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New Segmentation Method for Skin Cancer Lesions

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Abstract: Skin cancer lesioning one of the most skin lesions which cause death. Lesion segmentation is a very important step prior to detecting and classifying the skin cancer. In this study, we introduce a new method to extract the lesion from the surrounding of healthy skin. The proposed method starts with image preprocessing included image de-noising and removing the unwanted objects such as thin hair and air bubble by using the median filter, followed with edge detection using the Markov and Laplace filter. The current algorithm converts the color image to YUV color space and select the U channel for processing. Thick hair is removed from U channel by combining both morphological operation and median filter. Mathematical morphology such as close used to join narrow breaks regions in an object, fill the small holes and remove small objects. The final step is to find threshold based on Otsu's thresholding to separate the image to two regions one for lesion and the other for skin. The result image is binary image or can be color lesion with black background. The accuracy of the suggested method reaches up to 98%. The algorithm is tested with segmented images by an expert and give very promised results in many cases gives better results. Also hamming distance is imeasured and it was better value compared with other algorithms.

Key words: Segmentation, image processing, edges, YUV, Otsu's, morphological operation

INTRODUCTION

Skin lesion is a general term which is used to refer to a lot of phenomena. Generally, a skin lesion is any part of skin which has different characteristics from the surrounding skin. The most serious type of skin lesion is the skin cancer. Skin cancer represents 50% of cancers detected each year.

Melanoma accounts for approximately 75% of deaths related to skin cancer (Gohilavani *et al*., 2014). Due to the costs of dermatologists to monitor every patient there is a need for a computerized system to evaluate a patient's risk of melanoma using images of their skin lesions captured using a standard digital camera.

The segmentation of skin lesions is a crucial early step in the process of automatically diagnosing melanoma. Inaccurate segmentations will affect all downstream processes such as feature extraction, feature selection and the final diagnosis. Accurate segmentations are especially crucial for features that measure properties of the lesion border (Bhuiyan *et al*., 2013).

The most important stage in the automatic skin lesion diagnosis is the segmentation. The segmentation accuracy determines the eventual success or failure of a CAD Diagnosis system. Thus, the process of lesion segmentation is not easy due to its influence on the accuracy of the next stage (Xie and Bovik, 2013).

Even though, skin lesion classification might seem very similar to any other object recognition task at a first analysis, sharp differences emerge when closer attention is paid to its specific characteristics. At the highest level, these differences can be divided in two major classes. The first class regards specificities which make the assessment difficult for humans while the second class focuses on those aspects which challenge automatic classifiers. Obviously the boundary between the two classes is not always well defined but this subdivision provides a good general approximation. Lesion segmentation is a complicated process due to:

- Low contrast between the lesion and the surrounding skin
- Almost irregular border between lesion and skin
- Unwanted objects such as hair, air bubble or may be the different skin textures included in some lesions
- Some lesions may exhibit different colors

Literature review: Andrea Pennisi presented a new method to segment lesion region based on Delaunay triangulation. A quantitative experimental evaluation was conducted on a publicly available database. This method worked very well with good accuracy when dealing with benign lesion however the accuracy was highly decreases when dealing with melanoma images (Pennisi *et al*.,

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2016). Sumithra suggested a segmentation and classification method of skin lesion. The method initially removed noise and unwanted objects such as hair and air bubbles. In this study, automatic segmentation based on automatic initialization of seed points to implement theregion growing technique (Sumithra *et al*., 2015).

Alaa Ahmed proposed segmentation method based on using the green channel from RGB image which is rescaled into new intensities. The method started with preprocessing operations by using morphological operations and median filter to remove the noise, hair and reduce the reflective light. Threshold is determined to implement the segmentation (Al-Abayechia *et al*., 2014).

Otsu's method: Otsu method is an efficient method for automatic thresholding. Otsu separates the image to two regions (classes) (one as a foreground region while the other regards as background region). The threshold is the intensity value which maximizes the variance between the two classes. Practically, Otsu uses image histogram to determine the probability of each intensity level in the image.

The algorithm automatic divides the range into two classes by suggesting threshold (k). For each class, compute the probability and the mean. Then, calculate the variance. The algorithm tries to minimize the weighted within-class variance $\sigma^2_w(k)$ (Pablo and Nesmachnow, 2016).

MATERIALS AND METHODS

For skin cancer detection, it is necessary, before the examination, to start by pre-processing and segmenting the skin tumor image. Technical difficulties in image segmentation include variations of brightness, the presence of artefacts (e.g., hair, air bubble) and variability of edges. The idea is that if there is a transaction on edge detection of a source noised image, we can locate other additional edges due to the presence of noise. The proposed segmentation process is implemented by the following steps.

Step one (image de-noising): In our system, median filtering is applied to minimize the effects of thin hair, removing noise and unwanted objects (like small air bubbles). The median filter is a nonlinear filter which can be represented as a 3×3 window. This window scans the entire image and replaces each pixel by the median value of the neighboring pixels.

Step two (edges detection): An edge is defined as the set of pixels which separates two different regions: one of important steps in image segmentation is edge detection. It determines the presence of lines in an image and outlines them in an appropriate way. The suggested method for edge detection is based on Markov and Laplace filter. The input filter $Z_i^*(x, y)$ is one of filters with dimension 3×3 as suggested by El Abbadi *et al.* (2016). In this study, we use the filter in Eq. 1 mask used for edge detection:

$$\begin{bmatrix} 0 & -3 & -1 \\ -3 & 14 & -2 \\ -1 & -2 & -1 \end{bmatrix} \tag{1}$$

We process each band of color image (red, green and blue) as a separated image (matrix) to detect the edge. The three bands reconstruct the colored image with edge highlights as in Fig. 1.

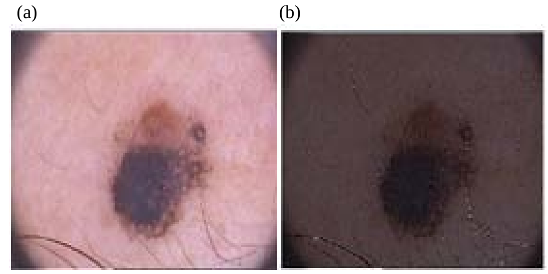

Fig. 1: The edges enhancement of image: a) Original image and b) Edge enhancement

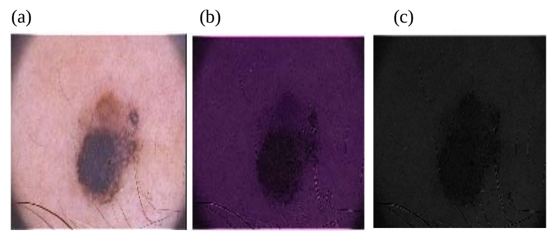

Fig. 2: Image transformation, RGB: a) Color image RGB; b) YUV image and c) U channel image

Step three (convert to YUV color space): The resulted image from step two is converted to YUV color space. For the purpose of image segmentation, we select the (U) channel as single channel for processing. Figure 2 shows the transformation process.

Step four (hair removal): Although, median filter is used to remove thin hair but sometimes it leaves traces of hair. For thick hair, we need another technique to remove it. In this study, we suggest to use both the morphological bottom-hat filtering and median filter technique. The output image is shown in Fig. 3.

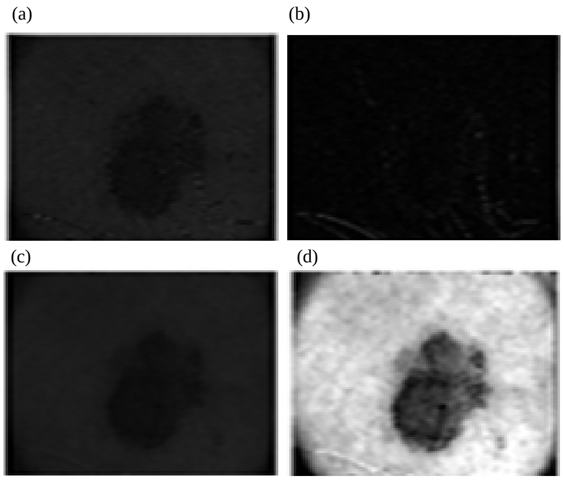

Fig. 3: Hair removal and contrast enhancement of image: a) U image; b) Hair detection image; c) After hair removal and d) After contrast enhancement

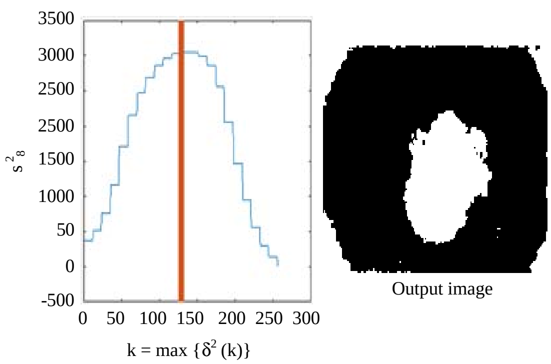

Fig. 4: Histogram which shows k* value represent maximum between-class variance

Step five (find threshold): The important step in the segmentation is to find the threshold which helps to convert image to binary image with two colors the white color represents the region of lesion while the black color represents the skin. In this step Otsu's method is used to find the threshold as shown in Fig. 4.

Step six (morphological operations): In this step, morphological operations are used to fill the holes and remove the small regions (Fig. 5a). Then, the big area is selected as the lesion area in the image and all other objects are regarded as background (skin region). The intensity value of input image to new value such that 1% of data is saturated at high and low intensities. This increases the contrast of image. The result image can be binary image (Fig. 5b) or colored image as in Fig. 5c.

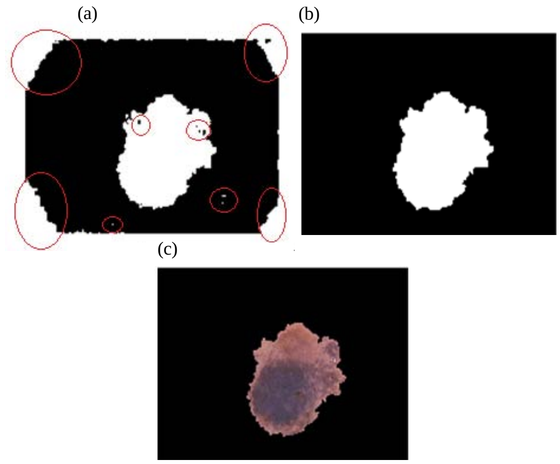

Fig. 5: The phases of new suggested method of segmentation: a) The holes and small regions; b) Image after morphological operation and c) Origin lesion from color image

RESULTS AND DISCUSSION

For testing the performance of the proposed method we use reference images from the PH2 images database which is segmented by an expert. We implemented the suggested method on 235 images (200 image from PH2 database and 35 image from the website (http://homepages.inf.ed.ac.uk/rbf/DERMOFIT/)). Performance are tested as follow: We compare the segmented images resulted by proposed method with expert segmented images in PH2 database. Figure 6 shows the compared result of some images:

- Original image
- Edge detection by the suggested method
- Segmented lesion is obtained by the suggested method
- Segmented image by expert physician
- Difference between expert and proposed method

Hammoude distance (HM): This distance measure is used to measure the errors between the segmented part of physicians and the segmented part of proposed algorithm. HM is based on a pixel by pixel comparison of the pixels enclosed by two boundaries as in the following relation: hamming distance for the suggested method is compared with hamming distance for other methods. The compared results are shown in Table 1:

$$HM(X,Y) = \frac{N(X \cup Y) - N(X \cap Y)}{N(X \cup Y)}$$

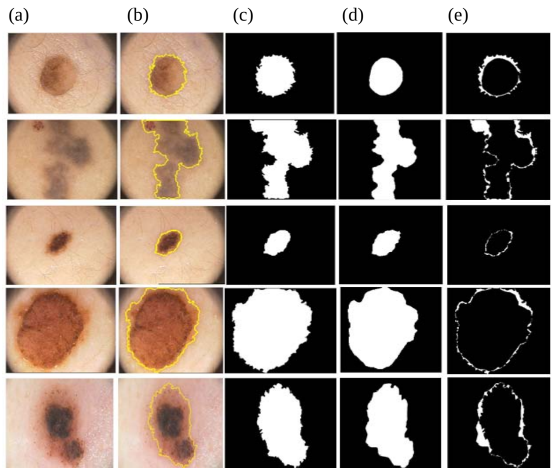

Fig. 6: Comparing the lesion segmentation between expert and proposed method

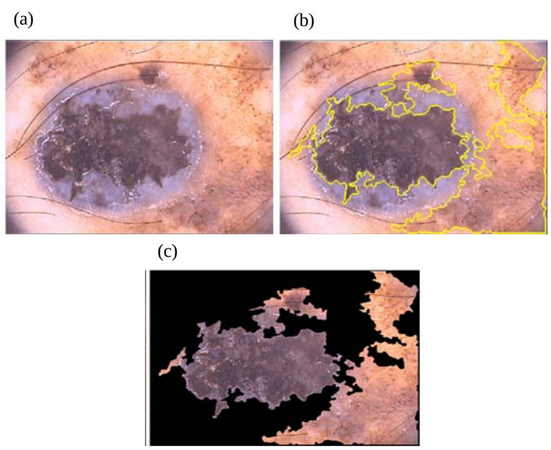

Fig. 7: An accurate segmentation

Table 1: Hamming distance of tested images for different methods (El Abbadi and Miry, 2014)

Methods	HM
K-means	13.87
Fuzzy k-means	13.07
Otsu	13.89
Niblack	16.73
Sauvola	16.45
Histogram	11.37
Proposed	7.78

Precision: From 235 images, there are just 5 images that do not segment accurately as in Fig. 7 this indicate that the precision of segmentation can reach about 98%.

It is clear as in Fig. 6 that the suggested method works very well. One important thing has to be mention here: the expert physician cannot segment the lesion with irregular boundary (almost the cancer lesion has irregular boundary) while this is implemented in the suggested method (the second image in Fig. 7).

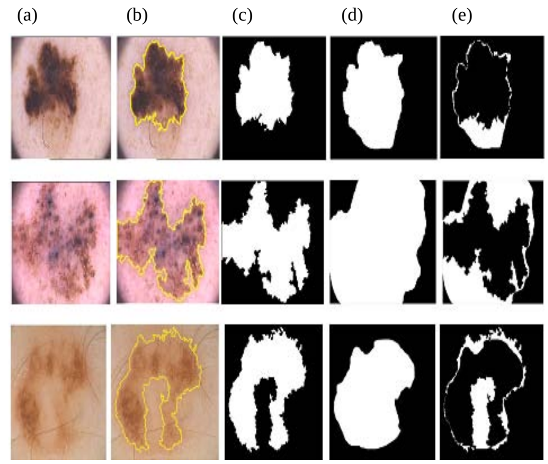

Fig. 8: Accuracy of suggested method compared with expert images

The suggested method is almost more accurate than expert segment image. It is clear from Fig. 8 that segmentation in is more similar to lesion in the image while the lesion segmented by expert highly differs from origin image:

- Original image with lesion
- Edge detection by the suggested method
- Segmented lesion is obtained by the suggested method
- Segmented lesion by expert physician
- Difference between expert and proposed method
- Hamming distance shows very good results compared with other methods as shown in Table 1
- The suggested method used the U channel from YUV color space which increases the segmentation accuracy
- Some of images do not segment correctly as in Fig. 8 due to the inflammation of the entire region around lesion

CONCLUSION

In this study, we suggest new method of segmentation based on edges enhancement of (RGB) image. The method has used the (YUV color space) for accurate segmentation. Proposed algorithm has been evaluated with segmented images by expert from PH2 database and the result for the proposed algorithm is more accurate in many cases. Also, the hamming distance show very promised results. Accuracy of segmentation reaches up to 98%. The hamming distance has been compared with other techniques and the result is promising encouraged.

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