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Skin lesion image segmentation using Delaunay Triangulation for melanoma detection

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ABSTRACT

Developing automatic diagnostic tools for the early detection of skin cancer lesions in dermoscopic images can help to reduce melanoma-induced mortality. Image segmentation is a key step in the automated skin lesion diagnosis pipeline. In this paper, a fast and fully-automatic algorithm for skin lesion segmentation in dermoscopic images is presented. Delaunay Triangulation is used to extract a binary mask of the lesion region, without the need of any training stage. A quantitative experimental evaluation has been conducted on a publicly available database, by taking into account six well-known state-of-the-art segmentation methods for comparison. The results of the experimental analysis demonstrate that the proposed approach is highly accurate when dealing with benign lesions, while the segmentation accuracy significantly decreases when melanoma images are processed. This behavior led us to consider geometrical and color features extracted from the binary masks generated by our algorithm for classification, achieving promising results for melanoma detection.

1. Introduction

Melanoma is one of the most aggressive tumors in humans [1] and it can be lethal, if not diagnosed on time. The incidence of melanoma among all dermatologic cancers is 4%, while melanoma-induced mortality accounts for about 80% of deaths from skin cancer; only 14% of patients with metastatic melanoma survive for five years [2]. Moreover, malignant melanoma has a cure rate of more than 95% if detected at an early stage [3]. The above statistics demonstrate that there is an urgent need to develop innovative strategies able to increase the diagnostic accuracy and to help dermatologists making early diagnosis. Indeed, given the current lack of effective therapeutic approaches, the early diagnosis is the main way to achieve a real impact on mortality from melanoma.

Novel approaches are being developed to help early diagnosis according to bio-physics analyses [4], molecular targets identifications [5], and novel image analysis criteria [6,7]. In particular, the development of robust and reliable image analysis tools can reduce the number of presumptive diagnoses that have to be confirmed histologically on skin biopsy. Dermoscopy is one of the most important tool in the early diagnosis of melanoma. Dermoscopic images are obtained by combining optical magnification with either cross-polarized lighting or liquid immersion, with a low angle-of-incidence lighting. The use of dermoscopy gives a magnification of the images of the nevus lesions and it allows for the analysis of particular characteristics of the lesion, including symmetry, size, borders, presence and distribution of color features.

The typical computer-aided diagnosis (CAD) pipeline for automated skin lesion diagnosis (ASLD) from digital dermoscopic images can be subdivided into the following steps [8]:

1. Image acquisition;
2. Noise and artifact filtering;
3. Lesion segmentation;
4. Feature extraction;
5. Classification.

The lesion segmentation step is fundamental in order to increase the effectiveness of the subsequent steps, since it strongly affects the results of the whole pipeline [9]. Indeed, an accurate segmentation allows for deriving border structure information, such as the asymmetry and the irregularity of the lesion area, which are

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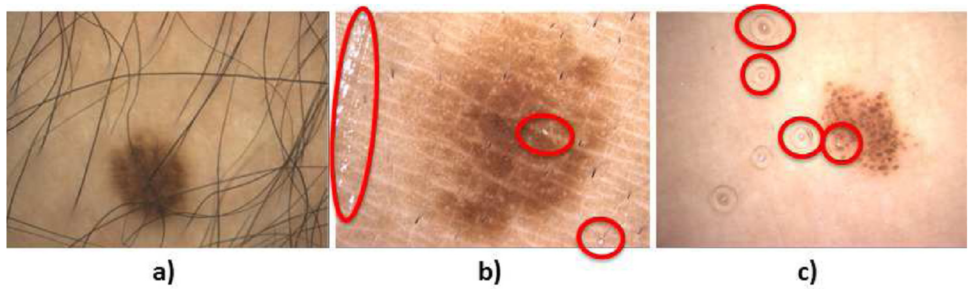

Fig. 1. Difficulties in lesion segmentation on dermoscopic images. (a) Presence of hair. (b) Reflections. (c) Air/oil bubbles. Images are from the PH^2 database [11,12].

essential for a correct presumptive diagnosis. Furthermore, important clinical features like blue-white areas, atypical pigment networks, and globules can be automatically extracted only when the accuracy of the detected lesion border is high [10]. However, the great variety of lesion shapes, size and colors, the different skin types and textures, as well as the possible presence of hair and air/oil bubbles make segmentation a hard task (three examples of typical challenges are shown in Fig. 1).

In this paper, we describe a fully-automatic lesion segmentation method, able to process dermoscopic images even when reflections, oil bubbles, hairs or other imperfections are present, extending the work presented in [13]. The proposed algorithm, called ASLM, does not require any training stage and comprises four steps: (i) artifact removal; (ii) skin detection and (iii) lesion segmentation, which generate two different images containing the detected lesion region; and (iv) a final stage where a binary mask is obtained by merging those images. In particular, ASLM is designed to be sensitive with respect to images containing irregular borders, multiple shades of pigmentation, and varying texture. This is demonstrated by experimental results, carried out on the publicly available PH^2 database [11,12], showing that the accuracy of the segmentation by ASLM is extremely high when dealing with benign lesions (common and atypical nevi), while the precision of the segmentation results significantly decreases when malignant lesions (melanoma) are analyzed. This behavior led us to consider the use of the binary masks generated by ASLM as input for a classification stage. The results for melanoma detection, obtained by considering only three geometrical features and three 16-bin color histograms, achieved 93.5% sensitivity and 87.1% specificity on a set of 200 dermoscopic images, demonstrating that ASLM can be a suitable tool for the development of CAD support systems for the early detection of malignant lesions.

The remainder of the paper is organized as follows. Related work is discussed in Section 2, while the details of the proposed skin lesion segmentation method are presented in Section 3. The description of the data set used for the experiments as well as a quantitative comparison of our method with six well-known segmentation algorithms are given in Section 4. Melanoma detection is discussed in Section 5 and conclusions are drawn in Section 6.

2. Related work

Automatic segmentation in dermoscopic images presents many difficulties related to the possible presence of hair, specular reflections, multiple colored lesion, low contrast between the lesion area and the surrounding skin, irregular and fuzzy lesion borders, and artifacts such as skin lines, blood vessels and air bubbles caused by dermoscopic gel [14]. Several segmentation algorithms have been proposed in the literature to deal with the problem of accurately segmenting skin lesion images and two surveys in this field have been realized by Celebi et al. [14,15]. According to Xie and Bovick [9] and to Silveira et al. [16], existing approaches can be grouped into three main categories:

Thresholding methods. Approaches in this category aim at comparing visual feature values for single or group of pixels in the dermoscopic image with threshold values (e.g., a pixel is labeled as a lesion point if it is darker than a given color threshold value). The output of the thresholding process is a binary image, which can be further processed to filter out outliers, to fill small holes, or to select the largest connected component. Examples of thresholding methods are adaptive thresholding [17], histogram thresholding [18], and clustering. In particular, a clustering-based segmentation method for dermoscopy images is described in [19], where *K*-means++ (KPP), a variation of the standard *K*-means algorithm with random seeding, is used.

Different thresholding methods can be combined together. In [20], pixel-based and region-based methods are used in combination with a region-growing approach for automatically extracting the lesion area. In [10], the results generated by an ensemble of different thresholding methods are fused together, thus obtaining a final mask that exploits the peculiarities of each specific method. In particular, four techniques are considered for constructing the ensemble: fuzzy similarity, maximum entropy, minimum error thresholding, and Otsu's clustering.

Thresholding methods performs well if there is a high contrast between the lesion area and the surrounding skin region, otherwise the segmentation accuracy can decrease. Moreover, thresholding methods can fail when processing images with significant amount of hair or air/oil bubbles [10].

Edge and contour-based methods. Algorithms in this group aim at identifying the discontinuities (i.e., the edges) in the dermoscopic images to detect the lesion borders. For example, an active contour method, which is based on gradient vector flow (GVF) snakes for contour extraction, is described in [21]. An extension of GVF based on mean shift (MSGVF) is proposed in [22]. Two contour based methods are applied to skin lesion images in [16], namely adaptive snake and active contour by level set. In the adaptive snake algorithm, detailed in [23], edge points are first grouped in strokes and then each stroke is classified as valid or not. A confidence level is associated to each stroke and the Expectation-Maximization (EM) algorithm is used to update the confidence levels and to estimate the object contour. The active contour by level set method, illustrated in [24], creates a model of the contour that does not exploit any edge detection function to stop the evolving curve on the boundary, but uses instead a stopping term based on Mumford–Shah segmentation techniques.

Edge and contour-based methods usually fail in the presence of hair or air bubbles and if the transition between the lesion and the surrounding skin is smooth.

Region-based methods. This category includes algorithms working at a global image level. The basic assumption is that the image in input contains always two different regions: lesion and skin.