A Software Approach for Border Detection using Pigmented Skin Lesions

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Summary
Artifacts removal and border detection (ARBD) are important and critical steps for automatic diagnosis of pigmented skin lesions (PSLs) using digital dermoscopy. In this article, a software approach is developed based on preprocessing step to remove artifacts without affecting the lesion-texture part, prior detection of edge candidate points, and finally detect lesion optimize border using adaptive dynamic programming (ADP) approach. The statistical measure based on dermatologist's manually marked annotation are utilized to evaluate the performance of proposed ARBD system. The ARBD system is tested on a total of 250 dermoscopic images. The obtained results demonstrate that the ARBD technique can enhance the segmentation accuracy of skin lesions.

Key words:
Skin Cancer, Dermoscopy, Artifacts removal, Image enhancement, Border detection, Dynamic programming.

1. Introduction

Skin cancer is the most common cancer [1] afflicting mankind and is rising double in incidence every year, despite the fact that it is often preventable. The digital dermoscopy is widely used by dermatologists to detect and classify skin cancer. There are two major types of skin cancer [2], namely malignant melanoma including Acral melanomas on volar sites and non-melanoma (basal cell, squamous cell, and Merkel cell carcinomas). In pigmented skin lesions (PSLs), the malignant melanoma is more unsafe compared to other skin tumors. Some cutaneous tumors remain an enigma. A good example, one even better than melanoma, is perhaps the deadliest of all skin cancers Merkel cell carcinomas (MCCs) [3]. Similarly, Acral melanomas on volar skin (palms, soles, and fingers) are the other dangerous type of melanomas among non-white populations [4] nearly 30%. The incident rate of Acral melanocytic nevi [5] has been also increased in Central Italy.

However, many clinical experts such as dermatologists [6] have an estimated diagnostic value below than 80% to recognize PSLs lesions. Due to this fact, dermatologists advised a computerize system to automatically diagnosis PSLs lesions instead of doing manual interpretations. To develop a computerize system [7], there are four main steps such as removal of noises, detection of tumor region, extraction and selection of features and finally, classify them through machine learning algorithms. In all these steps, the detection of skin lesions area is an important and difficult step. Still, the segmentation of tumor region is difficult because the lesion border are in different sizes, fuzzy border and irregular border. An example of these diverse lesions is visually displayed in Fig. 1. In particular, Acral melanomas on the volar site have a smooth, irregular, and fuzzy border as shown in Fig. 1(a) to 1(d) as well. Moreover, artifact noises such as dermoscopy-gel, specular reflection and outline lines (markers, skin lines, hair) would as well disturb the automatic computer-aided diagnosis (CAD) systems.

Therefore, artifacts removal and border detection of pigmented skin lesions (PSLs) are required to do accurate classification. To address these issues, there are many systems proposed that are briefly described here. In the beginning, an automatic method for extraction of tumor region is developed in [8]. Whereas in study [9], the authors utilized an intelligent technique to automatic segmentation of skin lesions through simulated annealing algorithm. A fast and automatic segmentation of skin tumor technique was developed in [10], [11] without removing artifacts from tumor regions by using statistical region merging algorithm. Afterwards, an automatic segmentation method using region-based active contours (RACs) model was developed in [12] with pre-processing steps to remove the artifacts from skin lesions. A snake-based algorithm is also proposed in [13]. Whereas in [14], the authors proposed an improved system based on perceptual- oriented color space and combination of region and edge-based segmentation techniques. Also in [15], the authors used mainly two steps such as pre-processing to enhance the lesion region and remove the noises and to detect lesion-area, the authors used active contour–based (AC) model.

However, these techniques are also limited in several ways: they are computationally complexity to detect lines; they will never control all artifact reductions, and in case of BCC or Acral melanomas would always decrease the

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outline detection rate. Since none of the research efforts have been paid to remove all artifacts.

Although, a significant research has been devoted to denoise the image and segmentation but still inefficient in case of special tumors like BCC, MCC, and Acral volar melanomas. In this paper, a software approach is developed to automatically delineate the border of skin lesions in an effective and efficient way along with the pre-processing steps. The pre-processing step is first performed to enhance the contrast, remove artifacts and then the tumor region is segmented using adaptive dynamic programming (ADP) with gray-scale plane fitting algorithm. The overall this proposed system is known as artifacts removal and border detection (ARBD). In practice, there are many applications of dynamic programming in medical images and computer vision domains [16]. In case of segmentation, the DP algorithm is widely used to find out optimal boundaries with an efficient solution.

2. Proposed Architecture

The proposed ADP-Skin system is developed based on four major steps such as pre-processing to enhance the contrast of lesions, artifacts removal, plane-fitting, detect candidate-regions and segmentation the tumor region by adaptive dynamic programming (ADP) algorithm. The major systems of proposed ARBD system is visually displayed in Fig.2 and these steps are explained in the subsequent sub-sections.

2.1 Utilization of Dataset

To test and compare the performance of proposed ARBD system, a dataset of 250 dermoscopy images was obtained from the department of Dermatology [17], Health Waikato New Zealand. This dataset contained hair and dermoscopy-gel artifacts. Also, a dermatologist was requested to manually draw the borders of these 250 dermoscopy images. These manually re-marked regions were delighted as the ‘‘gold standards’’ in this research for evaluating the performance of border detection method.

2.2 Software tools

The Kovesi [18] Matlab functions are utilized too for digital image processing, and to detect hair lines from dermoscopy images. To detect tumor region, the initial version of dynamic programming was used by using an open source IDP3 [19] solution. To developed this tool, an initial implementation of an adaptive and recursive weighted median filter developed is used, which is developed by Sweet [21]. Additionally, to obtain more smooth and continuous outline for the border, a cubic Bezier-Spline curve fitting algorithm was used. This algorithm is used to get smooth borders from region segmentation by dynamic programming approach.

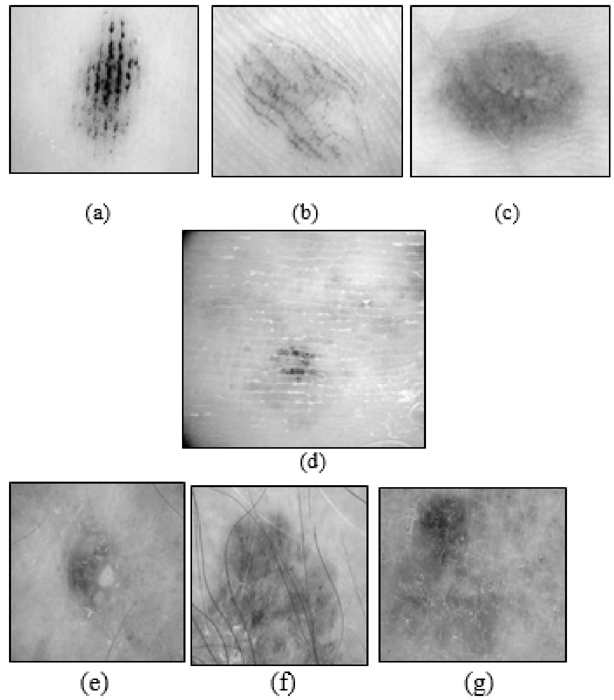


Fig. 1 Problems with border detection for dissimilar type of lesions which illustrate: (a, b, c, d) Acral melanoma on volar sites, (e) Non-pigmented basal cell carcinoma, and (f) Melanoma in situ, as well as, (g) melanotic melanoma.

2.3 Artifacts removal

Artifacts are the biggest thread for automatic analysis of dermoscopic images. These artifact noises make it difficult for computerize system to detect the features so impossible to classify the pigmented skin lesions (PSLs) through CAD systems. Therefore, there are many studies suggested that it is first and important step to remove artifacts from dermoscopy images. There are different artifacts presented in the dermoscopy images such as specular reflection, dermoscopy-gel and hairs. For this purpose, the pre-processing step is performed to enhance the contrast and reduce the effect of specular reflection on tumor region. In addition to contrast enhancement, the dermoscopy-gel effect is also reduced without affecting the patterns of tumor regions. Finally in the pre-processing step, the hairs are detected and repaired. All these pre-processing steps are briefly explained in the subsequent paragraphs.

The dermoscopy images have been captured from different digital dermoscopy cameras in variable environmental conditions so, it contains non-uniform illumination that definitely results in unsatisfying the detection of tumor region from dermoscopic images. For this reason, the homomorphic [20], fast-Fourier transform (FFT) and high pass filters are applied to compensate for uneven illumination or specular reflection variations even though these steps can be used to obtain the high contrast lesion images. For detailed information, the interested readers are requested to study the papers such as [14], [15] and [20]. After applying these contrast enhancement steps, the lesion area is having high contrast while maintaining the problem of specular reflection. The example of this step is visually represented in Fig 3.

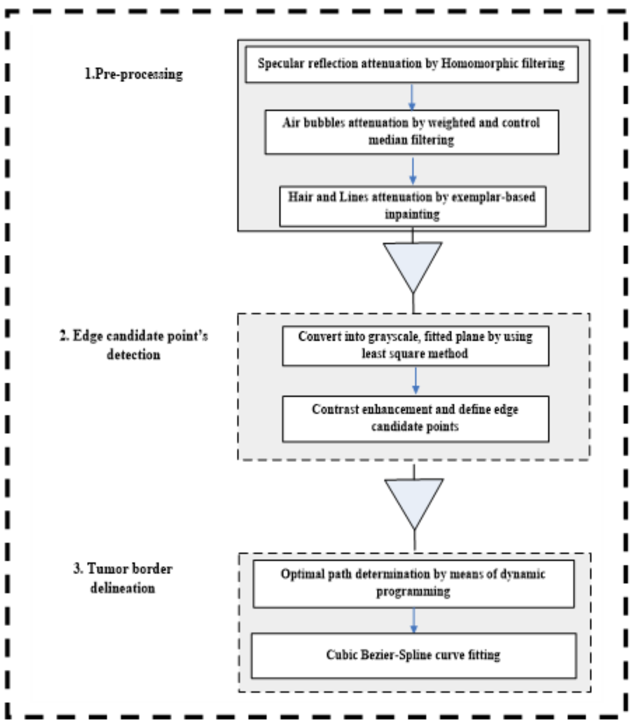
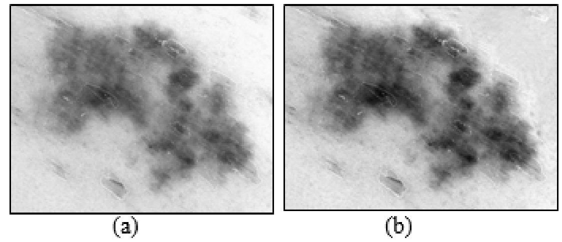


Fig. 2 A schematic diagram of the proposed skin lesions border detection using adaptive dynamic programming algorithm along with artifacts lessening steps.



(a) Original images, (b) after illumination correction.

After removing the effect of specular reflection and enhance the contrast of tumor region, the dermoscopic-gel effect is also needed to remove. As shown in Fig. 3 and Fig. 4, this artifact such as dermoscopic-gel interfere in the detection of skin tumor region from dermoscopy images. To remove these speckles and bubble noises (Fig.3 (b)), the weighted-median filter (WMF) [21] was performed on each dermoscopy images. In practice, the WMF filter is having an edge persevering capability. The visual enhance result is obtained after applying the WMF filter with adaptive window size as shown in fig. 4. Hence, the speckles and bubbles noised are removed by using WMF filtering algorithm.

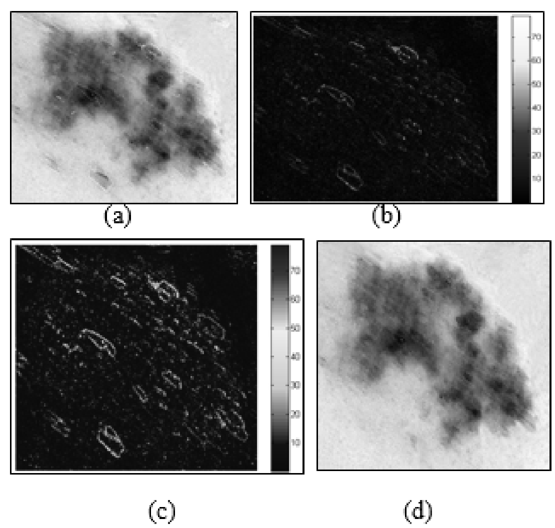


Fig. 4 An example of Pre-processing step to reduce air bubbles by using weighted median filtering. (a) Original ground truth image, (b) maximum gradient magnitude in the red channel, and (c) blue channel while (d) shows an output result after air bubbles artifact reduction.

After removing the effect of dermoscopy-gel, the hairs must be detected and removed from each dermoscopy images for better features extraction and classification of skin cancer. In order to solve this problem, the hairs [21] are detected through derivative of Gaussian and then removed by using inpainting algorithm. The detail of this algorithm has been displayed in [14], [15] and [22]. Moreover, if there were too many lines close to each other then it is very difficult to detect the accurate lines and also replacement of these lines by exemplar-based inpainting method. In some cases, if hair surrounded completely by the tumor surface, then the pixel replacement method will not give good enough results.

2.4. Segmentation

An optimal solution is applied known as dynamic programming algorithm to detect tumor region. However, the first step is to find out the candidate points from skin image. In order to find out these points, it is important to decrease the effect of texture patterns form tumor regions. To reduce the influence of texture patterns, a technique was used known as plane-fitting algorithm [23].

A gray-scale plane is fitted by using least-square method on to the enhanced skin image for reducing the effect of background and skin tumor patterns. An example of this plane-fitting technique is visually represented in Fig.5. This figure 5 (a, c and d) represents images of one Acral melanocytic lesion in gray-scale, its fitted plane, and the corresponding corrected image, respectively. After that, contrast can be adjusted with the help of Gaussian filter as shown in Fig. 6(d). This filter was applied by convoluting the image with a Gaussian function through of 1.5. The final tumor image with contrast enhancement is shown in Fig. 5(e).

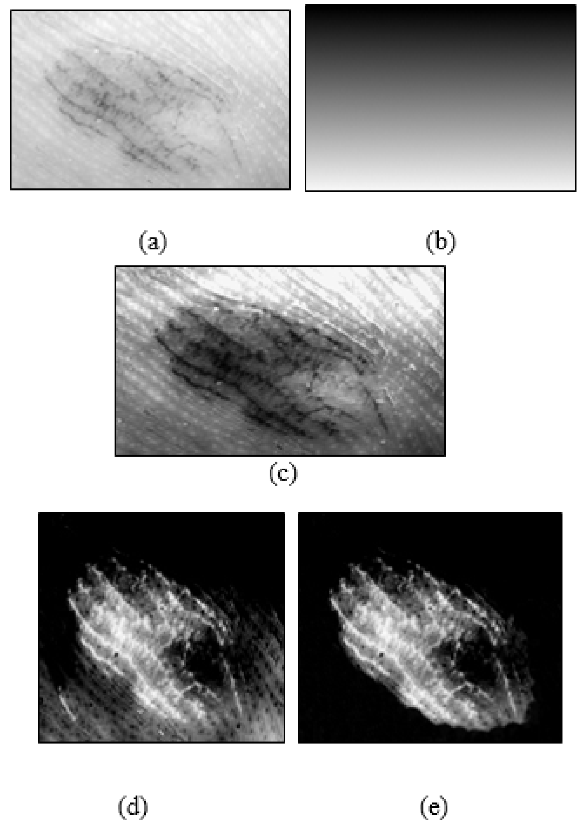


Fig. 5 A close-up view for Hair and outline lines reduction step, (a) original image after illumination reduction(b) False-positive line detections, (c) true-positive lines' detection and filling with RGB color intensity values, and (d) obtained results after Hair and lines reduction.

The gradient at the every pixel of interest was calculated. For edge point's detection, 126 radial profiles points were calculated with 8o distance between lines from the center of the tumor image. Then based on this gradient image, 24 points on each radial line were obtained. Finally, these points are neglected due to edge points that were far away (1.3 times the average distance) from the center of the tumor. At this instant, one can easily plot the associated errors over the radial profile using standard deviations (SD) and standard errors of the mean = SD/ sqrt (n)). The error is calculated as the radial profile is computed based on both ground truth and gradient profile. In contrast of this, the IDP3 algorithm can be also used to plot these errors and correct points by setting manual radius of the circle. Initially, this algorithm (IDP3) was used to draw residual errors of the radial profile.

3. Experimental Results

The Artifacts removal and border detection (ARBD) algorithm was tested and compared effectively on a dataset of 250 dermoscopic images. This obtained dataset contains the type of pigmented and non-pigmented skin lesions. Manual tracing of the tumors was also performed by an expert dermatologists. The Matlab was used as a primary tool to develop ARBD system.

To calculate the complexity of ARBD system, the core i7 with 16 GB ram was used. On average, the ARBD system is taking 1328ms for artifacts removal and contrast enhancement. However, the segmentation step is consuming only 600ms because of use of optimal dynamic programming approach. To test and compare the ARBD system with state-of-the-art segmentation algorithms, the statistical measures are utilized such as

TPR = (TP/ (TP+FN) x 100%)
FPR = (TN/ (FP+TN) x100%
Error Probability (P) = ((FP+FN)/ (TP+FN+FP+TN)) x100

As mentioned-above, the proposed ARBD system is also compared with ground truth obtained from an expert along with the state-of-the-art segmentation algorithms by using these statistical metrics. These metrics are explained here. The true positives (TP) are stored if the pixels are both recognized by the algorithms and the manual ground truth. Whereas true negatives (TN) are calculated if the pixels were identified by the both methods and the expert as non-lesion pixels. The state-of-the-art techniques such as Jseg [24], the region-based active contours (RACs) [25], and the gradient vector flow (GVF) [26] were utilized.

To compare the performance of ARBD with other state-of-the-art systems, the pre-processing and artifacts removal steps were first performed. All the skin images are improved by a developed pre-processing technique to each lesion type for removing artifacts.

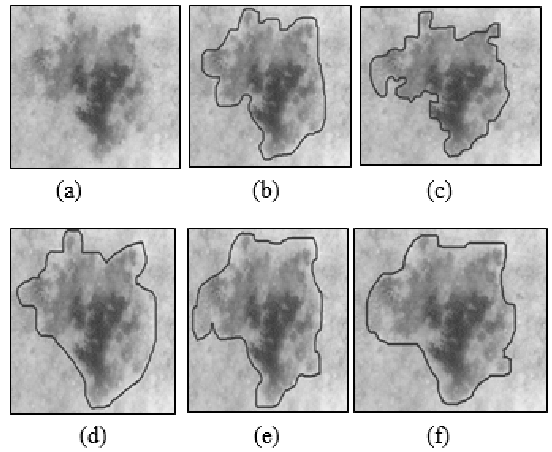


Fig. 6 (a) Original image containing a Acral melanoma, (b) the estimated background trend, (c) image after subtraction of the background trend, (d) background-trend corrected image, (e) after final gamma correction image.

Although, mostly parameters for RAC and GVF are the elasticity, rigidity, viscosity, and regularization parameters were and, as well as average iterations (t=256.4), respectively. The RACs, and GVF are parametric models and all these systems are executed to maximum iterations such as 300. The iteration is varying until reasonable contour has been reached. Three levels are fixed for lesion segmentation.

Currently, the border detection difficulty is encountered even from the point of view of detectors found in the literature one, can examine that many of these methods do not at hand good results when applied to images with this same degree of involvedness. This is an apparent when compared the result obtain by the advised method (Fig. 6 (c)) with the result obtained by other three systems. The work proposed here only exact lesion edges, while other three processes (GVF, JSeg and RACs) process many undesirable edges, which may be part of the skin.

Consequently, the paper present an algorithm designed for automatically border detection using dynamic programming with numerous types of lesions, which is also very useful for the elimination of artifacts. It has tested that this method not only melanomas but also in pigmented and non-pigmented (basal cell, squamous cell, and Markel cell carcinomas) lesions with Acral melanomas as shown in Fig. (7). It can be seen that the method performs well after reduction of noises such as specular reflection, dermoscopic-gel, and outline (Hair, blood vessels, and skin lines or ruler markings). The algorithm is robust, efficient and intuitive. This type of automated border detection technique with artifact reduction steps can increase the classification rate.

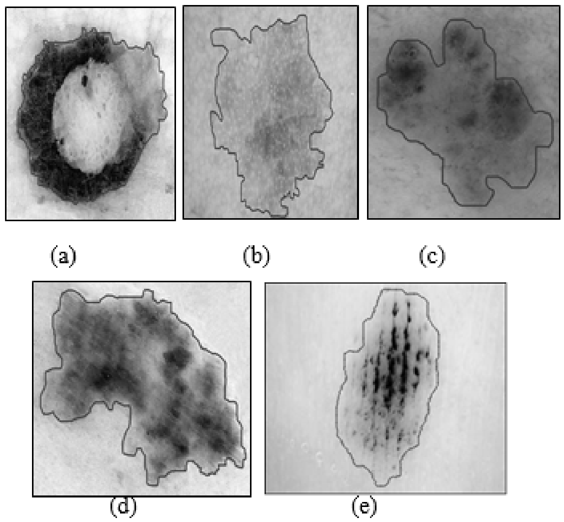


Fig. 7 the border detection results for proposed algorithm with the help of dynamic programming (ADP), and artifacts removal based technique.

On the further discussion of the classification method, it was confirmed that the border detection and artifact reduction steps are very important considerations. However, in some cases, the border detection may have greater mean border error when in comparison to ground truth. The border detection errors in four different cases have been shown in Fig. 7. In these cases, we have analyzed the results by a linear fitting model and notice standard deviation border errors. As this figure present, the border detection from other methods is not very precise as in comparison to developed algorithm (ADP). Moreover, it believes that the preprocessing stage for skin cancer image analysis is very necessary as compare to accurate border detection. Because in order to extract the texture features from tumors for digital dermoscopic images, first there is a step to remove noise pixels.

However, this study delivers good results for the big majority of the tested images, there are two foremost drawbacks exist in this algorithm. The biggest problem is that, in case of heavy hair surrounded by a lesion makes it difficult to detect all lines present in an image. Second reason is that when there are areas belonging to the lesion that is divided into multiple tumors makes it unworkable to detect an accurate outline of the lesion. Besides that, we have performed experiments on Acral melanomas on the volar site which had a smooth, irregular, and fuzzy border. This type of lesion border detection is also included in study, and got 4.8% mean border error in case of 20 lesions. The error for detection of these types of tumors is near to the ground, because of background-trend correction technique.

4. Conclusion

This software approach anticipated and evaluated border detection of skin lesions in digital dermoscopy with artifact‘s reduction steps. This work was applied to a set of 250 dermoscopic images from the clinical skin cancer patient’s database including 30 benign melanocytic, 60 malignant melanomas (MM), and 45 basal cell carcinoma (BCC), with 25 merkel cell carcinoma (MCC), 70 seborrhoeic keratosis (SK), and 20 acral volar melanocytic (AM) lesions. These images were segmented manually by two expert dermatologists and the output border of second expert was utilized for evaluation.

The output of the automatic border detection was compared with the other three (Jseg, GVF, and RACs) algorithms. In despite these, an efficient and fast artifact removal steps were developed to reduce effects of specular reflection, dermoscopic-gel, and lines (Hair, blood vessels, and skin lines or ruler markings). Furthermore, the concept of dynamic programming with “background-trend correction” was used to optimize the border detection problem in a variety of cases. For instance, we obtained mean border detection error in case of (1) 30 benign melanocytic 8.6%, (2) 60 MM: 4.04%, and (3) 45 BCC: 6.03%, in contrary to, (4) 25 MCC: 7.02%, (5) 70 SK: 2.01%, and (6) in 20 AM: 4.8%. There are several potential improvements as well, which have been developed in this study.

As a result, this new research for border analysis includes: an efficient skin lesion outline segmentation method, robust to boundary detection of the tumor in case of fuzzy or smooth lesion type (BCC, MCC, and AM tumors), and reduce the artifact's effects along with the recommended solution for better reduction of camera flash, bubbles and lines such as skin lines or ruler markings, hair, and blood vessels. In the further study, we should evaluate this outline detection algorithm with artifact’s reduction model to more cases of lesions by using dynamic programming method.

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