

# Segmentation of Lesions in Dermoscopy Images Using Saliency Map And Contour Propagation

Mostafa Jahanifar, Neda Zamani Tajeddin, Ali Gooya, Babak Mohammadzadeh Asl

Dept. of Biomedical Engineering

Tarbiat Modares University

Tehran, Iran

{m.jahanifar, n.zamanitajeddin, a.gooya, babakmasl} @ modares.ac.ir

**Abstract**—Melanoma is one of the most dangerous types of skin cancer and causes thousands of deaths worldwide each year. Recently dermoscopic imaging systems have been widely used as a diagnostic tool for melanoma detection. The first step in the automatic analysis of dermoscopy images is the lesion segmentation. In this article, a novel method for skin lesion segmentation that could be applied to a variety of images with different properties and deficiencies is proposed. After a multi-step preprocessing phase (hair removal and illumination correction), a supervised saliency map construction method is used to obtain an initial guess of lesion location. The construction of the saliency map is based on a random forest regressor that takes a vector of regional image features and return a saliency score based on them. This regressor is trained in a multi-level manner based on 2000 training data provided in ISIC2017 melanoma recognition challenge. In addition to obtaining an initial contour of lesion, the output saliency map can be used as a speed function alongside with image gradient to derive the initial contour toward the lesion boundary using a propagation model. The proposed algorithm has been tested on the ISIC2017 training, validation and test datasets, and gained high values for evaluation metrics.

**Keywords**—melanoma; segmentation; supervised saliency map; level sets; contour propagation; ISCI melanoma challenge.

## I. INTRODUCTION

Skin cancer-related death cases are increasing in all parts of the world, with over than 9000 deaths each year [1]. Melanoma, which is the most dangerous type of skin cancer, is a major public health problem. So it is very important to diagnose the melanoma as early as possible. The first step in the skin lesion image analysis is to detect the lesion border from the other regions of skin. A variety of methods has been proposed in the literature to achieve this aim [2]. Among these algorithms, thresholding techniques are very popular due to their automatic and straight implementation. Despite their simplicity, thresholding methods would not always lead to a perfect result, especially when deficiencies exist in image or lesion has a weak appearance in some regions.

Our goal in this article is to introduce a general method for lesion segmentation in dermoscopic images. There is several drawbacks in designing such a general algorithm. These problems originated from the fact that most of the dermoscopic images are defected with noise, hairs, dark corners, color charts, uneven illumination, marker ink, etc. In real terms, dermoscopy image datasets are complicated. They may have different

properties for each image and all kind of disturbance may exist, like the dataset we working on. A general framework for segmentation should be capable of overcoming these difficulties. Preprocessing is a way to handle most of these deficiencies. Therefore, in this work, we will first the preprocessing tasks to improve the image quality and facilitate the segmentation procedures. Then, in order to automate the segmentation procedure, a supervised saliency map is obtained from the image. From the saliency map, an initial mask can be extracted which may not contain all the lesion regions in the image. So, follow our previous work [3], a dual-speed function is constructed based on the image gradient and the saliency map (lesion color and texture probability map). A block diagram of proposed segmentation method can be seen in Fig. 1.

Rest of the paper is arranged as follow: in section II the methodology of proposed method is explained in details. In section III, the experimental results of applying the proposed method on the available dataset are presented qualitatively and quantitatively. And finally, the paper is concluded in section IV.

## II. METHODS

As block diagram of Fig. 1 displays, the algorithm designed for lesion border detection is comprised of two main different parts. Each of these parts is described in the following sections.

### A. Preprocessing

The preprocessing procedure has several tasks or steps. Each of which has been designed to eliminate the effect of particular deficiency in the image. These task can elevate the final segmentation results very much.

**Hairs and ruler marks inpainting:** Presence of hairs in some dermoscopic images could make the segmentation process more difficult. Even with a fair lesion segmentation, in further steps of image analysis, like feature extraction and classification, the hairs may confuse the results. So it is recommended to remove the hairs from the image before any further processing. In this article, we use the Koehoorn et al. [4] to remove the hairs from the image. Their algorithm for hair detection in the image is based on threshold decomposition. They convert the image to different binary images using different thresholds, and in each binary image they searched for long thin hairy-like structures using a gap detection method. Then, all potential hairs in different layers are fused in an initial hair mask. To removing

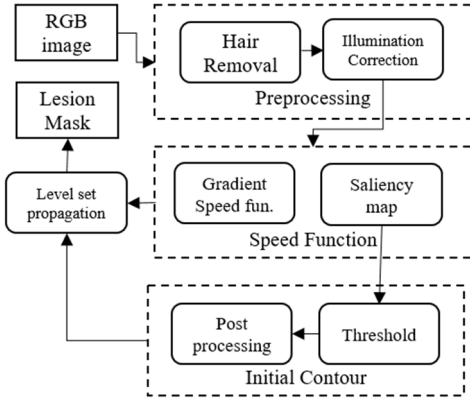


Figure 1: Overview of proposed segmentation algorithm.

the false positive hairs from the hair mask, they perform some constraint on the skeletonize mask of the hairs. Finally, true positive detected hairs have been removed from the image using a classical inpainting method [4].

**Illumination Correction:** Uneven illumination in the image add complexity to the image and can lead to a wrong regional features. We used homomorphic filtering [5] for this part of preprocessing. It simultaneously normalizes the brightness across an image and increases the contrast. These methods assume a multiplicative noise model for image, in which the object reflectance  $R$  is the signal we interested in and scene illumination  $L$  is the noise to be filtered:

$$I(x, y) = L(x, y)R(x, y) \quad (1)$$

To compensate for the non-uniform illumination, the key is to remove the illumination component  $L$  and keep only the reflectance component  $R$ . Illumination typically varies slowly across the image as compared to reflectance which can change quite abruptly at object edges. This difference is the key to separating out the illumination component from the reflectance component. In homomorphic filtering, we first transform the multiplicative components to additive components by moving to the log domain:

$$\begin{aligned} \ln(I(x, y)) &= \ln(L(x, y)R(x, y)) \\ \ln(I(x, y)) &= \ln(L(x, y)) + \ln(R(x, y)) \end{aligned} \quad (2)$$

then we use a high-pass filter in the log domain to remove the low-frequency illumination component while preserving the high-frequency reflectance component [5]. To apply this method to RGB color images, we first convert the image to  $L^*a^*b^*$  color space, correct the illumination component ( $L$ ), and convert the corrected image back to RGB color space.

### B. Segmentation Process

In this article, we use deformable models for melanoma segmentation. Usually, these approaches start from an initial condition and evolve through iterations to finally converge. We use level sets to represent the contour. This type of contour representation has been taken into consideration in many medical image applications. We used the level set approach introduced by Malladi et al. [6] in a novel framework to propagate an initial contour toward the lesion boundary. In addition to image gradient information, here we use lesion color

and texture information to form the speed function. So, our approach would benefit from both gradient and regional information. This property makes the algorithm robust against weak edges and faded color regions. The latter part of proposed speed function is captured using a saliency map. Saliency map of the image is created using a supervised multi-level approach which consider the saliency map construction problem as a regression problem.

The saliency map also can be used to obtain an initial contour (guess) of lesion boundary in the image. Such task can be done through thresholding on the saliency map or using H-maxima transform on it. Anyhow, the methods for construction of saliency map and propagation model is described more below.

#### 1) Initial mask through saliency map

We used a saliency map construction algorithm based on the work of Jiang et al. [7]. It has a multi-level segmentation scheme that uses supervised learning approach in each level to compute a saliency score based on the regional features in that level. At last, saliency scores from all levels are combined to construct the final saliency map. Unlike the other algorithms that construct the saliency map in an unsupervised manner using different type of features in the image, the method of Jiang [7] uses features that have been learned from a training set of images.

This supervised method learns a regressor that directly map the original feature vector to a saliency map. The algorithm in [7] has three main steps:

1. *Multi-level segmentation:* decomposition of the image to its constructing elements from a coarse level (bigger elements) to a fine level (small elements).
2. *Saliency regression:* Using a random forest regressor to map the regional feature vector (from each element in each level) to a saliency score.
3. *Saliency map fusion:* The final saliency map is constructed by fusing saliency maps obtained from different level segmentation.

In multi-level segmentation, a graph-based image segmentation algorithm has been used [7]. The first level of segmentation (the finest) has the most number of output regions. The segmentation in the next levels is based on their previous level segmentation, which is done by merging adjacent regions of it. In the second step, regional features are extracted from different segmented regions (at different levels) of the image. There are three type of regional features: regional contrast, regional property and regional backgroundness. These features construct a feature vector. After extracting these feature vectors from a training set of images, a random forest regressor is trained based on them, which later will be used to compute a saliency score for an input new feature vector of a test image. In the third step, saliency maps of different level are fused using a weighted integration to contract the final saliency map of the image,  $F_s(x, y)$ . The weights can be considered constant or be computed for the model in a separate training phase [7].

The final saliency map is thresholded to obtain the primary mask of the lesion boundary. The primary binary mask does not represent an ideal segmentation of the lesion and it is not appropriate to be used as the initial mask of active contour

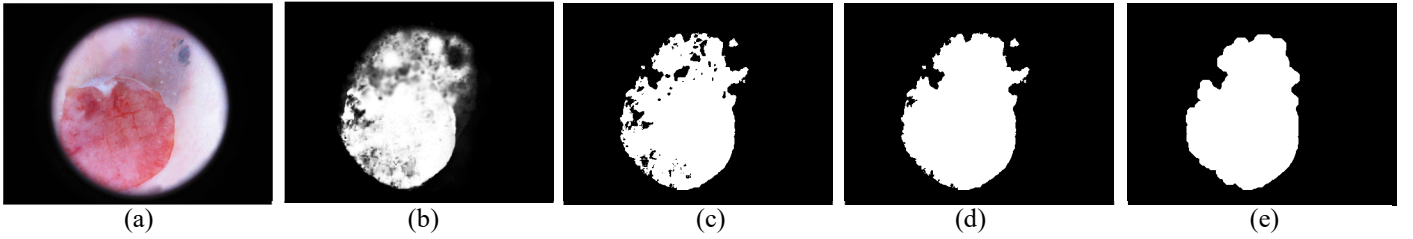


Figure 2: A sample dermoscopy image (a) and its saliency map in (b). Primary mask has been show in (c), it is filled and morphologically opened in (d) and (e) respectively. The mask in the (e) is used as initial mask for contour propagation.

because it has many noises and outside lesion objects. So we implement some post-processing task on the primary binary mask to make it more suitable for further operations. This post-processing generally contains morphological operations, like closing, opening, hole-filling, area filtering and border cleaning. In Fig. 2, a sample image alongside its obtained saliency map and initial mask is shown.

## 2) The propagation model

As we mentioned before, the initial mask obtained by saliency map is not an ideal segmentation of the lesion. Our goal in this subsection is to use the information in the initial mask region to evolve this initial boundary until it contains all the lesion. We realize this evolving process through the level set framework based on the work of Malladi et al. [6].

The initial curve is extracted from the boundary of the initial mask. Malladi’s method propagates this closed curve with a speed of  $F$  in its normal direction. They use the implicit representation of the curve i.e. the level set approach is used to embed the curve in a higher-dimensional function  $\psi(x, t)$  so that the initial curve would be the zero level set of that function  $\psi(x, t = 0)$  [13]. We consider the signed distance function (SDF) of the initial mask as the level set function. Malladi et al. proposed a partial differential equation for the evaluation of  $\psi$  as follow:

$$\psi_t + F |\nabla \psi| = 0, \quad \psi(x, t = 0) \text{ given} \quad (4)$$

This is a recursive formulation that can be used to iteratively update the  $\psi$  function. In every update, the zero level set (evolving contour) is getting closer to the border of the lesion. In (4),  $F$  is named as *speed function* and it should be define somehow to propagate the model correctly. In the original work of Malladi et al., speed is assumed to be a decreasing function of the image gradient. A practical way to implement this definition is as follow:

$$F_g(x, y) = \frac{1}{1 + \sigma |\nabla G(x, y)|} \quad (5)$$

In the above equation,  $G(x, y) = I(x, y) * g(x, y)$  is Gaussian filtered image with a standard deviation of  $\sigma$ , where  $g(x, y) = \exp(-(x^2 + y^2)/2\sigma^2) / 2\pi\sigma^2$ , and  $*$  stands for convolution operation. The  $|\nabla G(x, y)|$  part represent the magnitude of gradient function for every pixel. Gradient magnitude is normalized by multiplying it with the term  $\sigma$ .

Based on (5),  $F_g$  is small where  $|\nabla G(x, y)|$  is large, and vice versa. As one can see, this speed function captures the edge (gradient) information from the image and propagate the contour towards them using (4). But, as we said before in some cases the edge information are weak and are not reliable enough to drive the speed function. To address this problem, based on [3] we proposed a dual-component speed function: one member of which is based on gray-level image gradient and the other one is a image saliency map. Hence, the complete speed function,  $F$ , that has been used in (4) can be rewritten as follow:

$$F(x, y) = \alpha F_g(x, y) + \beta F_s(x, y) \quad (6)$$

The second term is the image saliency map, constructed as described in the previous subsection. The  $\alpha$  and  $\beta$  are the weights that specify the contribution of each component  $F_g$  and  $F_s$  in the construction of the final speed function, respectively. To better illustrate the effect of this phase on lesion segmentation, the sample in the Fig. 2 is segmented using the above mentioned algorithm and the result is show in the Fig 3. In this figure, green contour stands for ground truth segmentation, red contour delineate the initial segmentation and the blue contour is the final output of the proposed segmentation algorithm. As you can see, the output of propagation algorithm is much closer to the original boundary of the lesion.

## III. EXPERIMENTS AND RESULTS

In this section, we evaluate the performance of our proposed algorithm on a general multi-vendor pre-segmented dataset. The dataset that we used to train the random forest regressor in the saliency map algorithm consists of 2000 dermoscopy images. These images have been selected from the International Skin Imaging Collaboration (ISIC) archive to be used as a training set in the challenge of “Skin Lesion Analysis toward Melanoma Detection” at the International Symposium on Biomedical Imaging (ISBI) 2017. The ground truth segmentation of the lesion in each image is available as well, so we can evaluate our algorithm quantitatively. As this image are just used for training phase of saliency map contraction process, they can be used for testing of the overall segmentation algorithm. Anyway, there is another two dataset comprising 150 images for validation and 600 images for testing purposes. As these dataset are provided by ISCI2017 challenge organizers, the ground truth for them are not available for evaluation. But the participant are asked to upload their segmentation results on the challenge host website so their algorithm could be evaluated automatically. Therefore,

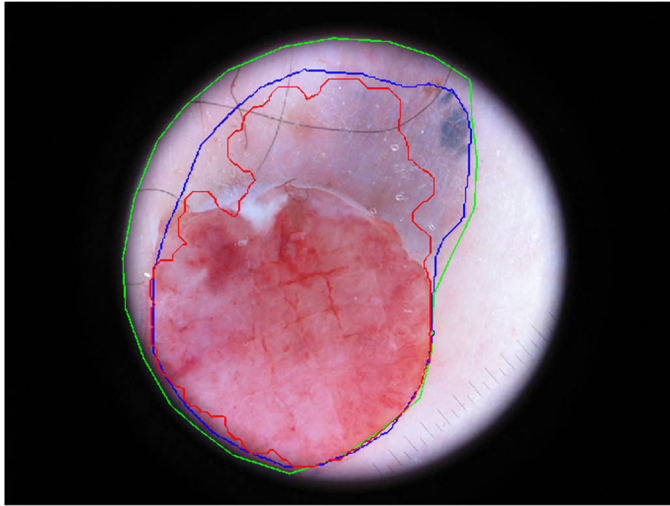


Figure 3: Result of proposed segmentation algorithm on a sample image (Red: initial contour, blue: final segmentation, green: ground truth).

all the result about the evaluation and test sets that are shown here is directly adapted from the challenge website<sup>1</sup>.

The evaluation metrics that have been used in this paper consist of two similarity coefficient (Dice and Jaccard) and three pixel based goodness measures (Accuracy, Sensitivity, and Specificity). Based on these evaluation metrics, the average results of an experiment on 2000 training images are provided in Table I.

Also, the average result for evaluation metrics from a segmentation experiment on 150 image of validation set are reported in Table II. As you can see the values of metrics for validation data are lower than the ones in training data, and the reason must be about the saliency map that has been trained from the training set itself. So, it is reasonable to achieve better results on training data. Properly tuning the algorithm parameters may elevate the result on the evaluation data.

TABLE I. RESULTS OF EVALUATION EXPERIMENT ON TRAINING DATA

Method	Evaluation metrics (Average)				
	Dice	Jaccard	Accuracy	Sensitivity	Specificity
Proposed	0.901	0.811	0.981	0.882	0.988

TABLE II. RESULTS OF EVALUATION EXPERIMENT ON VALIADATION SET

Method	Evaluation metrics (Average)				
	Dice	Jaccard	Accuracy	Sensitivity	Specificity
Proposed <sup>1</sup>	0.858	0.764	0.954	0.825	0.978

#### IV. CONCLUSION

In this article, we proposed a general algorithm for lesion segmentation in dermoscopic images. We use several stages of preprocessing before applying the main segmentation procedure. To start the segmentation automatically, we used a supervised multi-level saliency map creation algorithm to build a probability map of lesion color and texture in the image, the saliency map is thresholded and post processed to obtain an initial mask of the lesion. The initial mask does not represent an ideal segmentation of the lesion, so a novel dual-component speed function of the image has been constructed to be used in an iterative scheme and propagate the initial contour toward the desired boundary. This new dual-component speed function makes the segmentation algorithm robust against weak gradient and faded color intensities. The evaluation experiments of the proposed method on a training set of 2000 images result in Dice and Jaccard coefficient values of 0.901 and 0.811, respectively.

#### REFERENCES

- [1] B. W. Stewart and C. P. Wild, *World Cancer Report 2014*. World Health Organization, 2014.
- [2] M. Emre Celebi, H. A. Kingravi, H. Iyatomi, Y. Alp Aslandogan, W. V Stoecker, R. H. Moss, J. M. Malters, J. M. Grichnik, A. A. Marghoob, H. S. Rabinovitz, and S. W. Menzies, "Border detection in dermoscopy images using statistical region merging," *Ski. Res. Technol.*, vol. 14, no. 3, pp. 347–353, 2008.
- [3] B. Zamani, Neda; Mohammad Zadeh, "A General Algorithm for Automatic Lesion Segmentation in Dermoscopy Images," in *23th National and 1st International Iranian Conference on BioMediacal Engineering (ICBME2016)*, 2016.
- [4] J. Koehoorn, A. C. Sobiecki, D. Boda, A. Diaconeasa, S. Doshi, S. Paisey, A. Jalba, and A. Telea, "Automated digital hair removal by threshold decomposition and morphological analysis," in *International Symposium on Mathematical Morphology and Its Applications to Signal and Image Processing*, 2015, vol. 9082, pp. 15–26.
- [5] A. Oppenheim, R. Schafer, and T. Stockham, "Nonlinear filtering of multiplied and convolved signals," *IEEE Trans. Audio Electroacoust.*, vol. 16, no. 3, pp. 437–466, 1968.
- [6] R. Malladi, J. A. Sethian, and B. C. Vemuri, "Shape modeling with front propagation: A level set approach," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 17, no. 2, pp. 158–175, 1995.
- [7] H. Jiang, J. Wang, Z. Yuan, Y. Wu, N. Zheng, and S. Li, "Salient object detection: A discriminative regional feature integration approach," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2013, pp. 2083–2090.
- [8] D. Gutman, N. C. F. Codella, E. Celebi, B. Helba, M. Marchetti, N. Mishra, and A. Halpern, "Skin Lesion Analysis toward Melanoma Detection: A Challenge at the International Symposium on Biomedical Imaging (ISBI) 2016, hosted by the International Skin Imaging Collaboration (ISIC)," *arXiv Prepr. arXiv1605.01397*, 2016.

<sup>1</sup><https://challenge.kitware.com/#challenge/583f126bcad3a51cc66c8d9a> ; under the user name of "Jahanifar Zamani".