Detection of Melanoma Skin Cancer in Dermoscopy Images

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Abstract. Malignant melanoma is the most hazardous type of human skin cancer and its incidence has been rapidly increasing. Early detection of malignant melanoma in dermoscopy images is very important and critical, since its detection in the early stage can be helpful to cure it. Computer Aided Diagnosis systems can be very helpful to facilitate the early detection of cancers for dermatologists. In this paper, we present a novel method for the detection of melanoma skin cancer. To detect the hair and several noise from images, preprocessing step is carried out by applying a bank of directional filters. and therefore, Image inpainting method is implemented to fill in the unknown regions. Fuzzy C-Means and Markov Random Field methods are used to delineate the border of the lesion area in the images. The method was evaluated on a dataset of 200 dermoscopic images, and superior results were produced compared to alternative methods.

Keywords. Dermoscopy image, melanoma, lesion detection.

1. Introduction

Skin cancers can be classified into melanoma and non-melanoma. Melanoma is a malignancy of the cells which gives the skin its color (melanocytes) and it can invade nearby tissues. Moreover, it spreads through the whole human body and it might cause to patient death and non-melanoma which is rarely spread to other parts of the human body. Malignant melanoma is the most aggressive type of human skin cancers and its incidence has been rapidly increasing [1] [2] [3] [4]. Nevertheless, it is also the most treatable type of skin cancer if detected or diagnosed at an early stage [5]. The diagnosis of melanoma in early stage is a challenging and fundamental task for dermatologists since some other skin lesions may have similar physical characteristics. Dermoscopy is considered as the widely common technique used to perform an in-vivo observation of pigmented skin lesions [6]. In early detection of malignant melanoma, dermoscopic images have great potential, but their interpretation is time consuming and subjective, even for trained dermatologists. Therefore, the need to build a system which can assist dermatologists to get right decision for their diagnosis has become very important.

Computer Aided Diagnosis (CAD) systems have been proposed by many different researchers to identify malignant melanomas in dermoscopy images. CAD systems based on medical knowledge try to mimic the performance of dermatologists for the detection of pigmented region [3] [6] [7]. Image segmentation stage is the most important one since it affects the accuracy of the subsequent steps. However, dermoscopic image segmentation and detect the lesion area is a challenging task since there is a smooth transition between the color of the lesion area and the background, it means there is low contrast between the pigmented lesion and background. Moreover, presence of dark hair covering the lesions and existence a few artifacts such as air bubbles and lighting reflection. This paper presents an automatic method for skin cancer detection on dermoscopy images. First, the image is pre-processed in order to remove the noise and enhance its quality. Second, Fuzzy C-Means (FCM) and Markov Random Field (MRF) are used to segment the pigmented lesion from images. Upon comparison, the proposed method provided good performance in achieving automatic image segmentation over dermoscopy images. The paper is organized as follows. Section 2 provides an overview of the methods developed previously. An overview of the MRF method is described in Section 3. The proposed method is described in details in Sections 4. The experiments and result analysis are discussed in Sections 5. Finally, conclusions are presented in Section 6.

2. Previous Work

Yukse et al. [8] proposed a method which used type-2 fuzzy logic technique for automatic threshold determination to detect the border of the pigmented skin lesion. Celebi et al. [9] presented a method to segment skin lesion in dermoscopy images through statistical region merging method. The method is a technique developed to segment images based on region growing and merging. A method to segment pigmented lesion images through iterative stochastic region merging has been implemented by Wong et al. [10]. K-means clustering method has been applied by Castillejos et al. [11]. The authors presented a novel approach to segment and detect the border of the skin lesion based on the wavelet transform for K-Means, Fuzzy C-Means and Cluster Preselection Fuzzy C-Means methods. Zhou et al. [12] proposed a new type of dynamic energy for the segmentation of pigmented skin lesions in dermoscopy images. The authors combined the classical gradient vector flow (GVF) model with the mean shift method. Threshold method is used by Pirnog et al [13] to extract the lesion area from health skin in dermoscopy images. The RGB image is converted into HSV representation, the image histogram of the saturation (S) image component is computed. Therefore, the authors selected the threshold value and determined the binary mask. A new mean shift approach based on FCM method is proposed by Zhou et al [14] to segment dermoscopy images. It is more effective than the FCM method and less computational time than the mean shift method. Abbas et al [15] proposed a novel perceptually oriented approach for melanoma border detection by combing region and edge-based segmentation techniques. A hill-climbing method is performed to detect the region-of-interest (ROI) and an adaptive thresholding is applied to determine the optimal lesion border. A new approach for lesion segmentation is proposed by Pennisi et at [16]. Closing operation is used to remove the hair and few outlier pixels. And therefore, two segmentation processes are implemented in parallel, providing two different images. One image is built by detecting the skin region and the other one is created by applying edge detected with Delaunay Triangulation. Finally, the authors combine these tow images to extract the final lesion area. Bi et al [17] proposed a new automatic melanoma detection method for dermoscopic images via multi-scale lesion-biased representation and joint reverse classification. They tried to represent the skin lesions using multiple of closely related histograms derived from different rotations and scales of the image.

3. Overview of the MRF Method

The MRF method is a statistical model, but can be used for segmentation methods, it was introduced in image analysis by Geman and Geman [18]. MRF theory provides a tool for modelling a vision problem within the Bayes framework using spatial continuity. The image pixels are indexed by a rectangular patch S and each image pixel s is characterized by the gray level y_s from the set $y = y_s : s \in S$. The labelling process consists of accurately labelling each image pixel $s \in S$ with a class label representing the pattern class in the image. A label set is defined as$\Lambda = 1, 2, ..C$ where C is the number of classes. A labelling is indicated by $x = x_s : x_s \in \Lambda, s \in S$ where $x_s = l$ denotes that the class label l is assigned to the pixel s. The goal is to find the labelling $\hat{x}$ of the image, which is the estimation of the true but unknown labelling x^*. According to the MAP estimate [18] we have

$$\hat{x} = argmaxP(x|y) \tag{1}$$

According to Bayes theorem we have

$$P(x|y) = \frac{P(y|x)P(x)}{P(y)} \tag{2}$$

Where $P(x)$ is the prior density of the labelling x and $P(y|x)$ is the conditional probability density of the image y.
The prior probability of the image $P(y)$ is independent of the labeling x, therefore, it is rewritten as follows:

$$\hat{x} = argmax\{P(y|x).P(x)\} \tag{3}$$

The Gaussian distribution is used with the assumption of the existence of Gaussian noise in images. Therefore, the possibility of pixel s with the assumption of belonging to class x_s is equal to y_s and can be calculated as follows:

$$P(y_s|x_s) = \frac{1}{\sqrt{2\pi\sigma_{xs}^2}} \exp\{-\frac{(y_s - \mu_{xs})^2}{2\sigma_{xs}^2}\} \tag{4}$$

Based on the conditional independence assumption of y, the conditional density $P(y|x)$ takes the form of

$$P(y|x) = \prod_{s \in S} P(y_s|x_s) \tag{5}$$

Therefore, $P(y|x)$ can be written as follows.

$$P(y|x) = \prod_{s \in S} [\frac{1}{\sqrt{2\pi}} \exp(-\frac{(y_s - \mu_{xs})^2}{2\sigma_{xs}^2} - \log(\sigma_{xs}))] \tag{6}$$

This can be written as

$$P(y|x) = \frac{1}{(2\pi)^{\frac{s}{2}}} \exp[-\sum_{s \in S} (\frac{(y_s - \mu_{xs})^2}{2\sigma_{xs}^2} + \log(\sigma_{xs}))] \tag{7}$$

where μ_{xs} and σ_{xs} indicate the mean and variance of the class x_s respectively.

The prior model is based on 2D MRF and assumes that the adjacent pixels are probably having the same class label. The Hammersley-Clifford theorem [19] establishes a relation between the MRF and Gibbs distribution. According to this theorem, the prior model $P(x)$ is given by a Gibbs distribution with respect to the neighbourhood system N and it takes the form of

$$P(x) = \frac{1}{Z} \exp[-\sum_{c \in C} V_c(x)] \tag{8}$$

where Z is the normalization constant or partition function, $V_c(x)$ is the potential function for clique c and C is the set of all cliques in the image. According to the equations (7) and (8), we can rewrite the posterior probability as:

$$P(x|y) =\propto exp[-U(x)] \tag{9}$$

where the energy function $U(x)$ has the form

$$U(x) = [\sum_{s\in S} \frac{(y_s - \mu_{xs})^2}{2\sigma_{xs}^2} + \sum_{s\in S} \log(\sigma_{xs}) + \sum_{c\in C} V_c(x)] \tag{10}$$

4. Proposed Method

The proposed approach is divided into two steps, image pre-processing and image segmentation. First, the pre-processing stage includes reflection artifact, hairs detection and removal. Second, the segmentation step includes applying the FCM method on images in order to get two benefits: estimate the initial parameters and segment the lesion area and implementing the MRF method based on the previous parameters. Full details will be described in the following section.

4.1. Dermoscopic Image Preprocessing

Pre-processing stage is responsible for detecting and reducing amount of artifacts from the image. In dermoscopy images, this step is mandatory since many dermoscopy images contain a lot of noise such as reflection artifacts and hairs which are covering the lesion area. Incorrect segmentation of pigmented lesion can be obtained if hairs covering the images and reflection artifacts are not removed. This process involves two key operations: hairs, reflection artifact detection and removal. The original RGB images were separated to three color components and the blue component is selected for its best discriminative capacity [20].

4.1.1. Reflection Detection Reflection artifacts and air bubbles appear like noise in dermoscopy images. To detect this kind of noise, a simple threshold method is applied. Every single pixel (x, y) can be detected and classified as a reflection artifact if its intensity value is higher than threshold T_{R1} and if its intensity value minus the average intensity $I_{avg}(x, y)$ of its surrounding neighborhood is higher than threshold T_{R2} ,i.e.

$$\{I(x, y) > T_{R1}\}and\{(I(x, y) - I_{avq}(x, y)) > T_{R2}\}. \tag{11}$$

where I is the image, $I_{avg}(x, y)$ is the average intensity value in a local neighborhood of the selected pixel which is computed using a local mean filter with dimensions 11x11 and T_{R1}=0.7, T_{R2}=0.098.

4.1.2. Hair Detection and Inpainting For effective segmentation in dermoscopy images, hairs should be extracted and removed. Many methods have been applied for hair removal and they were mostly based on adaptive thresholding and morphological operations or used median filter method [9]. The directional Gabor filters are implemented to extract the hairs from dermoscopy images. However, the parameters used in the Gaussian filters at each stage are different. A bank of 64 directional filters has been used to perform the hair detection. The image is filtered by each directional filter with different parameters and the difference of Gaussians is used followed by finding the local maximum at each pixel location. Therefore, the threshold method is applied to classify each pixel as either hair or background. A detailed explanation of the method can be obtained from [6].

After reflection artifacts and hairs are detected, their binary masks are multiplied by gray scale image. This operation leads to appearance of gaps which can be filled by propagating the information from known region which it is the neighborhood into the unknown region. Image inpainting method is implemented to fill in the unknown regions and remove the hairs

Figure 1: Examples of hair detection process and inpainting images: original (first column), hair detection (second column) and inpainted image (third column).

with reflection artifacts. Patch priorities (data term and confidence term) are computed in the borders of the unknown regions based on their neighbours. And therefore, the patch with the highest priority is filled out with data extracted from the source region, and then the patch priorities are updated. This continues until no more gaps exist. Details of the method can be found in [21]. By this way all reflection artifacts and hairs are removed from dermoscopy images. Examples are illustrated in figure 1.

4.2. Skin Lesion Segmentation

The segmentation stage is one of the most important and challenging steps in dermoscopic image processing. It must be fast and accurate because the subsequent steps such as feature extraction, classification and final decision are dramatically dependent on the performance of the segmentation step. As we mentioned previously, segmentation process for dermoscopy images is extremely difficult due to existence of several factors such as: the low contrast between the lesion and the healthy skin, variance of colors inside the pigmented region and other artifacts. Useful information can be obtained by applying suitable segmentation method. FCM and MRF were incorporated to perform the final segmentation of the images.

The FCM method is used to initiate the segmentation process. The pixels of an input image are divided into two clusters: cancerous pixels as the foreground (ROI) and normal skin pixels as the background. The major drawback with the FCM method is that it deals with pixels individually by their intensity values only, so lacks the capacity to model the overall appearance of a local neighbourhood region. In order to address this issue, The MRF method is implemented to refine the previous segmentation of the image. The main goal of the image segmentation using the MRF method is to minimize the energy function or maximize the probability of pixel allocation to a cluster by using Maximum A Post Priority (MAP) equation (3). The iterated conditional modes (ICM) method is performed in order to minimize the energy function. In this paper we assume that one pixel has 8-neighbors. Then the clique potential is defined on pairs of neighbouring pixels:

$$V_c(xi, xj) = (1 - i_{xi,xj}) \tag{12}$$

where $i_{xi,xj} = 0$ if $xi \neq xj$ and 1 if $xi = xj$

To refine the image segmentation, we obtained the mean and the variance which can be used as initial parameters for the MRF method. The MRF method is then iterated as follows. Each pixel is assigned to a cluster based on the highest probability $P(y|x)$ using equation (7). Then calculate the prior probability using equation (8). All pixels will be assigned again to different classes by getting the minimum cost, equation (10). This process continues until there is no further change between clusters. Finally, Morphological operations such as filling were used to

Table 1: Segmentation performance on the complete dataset SE-sensitivity, SP-specificity and AC-accuracy.

Method	SE	SP	AC
FCM	88.0%	95.1%	92.0%
Proposed method	93.2%	98.0%	94.0%

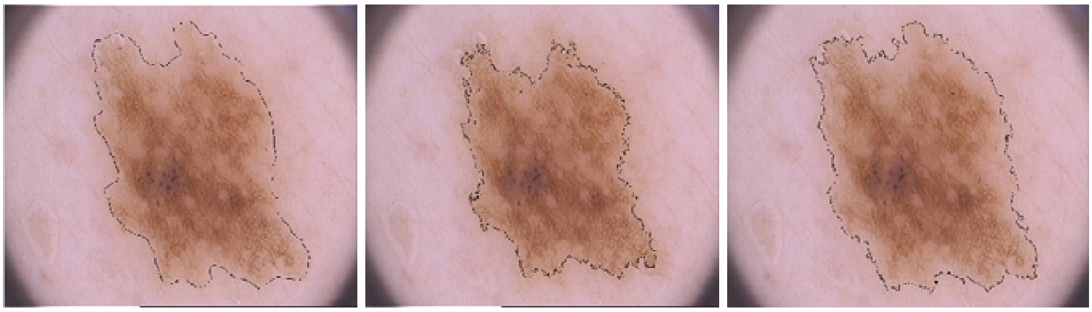

Figure 2: Results of skin cancer detection: ground truth (first column), FCM (second column) and proposed method (third column).

fill in the small holes inside the segmented lesion. As well as, several parts that related to the background were removed, by comparing its area with the lesion area.

5. Results and Discussions

The proposed approach was tested on the PH2 dataset [22] which provides 200 dermoscopic images, including 80 common nevi, 80 atypical nevi, and 40 melanomas. Manually segmentations were also available and used as ground truth. Quantitative comparison between various methods is difficult because different datasets and criteria have been used. Three criteria namely: sensitivity, specificity and accuracy are used to evaluate the performance of our proposed method. Segmentation of skin cancer was carried out using FCM and proposed method. And therefore, the comparison of these methods was performed with the lesions obtained by expert dermatologist in order to evaluate the performance of our method. Figure 2 illustrates the results of the manual segmentation by expert radiologist together with the results by two methods. In general, the proposed approach has the best performance in terms of the accuracy. For instance, in the second column, the FCM method did not detect the whole lesion area which leads to misclassification. As well as, the edges of the test images are not close to the real boundaries of the lesions, which means part of the lesion was classified as background. Images in the third column show the results obtained by our method. As it can be seen, the obtained edges are more close to the actual boundaries of the skin lesions and its shape is very similar to that of the ground truth compared to the previous method. The experimental results of the total dermoscopy images are described in table 1. All results confirm that the proposed approach outperforms the FCM method. Eventually, the obtained experimental results indicated that the proposed method is suitable to apply for detection of skin cancer.

6. Conclusions

An approach to the detection of melanoma skin cancer from dermoscopy images has been presented in this paper. To facilitate the process of image enhancement and segmentation, hairs and several artifacts were detected and removed by applying the Gabor filter and image inpainting respectively. Regions of melanoma cancer is extracted by combining the Fuzzy C-Means and Markov Random Field methods. The particles obtained by applying FCM method are preserved, then the binary image is created and incorporated with the MRF method. The results of the proposed method were compared with the ground truth lesions. Our experimental results indicated that the proposed method provided high accuracy of skin lesion segmentation; it successfully achieved 93.2% sensitivity, 98.0% specificity and 94.0% accuracy

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