Mrs.Mongra Sahu, Mr.Devesh Narayan / International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 www.ijera.com
Vol. 3, Issue 1, January -February 2013, pp.494-497

Computer image analysis of skin lesions

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Abstract

An automatic method for segmentation of images of skin cancer and other pigmented lesions is presented. This method first reduces a color image into an intensity image and approximately segments the image by intensity thresholding. Then, it refines the segmentation using image edges. Double thresholding is used to focus on an image area where a lesion boundary potentially exists. Image edges are then used to localize the boundary in that area. A closed elastic curve is fitted to the initial boundary, and is locally shrunk or expanded to approximate edges in its neighborhood in the area of focus.

Key words: Early diagnosis, image analysis.

Introduction

Skin Cancers are the most common form of cancers in humans [1]. The American Cancer Society estimates that more than 700 000 new skin cancers are diagnosed annually in the United States., Image segmentation is perhaps the most studied area in computer vision, with numerous methods reported [2,3].

A segmentation method is usually designed taking into consideration the properties of a particular class of images. In this paper, we develop a three-step segmentation method using the properties of skin cancer images. The steps of our method are as follows:

1. Preprocessing: a color image is first transformed into an intensity image in such a way that the intensity at a pixel shows the color distance of that pixel with the color of the background. The color of the background is taken to be the median color of pixels in small windows in the four corners of the image.
2. Segmentation: a threshold value is determined from the average intensity of high gradient pixels in the obtained intensity image. This threshold value is used to find approximate lesion boundaries.
3. Region Approaches: a region boundary is refined using Edge information in the image. This involves initializing a closed elastic curve at the approximate boundary, and shrinking and expanding it to fit to the edges in its neighborhood.

1. Preprocessing

The first step in our image segmentation method can be Considered a preprocessing operation that transforms a color image into an intensity image. This operation is motivated by two observations:

1. Skin lesions come in a variety of colors; therefore, absolute colors are not very useful in segmenting images. However, changes in color from a lesion to its background (it's surrounding healthy skin) are similarly observed in all images; therefore, changes in color can be used to effectively segment images.
2. When segmenting a skin image, significant color variations may exist within a lesion or in the background. Such variations should be suppressed since our interest is in color changes from the background to a lesion or from a lesion to the background.

Observation 1 suggests that we should use changes in color rather than absolute colors to segment images. Therefore, we transform pixel colors that are vector quantities into intensities that are scalars and represent color differences.

Observation 2 states that, among the color changes, only those belonging to a lesion boundary are important in Image segmentation, and color changes inside a lesion or in the background should be ignored.

We transform our images that are in RGB color coordinates into images that are in CIELAB or CIE 1976 $L^*a^*b^*$color coordinates [4]. CIELAB is a color space standardized by the CIE (Commission Internationale de l'E´ clairage) in 1976 to measure color differences. This is a uniform color space defined in such a way that Euclidean distance between two colors (defined as D*E*) is proportional to their visual difference. Color in the CIELAB space can be described with less redundancy than in the RGB space.RGB color coordinates can be transformed into $L^*a^*b^*$ color coordinates using the following formulae [4]:

$L^* = 116\square Y/Yn\square^{1/3} - 16\square\ \square\ \square Y/Yn\square\ \square > 0.008856$

$L^* = 903.3\square Y/Yn\square\square\square\ \square\ \square Y/Yn\square\ \square =< 0.008856$

$a^* = 500\square f\ \square X/Xn\square - f\ \square Y/Yn\square\ \square$

$b^* = 200\square f\ \square Y/Yn\square - f\ \square Z/Zn\square\ \square$

where $f(t) = t^{1/3}$ when $t > 0.008856$ and $f(t) = 7.787t + 16/116$ when $t =< 0.008856$. *Xn*, *Yn* and *Zn* are the coordinates of the CIELAB reference white, which are usually chosen to be 0.9642, 1.0 and 0.8249, respectively. If we require that the images be taken such that lesions do not fall on image corners, we can then use colors in the four corners of an image to estimate the color of the background. We take small windows, typically 10 * 10 pixels in size, from the four corners of an image and determine the median *L**, *a** and *b** of the pixels. We use this median color as an estimate to the color of the background. We use median color rather than average color because image averaging uses the hair colors as well as the skin colors to estimate the color of the background. Since the number of hair pixels is usually much smaller than the number of skin pixels in an image, when the median color is used, the color of a pixel belonging to the hair will not be used and the color of a pixel belonging to the skin will be used to estimate the color of the background. If the intensities assigned to pixels are proportional to color distances of the pixels to the color of the background, we will obtain an image that has high values in lesions and small values in the background. An image generated in this manner will, therefore, show lesions as bright spots.

Therefore, they are more likely to belong to a lesion. Image gradients have been used in the past to determine region boundaries [16]. However, detection of lesion boundaries using pure image gradients is a difficult task. We need to preprocessing operation so that edges on lesion boundaries are distinguished from edges inside a lesion or in the background.

To implement observation 2, we will need a function that provides the property shown in Fig. 1(a). For a wide range of intensities in the background, this function produces very similar intensities. Therefore, the function reduces image gradients in the input corresponding to details in the

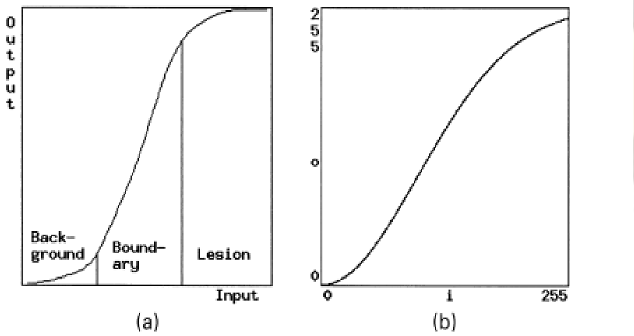

Fig. 1. (a) A desirable function for mapping color distances to image intensities. *i* and *o* show the input and output image intensities, respectively.

background. Similarly, it reduces image gradients belonging to a lesion. For intensities falling on lesion boundaries, however, we see that gradients are increased. Therefore, if we map image intensities according to the function depicted in Fig. 1(a), we will increase gradients on lesion boundaries, while decreasing gradients inside a lesion or in the background. Mapping intensities in this manner facilitates detection of lesion boundaries. As can be observed, most details within the lesion and some details in the background have been suppressed, while variations from the lesion to the background and from the background to the lesion have been enhanced. We segment the image of Fig. 2(a) to isolate lesion boundaries. Note that the preprocessing operation not only reduces a color image into an intensity image, it enhances the boundary of a lesion while suppressing details inside and outside a lesion.

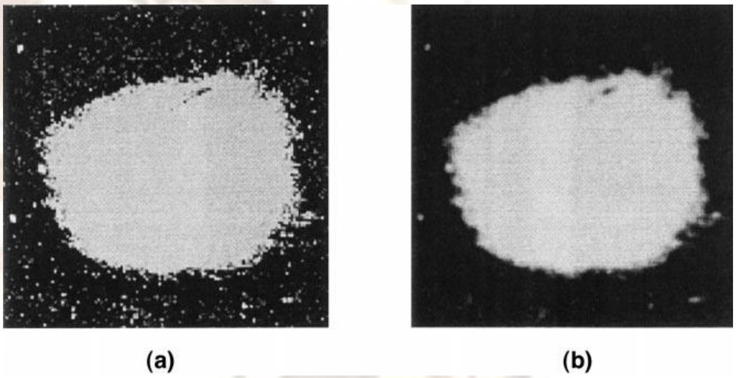

Fig. 2. (a) Transforming intensities , (b) Smoothing of (a) with a 2D Gaussian kernel of standard deviation 2 pixels.

2. Segmentation

To reduce the effect of image noise and intensity variations due to skin's repetitive texture and hair, an image is first low-pass filtered before being segmented. Fig. 2(b) shows the image of Fig. 2(a) after being smoothed with a 2D Gaussian kernel of standard deviation 2 pixels. As can be observed, although smoothing reduces details in the image, the smoothed image still contains information about the lesion, which is brighter than the background. The objective in the initial segmentation is to determine the approximate position and shape of a lesion, and then the optimal lesion boundary exists. Since the optimal threshold value at one boundary point may differ from that at another boundary point, the objective in double thresholding is to select a range of threshold values that includes the optimal threshold value at every boundary point. To determine an initial threshold value automatically, we observe that gradients of pixels on lesion boundaries are generally higher than gradients of pixels inside or outside lesions. We will, therefore, use the average intensity of the top *p*% highest

gradient pixels in the image to compute the threshold value. *p* is typically a small number, e.g. 5.
Because noise and details from skin texture and hair could also result in high gradients, this process may detect details from noise, skin texture and hair. Such regions, however, are often small and can be removed. Threshold techniques can be categorized into two classes: global threshold and local (adaptive) threshold. In the global threshold, a single threshold value is used in the whole image. In the local threshold, a threshold value is assigned to each pixel to determine whether it belongs to the foreground or the background pixel using local information around the pixel. Because of the advantage of simple and easy implementation, the global threshold has been a popular technique in many years [6][7][8].

2.1 Thresholds

Threshold is one of the widely methods used for image segmentation. It is useful in discriminating foreground from the background. By selecting an adequate threshold value T, the gray level image can be converted to binary image. The binary image should contain all of the essential information about the position and shape of the objects of interest (foreground). The advantage of obtaining first a binary image.

2.2 Watershed Algorithm

The watershed segmentation has proven to be a powerful and fast technique for both contour detection and region-based segmentation. In principal, water-shed segmentation depends on ridges to perform a proper segmentation, a property which is often fulfilled in contour detection where the boundaries of the objects are expressed as ridges. For region-based segmentation it is possible to convert the edges of the objects into ridges by calculating an edge map of the image. Watershed is normally implemented by region growing based on a set of markers to avoid severe over-segmentation [10, 11,10]. Different watershed methods use slightly different distance measures, but they all share the property that the watershed lines appear as the points of equidistance between two adjacent minima. Meyer [9] use the topographical distance function for segmenting images using watershed segmentation, while Najman and Schmitt [8] present the water- shed differences with classical edge detectors. Felkel et al. [10] use the shortest path cost between two nodes which is defined as the smallest lexicographic cost of all paths between two points, which reflects the flooding process when the water reaches a plateau. The success of watershed segmentation relies on a situation where the de-sired boundaries are ridges. Unfortunately, the standard watershed framework has a very limited flexibility on optimization parameters. As an example, there exists no possibility to smooth the boundaries.

3. Region Approaches

Within this category the thresholding operation is most often used [4]. The pixels of an image are grouped into regions using some similarity criteria of some characteristic features such as intensity. The digital photography is made up of a number of pixels each of a known brightness (shade of grey). Two peaks can be seen representing the paler skin tones and the darker lesion. Segmentation can be performed by choosing a value of the threshold between the peaks [9].

Conclusions

Image segmentation is the first step in many image analysis problems. To analyze skin lesions, it is necessary to accurately locate and isolate the lesions. In this paper, an automatic method for segmentation of skin cancer images was presented. The method starts with an initial segmentation and uses edge information in the neighborhood of the initial segmentation to refine the results. An elastic curve model is used to represent the final segmentation. Although the method is devised for segmentation of color images, early on in processing, a color image is transformed into an intensity image where the intensity at a pixel shows the color distance of that pixel to the background. Intensities in the image obtained in this manner are then transformed according to a function shown in Fig. 2 to suppress details in the background and in a lesion while enhancing details across lesion boundaries. Transformation of a color image into an intensity image and mapping of image intensities to enhance lesion boundaries are considered to be the main contributions of this work.

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