Statistical Implementation of Segmentation of Dermoscopy Images using Multistep Region Growing

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Abstract - A method for segmentation of skin cancer images, 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 adaptive, 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.

Keywords - region growing, segmentation, texture-controlled

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. Existing Algorithm Description

a. 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.

b. Color Information

Wavelet denoising

The color image is converted to grey level image and stationary wavelet is applied to decrease noise. We use Stationary wavelet Transform (SWT) for decreasing noise in image. For this, we used r.r.coifman et al [7] work. Their algorithm is as follow: Image transformed to wavelet coefficients. Soft or hard thresholding is applied to detail coefficients. Therefore, coefficients smaller than threshold are eliminated. At last, inverse Stationary wavelet transform is applied to approximation and detail coefficients.

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].

c. 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 FCM algorithm in the
L*a*b* color space. To obtain the value k (number of clusters) automatically, we use Dunn’s coefficient [3]

\[
D = \min_{1<i<j} \left\{ \min_{1<k<n} \left\{ \frac{d(c_i,c_j)}{\sum_{1<m<n} d'(m)} \right\} \right\}
\]

where \(d(c_i,c_j)\) is the distance between cluster I and cluster j, that is, the inter-cluster distance. \(d'(m)\) 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.

d. 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 the distance metric. This measure has been extensively tested and outperformed other existing color difference formulae [4]. As a consequence, the CIE 2000 is color difference formula. Then, a new set of images is built, where each pixel value will be the 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, (a). The original image , (b). the two reference colors using FCM.

3. Proposed Approach

a. Conventional FCM

Clustering is the process of finding groups in unlabeled dataset based on a similarity measure between the data patterns (elements) [12]. A cluster contains similar patterns placed together. The fuzzy clustering technique generates fuzzy partitions of the data instead of hard partitions. Therefore, data patterns may belong to several clusters, having different membership values with different clusters. The membership value of a data pattern to a cluster denotes similarity between the given data pattern to the cluster. Given a set of n data patterns, \(X = x_1,\ldots,x_k,\ldots,x_n\), the fuzzy clustering technique minimizes the objective function, \(O(U,C)\):

\[
O_{km}(U,C) = \sum_{k=1}^{v} \sum_{i=1}^{n} u_{ik}^m \left\| x_i - c_k \right\| ^2
\]

where \(x_k\) is the k-th D-dimensional data vector, \(c_i\) is the center of cluster i, \(u_{ik}\) is the degree of membership of \(x_i\) in the i-th cluster, \(m\) is the weighting exponent, \(d (x_i, c_j)\) is the distance between data \(x_k\) and cluster center \(c_i\), \(n\) is the number of data patterns, \(v\) is the number of clusters. The minimization of objective function \(J(U,C)\) can be brought by an iterative process in which updating of degree of membership \(u_{ik}\) and the cluster centers are done for each iteration.

\[
u_{ik} = \frac{1}{\sum_{j=1}^{v} \left( \frac{d_{ik}}{d_{jk}} \right)^{m-1}}
\]

\[
c_i = \frac{\sum_{k=1}^{n} u_{ik}^m x_k}{\sum_{k=1}^{n} u_{ik}^m}
\]

where \(\forall i\) \(u_{ik}\) satisfies: \(u_{ik} \in [0,1]\), \(\forall k\) \(\sum_{i=1}^{v} u_{ik} = 1\) and \(0 < \sum_{k=1}^{n} u_{ik} < n\).

Thus the conventional clustering technique clusters an image data only with the intensity values but it does not use the spatial information of the given image.

b. Initialization

The theory of Markov random field says that pixels in the image mostly belong to the same cluster as their neighbors. The incorporation of spatial information[8][9] in the clustering process makes the
algorithm robust to noise and blurred edges. But when using spatial information in the clustering optimization function may converge in local minima, so to avoid this problem the fuzzy spatial c means algorithm is initialized with the histogram based fuzzy c-means algorithm. The optimization function for histogram based fuzzy clustering is given in the equation 5

$$O_{hfc}(U, C) = \sum_{l=1}^{L} \left( u_{il} \right)^{m} H(l) d^{2}(l, c_{l}) \quad (5)$$

where H is the histogram of the image of L-gray levels. Gray level of all the pixels in the image lies in the new discrete set G= \{0,1,...,L-1\}. The computation of membership degrees of H(l) pixels is reduced to that of only one pixel with l as grey level value. The membership function \(u_{il}\) and center for histogram based fuzzy c-means clustering can be calculated as.

$$u_{il} = \frac{1}{\sum_{j=1}^{V} \left( \frac{d_{ij}}{d_{ij}} \right)^{m-1}} \quad (6)$$

$$c_{l} = \frac{L}{\sum_{l=1}^{L} \left( u_{il} \right)^{m}} \quad (7)$$

Where \(d_{ij}\) is the distance between the center \(i\) and the gray level \(l\).

c. **Proposed ISFCM**

The histogram based FCM algorithm converges quickly since it clusters the histogram instead of the whole image. The center and membership values of all the pixels are given as input to the fuzzy spatial c-means algorithm. The main goal of the FSCM is to use the spatial information to decide the class of a pixel in the image.

The objective function of the proposed ISFCM is given by

$$O_{fc}(U, C) = \sum_{k=1}^{n} \sum_{i=1}^{v} \left( u_{ik}^{s} \right)^{m} \frac{1}{p_{ik}} \left( \frac{d_{ik}}{d_{jk}} \right)^{m-1} \quad (8)$$

Two kinds of spatial information are incorporated in the member ship function of conventional FCM. Apriori probability and Fuzzy spatial information

**Apriori probability:** This parameter assigns a noise pixel to one of the clusters to which its neighborhood pixels belong. The noise pixel is included in the cluster whose members are majority in the pixels neighborhood.

**Fuzzy spatial information:** In the equation (9) the second term in the denominator is the average of fuzzy membership of the neighborhood pixel to a cluster. Thus a pixel gets higher membership value when their neighborhood pixels have high membership value with the corresponding cluster. The figure 2 shows the distance images using ISFCM, our proposed algorithm.

![Figure 2: Two distance images obtained with CIEDE2000 color distance formulae. (a). The original image, (b). The two reference colors using ISFCM.](image)

d. **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 mpq 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).
\[ m_{pq} = 1 - \frac{1}{w^2} \sum_{m=-w/2}^{j+w/2} \sum_{n=-w/2}^{j+w/2} f(m,n) x_m^p y_n^q \]

\[ x_m = \frac{m-i}{w/2}, \quad y_n = \frac{n-j}{w/2} \]

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).

\[ E_{pq}(i,j) = 1 - \frac{1}{w^2} \sum_{m=-w/2}^{j+w/2} \sum_{n=-w/2}^{j+w/2} m_{pq}^2 (m,n) \]

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 3. This image will be used afterwards in the region-growing process.

\[ \text{Figure 3 The original image is processed in order to isolate the lesion. Image (a) is the result of the ISFCM algorithm for } k=2. \text{ The value of } D \text{ is 0.94. Image (b) is the result for } k=3. (c). \text{ Image with texture information, (d). Image with boundary.} \]

\[ e. \text{ Multistep Region Growing Algorithm} \]

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.

\[ f. \text{ Seed selection} \]

The seed selection is the very critical task in region growing segmentation. This seed determines the region. 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) election 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.

g. Multistep Region Growing Refinement

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 grown 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):

$$\frac{F_{max,n} + F_{min,n}}{2} - \tau \leq F_{i,j,n} \leq \frac{F_{max,n} + F_{min,n}}{2} + \tau$$

and n=1,...,N, where n refers to the distance image corresponding to the reference color n, N is the number of reference colors, Fmax,n and Fmin,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 2 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.

$$\text{Contrast} = \frac{\text{Inside edge} - \text{Outside edge}}{\text{Inside edge} + \text{Outside edge}}$$

(13)

where Inside edge and 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 D, 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.

4. Experimental Results

The algorithm has been validated with many skin cancer lesion images achieving high quality results in all cases. We can see some examples in Figure 4. 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
5. Conclusions

An automatic method for segmentation of skin cancer images is presented. We take into account all the colors in the change in colors, performing a statistical based multistep region growing procedure which has an adaptive 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 color changes due to disease. Figure shows the segmentation result.

![Original Image](image1)
![Segmented Image](image2)

Figure 4. Example of the segmentation. Images (a)-(d) are the original images and images (e)-(h) are the results, in pink, obtained with our algorithm.

REFERENCES


