# A Region Growing Method Based on Statistical Attributes of Infrared Images for Finger Vein Pattern Extraction

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*Abstract-* In this paper a method for finger vein pattern extraction from infrared images of human finger is proposed. The finger vein pattern is extracted by the execution of a two-step region growing procedure, based on statistical properties of derivatives of the acquired infrared images. Initially, original image is filtered by four different Gaussian kernels (in order to take into account the different orientations of veins). Afterwards, the second partial derivatives of the obtained images are computed. Sequentially, the Hessian matrix of these images is constructed and its eigenvalues are computed in a pixel by pixel basis. The minimum eigenvalue and the absolute value of its gradient comprise the two characteristics (features) used in the two step region growing procedure which follows. The region growing procedure is restricted by statistical attributes such as the mean value and the standard deviation of the segmented regions (vein and tissue) and the mean value and the standard deviation of the gradient of the minimum eigenvalue image. Due to the occurrence of some misclassifications a final post processing step, based on morphological operations, is performed. The developed method achieves to efficiently segment the image despite of intensity variations which are evident in the original image. Moreover, an improved version of the proposed method, which uses the multidirectional response of a specially designed matched filter and its gradient as the two features used in the two stage region growing procedure, is also presented. The modified version, as experimental results show, outperforms the classic version and leads to more robust finger vein pattern extraction.

Keywords- Vein Pattern; Region Growing; Hessian Matrix; Eigenvalue; Gradient; Matched Filter; Morphological Postprocessing

#### I. INTRODUCTION

The problem of finger vein extraction arises mainly for biometrics purposes but it is also very important for the biomedical research community. A low number of studies have been presented in the literature due to the small time distance from the first corresponding work.

In the pioneering work of Park et al.<sup>[1]</sup>, an application specific processor for vein pattern extraction and its application to a biometric identification system is proposed. The conventional vein-pattern-recognition algorithm consists of a preprocessing part, applying sequentially an iterative Gaussian low-pass, a high-pass, and a modified median filter and a recognition part which includes the extraction of the binary veins via local thresholding and finally the matching between the individual patterns. Consequently the conventional algorithm <sup>[1, 2, 4]</sup> consists of low pass spatial filtering for noise removal, high pass spatial filtering for emphasizing vascular patterns, thresholding and matching.

An improved vein pattern extracting algorithm is proposed in [3], which compensates the loss of vein patterns in the edge area, gives more enhanced and stabilized vein pattern information, and shows better performance than the existing algorithm. Also, the problem arising from the iterative nature of filtering preprocess is solved by designing a filter that is processed only ones, increasing significantly the recognition speed and reducing the hardware complexity. The proposed algorithm is implemented with a FPGA device and the Fa1se Acceptance Rate shows five times better than the existing algorithm and the recognition speed is measured to be 100 [ms/person].

The problem with conventional hand vascular technology mentioned above is that the vascular pattern is extracted without taking into account its direction. So, there is a loss of vascular connectivity which leads to a degradation of the performance of the verification procedure. An attempt to improve this problem can be found in [5], where a direction-based vascular pattern extraction algorithm based on the directional information of vascular patterns is presented for biometric applications. It applies two different filters: row vascular pattern extraction filter for abscissa vascular pattern extraction, and column vascular pattern extraction filter for effective extraction of the ordinate vascular patterns. The combined output of both filters produces the final hand vascular patterns. Unlike the conventional hand vascular pattern extraction algorithm, the directional extraction approach prevents loss of the vascular pattern connectivity.

Although, the above algorithm considers the directionality of veins, assumes that the veins oriented in only two principal directions. In [6-7] a method for personal identification based on finger-vein patterns is presented and evaluated using line tracking starting from various positions. This method allows vein patterns to have an arbitrary direction. Local dark lines are identified and line tracking is executed by moving along the lines pixel by pixel. When a dark line is not detectable, a new tracking operation starts at another position. This procedure executes repeatedly, so the dark lines that tracked multiple times are classified as veins.

The performance of the above method is strongly related to the number of repetitions. To achieve meaningful results, the

number of repetitions must be large and consequently the computational complexity increases dramatically. Despite these drawbacks  $[^{[8, 9]}$ , this algorithm is still used.

In [9], authors introduce a wide line detector for feature extraction, which can obtain precise width information of the vein and increase the information of the extracted feature from low quality image. They also developed a new pattern normalization model based on a hypothesis that the finger's cross sections are approximately ellipses and the vein is close to the finger surface.

Methods for vein pattern extraction using non-adaptive techniques based on curvlets for multi-scale object representation are presented in [10] and [11]. In [11], the maximum curvature model is adopted to extract the finger-vein pattern with regard the both characteristics of low contrast and intensity inhomogeneity in the infrared vein images. Then, seven moment invariants are extracted to be matched by the Euclidean distance. The problem of high false rate in finger-vein recognition is solved using the single-feature method and the equal weights fusion strategy, the matching scores are fused by the weighted average strategy, and the equal error rate (EER) is minimized to obtain the optimum weights. Finally, the fused matching score is used to make the final decision.

In [12], dyadic wavelet transform is adopted to extract finger-vein pattern from finger images. Images are transformed from spatial domain to wavelet domain, and wavelet coefficients of the vein patterns and the noise are processed by soft-thresholding denoising method, which can recover the vein pattern from noisy data. Then modified moment invariants are computed as the features to represent the vein pattern and matching is performed using Hausdorff distance. Researchers propose different thresholding methods. One of them (local adaptive threshold) is described and used in [13] and [14].

In [15] the authors propose a method based on the position-gray-profile curve. Using local minimal gray-profile-curves across the image for a given line, the local minima are located line by line. Unfortunately, in some cases veins cannot be detected. In low contrast images, veins are not visible in the histogram as peaks. For this reason the algorithm uses six profiles to extract exactly the vein positions associated with high computational complexity.

An innovative method for finger vein image binarization is given in detail in [16]. The main purposes in the developed method are: lower time consuming comparing to other methods, simplicity and promising results achievement in spite of working with low contrast images.

Typically, the infrared images of finger veins are low contrast images, due to the light scattering effect. An algorithm for finger vein pattern extraction in infrared images is proposed in [17]. This algorithm embeds all the above issues and proposes novel preprocessing and postprocessing algorithms. Initially, the image is enhanced and the fingerprint lines are removed using 2D discrete wavelet filtering. Kernel filtering produces multiple images by rotating the kernel in six different directions, focus into the expected directions of the vein patterns. The maximum of all images is transformed into a binary image. Further improvement is achieved by a two-level morphological process, i.e. a majority filter smoothes the contours and removes some of the misclassified isolated pixels, and a reconstruction procedure removes the remaining misclassified regions. The final image has segmented into two regions, the vein and the tissue.

In [18] new issues are considered and a certification system that compares vein images for low-cost, high speed and high precision certification is proposed. The equipment for authentication consists of a near infrared light source and a monochrome CCD to produce contrast enhanced images of the subcutaneous veins. The phase correlation and template matching methods are used for classification. Several noise reduction filters, sharpness filters and histogram manipulations tested for best effort. As a result, a high certification ratio in this system obtained.

In [14], the theoretical foundation and difficulties of hand vein recognition are introduced at first. Then, the optimum threshold of the segmentation process and the vein-lines thinning problem of infrared hand-images are deeply studied, followed by the presentation of a novel estimator for the segmentation threshold and an improved conditional thinning method. The method of hand vein image feature extraction based on end points and crossing points is studied initially, and the matching method based on a distance measure is used to match vein images. The matching experiments indicated that this method is efficient in terms of biometric verification.

However, the finger vein technology, as mentioned above, has important applications and in biomedical field from which is originated from. An initial work for localizing surface veins via near-infrared (NIR) imaging and structured light is presented in [19]. The eventual goal of the system is to serve as the guidance for a fully automatic (i.e., robotic) catheterization device. The proposed system is based upon near-infrared (NIR) imaging, which has previously been shown effective in enhancing the visibility of surface veins. The vein regions in the 2D NIR images located using standard image processing techniques. A NIR line-generating LED module used for to implement structured light ranging and construct a 3D topographic map of the arm surface. The located veins are mapped to the arm surface to provide a camera-registered representation of the arm and veins.

Also in [20, 21], a Vein Contrast Enhancer (VCE) has been constructed to make vein access easier by capturing an infrared image of veins, enhancing the contrast using software, and projecting the vein image back onto the skin. The VCE also uses software to align the projected image with the vein to 0.06 mm. Clinical evaluation of earlier monitor-based vein enhancement test systems has demonstrated the clinical utility of the infrared imaging technology used in the VCE.

In [22], a finger-vein verification system using the mean curvature that can be used for personal verification is proposed. As a robust extraction method, authors propose the mean curvature method, which views the vein image as a geometric shape and finds the valley-like structures with negative mean curvatures. When the matched pixel ratio is used in matching vein

patterns, experimental results show that, while maintaining low complexity, the proposed method achieves 0.25% equal error rate, which is significantly lower than what existing methods can achieve.

In this paper a finger vein pattern extraction method, based on a two-step region growing procedure is presented. The region growing procedure is restricted by statistical attributes such as the mean value and the standard deviation of the segmented regions (vein and tissue) and the mean value and the standard deviation of the gradient of the minimum eigenvalue image. The minimum eigenvalue obtained from the analysis of Hessian matrix for every pixel. The output of this region growing procedure is the initial segmentation result. Due to the occurrence of some misclassifications in this image, a final post processing step, based on morphological operations, is performed. The developed method achieves to efficiently segment the image despite of intensity variations which are evident in the original image. Moreover, an improved version of the proposed method, which uses the multidirectional response of a specially designed matched filter and its gradient as the two features used in the two stage region growing procedure, is also presented.

The remaining of this paper is organized as follows. Section II presents the classic and the improved version of the two step region growing procedure while in Section III both versions of the method are evaluated and the experimental results are shown. Finally, Section IV contains some conclusions extracted from this study.

### II. METHOD DESCRIPTION

The developed method can be used (as mentioned above) either for biomedical or biometrics purposes and consists of eight steps which are presented in the flowchart shown in Fig. 1.

Step A. Image acquisition and Region of Interest extraction

Step B. Preprocessing

Step C. Compute minimum eigenvalue image and its gradient

Step C.1 Compute the second partial derivatives of preprocessed images

Step C.2 Construct Hessian matrixes

*Step C.3* Find eigenvalues

*Step C.4* Compute the gradient of the minimum eigenvalue image



Fig. 1 The flowchart of the proposed method

Step D. Initial segmentation of the minimum eigenvalue image by global thresholding

Step E. Compute the mean value and the standard deviation of the segmented regions

Step F. Compute the mean value and the standard deviation of the gradient image

#### Step G. Region growing

Step G.1 Initial seed generation based on mean values of two regions

Step G.2 Iterative region growing based on statistical properties of the minimum eigenvalue image and its gradient and spatial restrictions

Step G.3 Iterative region growing based on statistical attributes of the minimum eigenvalue image and spatial restrictions

Step H. Post processing

Step H.1 Directional morphological filtering

Step H.2 Morphological neighbourhood filtering

### A. Image Acquisition and Region Of Interest Extraction

The infrared digital image acquired using a low-cost CCD camera. The finger is placed between the camera and an array of infrared leds (five elements) with adjustable illumination. Haemoglobin, a substance of blood, has strong absorbance in infrared wavelengths. Thus, veins, which carry blood, have strong absorption of light and are related to the darker regions of the image. The goal of our study is to extract these dark regions from the background consists of other human tissues. The original image is shown in Fig. 2 (the original image obtained by the Study [6], [7]). The image after ROI extraction is shown in Fig. 3. A ROI extracted from the original acquired image in order to isolate the background which does not contain any useful information and to emphasize in our target which is a robust segmentation of infrared image of the finger in two regions (vein and tissue).



Fig. 2 Original image



Fig. 3 Image after ROI extraction

## B. Preprocessing

ROI image is convolved with four Gaussian kernels, constructed in order to take into account the directional attributes of veins. It is obvious from the acquired images that the veins travel horizontally from left to right and they form small angles with the horizontal axis. So, the Gaussian kernels have the form:

$$G = \frac{1}{2 \cdot \pi \cdot \sigma^2} \cdot e^{-\frac{x^2 + y^2}{2 \cdot \sigma^2}},\tag{1}$$

where  $\sigma$  is the standard deviation which depends on the vein's diameter. In our experiments the vein diameter has the value of 11, so an appropriate value for  $\sigma$  is used. Four Gaussian kernels of the size *11x11* are constructed. Their spectrums are shown in the Fig. 4.





Fig. 4 Gaussian filter kernels' spectrums

## C. Compute Minimum Eigenvalue Image and Its Gradient

Our aim is to look for features which are independent of variations in image intensity. Ridges and peaks are topological descriptors that have this property, and veins expected to be ridge-like. The second directional derivatives describe the variation in the gradient of intensity in the neighbourhood of a point. A ridge is located on top of a line structure where the gradient undergoes large changes and occurs where there is a local maximum in one direction. Therefore it must have a negative second directional derivative and also a zero first directional derivative in the direction across the ridge<sup>[23]</sup>.

## 1) Compute the Second Partial Derivatives of Preprocessed Images:

Original infrared image *I* is convolved with four Gaussian kernels *Gxx*, *Gxy*, *Gyx*, *Gyy* one for each expected vein's direction. The filtered images are denoted respectively as *IGxx*, *IGxy*, *IGyx* and *IGyy*. Thus:

$$IGxx = I * Gxx$$

$$IGxy = I * Gxy$$

$$IGyx = I * Gyx$$

$$IGyy = I * Gyy$$
(2)

where \* denotes the convolution of image I with the Gaussian kernel.

The second directional partial derivatives, used in the construction of Hessian matrix, obtained using the following approximations:

$$Ixx = \frac{\partial^2 IGxx}{\partial x^2} = \frac{IGxx(x+dx,y) - 2 \cdot IGxx(x,y) + IGxx(x-dx,y)}{dx^2}$$

$$Ixy = \frac{\partial^2 IGxy}{\partial x \cdot \partial y} = \frac{IGxy(x+dx,y+dy) - IGxy(x+dx,y-dy) - IGxy(x-dx,y+dy) + IGxy(x-dx,y-dy)}{4 \cdot dx \cdot dy}$$

$$Iyx = \frac{\partial^2 IGyx}{\partial y \cdot \partial x} = \frac{IGyx(x+dx,y+dy) - IGyx(x+dx,y-dy) - IGyx(x-dx,y+dy) + IGyx(x-dx,y-dy)}{4 \cdot dy \cdot dx}$$

$$Iyy = \frac{\partial^2 IGyy}{\partial y^2} = \frac{IGyy(x,y+dy) - 2 \cdot IGyy(x,y) + IGyy(x,y-dy)}{dy^2}$$
(3)

#### 2) Construct Hessian Matrixes:

In order to obtain useful information from the partial derivatives, a 2x2 Hessian matrix is constructed for each pixel:

$$H = \begin{bmatrix} Ixx & Ixy\\ Iyx & Iyy \end{bmatrix}$$
(4)

Since Ixy = Iyx the Hessian matrix is symmetrical with real eigenvalues and orthogonal eigenvectors which are rotation invariant <sup>[24]</sup>.

## 3) Find Eigenvalues:

The eigenvalues of the Hessian matrix,  $\lambda_1$  and  $\lambda_2$ , measure convexity and concavity in the corresponding eigendirections. A ridge is a region where  $\lambda_1 \approx 0$  and  $\lambda_2 \ll 0$ . Therefore, we are interested in the minimum eigenvalue. The sign is an indicator of brightness darkness. The magnitude of this eigenvalue is designated as the Feature  $\lambda$ . Fig. 5 shows the minimum eigenvalue image and its histogram.



Fig. 5 The minimum eigenvalue image and its histogram (The image has enhanced by a factor of 3 for visualization purposes)

#### 4) Compute the Gradient of the Minimum Eigenvalue Image:

From the above analysis, the Hessian matrix is constructed for every pixel, and the minimum eigenvalue is selected. The result of this process is an image which is called the minimum eigenvalue image and is denoted as *Lmin*. This image is used as the first feature for the region growing procedure. The second feature is the magnitude of gradient of the minimum eigenvalue image which is computed as follows:

$$GradL\min = |\nabla L\min| = \left|\frac{\partial L\min}{\partial x} + \frac{\partial L\min}{\partial y}\right|$$

where

$$\frac{\partial L\min}{\partial x} = \frac{L\min(x+dx, y) - L\min(x, y)}{dx}$$

and

$$\frac{\partial L\min}{\partial y} = \frac{L\min(x, y+dy) - L\min(x, y)}{dy}$$
(5)

The gradient image and its histogram are shown in Fig. 6.



Fig. 6 The magnitude of gradient of minimum eigenvalue image and its histogram (The image has enhanced by a factor of 5 for visualization purposes)

## D. Initial Segmentation of the Minimum Eigenvalue Image by Global Thresholding

The minimum eigenvalue image is divided in two regions by global thresholding obtained using Otsu's method <sup>[25]</sup>. The pixels which have greater values than the computed threshold are considered as veins. The remaining pixels are considered as tissue. This procedure results in the initial segmentation of the minimum eigenvalue image in two regions (vein and tissue). Otsu's method is selected for thresholding the image because it is simple, full automatic and performs well. Alternately, instead of Otsu's there is a variety of thresholding methods that could be used.

## E. Compute the Mean Value and the Standard Deviation of the Segmented Regions

After the initial segmentation of the minimum eigenvalue image, this image has been segmented in two regions (vein and tissue) each of them has different statistical attributes such as mean and standard deviation. In this step the mean value and the standard deviation both of the vein and the tissue region are computed. The mean value and the standard deviation of the vein and tissue region are denoted as  $\mu_{vein}$ ,  $\sigma_{vein}$  and  $\mu_{tissue}$ ,  $\sigma_{tissue}$  respectively. The mean values and standard deviations are computed using the preceding formulas:

$$\mu_{vein} = \frac{1}{N} \cdot \sum_{i=1}^{N} vein(i), \ \sigma_{vein} = \left(\frac{1}{N-1} \cdot \sum_{i=1}^{N} (vein(i) - \mu_{vein})^2\right)^{1/2} \text{ and}$$

$$\mu_{tissue} = \frac{1}{N} \cdot \sum_{i=1}^{N} tissue(i), \ \sigma_{tissue} = \left(\frac{1}{N-1} \cdot \sum_{i=1}^{N} (tissue(i) - \mu_{tissue})^2\right)^{1/2}.$$
(6)

#### F. Compute the Mean Value and the Standard Deviation of the Gradient Image

Then the mean value and standard deviation of the gradient image is computed using the above formulas:

$$\mu_{gradient} = \frac{1}{N} \cdot \sum_{i=1}^{N} gradient(i) , \quad \sigma_{gradient} = \left(\frac{1}{N-1} \cdot \sum_{i=1}^{N} (gradient(i) - \mu_{gradient})^2\right)^{1/2}. \tag{7}$$

## G. Region Growing

The labelling algorithm is designed using information from the histograms of the images *Lmin* and *GradLmin* and spatial information from the 8-neighbouring pixels. The growing for both classes, at the first stage, is restricted to regions with low gradients, allowing rapid growth of regions outside of the boundaries, and allowing veins to grow where the values of *Lmin* lie within a wide interval.

#### 1) Initial Seed Generation Based on Mean Values of Two Regions:

The region growing algorithm begins by considering as seeds for its region those pixels that satisfies a specific condition. So, a candidate pixel is considered as vein seed if its value is greater than or equal to the mean value of the vein region and as tissue seed if its value is smaller than or equal to the mean value of the tissue region. Thus:

vein seed=pixel (i,j), 
$$if(L\min(i,j) \ge \mu_{vein})$$

tissue seed=pixel(i,j), 
$$if(L\min(i,j) \le \mu_{tissue})$$
 (8)

These conditions provide pixels with high probability to belong to one or another class. The initial seeds are shown in Fig. 7 that follows. In this figure vein seeds are white, tissue seeds are gray and black are pixels that have not been classified yet.



Fig. 7 Initial seeds

2) Iterative Region Growing Based on Statistical Properties of the Minimum Eigenvalue Image and His Gradient and Spatial Restrictions:

In this step the vein and tissue region are growing based on the following conditions:

 $if((L\min(i, j) \ge \mu_{vein} - 2 \cdot \sigma_{vein}) \& (GradL\min(i, j) \le \mu_{gradient} + \sigma_{gradient}) \& (N_{vein} \ge 1)) \text{ the pixel (i,j) is considered as vein.}$ 

 $if((L\min(i, j) \le \mu_{itssue} + 2 \cdot \sigma_{itssue}) \& (GradL\min(i, j) \le \mu_{gradient} + \sigma_{gradient}) \& (N_{itssue} \ge 1)) \text{ the pixel } (i,j) \text{ is considered as tissue.}$ 

 $N_{vein}$  and  $N_{tissue}$  are the number of neighbours of the pixel (i,j) which has been characterized as vein or tissue respectively.

These conditions restrict the growing in regions with low gradient values. This step is repeated until no more pixels can be aggregated in either region. The result is shown in Fig. 8.



Fig. 8 Region growing based on statistical properties of the minimum eigenvalue image and his gradient and spatial restrictions

3) Iterative Region Growing Based on Statistical Attributes of the Minimum Eigenvalue Image and Spatial Restrictions:

The second stage of the region growing procedure lies only on statistical attributes of the two regions and on spatial restrictions. Unlike the previous stage of region growing procedure here the growing does not restrict by the gradient values. The pixel (i,j) here is aggregated in a region if it satisfies the desired condition. The conditions for the two classes are:

 $if((L\min(i, j) \le (\mu_{vein} + \sigma_{vein})) \& (L\min(i, j) \ge (\mu_{vein} - \sigma_{vein}))) \text{ the pixel } (i,j) \text{ is considered as vein.}$ 

 $if((L\min(i, j) \le (\mu_{tissue} + \sigma_{tissue})) \& (L\min(i, j) \ge (\mu_{tissue} - \sigma_{tissue})))$  the pixel (i,j) is considered as tissue.

Also this stage is iterative and it converges when no more pixels can be classified in each region. The segmented regions can be seen in Fig. 9.



Fig. 9 The final result of the region growing procedure

## H. Post Processing

The result of the two-step region growing procedure is adequate for visualization purposes compared with the original ROI image. However, this result could be used for disease treatment or for pattern matching. In such cases the misclassifications may cause trouble in the preceding operations. So, a final post processing step is usually required. This step consists of two morphological sub-steps. Firstly, a directional morphological filtering is performed and then a morphological neighbourhood filtering is applied.

## 1) Directional Morphological Filtering:

In order the image to be cleaned from large regions which have been erroneously classified as veins, the fact that veins orientates mainly in the horizontal direction and forms small angles with the horizon is exploited. So, in the segmented image are performed five morphological openings with different line structuring elements. These elements have 11 pixel length and they orientated in different directions (form with horizon angles of 0, 30, 60, 120 and 150 degrees respectively). The final result of the region growing procedure and the five morphological openings are shown in Fig. 10.



Fig. 10 Final result of the region growing procedure and morphological openings in five different structuring elements

A structuring element that forms with horizon an angle of 90 degrees is excluded from the above morphological opening procedures because veins do not direct in the vertical direction and this helps us to clean the image from erroneous regions. Finally, the logical OR of those five openings is computed and is shown in Fig. 11.



Fig. 11 The logical OR image of the five morphological openings

## 2) Morphological Neighbourhood Filtering:

Although the main erroneous regions have been sufficiently removed by using the above procedure there are still some outliers in the binary image. These are removed by the application of a morphological neighborhood filter called majority. This filter sets a pixel to 1 if five or more pixels in its 3-by-3 neighborhood have the value 1 otherwise, it sets the pixel to 0. The filtering process is applied iteratively until the output image in two successive steps remains unchanged. This filtering process removes the small miss-classified regions, which appears in image. The image after the application of the iterative majority filter is shown in Fig. 12. This image is the final extracted finger vein pattern.



Fig. 12 Output of majority filter. Extracted finger vein pattern

#### Improved method

An improvement of the above method is achieved by using the maximum multidirectional response of a specially designed matched filter and its gradient as the two attributes of the two stage region growing procedure.

A symmetrical filter kernel of size  $w \times w$  with odd number of coefficients is designed in a manner that represents the intensity distribution across a cross sectional profile of vein. The centre element has the minimum negative value and the value of the neighbour elements is increasing by one ensuring that the sum of the values of all elements belonging to the same line would be zero. The number of the negative elements represents the width of the cross sectional profile of vein. If *w* is even the number of negative elements is w+1. If *w* is odd the number of negative elements is *w*. The coefficients of the designed filter are given by the following formula:

$$K_{f}^{w}(x, y) = \begin{cases} x - w \frac{w+1}{2w+1}, & 0 \le x \le w \land -w \le y \le w \\ -x - w \frac{w+1}{2w+1}, & -w \le x < 0 \land -w \le y \le w, \\ 0, & \text{otherwise} \end{cases}$$
(14a)

if w is odd.

$$K_f(x) = \begin{cases} x - 0.5w - 0.25, & x \ge 0\\ -x - 0.5w - 0.25, & x < 0 \end{cases}$$
(14b)

if w is even.

In order to detect a vein with large diameter the number of negative elements should be large. In this paper, multiscale analysis has been adopted, in order to detect veins with various diameters. All kernel lines are the same. This fact orientates a filter in a specific direction. Filter spectrum is similar with the intensity distribution across a cross sectional profile of a vein because the absorption of light by blood is higher than by the other human tissues.

The maximum response along multiple scales is computed as:

$$M_{f}(x, y) = \max_{w_{\min} \le w \le w_{\max}} M_{f}^{w}(x, y) = \max_{w_{\min} \le w \le w_{\max}} I(x, y) \otimes K_{f}^{w}(x, y).$$
(15)

Fig. 13 shows the maximum multidirectional response of the multiscale matched filter designed using the methodology described above, while Fig. 14 shows the gradient of this response. Fig. 15 shows the initial seeds for the two regions (vein, no vein) which produced using the same conditions as in the classic version and they depicted using the same colours. The segmented image produced after the application of the two stage region growing procedure is shown in Fig. 16. In Fig. 17, the segmented image and the five morphological openings are shown, while Fig. 18 shows the logical OR of the five morphological openings. Finally, Fig. 19 shows the output of the majority filter which is the extracted, by the proposed method, finger vein pattern.



Fig. 13 Maximum multidirectional response of a specially designed multiscale matched filter



Fig. 15 Initial Seeds



Fig. 14 Gradient of maximum multidirectional response of a specially designed multiscale matched filter



Fig. 16 Segmented image (output of the two stage region growing procedure)













Fig. 17 Segmented image and the five morphological openings



Fig. 18 Logical OR of the five morphological openings



Fig. 19 Output of the majority filter, finger vein pattern

#### III. EXPERIMENTAL RESULTS

#### A. Artificial Image Database

A quantitative evaluation of the proposed algorithm in real infrared images is difficult obtained due to the absence of manual segmentation data. The extremely low-contrast images increase the disagreement of human annotation. Therefore, the proposed method is evaluated using a small set of images each one created according to the following procedure. This construction involves the multiplication of two different layers. The first layer is a vein-like pattern. This pattern consists of connected lines of different widths with junctions and bifurcations which drawn by hand. The second layer is the non uniform image background which created by applying an iterative spatial low pass Gaussian filter with large window size to the original infrared image. The multiplication of the two layers gives the artificial infrared image used in the experiments.

#### B. Evaluation Rates

In the finger vessel segmentation process, each pixel is classified as tissue of vessel. Consequently, there are four events, true positive (TP) and true negative (TN) when a pixel is correctly segmented as a vessel or non-vessel, and two misclassifications, a false negative (FN) appears when a pixel in a vessel is segmented in the non-vessel area, and a false positive (FP) when a non-vessel pixel is segmented as a vessel-pixel.

Two widely known statistical measures are used for algorithm evaluation: sensitivity and specificity, which are used to evaluate the performance of the binary segmentation outcome. The sensitivity is a normalized measure of true positives, while specificity measures the proportion of true negatives:

$$sensitivity = \frac{TP}{TP + FN},$$
(9)

$$specificity = \frac{TN}{TN + FP}.$$
(10)

The tradeoff between the two measures is graphically represented with the receiver operating characteristic curve (ROC), which is a plot of the sensitivity versus 1-specificity. Equivalently, ROC curve can be represented by plotting the true positive rate (TPR) versus the false positive rate (FPR). These rates are the fractions of TPs and FPs:

$$TPR = \frac{TP}{TP + FN} = sensitivity, \qquad (11)$$

$$FPR = \frac{FP}{FP + TN} = 1 - \frac{TN}{TN + FP} = 1 - specificity$$
(12)

The accuracy of the binary classification is defined by:

$$accuracy = \frac{TP + TN}{P + N},\tag{13}$$

where P and N represent the total number of positives (vessel) and negatives (non-vessel) pixels in the segmentation process and is the degree of conformity of the estimated binary classification to the ground truth according to a manual segmentation. Thus, the accuracy is strongly related to the segmentation quality and for this reason is used to evaluate and compare different methods.

## C. Results

Fig. 20 shows the original images (left) and the corresponding finger vein patterns (right) extracted by the application of the proposed method (classic version). Table I summarizes the evaluation rates of the proposed method in the artificial image database, in terms of sensitivity, specificity and accuracy.





Fig. 20 Original images (left), corresponding finger vein patterns (right)

TABLE I EVALUATION RATES (SENSITIVITY, SPECIFICITY, ACCURACY) OF THE PROPOSED METHOD

Image	Sensitivity	Specificity	Accuracy
Fv01.bmp	0.740	0.968	0.913
Fv02.bmp	0.878	0.960	0.942
Fv03.bmp	0.683	0.977	0.904
Fv04.bmp	0.690	0.997	0.926
Fv05.bmp	0.735	0.996	0.942
Fv06.bmp	0.526	0.909	0.828
Fv07.bmp	0.791	0.986	0.950
Fv08.bmp	0.728	0.995	0.942
Fv09.bmp	0.666	0.998	0.920
Fv10.bmp	0.670	0.996	0.919
Mean Value	0.711	0.978	0.919
Standard Deviation	0.091	0.027	0.035

Fig. 21 presents the artificial infrared images (left) and the corresponding finger vein patterns extracted after the application of the proposed method (improved version) while Table II summarizes the evaluation rates in terms of sensitivity, specificity and accuracy.



Fig. 21 Original images (left), finger vein patterns (right)

TABLE II EVALUATION RATES (SENSITIVITY, SPECIFICITY, ACCURACY) OF THE PROPOSED METHOD (IMPROVED VERSION)

Image	Sensitivity	Specificity	Accuracy
Fv01.bmp	0.932	0.953	0.948
Fv02.bmp	0.926	0.967	0.958
Fv03.bmp	0.832	0.976	0.940
Fv04.bmp	0.868	0.990	0.962
Fv05.bmp	0.849	0.990	0.961
Fv06.bmp	0.533	0.892	0.817
Fv07.bmp	0.909	0.981	0.968
Fv08.bmp	0.762	0.994	0.948
Fv09.bmp	0.900	0.985	0.965
Fv10.bmp	0.852	0.990	0.958
Mean Value	0.836	0.972	0.942
Standard Deviation	0.118	0.030	0.045

By observing Table I and Table II and the images and finger vein patterns shown in Figures 12 and 19 respectively, the modified version of the proposed method that uses the maximum multidirectional response of a specially designed matched filter and its gradient instead of the minimum eigenvalue of *Hessian* matrix and its gradient, as the two features used in the two stage region growing procedure, presents higher sensitivity and accuracy in the same levels of specificity and leads to robust finger vein pattern extraction.

#### IV. CONCLUSIONS

In this paper, a two-step region growing method based on statistical attributes of derivative infrared images for finger vein pattern extraction is presented. As the experimental results show this method performs good in spite of variations in image intensity and non uniform illumination which is unavoidable in infrared images with the available technology. The good behavior of the method is due to the usage of information obtained by the derivatives of the initial image. A novel post processing step based on mathematical morphology and on directional properties of the infrared finger images is included in order to remove the erroneous misclassified regions from the segmentation result. The extracted finger vein pattern is robust enough in order to be used in multiple applications such as biomedical imaging and biometrics. In case of biometrics, as pattern can be used either the finger vein pattern shown in Fig. 12 or its thinning version contains one pixel wide veins. This image can be produced by applying a thinning algorithm to finger vein pattern, like the algorithms proposed in [26] (the matching procedure is easiest for a pattern which has one pixel width).

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