



# Automatic segmentation of dermoscopy images using self-generating neural networks seeded by genetic algorithm

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## ABSTRACT

A novel dermoscopy image segmentation algorithm is proposed using a combination of a self-generating neural network (SGNN) and the genetic algorithm (GA). Optimal samples are selected as seeds using GA; taking these seeds as initial neuron trees, a self-generating neural forest (SGNF) is generated by training the rest of the samples using SGNN. Next the number of clusters is determined by optimizing the SD index of cluster validity, and clustering is completed by treating each neuron tree as a cluster. Since SGNN often delivers inconsistent cluster partitions owing to sensitivity relative to the input order of the training samples, GA is combined with SGNN to optimize and stabilize the clustering result. In the post-processing phase, the clusters are merged into lesion and background skin, yielding the segmented dermoscopy image. A series of experiments on the proposed model and the other automatic segmentation methods (including Otsu's thresholding method, *k*-means, fuzzy *c*-means (FCM) and statistical region merging (SRM)) reveals that the optimized model delivers better accuracy and segmentation results.

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## 1. Introduction

Malignant melanoma (MM), the most deadly form of skin cancer, is one of the most rapidly proliferating cancers in the world, with an estimated annual incidence of 70,230 and 8790 deaths in the United States in 2011 [1]. In China, the incidence of MM has increased 3%–8% annually and has doubled over the past decade [2]. The earlier the diagnosis, the lower the metastatic risk: investigations have shown that the cure rate is nearly 100% if the skin cancer is recognized early enough and treated surgically [3].

Advances in dermoscopy (skin-surface microscopy or dermatoscopy) technology have contributed significantly to improved detection and survival rates [4,5]. Dermoscopy [6] is a non-invasive technique that combines optical magnification and liquid immersion with angle-of-incidence lighting or crosspolarized lighting to make the contact area translucent, consequently revealing subsurface structures of the skin. Dermoscopy yields 10%–27% higher sensitivity than clinical diagnosis, significantly improving the accuracy of dermatologists when diagnosing melanoma [4,5]. Yet, dermoscopic diagnosis remains subjective and is therefore associated with poor reproducibility. Because of this there has been a significant increase in interest in the development of automatic

digital dermatoscopic image analysis methods over the last decade. Such processes typically consist of four stages: image acquisition, lesion segmentation or border detection, feature extraction, and classification. The segmentation stage is quite important, since it affects the accuracy of the subsequent steps. However, segmentation is quite difficult because [7]: (i) the transition between the lesion and the surrounding skin is usually of low contrast; (ii) the lesion borders are usually irregular and fuzzy; (iii) complicating artifacts are often present such as skin texture, air bubbles and hairs; and (iv) the interior of the lesion may exhibit variegated coloring.

To address these problems, a number of dermoscopic segmentation algorithms have been developed [8]. For convenience, we broadly classify these into three categories: thresholding, edge/contour-based and region-based. An effective thresholding method proposed by Grana et al. [9] uses Otsu's threshold to automatically segment the melanoma image, then selects *k* points for spline-based interpolation, yielding a smoothed lesion border. Thresholding methods such as this can achieve good results when there is good contrast between lesion and skin, but encounter problems when the modes of the two regions overlap. Edge/contour-based approaches were used in [10,11]. Rubegni et al. [10] segmented dermoscopy images using the zero-crossings of a LoG edge operator, while Zhou et al. [11] used an improved snake model to detect lesion borders. Edge and contour-based approaches perform poorly when the boundaries are not well defined, for instance when the transition between skin and lesion

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is smooth. In such situations, the edges have gaps and the contour may leak through them. Region-based approaches have also been used. Some examples include multi-scale region growing [12], fuzzy *c*-means based on anisotropic mean shift [13], multi-resolution markov random fields [14] and statistical region merging (SRM) [7]. Region-based approaches have difficulties when the lesion or the skin region are textured, or have different colors present, which can lead to over-segmentation.

With the increasing availability of methods for segmenting dermoscopic images of skin lesions, the relative performances of the various models are of interest. In [15], four widely used color clustering algorithms were compared: median cut, *k*-means, fuzzy *c*-means and mean shift, without employing any spatial constraint. The mean shift algorithm gave the best results. In [16], six methods were compared: gradient vector flow (GVF), a level set method of Chan (C-LS), adaptive thresholding (AT), adaptive snakes (AS), EM level sets (EM-LS), and a fuzzy-based split-and-merge algorithm (FBSM). The authors concluded that the best semi-supervised methods are AS and EM-LS, while the best fully automatic method is FBSM.

Color is a significant feature for image segmentation and unsupervised color clustering has been successfully used for region-based segmentation [17]. Such data-driven methods have great potential for dealing with varied imaging situations, provided that an accurate model that is flexible enough to span the space of possible lesion image environments can be found. Since modeling such a high-dimensional complex space of possibilities is quite difficult, learning-based methods that can be trained on large datasets are of interest. Towards this end, we study and develop a color clustering model for dermoscopic images that combines the technique of the self-generating neural network (SGNN) [18] with genetic algorithms (GA). Using a measure of cluster validity, the clustering algorithm that we develop automatically determines an appropriate number of clusters. By merging the clustering regions into lesion and background skin, segmentation of dermoscopic images is achieved. When compared with other segmentation algorithms that use Otsu’s thresholding method, *k*-means, fuzzy *c*-means and SRM, our model is shown to deliver high-quality segmentation results.

**2. Self-generating neural networks (SGNN)**

We briefly describe the learning tool that we will use. SGNN was developed in 1992 [18] using the idea of self-organizing maps (SOM) implemented within a self-generating neural tree (SGNT) architecture. It was studied in depth in [19,20], and is characterized by simplicity in network design, and speed of learning and self-organizing capability. As such, it is a good choice to learn clustering or classification with high performance [21].

As shown in Fig. 1, the SGNN can be implemented as a self-generating hierarchical neural tree (SGNT). Fig. 1(a) depicts a clustering sample set, where  $e_i, i = A, B, \dots, E$  are the sample attributes. Fig. 1(b) is the generated SGNT following the SGNT

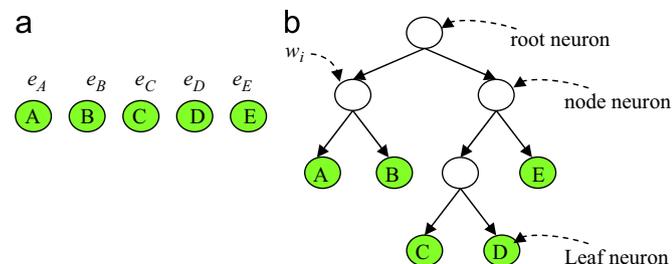


Fig. 1. Structure of the SGNT. (a) 5 samples and (b) Generated SGNT for (a).

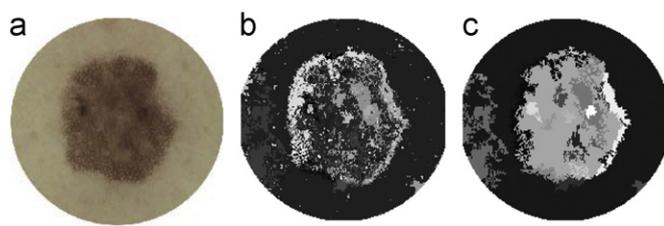


Fig. 2. Coarse segmentation with region growing. (a) Original image, (b) Region growing and (c) Filtering small sub-regions.

generating rules [18–21], where  $w_i$  notes neuron weight. Each leaf neuron corresponds to one or multiple samples, and its weight is the average attribute of the corresponding samples. The weight of every node neuron (non-leaf neuron) is the average attribute of all the leaf neurons it covers. Taking each child of the root neuron as a cluster center, each leaf neuron in the sub-network rooted by this child belongs to the same cluster. The number of clusters is consequently equal to the number of the root neuron’s children. In Fig. 1(b), A is in the same cluster as B, and C is in the same cluster as D and E, while the number of clusters in the SGNT is 2. By taking image pixel values as the data, and color or location information as sample attributes, the SGNN can be used for image clustering.

For image segmentation purposes, the SGNT structure becomes excessively large if all pixels are trained. To reduce the complexity, we deploy a coarse-to-fine segmentation strategy. The region growing method is used to coarsely segment the original image. The image is scanned and the unlabeled pixels are taken as seeds. The pixel neighbors whose mean color has a distance less than 15 to the seed pixel color, are added to the region. Fig. 2(b) is the sub-regions segmented by region growing method, and very small regions are removed in Fig. 2(c); the size of these can be taken to be a small fraction of typical lesion size. Using these sub-regions as the data set, the clustering task is well adapted to learning by the SGNN.

**3. Automatic segmentation based on SGNN and GA**

In spite of its fitting capacity for clustering, the SGNN algorithm is influenced by the input order of the training samples, which can cause inconsistent clustering results, as depicted in Fig. 3, where Fig. 3(a) is the original image, and Fig. 3(b) and (c) are the results that are arrived at when different samples are selected as the first input into the SGNT.

In Fig. 3(b), the area of the lesion is under-segmented, whereas a more accurate result is obtained in Fig. 3(c). To ameliorate this, we propose an adaptive clustering algorithm, termed ACluster-GA-SGNN, wherein the SGNT is generalized to a Self-Generating Neural Forest (SGNF), and GA is subsequently employed to consistently select an appropriate group of seed samples as the first input into the SGNF, thereby yielding optimized clustering results.

**3.1. Self-generating neural forest**

The SGNT can be generalized to a Self-Generating Neural Forest (SGNF) as follows. Suppose that a given sample set has *c* cluster centers. Then the SGNF generating algorithm can be described as follows:

*Step 1:* Remove *c* seed samples randomly from the sample set, treating these seeds as initial neural trees to form an initial forest.

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