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Methodology to Segment Lesions That Have Actinic Keratosis

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Abstract

The actinic keratosis is a type of atypical intraepidermal proliferation of keratinocyte that it develops on the skin of people who have been exposed for long periods of time to ultraviolet radiation. It looks like macula, flaky papules or keratotic with a diffuse erythematous base that progressively covers itself with an adherent scale that, when detached, leaves a superficial erosion. The actinic keratosis can be the beginning for the appearance of skin cancer (precancer), so it must be treated in early stages. It constitutes an incipient form of non-melanoma skin cancer that in its form of superficial squamous cell carcinoma can evolve into metastases in such a way that a more aggressive treatment is required. The computer aided diagnosis systems (CAD), carry out a pre-diagnosis of the lesion based on information regarding clinical criteria. The first stage to develop a CAD system consists of the segmentation of images to later carry out a pre-diagnosis. This paper proposes the proposal of a methodology that allows segmentation of lesions affected by actinic keratosis using methods in the spatial domain.

1. Introduction

The extraction of different entities that make up an image is a fundamental task in image processing This process, called segmentation, is often mandatory in all systems that handle artificial vision, and depending on the problem to be solved, different methodologies have been developed to attack each of these problems. In general terms, the segmentation of images is the process of isolation of the objects that make up an image, that is, it is the partition of the image in disjoint regions, such that each region is homogeneous with respect to certain properties, such as gray levels, contrast, texture, etc. [1, 2, 3]. Medical imaging segmentation serves as an important tool for clinical evaluation and diagnosis [4,5]. The results are useful for doctors to recognize organs and tissues correctly, thus increasing the efficiency of the diagnosis and reducing the workload in the analysis of medical images. However, segmentation in medical images is particularly difficult due to the restrictions imposed by the acquisition of images, pathologies and biological variations [6, 7, 8].

Actinic keratosis (AK) are cutaneous neoplasms resulting from the abnormal proliferation of epidermal keratinocytes, which commonly appear in areas exposed to ultraviolet radiation such as the arms, hands, face and neck. If it is not treated in time, it can become squamous cell carcinoma also known as squamous cell carcinoma or squamous cell carcinoma, being the second most common skin neoplasm after basal cell carcinoma, and the leading cause of death of non-melanoma skin cancer type [9], the risk of mutating to a cancerous neoplasm is 0.075% to 0.096% due to AK lesion per year, increasing the probability of risk for people suffering from multiple AK lesions [10]. AK is expressed as macules or erythematous papules that progressively cover themselves with an adherent scale. In the United States, AK represents the most frequent dermatological lesion that people visit the dermatologist.

A computer-assisted diagnostic system (CAD) for the detection of skin lesions such as actinic keratosis must accurately detect the edge of the lesion to carry out an adequate analysis of the indicators present in the lesion. Garcia-Arroyo et al [11] propose a CAD system that allows the segmentation of skin lesions into dermoscopy images by means of fuzzy pixel classification that allows to discriminate a skin lesion and other factors such as facial hair, also make use of histogram thresholding. Celebi et al [12] propose an automated method to detect irregular, unstructured areas of blue pigmentation in dermoscopy images; To carry out the method they propose, they use segmentation of injuries manually. Spyridonos et al [13] propose a method that allows to discriminate AK lesions in clinical photographs of patients, however, the regions of interest where there is presence of AK type lesions were highlighted by experts. On the other hand, Hames et al [14] show an automated method that allows detecting AK-type lesions in clinical photographs, the photographs show lesions on the face and forearm, the lesions were segmented using color space transformations and morphological characteristics. to detect erythema. The result was corroborated with a dermatologist specialist. Hardie et al [15] propose a method to classify lesion images using the ISIC 2018 image bank, for the segmentation task they use a Bayesian classifier that by means of color distinguishes skin lesions of normal tissue based solely on an RGB color vector. Schmid in [16] proposes an unsupervised technique for the detection of multiple objects with background noise, the technique that makes use of anisotropic diffusion and mathematical morphology is applied to segment lesions in dermoscopy images, while in [17] he proposes another Color-based segmentation technique applied again to dermoscopy images. It makes use of Gaussian low-pass filters, **fuzzy c-means clustering** and mathematical morphology. Guillod et al [18] considers the segmentation techniques obtained in [16, 17] and compare them with the segmentation obtained manually by five dermatologists. Al-masni et al [19] propose an automatic technique that allows to segment skin lesions in dermoscopy images and apply it to recognize melanoma skin cancer, the proposed technique is performed **via full resolution convolutional networks**. Ximenes et al [20] show an automatic procedure to segment skin lesions based on mathematical morphology approaches **via geodesic active contour**, they apply to melanoma skin cancer.

2. Basic concepts

Digital image

An image is a dimensional function $f(x, y)$, with (x, y) coordinates in the Cartesian plane. The amplitude of f in a pair of coordinates (x, y) is called image intensity of that point in space. An image is digital if both f and the value of the amplitude of the x and y coordinates are nite and discrete. [21]. Since a digital image is a function $f(x, y)$ discretized in both spatial coordinates and amplitude, it is often represented as a two-dimensional matrix $F_{ij} = (f_{ij})_{H \times W}$, where H and W represent the size of the image, (referring H and W to the height and width of the image respectively) with $f_{ij} = f\left(x_i, x_j\right)$ (figure 1).

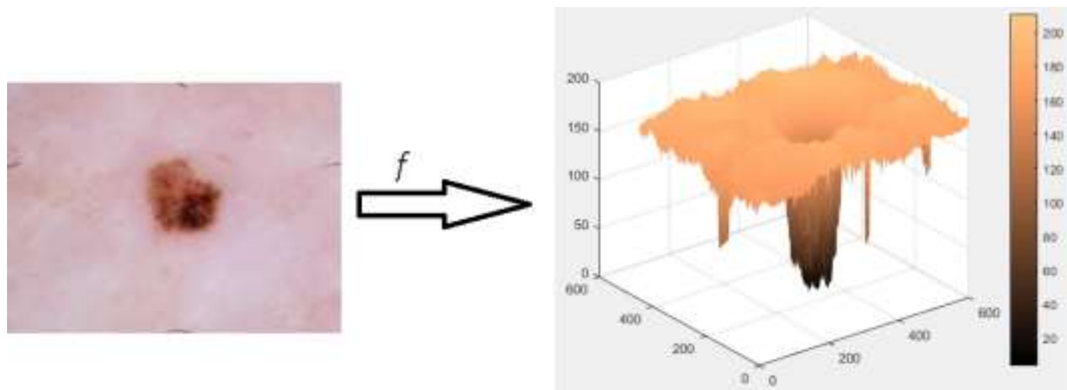

Fig. 1: Digital image.

3. Proposed model

This section presents the proposed methodology that allows the segmentation of dermoscopy image lesions applied to AK-type lesions. First, the RGB model of the decomposition of a digital image obtained from a dermatoscope is considered. Four ways of obtaining the gray scale were considered, considering that $I(x,y) = I_R(x,y) + I_G(x,y) + I_B(x,y)$. As seen in figure 2, in a) the grayscale image is obtained considering only the red plane ($I_R(x,y) = R(x,y)$, $I_G(x,y) = I_B(x,y) = 0$), in b) only the green plane ($I_G(x,y) = G(x,y)$, $I_R(x,y) = I_B(x,y) = 0$), in c) only the plane blue ($I_B(x,y) = B(x,y)$, $I_R(x,y) = I_G(x,y) = 0$), and in d) the average $(I\_R\ (x,y) = R(x,y)/3,\ 〖I〗\ \_G + G(x,y)/3, I\_B = B(x,y)/3)$. The proposed methodology was tested with each of these compositions of the grayscale image, however, the one with the best results was that of the blue plane. So, in everything that follows the methodology on the blue plane is considered.

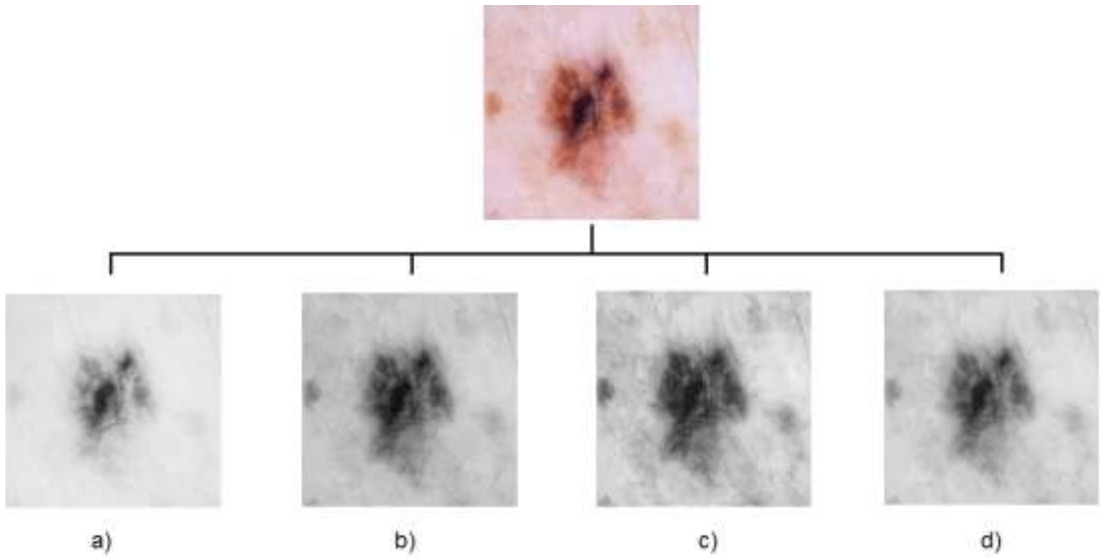

Fig. 2: Decomposition of a grayscale digital image using a) red plane, b) green plane, c) blue plane and d) average.

Once the grayscale image was obtained using the blue plane, the optimal binarization threshold was calculated using the Otsu method. The Otsu method consists of splitting an image in gray levels with N pixels and L possible different levels. The probability of occurrence of the gray level i in the image is given by $p_i = \frac{f_i}{N}$, with f_i the repetition frequency of the i-th gray level $(i = 1,2,\ldots,L)$. Consider $\omega_1 = \sum_{i=1}^{t} p_i$ and $\omega_2 = \sum_{i=t+1}^{L} p_i$, where $1,2,\ldots,t$ y $t+1, t+2, \ldots, t$ are the gray levels corresponding to the classes C_1 y C_2 (binarization), then the probability distributions of the lessons

C_1 and C_2 are given by $\frac{p_1}{\omega_1(t)}, \frac{p_2}{\omega_1(t)}, \ldots, \frac{p_t}{\omega_1(t)}$ y $\frac{p_{t+1}}{\omega_2(t)}, \frac{p_{t+2}}{\omega_2(t)}, \ldots, \frac{p_L}{\omega_2(t)}$ respectively.

The average for each class respectively they are defined as $\mu_1 = \sum_{i=1}^{t} \frac{iP_i}{\omega_1(t)}$, $\mu_2 = \sum_{i=t+1}^{L} \frac{iP_i}{\omega_2(t)}$.

The variance between classes of a threshold image is given by $\sigma_B^2 = \omega_1(\mu_{1-}\mu_2)^2 + \omega_2(\mu_{2-}\mu_T)^2$ con $\mu_T = \omega_1\mu_1 + \omega_2\mu_2$. The optimal threshold that maximizes variance is $t^* = Max_t\{\sigma_B^2(t)\}$. Figure 3 shows the result of applying the Otsu threshold method to figure 2.

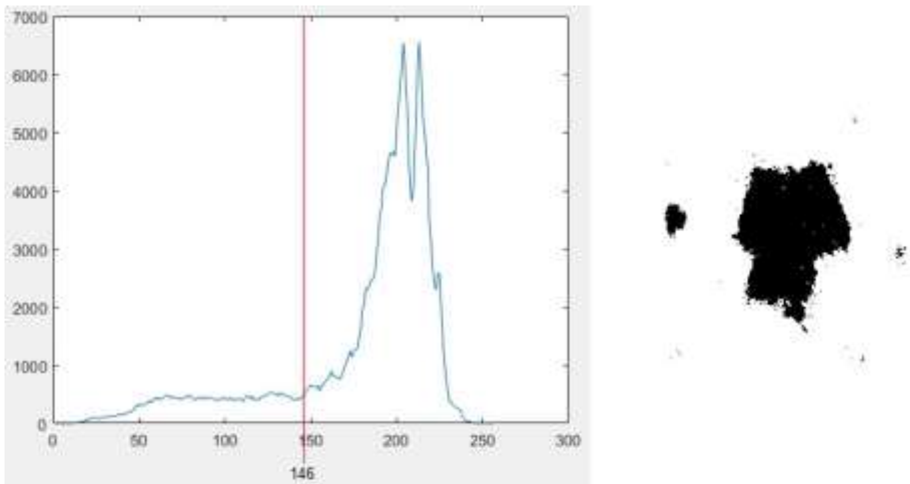

Fig. 3: Threshold by Otsu method.

Once the binarized image was obtained using the Otsu method, all those pairs of coordinates (x, y) such that $(C_x - x)^2 + (C_y - y)^2 \geq r^2$ were removed, where the point (C_x, C_y) is the center of the image $r = \min\{H/2, W/2\}$, this is:

$$f(x, y) = \begin{cases} 255 & if \quad (C_x - x)^2 + (C_y - y)^2 \geq r \\ f(x, y) & otherwise \end{cases} \tag{1}$$

Figure 4 shows in yellow the result of eliminating those points (x, y) that are outside the radius of the circumference.

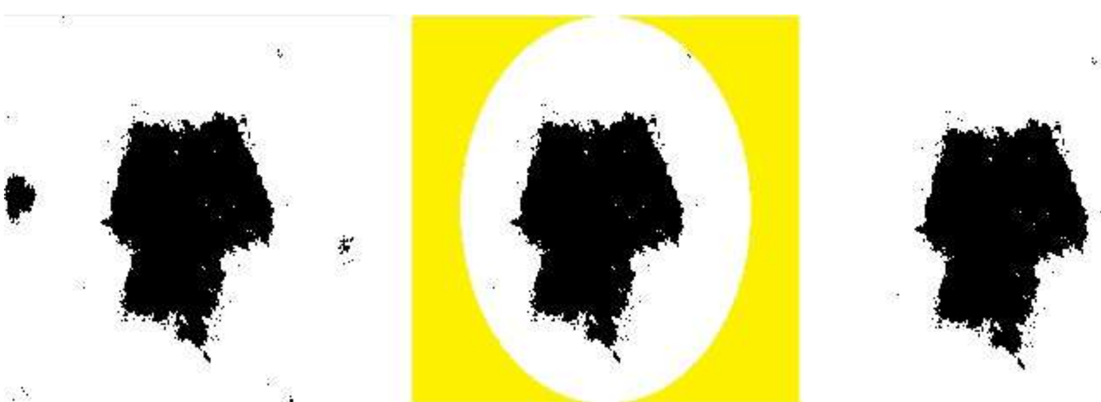

Fig. 4: Elimination of points that are in the yellow zone.

Once those pixels that are outside the radius of the circumference r have been eliminated, work is carried out on the segmented image obtained as in figure 4 but in grayscale as shown in figure 5 a). For each coordinate

pair (i, j) of the image a mask of size L is taken, the function is considered $g(i, j) = \sum_{(x,y) \in L_{(i,j)}} f(x, y)$ where $L_{(i,j)}$ is the mask of size L transferred to the coordinate (i, j) and $f(i, j)$ the value of the grayscale image (figure 5 b)). So that the resulting binary image is obtained as follows, for each coordinate pair (i, j), you have:

$$f(i,j) = \begin{cases} 255 & if\ g(i,j) > 0.25L^2 \\ 0 & otherwise \end{cases} \tag{2}$$

Figure 5 c) shows the result of applying the equation of function (2) to the image in Figure 5 a). Subsequently, a dilation was applied with a von Neumann neighborhood of size9×9. Figure 5 d) shows the result of the dilation, then figure 5 e) shows the color segmented image, figure 5 f) the outline of the segmented image and figure 5 g) the contour of the segmented image on the color image.

Fig. 5: Obtaining the segmented image.

4. Experiments and Results

The International Skin Imaging Collaboration (ISIC) is an academic project with the objective of developing tools for image analysis for automated segmentation and diagnosis of skin lesions that allow the detection of melanoma in dermoscopy images [22].

ISIC archive consists of an extensive bank of dermoscopy images of different types of skin lesions (nevus, basal cell carcinoma, dermatofibroma, melanoma and actinic keratosis, among others). This work focused on actinic keratosis skin lesions.

For this, a total of 132 images were used that present actinic keratosis, likewise, the methodology was also used in dermoscopy images that did not present actinic keratosis but if another type of lesion was used to observe the behavior of the proposed methodology.

Figure 6 shows the proposed methodology applied to three images of the ISIC archive repertoire. The color image was considered, from which the gray-scale image was extracted using the blue plane, then the Otsu method was applied to find the optimal threshold that would allow binarizing the image, then those points that were outside were eliminated of the radius of the circumference of equation (1).
Then, considering the segmented grayscale image, it was again binarized by using equation (2) with a 20x20 mask, then a morphological dilation was used with a structuring element in the form of a von Neumann neighborhood in size 9 x 9 to finally obtain the contour of the segmented image and the segmented color image. In Figure 6, a) and b) they are dermoscopy images that present actinic keratosis, and 6 c) is a dermoscopy image that presents some type of lesion other than actinic keratosis.

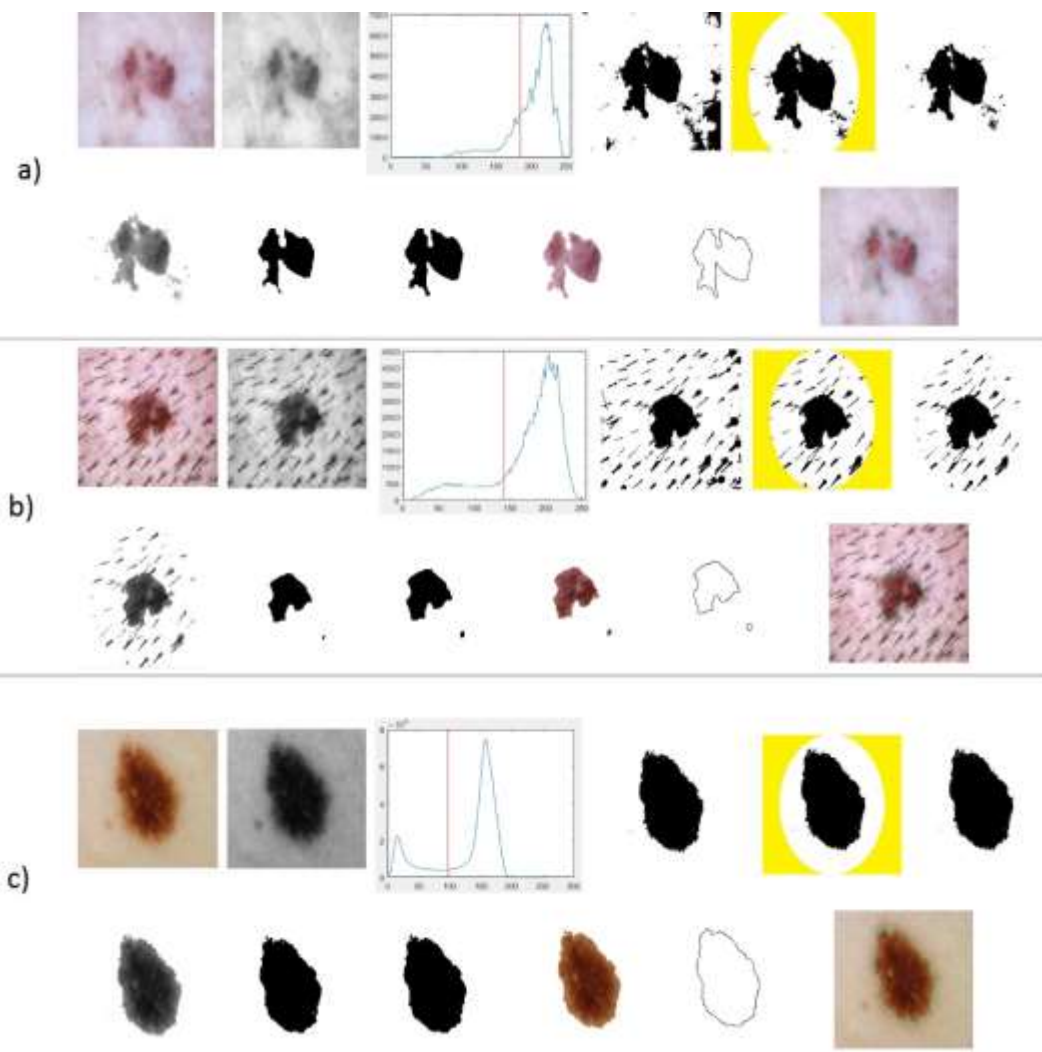

Fig. 6: Methodology applied to three dermoscopy images of ISIC archive.

5. Conclusions

Currently, CAD systems have been developed in different areas of medicine with the aim of supporting pre-diagnosis in the medical area. A CAD system generally comprises from the acquisition of the image to the classification of the disease in question, through an image segmentation module. This work that was presented focuses on the segmentation module in dermoscopy images that present lesions of actinic keratosis type, which although the main objective is to segment lesions of this type, the methodology was applied to dermoscopy images that presented other types of lesions, for this purpose The ISIC archive image bank was used. Figure 6 shows the result of the proposed methodology applied to three images that show lesions, in the case of a) and b) actinic keratosis.

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