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Hair segmentation using adaptive threshold from edge and branch length measures

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ABSTRACT

Background: Non-invasive imaging techniques allow the monitoring of skin structure and diagnosis of skin diseases in clinical applications. However, hair in skin images hampers the imaging and classification of the skin structure of interest. Although many hair segmentation methods have been proposed for digital hair removal, a major challenge in hair segmentation remains in detecting hairs that are thin, overlapping, of similar contrast or color to underlying skin, or overlaid on highly-textured skin structure.
Methods: To solve the problem, we present an automatic hair segmentation method that uses edge density (ED) and mean branch length (MBL) to measure hair. First, hair is detected by the integration of top-hat transform and modified second-order Gaussian filter. Second, we employ a robust adaptive threshold of ED and MBL to generate a hair mask. Third, the hair mask is refined by *k*-NN classification of hair and skin pixels.
Results: The proposed algorithm was tested using two datasets of healthy skin images and lesion images respectively. These datasets were taken from different imaging platforms in various illumination levels and varying skin colors. We compared the hair detection and segmentation results from our algorithm and six other hair segmentation methods of state of the art. Our method exhibits high value of sensitivity: 75% and specificity: 95%, which indicates significantly higher accuracy and better balance between true positive and false positive detection than the other methods.

1. Introduction

Accurate segmentation of pathological skin features is a major research area in computational skin analysis. For example, segmentation of a PSL allows algorithms to ascertain whether melanoma is present using the ABCDE criteria [2]: the shape of the segmentation is used to assess Asymmetry, Border, Color, Diameter and Evolving Characteristics of mole. However, oftentimes hair occludes these skin images and reduces the accuracy of PSL segmentation [3].

Therefore, a number of digital hair removal (DHR) algorithms were developed to address this problem. Traditionally, the first step is to identify pixels in the image that contain hair, and the second step is to replace these pixels with plausible skin colors based on neighboring skin colors and structure by image impainting. However, these methods primarily solve the removal of only dark thick hair on comparatively light skin; the main challenges remain to detect hairs that are thin, overlapping, or of similar contrast or color to underlying skin [3].

In this paper, we solve the hair segmentation problem, the first step of DHR: to optimally partition pixels in a skin patch image into hair and skin pixel classes. We take a step-by-step approach to designing a novel hair segmentation algorithm by integrating top-hat transform and modified second-order Gaussian filter and designing an adaptive threshold based on observations of the hair segmentation mask. First, top-hat transform extracts hair from background by enhancing the contrast of hair-occluded skin image. Second, modified second-order Gaussian filter is implemented to detect hair segment by testing if the maximum response of the hair Gaussian profile and the filter meet over various hair widths and orientations. This matched filter can evaluate the fitness of estimating hair profiles with Gaussian function while ignoring background noises for hair detection. Third, the density and branch length of curvilinear structures in the detection resulting mask are characterized for optimally thresholding the mask. As the dissimilarity of geometry and distribution of hair and skin in the image is considered in the threshold, the segmentation result is robust even when hair and skin pixels have similar intensity. Finally, we comparatively evaluate our algorithm with seven other popular hair segmentation algorithms. To our knowledge, this is the first quantitatively comparative evaluation of traditional hair segmentation methods across various skin images.

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We organize the paper as follows: Section 2 reviews state of the art methods for hair segmentation. Section 3 contains the proposed hair segmentation methods. Section 4 demonstrates the experimental results, and section 5 presents conclusions. All the hair segmentation results are available at MIT hair segmentation results [22].

2. Related work

In DHR, hair detection based on mathematical morphology [1] is widely used. Many of these methods are based on the closing-based top-hat transform. This morphological operation returns objects that are smaller than the structuring elements and are darker than their surroundings. In DullRazor [4], Lee et al. apply top-hat and generalized morphological closing operations to detect thick and dark hairs. Schmid-Saugeon et al. [5] use a method similar to DullRazor by applying generalized morphological closing operations with a disk structuring element in the luminance component of the CIELUV color space to obtain a hair mask. Moreover, Xie et al. [6] and Fiorese et al. [7] both use variants of the top-hat transform and hard thresholding to obtain a hair mask. The top-hat transform used in these methods is reportedly generally effective at enhancing dark hairs with sufficient contrast on light skin, including both thin and thick hair. In addition, to find light hair on dark skin, the opening-based top-hat operator can be used.

Koehoorn et al. [3] decompose the skin image into its luminance threshold set (256 binary image layers) and apply a multiscale morphological gap detection technique to find thin structures in each threshold layer. The layers are then merged to create a hair mask. The authors evaluate their algorithm to be effective at detecting many types of hair on different skin types. Due to the need to apply morphological operations on up to 512 binary threshold layers to detect dark and light hair, the algorithm requires fast parallel processing techniques in order to process the skin image in a comparable time frame to other methods.

The next group of hair detection methods are edge detection-based. The authors of E-shaver [18] use the Radon transform to detect the predominant orientation of hair and then use the Prewitt edge filter and thresholding to find light and/or thin hair edges in the predominant orientation. Tossi et al. [19] propose a hair detection method using the adaptive canny edge detector. Lastly, Maglogiannis [20] compare edge detection results from a combination of Laplacian, Laplacian of Gaussian and Sobel methods. In these hair detection methods, the hair mask is obtained from the edge image by dilation with a fixed structuring element to fill holes in the interior regions of hair edges. However, we observed that this group of methods is prone to identifying non-curvilinear objects on the skin as hair because they assume that all high-contrast edges in skin images belong to those of hair objects.

Matched filtering methods make up another group of methods used for hair detection. A 2D kernel, designed to model the cross-sectional intensity profile of hair in the image at some unknown orientation and position, is convolved with the skin image. The resulting matched filter response indicates confidence in the presence of a feature at each pixel. These methods assume that the intersectional intensity profile of hair can be approximated by a Gaussian, and that hair has a small curvature and can be approximated by piecewise linear segments. In addition, the Gaussian profile may be inverted to extract dark or light hair.

Abbas et al. [3] present a matched filter with a 1D Gaussian profile and adaptive threshold based on the local mean of the 1D first derivative of Gaussian that helps to deemphasize step edges that arise from a PSL in the image. Huang et al. [11] find the maximum normalized correlation response using a multiscale 1D Gaussian profile and use hysteresis thresholding to obtain a hair mask. Thereafter, local linear discriminant analysis using the partial information of hair colors in the Lab color space and region growing recover hair pixels at intersections. However, Koehoorn et al. [3] report that this method is susceptible to producing dark halos where hairs were identified and removed. In general, matched filtering methods are able to produce smooth hair outlines and recover small gaps in the hair structure due to noise in hair pixels. But the skin image needs to be convolved with a large set of filters, which increases its computational cost.

These techniques mainly exploit the property that hair is curvilinear, and use local operators to enhance the ridge or valley structure for detecting lines in images. These algorithms only perform well on high contrast hair-skin images with thick, dark hair with few intersections between the hair and skin. However, it remains challenging for algorithms to distinguish between hair and skin structure with similar contrast in intensity, differentiate thin, faintly colored intermediate hair and skin, and to discriminate dark and light hair structure.

Also, difficulty arises when hair clumps together as it does not look like curvilinear structure. Moreover, the imaging system introduces artifacts in hair-occluded skin images. At certain viewing angles, severe amounts of specular reflections are observed on hair; this occasionally causes gaps in detected hair strands. In addition, hair may be out of focus as the depth of field of the camera is small at a short working distance. Compared to hair in focus, hair out of focus has larger widths and exhibits lower contrast with respect to skin, thus making it more difficult to extract. For example, in contrast to dermoscopic images [8], the camera imaging system does not flatten hair onto the skin with a transparent glass plate or lens, such that if the focus is on the skin, the hair will lose the focus. The Bayer filter RGB camera sensor also causes demosaicing artifacts [9] during image conversion that is made worse by the high contrast between skin and hair. This makes it difficult to ascertain the true edges of the hair.

Given a response image I_r of the hair detection result, a single threshold is usually applied to determine a binary skin mask. As an inappropriate threshold can result in high false hair detection rate or low positive hair detection rate, finding an optimal threshold for response image I_r is very important for accurate segmentation. Hair detection methods in the literature use various thresholding methods: the MF-FDOG uses the FDOG as multiplicative pixel-wise weights on a fixed threshold; Fiorese et al. employ Otsu's method [21] to threshold the top-hat transform; the INF is thresholded based on learned parameters of the test dataset from linear regression. These thresholding methods are optimized for detecting high contrast, dark hair.

3. Proposed method

As shown in Fig. 1, the flowchart of our proposed hair segmentation scheme is composed of three steps. First, the likelihood of hair-like structures in the input hair-occluded skin image is encoded in a response image by curvilinear structure detection. Second, an adaptive threshold gives an initial guess of the hair pixels in the response image to output a hair segmentation mask. Third, a k-nearest neighbor (k-NN) classifier refines the mask by taking hair and skin colors into account.

3.1. Curvilinear structure detection

3.1.1. Selection of single-channel color space

Most hair-occluded skin images are acquired in RGB color space, though it is much easier to design curvilinear structure detection for single-channel images. It is desirable to preserve color information from RGB images for sufficient contrast in image intensities between true hair and skin pixels. It is also advantageous to de-emphasize pixels belonging to the skin structure. A single channel, including the red, blue and green channels, L component of Lab, Y component of YUV (BT.601), V component of HSV, 1st component of principal component analysis (PCA), 1st component of JADE independent component analysis (ICA) and 1st component of Fast ICA, can be extracted from a RGB color image using various color conversion methods. In Ref. [10], we conducted a visual comparison of various color spaces on two potentially challenging hair segmentation tasks, dark hair with a high contrast skin structure and a mixture of dark and light hair with a low contrast skin structure. In this paper, we experimentally and quantitatively determine the most appropriate single channel for hair detection.