Lesion Detection in Dermoscopy Images Using Sarsa Reinforcement Algorithm

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***Abstract*–Dermoscopy is one of the major imaging techniques used in diagnoses of Melanoma and other skin diseases. Because of difficulties and subjectivity of human interpretation, automatic and computerized analysis of dermoscopic images has opened an important research area. Skin lesion detection is as the first step in this analysis. Finding an optimal threshold for segmenting the lesion is a severe task in image processing. Different methods for thresholding already exist. In this work, we use a combination of well-known thresholding methods and fuse them by Sarsa Reinforcement algorithm which leads to a reinforced threshold. The reinforced agent learns optimal weights for different thresholding methods and finally segments the dermoscopic image with optimal threshold. A reward function is designed for achieving the similarity ratio between the binary output image and original gray level image and calculating reward/punish signal which should be exerted to reinforced agent. We use three thresholding methods for combination in the reinforced agent and the detected lesions are compared with the ground-truth which is determined by three different dermatologists.**

Key words- Dermoscopy; Detection; thresholding; Reinforcement; Melanoma

I. INTRODUCTION

MALIGNANT MELANOMA has become one of the most dangerous and the rapidly increasing kind of skin cancer with an estimated incidence of 68,720 and an estimated total of 8,650 deaths in the United States in 2009 [1]. Early diagnoses are very important since the cancer can be cured with a simple excision in its early stages. Dermoscopy is one of the most important tools in the diagnoses of the skin cancers. In compare with conventional imaging systems, dermoscopy caused the skin surface structures more clearly by the use of its optical magnification [2]. Automatic lesion detection is as the first step in analyzing of the dermoscopic images, and because of two reasons it is very important: first, the lesion border structure contains very important information for diagnose step such as asymmetry, irregularity of the border and border cutoff. Second, important clinical features such as atypical pigment network, blue-white areas and globules, directly depends on the accuracy of the detected border [3,4]. Automatic lesion detection is a challenging issue because of several reasons: (1) low contrast between lesion and the surrounding skin, (2) irregular borders, (3) artifacts such as skin lines, hairs, black frames and blood vessels. Many different methods have been developed for lesion detecting in dermoscopy images. Here we mention some of these methods. Different kinds of segmentation such as thresholding, clustering, morphology, edge and region based segmentation, and also their evaluation parameters are presented in [5]. In [6], by selecting an appropriate color channel and also OTSU thresholding method, the lesion is detected. In [7], a modified JSEG algorithm is used for detecting skin lesion. In [8,9]with use of Statistical Region Merging the lesion is separated from surrounding skin, and in [10] a multi directional GVF[1] snake is used for segmenting skin cancer images.

In this paper we present an accurate method for detecting lesion in dermoscopy images. The method includes preprocessing, and then combining several well-known thresholding methods by Reinforcement algorithm, and finally post-processing steps. The rest of the paper is as follows: section 2 describes lesion detecting process, section 3 presents the experimental results. Finally, section 4 gives conclusions.

II. LESION DETECTING PROCESS

Lesion detection in this paper involves 3 steps: (a) pre-processing, (b) using Sarsa Reinforcement Algorithm for

[1] Gradient Vector Flow

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finding optimal threshold and (c) post-processing. We describe each of these steps briefly here:

A. Pre-processing

- *Hair removal*: before exerting thresholding algorithm to the image, it is needed to remove hair from lesion. The hair removal process consists: (i) localizing dark hairs, using morphological closing operation, (ii) interpolating the removed hair pixels by neighbor non-hair pixels, and (iii) smoothing the final result using a median filter [11].
- *Color space transformation*: since color information plays an important role in skin image processing, the original RGB image is converted to different color spaces, and appropriate color channels are extracted. According to [6], X and XoYoR color channels, leads to the best result and high accuracy for segmentation in dermoscopic images. In this paper, we use X-color channel.
- *Contrast enhancement*: in this part we try to adjust the intensity of the image by mapping the dynamic range of pixels values into a new range. The purpose is to smooth and stretch the image histogram and increase the contrast of the image to be able to find a more accurate threshold value.

B. Thresholding Using Reinforcement Algorithm

Image thresholding is one of the common segmentation techniques in image processing. Since each of the thresholding methods uses different techniques for achieving the threshold value and may be suitable for a specified kind of image set, according to their statistical characteristics, thus a possible approach to overcome this problem is to fuse the thresholding algorithms and thus arriving at amore accurate threshold than is possible with a single thresholding algorithm. In this paper we used the fusion method proposed in [12] with little change, which we describe briefly in the following:

Reinforcement Learning can be defined as a computational method for learning through interacting with environment [13]. The RL[2] agent maps the states of the environment to appropriate actions and tries to maximize the reward and minimize the punishment it receives from the environment [13, 14]. Figure 1 illustrates the components of this algorithm. The agent as the central part and decision maker of the algorithm, does not need a set of training examples, instead it learns on-line. The RL agent by taking an action, influence the environment and changes the states. For a RL agent learning includes 2 stages: exploration and exploitation. Exploration means searching to discover which actions cause maximum reward and exploitation is taking these actions.

[2] Reinforcement learning

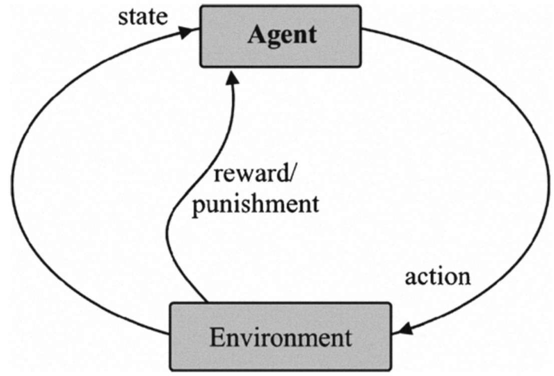

Figure 1- Basic component of reinforcement algorithm

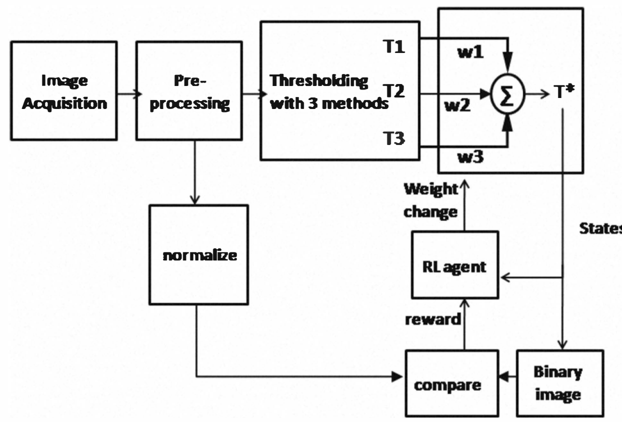

Figure 2- Threshold fusion scheme for lesion detection.

In this paper we use Sarsa Reinforcement Learning that its state-action values are updated by the following rule:

$$Q(S_t, a_t) \leftarrow Q(S_t, a_t) + \alpha\left[r_{t+1} + \gamma Q(S_{t+1}, a_{t+1}) - Q(S_t, a_t)\right] \quad (1)$$

In which $Q(s_t,a_t)$ is a learned value function for a given state of s_t and action a_t at time t. α is learning rate, γ is discount factor and r is reward.

After pre-processing step, we segment the image with three well-known methods individually; these methods are Otsu, Kittler and Kapur. Then a RL agent is used for weighting these methods. We use ε – greedy policy for mapping current states to appropriate actions. The block diagram of Figure 2 illustrates the process.

Initial weights for threshold can be chosen randomly, in a way that the sums of them become one. Then RL agent changes the weights until they converge to their optimal values. Imagine initial weights are $w_1, w2, \ldots, w_n$. Then $d=w_{max}-w_{min}$ is applied for adjustment factor Δ which we use for changing weights. Seven actions is defined through each, we go from one state to another state. For each weight three state probabilities is available.

$$\begin{cases} w_i(t+1) = w_i(t) & or \\ w_i(t+1) = w_i(t) + \Delta & or \\ w_i(t+1) = w_i(t) - \Delta \end{cases} \tag{2}$$

In each of learning scenario step, fused threshold:

$$T^* = \sum w_i \times T_i \tag{3}$$

Is considered as a state of the environment, and by changing the weights and taking a new action, we go to a new state. The process continues until achieving optimal thresholds.

A separate copy of original image is normalized and saved as matrix M. If we consider B as binary output image, the difference between B and M is used in reward function as follows:

$$\begin{cases} F_{dissim} = \sum \| B - M \| \\ r = \dfrac{1}{F_{dissim} + \delta} \end{cases} \tag{4}$$

Which δ is a positive small number. This reward is feedback to RL agent as an evaluation signal, in a way that a more similarity, a more reward received, and Q(s,a) matrix will be updated.

C. *Post-processing*

In some skin images extra objects appears in final binary image, such as blue marks, which have not been removed in the de-noising step, and may be misclassified as lesion. The aim of this step is to eliminate these artifacts. To this end, the numbers of connected objects are counted and labeled. Then two largest areas (lesion and normal skin) are kept and the rest are removed. Finally the holes inside the boundary are filled using morphological operation.

The result of exerting all above process with its ground truth is shown in Figure 3.

III. EXPRIEMENTAL RESULTS

The algorithm is tested on a set of 30 dermoscopy images, whether Melanoma or Non-Melanoma images. As the ground-truth, the automatic borders are compared with those manual borders which are determined by 3 dermatologists.

As evaluation metrics we use 4 parameters for quantitatively comparsion between the borders drawn by dermatologists and the computer derived borders. These metrics are as follows:

$$Sensitivity = \frac{TP}{TP + FN} \tag{5}$$

$$Specificity = \frac{TN}{TN + FP} \tag{6}$$

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{7}$$

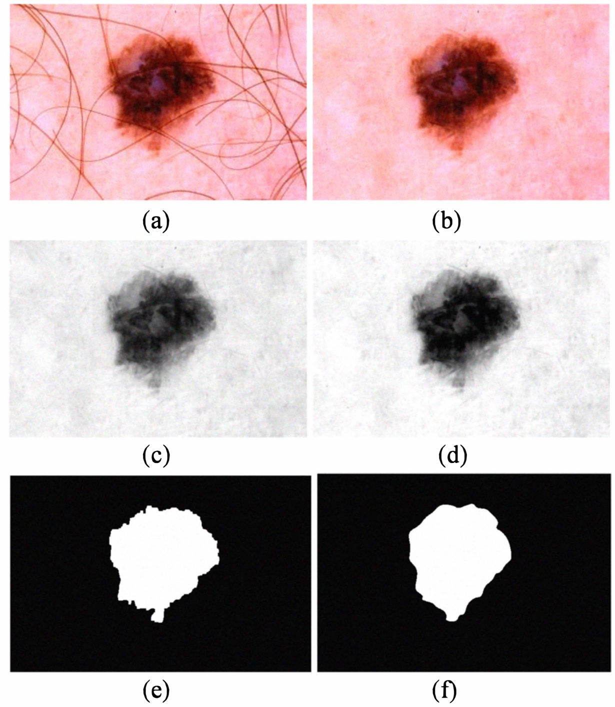

Figure 3- a) original image ; b) hair removal ; c) color channel transformation ; d) intensity adjustment ; e) lesion detected by RL ; f) ground truth.

$$Similarity = \frac{2 \times TP}{2 \times TP + FN + FP} \tag{8}$$

TP is true positive and shows the number of pixels which are classified as lesion in both manual and automatic segmented images. TN represents the number of pixels which are classified as surrounding skin in both images. FP shows the number of pixels which are lesion in automatic border and as normal skin in manual segmentation. FN indicates the number of pixels which are normal skin in automatic border but as lesion in ground truth.

For all the experiments episode number is $e = 50$ and the iterations number per episode is $i = 1000$. The learning rate is $\alpha = 0.4$ and discount rate is $\gamma = 0.7$. In table 1 the results of simulation by using MATLAB software is shown. The averaged evaluation metrics on 30 dermoscopic images is shown in this table, which we achieve an average value of %92.34 for similarity and %97.18 for accuracy.

IV. *Conclusion and Future Work*

In this paper we present lesion detection in dermoscopy images using reinforcement algorithm for threshold fusion. After preprocessing step, a reinforcement agent is used for fusing some thresholding methods and achieving optimal threshold for segmenting the image. The process is followed by post processing step.

Table 1- Simulation results of the proposed algorithm.

Parameters / Dermatologist	*Accuracy*	*Similarity*	*Sensitivity*	*Specificity*
Dermatologist#1	%94.30	%89.15	%85.52	%99.09
Dermatologist#2	%94.31	%89.46	%85.84	%99.08
Dermatologist#3	%97.18	%92.34	%87.18	%99.09

The comparison between automatic borders and ground truth determined by three different dermatologists shows accuracy of 97.18% and similarity of 92.34%. Although if we increase the number of episodes and iterations the RL agent will get more time for exploration and the results would be better.

The proposed method is compared with two sate-of-the-art skin lesion detection methods, namely JSEG method [7] and Statistical Region Merging [8], both of them are unsupervised and vector processing approaches toward lesion detection in dermoscopy images. Table 2 shows the evaluation metric results obtained by SRM and JSEG and proposed fusion thresholding method. The results demonstrate that the proposed method is highly competitive with other well-known mehods. It is shown that we arrive to better accuracy in compare with two other methods which is the result of fusion.

Table 2: COMPARATION RESULTS

Metric / Method	*Accuracy*	*Similarity*	*Sensitivity*	*Specificity*
SRM	96.27	%91.55	%92.45	%97.43
JSEG	%96.70	%93.23	%92.05	%99.02
Proposed Method	%97.18	%92.34	%87.18	%99.09

In future work we try to use other thresholding methods in fusion part and also a different value function for achieving better results.

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V. *REFRENCES*

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