

Segmentation of Skin Cancer Images based on Multistep Region Growing

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Abstract

*An automatic method for segmentation of skin cancer images is presented. Firstly the algorithm automatically determines the compounding colors of the lesion, and builds a number of distance images equal to the number of main colors of the lesion (reference colors). These images represent the similarity between reference colors and the other colors present in the image and they are built computing the CIEDE2000 distance in the $L^*a^*b^*$ color space. Texture information is also taken into account extracting the energy of some statistical moments of the L^* component of the image. The method has an adaptative, N -dimensional structure where N is the number of reference colors. The segmentation is performed by a texture-controlled multi-step region growing process. The growth tolerance parameter changes with step size and depends on the variance on each distance image for the actual grown region. Contrast is also introduced to decide the optimum value of the tolerance parameter, choosing the one which provides the region with the highest mean contrast in relation to the background. The method has been tested with a database of 20 images obtaining excellent results*

1. Introduction

Skin cancers are one of the most common forms of cancers in humans. Skin cancers can be classified into melanoma and non-melanoma. Although melanomas are much less common than non-melanomas, they account for most of the mortality from skin cancers [1]. Automatic image segmentation applied to the detection of this kind of lesions could result in the detection of the disease at an early stage and a subsequently increment in the likelihood that the patient will survive. Although color is the most important information in this kind of images, it is not the only source of knowledge available. Because these types of pigmented lesions are rich in color and texture, those segmentation processes that take into account only color information will probably fail in giving us a proper result. That is why texture information must be included.

2. Algorithm Description

2.1. Selection box

In the first step the user selects an area (*selection box*) from the image with the mouse. The algorithm will segment all pixels in the image with colors and textures similar to the ones present in this selected region.

2.2. Color information

2.2.1 $L^*a^*b^*$ color space

In a further step the color of each pixel will be substituted by its distance to the reference colors. Therefore, a perceptually uniform color space is needed so that distances between colors measured in this space are correlated with color differences according to human perception. We have chosen the $L^*a^*b^*$ color space [2].

2.2.2 Anisotropic diffusion

Original images may include some noise that could change the result of the segmentation. For the denoising step we use anisotropic diffusion filtering.

2.2.3 Reference Colors

We consider all the colors present in the selection box, and we will call them reference colors. In order to find these reference colors, we perform a clustering operation with the well known *k-means* algorithm in the $L^*a^*b^*$ color space. To obtain the value k (number of clusters) automatically, we use Dunn's coefficient [3]

$$D = \min_{1 \leq i \leq k} \left\{ \min_{1 \leq j \leq k, j \neq i} \left\{ \frac{d(c_i, c_j)}{\max_{1 \leq n \leq k} (d'(c_n))} \right\} \right\} \quad (1)$$

where $d(c_i, c_j)$ is the Euclidean distance between cluster i and cluster j , that is, the inter-cluster distance. $d'(c_n)$ is the intra-cluster distance. We assume that, in skin lesions, the number of different colors is less or equal to 16. So, we perform 16 clusterings beginning from $k=1$ to $k=16$. Each

time, the Dunn's coefficient (1) is computed and stored. When the last clustering is done, the obtained D coefficients are compared, selecting the k value that provides the highest value of D , which leads to a maximum inter-cluster distance and a minimum intra-cluster distance. Then, the k reference colors are defined as the centroids of the k clusters in $L^*a^*b^*$ color space. Figure. 1 shows an example.

2.2.4 Distance images

Once the reference colors are obtained, the distances between every single pixel of the image and each of the reference colors are calculated. We have chosen CIEDE2000 as the distance metric. This measure has been extensively tested and outperformed other existing color difference formulae [4]. As a consequence, it has been approved by CIE and adopted as the CIE 2000 color difference formula.

Then, a new set of images is built, where each pixel value will be the CIEDE2000 color difference to each of the reference colors. In order to obtain a better visualization, we invert this image, that is, those pixels whose values are similar to the reference ones, will appear light in a dark background. These inverted images are called the *distance images*. We can see an example in Figure 1.

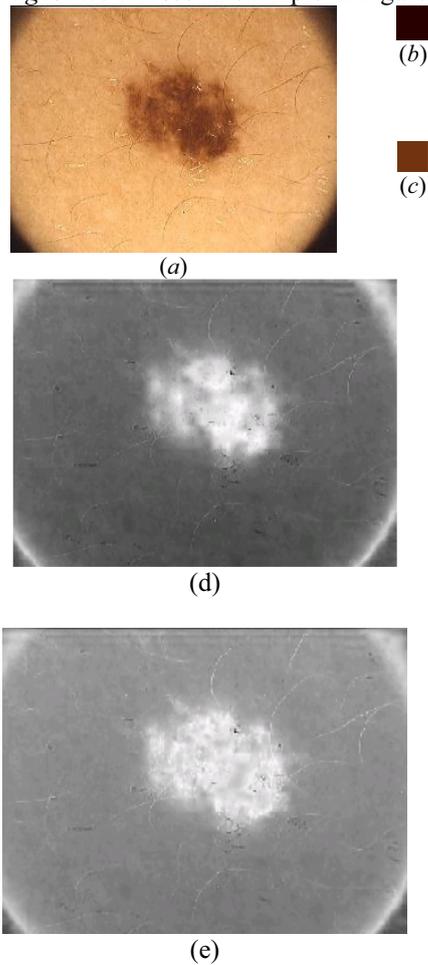


Figure 1: Two distance images obtained with CIEDE2000 color distance formulae, for the original image (a), (b) and (c) are the two reference colors and images (d) and (e) their correspondent distance images.

2.3. Texture information

The proposed method extracts texture features only from the luminance component (L^*) of the original image. These features are based on some local low statistical moments [5]. The algorithm calculates for every pixel, four statistical moments m_{pq} with $p, q = \{0, 1\}$ by processing the L^* component with local masks expressed in a normalized coordinate system. A formal expression of these moments is shown in equation (2).

$$m_{pq} = \frac{1}{W^2} \sum_{m=i-W/2}^{i+W/2} \sum_{n=j-W/2}^{j+W/2} f(m, n) x_m^p y_n^q; \quad (2)$$

$$x_m = \frac{m-i}{W/2}; \quad y_n = \frac{n-j}{W/2};$$

$$i, j \in \text{image} \quad p, q = 0, 1$$

where W is the window width, (i, j) are the pixel coordinates for which the moments are computed, (m, n) the coordinates of another pixel which falls within the window, (x_m, y_n) are the normalized coordinates for (m, n) , and $f(m, n)$ is the value of the L^* component at the pixel with coordinates (m, n) . This normalized expression leads us to compare among pixel moments and it is equivalent to the finite convolution of the image with a mask. The sizes of these masks have been fixed to the size of the selection box. Usually, for each segmentation this size will be different, so *CTREG* will be automatically adapted to the texture we want to isolate.

With all these parameters, we can build four new images M_{pq} with $p, q = \{0, 1\}$ corresponding to each statistical parameter. To this purpose we assign to each pixel a value equal to the previously calculated moment m_{pq} . For example, in the case of pixel $(30, 20)$ if we want to build the image M_{11} we define the value at position $(30, 20)$ as the moment m_{11} , calculated with a window centered in that pixel.

Afterwards, we defined new images calculated from the energy of the moments. We called them *energy images*, E_{00}, E_{01}, E_{10} and E_{11} , and they represent the strength of each moment around the pixel location. The computation of the energies follows equation (3).

$$E_{pq}(i, j) = \frac{1}{W^2} \sum_{m=i-W/2}^{i+W/2} \sum_{n=j-W/2}^{j+W/2} M_{pq}^2(m, n). \quad (3)$$

where $E_{pq}(i, j)$ is the energy corresponding to the pixel with coordinates (i, j) in the image M_{pq} , W is the window width, $M_{pq}(m, n)$ is the value of the pixel with coordinates (m, n) in the moment image M_{pq} and $p, q = \{0, 1\}$

Each pixel is now characterized with four values, one from each energy image. They are considered as coordinates in a four-dimensional space. Subsequently, in order to assign each pixel to one texture in the image, we apply the same clustering procedure previously described in section 2.2.3 but in this four-dimensional texture space.

We again assume that, the number of different textures is less or equal to 16. Once each pixel in the image has been classified, we select only those pixels whose texture is equal to the desired one, obtaining a black and white image in which white pixels are those with the desired texture, as shown in Figure 2. This image will be used

afterwards in the region-growing process.

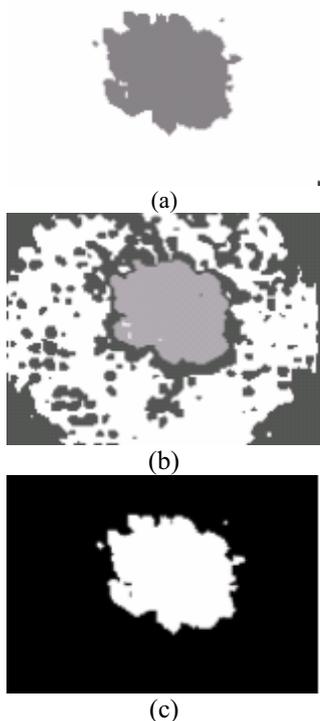


Figure 2 The original image in Figure 1 is processed in order to isolate the lesion. Image (a) is the result of the k-means algorithm for $k=2$. The value of D is 0.9462. Image (b) is the result for $k=3$ and $D=0.7469$. Finally, the maximum D value is obtained for $k=2$, which leads to the texture information shown on image (c).

2.4. Multistep Region Growing Algorithm

Once the color distance images and the texture information are obtained, the region-growing process starts. As explained before, region-growing techniques have two critical tasks: the seed selection and the choice of the belonging condition.

2.4.1 Seed selection

To identify possible seeds we take advantage of the knowledge about how the distance images have been built. Those pixels more similar to the reference color have been assigned a high value (note that we have inverted the distance image). In order to select the seeds, the next three steps are followed for each distance image: 1) Selection of the local maxima of the image, which represent the candidates to seeds. Not all these candidates will be seeds for the region growing, because these local maxima do not belong necessarily to the region of interest. 2) Application of a threshold to these candidate seeds. The threshold is determined from the histogram of the distance image, more specifically, the threshold will be the position of the peak closest to the right part of the histogram, as seeds should have high values as explained before. In images where different objects are present, the histogram typically presents different modes, each representing an object or the background, and each mode contains at least a local maximum. In the distance image, the rightmost

mode corresponds to the object to be segmented. Therefore, any pixel with values belonging to this mode is a valid seed for the region growing. One way of assuring that seeds belong to the rightmost mode is to choose pixels with values on the right of the rightmost peak in the histogram, because this peak will correspond for sure to this mode. Obviously, the only thing what matters for the good performance of the algorithm is that seeds belong to the region to be segmented and, provided this condition is met, the choice of a particular threshold for the seeds is not decisive in the success of the segmentation. The procedure to find significant peaks and valleys and the threshold follows an automatic algorithm [6]. 3) Finally, texture information is applied to reject some of the seed candidates: the final seeds must have, not only the desired color, but also the desired texture. That is, among the group of color seeds, only those pixels that appear white in the texture image are selected. The group of final seeds will be formed by the seeds obtained with the described method and with each of the color distance images.

2.4.2 Multistep Region Growing

In an ordinary region growing, the belonging condition is always the same. For each seed, the algorithm grows a region with a determined condition. With this multi-step technique, the belonging condition automatically changes in order to find its optimum value, which will correspond to the highest value of the contrast parameter explained later on in this subsection.

Let us take a particular seed. The process begins with a region growing with three conditions:

- 1) Not belonging to another region growing before.
- 2) The texture of the pixel must be the desired one. That means that a pixel only will be added to the region if it has a value equal to one (for normalized values) in the texture image.
- 3) The new pixel must be similar to the pixels that already are in the region for all the distance images. This similarity is measured according to (4):

$$\frac{F_{\max,n} + F_{\min,n}}{2} - \tau \leq F_{ij,n} \leq \frac{F_{\max,n} + F_{\min,n}}{2} + \tau, n=1, \dots, N \quad (4)$$

where n refers to the distance image corresponding to the reference color n , N is the number of reference colors, $F_{\max,n}$ and $F_{\min,n}$ are the maximum and minimum values of the pixels in the distance image n inside the region, i and j are the coordinates of the pixel, F is the value of the pixel in the distance image n , and τ is the tolerance step, which will be iteratively increased.

It must be emphasized that the region growing does not depend on the position of the seed within the region. Although a boundary is encountered on one side, the algorithm will continue growing with the same parameter of tolerance in the other directions until no other pixel can be included in the region; and only then, the contrast is calculated to determine if we should increase the tolerance and continue growing.

$$\text{contrast} = \frac{\overline{\text{Inside edge}} - \overline{\text{Outside edge}}}{\overline{\text{Inside edge}} + \overline{\text{Outside edge}}} \quad (5)$$

where $\overline{Inside\ edge}$ and $\overline{Outside\ edge}$ represent the mean values of the pixels belonging to the inner border and outer border of a region respectively. We then use the mean of the contrast values to determine whether the region is the best or not.

At the beginning, the region growing has a very restrictive belonging condition. This will lead us to obtain a small region. While repeating the process, the contrast parameter of equation (5) is calculated. While the grown region is inside the object, the contrast parameter increases its value in a smooth way, because pixels belonging to the inner border and to the outer border of the region are similar. When the region matches the object, the contrast parameter has a high value because pixels surrounding the region will differ from those inside the region. If we continue growing, the contrast parameter will be low again because both the inner border and the outer border are similar. Therefore when the contrast parameter reaches its maximum we have obtained the best region. A steep slope in the contrast parameter evolution corresponds to those values of tolerance for which boundaries are reached. This increase may be either because the whole boundary of the lesion has been reached or because the boundary of the region grown matches in part the boundary of the lesion. In the second situation, the tolerance will continue being increased until the whole boundary is reached. During this increase of the parameter α , the contrast parameter never decreases and, as a consequence, the stop condition is not reached, for the increase of the tolerance is not high enough to overcome a boundary. Once the whole boundary is reached, if the tolerance is being enlarged again the region will exceed the limits of the lesion and, therefore, the contrast will decrease. In such a situation the region growing will stop because the stop condition has been attained.

3. Experimental results

The algorithm has been validated with 20 skin cancer lesion images achieving high quality results in all cases. We can see some examples in Figure 3. It is important to note the similarity in color between the normal skin and the lesion in some of the images. In this sense, the inclusion of texture descriptors is crucial for the good performance of the algorithm.

4. Conclusions

An automatic method for segmentation of skin cancer images is presented. We take into account all the colors in the lesion, performing an N -dimensional multistep region growing procedure which has an adaptative structure. For each of the distance images built, contrast is introduced to decide whether a region is the best or not, and the step which provides a region with the highest contrast in relation to the background is chosen. Color and texture information are used in order to fulfill the requirements of pigmented skin lesions. We have proven its good segmentation performance validating it with 20 melanoma images.

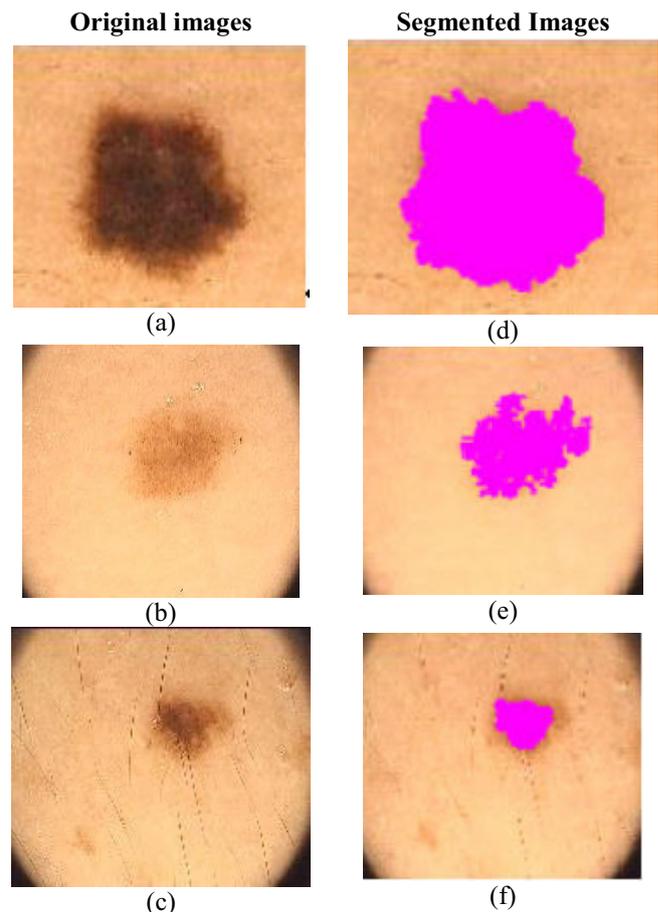


Figure 3: Example of the segmentation. Images (a)-(c) are the original images and images (d)-(f) are the results, in pink, obtained with our algorithm.

Acknowledgements

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References

- [1] L. Xua, M. Jackowska, A. Goshtasbya,*, D. Rosemanb, S. Binesb, C. Yuc, A. Dhawand, A. Huntleye, "Segmentation of skin cancer images," *Image and Vision Computing* **17** 65–74 (1999).
- [2] K. N. Plataniotis and A. N. Venetsanopoulos, *Color Image Processing and Applications*, Springer, Berlin 35-37 (2000).
- [3] U. Maulik and S. Bandyopadhyay, "Performance evaluation of someclustering algorithms and validity indices," *IEEE Trans. PatternAnal. Mach. Intell.* **24** (12), 1650–1654 (2002).
- [4] M. R. Luo, G. Cui, and B. Rigg, "The development of the CIE 2000 colour-difference formula: CIEDE2000," *Color Res. Appl.* **26** (5) 340–350 (2001).
- [5] M. Tuceryan, "Moment based texture segmentation," *Pattern Recogn.Lett.* **15** (7) 659–668 (1994).
- [6] I. Fondón, C. Serrano, B. Acha. "Color-Texture Image Segmentation based on Multi-Step Region Growing," *Optical Engineering*, **45** (5) 057002_1-057002_9 (2006).