PRELIMINARY WORK ON DERMATOSCOPIC LESION SEGMENTATION

Alina Sultana[1], Mihai Ciuc[1], Tiberiu Radulescu[1],Liu Wanyu[3], Diana Petrache[2]

[1]Faculty of Electronics, Telecommunications and Information Technology, University “Politehnica” of Bucharest
[2]Elias Emergency Hospital Bucharest,
[3]HIT- INSA Sino - French Research Center for Biomedical Imaging, Harbin Institute of Technology, HeiLongJiang Province, P. R. China

ABSTRACT

Dermoscopy has become the primary tool used for pigmented skin lesion diagnosis providing better quality and accurate images. Computer-Assisted Image Interpretation is a new direction that involves the automatical lesion detection, feature extraction and classification (benign or malignant). This paper refers to several prior pre-processing enhancement techniques and an automated segmentation method. We have tested our methods on 60 dermoscopic images and compared the automated segmentation results with dermatologist-determined segmentation using an area percentage error.

Index Terms **—** Dermoscopy, pre-processing hair removal, contrast enhancement, Mean Shift segmentation.

1. INTRODUCTION

Skin cancers are the most common malignant tumors in fair-skinned persons in the western world, representing 25% of all cancers [1] with an increasing incidence world-wide. Although melanoma is almost completely curable if detected in an early stage, with a simple excision procedure, the problem is far from being solved. For an early detection of cancerous lesions, many countries promote self screening programs based on the classical **ABCD** rule (**A**symmetry, **B**order irregularity, **C**olor variegation, **D**iameter) or **Seven point checklist** guidelines [2]; they aim to differentiate benign from malignant nevi on the basis that melanocytic nevi are often described as oval lesions areas with uniform color, while melanomas are asymmetrical lesions with irregular borders and large different shades of colors. However, due to large variation in skin lesions and acquisition conditions (figure 1), the melanoma detection remains a difficult task for the clinician.

The difficulty in detecting/analyzing different kinds of nevi leads to a large number of biopsy examinations. A reduction of the current mis-readings and interpretation will reduce health care cost by avoiding unnecessary biopsies and it will, also, provide a better patient care. Moreover, Guillod [3] has been stated in one of his recent study that a single experienced dermatologist cannot be used as an absolute reference for the evaluating lesion detection accuracy.

One of the most recent techniques for non invasive diagnosis of skin cancer is digital dermoscopy based on epiluminescent microscopy principle. It allows the evaluation of high resolution dermoscopic images of skin lesions, using a color video camera equipped with lenses providing high magnification factors (×10 to ×1000) and better visualization of the subsurface structures. Advantages of the digital dermoscopy are the mole mapping, a good identification of different and subtle morphological structures (pigmented network, dots, globules, blue-white veils, blotches and streaks), a long-term observation and documentation of melanocytic lesions, independence of the investigator, reducing errors and allowing screening differentiate between difficult to diagnose lesions and benign lesions and format ready for teledermatology. Due to higher quality and diagnostic accuracy, compared to simply using the clinic view, dermoscopy has become the primary tool for skin lesion diagnosis.

The idea of using a computer assisted tool in order to assist in skin lesion diagnosis was proposed for the first time around 1985. This approach involves, as a first step, the lesion area detection, followed by an automatic features extraction step; based on these features, a classification and a diagnosis step follow. Over time, automatic acquisition, reference and digital storage of images (e.g.: PhotoFinder and MoleMax) have been developed, but embedded software and applications performance are still low.

Nowadays, numerous methods have been developed for the automatic lesion detection in dermatoscopy images. Recent approaches consist in applying fuzzy C means clustering algorithms [4-5], gradient flow snakes methods [6], thresholding followed by region growing approaches [7], statistical region merging techniques [8] or contrast enhancement combined with k-means clustering [9].

Due to several important factors: non-uniform coloring inside of the region of interest, irregular and fuzzy lesion borders, artifacts such as black frames, hair, thin blood vessels, ruler measures (vignettes), low contrast between the skin and the lesion areas, fragmentation of the same lesion in more areas, etc. (as one can see in figure 1) automatic extraction of lesion is not a trivial task.

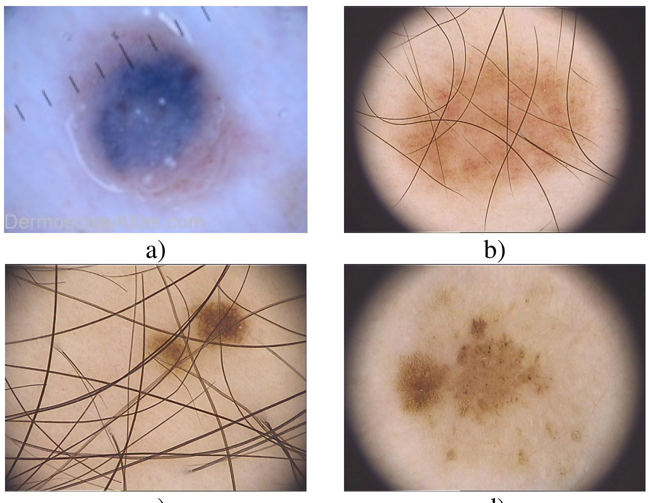


Fig. 1. Problems with lesion detection: several complex cases examples of dermatoscopic images: ruler and immersion liquid a); hair and low contrast b), c) and d).

In this paper, we focus on correctly isolating suspicious lesions from normal skin, an essential step in achieving a computer assisted diagnosis (CAD) skin cancer tool. The proposed automatic computational system consists of two major steps: preprocessing the images to facilitate the lesion detection procedure and automatic lesion detection.

In turn, the preprocessing step consists of two sub-steps: first consists in image contrast enhancement and the second deals with image artifacts removal.

The rest of the paper is organized as follows: section 2 describes the data set collection used in the study; section 3 details the pre-processing image techniques; section 4 describes the automatic segmentation approach used for isolating suspicious areas while section 5 gives several conclusion and future work plans.

2. DATABASE DESCRIPTION

In this paper, we evaluate the performance of three recent automated detection methods on a set of 60 dermoscopy images (35 melanomas and 25 benign nevi) using two sets of manually marked borders as the ground truth. The images are true-color images with a typical resolution of 576x768 pixels. The manually marked border contours are provided by two experimented dermatologist clinicians. The lesions were biopsied and diagnosed histopathologically in cases of increased risk; otherwise, they were diagnosed by follow-up examination.

3. THE PROPOSED METHOD

As a starting point in our algorithm, we use several preprocessing steps, whose aim is to increase the contrast of the original images and to remove the artifacts occluding potentially useful information, followed by a Mean-Shift segmentation step,that will extract the possible lesion areas.

3.1. Preprocessing original images

A common feature of dermatoscopic images is the nonuniform background; the nonuniformity is caused by several inherent factors such as water or air bubbles (resulted from the immersion acquisition step), the thick hair that occlude areas of interest, thin blood vessels, skin lines and other cutaneous skin lesions (desquamation, dry skin) that can prevail upon on wrong diagnostic or obstruct useful information in the regions of interest.

To minimize the factors mentioned above, several enhancement techniques will be applied in order to improve the low contrast of the image and fine smoothing of small artifacts, that may corrupt the image quality. To improve the low contrast between the nevi region and the surrounding skin area, an adaptive histogram equalization step is employed. This technique has the advantage of using processing blocks (tiles) of area instead of using the entire image; this implies that each block's contrast is enhanced independent of the dominant image information. A simple histogram equalization provides a better visualization of the nevi area but it also increases the little nonuniformity artifacts from the image (ex. skin lines).

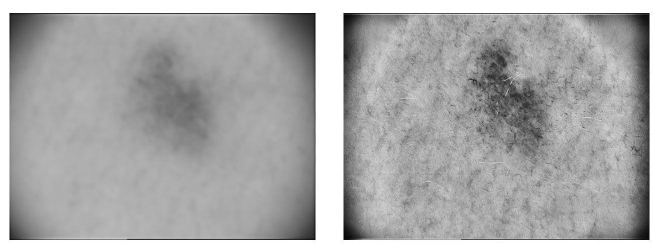


Fig.2. a) A low contrast dermatoscopic original image; b) contrast-limited adaptive histogram equalization (CLAHE Matlab implemented function) assures an increased contrast in the image preserving a good quality of the background.

3.2. Artifacts removal

3.2.1. Hair removal

Once the image contrast has been enhanced, the artifacts removal step is done. The most disturbing elements that affect the image quality are the hair (or hair stubbles), skin lines, black frame removal and ruler markings (vignettes).

Many skin images contain hair. These strands of hair (especially the dark and thick ones), by occluding the region or part of the region of interest, yield a missed detection of subtle signs. This is why it's important to employ a hair removal step. A number of methods have been developed for hair removal on dermoscopic images. Schmidt [4] et al. has used mathematical morphology methods; Flemming et al. [10] applied curvilinear structure detection with different parameters; Zhou et al. [11] have enhanced Flemming method by introducing an inpainting based method approach. Lee et al. [12] have implemented an automated software, called DullRazor, that performs dark thick hair removal and then automatic segmentation to extract the lesion contour.
In this study, two removal hair approaches are applied.
First method is based on a simple morphological closing operation with a disk-shaped structural element. Based on the assumption that hair strands are thin structures, a simple morphological technique is applied; next, a hair mask is retained by using a global automatical threshold over the image intensity information. Each hair pixel from the resulted mask is replaced by an average mean of the neighbors' pixels. This method has the advantage of being fast. Results are very good in many cases.
Using a global and a rough thresholding approach can lead to unsatisfying results. As the replacing mask hair pixel is based only on the mean value of the pixel from the neighborhood, this can generate an unwanted blur on the result images. Moreover, in many cases, we deal with tick hair strands cases that will lead to darker progressive traces (the calculated mean of a new replaced pixel of a thick hair is too small); another issue related to this method is the segmentation approach (global thresholding function), based on the assumption that hair strands are darker than skin or lesion, is that it can remove subtle and important features misinterpreted as artifacts.
The second approach for hair removal is using the Top Hat Transform combined with a bicubic interpolation approach. First of all, the hair mask is extracted using a Top Hat Transform and, for each hair pixel resulted in a mask, a bicubic interpolation is applied in order to fill in the hair position gaps. This method, as one can see in the figure 3, is stronger and more effective than the first method, as it is not depend on the automatic threshold value and the thickness of hair strands. The Black Top-Hat Transform preserves structures having the size smaller than that of the structuring element and being darker than the background.
The hair mask, obtained using the Top Hat Transformation, properly retains the hair strands, even if there are also other occluding structures. It also removes the background while preserving the hair strands, regardless of the nature of the neighbor areas.
A bicubic interpolation fills the gaps resulted after obtaining the hair mask, by using the whole image information without any neighboring spatial dependency. The results are shown in figure 3:

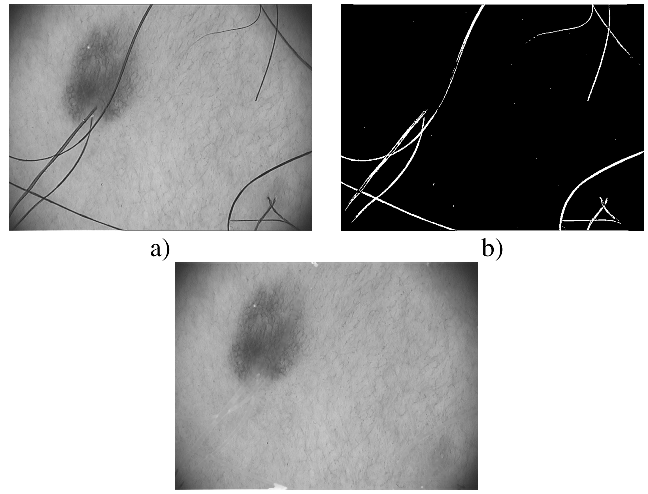
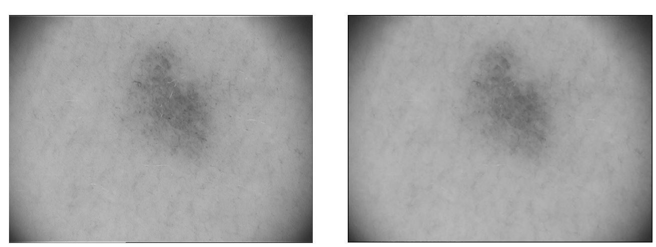


Figure 3. Hair removal results. a) Original image; b) Top-Hat transform applied on a); the final result after the interpolation and a simple smoothening step.

3.2.2 Thin blood vessels and skin lines removal

Other removed artifacts are the thin blood vessels and skin lines. This is achieved by using a simple median filtering operation (kernel size [3x3]) or smoothing filters, such as Nagao and Kuwahara filter. The last two filters mentioned above are both edge preserving blur filters, smoothing out small details while preserving, and eventual sharpening, larger-scale contours.
The Nagao filter is based on the minimization of the radiometric variation in the neighborhood of the processed pixel, while keeping the median value of the lowest entropy window. The result is a smoothed image with finely preserved edges.
The Kuwahara filter is another edge preserving blur filter. It works by calculating the mean and variance for four sub-quadrants, outputting the mean value for the region with the smallest variance. The best results are obtained by using the Nagao filter.



a) b)

Figure 4. Blur filters for background smoothening: a) the original image; b) Nagao filter result.

Before the preprocessed images can be used for the Mean Shift final segmentation step, another preprocessing step is needed: black frame and ruler marking removal.
For a fast and efficient black frame removal step on a labeled mask image, we compute the Euclidian distance between each object's and the image's centers. The minimum distance corresponds to the lesion area.
The ruler marking image is removed by a morphological closing operation.

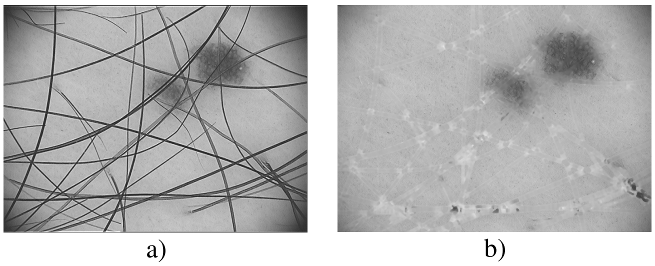


Figure 5. Another pre-processing example result: a) original image and the pre-processing algorithms result.

4. A MEAN-SHIFT AUTOMATIC SEGMENTATION APPROACH

For the second lesion isolation step, a Mean Shift segmentation approach is used.

Mean Shift segmentation technique is a non-parametric clustering technique. It means it does not require the number of clusters as „apriori” information. This represents a major advantage because, generally, when using automatic segmentation, one can easily obtain incorrect results, since the classical segmentation techniques are often based only on assumption of "guessing" the number of classes existing in the image. Another important advantage of the Mean-Shift method is its excellent tolerance to nonuniform background [13]. Due to intrinsic complexities of the lesions, such as blurriness, noise, the overlapping hair and other factors mentioned in the section above, and also due to a large variability in the texture and color and the non-homogeneous nature of lesions, there is a number of problems associated with the accuracy of Mean-Shift segmentation results.
We have tested different kernel sizes. As a result of numerous tests on our image database, it has turned out that the best results are obtained for a standard deviation value $\sigma = 6$. As one can see in figure 7, we obtain good quality segmentation results for difficult segmentation cases. A last step of brighter regions segmentation extraction is applied based on extracting a connectivity map for each region resulted from mean shift segmentation and finding the brightest region in relation to surrounding areas, mentioned in [14].

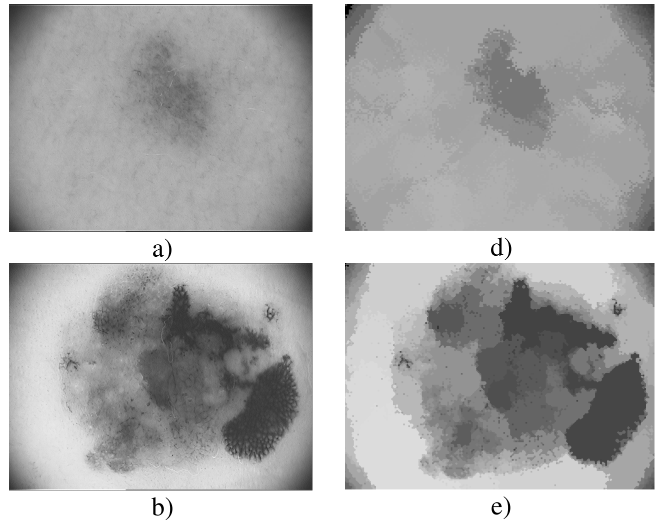


Figure 6. Mean Shift segmentation results. Original dermatoscopic images with very low contrast a), and dysplastic melanoma b); Mean Shift segmentation results after preprocessing steps: c) and d).

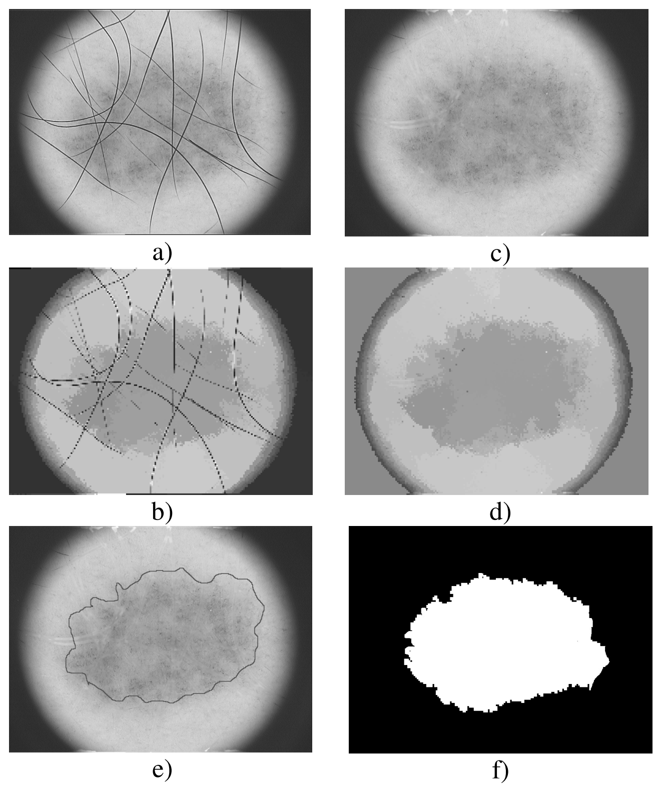


Figure 7. Another Mean- Shift Segmentation result. a) Low contrast dermatoscopic original image; b) Mean-Shift segmentation applied on the original un-preprocessed dermoscopic image; c) Original image with hair removal and black frame removal d); the clinician markings contour, f) brighter regions extracted from Mean-Shift resulted map.

5. DISCUSSIONS AND CONCLUSIONS

This paper presents a preliminary study in detection of melanocytic lesions and contains two major parts: the first deals with pre-processing operations of dermoscopic images, while the second part contains a segmentation based on Mean Shift algorithm.

The first part is dedicated to the preprocessing operation of the original images. Due to the complex nature of the images (see the discussion mentioned in Section 2), the preprocessing steps are needed before applying any extraction or classification algorithm.

Preprocessing algorithms are focused on removing artifacts in the image, but also to increase the contrast and to smooth the background area, factors that could lead to wrong segmentation in a further step. The best smoothing results were obtained by applying the Nagao filter. As many dermoscopic images have a low contrast, an enhancement step is also employed; a contrast limited adaptive histogram equalization approach is applied. The second part of the preprocessing step describes two hair removal algorithms: the first consists of using a closing morphological technique, while the second, stronger method consists in a combination of bicubic interpolation and Top Hat Transform. The artifact removal step eliminates other non-useful regions, such as rulers and inherent black frames produced in the acquisition step.

The second major part of the paper is focused on a first segmentation technique based on the Mean Shift segmentation approach. Due to the nonuniform lesion or background areas, Mean Shift segmentation methods provide good quality results.

Currently, the database consists of 60 images and includes a wide variety of cases that are difficult to diagnose. Each image is paired by a dermatologist manually outlined contour line.

After the segmentation, a validation step is also needed. We have compared the segmentation results with the marking areas provided by the clinicians. The border error is calculated as the product between the ground-truth areas (the clinician border line) and the segmentation mask divided to the ground truth area.

As this paper is only a preliminary work focused on the pre-processing of dermoscopic images, future improvement will be obtained by applying the pre-processing methods on extensive databases, allowing for precise further segmentations and classification tasks.

6. ACKNOWLEDGEMENT

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