Feature Extraction of Epiluminescence Microscopic Images by Iterative Segmentation Algorithm

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Abstract: - Since the introduction of epiluminescence microscopy (ELM), image analysis tools have been extended to the field of dermatology, as an attempt to algorithmically reproduce clinical evaluation. Accurate image segmentation of skin lesions is one of the key steps for useful, early, and non-invasive diagnosis of cutaneous melanomas. In this paper, a modified segmentation algorithm has been used to extract the true border that reveals the global structure irregularity (indentations and protrusions), which may suggest excessive cell growth or regression of a melanoma. The algorithm is applied to the blue channel of the RGB colour vectors to distinguish lesions from the skin and uses background noise reduction to enhance and filter the image of lesion. The algorithm also does not depend on the use of rigid threshold values, because an optimal thresholding algorithm “isodata algorithm" that is used determines an optimal threshold iteratively. Preliminary experiments are performed on diversity of clinical skin images and high resolution ELM images to verify the capability of the segmentation algorithm in extracting and characterizing the true features of the processed skin lesions. We demonstrate that we can enhance and delineate pigmented networks in skin lesions visually, and make them accessible for further analysis and classification.

Keywords: - Skin lesion, optimal thresholding, image segmentation, epiluminescence microscopy, SIAscope images.

1 Introduction

Trained dermatologists in the use of dermatoscopy or epiluminescence microscopy (ELM) can improve their diagnostic accuracy of melanoma from about 65% using the unaided eye to approximately 80% with the benefit of ELM [1]. However, even with ELM, a trained dermatologist can be deceived at least 20% of the time by the appearance of a melanoma. Low rate of correct classification of clinical diagnosis [2] calls for the development of both digitised ELM (DELM) and automated image analysis systems. For example, a recently developed PC-based pilot system by Binder et al. [3] promises to automatically segment the digitised ELM images, measuring 107 morphological parameters. A neural network classifier trained with these features is able to differentiate between benign and malignant melanoma.

This paper demonstrates the use of an iterative segmentation algorithm as a tool for determining the borders of real skin lesions as an aid to skin lesion diagnosis. The algorithm has been developed and compared with other developed Neural Network techniques and also the automatic segmentation method by Xu et al [4]. Initial experiments have been done on *synthetic lesions*, and the work has been written up in a paper [5]. The next section shows the method applied. This is followed in section 3 by results and discussions demonstrating the segmentation method. Conclusions are drawn in section 4.

2 Processing a Skin Lesion

The incidence of a weak contrast within the skin lesion does not allow colour-based segmentation to extract pigmented networks directly. However, extracting homogeneous and differently coloured regions within the lesions is a robust method for separating lesions from surrounding skin [2]. As an example of analysing pigmented network, Fisher et al. [2] develop a colour based segmentation algorithm, which is applied to Karhunen loeve transformation of the RGB colour vectors. Because the pigmented network and the background do not have homogeneous luminance, the result of segmentation is enhanced in a circular region to limit the problem of heterogeneous regions.

In this work the following processing steps are followed to delineate pigmented networks and make them accessible for further statistical analysis and classification. We suggest the processing of lesion images using the Blue channel of the RGB colour space followed by noise reduction imaging tasks and intensity mapping to filter and enhance the region of skin lesion. If we assume that the previous steps assist to provide equal region probabilities then a simple iterative scheme would segment the image into binary regions containing the lesion and the background. This process is depicted in Table.1. In contrast with the above example of segmentation, the region processed is equal to the full size of image.

Table 1. Modified algorithm steps to delineate colour lesion [6].

Step1*: {Source image}*

Source image = Blue channel of {R,G,B} colour image

Step2*: {Noise reduction}*

Median filtering and grey morphology {reduce skin hair}

Analyse and reduce median background noise

Step3*: {Lesion enhancement}*

Map intensities with appropriate function

Smooth image; optimal kernel size is estimated

Step4*: {Iterative thresholding}*

Use the isodata Algorithm of Madisett et al. to find the optimal auto-threshold value T for an image

Step5*: {delineate object}*

Outline binary object.

Step6*:* {Object analysis}

Set the minimum object *Diameter* and *Area*

Scan the binary image *Until*

MinSize < *Area* < *MaxSize*

Step 1. We use the blue channel of the intensity of an RGB colour skin lesion image as the first step. This approach has been demonstrated to provide the best results in global and dynamic thresholding algorithms [7]. ***Step 2.*** Because real skin images often contain features such as hair and other small objects, we have added a statistical median filter as the first step of data reduction followed by grey scale morphological opening and closing operations as the first step of data reduction without destroying the morphological structure of the pigmented network [2,7] .For optimum use of the algorithm it is useful to remove the background intensity of skin surrounding the lesion. This is estimated by calculating the median of two strip windows from the top and bottom of an image; each strip of size $w \times 10$ pixels, where w is the full image width [4]. ***Step 3.*** A mapping function *G(f)* is used here to map the intensities I to enhance features at the boundary;

$$G(f) = k\left(1 - \exp\left(-f^2 / 2\sigma^2\right)\right) \tag{1}$$

where

$$f(I) = c^2 I^3 + c^4 I^5 + c^5 I^7 \tag{2}$$

where

$$c = 1/k \tag{3}$$

G(f) achieves less redundancy in the colour map than the Gaussian transformation used in [4] which makes it more suitable to map a wide range of intensities so that the lesion can be distinguished from the background. Another advantage here is that when mapping images of low noise variations, small σ, in the background (e.g. ELM images) then the function tends not to magnify that noise. The selection of the standard deviation (σ) of this mapping function is automatically determined according to the estimated standard deviation of the background surrounding the lesion; in the same manner when subtracting background median noise (Step 2). Small smoothing Gaussian kernels are adopted at this stage for two reasons: (i) to assist the extraction of morphological structure of the pigmented network, (ii) large smoothing is not necessary because the pre-processing steps (step 2) already provide the robust noise reduction. ***Step 4.*** The iterative thresholding algorithm described by Madisett et al as an isodata algorithm [8] is used here to find an optimum auto-threshold value T for an image. This value would segment the image into binary regions containing the lesion and the background. It is interesting to mention here that synthetic data were used in a previous publication [5] to study the performance of this algorithm in extracting the reference synthetic lesion model. ***Step 5.*** Delineation is applied to binary objects that result from optimal thresholding (step 4). The logic rule in this binary process simply follows "any foreground pixel with at least one background pixel in the 3x3 neighbourhood is left unchanged, otherwise it is changed to the background colour" [9]. ***Step 6.*** This process is useful to analyse the final binary image with multiple lesions or to correct errors caused in the delineation process such as the delineation of thick and dark hair. Scanning across the image is performed and a condition or a set of conditions reached. For example, a condition to check the area of the object

between minimum and maximum size would eliminate unnecessary size of object: $MinSize < Area < MaxSize$.

3 Results and Discussions

We have processed sixty images of skin images. The first twenty images are captured by digitised clinical photographs [4]. We have chosen these low quality images to test the robustness of the algorithm to delineate images with clear skin texture. The other forty images are captured with the ELM technique; SIAScope images [10]. Successful delineated of the most noisy clinical photograph colour lesions are achieved. This preliminary test experiment demonstrates the robustness of the algorithm against wide range of noise such as skin texture, and hair noise (see fig.1).

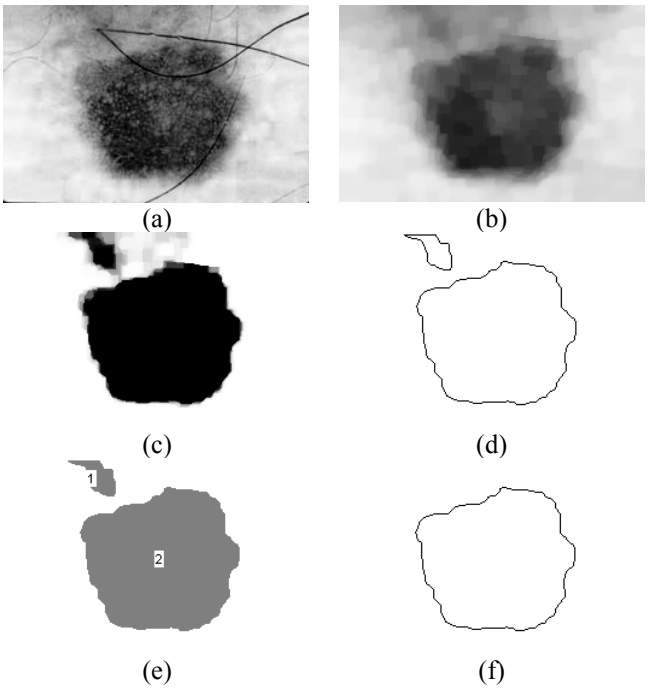

Fig.1. Demonstration of iterative segmentation algorithm. (a) Gray intensities of blue channel. (b) The resulting image after noise reduction (step 2 in the algorithm). (c) Intensity mapping by function *G(f)*. (d) Edge outline of binary segment at an optimal threshold. (e) Analysis of the resulting objects and eliminating the small objects. Labels are also used to check the success of the process, MinSize=0. (f) Excluding small objects, which are labelled as No. 1.

Fig. 2 compares the final outputs results from the developed algorithmic method and the Xu et al. method [4], when they are applied to a SIAscope image. In most of the processed SIAscope images, the Xu et al. method poorly delineates the boundary of the lesion. The figure demonstrates the failure of this method to delineate the boundary of a melanoma. The intensities mapping function of the Xu et al. method is the major drawback. When an image contains low variations in its background

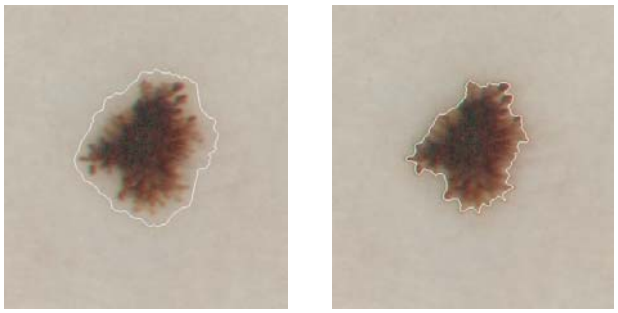

Fig.2. SIAscope image for melanoma is segmented by: (a) Automatic skin segmentation method [4], (b) the developed iterative segmentation algorithm.

4 Conclusions and Future Works

In this paper we have discussed the development of the new algorithm to delineate skin lesions. A combination of moles and pigmented networks of ELM skin lesion images are chosen here to provide preliminary tests of the algorithm performance. Visual enhancement and delineation of skin lesions can make them accessible to further analysis and classification. Other noise sources such as light reflections, and noise artefacts will be considered in the development of this algorithm.

Acknowledgments **-** The authors would like to thank Astron Clinica, Cambridge, UK, for the support in providing the real color skin lesion images, which facilitate the work throughout this study. I would also like to extend my grateful thanks to MD Dermatologist Majd Abdul Khalek for sharing his medical knowledge.

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