Segmentation of skin cancer images using a structured sequence of image processing steps for optimizing decision support consultations in melanoma diagnosis

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Abstract

The aim of this study is to design, develop and implement a structured sequence of image processing steps to facilitate mole segmentation in skin cancer images. The proposed segmentation scheme consists the DullRazor method, which is utilized for hair removal, the mean shift filtering algorithm, which is used for image smoothing, the Otsu's thresholding approach, which is utilized for a preliminary estimate of the mole region boundaries and the region growing algorithm, which is applied to finalize the segmentation result. The proposed method was integrated into MARK1 platform, which is a web application and API technology used for early stage detection of melanoma. The accuracy of MARK1 platform in predicting melanoma cases converged to 85 % using the proposed segmentation framework.

Introduction

Early diagnosis of melanoma is essential for successful treatment outcomes, since the disease is more vulnerable to available treatments at its early stages (Robinson, 2000). Computer-based image analysis and Decision Support Systems (DSS) have been proposed as potential second opinion tools to enhance the accuracy of self-skin examination and guide patients towards the urgency of a physician visit (Gilmore et al., 2010, Rahman and Bhattacharya, 2010, Dreiseitl et al., 2007). DSS systems rely on pattern recognition and artificial intelligence approaches in order to assess the nature of suspicious moles. The advent of smartphone technology has made feasible the incorporation of DSS into web applications and Application Program Interfaces (APIs) (Rexhepaj et al., 2013, Do et al., 2014, Vano-Galvan et al., 2015). Such systems may offer complementary information to the physician, assisting towards early diagnosis and reduction of falsely characterized as disease-free cases for people who actually suffer by the disease. Additionally, such systems may alert patients to visit the dermatologist for suspicious moles increasing the probability of early stage detection of the disease. The reliability and accuracy of DSS consultation greatly depends on the reliability and accuracy of the segmentation algorithm that is used to isolate pixels belonging to the mole region from pixel belonging to the surrounding background region (Kiani and Sharafat, 2011). Erroneously circumscribed moles are likely to produce misguiding DSS consultations failing to properly guide patients and physicians towards successful advices. The aim of this study is to design, develop and implement a structured sequence of image processing steps to facilitate mole segmentation in skin cancer images.

Methods and Material

The proposed image segmentation algorithm consists of four stages: **Stage 1:** Application of DullRazor algorithm for hair removal. The DullRazor algorithm is based on a method that has been presented by T. Lee (T. Lee, 1997) as a pre-processing method for removing dark hairs from an image. The algorithm consists of three main steps: 1) identifying the dark hair locations, 2) replacing the hair-pixels by the nearby non-hair pixels and 3) smoothing the final result. *Step 1:* in order to locate the dark hairs a generalized grayscale morphological closing operation has been applied to each one of the three color bands separately. This operation smooth out the low intensity values such as the thick dark hair pixels along the structure element direction. Three structure elements at different directions, horizontal ($0°$), vertical ($90°$) and diagonal ($45°$) are adequate to smooth out the black hairs. Let G, be the generalized grayscale closing image of the original red band, O_r, and S_0, S_{45} and S_{90} are the structure elements in the horizontal, diagonal, and vertical direction. G, can be expressed as:

$$G_r = |O_r - max\{O_r \bullet S_0, O_r \bullet S_{45}, O_r \bullet S_{90}\}| \quad (1)$$

Symbol $\{\bullet\}$ denotes the grayscale closing operation. Additionally, the binary hair mask pixel at the location (x,y), $M_r(x,y)$, is computed as:

$$M_r(x,y) = \begin{cases} 1, G_r(x,y) > T \\ 0, G_r(x,y) \leq T \end{cases} \quad (2)$$

where T is a pre-defined threshold value. *Step 2: Interpolation Function* represents the interpolation step where the acquired, in step 1, binary hair mask is used for replacing the corresponding pixel value in the original image by the nearby non-hair pixel values. For each pixel inside the hair region of M, line segments are drawn in eight directions, up, down, left, right and the four diagonals, radiating from the pixel until the segment reaches the non-hair region. These eight line segments form four straight lines centering at the pixel. Lengths of the lines are calculated and the longest one is noted. The longest line must be longer than 20 pixels. Otherwise, the pixel is rejected. Let $I(x,y)$ be the intensity value for the replacing pixel, $I_1(x_1,y_1)$ and $I_2(x_2,y_2)$ be the selected non-hair pixel intensities along the shortest direction. The new intensity value $I_n(x,y)$ can be expressed as following:

$$I_n = I_2(x_2,y_2)\frac{D(I(x,y),I_1(x_1,y_1))}{D(I_1(x_1,y_1),I_2(x_2,y_2))} + I_1(x_1,y_1)\frac{D(I(x,y),I_2(x_2,y_2))}{D(I_1(x_1,y_1),I_2(x_2,y_2))}, \quad (3)$$

where: $D\left(A(a,b),B(c,d)\right) = \sqrt{(c-a)^2 + (d-b)^2}$

Stage 2: Mean shift filtering algorithm. The mean shift filtering algorithm produces a filtered "posterized" image with color gradients and fine-grain texture flattened. At every pixel (X,Y)

of the input image the function executes mean shift iterations, that is, the pixel (X,Y) neighborhood in the joint space-color hyperspace is considered:

$(x,y): X - sp \leq x \leq X + sp, Y - sp \leq y \leq Y + sp, \|\|(R,G,B) - (r,g,b)\|\| \leq sr$	(4)

where sp, sr are the spatial and color window radius respectively. (R,G,B) and (r,g,b) are the vectors of color components at (X,Y) and (x,y), respectively (though, the algorithm does not depend on the color space used, so any 3-component color space can be used instead). **Stage 3:** Otsu's thresholding (Gonzalez and Woods, 2002) for obtaining a preliminary gross estimation of the mole's boundaries. Otsu's thresholding is an optimum method for global thresholding because it maximizes the variance between classes. The concept is that well thresholding classes should be distinct with respect to the intensity values of their pixels and, conversely, that a threshold giving the best separation between classes in terms of their intensity values would be the best (optimum) threshold.. **Stage 4:** Otsu's thresholding provides an initial rough segmentation of the mole region. The final segmentation is obtained by applying the region growing algorithm (Gonzalez and Woods, 2002). The region growing algorithm starts from an initial seed point. Then, if the color of its neighboring pixels is similar to the color of the seed point, the points will be added to the region. The same process is repeated for the neighboring pixels of the lastly added points, until no points with similar to the seed's color point are found. Specifically, Otsu's thresholding provides a set of points, S, with value below a value, that is

$S = \{(x,y): I(x,y) < k^*\}$	(5)

The seed point (x_s, y_s) is defined by the center of mass of the set S:

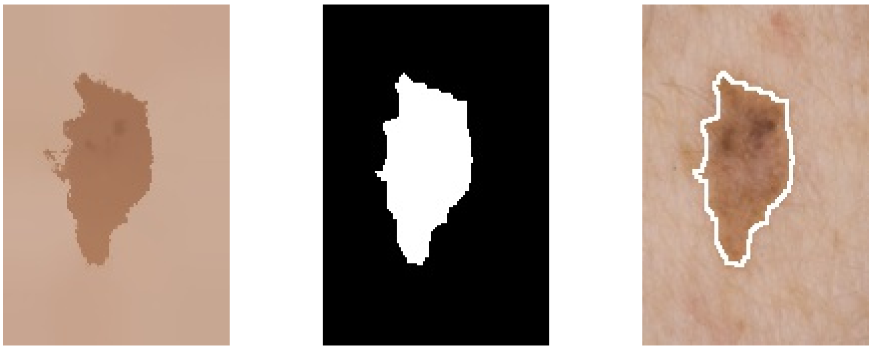
$x_s = \frac{1}{\|\|S\|\|}\sum_{(x_t,y_t)\in S} x_t$, $y_s = \frac{1}{\|\|S\|\|}\sum_{(x_t,y_t)\in S} y_t$, where $\|\|S\|\|$ denotes the cardinality of the set S. Then a point (x',y') is added to the region if $\|I(x',y') - I(x_s,y_s)\| \leq 2.5\sigma$, where σ is the standard deviation of the color of the pixels that belong to the set S.	(6)

Results-Discussion

Figure 1 illustrates an example of image pre-processing. It is apparent that hair pixels are effectively smoothed out following the application of DullRazor algorithm, whereas the application of the mean filtering algorithm facilitates separation of the mole region from surrounding background. Figure 2 depicts an example of image segmentation. Initially, an estimation of the mole region is obtained using Otsu's thresholding. The final contour of the mole is obtained following the application of region algorithm. The proposed segmentation pipeline was integrated into MARK1 platform, which may be used for early stage detection of melanoma. The accuracy of MARK1 platform in predicting melanoma cases using the proposed segmentation pipeline converged to 85% platform using both dermatology and normal smartphone camera images. This accuracy was obtained using a pattern recognition system employing the Probabilistic Neural Network classifier, the leave-one-out method for classifier performance evaluation, the exhaustive search for feature selection and quantitative features describing the mole's texture (first order, second order), morphology and shape.

(a) (b) (c)

Figure 1**.** Example of image smoothing (a) Original Image, (b) Application of the DullRazor algorithm for hair removal. (c) Mean shift filtering



(a) (b) (c)

Figure 2. Example of image segmentation (a) Smoothed Image, (b) Segmented, (c) Final delineation of mole's boundary.

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