34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

# An Incremental Approach to Pigmented Skin Lesion Segmentation with Classification Refinements in Uncertain Regions

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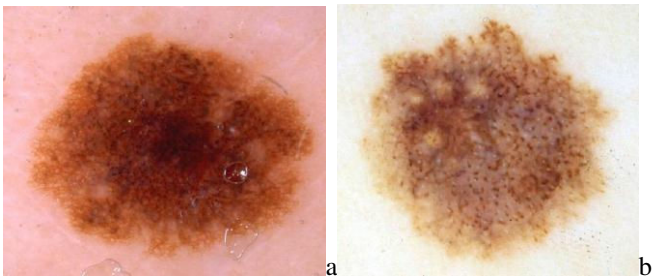
*Abstract*— **Skin lesion segmentation in dermatoscopic images is difficult because there are large inter variations in shape, size, color, and texture between lesions and skin types. Hence, computational features learned from a training set of lesion images may not be applicable to other lesion images. In this paper, we propose an incremental method for lesion segmentation. It leverages the Expectation-Maximization algorithm to find an initial segmentation. A new adaptive method is proposed to define two types of segmented regions: the high-confident and the low-confident. We train a support vector machine, using computational features from the high-confident regions, to further refine segmentation and, hence, achieve improved results for the low-confident regions. Validation experiments of our proposed method are performed on 319 dermatoscopy images and we have achieved good results with precision and recall to be 0.864 and 0.875 respectively.**

## I. Introduction

Malignant melanoma is one of the most frequent skin cancers. Early detection of melanoma is crucial as it is often curable in its early stages [1], and computer vision techniques can help in this aspect. Pigmented skin lesion segmentation is a critical step as it may affect the accuracy of the subsequent lesion classification results. However, large inter variations of the shape, size, color and texture of the lesions and skin types pose a challenge for computer aided algorithms [2]. As a result, computational features learned from a training set of lesion images may not be applicable to other lesion images in supervised approaches.

Skin lesion segmentation methods are comparedin reference [3] for early works and [4] for recent research, and reviewed in [5,6]. They can be categorized into three types: region-based, contour- or edge-based and local pixel/patch based methods. Region-based methods, such as region growing [6], and fuzzy c-means, require the skin/lesion regions to be homogeneous in colors and textures; or else over-segmented results are produced. Edge-based methods utilize edge differential information, such as zero-crossings and gradient vector flow snakes [7]. Such methods have difficulties when the transition between the lesion and background is smooth or when there are noisy edges. Segmentation based on intensities or features at pixels or local patches includes thresholding [8] and pixel classification, etc. . An adaptive thresholding was proposed in [4] using color histograms. These methods are very efficient, but produce errors when the histograms of the lesion and the skin overlap. Fig.1 shows two lesion images with different lesion and skin color, texture and lesion boundaries.



a b

Fig.1. Two skin lesion images in different color, with different lesion texture and boundaries.

Although there are many computer-aided automatic segmentation techniques, most of them focus on the core part of the lesion. It is often difficult to differentiate the light colored peripheral region from the healthy skin, which was discussed in [9]. Different from [9], an incremental method is proposed in this paper for skin lesion segmentation to handle such difficulties. The lesion images are assumed to be bimodal in their intensity probability distributions and follow the Gaussian mixture model (GMM). This is applicable in this context as there are (possibly more than) two classes of pixels in each skin lesion image. The Expectation-Maximization (EM) algorithm is used to find the probability density functions (PDFs) and the GMM with Bayesian rule to classify each pixel to either the foreground (i.e. the lesion) or the background (i.e. the skin). Since there might be overlaps between the two modes, the segmentation is not always accurate. We propose a new adaptive thresholding method to differentiate and identify two types of segmented regions - the high confident and the low-confident. We further refine the low-confident region by using a supervised classifier trained from the high-confident region. Validations with expert-labeled images show that this simple approach is efficient, robust and accurate.

## II. Methodology

Working on gray level images, the proposed segmentation method consists of four steps: 1) EM-Bayesian image segmentation, 2) adaptive thresholding, 3) supervised classification, and 4) region merging and morphology processing. Here adaptive thresholding and supervised classification are two major components. They are described in detail below.

We apply the EM-Bayesian algorithm to segment 160 skin lesion images and evaluate the results against ground truth data. They are randomly chosen from a dataset of 319

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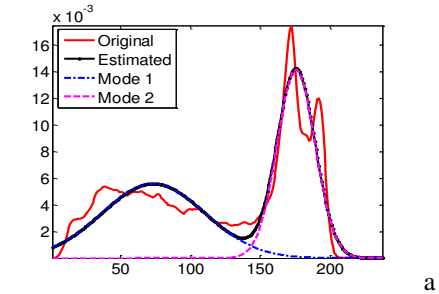
images used in the experiments in this work. The precision and recall are 0.95 and 0.77 respectively. With the high precision, we can trust its judgment on the classification of lesion pixels. However, the low recall score means there are many lesion pixels classified as normal skin background. We also find that the PDF estimation of the lesion class is not as accurate as that of the background, probably because the normal (background) skin region is more coherent in grayscale intensities. Fig.2 shows the intensity PDFs derived from the two color images presented in Fig. 1 (Fig. 2a for Fig. 1a and Fig.2b for Fig.1a). They are those for the original image (the curve "Original"), the estimated GMM (the curve "Estimated"), the skin background (the curve "Mode 1") and the lesion (the curve "Mode 2"), respectively. It is found that the estimated Gaussian modes approximate the original PDFs for the skin backgrounds for both images. The width of the signal in this portion ("Mode 2") or alternatively the standard derivation of the Gaussian can be used for adaptive image analysis.

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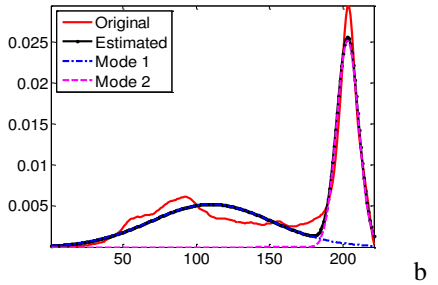



b

Fig.2. Estimated intensity PDFs for skin lesion images. Subfigure a for Fig.1a and subfigure b for Fig. 1b, respectively. Curves "Original" PDF are computed for their gray-level images. Curve "Estimated" is the GMM model. Curves "Mode 1" and "Mode 2" are the estimated Gaussians for the lesion and skin background respectively.

Here since we only use a single feature for the GMM and the EM-Bayesian image segmentation, each segmentation actually corresponds to a single intensity threshold $T_{EM}$. We now propose an adaptive thresholding scheme based on the above conservative lesion segmentation by allowing a margin $T_a$. We define $T_a = a \times d$, where $a$ is a constant coefficient and $d$ is the standard derivation of the estimated Gaussian corresponding to the normal skin background. The new threshold in the adaptive scheme is

$$T_N = T_{EM} + T_a .$$

In order to determine the parameter $a$, we examine the segmentation performance on the 160 lesion images by changing $a$ in the range 0.5 to 5. Fig. 3 shows the Receiver Operating Characteristic (ROC) curve with the horizontal axis for (1-specificity) and the vertical axis for sensitivity. From left to right along the curve, with the parameter $a$ increasing from 0.5 to 5 monotonically, the sensitivity values increase but the specificity drops. The range [0.5, 5] was experimentally determined. The best parameter is $a = 3.0$ where the specificity, sensitivity, precision and recall are 0.919, 0.904, 0.821 and 0.904, respectively.

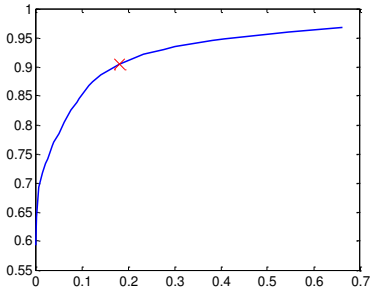



Fig. 3. ROC curve illustrating the performance of the adaptive thresholding algorithm. The horizontal axis is for (1-specificity) and the vertical axis is for sensitivity. From left to right along the curve, the parameter $a$ increases from 0.5 to 5 monotonically. The red cross is the point for $a = 3.0$.

With the EM-Bayesian segmentation and this adaptive thresholding, we partition the skin image into three areas, as shown in Fig. 4. Area 1 is the innermost part derived by the EM-Bayesian segmentation (within the inner cyan contour). Area 2 is outside the outer contour (in blue) determined by adaptive thresholding. Area 3 lies between the inner and outer contours. The union of Area 1 and Area 3 is the segmentation result of the adaptive thresholding.

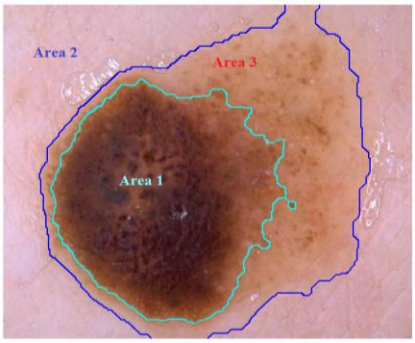



Fig. 4. Different regions derived by the EM-Bayesian algorithm and adaptive thresholding algorithm. Area 1 is the innermost region (within the inner cyan contour). Area 2 is outside the outer contour (in blue). Area 3 is between the inner contour and the outer contour.

The segmentation results in Area 3 need further improvements. We invoke a support vector machine (SVM) for this. The real part of the Gabor filter

$$G_a = \exp[-\pi s^2 (x^2 + y^2)](h_1 - h_2)$$

where,

$$h_1 = \exp[\, j2\pi f\,(x\cos(w) + y\sin(w))]$$

$$h_2 = \exp[-\pi(f\,/\,s)^2]\,,$$

with $s = 2$, $f = w = 4$, is used to compute the texture features within a 3-by-3 centered patch for each pixel. Here $s$ and $f$ are frequency-like parameters, and $w$ is angle; $x$ and $y$ are the pixels coordinates in the image. Texture features for pixels in Area 1 and Area 2 are the training data for the lesion and the normal skin classes, respectively. The trained SVM is used to classify the pixels in Area 3 into the lesion class and the normal skin class. The classification results and areas are merged by taking the union of their binary results, followed by morphology processing to fill in holes, to produce the final lesion segmentation.

## III. Experiments and Results

Experiments are performed on an image dataset of 319 melanocytic lesions. The images have been used in quantitative assessment of skin lesion extraction from dermatoscopic images [9,11]. It includes manually labeled lesion contours by five experts on each image. The ground truth is chosen using the criterion "at least two experts agree a pixel is a positive lesion area". The rationale in this is to take into account the subjective standards between different experts, and include that subjectivity difference into the study of our automated segmentation process. Here 160 of them were used in the above experiments to determine the best parameter $a$. Among the remaining 159 images, 32 are used for validation and 127 for testing.

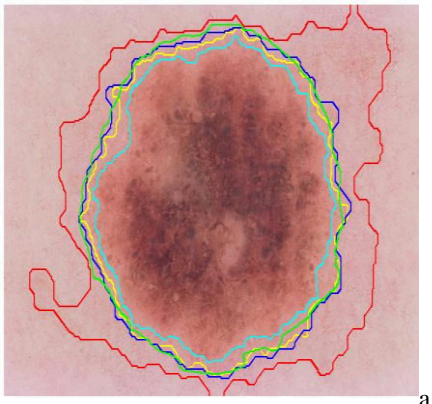
We compare, against the ground truth, the segmentation results of the EM-Bayesian algorithm and the adaptive thresholding with different values of $a$. In subfigure Fig. 5a with $a = 3$, the adaptive thresholding indeed performs better. In subfigure Fig. 5b, the region for $a = 3$ covers all two expert labels, while the region for $a = 2$ may exclude some lesion pixels.

Next, we apply the proposed method on 32 new lesion images. We compare the segmentation performance in terms of sensitivity and specificity for $a$ equal to 2, 3, 4. Table 1 shows the results. With $a$ equal to 2 or 3, both sensitivities and specificities are above 0.87, for all images.

TABLE I. Segmentation comparisons with different values of $a$ on 32 skin lesion images.

| $a$ | Specificity | Sensitivity |
|---|---|---|
| 2 | 0.8857 | 0.8866 |
| 3 | 0.8760 | 0.9075 |
| 4 | 0.6937 | 0.9641 |

We test our method on the rest of the 127 images in the database with results shown in Table 2. On average, our method gives sensitivity and specificity to be 0.875 and 0.872 respectively. In comparison, the EM-Bayesian method achieves with a score of 0.794 and 0.997 for sensitivity and specificity respectively. If only the adaptive thresholding is used, the sensitivity and the specificity are 0.904 and 0.819 respectively, which is worse in specificity than the proposed method with supervised classification for segmentation refinements.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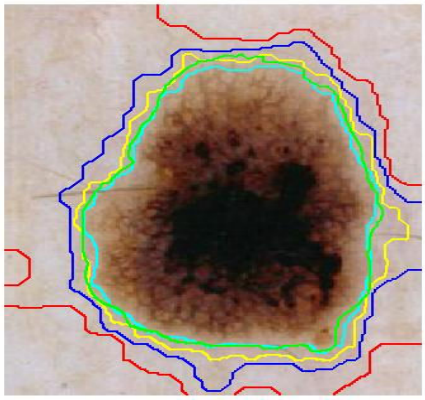
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Fig. 5. Comparisons segmentation results: the EM-Bayesian algorithm (subfigure a) and the adaptive thresholding with different values of parameter $a$ (subfigure b). In both images, green contour is the ground truths; cyan contour is for EM-Bayesian; blue, yellow, red contours are for adaptive thresholding with $a$ equal to 2, 3, and 4, respectively.

TABLE II. Segmentation comparisons with different methods tested on 127 skin lesion images. EM-B is for the EM-Bayesian method; Ada-T is for the adaptive thresholding and "Proposed" for the incremental method.

| | Specificity | Sensitivity | Precision |
|---|---|---|---|
| EM-B | 0.997 | 0.794 | 0.997 |
| Ada-T | 0.819 | 0.904 | 0.821 |
| Proposed | 0.872 | 0.875 | 0.864 |

Finally some sample segmented images are shown in Fig. 6. In these images, green contours are the ground truths; cyan contours for EM-Bayesian segmentation; blue contours for adaptive thresholding with $a = 3$; and red contours for the final result after SVM followed by simply morphology processing. It is seen that, the contours of proposed incremental method are closest to the ground respective truths and the worst segmentation is produced by the EM-Bayesian method for all the images.

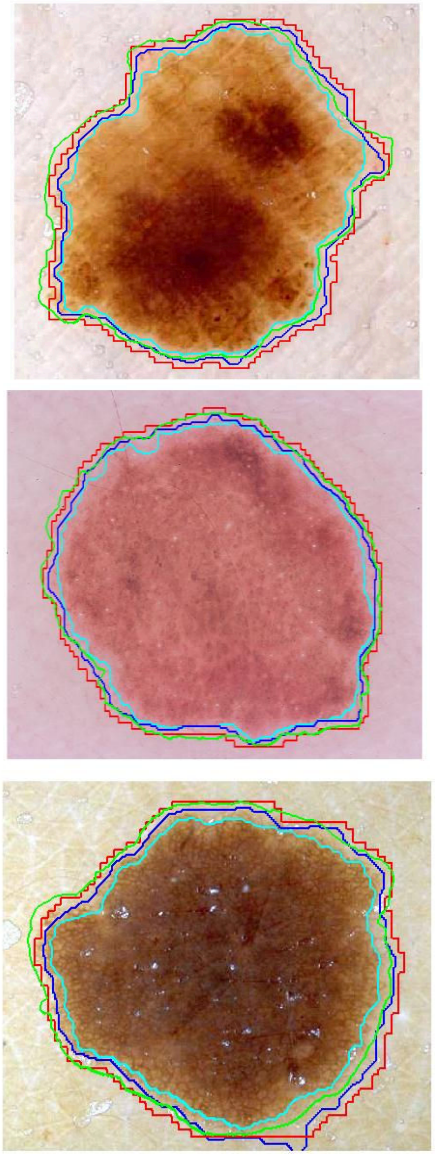

Fig. 6. Segmentation result comparisons: green contours are the ground truth; cyan contours for EM-Bayesian segmentation; blue contours for adaptive thresholding with $a = 3$; and red contours for the final result after SVM.

## IV. Discussion and Conclusion

We have proposed an incremental method for skin lesion segmentation. It is based on a newly proposed adaptive thresholding method by allowing a varying threshold derived from the test image. This adaptive method helps identify segmented regions with high confidence as well as those uncertain regions with low confidence. This is reasonable for the EM-Bayesian image segmentation approach, because in some intensity ranges, the two PDF modes of the foreground and the background are overlapped and hence the classification is of low confidence. Finally a support vector machine is then trained with texture features from areas with high classification confidence to refine the pixel classification in regions of low confidence.

Improvement in performance of the newly proposed segmentation framework over the original EM segmentation method can be seen because it allows adaptive adjustable margins which are further classified by supervised machines using extra texture information.

The applicability of this framework is expected to be reasonably high, but further testing could be done on more extensive databases. More universally applicable processes or exception handling rules could be applied as new cases arise. More texture features could also be tested to increase the overall efficiency/accuracy of the current system framework.


## Acknowledgment

We would like to thank Dr. Hitoshi Iyatomi from Hosei University, Japan, who has kindly provided the raw dermatoscopic images with expert annotations.


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