was suggested as a possible improvement of the segmentation algorithm.

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