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# A Brief Survey about Existed Segmentation Techniques in Automatic Detection and Segmentation of Skin Melanoma Images

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***Abstract-***

***Melanoma is a cancerous lesion in the pigment-bearing basal layers of the epidermis and is the most deadly form of skin cancer, yet it is also the most treatable, with a cure rate for early-stage melanoma of almost 100%. Therefore, there is a need to develop computer-aided diagnostic systems to facilitate the early detection of melanoma. The first step in these systems is skin lesion segmentation. The next essential step is feature extraction and pattern analysis procedures to make a diagnosis. According to the literature, pigment network or reticular pattern is an important diagnostic parameter for melanoma. We decided to work on this automatic melanoma detection system. In this paper, a brief study has been carried out about the existing segmentation methods adopted by different scholars. Various methods i.e. Region refinement, adaptive thresholding (AT), gradient vector flow (GVF),adaptive snake (AS);fuzzy-based split-and-merge algorithm (FBSM), k-nearest neighbour, k-means, log filtering etc. has been used for the segmentation of melanoma images. As we also need segmentation for our collected dataset, some of these similar methods have been discussed in this paper.***

***Keywords: FBSM, GVF, RGB, CIE***

## I. 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 alone [2]. 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 [2]. Detection of malignant melanoma in its early stages considerably reduces morbidity and mortality. Early detection also saves hundreds of millions of dollars that otherwise would be spent on the treatment of advanced diseases [3]. If cutaneous melanoma is detected in its early stages and removed, there is a very high likelihood that the patient will survive [4,5]. Clinical features of pigmented lesions suggestive of melanoma are what are known as the ABCDs of melanoma [3]: asymmetry, border irregularity, color variegation, and diameter greater than 6 mm. Image analysis techniques for measuring these features have been developed [6].

Measurement of image features for diagnosis of melanoma requires that first the lesions be detected and localized in an image. It is essential that lesion boundaries are determined accurately so that measurements, e.g. maximum diameter, asymmetry, irregularity of the boundary, and color characteristics can be accurately computed. For delineating lesion boundaries, various image segmentation methods have been developed.

These methods use color and texture information in an image to find the lesion boundaries. To segment a skin image into lesions, Umbaugh et al. [7] transformed the RGB color space into a spherical color space with coordinates defined by quantizing the AB space into four colors, they were then able to partition a color image into different regions and isolate lesions from the background. In a separate study, Umbaugh et al. [8] developed a principal-components transform in a userselected color space to segment skin cancer images. Green et al. [9] segmented a color image by first finding the average color of a small area of a lesion and the average color of a small area of the background interactively. Then, by mapping the image colors to the vector connecting the two average colors, they obtained a histogram.

The color corresponding to the valley between the two peaks in the histogram was then used as the threshold value to segment the image. Dhawan and Sicsu [10] used image gray values and textures separately to segment skin images. They then combined the results to obtain the lesion boundaries. Hance et al. [11] compared the accuracy of six different color segmentation techniques, and found that when two or more of the techniques are combined, an accuracy that is considerably higher than the accuracy of any one of the individual techniques will be obtained [12]. Dermoscopic images have great potential in the early diagnosis of malignant melanoma, but their interpretation is time consuming and subjective, even for trained dermatologists [13]. Therefore, there is currently a great interest in the development of computer-aided diagnosis systems that can assist the clinical evaluation of dermatologists.

The standard approach in automatic dermoscopic image analysis has usually three stages: 1) image segmentation; 2) feature extraction and feature selection; and 3) lesion classification. The segmentation stage is one of the most important since it affects the accuracy of the subsequent steps. However, segmentation is difficult because of the great variety of lesion shapes, sizes, and colors along with different skin types and textures. In addition, some lesions have irregular boundaries and in some cases there is a smooth transition between the lesion and the skin. Other difficulties are related to the presence of dark hair covering the lesions and the existence of specular reflections.

## II. VARIOUS SEGMENTATION TECHNIQUES

1. Preprocessing
2. Initial segmentation
3. Region refinement• adaptive thresholding (AT);
4. Gradient vector flow (GVF);
5. Adaptive snake (AS);
6. Fuzzy-based split-and-merge algorithm (FBSM).

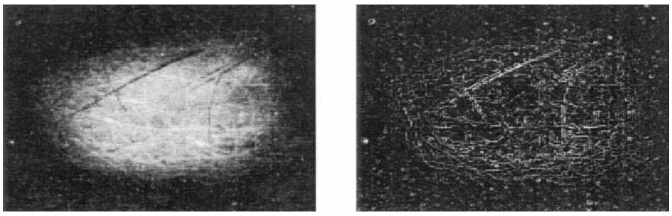
### 1. Preprocessing

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 (its 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 [14]. 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 DE) 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

(a)



(b) (c)

Fig. 1. (a) A color image showing an atypical lesion. (b) Image obtained after mapping colors into intensities in such a way that the intensity at a pixel is proportional to the CIELAB color distance of the pixel to the color of the background. (c) Gradient magnitudes of (b) obtained by the Sobel operator. Larger gradients are shown brighter.

### 2. Initial 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. 3(b) shows the image of Fig. 3(a) after being smoothed with a 2D Gaussian kernel of standard deviation 2 pixels. As can be observed, although smoothing reduce 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 use double thresholding to narrow in on an image area where 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. Double thresholding also reduces the number of noisy regions obtained as a result of intensity thresholding. Consider an image scanline, The horizontal axis shows pixels in the scanline, while the vertical axis shows the intensities of the pixels. As can be observed, if the threshold value is not selected properly, noisy regions from intensity variations in the lesion or background will be obtained. If there were no details from hair or skin texture, or if there were no intensity variations inside a lesion, a single threshold value T would have been sufficient to isolate a lesion from its background. However, since image variations from hair and skin texture usually exist in an image, a single threshold value may detect noisy regions from hair and skin texture. If such regions are close to each other, they may merge and create larger regions. By increasing the threshold value, we will observe that the number and size of noisy regions in the background will decrease.

If we decrease the threshold value, we will see that the number and size of noisy regions in the lesion will decrease. The use of two threshold values will, therefore, make it possible to obtain rather noise-free regions for both the lesion and background. Double thresholding will produce a segmentation that either will be free of noisy regions, or will contain fewer and smaller noisy regions than when a single threshold value is used. Double thresholding, however, requires the use of an initial threshold value.

**3. Region refinement**

The double thresholding process described in the preceding section determines an image area where a lesion boundary obtained from a range of threshold values will exist. Since the best threshold value in one local area may be different from the best threshold value in another local area, this range of threshold values is expected to include the best threshold value for all boundary pixels. We will assume that an optimal threshold value produces a boundary pixel that has a locally maximum gradient magnitude. Therefore, we will move an initial boundary pixel to the pixel in its neighborhood having a locally maximum gradient magnitude. Region boundaries in an image are best described by pixels with locally maximum gradient magnitudes [14– 17]. Pixels with locally maximum gradient magnitudes can be determined without any user interaction; therefore, the process is automatic. Locally maximum gradients in an image, however, not only represent lesion boundaries, they also represent small details inside and outside a lesion. In addition, an obtained boundary may merge with another boundary due to image noise and produce a false lesion boundary

**4. Adaptive Thresholding**

(AT) Lesion segmentation can be obtained by comparing the color of each pixel with a threshold . The pixel is classified as active (lesion) if it is darker than the threshold. The output of this step is a binary image. Morphological post-processing is then applied to fill the holes and to select the largest connected component in the binary image

**5. Gradient Vector Flow (GVF)**

The GVF snake is a well-known algorithm proposed in [32] which has been successfully used in many medical imaging

**6. Adaptive Snake (AS)**

Active contours are often attracted by spurious edges which do not belong to the lesion boundary. These normally appear in dermoscopic images due to artifacts such as hair, specular reflections or even from variations in the skin texture. Therefore, we need robust methods which are able to discard the influence of outlier edges. The adaptive snake tries to achieve this goal [22]. First, the method detects contour segments (strokes) in the image, using edge linking, and then approximates a subset of them using a robust estimation algorithm based on the expectation- maximization (EM).

**7. Fuzzy-Based Split-and-Merge Algorithm (FBSM)**

The sixth method used in this study is a fuzzy-based splitand- merge algorithm (FBSM), recently proposed in [17], [18]. The algorithm originally aims at unsupervised perceptual segmentation of natural color images. Since the algorithm has the significant advantage to stop the process at the specified number of segmented regions, it is applicable to the segmentation of dermoscopic images. First, the FBSM algorithm extracts color features and texture features from an original image. The values of L*,A*and b* , and are used as color features, and the statistical geometrical features (SGF) [9] are used as texture features. Then, a split-and-merge technique is executed in four stages: simple splitting, local merging, global merging and boundary refinement. During the latter three stages, the similarity of any adjacent regions is estimated using the fuzzy-based homogeneity measure that combines the similarity of color features and texture features with different degrees of importance. The adoption of a fuzzy-based homogeneity measure simplifies the complex mechanism of integrating different features by means of symbolic representations.

## III. CONCLUSION

Different literature work address the problem of how to determine the absence or presence of pigment networks in a given dermoscopic image. Most of the methods are robust, reliable, computer-aided diagnostic tool for analysing the texture in lesions of the skin to detect pigment networks in the presence of other structures such as dots. All these methods have some drawbacks, in which methods are defined according to a particular feature of the melanoma image such as intensity, streaks and their regularity and non-regularity characteristics. Different methods used different methods for extraction of feature set as well as final classification in terms of present or absent of the melanoma cancer in the image. In this work, different segmentation methods like adaptive thresholding (AT), gradient vector flow (GVF),adaptive snake (AS);fuzzy-based split-and-merge algorithm (FBSM), etc. has been discussed. There are many methods of segmentation used for melanoma cancer images. We decided to explore fuzzy methods of clustering in our proposed method for segmentation of melanoma images.

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