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Extraction of Tumor Region in Color Images Using Wavelets

JIANN-DER LEE* AND YU-LIN HSIAO
Department of Electrical Engineering
Chang Gung University
Tao-Yuan, Taiwan 333, R.O.C.

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Abstract—In this paper, a wavelet-based method is proposed to extract the tumor region from a color medical image. In the past, the diagnosis of tumors usually relied upon the tissue section stained by methylene blue. However, traditional approaches have relied primarily on manual processes and erroneous assessment may arise from subjective judgement and eye measurement. Instead of the previous method, we propose an improved radial search technique to increase the accuracy of the extraction of the tumor border. Experimental results show that the proposed method is fast and can extract the tumor region successfully. Moreover, the results of this research will be helpful in the development of a computer-aided image analysis system that will automate visual feature extraction for tumor evaluation. © 2000 Elsevier Science Ltd. All rights reserved.

Keywords—Color image processing, Wavelet transform, Border extraction.

1. INTRODUCTION

In the application of medical image processing, it is an important task to detect the abnormal region of an organ, independent of position and size. In fact, this capability is fundamental to any automatic diagnostic system, since the post-processing, such classification of an organ into a pathological class, cannot be realized unless the tumor region is identified. An automatic system would also be useful in training students because of its explicit processing strategy.

Although the identification of object and surface boundaries comes naturally to a human observer, accurate color image segmentation has proved to be difficult and complex. Achieving adequate segmentation results depends mainly on devising techniques to detect uniformity among the feature values of the picture points, and then isolating the areas of the picture exhibiting this uniformity. Several techniques have been used to accomplish this, such as edge detection, region growing, histogram thresholding, and clustering. Among these, histogram thresholding and clustering techniques have been extensively used for segmenting the color images. For example, Umbaugh [1] described a computer vision system to serve as the front-end of a medical expert system that will automate visual feature identification for skin tumor evaluation. Ohlander *et al.* [2] suggested a multidimensional histogram thresholding scheme. In their method, the threshold values obtained from three different color coordinate systems RGB, YIQ, and HLS

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*Author to whom all correspondence should be addressed.

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were used to split a region into smaller parts. A 2D clustering technique based on projecting the XYZ normalized color space onto the X-Y, X-I, and Y-I planes was proposed by Underwood and Aggarwal [3]. In this interactive method, rectangular-type broad and refined color bandpass filters are used to detect insect infestations in citrus groves from infrared aerial photographs. Rosenfeld [4] proposed a 3D clustering technique in which the 3D image histogram is stored in a binary tree with the key RGB values and the information of the number of parts associated with these key values. A cluster is detected if the number of points located within some distance from each other exceeds some threshold. A probabilistic relaxation process for initial cell segmentation followed by a color classification process to separate different object types on a liver cell image was proposed by Wu [5].

Color image segmentation is basically a three-dimensional (3D) image clustering technique, which is usually computationally expensive. To speed up the process, instead of using a multi-thresholding technique to segment the color image, a previous solution such as X-transform [6] to this problem is to project the 3D feature space into 1D subspace. Operation of this method can be described as follows. The input image data are mapped from the device coordinates into an approximately uniform perceptual color space, and then projected onto the selected coordinate axis repeatedly until the image clusters are enclosed in some specified decision volume. From each projection of the space, the boundary surface of the decision volume can be determined uniquely. Success of this method mainly relies on the existence of uniformity for 1D clusters in the initial projections of the space.

Also, Lim and Lee [7] proposed an algorithm based on thresholding and the fuzzy c-means techniques for the segmentation of color image. For histogram thresholding techniques, the adaptive thresholding [8] use a scale-space filter (SSF) process to extract the number of peaks and valleys from the histograms. If *a priori* knowledge is available about a particular type of image, we can choose the desired number of peaks and valleys, and the process can be made unsupervised. After histogram analysis, valid classes are determined and each pixel is mapping into a class. Each class represents a different object within the image. These methods include SCT/center split and PCT/3D median split [8]. However, this kind of approach is not suitable for our case because the number of peaks is hard to determine in advance and the region of tumor is not homogenous.

The segmentation process is also considered as a pixel classification process, either supervised or unsupervised. One technique to solve this problem is the use of neural networks due to their superior capability in the classification problem. In early years, Huang [9] described the segmentation problem as minimizing a suitable function for a Hopfield network. Campadelli [10] changed the network initialization and its dynamic evolution of segmentation algorithms for color image segmentation based on Huang's idea. Liu and Yang [11] proposed a multiresolution algorithm for color image segmentation using Markov random field. Their approach is a relaxation process that converges to the maximum *a posteriori* estimate of the segmentation. The multiresolution approach is used to refine the segmentation and the result is encouraging. However, these processes are computationally expensive and cannot detect the accurate tumor boundary if the region is mixed with noise. In addition, Huang *et al.* [12] present an algorithm that combines the SSF and Markov random fields (MRFs) for color image segmentation. The most important feature of the MRFs is that the probability of a particular site to assume a certain value depends only on its neighbors, and not on the whole image. So, this approach based on MRFs can effectively estimate the edge in the image. However, since the closed contour is needed for area measurement, some other methods such as deformable line models must be used to achieve this requirement after edge detection. Nevertheless, it is well known that the performance of the deformable models depends on the proper selection of the model parameters and initial contours. Without this condition, the contours often fail to converge to the desired solution. Obviously, these considerations will make this kind of approach more complex than the others. In this paper, we propose an improved radial search method based on wavelet transform to extract the region of the tumor.

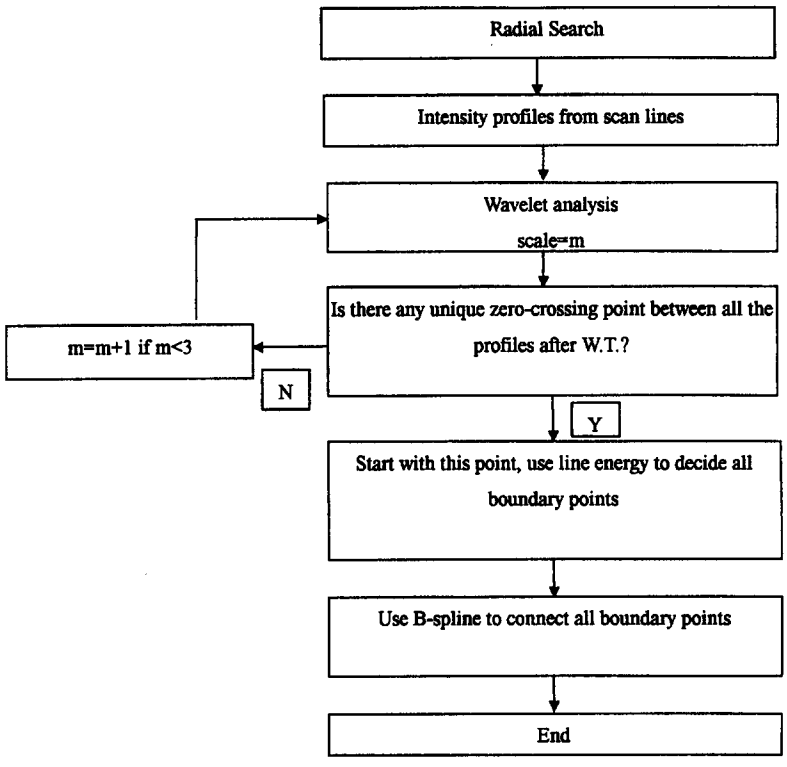


Figure 1. The flow chart of the proposed method.

For real-time application, the method is fast (not iterative), needs less manual operation, and is easy-to-implement. The block diagram of the proposed method is shown in Figure 1.

The remainder of this paper is organized as follows. Section 2 illustrates various color spaces, which is important for color image processing. Section 3 presents the proposed wavelet-based algorithm for segmenting bladder cancer with radial search. The experimental results and conclusions are presented in Sections 4 and 5, respectively.

2. COLOR SPACES

The combinations of frequencies presented in the reflected light determine what we perceive as the color of the object. Other properties besides frequency are useful for describing the characteristics of light. When we view a light source, our eyes respond to the color (or dominant frequency) and two other basic sensations, one of these we call the luminance or brightness of the light, the other characteristic is the purity or saturation of the light. These three characteristics, dominant frequency, brightness, and purity, are commonly used to describe the different properties we perceive in a light source. The term of chromaticity is used to refer collectively to the two properties describing the color characteristic, purity and dominant frequency [13].

In color image processing, color of a pixel is usually given as three values corresponding to the tristimuli R (red), G (green), and B (blue). Various kinds of color models such as intensity, saturation, and hue can be calculated from the tristimuli by using either linear or nonlinear transformations. Each color model has its own characteristic. For instance, the set of H (hue), I (intensity), S (saturation) is convenient for representing the human color perception. The set of Y, I, Q is used to efficiently encode color information in the TV signal. The normalized color r, g, b is convenient to be represented in the color planes, etc. In computer processing of color images, various color models are used for different purposes [13].

Also, a lot of color models such as HLS, XYZ, La^*b^*, UVW, I1 I2 I3, and A C1 C2 have been proposed to solve different problems [8,14]. For color clustering, it is desirable that the selected

color features define a space possessing uniform characteristic. By systematic experiments and comparative study in region segmentation [15], the La^*b^* color coordinate system is proved to be an effective color model in a color clustering problem. In addition, since the cylindrical coordinates HLS of the La^*b^* color coordinate system concur almost with the accepted physiological model of color vision, the HLS color model can then be used to estimate the distributions of different clusters in some circular-cylindrical decision volume in the La^*b^* space. The expression to compute H, L, S component are expressed as below:

$$\begin{aligned} \mathrm{L} &= \mathrm{L}, \\ \mathrm{H} &= \arctan\left(\frac{b^*}{a^*}\right), \\ \mathrm{S} &= \left(a^{*^2} + b^{*^2}\right)^{1/2}. \end{aligned}$$

Although the color spaces mentioned above play a very important role in image segmentation problems for clustering approach, a simple RGB color model is enough for our radial search approach. This merit makes the proposed method more suitable than others do in real applications. More specifically, in order to speed up the processing time, the RGB value of each pixel is mapped to an intensity value, i.e., gray-level. For each pixel (i, j), the mapping function to transfer its RGB value to an equivalent intensity value $I(i, j)$, ranging from 0 to 255, is described as below.

$$I(i,j) = \alpha R(i,j) + \beta G(i,j) + \gamma B(i,j), \tag{1}$$

where

$$\alpha = \frac{w_r}{w_r + w_g + w_b}, \qquad \beta = \frac{w_g}{w_r + w_g + w_b}, \qquad \gamma = \frac{w_b}{w_r + w_g + w_b},$$

and

$$\begin{aligned} w_r &= \sum_{i=1}^{m}\sum_{j=1}^{m} (R_a(i,j) - R_b(i,j))^2 + (R_a(i,j) - R_c(i,j))^2 + (R_b(i,j) - R_c(i,j))^2, \\ w_g &= \sum_{i=1}^{m}\sum_{j=1}^{m} (G_a(i,j) - G_b(i,j))^2 + (G_a(i,j) - G_c(i,j))^2 + (G_b(i,j) - G_c(i,j))^2, \\ w_b &= \sum_{i=1}^{m}\sum_{j=1}^{m} (B_a(i,j) - B_b(i,j))^2 + (B_a(i,j) - B_c(i,j))^2 + (B_b(i,j) - B_c(i,j))^2, \end{aligned}$$

where R_a, G_a, B_a are pixel values of small-size window extracted from the object region of the training data, R_b, G_b, B_b are pixel values of small-size windows extracted from the background of the training data, and R_c, G_c, B_c are pixel values of small-size windows extracted from the undetermined region of the training data. In this approach, the window size is defined as 10×10.

3. BORDER DETECTION USING WAVELET

In this section, we propose an improved radial search method to detect the tumor boundary. There are two advantages to using the radial search method. First, the boundary of the tumor can be obtained directly without image segmentation. The segmentation is often time consuming and easily affected by the characteristics of the object region. Second, the developed algorithm is a user-friendly semiautomatic mechanism, which equips a user to extract the tumor boundary by assigning a point inside the region as the start point and the border of the tumor is automatically produced.

Conventional radial search methods detect the object boundary only by analyzing the gradient information obtained along the search line. Because the tumor areas often include some noise and

inhomogeneous structures, the border detected may be unsatisfactory. Especially, when there are holes or broken chunks in the region of interest, the detected border is usually not continuous. This broken border makes it difficult to calculate the tumor area, an important factor in clinical diagnosis of the tumor. To overcome this problem, a wavelet-based approach for profile analysis is proposed. In the past, it was well known that a multiscale edge detector using wavelet transform can smooth a 1D gray-level profile at various scales and then detect the sharp variation points from their second-order derivation. Based on this concept, we apply the 1D profile analysis for border extraction in color images. In other words, for a color image, its intensity profile obtained by equation (1) is employed to detect the real border of the tumor region by using wavelet transform.

Figure 2. The radial search method proposed.

The first step of the algorithm is to choose a centroid point inside the tumor region, then the search radius which covers the regions of interest is determined. As shown in Figure 2, the radial search method samples the original image per 20 degrees, and then we use wavelet transform to choose the edge point via the intensity profiles. The profiles of each scan lines radiated from a centroid inside the tumor region are shown in Figure 3. A wavelet transform $Wf_s(x)$ is a convolution between a signal $f(x)$ and a set of dilated wavelets, $h_s(x)$, with scale parameter s. In our case, the profile of each search line is denoted as the signal $f(x)$, and the second deviation of Gaussian function is served as the dilated wavelets, the $h_s(x)$. For each obtained profile, three-scale wavelet analysis is used to detect a unique zero-crossing point as the boundary point. That is,

$$Wf_s(x) = f(x) * h_s(x) = \int_{-\infty}^{\infty} f(x)h_s(x-u)\,du, \tag{2}$$

where

$$h(x) = \frac{x^2-1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right).$$

$$h_s(x) = \frac{1}{s}h\left(\frac{x}{s}\right) = \frac{1}{\sqrt{2\pi}s}\left(\frac{x^2}{s^2}-1\right)\exp\left(-\frac{x^2}{2s^2}\right).$$

Figure 4 shows the results after applying wavelet transform to the first profile in Figure 3 with scale 1, 2, and 4. It is seen that the real boundary point is extracted. However, when there is a

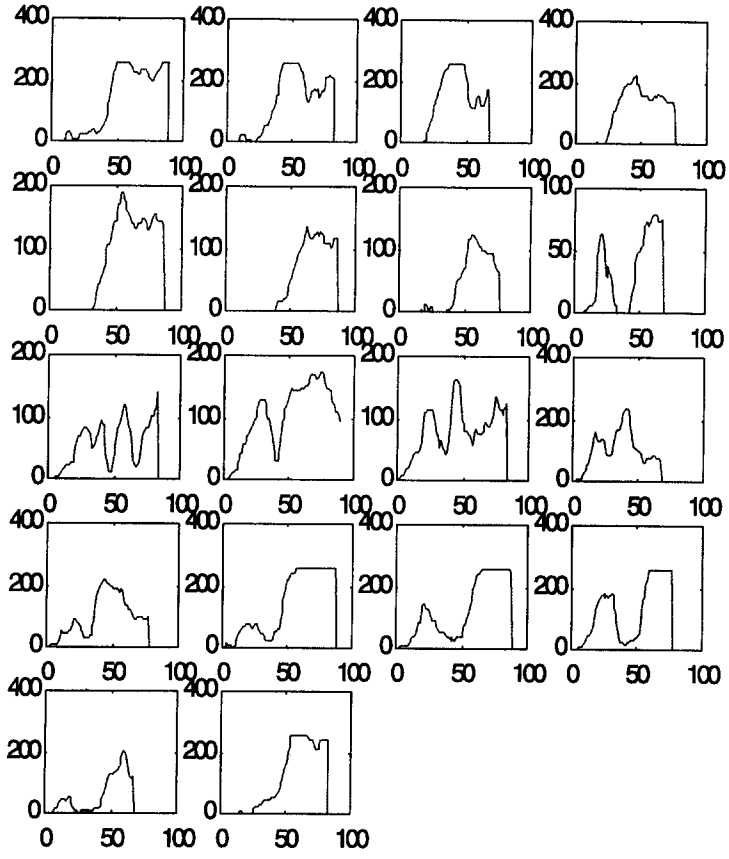


Figure 3. The profiles of each scan line radiated from a centroid inside the tumor region.

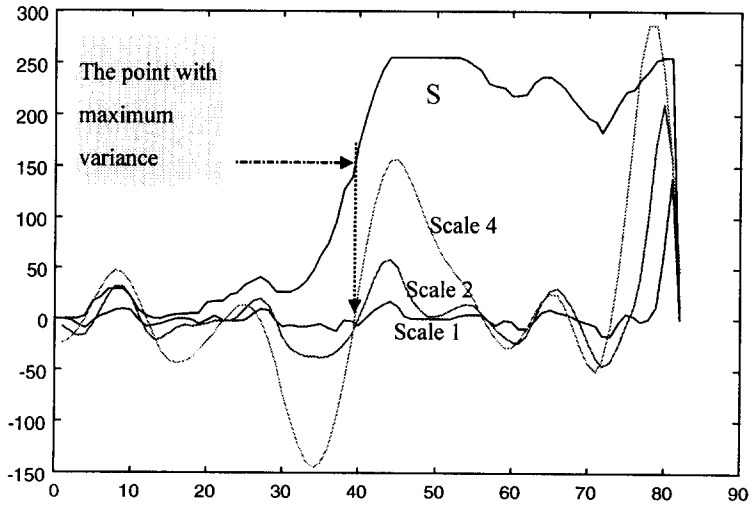
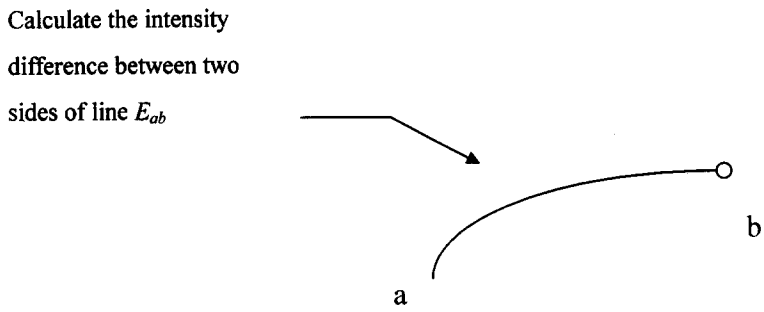
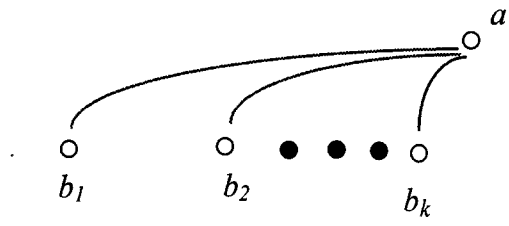


Figure 4. The result profile after applying wavelet transform with scale 1, 2, 4, where curve S denotes original profile, curve 1 denotes scale 1, curve 2 denotes scale 2, and curve 4 denotes scale 4.

large gap inside the tumor, the detected border bends toward the concave part of the region if only the extreme points on the profile are under consideration. In other words, the occurrence of this situation is due to region inconsistency, which usually results in false boundary points. Here, we propose a refined strategy based on line energy to eliminate the false boundary point and the real boundary points can then be detected accurately.



(a) Calculation of the line energy E_{ab}.



(b) The point b_i with the maximum line energy is selected as a real boundary point.

Figure 5.

Border Refinement Strategy

For a boundary point candidate a, each possible corresponding point located on its neighboring scan lines are denoted as b_i. The line energy of line $\overline{ab}$ is defined as $E_{ab} = A^2 - B^2$, where A and B are the average intensity of the pixels neighboring both sides of $\overline{ab}$, respectively (see Figure 5). That is, for a point P_i on $\overline{ab}$ with intensity $I(P_i)$, its two neighboring points are denoted as P_{i-1} and P_{i+1}. Then we obtain $A = (1/L)\sum_{i=1}^{L} I(P_{i-1})$ and $B = (1/L)\sum_{i=1}^{L} I(P_{i+1})$, where L is the length of the line $\overline{ab}$. In other words, we compare the intensity of the pixels located on both sides of line $\overline{ab}$ to determine if it is inside the tumor region or not. Obviously, the variation of the intensity in a region is not sharp except that the line is near to the border. Therefore, the line energy can be used to remove the false connection between two boundary candidates on adjacent scan lines. Thus, the border point candidate b_i, $i = 1, \ldots, k$, with the maximum energy E_{ab} is selected as the real boundary point. Once the boundary points on each search line are extracted, the border of the tumor region is obtained via connecting these detected boundary points with B-Spline function [16].

4. EXPERIMENTAL RESULTS

A series of experiments have been carried out to evaluate the performance of the proposed algorithms in different color spaces. These algorithms developed for this approach were written in C programming language on a Pentium-200 PC.

For comparison, several methods for color image segmentation, which include SCT/center split and PCT/3D median split are used. The reason of using these methods is based on the recent report [8], which illustrated their good performance for skin tumor identification. These methods generally adopt the thresholding and pixel classification techniques to find the tumor area. After a series of transforms, the pixels are assigned to one of the two categories, the object and background. However, the segmented results usually appear as fractional parts and a morphology operation is then required to eliminate these redundant fractional parts. Finally, we use an edge operator to detect the boundary of the tumor region. The experimental results are shown in Figure 6.

(a) The result image using SCT method.

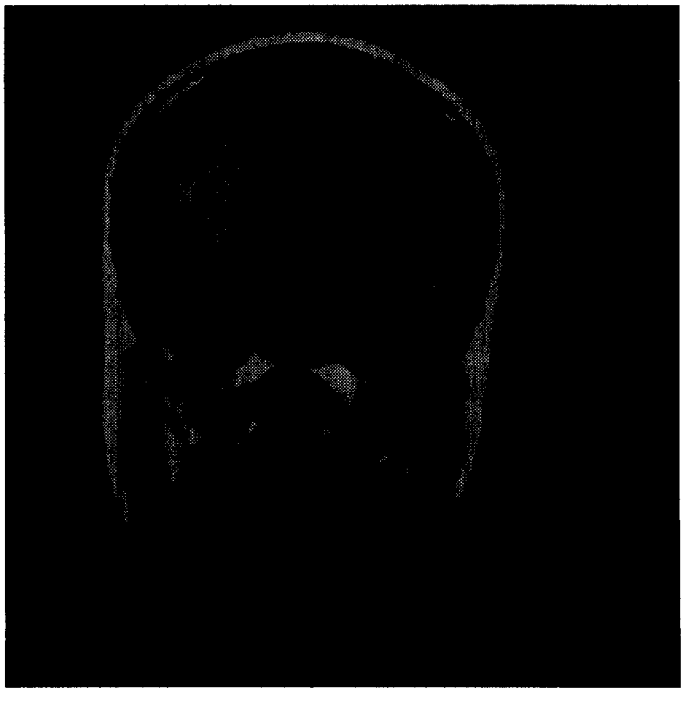
(b) The result method using PCT method.

Figure 6.

Note, the experimental results indicate that SCT has better results than other algorithms mentioned in this paper. This algorithm also has the advantage of fast speed and simpler transform. Since PCT can maximize the variance between various regions in the original image, it does not have good performance in tumor region segmentation. In other words, the precondition for PCT is that both the object and background must have uniform attributes. Since there are blood area and white tissue in the tumor region, the PCT cannot perform well.

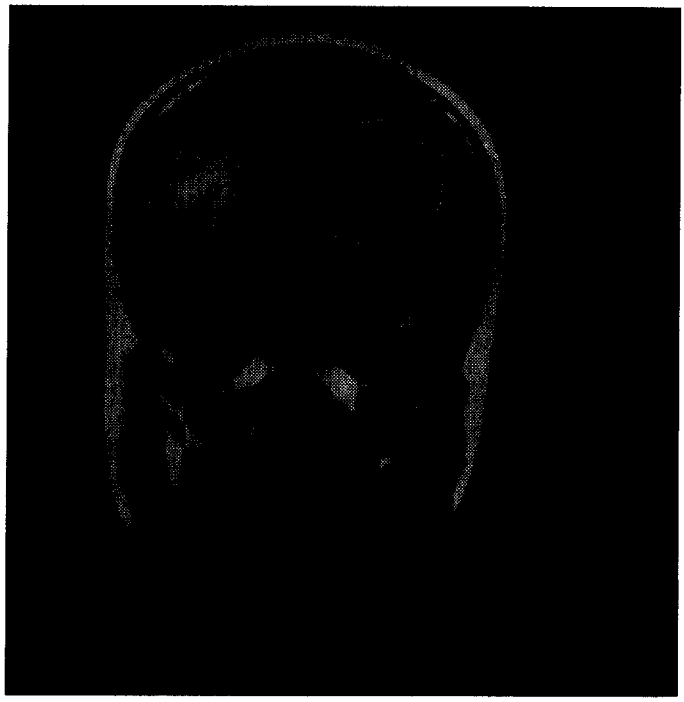
The experimental result after using the proposed method for border detection is shown in Figure 7. It is clear that the algorithm has good performance in detecting the color tumor region. In addition, this method can be applied to other medical image for tumor detection. Figure 8 is the result after using this method for a brain CT image to extract the tumor region. It is seen that the border of tumor region is detected accurately.

Figure 7. The result image using the proposed radial search method with wavelet analysis.



(a) The source image.

Figure 8. Using proposed algorithm to extract the tumor border from a brain CT image.



(b) The result image.

Figure 8. (cont.)

5. CONCLUSIONS

Color is an important attribute for object description, hence, using the color attributes effectively is important an image analysis. In this paper, a novel method based on wavelet transform for boundary detection is proposed. Several methods of color segmentation techniques are used to compare the performance with our methods. Experimental results demonstrate that this method is simple, fast, and robust. The proposed algorithm can be used as a kernel in the image processing part of PACS (Picture Archiving and Communication System). So, the doctors can see the results of border extraction from their local personal computer before diagnosing the symptom.

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