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An effective hair removal algorithm for dermoscopy images

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Background/purpose: Dermoscopy is one of the major imaging modalities used in the diagnosis of pigmented skin lesions. Due to the difficulty and subjectivity of human interpretation, computerized image analysis techniques have become important tools in this research area. Hair removal from skin lesion images is one of the key problems for the precise segmentation and analysis of the skin lesions. In this study, we present a new scheme that automatically detects and removes hairs from dermoscopy images.

Methods: The proposed algorithm includes two steps: firstly, light and dark hairs and ruler marking are segmented through adaptive canny edge detector and refinement by morphological operators. Secondly, the hairs are repaired based on multi-resolution coherence transport inpainting.

Results: The algorithm was applied to 50 dermoscopy images. To estimate the accuracy of the proposed hair detection algorithm, quantitative analysis was performed using TDR, FPR, and DA metrics. Moreover, to evaluate the performance of the proposed hair repaired algorithm, three statistical metrics namely entropy, standard deviation, and co-occurrence matrix were used.

Conclusion: The results demonstrate that the proposed algorithm is highly accurate and able to detect and repair the hair pixels with few errors. In addition, the segmentation veracity of the skin lesion is effectively improved after our proposed hair removal algorithm.

Key words: dermoscopy images – hair detection – hair removal – melanoma – skin lesions

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Dermoscopy also known as epiluminescence microscopy, is a non-invasive skin imaging technique that makes subsurface structures more easily visible when compared with conventional clinical images. Close examination of pigmented skin lesions in this way increases the effectiveness of clinical diagnostic tools by providing new morphological criteria for distinguishing melanoma from other melanocytic and non-melanocytic pigmented skin lesions (1, 2).

However, it has been demonstrated that dermoscopy may actually lower the diagnostic accuracy in the hands of inexperienced dermatologists. Therefore, due to the lack of reproducibility and subjectivity of human interpretation, the development of computerized image analysis techniques is of paramount importance (3).

Presence of hair in dermoscopic images is a challenge in an automated diagnostic system for the early diagnosis of melanoma. Hair pixels usually present in dermoscopy images and occlude some of the information of the lesion such as its boundary and texture. Hence, the removal of hair is an important pre-processing step in such systems. Ineffective hair removal algorithms lead to weak segmentation and poor pattern analysis of dermoscopy images (4, 5). Hair removal can be broken into two distinct steps: (1) Detecting and removing the hair pixels in the image, then (2) Estimating the color and texture of skin behind the detected hairs and replacing the hair pixels by estimated skin pixels (6).

Hair detection is complicated due to thin and thick hair, hairs with different colors and similar color with the lesion. Moreover, repairing techniques often disturb the texture of lesion patterns. There are a few methods developed in the literature to repair thin and thick hairs. These techniques often create undesirable blurring and disturb the texture of the tumor and result in color bleeding. Furthermore, these methods require high computational time (7).

Numerous methods have been developed for hair removal in dermoscopy images. The first method in digitally removing hairs from dermoscopic images is proposed by Lee et al., using a freely available program called DullRazor. The algorithm consists of three basic steps: Identifying the dark hair locations by morphological closing operation, replacing the hair pixels by bilinear interpolation, and smoothing the final result by adaptive median filter. The goal of DullRazor's method is removing dark thick hairs, thus it cannot remove light colored or thin hairs (8).

Schmid saugeon et al. used a similar approach but the morphological closing operator is applied to the three components of the LUV color space. The accuracy of the proposed method was not reported in this research and it has similar applicability limitations as DullRazor (9).

Zhou et al. implemented automatic hair and ruler marking detection using curvilinear structure analysis and performed explicit curve fitting to increase the robustness of their detection algorithm. Finally, the artifact pixels were replaced by a feature guided exemplar-based inpainting method. This algorithm is applicable to dark hair only (10).

Xie et al. used the morphological closing top-hat operator to enhance hair and applied a statistical threshold to the resulted image to detect the hair regions. Then, they used an inpainting method based on partial differential equation (PDE) to remove hairs. This study focuses mainly on dark hair (11).

Abbas et al. proposed novel hair detection and repairing algorithm. Hairs are detected by a derivative of Gaussian method and subsequently enhanced by a morphological technique which are inpainted by a fast marching method (12). Moreover, in this article, a comparative study for several hair removal methods of the three classes is presented: (1) Linear interpolation, (2) Inpainting by non-linear partial differential equation, and (3) Exemplar-based repairing methods. The comparisons results obtained and indicated that hair-repairing algorithm based on the fast marching method achieves an accurate result (4).

In this article, we present an algorithm to segment both dark and light colored hairs with any thickness and ruler marking, and remove them from dermoscopy images. The remainder of the article is organized as follows. The proposed algorithm is presented in the following section. The Experimental Results and discussion section contains an assessment of our algorithm with discussion and comparison to other published methods and finally, there is the Conclusion section.

The proposed algorithm

The proposed hair removal algorithm consists of two steps: (1) Hair detection with the use of adaptive canny edge detector and refinement by morphological operators and (2) Hair repair by multi-resolution coherence transport inpainting technique. The main contribution of the proposed method is the second step of hair removal algorithm which is a multi-resolution inpainting method.

Hair detection from dermoscopy images

In the first step, the Principal Component Analysis (PCA) transform is applied to the image to facilitate the hair segmentation process by enhancing its contrast. By applying the PCA, the RGB image is converted into a gray scale image which has the maximum contrast within the image.

Afterward, a Wiener filter was used for noise removing. Size of the filter is 3×3 pixels. The Wiener mask size is very small compared with the size of the images because we want to preserve the edges in the image.

After filtering, an improved canny edge detection method is used for detecting the boundaries of hairs. In this method, the gradient magnitude histogram concavity analysis is used to automatically select the dual threshold. The traditional canny edge detector gets the high threshold from the gradient cumulative histogram, therefore when the noise density increases, some noise pixels may be calculated as edge points. Rosenfeld et al. proposed an image threshold segmentation method based on histogram concavity analysis (13). We use this method to select the dual threshold.

The method is based on obtaining the convex hull of the gradient magnitude histogram and analyzing the concavities of convex hull. When the convex hull is calculated, the deepest concavity points become candidates as high threshold (Th) for canny operator and the low threshold is equal to $0{\cdot}4 \times$ Th.

The boundaries of hairs are detected by adaptive canny edge detection and the hairs are segmented by applying the morphological dilation operator on the edge detected image. It can be noticed that segmented image contained misclassified pixels which may be related to lesion pigment network or skin lines. The length of many unwanted segmented objects is usually less than the length of normal hairs. Considering the fact that hairs are thin and long, special labeling and morphological operations are utilized to detect them. Morphological opening is performed by lines structuring elements oriented in different directions. Eventually, to obtain smooth hair lines, dilation and filling operators are applied to the hair mask. By removing unwanted objects from hair mask, hair segmentation result is obtained as illustrated in Fig. 1.

Hair repair

The effect of hairs on diagnosis analysis can be reduced by replacing them with patches which are similar to the neighboring pixels. Image inpainting is used for removing and repairing unnecessary elements such as hairs from images. Bornemann et al. proposed fast image inpainting based on coherence transport. It traverses the inpainting domain by the fast marching method just once while transporting, along the way, image values in a coherence direction robustly estimated by means of the structure tensor (12).

We proposed a multi-resolution coherence transport inpainting for dermoscopy images. The proposed multi-resolution inpainting method repairs the image using a wavelet-based structure. This method combines the simple coherence transport inpainting with a wavelet decomposition/reconstruction method in an iterative and multi-resolution structure. A set of instructions is performed in each iteration until the maximum number of iterations is reached. The pseudo-code of the proposed multi-resolution iterative coherence transport inpainting algorithm is presented in Fig. 2.

Experimental results and discussion

The proposed method was tested on a set of 50 dermoscopy images acquired from an atlas of dermoscopy http://www.dermoscopyatlas.com. These images obtained from different sources and stored in the RGB color format with dimensions ranging from 520×340 pixels to 1600×1200 pixels. Manual hair segmentation given by dermatologist is used as ground truth for the performance evaluation.

The proposed method was developed in MATLAB version 7·12·0·635-R2011a (Mathworks inc., Natick, MA, USA). All computations were

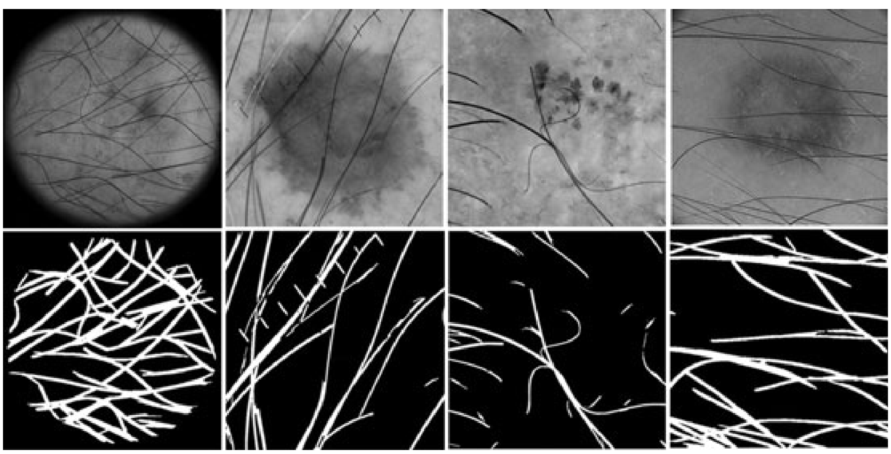

Fig. 1. The results of the hair segmentation algorithm.

$Image_{inpainted} \leftarrow$ IterativeInpainting ($Image$, $Mask$, $MaxIteration$)
Input: $Image$, $Mask$, $MaxIteration$;
Output: $Image_{inpainted}$;
Parameter: $WaveletName$, $InpaintingParameter$;

$Image^{1}_{inpainted} \leftarrow$ CoherenceTransportInpainting ($Image$, $Mask$, $InpaintingParameter$);
If $MaxIteration = 0$
  $Image_{inpainted} = Image^{1}_{inpainted}$;
  Return $Image_{inpainted}$;
($Approximation$, $Detail^{Horizontal}$, $Detail^{Vertical}$, $Detail^{Diagonal}$) $\leftarrow$ DWT2D($Image$, $WaveletName$);
$Mask_2 \leftarrow$ resize($Mask$, 0.5);
$Approximation_{inpainted} \leftarrow$ IterativeInpainting ($Approximation$, $Mask_2$, $MaxIteration - 1$);
$Detail^{Horizontal}_{inpainted} \leftarrow$ IterativeInpainting ($Detail^{Horizontal}$, $Mask_2$, $MaxIteration - 1$);
$Detail^{Vertical}_{inpainted} \leftarrow$ IterativeInpainting ($Detail^{Vertical}$, $Mask_2$, $MaxIteration - 1$);
$Detail^{Diagonal}_{inpainted} \leftarrow$ IterativeInpainting ($Detail^{Diagonal}$, $Mask_2$, $MaxIteration - 1$);
$Image^{2}_{inpainted} \leftarrow$ IDWT2D($Approximation_{inpainted}$, $Detail^{Horizontal}_{inpainted}$, $Detail^{Vertical}_{inpainted}$, $Detail^{Diagonal}_{inpainted}$);
$Image_{inpainted} = \left(Image^{1}_{inpainted} + Image^{2}_{inpainted}\right)/2$;
Return $Image_{inpainted}$;

Fig. 2. The pseudo-code of the proposed multi-resolution iterative coherence transport inpainting algorithm.

performed on a personal computer with AMD phenom II X4 955 processor 32 GHz (AMD Inc., Sunnyvale, CA, USA) and 4 GB RAM with Microsoft Windows 7, 32-bit, as the operating system.

Assessment of the proposed hair detection method

To estimate the accuracy of the proposed algorithm and to quantify the automatic hair detection error, quantitative evaluations were performed using three statistical metrics: True Detection Rate (TDR), False Positive Rate (FPR), and Diagnostic Accuracy (DA).

TDR measures the rate of pixels which were classified as hair by both the automatic algorithm and the medical expert, and FPR measures the rate of pixels which were classified as hair by the automatic segmentation and were not classified as hair by the medical expert. These metrics are calculated as follows:

$$True\ Detection\ Rate(TDR) = \frac{TP}{TP + FN} \times 100\%$$

$$False\ Positive\ Rate(FPR) = \frac{FP}{TP + FN} \times 100\%$$

$$Diagnostic\ Accuracy(DA) = \frac{TP}{TP + FP + FN} \times 100\%$$

where TP, FP, and FN stand for the number of true positive, false positive, and false negative, respectively. These metrics are computed to compare the proposed hair detection algorithm with the DullRazor hair removal software (8) that identifies the dark hair locations by a generalized grayscale morphological closing operation. Fig. 3 shows the results of hair detection using two methods. It can be seen that DullRazor is not suitable for the thin and light hairs. Moreover, this software selects parts of the lesion structure as hair, so the lesion pattern is destroyed. The quantitative results of the proposed algorithm and DullRazor software are presented in Table 1. It can be noticed that the proposed algorithm achieves high DA of 88·3% (TDR = 93·2% and FPR = 4%), whereas DullRazor achieves DA of 48·6% (TDR = 70·2 and FPR = 33·4).

Assessment of the proposed hair repaired method

To quantitatively evaluate the performance of the proposed multi-resolution coherence transport inpainting method, three statistical metrics are used: entropy, standard deviation, and co-occurrence matrix. These metrics are used to compare the texture of original images (without hair pixels) and the images that inpainted by the proposed multi-resolution method. Normalized Differences of Entropy (NDE), Normalized Difference of Standard Deviation (NDSD), and Mean Normalized Difference of Co-Occurrence Matrix (MNDCOM) are calculated between the two types of images. Lesser differences are expected for a better inpainting method. The comparative results between our proposed method and the coherence transport algorithm (12) on 50 dermoscopy images are presented in

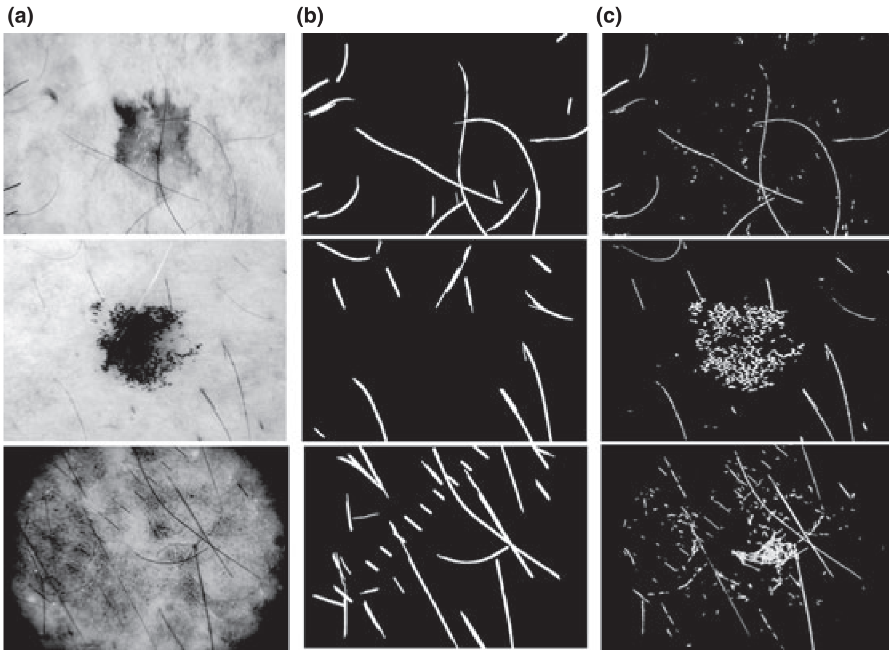

Fig. 3. (a) The original images, (b) The results of hair detection using the proposed algorithm, and (c) The results of hair detection using DullRazor.

TABLE 1. Comparison of the hair detection algorithms for 50 dermoscopy images

Hair detection method	DA (%)	TDR (%)	FPR (%)
The proposed algorithm	88·3	93·2	4
DullRazor (8)	48·6	70·2	33·4

Table 2. It can be noticed that our proposed multi-resolution coherence transport method achieves better results than simple coherence transport method.

Skin lesion segmentation after hair removal

To evaluate skin lesion segmentation, the manual segmentations are carried out on the original images by some dermatologists. Then, images that their containing hairs are detected and repaired by the proposed algorithm are segmented automatically using the region-based active contour method (14). The percentage of segmentation error is calculated by comparing the results of manual and automatic segmentations using the following equation:

$$Segmentation\ Error = \frac{Area(AS \oplus MS)}{Area(MS)} \times 100\%$$

where AS and MS are the binary images obtained by automatic and manual segmentation, respectively, and $\oplus$ is the logic exclusive-OR operation. Table 3 shows the segmentation error on the images before and after hair removal. It can be seen that the segmentation error is effectively reduced after hair removal. Specially, skin lesion segmentation after our proposed hair detection and hair-repairing algorithm has minimum error with respect to other cases.

TABLE 2. The comparison between the simple coherence transport method and the proposed multi-resolution coherence transport method for hair repairing

Hair repairing method	NDE (%)	NDSD (%)	MNDCOM (%)
Multi-resolution coherence transport inpaintimg (the proposed algorithm)	0·72	2·1	0·40
Coherence transport inpainting algorithm (12)	0·95	2·5	0·42

TABLE 3. The results of skin lesion segmentation before and after hair removal algorithms

Hair detection method	Hair repairing method	Segmentation error (%)
None	None	16·26
DullRazor (8)	DullRazor (8)	12·11
The proposed hair detection method	Coherence transport method (12)	10·74
The proposed hair detection method	The proposed multi-resolution coherence transport method	9·9

Conclusion

In this article, a novel approach to hair removal from dermoscopy images was presented. The proposed approach involved hair detection using adaptive canny edge detector and hair repairing using multi-resolution coherence transport inpainting. The algorithm was applied to 50 dermoscopy images that were collected from different sources and in various conditions. Statistical analysis was used to evaluate the performance of the proposed algorithm. The results indicate that the proposed algorithm is highly accurate and able to detect and inpaint the hair pixels with few errors. In addition, in the case of using our proposed method for hair detection and repairing, the segmentation error of the skin lesion is lesser than the cases that the image contains hairs or the hairs were detected/repaired by other methods. Therefore, the proposed method is an efficient approach to process the hairy dermoscopy images before diagnosing the skin lesions.

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