

Segmentation and characterization of skin tumors images used for aided diagnosis of melanoma

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Abstract

In this paper, a methodological approach devoted to the segmentation and the characterization of tumors skin lesions is presented. Melanoma is the most malignant skin tumor, growing in melanocytes cells that are responsible of pigmentation. Nowadays, this type of cancer is increasing rapidly. Besides, its related mortality rate increases by more modest and inversely proportional to the thickness of the tumor. Fortunately, this rate can be decreased by an earlier detection and a better prevention. Indeed, the segmentation is very helpful in the lesion shape information extraction and consequently it is an essential step to locate the tumor. In this domain, we have evaluated several techniques for the segmentation of dermatoscopic images like Region growing, thresholding segmentation...etc. All these methods do not separate exactly the lesion from the background. In this work a fast approaches in border detection of dermoscopy pigmented skin lesions images based on multi-level decomposition and on classification method are presented. These methods are tested on a set of 60 dermoscopy images. The obtained results than that the presented method achieves both fast and accurate border detection.

Keywords: Skin lesions; Melanoma; Segmentation; Border detection; multi-level decomposition; classification.



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Introduction

Recently, the melanoma becomes one of the most dangerous diseases. However, the mortality rate can be decreased by either earlier detection or better prevention. It is the eighth most frequently diagnosed cancer in the world and its survival rate is directly related to early diagnoses [1], [2]. The development of computerized image analysis techniques is of paramount importance [5]. The first step in the computerized analysis of skin lesion images is the detection of the lesion border. The importance of border detection for the analysis is two-fold. First, the border structure provides important information for accurate diagnosis. Many clinical features such as asymmetry, border irregularity, and abrupt border cutoff are calculated from the border. Second, the extraction of other important clinical features such as atypical pigment networks, globules, and blue-white areas critically depends on the accuracy of border detection.

Therefore, the separation of lesion from background is a critical early step in the analysis of dermatoscopic imagery. Although most segmentation methods are semi-automatic, requiring an interaction between the user and the software in order to establish the proper segmentation. Several techniques have been reported for segmentation of pigmented lesions, in dermatoscopic or conventional macro images. The most commonly used technique is not a straightforward task due to the great variety of lesions, low contrast between the lesion and the surrounding skin, irregular and fuzzy lesion borders skin types and presence of hair. In this purpose, a variety of image segmentation methods have been proposed, such as thresholding [3], [4], and hybrid algorithms [5], [6].

In this paper, an approach to border detection in dermoscopy images based on the multi-level decomposition and classification method is presented. The rest of the paper is organized as follows: In the First step, we present a multi-level decomposition methodology for edge characterization

to improve the tumors classification. Therefore, the difficulty encountered in analyzing the skin tumors images is related to the interpretation of the tumor type. In the second step, the classification method of tumors skin lesions is presented. Finally, a comparison of some alternative segmentation methods proposed in the literature for image segmentation is performed.

Multi-level decomposition for analysis of the skin tumors

The wavelet decomposition is achieved in the Fourier domain. This decomposition combines both of the frequency appearance study and the time domain study. In this paper, we apply the 2D wavelet decomposition on image. Especially, we will interest on the discrete wavelet study.

In this part, we use the wavelet decomposition for multi-scale edge detection of skin tumors. For this, we use decomposition by a Gaussian filter.

First, the low-pass filter and high-pass filter obtained respectively by Gaussian and Gaussian derivative are used. The low-pass filters and the high-pass filters are defined by the following equation [7]:

$$H(\omega) = \frac{1}{2} \left(1 + \cos\left(\frac{\omega}{2}\right) \right)$$

In Fourier Domain the filters are defined by the following equation [7]:

$$F_{x,y}(\omega) = \frac{\partial}{\partial \omega_x} H(\omega) \quad F_{y,x}(\omega) = \frac{\partial}{\partial \omega_y} H(\omega)$$

Figure 1 illustrates the filters shape in the Fourier domain for different scales.

When the image is filtered on the scale, we will obtain a gradient vector according the x direction and according the y direction. Indeed, in low frequencies, the image is filtered and only the major variations are detected. Contrary, when the scale increases the high-pass filter takes the most important frequencies. In this situation, we can distinguish the smallest variations. **Figure 3** represents the wavelet decomposition of the skin tumors illustrated in **figure 2**. The edge is obtained by thresholding operation to keep only the borders.

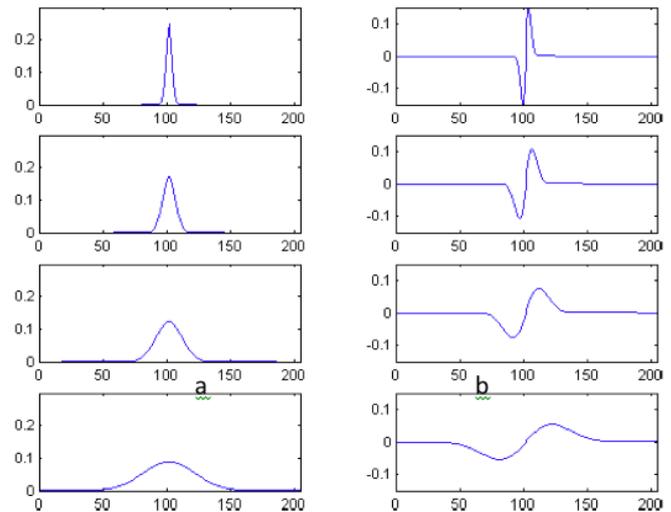


Fig. 1. Figure illustrates different filters shape in the Fourier domain, a: real part of the low-pass filters for the scales $j = 4, 5, 6$ and 7 , b: imaginary part of high-pass filters ψ for the same scale.



Fig. 2. skin tumors image

The wavelet decomposition result is a gradient vector (x, y) that depends on the scale. Indeed, we obtained an image contained only the edge. To improve the segmentation results, we use threshold operation to obtain only the tumor edge. Then, the different boundaries obtained at different scales are superimposed on the original image (**Fig. 2**).

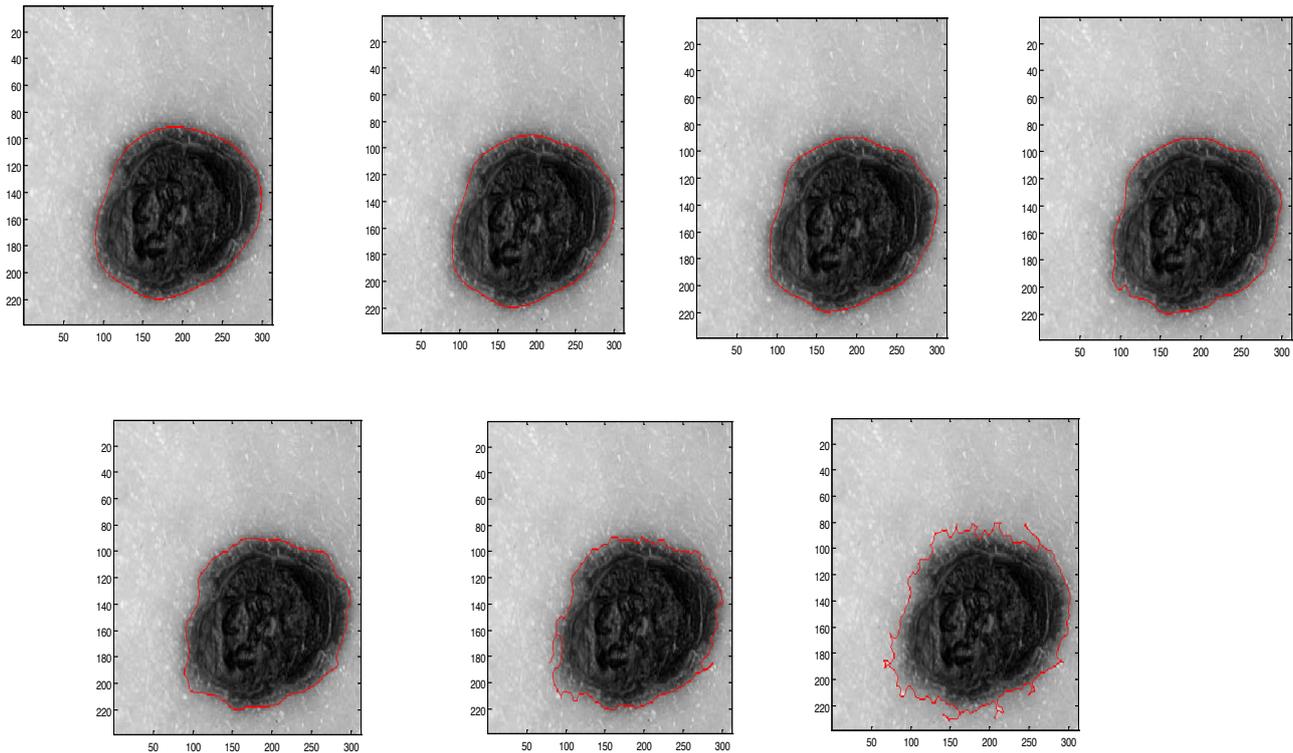


Fig. 3: Edges obtained at the scales 4, 4.5, 5, 5.5, 6, 6.5 and 7.

In our proposed method, the segmentation operation searched to locate only the lesion. The analysis level evolves according to the observation window. The first level provides a “coarse segmentation” and the system has only a vague vision of the lesion (the edge is drawn with the white color). The second level produces an edge which has a great correlation with the edge of the lesion (the edge is drawn with blue color). This level is corresponding to first level analysis. The third level is carried on smaller windows and it provides

a finer edge (the edge is drawn with green color). In addition, the system is more sensitive to the local variations. Indeed, at this scale, we can observe the atypical pigment networks, globules, and blue-white. In the **figure 4**, we present the results that have been obtained.

Segmentation by classification method

A second lesion segmentation method is described. The methodology containing four steps (**fig. 5**):

- Step 1: constitution of the training set.
- Step 2: coding of small images.
- Step 3: classification of this small images.
- Step 4: presentation of the result.

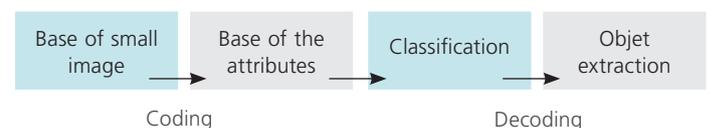


Fig. 5. Figure illustrate the segmentation of the skin tumors by classification method.

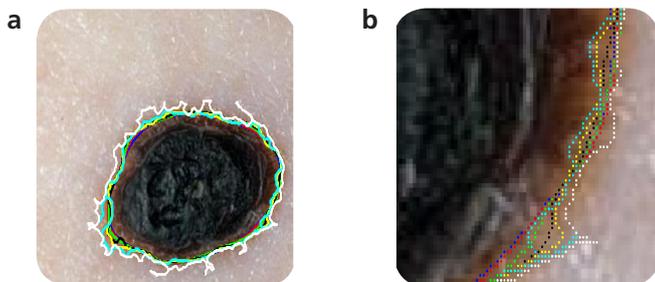


Fig. 4. Superposition of the different boundaries, **a:** Edges obtained for different scales, **b:** a part of image segmented by different scales.

Extraction of statistical descriptors

In the segmentation context, a selection of statistical descriptors is often simple to implement and its can give good segmentation results of skin tumors. In our paper, we have calculated some parameters such as mean, standard deviation, and variance for each small image.

Texture information has always been an important and efficient measure to estimate the structure, orientation, roughness, or regularity of various regions in a set of images that enables us to distinguish between different objects [8]. This is high-level processing that allows us to extract condensed numerical information that will serve as a basis for our classification. In Dermatoscopic images, we can estimate that the measure of the parameters texture between the melanoma and benign lesion is very different. Texture is a property of images that is related to their structural aspect. Haralick [9] have proposed a method to characterize texture in digital images using statistical parameters. This involves extracting 14 different textural parameters from a pre-computed co-occurrence matrix. The co-occurrence matrix is a representation of how pixels are related to their neighbors. It is a square matrix in which the number of columns is the number of grey levels present in the images. Each element (i, j) represents the number of co-occurrences between pixels of grey level i and pixels of grey level j. Co-occurrence matrix is when two pixels are neighbors in a given direction. Four main directions were used: 0, 45, 90, and 135 degrees, giving four different matrices. This definition of the co-occurrence matrix takes into account the orientation of the textural pattern. For example, the parameters computed using the matrix will differ according to the direction chosen in patterns such as lines or grids. However, in our images, the texture is clearly oriented; making oriented texture characterization pertinent. To remove the directional information, two simple methods are possible. The first is to compute the parameters on each of the four matrices and average them. The second is to sum in a single matrix the number of cooccurrences computed in each of the four usual directions, and then compute the parameters using the resulting matrix. We chose the second method for its simplicity and efficiency. The last step is the extraction of the statistical parameters from this single matrix [p_{ij}]. We selected 04 parameters of the 14 proposed by Haralick[9]. Parameters Extracted from Haralick’s Textural Features are:

Correlation: this attribute evaluate the color distribution on the lesion. It consists in describing the evaluation of the color level from the centroid towards the boundary of a lesion.

$$Cor = \sum_{i=0}^{Ng} \sum_{j=0}^{Ng} \frac{(i - \mu_i)(j - \mu_j)}{\sigma^2} p(i, j) \quad (1)$$

Colors homogeneity: this parameter indicates a measurement of the uniformity of the grey levels of the image.

$$CH = \sum_{i=0}^{Ng} \sum_{j=0}^{Ng} \frac{p(i, j)}{1 + |i - j|} \quad (2)$$

Energy: This parameter has a low value when the p(i, j) have very close values and a great value when the p(i, j) values are large.

$$CH = \sum_{i=0}^{Ng} \sum_{j=0}^{Ng} \frac{p(i, j)}{1 + |i - j|} \quad (3)$$

Contrast: This parameter has a important numerical value if the p(i, j) are concentrated except the diagonal.

$$E = \sum_{i=0}^{Ng} \sum_{j=0}^{Ng} [p(i, j)] \quad (4)$$

Classification

We have seen that, in addition to the difficulty of standardizing the diagnosis criteria and the wide variability of the encountered structures, discrimination of some types of lesions remains problematic. A system that allows analysis of tumors would be useful, especially for general practitioners who do not often observe melanomas (one case every four years on average) [10]. Such system is introduced in **figure 5** which presents a general methodology based on segmentation of skin lesion. The previous steps allow a set of texture parameter to be calculated that will describe the tumor. In order to achieve the skin tumors images segmentation, a multilayer neural network with supervised learning algorithms is used [11].

Multilayer neural network

In the multilayer neural network the neurons are arranged by layer. The neurons of the first layer are related to external data and receive the input vector. The characteristic vector of an object is transmitted to all the neurons in the first layer of the neural network. The outputs of the neurons in this layer are then communicated to the neurons in the next layer, and so forth (**figure 6**). The last layer of the network is called the output layer, and the others are hidden layers [12].

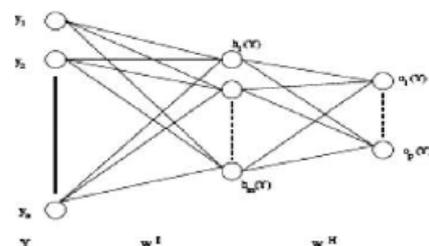


Fig.6: Multilayer neural network.

$Y = (y_1, \dots, y_n)$ where n is the number of input attributes.

$$\forall j \in \{1, 2, \dots, m\} h_j[Y] = \tanh\left(\sum_{i=1}^n w_{ji}^j y_i + w_{j0}^j\right)$$

Where: h : Represents the activation function. w_{ji}^j Is the weight vector connecting the input i and layer j ; w_{j0}^j is the threshold of the hidden unit. m : is the number of units in the hidden layer.

The learning algorithm of multilayer networks, known as the back-propagation algorithm, requires that the activation functions of neurons are continuous and derivable [13, 14]. In our case, the network architecture is defined by six entries units representing different attributes describing the tumors (Correlation, Colors, homogeneity, Energy, Contrast, etc...). The classifier differentiates between skin and tumors. In this case, the back-propagation algorithm minimizes squared error ϵ_r between the desired output and the input. There are a number of arbitrary parameters whose values must be defined for the network to get good performance, in particular, the number of hidden layers and the number of iterations. In our case, the errors ϵ_r are less than 0.1, the number of hidden layers is equal to 1 and the number of iterations which ensure the convergence of the network is equal to 1000 iterations

Results

In this application, we used over 60 images from Joaquim database [15] which has been validated by a survey of dermatologists in the CHUT (University hospital Centre, Tlemcen, Algeria). These selected images represent melanocytic lesions and benign lesion. The used images are in color with a 512 pixel x 486 pixel format. Each tumor of the selected image is located at the center and surrounded by the skin color. These lesions vary in size, shape, color, saturation and in most cases, the margin between the lesion and the surrounding skin is poorly defined clinically, and this introduces sometimes some error decisions. Therefore, the data are arranged according to a desired output calculated from previous steps which represent both cases. The size of the learning vector should be large and represent all data to ensure a good rate of classification.

To better validate the proposed method, we calculate the relationship between the intersection and the union of the initial contour (M) of the exudates segmented manually by a specialist and contours (A) obtained by the proposed method.

$$D = \frac{M \cap A}{M \cup A}$$

D: Resemblance degree (Rd) [16].

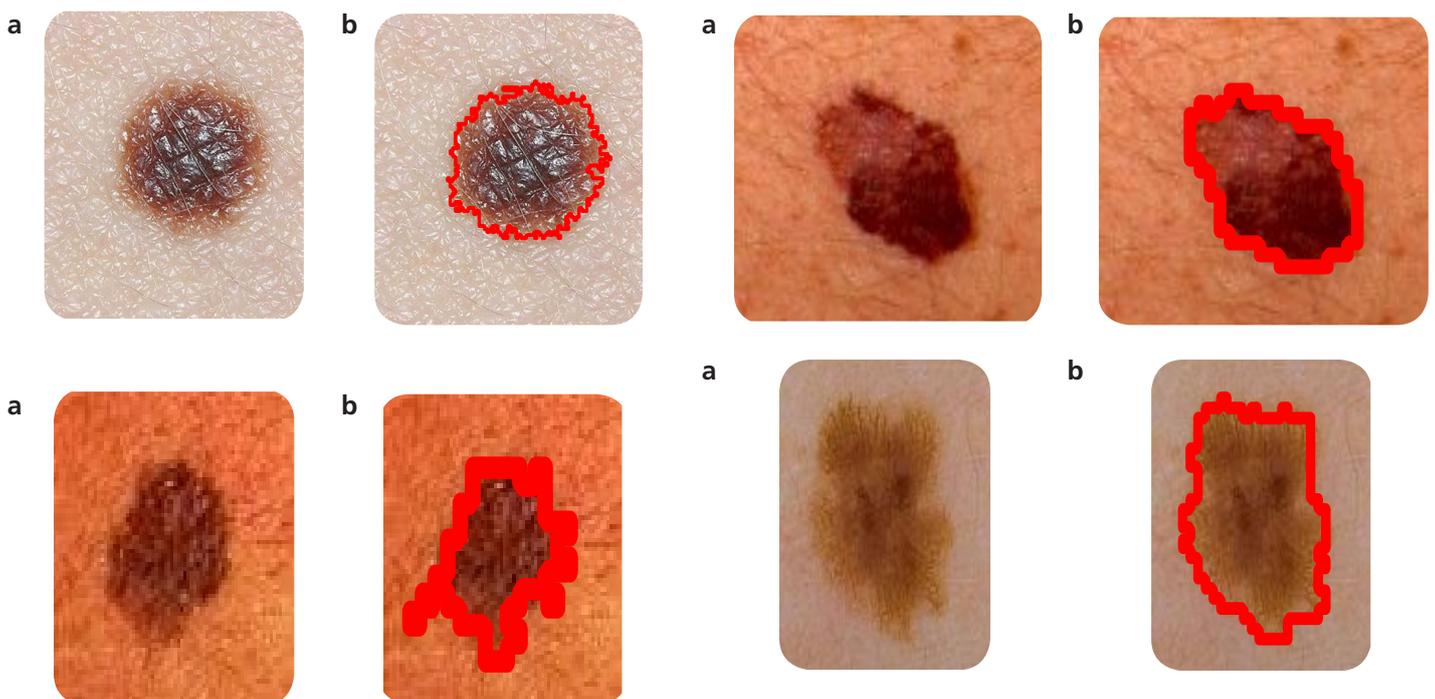


Fig. 6. Segmentation of skin tumor by the classification method, **a**: original image, **b**: segmented image.

The objective of this operation is to quantify the resemblance degree of images which are classified like very good, average and bad (**table 1**).

The calculation of the resemblance degree is illustrated in **table 1**:

Image classification	Bad	Average	Very good
Calculation of D (Rd)	[0 – 0.2]	[0.3 – 0.5]	More than 0.8

Table1. The calculation of the Resemblance Degree.

According to table 1, we can notice that all classified images as very good have a D (Rd) close to 1. Where M is a binary images such all pixels inside the curves produced by a clinical expert and A is the set of all lesion pixels labelled by a classification method. This studies gives the mean, standard deviation border error and shows the performance of the three segmentation methods (Thresholding, region growing and classification method) according to the clinical evaluation (manual method). The classification method was evaluated by a dermatologist and rated in one of three possible labels: Vg-very good, Av-average, B-bad. The manual segmentation was the highest rated method, with all of images rated very good (Vg). The best of the automatic methods was the clas-

sification method, with 75% of images rated very good (Vg). However, the number of bad cases (B=4) was few for both this method. The segmentation methods like Thresholding and region growing are semi-automatic, requiring an interaction between the user and the software in order to establish the proper segmentation. Classification method is adapted to this problem due to its simplicity, computational efficiency, and excellent performance on a variety of image domains.

Conclusion

In this paper, a fast approach to border detection in dermoscopy images based on the classification method and characterization of the border is presented. This approach will be using for extraction efficiency of specific parameters for skin tumors. In this work, the two segmentation methods (multi-level and classification method) was presented in order to localize the tumor and to extract the contour. In this paper we have compared and evaluated different methods for getting adequate segmentation of dermatoscopic images. Our approach based on classification method produced better results. This result is very encouraging as a system based on this segmentation method can provide an acceptable lesion segmentation which requires only a minor intervention from the operator.

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