Automatic skin tumour border detection for digital dermoscopy using a new digital image analysis scheme

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ABSTRACT

Malignant melanoma and basal cell carcinoma are common skin tumours. For skin lesion classification it is necessary to determine and calculate different attributes such as exact location, size, shape and appearance. It has been noted that illumination, dermoscopic gel and features such as blood vessels, hair and skin lines can affect border detection. Thus, there is a need for approaches that minimise the effect of such features. This study aims to detect multiple borders from dermoscopy with increased sensitivity and specificity for the detection of early melanoma and other pigment lesions. An automated border detection method based on minimising geodesic active contour energy and incorporating homomorphic, median and anisotropic diffusion (AD) filtering, as well as top-hat watershed transformation is used. Extensive experiments on various skin lesions were conducted on real dermoscopic images and proved to enhance accurate border detection and improve the segmentation result by reducing the error rate from 12.42% to 7.23%. The results have validated the integrated enhancement of numerous lesion border detections with the noise removal algorithm which may contribute to skin cancer classification.

KEY WORDS: Carcinoma, basal cell.
Dermoscopy.
Image processing, computer assisted.
Skin neoplasms.

Introduction

Skin cancer is one of the most common types of cancer[1] among populations worldwide. Generally, skin cancer is divided into two groups, melanoma and non-melanoma. Malignant melanoma[2] usually appears as an enlarged naevus with multiple shades of colours, and its border tends to be irregular and asymmetric with protrusions and indentations. This is a potentially fatal malignancy[3] of the epidermal melanocyte which invades the dermis of the skin, and thus early detection is vital to the treatment process.

Basal cell carcinoma[4] is the most common form of cancer in the United States. According to the American Cancer Society, 75% of all skin cancers are basal cell carcinomas. It develops in the epidermis and grows slowly and painlessly. A new skin growth that bleeds easily or does not heal well may suggest basal cell carcinoma. The majority of such tumours occur on areas of skin regularly exposed to sunlight or other ultraviolet (UV) radiation.

There is no effective treatment for advanced melanoma, and the only way to treat it is to excise it as early as possible. However, the identification of melanoma at an early stage is difficult, as is discrimination between melanocytic and non-melanocytic lesions. Dermatologists have an accuracy of approximately 75% when diagnosing melanoma.

The use of automated image border detection is motivated by the need to identify them objectively and reproducibly. Clinicians mainly use the ABCD rule for diagnosing skin lesions. This states that the skin lesion is likely to be a melanoma if the following criteria are fulfilled: asymmetry, border irregularity, colour variation and diameter >6 mm. Using digital dermoscopy to evaluate pigmented lesions, the abnormal structural features of melanoma can be identified, borderline lesions may be observed and benign lesions can be diagnosed without the need of biopsy.

Tumour border detection is also difficult because of the considerable variation seen in lesion shape, size and colour, along with different skin types and textures. In addition, some lesions have irregular boundaries and in some cases there is a smooth transition between the lesion and the normal skin (e.g., basal cell carcinoma). However, difficulties mainly relate to the presence of dark hair[5] covering the lesion, dermoscopic gel bubbles and specular reflections. The segmentation or border detection of multiple lesions is a very important consideration in accurate and quick skin cancer analysis (Fig. 1).

To address these problems, several segmentation or border detection methods for skin cancer have been proposed. For example, Xu *et al*.[6] proposed an automatic method for segmentation of images of skin cancer and other pigmented lesions. Another method was proposed by Joel *et al*.[7] to demonstrate automatic contour detection. Then the simulated and analysis algorithm of optical skin lesion images was proposed by She *et al*.[8] All used a snake algorithm for single lesion segmentation. Fondón *et al*. demonstrated that the segmentation of skin cancer images can be performed well by a texture-controlled multistep region growing process, then Elena and Whelan developed an adaptive segmentation algorithm. A different evolutionary strategy (ES) was adopted by Situ *et al.*, and

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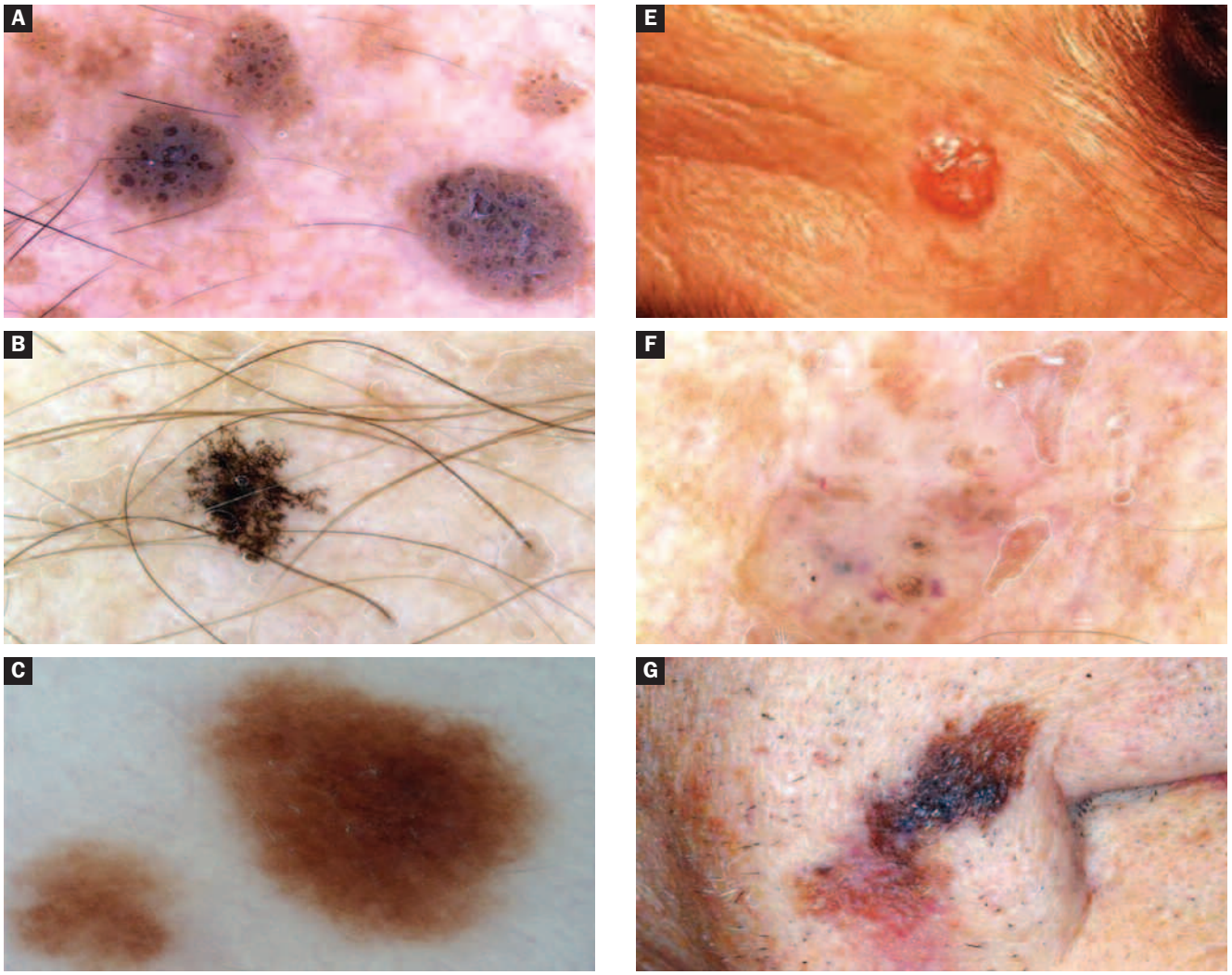


Fig. 1. A dataset consisted of 130 digital dermoscopy images of different types of lesions, for example, A) seborrhoeic keratosis with comedo-like openings; B) epidermal melanin; C) benign melanocytic naevus with amorphous areas; D) dysplastic naevus; E) basal cell carcinoma (BCC) with flesh-coloured verrucal non-scaling papule; F) BCC with fecks of pigment and blue ovoid masses; and G) malignant melanoma.

Celebi *et al*. proposed a fast and unsupervised approach to border detection in dermoscopy images of pigmented skin lesions based on the statistical region merging algorithm. A multi-direction gradient vector flow (GVF) snake-based scheme was proposed by Tang,[9] with the help of an anisotropic diffusion (AD) scheme. Yuan *et al*.[10] proposed a novel multimodal skin lesion segmentation method based on region fusion and narrow band energy graph partitioning.

Most recently, Silveira *et al*.[11] evaluated six segmentation methods of three types. Barcelosa and Pires[12] used the advantage of smoothing the image and at the same time preserving the edges of interest, permitting subsequent true edge detection. Then, Sethumadhavan and Sankaran proposed a Six Sigma-based segmentation method to identify the border between the normal skin and the lesions. Li *et al*. have shown that adding three-dimensional (3D) depth information to RGB colour images improves the segmentation of pigmented and non-pigmented skin lesions.

This study proposes a method to detect the borders of multiple skin lesions. The authors have observed three major problems present in previous studies. First, use of hair removal algorithms like DullRazor,[13] which has been used to remove thick, dark hair,[14] work in preprocessing steps but result in disordered pixels near lesions or lesion boundaries. Second, the presence of other objects (Fig. 1g) on skin images will make it impossible to differentiate skin tumours and other objects. Third, in some cases of basal cell carcinoma the border is not clear, which will decrease the detection rate.

This study presents an advance border detection algorithm for multiple skin lesions by means of adaptive anisotropic diffusion with filters,[21,22] top hat with watershed

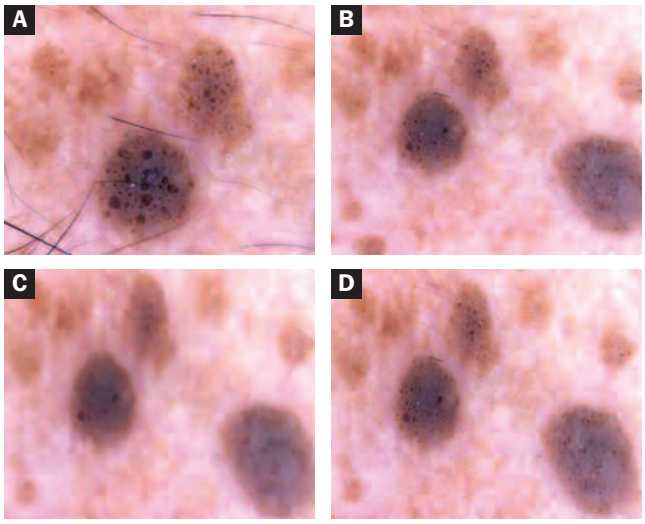


Fig. 2. Proposed artefact removal algorithm: A) original input skin image; B) after reduction of uneven illumination and dermoscopic gel using homomorphic filtering and weighted median filter; C) adaptive anistropic diffusion to reduce skin lines, blood vessels and hair; and D) display after direct DullRazor hair removing algorithm.

transformation and variation of a level set shape prior method. The adaptive anisotropic diffusion scheme[9] is used to remove artifacts. However, this approach has two main problems. First, it uses a direct median filter, which does not give good results in the presence of dermoscopic gel bubbles and long, thick hairs. The other problem is that it diffuses skin images after removing artifacts. Thus, the authors use another anisotropic diffusion scheme[18] with a Gaussian and neighbourhood pixel method to estimate and remove the noise area and provide more lesional border detail. Another main contribution of this work is the assimilation of a shape representation into a variational segmentation framework. This uses an initial variational scheme with shape prior[20] and a derived robust border detection method with the help of top hat and watershed transformation. The resulting segmentation is optimal for a fixed shape prior and provides a GPU implementation for a fast optimisation procedure defining a definite convergence criterion. In this study, experiments are conducted on tumours that have both clear and unclear borders in clinical and dermoscopic views.

Materials and methods

Image database

A clinical online database of 130 colour dermoscopic lesion images were obtained from different sources but mostly from the Department of Dermatology, University of Auckland.[15] These are 24-bit RGB colour images with dimensions of 636 x 406 pixels. The database was subdivided into five categories: i) 20 images of benign melanocytic lesions, ii) 30 images of atypical naevi, iii) 55 images of malignant melanoma, iv) 15 images of seborrhoeic keratosis and v) 10 images of basal cell carcinoma.

Software

The study used initial implementation of adaptive anisotropic diffusion,[18] top hat with watershed transformation[19] and geodesic active contour energy incorporating shape prior,[20] as well as the homomorphic and weighted median filtering algorithms to perform digital image processing and tumour border detection. These methods are not fully automated, and were modified to fulfil the authors' requirements.

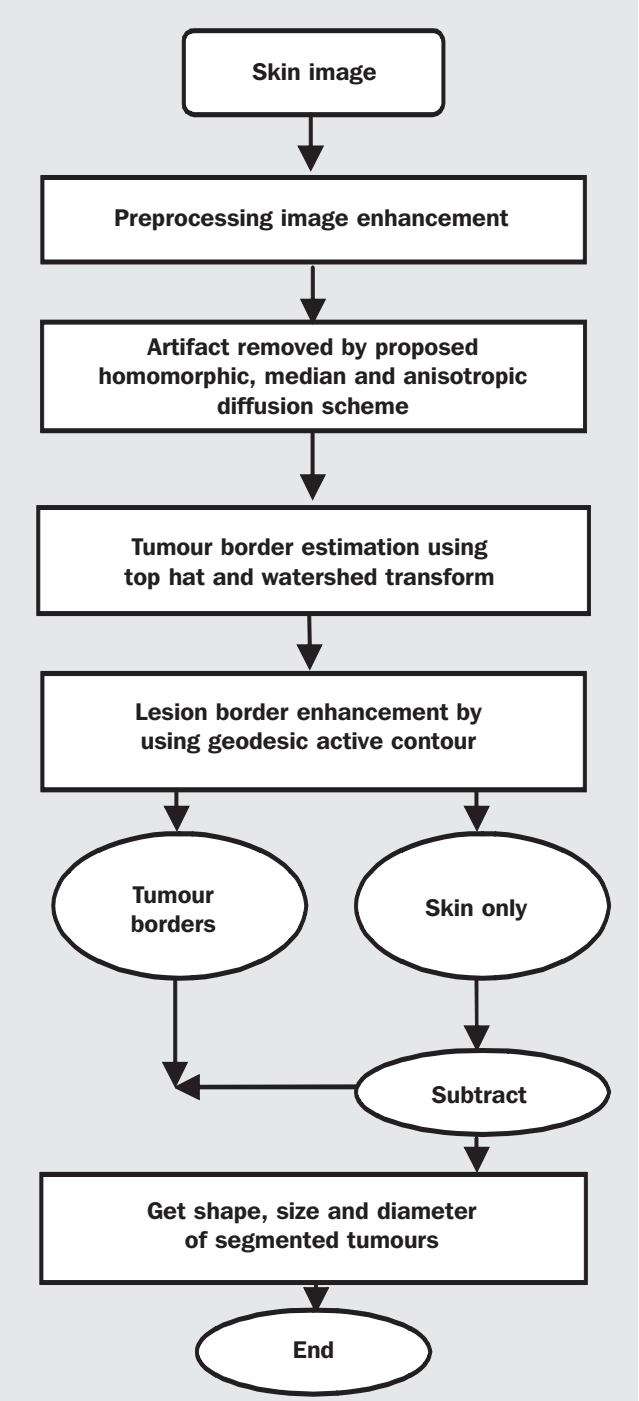


Fig. 3. Flow chart of proposed algorithm for multiple tumour border detection using two-dimensional digital image analysis scheme.

Skin border shape prior

In order to define fixed shape prior constraints, a shape learning concept was used which consisted of collecting shape statistics from training shapes and estimating the

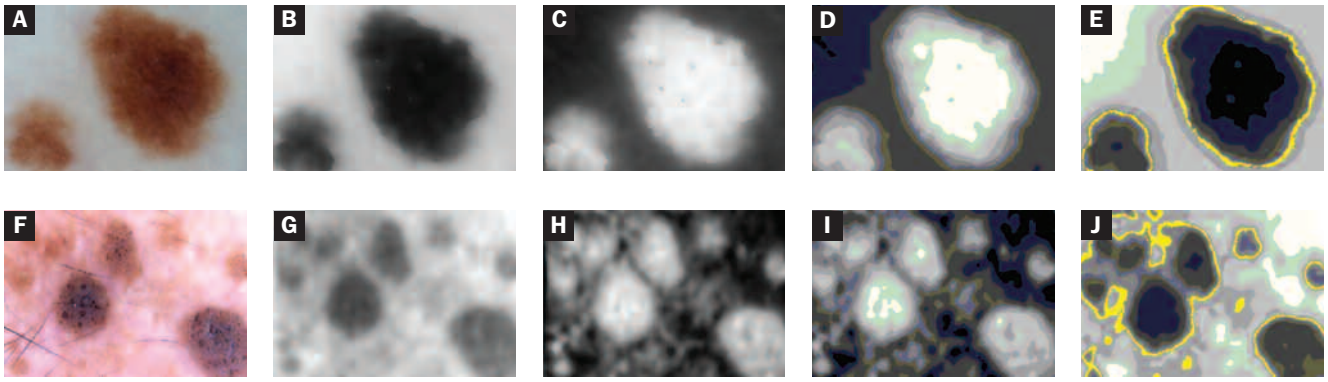


Fig. 4. Examples of multiple lesion border detection for two types of lesion: (A–E) benign melanocytic naevi; (F–J) seborrhoeic keratoses with comedo-like structure – (A,F) input images; (B,G) images after artefact removal with filtering method and gray scale conversion; (C,H) image after top hat watershed transformation; (D,I) initial estimation of border using watershed transformation; and (E,J) enhaced border image by geodesic active contours.

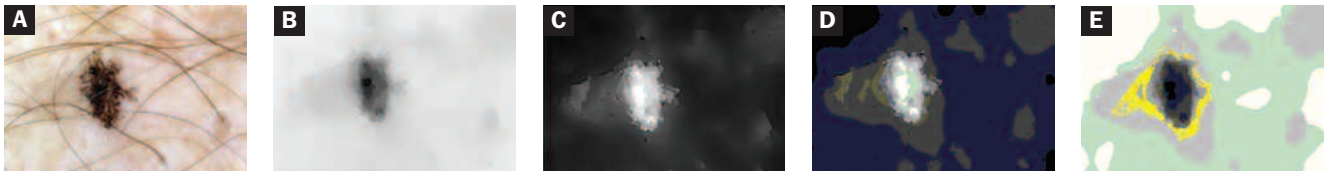


Fig. 5. Epidermal melanin lesion border detection: A) input image; B) image after artifact removal with filtering method and gray scale conversion; C) image after top hat watershed transformation; D) initial estimation of border using watershed transform; and E) enhaced border image by geodestic active contours.

distribution of shapes in that space. The estimated border shape of the lesions in the format of binary contour image was calculated. The manual drawn contour curve after preprocessing the artifacts was reduced by a principal component analysis (PCA) technique. This defined the average border shape that was used as a shape prior constraint for active contours to just move across the tumour border. Image preprocessing, initial tumour border detection and border enhancement proceeded as shown in Figure 3.

Preprocessing the original skin image

Dermoscopic images often contain artifacts such as uneven light illumination, air bubbles or dermoscopic gel, as well as features that can affect border detection and classification (e.g., blood vessels, hair and skin lines). The way to remove these artifacts is to smooth the image using several filters (e.g., median [MF], Gaussian [GF] or non-linear anisotropic diffusion [ADF][18] filters). However, the use of some depends on tumour size, prior knowledge of tumour location and computational complexity. An alternative approach to artifact reduction is to use more dedicated methods for each artefact.

Uneven illumination

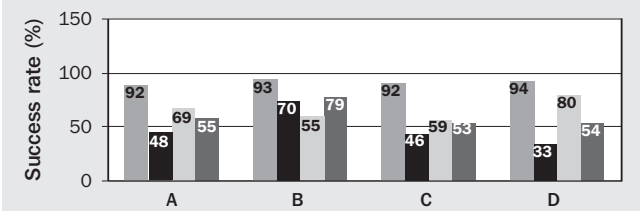
The study used homomorphic,[21] FFT and high-pass filters to compensate for illumination variations and to obtain a high-contrast lesion image. Homomorphic filtering[21] is a generalised technique for non-linear image enhancement and correction. It concurrently normalises the brightness across an image and increases contrast.

Air bubbles or dermoscopic gel

Dermoscopic images frequently include air bubbles or dermoscopic gel, and it is imperative to recognise them so as not to interfere with the border detection. Bubbles contain speckles and have a strong, bright edge. As previously discussed,[24] Fleming *et al*.[23] suggested a method to remove air bubbles using a morphological top hat operator with radial search. However, this study used median filtering[22] with white-level noise reduction and a weighted window (3 x 3 pixels). This method effectively removes air bubbles and has edge-persevering capabilities.

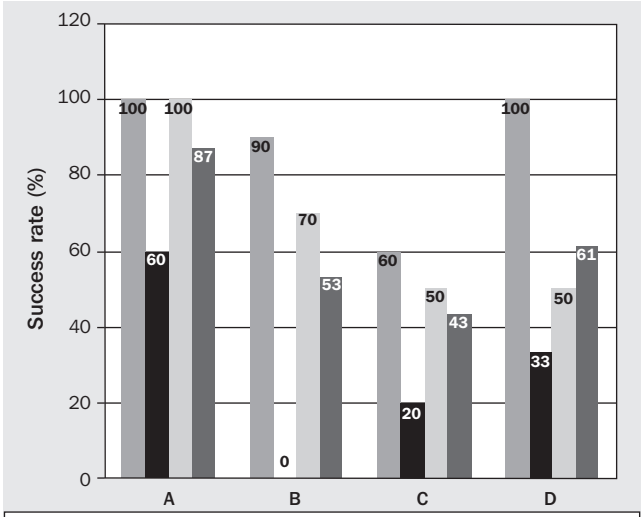
Hair and skin lines

In order to minimise artifacts such as blood vessels, hair and skin lines, an adaptive AD scheme was used. It has been shown that AD[9] with a median filter can remove the independent spots effectively. However, this technique does not have edge-preserving capabilities when thick, long hair is present. A current speckle-reducing anisotropic diffusion (SRAD) scheme[18] has been developed which has edge-preserving capabilities. Initially, this method is applicable when signal-dependent, spatially correlated multiplicative



	A	B	C	D
Proposed	12%	93%	8%	11
Multi-GVF	35%	62%	50%	33
JSeg	43%	43%	39%	54
SkinSeg	30%	68%	45%	65

Fig. 6. Results of dataset 1 for 20 images of benign melanocytic lesion: A) Hammoude distance (HM); B) true detection rate (TDR); C) false-positive rate (FPR); D) Hausdorff distance (HD).



	A	B	C	D
Proposed	7%	90%	30%	6
Multi-GVF	60%	0%	50%	33
JSeg	100%	70%	46%	50
SkinSeg	87%	53%	76%	61

Fig. 7. Results of dataset 2 for 30 images of atypical naevi. A) Hammoude distance (HM); B) true detection rate (TDR); C) false-positive rate (FPR); D) Hausdorff distance (HD).

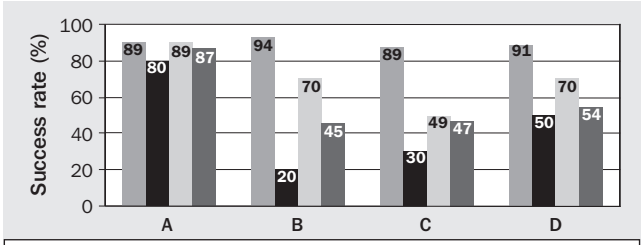
noise is present. This SRAD scheme was modified to decrease these types of artifact. Briefly, the authors estimated the position of each line and tumour with the help of maximum gradient magnitude in the blue channel of the RGB image then used this edge information to fill gaps in the input image with the help of neighbouring pixels and the SRAD method (Fig. 2).

Initial tumour border detection

After minimising the artifacts, the RGB colour values were converted into grey-scale values, and the lesions were segmented in two steps. First, an initial guess was made using the algorithm of top hat with watershed transformation.[19] In order to smooth the shapes of image objects, projections were pared and holes were filled using a 15 pixel-diameter disk as a structuring element. Second, a variational level set approach with shape prior was used.

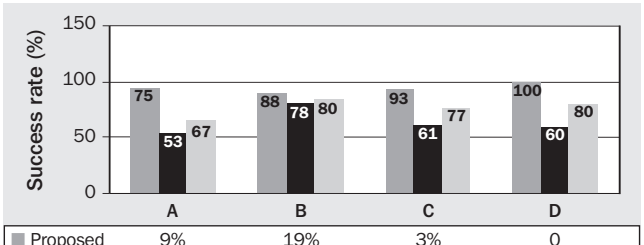
Lesion border enhancement

The initial guess of border detection did not give accurate segmentation results due to the presence of asymmetrical lesion boundaries and other non-lesion objects. A variational level set approach with the help of geodesic active contours and global shape prior constraint was used. The main drawback of this algorithm is that it requires an initial step to initialise the level set function, but this problem has been resolved by using initial segmentation with top hat and watershed transformation. This framework permits local optimisation of the shape position to obtain a correct segmentation of skin objects. A great advantage of this variational method is the parallelisation capability of modern graphics hardware that is able to boost the performance of such highly parallel algorithms. Border detection is very difficult in cases of low-contrast basal cell carcinoma images. This technique may provide benefits from the additional shape information.



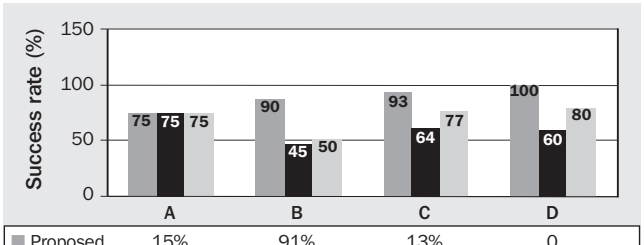
	A	B	C	D
Proposed	11%	94%	13%	15
Multi-GVF	80%	20%	30%	50
JSeg	90%	70%	89%	70
SkinSeg	87%	45%	47%	54

Fig. 8. Results of dataset 3 for 55 images of malignant melanoma. A) Hammoude distance (HM); B) true detection rate (TDR); C) false-positive rate (FPR); D) Hausdorff distance (HD).



	A	B	C	D
Proposed	9%	19%	3%	0
Multi-GVF	74%	45%	54%	60
JSeg	60%	53%	77%	80

Fig. 9. Results of dataset 4 for 15 images of seborrhoeic keratosis. A) Hammoude distance (HM); B) true detection rate (TDR); C) false-positive rate (FPR); D) Hausdorff distance (HD).



	A	B	C	D
Proposed	15%	91%	13%	0
Multi-GVF	30%	30%	51%	60
JSeg	42%	12%	77%	80

Fig. 10. Results of dataset 5 for 10 images of basal cell carcinoma. A) Hammoude distance (HM); B) true detection rate (TDR); C) false-positive rate (FPR); D) Hausdorff distance (HD).

Tumour feature extraction

A variety of feature vectors were generated (e.g., tumour size, radius and diameter). In some experiments, the above features were extracted from the datasets that included clear or unclear borders. Moreover, this feature vector can be used to describe the border irregularity measure of benign and malignant skin tumours.

Results

The border detection method was applied to 130 skin lesion images previously manually segmented by an experienced dermatologist. This manual segmentation was regarded as the gold standard and the algorithm was validated by comparison using four different metrics and another three

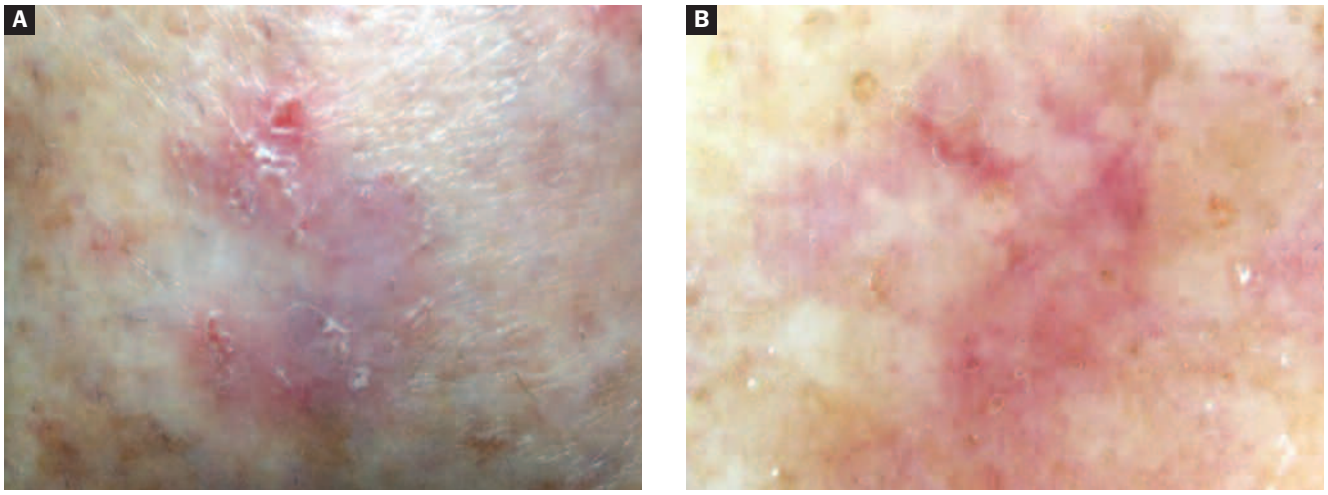


Fig. 11. Dermoscopic features of pigmented and non-pigmented basal cell carcinoma: A) bluish, scale, ulceration, regression; B) flecks of pigment and blue ovoid masses in structureless areas.

developed segmentation methods.[9,16,17] However, such differentiation is complicated and these algorithms can only detect the border if the lesion is single, there is not enough noise and the border is very smooth. However, compared with these methods, the experimental results show that the proposed method performs better and is more robust when applied to images with higher noise levels, very small lesions or even weak edges.

In order to evaluate the border detection method, the study used four metrics to quantify boundary differences. The Hammoude distance (HM), the true detection rate (TDR) and the false-positive rate (FPR) are area-based metrics, while the Hausdorff distance (HD) metric measures the distance between the boundaries in pixels. This study used the same mathematical metrics as adopted by Silveira *et al.*[11] to compare different segmentation methods for melanoma diagnosis in dermoscopy images.

Figures 4 and 5 show examples of the border detection results for different types of lesion. In all cases, the proposed border detection method produced better results and were closer to the gold-standard control. More complex cases are shown in Figure 1g and Figure 5, which demonstrate the effect of noise and hair, respectively. The basal cell carcinoma in Figure 12 contains regions with hair and dermoscopic gel bubbles and shows an unclear border, but the proposed method shows accurate border detection.

The training dataset was divided into five lesion groups. In each group, multidirection GVF,[9] SkinSeg[16] and JSeg[17] methods using four evaluation matrices were evaluated. The performance of the border detection method with the five different types of lesion is displayed statistically in Figures 6–10. In all cases, the proposed method performed well when compared with the other three methods. Each bar (Figs. 6–10) represents the mean success rate of border detection algorithms in terms of true detection whereas statistical data provide the average metrics calculations.

Discussion

Although the proposed method delivered good results for the majority of the tested images, two groups of lesions were not correctly border detected. One group includes those lesions where areas are lighter than the surrounding normal skin and are situated on the boundary of the lesion. In such cases, the light area will be regarded as normal skin (Fig. 11). The other group comprises images of multiple lesions very close together and are very light (Fig. 12). In this case, the new border detection method can accurately track borders but cannot separate lesions.

All images in the training dataset were taken from people with fair (white) skin, as this is the population in which melanoma is most likely to develop. However, there is no guarantee that a person with darker skin will not develop melanoma. Thus, the border detection method must also be tested on images taken from persons with darker skin to verify that the method is skin-colour independent.

From expert evaluation of the 130 test images, there is a tendency for the border detection method to fail when the lesion is diffuse and not well separated from normal skin. There should also be defined strong criteria for representing the shape prior knowledge including objects located near the lesion. The hair-removing algorithm performs well, removing the hair that otherwise would affect the border detection method. The hair pixels are replaced by skin-colour pixels for outside the lesion, and by lesion-coloured pixels for

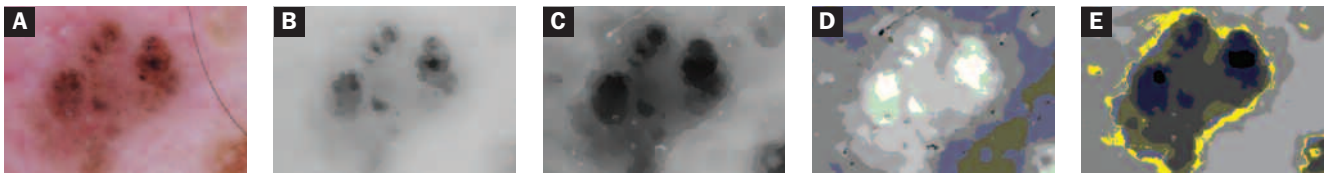


Fig. 12. Example of flecks of pigment in structureless areas in pigmented basal cell carcinoma: A) input image; B) image after artifact removal with filtering method and gray scale conversion; C) image after top hat watershed transformation; D) initial estimation of border using watershed transformation; and E) enhaced border image by geodesic active contours.

hair inside the lesion. Testing the border detection algorithm on more cases of malignant melanoma needs to be done to ensure that the algorithm performs well in all cases, and more lesion samples should be included in the evaluation.

This study proposed and evaluated a border detection method for skin lesions in dermoscopic images. It was assessed against state-of-the-art techniques that have been used successfully, such as multi-direction GVF snake.[9] Several improvements have been proposed in this research study. These relate to skin cancer research analysis including i) a new and efficient method for skin lesion image analysis, ii) a robust method to integrate shape prior constraint to segment tumours in cases of non-lesional objects or artifacts, iii) to reduce the artifact effects and propose a solution for the reduction of camera flash, bubbles and lines (e.g., skin lines, hair and blood vessels) and iv) use in basal cell carcinoma for which early and correct diagnosis is of great importance.

In addition, the authors performed a separate evaluation of the methods for the segmentation of different types of lesion. This kind of analysis has been addressed[11] to some extent but only considered melanomas and basal cell carcinoma. These methods displayed increased TDR for the melanoma cases and also a decreased FPR in basal cell carcinoma. Thus, it is low contrast between the lesion and the skin which characterises this type of lesion. The proposed method is robust and can be used to define any type of lesional border in a computer-aided system to aid clinical diagnosis of skin lesions. □

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