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Feature Extraction in Medical Images Based on Curvelet Transform

Mohd Shahajad, Manish Kumar Sharma

Department Of Computer Science& Engineering

Galgotias College of Engineering & Technology

India

***Abstract:** Now a day's feature detecting is an important factor in evaluation and diagnosis of skin's activities and diseases. In this paper, a novel skin cancer algorithm in medical images based on Curvelet Transform (CT) and Shape prior is proposed. In this algorithm, to segment the skin's tissue, shape prior and signed distance functions are used to extract variable shape model, and to enhance image and noise removal, applying a nonlinear function on Curvelet Transform coefficients. In this shape-based algorithm, segmentation is carried out using calculating the parameters of shape model to minimize the energy function. Using minimizing of energy function, image divides into two regions, textures with low and high variances, inside and outside of the border curve. The proposed algorithm is evaluated on a standard set of the medical images. Obtained segmentation results show that more precisely of pixels inside of skin's tissue are extracted correctly.*

***Keywords—** Image segmentation, image analysis, Curvelet transforms, shape model, Energy Function.*

I. INTRODUCTION

Nowadays, medical imagery plays an important role in diagnosing and preventing the diseases and complications of various body organs such brain, hear, kidney, liver, and so on. In most cases, tissue segmentation [1] in medical images is the first step in analyzing these images. Using tissue segmentation and extracting the data such as tissue placement, the shape and size of tissue, the relevant diseases can be diagnosed. This study deals with the skin's segmentation in medical images. Ultrasound images have very low qualities, due to the intrinsic noise in such images, compared to images by MRI and CT. But, using this type of imagery is increasing because of non-expensive equipments, rapid and easy imagery. Among common methods used to segment the tissue in medical images, Region Growing method [2], Active Contours method [3] and Active Shape Model [4] can be referenced. Because of the intrinsic noise in medical images, reliability of the region growing method is reduced considerably. The active contour method cannot be used to segment the skin's tissue, because the skin's contour is not separated completely from adjacent tissues and hasn't distinct borders with the adjacent tissues. In the active shape model, the user has to select some points in the image as the guide points and it, in turn, is very difficult and time consuming, and there isn't also reliable automatic algorithm to determine such land-marks. A method using shape prior and region-based segmenting energy functions is given in [5], which can segment the tissue in MRI images very well, but it cannot segment medical images because of the high intrinsic noise in ultrasound images and the lack of appropriate preprocessing in this method. A method based on the shape prior to model the kidney's shape and on Gabor filter bank to extract texture feature and to segment the medical image is given in [6]. In this paper is so that, at first using the shape prior in the training images the shape model of skin cancer is obtained, then Curvelet Transform is used to improve the contrast, to uniform the illumination of image and to reduce the noise as possible as in the skin cancer images. Then by setting the shape model of skin cancer on the test image and using the tissue prior of skin cancer and region-based segmenting energy function, the segmentation is performed. Applying the Curvelet Transform on the image to reduce the noise, improve contrast, enhance edges is one of the advantages of the proposed algorithm. Also the changeable shape model that can be changed by changing some coefficients instead of changing individual pixels on the skin cancer's boundary is effective in ability of the proposed algorithm.

The rest of the paper is organized as follow: In section II, the proposed algorithm is described. The pre-preprocessing phase using Curvelet Transform and a nonlinear function, the shape model extraction method and a region-based model for segmentation are described in this section .The shape modeling method of [7] is also introduced as it is a part of our segmentation scheme for extracting variable shape model of skin cancer. Our conclusions are presented in section III.

II. PROPOSED SKIN CANCER SEGMENTATION ALGORITHM

Fig. 1 shows a summary of the proposed algorithm. In the training phase, a set of training images are used in order to obtain the variable shape model of skin cancer. At first, these images are pointing in the same direction; same center and are approximately equal in size with a reference image in order to be created the maximum alignment between them [11]. Then, using the level-sets method [5], and obtaining the mean shape from training images and a set of eigenshapes, variable shape model of medical iamge is achieved so that by adding average of signed distance functions [7] in training images

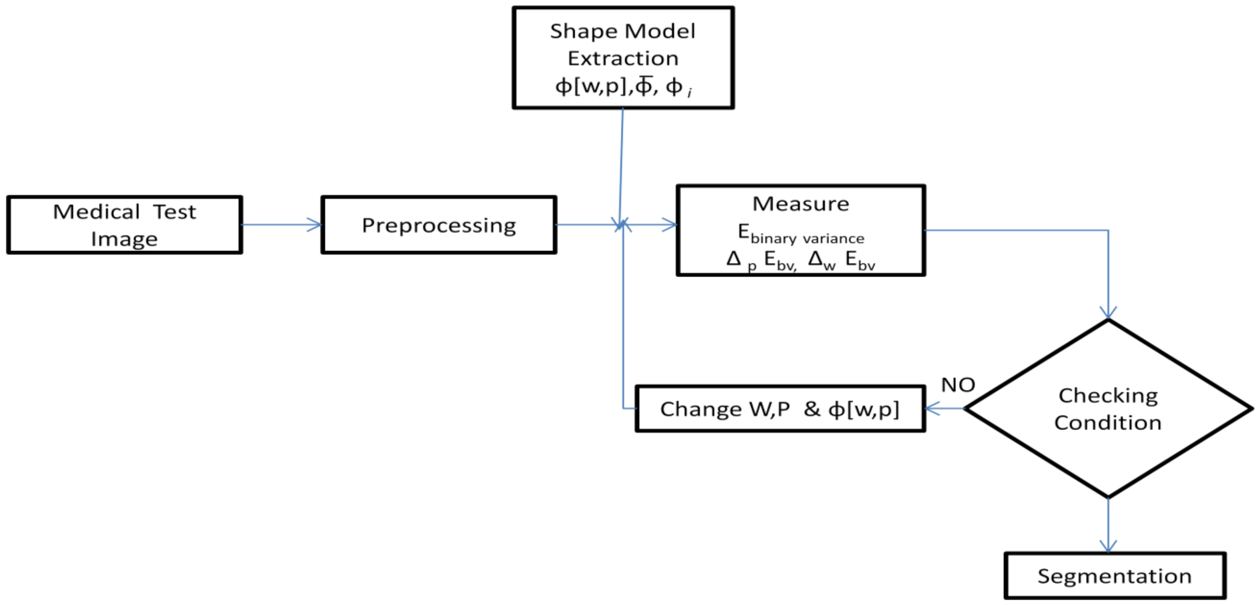

Fig.1.Flow of algorithm

and coefficients of eigenshapes which have the most effect on creating basic changes in the shape model of skin cancer, the variable of skin cancer's shape is achieved, which by changing the coefficients of eigenshapes and transition parameters are extracted. In the pre-processing phase, after examining various filters, the powerful and multi scale Curvelet transform [8] is used to improve the performance of algorithm, improve the contrast, reduce noise and edges enhancement in images from skin cancer test. In this stage, after executing the Curvelet Transform on the image and extracting the coefficients, by implementing the nonlinear function [9] on the Curvelet coefficients, the coefficients related to the noise are weakened and the coefficients related to the desire signal are improved. Now, by reconstructing the improved coefficients, in which the noise reduction is so that the distinction between the skin cancer and the adjacent organs is increased in human's eye, an image with high contrast is achieved. In the segmentation phase, by implementing the shape model on the improved test image and using the tissue prior of skin cancer and region-based segmenting energy function, the segmentation is performed. The energy function of binary variance [10] is used to perform the segmentation. The performance of this energy function is so that divides the images into two regions, one with low variance and the other with high variance, and tries to perform maximum separation between these two regions, in other words, the energy function reaches to its minimum value. It is possible by changing the weight of eigenshapes and transition parameters. The gradient descent method is used to optimize the energy function [10] and updating the weight of eigenshapes and transition parameters. By taking gradients from the energy function with respect of weight of eigenshapes and transition parameters and updating these weights by using the gradient from the energy function [5], the new shape model of skin cancer is created and set on the test image, and then the new energy function and its gradient are achieved. Now, if the stop condition is achieved, i.e. being in minimum value of energy function, the algorithm is stopped, otherwise, the process is repeated.

A. Shape Model Extraction

1. Level Sets:

All the training images must be changed so that the maximum joint alignment is achieved between them [11], Then it is used the level-sets method [5] and signed distance function [7] to extract the final shape model. A signed distance function is defined for each of the images, which is the least Euclidean distance of each pixel to the nearest point on the skin cancer border, which is multiplied in -1 or +1, depending on that the pixel is inside or outside the tissue. Now, we have a set of signed distance functions as $\{\psi_1, \psi_2, \ldots, \psi_k\}$ Also, the average of this signed distance function is defined as:

$$\bar{\Phi} = \frac{\sum_{i=1}^{n} \Psi_i}{n} \qquad (1)$$

Now, by subtracting the average value from individual signed distance functions, the mean offset function is achieved as $(\bar{\Psi}_1, \bar{\Psi}_2, \ldots\ldots\ldots \bar{\Psi}_n)$.

These mean-offset functions are used to capture the variabilities of the training shapes. Now, each of ψ_n is converted to a vector column, then the matrix S is formed by putting all this vectors together. Eigenvectors of matrix S consists of eigenshapes (Φ_i) which are achieved by converting each column of the matrix of eigenvectors to the form of major image. All achieved eigenshapes are not affected in forming the shape model of skin cancer , only a number of them (k number of them) have the major role in creating the basic changes in new shape model. One way to choose the value of k is using the eigenvalue matrix of S, that is, only those eigenshapes are selected which the eigenvalues are among the largest values in the matrix of eigenvalue. Now, using the equation (4) and changing the weights related to the eigenshapes and transition parameters, we are able to create various shapes for skin cancer tissue.

$$\Phi[w,p](x,y) = \overline{\Phi}(\bar{x},\bar{y}) + \sum_{i=1}^{k} \mathrm{wi}\,\Phi\mathrm{i}(\bar{x},\bar{y}) \qquad (2)$$

Where W= $\{w_{1,}\ w_{2,\ldots\ldots}w_k\}$ are the weights for the k eigenshapes, $\overline{\Phi}$ is the average of sign distance functions and Φ_i={ $\Phi_{1,}\ \Phi_{2,\ldots\ldots}\ \Phi_k$} are the most effective eigenshapes.

It is use many number of training images in this paper in order to reach to the shape model of skin cancer in training phase. After calculating the eigenvalues of matrix S for these images, it is selected 8 eigenshapes as the most influencing Fig. 2 and Fig. 3 show the graph related to the eigenvalue of S, and various shape models for skin cancer obtained by changing 12 weights, respectively.

B. Pre-processing:

1. **Curvelet Transform***:*

The Curvelet Transform [8] is considered of new generation multi-scale transforms, which results in a set of coefficients in various directions and scales by applying a specific wavelet in different directions and scales on the image. Each of these set of coefficients, located in a polar wedge, indicates data from image in that scale and direction. The Curvelet coefficients are defined as

$$C(j,l,k) = \frac{1}{(2\pi)^2}\int f(\omega)Uj\ (R_{\theta l},\omega)e^{i}\ \ (x_k^{(j,l)},\omega) \qquad (3)$$

Where, f is Fourier transform of signal and U_j is frequency window applied in frequency domain. U_j is in fact a set of polar wedges covering the image radially and angularly. $R_{\theta l}$ is rotation by$R_{\theta l}$ radian and is defined in the following relation:

$$R_{\theta l} = \begin{bmatrix} \cos\theta l & \sin\theta l \\ -\sin\theta l & \cos\theta l \end{bmatrix} \qquad (4)$$

So, C (j, l, k) is achieved in the scale j, direction l, with the transition parameter k. x and ω are the variables of spatial domain and frequency domain, respectively. R and θ are introduced as polar coordinates in frequency domain. Fig. 4 shows the tiling of Curvelet transform in frequency plane. The Curvelet transform in frequency domain covers approximately parabolic wedges. Shaded area shows one of typical wedges.

C. Applying Local Adaptive Function on Curvelet Coefficients of Image

The parameters for adaptive function [9] are defined (7) based on some statistical characteristics of Curvelet coefficients of input image, which result in Curvelet coefficients to be improved more effectively.

Because of defining the parameters of adaptive function based on statistical characteristics of Curvelet coefficients of input image [9], if we apply the following adaptive function on uniformed image coefficients, the function acts adaptively and adapt itself to each input image and based on statistical characteristics of Curvelet coefficients of that image. In addition to amplify the desired signal, it prevents noise to be increased simultaneously, so the inadequacy of previous methods is resolved.

$$y(x) = \begin{cases} k1(\frac{m}{c})^p & if\ |x| < ac \\ k2\left(\frac{m}{|x|}\right)^p & if\ c \le\ |x| < m \\ k3 & if\ m \le\ |x| \end{cases} \qquad (5)$$

Where, p is the degree of function nonlinearity. K_1, K_2, and K_3 are the coefficients of such function and m is obtained from the following equation:

$$m = k(M_{ij} - \sigma\,) \qquad (6)$$

Where, M_{ij} is the greatest coefficient in specific scale and direction indicating that the coefficients are improved in every band according to their maximum value. C=σ is also standard deviation of estimated noise from image[9], which prevents noise to be increased while amplifying desired signal simultaneously. Two parameters, M_{ij} and C, lead the above function to act adaptively and to adapt itself to different input images. The above function increases the small coefficients more than the bigger ones. This function is applied on the coefficients locally, that M_{ij} is calculated in any specific scale and direction and then the aforesaid function is applied on the coefficients of this polar wedge (frequency band with specific scale and direction), this in turn influences the image more.

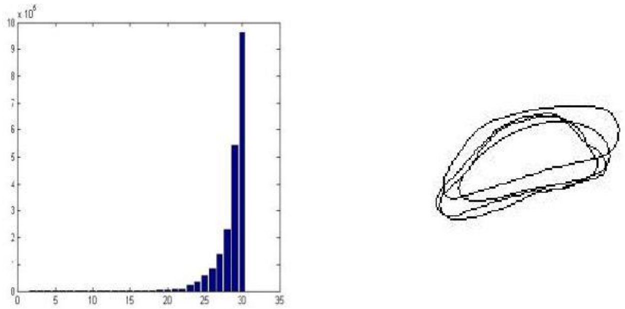

Fig.2. Eigenvalue of matrix S & some skin cancer curves achieved by changing weights of eigenshapes

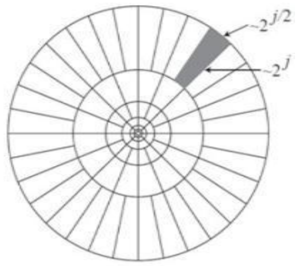

Fig.3. Curvelet tiling of frequency plane.

D. Region-Based Model for Segmentation

1. Energy Function of Binary Variance

Now, the obtained shape model of skin cancer is set on the improved test image, and by changing the shape model, the best segmentation is obtained. Using a region-based segmenting energy function and finding its maximum point, the desired segmentation is achieved. The energy function of binary variance was used after examining various segmenting functions. Dividing the image into two regions, one with high variance and the other with low variance, this function tries to create the most separation and best segmentation between these two regions. Here, the segmentation is based on the variance of image intensity inside the shape model and the regions outside it.

The energy function of binary variance is defined as:

$$E_{bv} = -\frac{1}{2}(\sigma_\mu^2 - \sigma_v^2)^2 \qquad (7)$$

Where σ_μ^2 and σ_v^2 are the variances of image intensity and outside skin cancer tissue, respectively.

2. Optimizing the Energy Function and Updating the Weights:

It was used gradient descent method in order to optimize the energy function [9] and update the weights related to the eigenshapes and transition parameters. By taking gradient from the the energy function and leading the energy function to its minimum value, best segmentation is achieved. The gradient of energy function taken with to w and p, is define as:

$$\Lambda_w E_{bv} = \left(\sigma_v^2 - \sigma_\mu^2\right).\left(\Lambda_w \sigma_\mu^2 - \Lambda_w \sigma_v^2\right) \qquad (8)$$

$$\Lambda_P E_{bv} = \left(\sigma_v^2 - \sigma_\mu^2\right).\left(\Lambda_p \sigma_\mu^2 - \Lambda_p \sigma_v^2\right) \qquad (9)$$

After calculating the energy functions and taking gradient, checking condition of algorithm, means getting the minimum of energy function, is measured. If it has reached, the segmentation is to be performed, otherwise weight are changed [5] by using following equation:

$$w(t+1) = w(t) - \alpha_w \Lambda_w E \qquad (11)$$
$$p(t+1) = p(t) - \alpha_p \Lambda_p E \qquad (12$$

Where α_w and α_p are the constant coefficients of steps of changes, w(t+1) and p(t+1) represents the values of w and p at the i^{th} iteration. Now new weights above steps are repeated with test image.

III CONCLUSION

Since the preprocessing phase plays an important role in final extraction results, applying curvelet transform and a nonlinear function to set the curvelet coefficients on skin cancer image will have a noticeable effect on uniform illumination of the skin cancer image and improving performance of the algorithm. This algorithm was capable of segmenting skin cancer images contain of heavy noise and delineate structures complicated by missing boundaries. In the proposed algorithm for shape modeling, it was used level sets method which is so flexible to extract the shape priors from limited number of image. It is obvious that if the differences in training images are more, presented shape model will be more effective. In this paper, proposed algorithm was applied on 2-D images. However; this algorithm can be easily expanded to apply on 3-D images by using [12]. Considering that the algorithm can segment the skin cancer tissue with high accuracy in nearly good time, it can be used as the fast and reliable method in segmentation of organs in skin images. This work will help improving the efficiency of clinical interpretation of skin cancer detecting.

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