Pigmented Skin Lesion Segmentation on Macroscopic Images

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Abstract

Several pigmented skin lesion segmentation methods have been proposed for dermoscopy images, however skin lesion segmentation on macroscopic images have not received much attention. Despite the fact that dermoscopy is a very specialized technique, in some practical situations, patients do not have a fast access to an specialist. In this situations, pre-screening systems can be used to evaluate a suspect skin lesion by a non-specialist, and lesion segmentation is very important for the success of such systems. This paper proposes a new method for segmenting pigmented skin lesions on macroscopic images acquired with standard cameras. Our method is simpler than comparable methods proposed for dermoscopy, and our experiments based on publicly available datasets of pigmented skin lesion images show promising results. Our approach can achieve an average segmentation error of 24.85%, which is better than the accuracy of comparable methods available in the literature (even for illumination corrected images).

Keywords: Image Segmentation, Dermatological Images, Melanoma.

1 Introduction

Melanoma is a kind of malignant skin lesion, and currently is among the most dangerous existing cancers, resulting in about 10000 deaths from the 40000 to 50000 diagnosed cases per year, just in United States of America [1]. According to World Health Organization [2], about 132000 melanoma cases occur globally each year. Benign pigmented skin lesions are called moles, or nevi. However, differentiating benign and malignant lesions can be challenging, specially based on digital images.

It is consensual that the early diagnosis of malignant skin lesions (melanomas) is very important for the patient prognosis, since most malignant skin lesion cases can be treated successfully at the early stages. To facilitate the diagnosis, physicians often use dermoscopy, which is a non-invasive technique that magnifies submacroscopic structures with the help of optical lens (a dermoscope) and liquid immersion. However, even with the help of a dermoscope, differentiating malignant and benign lesions is a hard task even for experienced specialists.

Considering that early detection of malignant skin lesions is of fundamental importance, there are practical situations where a non-specialist (e.g. a physician not trained on Dermatology) wishes to have a qualified opinion about a suspect skin lesion, but only standard camera imaging is available on site. In such situations, telemedicine is justifiable, and the non-specialist can capture an image of the suspect skin lesion and send it to an specialist analyze in higher detail. In this particular situation, a teledermatology consultation brings benefits, like the easier access to health care and faster clinical results [3]. Besides, comparing the physical patient examination and diagnosis (face-to-face) with the remote diagnosis by teledermatology, the experimentation suggests that teledermatology also is effective and reliable [4].

Therefore, nowadays there is a growing interest in methods for pre-screening pigmented skin lesion images to help in a remote diagnosis. Usually, such pre-screening methods take as input a segmented skin lesion image [5]. Nevertheless, skin lesion segmentation has been posing a challenge for the researchers in this area, mostly because such lesions can vary significantly in aspects (e.g. shape, texture and color).

Many segmentation methods have been proposed in the literature for dermoscopy images. The techniques are based in different strategies, namely: region-based, using mainly region-growing approaches [6] [7] [8]; clustering algorithms, separating heal-

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thy and unhealthy pixels in homogeneous regions [9] [10]; thresholding methods, computing values that can identify the lesion in histograms [11] [12]; and, active contours procedures, where the lesion borders are detected iteratively [13] [14]. Most of these methods are automatic and operate on color images [15]. Unfortunately, macroscopic pigmented skin lesion image segmentation did not receive much attention in the literature, and we propose in this paper a new segmentation method for this type of images in Section 3.

In Section 2 we review the literature, and identify techniques that represent the state-of-the-art in terms of pigmented skin lesion segmentation in dermoscopy images. Section 3 introduces a new pigmented skin lesion segmentation method designed for macroscopic images, and shows that it is more efficient than comparable methods available in the literature. Section 4 compares this method with other state-of-the-art techniques in terms of performance, and discusses where they fail or succeed. Finally, Section 5 presents our conclusions and directions for future work.

2 Review of Recent Pigmented Skin Lesion Segmentation Methods

As mentioned before, our main focus is on macroscopic images, but dermoscopy is a very popular imaging method for pigmented skin lesion image analysis. In a recent paper, Celebi et al. [15] reviewed several different segmentation approaches for dermoscopy proposed in the literature, and indicated two methods among the best performing published approaches: (a) Statistical Region Merging, proposed by Celebi et al. [7]; and (b) Independent Histogram Pursuit, proposed by Gómez et al. [9]. Also recently, Iyatomi et al. [6] proposed a method named "Dermatologist-like", which based on their experiments, obtain segmentation results similar to that obtained by the Celebi et al.[7] approach. In this section, we briefly review these three techniques since they are representative of the state-of-the-art in pigmented skin lesion segmentation using dermoscopic images.

2.1 Method Proposed by Celebi et al.[7]

Usually, there are artifacts in dermoscopic or macroscopic skin lesion images, such as skin lines and hair, that may affect the segmentation process. To attenuate the influence of these artifacts, Celebi et al.[7] proposed to smooth the input image with a median filter using a mask size n of:

$$n = floor(5 * \sqrt{(M/768) * (N/512)}), \quad (1)$$

where, $M \times N$ is the image size. After this preprocessing step, the method proposed by Celebi et al.[7] uses Statistical Region Merging (SRM) to segment the skin lesion; SRM will merge two regions A and B of the image I :

$$\left|\overline{B_i} - \overline{A_i}\right| \leq \left|\sqrt{b^2(A) + b^2(B)}\right| \; ; \; \forall i \in R, G, B, \quad (2)$$

$$where \;\; b(R) = g\sqrt{\frac{1}{2Q\left|R\right|} ln(6\left|I\right|^2 R_{|R|})},$$

where $g = 256$ for images with 8-bits per color channel, Q is a parameter that quantifies the statistical complexity of I, $\overline{B_i}$ and $\overline{A_i}$ are the average of the two regions in the i color channel, and $R_{|R|}$ denotes the number of regions in I with the same number of pixels in R. The implementation of SRM used by Celebi et al. can be found in the Fourier library[1], where Q receives as default value 32.

Next, their method identifies the segmented regions that correspond to skin lesions. It calculates the mean of the R, G and B channels in patches of 20×20 pixels in the four image corners, and eliminates the segmented regions with average colors less than a threshold from the R, G and B mean values calculated for the image corners. In addition, regions that touch the image borders are also eliminated. The last step of the method is to dilate the lesion borders of the remaining regions by a circular structuring element of size m:

$$m = floor(k * (d/500)), \quad (3)$$

where, d is the lesion diameter, and k is a scaling factor (which was defined as 6 in their experiments).

Fig. 1 illustrates some segmentation results using this method. Since it was designed for the very specific conditions of dermoscopy images (e.g. even illumination and submacroscopic vision), and the imaging conditions in which standard cameras operate are different, several lesions regions are not merged by SRM or are eliminated in the post-processing step. In some skin lesion images, their method can fail completely, not identifying any lesion.

2.2 Method Proposed by Gómez et al. [9]

Gómez et al. [9] proposed a segmentation method called the Independent Histogram Pursuit (IHP), that searches for a linear transformation of the

[1] `http://sourceforge.net/projects/fourier-ipal/`

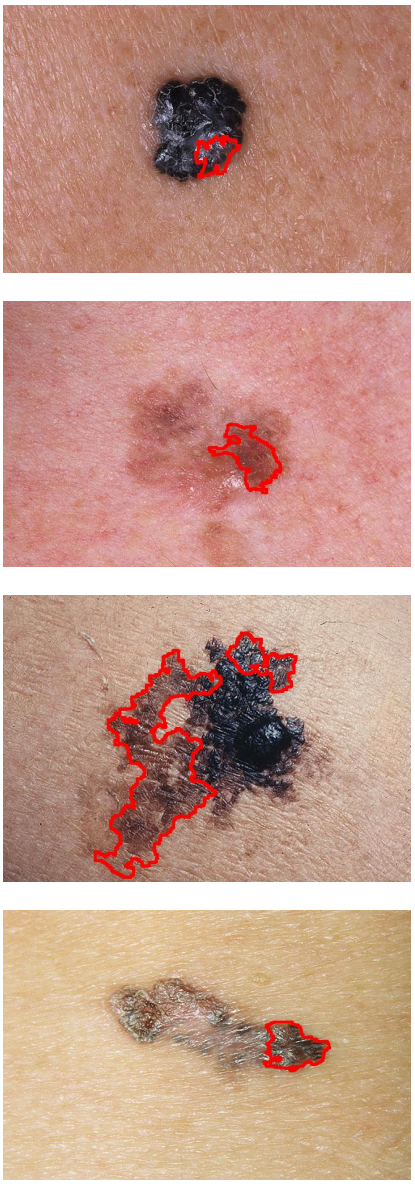

Figure 1: Illustrations of the segmentation results obtained with the approach proposed by Celebi et al. applied on macroscopic images.

RGB color space such that the discrimination between healthy and unhealthy pixels is maximized in this new color space.

The IHP method is based on the assumption that image histograms are bimodal, and have pixels associated to lesion and normal skin. Obtained a projection of the original color space, the histogram bimodality is tested by filtering it with a box filter. If the filtered histogram has just two local maxima, the area between these two modes is computed. A Genetic Algorithm is used to search for the projection that maximizes this area, and k-means clustering is used to identify the two classes (lesion and normal skin).

The authors use the DullRazor [16] technique as a pre-processing step (prior to the IHP algorithm) for morphological hair removal. As post-processing step, they proposed a morphological closing and a morphological opening with a 5×5 square structuring element. The largest remaining region is the lesion, and the process finishes by hole filling this region.

Fig. 2 illustrates some segmentation results using this method. As can be seen, this method provides better results for macroscopic images in comparison with the method proposed by Celebi et al. However, since it is based on histogram distributions, often regions affected by shading effects are allocated to the same mode as the lesion, and consequently are assigned to the same cluster as the lesions.

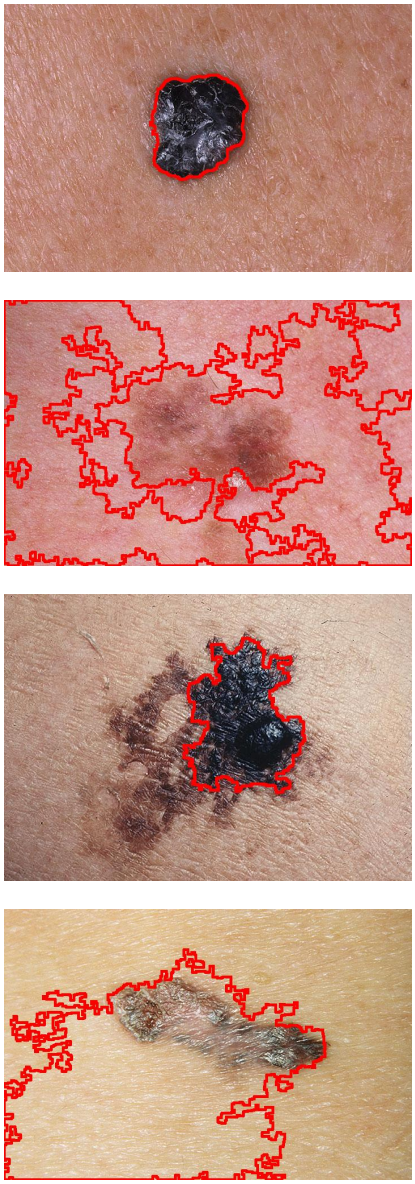

Figure 2: Illustrations of the segmentation results obtained with the approach proposed by Gómez et al. applied on macroscopic images.

2.3 Method Proposed by Iyatomi et al. [6]

This method combines pixel-based and region-based methods, and was called "Dermatologist-like" by the authors. It starts by eliminating possible noise with Gaussian filtering. After that, the Laplacian filter is applied on the blue channel, and the pixels with the highest 20% values are used to calculate a threshold. Pixels with values higher than this threshold are selected as an initial lesion localization.

In the second method step, small regions are merged to their adjacent regions. The remaining regions pass though 5 conditional tests where regions with size to small in comparison to the largest image region, or that contains many pixels in the borders of the image, are eliminated.

The final method step is region-growing, where the lesion regions become larger in the direction of the pixels that have low contrast with respect to the lesion border pixels.

This system is part of a telemedicine system, and the segmentation and pre-diagnosis results can be obtained uploading an image in the project website[2]. As can be seen in Fig. 3, this approach achieves some good results, but usually the segmented region is smaller than the lesion, and some cases it may fail completely (by not segmenting the lesion in the image provided).

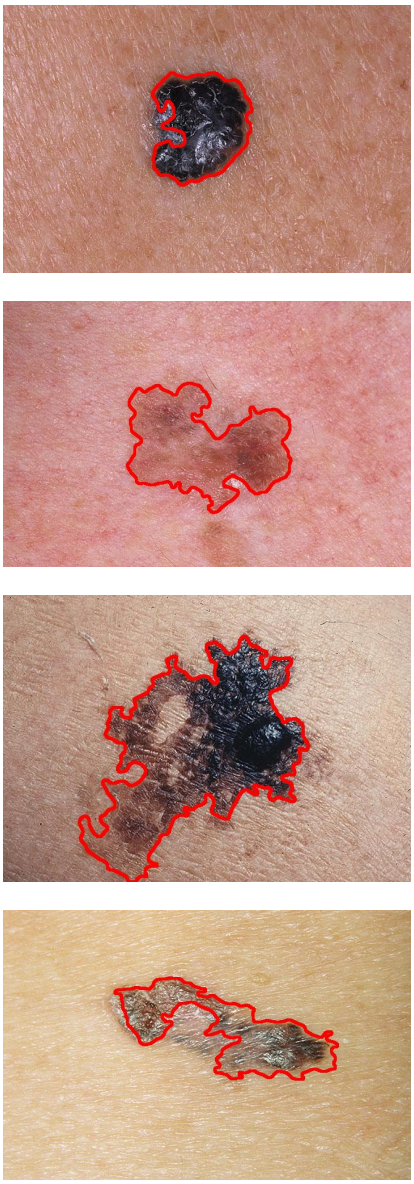

Figure 3: Illustrations of the segmentation results obtained with the approach proposed by Iyatomi et al. applied on macroscopic images.

3 Our Proposed Skin Lesion Segmentation Method

A common difficulty for segmenting standard camera images of skin lesions is the presence of shading effects. Since most segmentation techniques are based on the principle that melanomas are darker than healthy skin, areas affected by shading are usually confused with lesions. To avoid these situations, we recently proposed a method to significantly attenuate shading effects in such images [17].

Our method assumes that images are acquired such that the lesion appears in the image center, and is not touching the image outer borders. The first step of the method is to convert the image from the original RGB color space to the HSV color space, and retain the Value channel V. This is justified by the fact that this channel presents a higher visibility of the shading effects. We extract 20×20 pixels in each V corner and define S as the union of these four sets. This pixel set is used to adjust the following quadric function $z(x, y)$:

$$z(x,y) = P_1x^2 + P_2y^2 + P_3xy + P_4x + P_5y + P_6, \quad (4)$$

where the six quadric function parameters P_i $(i = 1, ..., 6)$ are chosen to minimize the error ϵ:

$$\epsilon = \sum_{j=1}^{1600} \left[V(S_{j,x}, S_{j,y}) - z(S_{j,x}, S_{j,y})\right]^2, \quad (5)$$

where, $S_{j,x}$ and $S_{j,y}$ are the x and y coordinates of the jth element of the set S, respectively.

Calculating the quadric function $z(x, y)$ for each image spatial location (x, y), we have an estimate z of the local illumination intensity in the image V. Dividing the original V channel by z, we obtain a new Value channel where the shading effects have been attenuated. The final step is to replace the original Value channel by this new Value channel, and convert the image from the HSV color space to

[2] http://dermoscopy.k.hosei.ac.jp/

the original RGB color space. In Fig. 4 we present an example of applying this method to a skin lesion image. The result is a color image easier to be segmented.

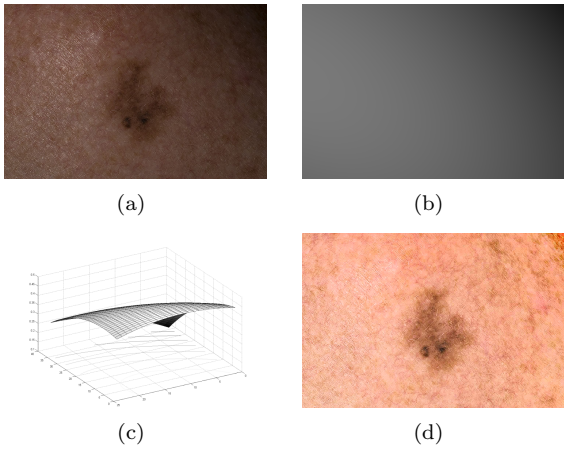

Figure 4: Shading attenuation example. (a) Input image; (b) Obtained quadric model using the corners of the input Value channel; (c) Obtained quadric model in 3D; (d) Result obtained by the division of the Value channel by the obtained quadric model.

Healthy skin (of virtually any ethnic group) tends to present a reddish tone. Assuming that pigmented skin lesions are skin discolorations, the lesion segmentation process can be computed just using the R (i.e. red) image channel. After illumination correction, the healthy skin pixels assumes higher values in this channel, while lesion pixels assume lower values. This healthy/unhealthy skin tones distinction is quite evident in macroscopic images. Therefore, we use the Otsu's thresholding method [18] to segment the skin lesions in the R channel of the illumination corrected images. This algorithm assumes two pixel classes, usually background and foreground pixels (specifically in our case, healthy and unhealthy skin pixels), and searches exhaustively for the threshold th that maximizes the inter-class variance $\sigma_b^2(th)$:

$$\sigma_b^2(th) = \omega_1(th)\omega_2(th)\left[\mu_1(th) - \mu_2(th)\right]^2, \quad (6)$$

where, ω_i are the a priori probabilities of the two classes separated by the threshold th, and μ_i are the class means. To segment the color images, we determine a threshold th for the R channel, and establish a pixel as lesion candidate if its R value is lower than the computed threshold.

After the segmentation step, we postprocess the obtained regions by computing the number of pixels in each segmented region, and largest segmented region contains the lesion. Afterwards, we perform hole filling on the remaining regions, and a morphological dilation with a disk with 5 pixels of radius.

Although the proposed method is simple, it achieves interesting results, as can be seen in Fig. 5. In some difficult cases for other methods, such as images containing much hair or freckles, the segmentation may result in a region larger than the lesion. However, lesions are identified in general (i.e. not missed as in other methods).

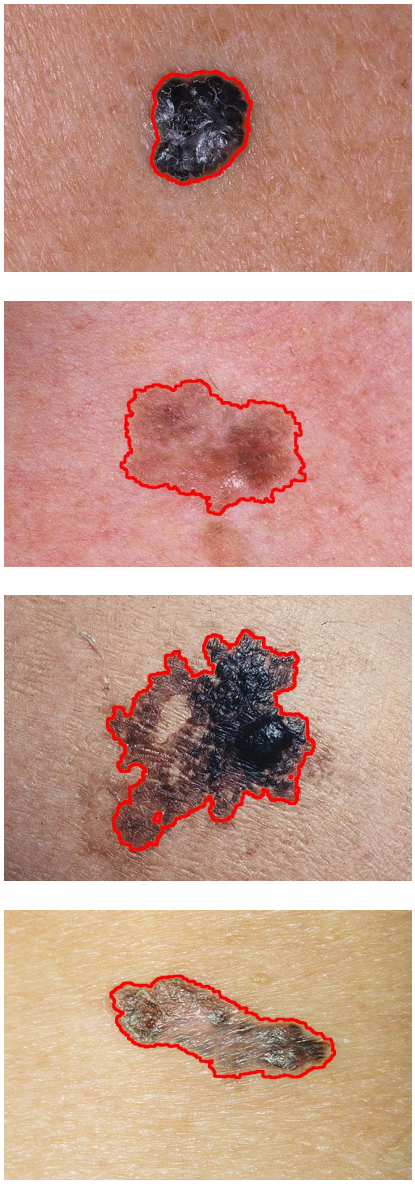

Figure 5: Illustrations of the segmentation results obtained with our proposed approach applied on macroscopic images.

4 Experimental Results and Discussion

In order to compare the three segmentation methods presented in Section 2 with our method proposed in Section 3, 140 macroscopic images of skin lesions were collected from the Dermnet database [19]. In these 140 images, 96 are malignant melanomas

images and 44 are Clark Nevi images, a benign lesion with difficult diagnosis since it contains similar characteristics to melanomas. The segmentation error measure that we use is the same that have been used in the experiments of the three presented approaches [7] [9] [6]:

$$Error = \frac{Area(Segmentation \oplus GroundTruth)}{Area(GroundTruth)} \times 100\%, \quad (7)$$

where, $Segmentation$ is the result of the method in test, $GroundTruth$ is the manual segmentation of the same lesion, $Area(S)$ denotes the number of pixels indicated as lesion in the segmentation result S, and $\oplus$ indicates the exclusive-OR, operation that gives the pixels for which the $Segmentation$ and $GroundTruth$ disagree.

In their experiments with dermoscopy images, the presented segmentation methods achieved very low error measures. These results are show in Table 1. However, as already mentioned in Section 2, these methods do not achieve good segmentations results for our macroscopic images. In Table 2, we present the computed error measures for the three proposed in the literature and for our proposed method. Despite the simplicity of our proposed method, it achieves the lowest error measure in average, i.e. 24.85%. We also tested the other methods using illumination corrected images provided by our illumination correction method, but the segmentation error results still favor our approach that is significantly simpler. For example, for illumination corrected images, the segmentation average error obtained by the method proposed by Celebi et al.[7] was 43.32% (lower than 65.66% obtained for uncorrected images), but still much higher than the segmentation error obtained with our approach. Visually analyzing the segmentation results, we can observe that the thresholding procedure employed by our approach identified the lesion area in all the 140 images, and the segmentation errors are more visible very close to the lesion rim. The results generating higher segmentation errors occurred in the presence of hair or freckles near to the lesion. Below, we provide some insights on where the other three methods tend to fail when analyzing macroscopic images:

- Celebi et al. approach : Color information in macroscopic images is not well handled by this method; healthy skin regions near the lesion are erroneously merged with the lesion, and often lesion areas are eliminated in the post-processing step for having similar colors with the healthy skin. Post-processing tends to eliminate all segmented regions in some images, which contributed to the increase of the error measure in average.

- Gómez et al. approach : This method is very sensitive to shading effects. Since shading tends to affect large areas, the segmented regions tend to be larger than the actual lesion, and the segmentation error tends to increase significantly. However, this method presents good results for images without shading, specially because its hair removal pre-processing step.

- Iyatomi et al. approach : This method has the higher complexity, since it combines different segmentation techniques and obtains good segmentation results, especially considering the fact that it has been developed for dermoscopy images. However, the lesion border is not well defined in general, and lesions can be missed in some images, which increased the average of the error measure.

Table 1: Comparing the three literature methods performance for dermoscopy images.

Approach	Error in Average
Celebi et al. [7]	10.63%
Gómez et al. [9]	2.73%
Iyatomi et al. [6]	11.44%

Table 2: Comparing the presented method for macroscopic images.

Approach	Error in Average
Celebi et al. [7]	65.66%
Gómez et al. [9]	280.52%
Iyatomi et al. [6]	29.56%
Our method	**24.85%**

5 Conclusions

Several pigmented skin lesion segmentation methods have been proposed for dermoscopy images, however skin lesion segmentation on macroscopic images have not received much attention. This paper proposes a new method for segmenting pigmented skin lesions on macroscopic images acquired with standard cameras, which is simpler than comparable methods proposed in the literature.

Our experiments based on publicly available datasets of pigmented skin lesion images show promising results, and our approach can achieve a segmentation error of 24.85%, which is lower in average than comparable methods available in the literature (even for illumination corrected images).

We intend to further improve our approach by removing skin artifacts before the lesion segmentation, and make it fully integrated in a pigmented

skin lesion pre-screener that works with macroscopic images and can be used by non-specialists.

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References

[1] Melanoma research project. [Online]. Available: http://www.melresproj.com

[2] How commom is skin cancer? World Health Organization. [Online]. Available: http://www.who.int/uv/faq/skincancer/en/index1.html

[3] C. Massone, E. M. T. Wurm, R. Hofmann-Wellenhof, and H. P. Soyer, "Teledermatology: an update." Semin. Cutan. Med. Surg., vol. 27, no. 1, pp. 101–105, Mar 2008.

[4] J. D. Whited, "Teledermatology research review." Int. J. Dermatol., vol. 45, no. 3, pp. 220–229, Mar 2006.

[5] P. G. Cavalcanti and J. Scharcanski, "Automated prescreening of pigmented skin lesions using standard cameras," Instituto de Informática, Universidade Federal do Rio Grande do Sul, Porto Alegre, Brazil, Preprint, Tech. Rep., 2010.

[6] H. Iyatomi, H. Oka, M. Celebi, M. Hashimoto, M. Hagiwara, M. Tanaka, and K. Ogawa, "An improved internet-based melanoma screening system with dermatologist-like tumor area extraction algorithm," Computerized Medical Imaging and Graphics, vol. 32, no. 7, pp. 566 – 579, 2008.

[7] M. E. Celebi, H. A. Kingravi, H. Iyatomi, Y. A. Aslandogan, W. V. Stoecker, R. H. Moss, J. M. Malters, J. M. Grichnik, A. A. Marghoob, H. S. Rabinovitz, and S. W. Menzies, "Border detection in dermoscopy images using statistical region merging." Skin Res. Technol., vol. 14, no. 3, pp. 347–353, Aug 2008.

[8] M. E. Celebi, Y. A. Asl, W. V. Stoecker, H. Iyatomi, H. Oka, and X. Chen, "Unsupervised border detection in dermoscopy images," Skin Res. Technol., 2007.

[9] D. D. Gomez, C. Butakoff, B. K. Ersboll, and W. Stoecker, "Independent histogram pursuit for segmentation of skin lesions," IEEE Transactions on Biomedical Engineering, vol. 55, no. 1, pp. 157–161, Jan. 2008.

[10] R. Melli, C. Grana, and R. Cucchiara, "Comparison of color clustering algorithms for segmentation of dermatological images," in Medical Imaging 2006: Image Processing, J. M. Reinhardt and J. P. W. Pluim, Eds., vol. 6144, no. 1. SPIE, 2006.

[11] H. Ganster, A. Pinz, R. Rhrer, E. Wildling, M. Binder, and H. Kittler, "Automated melanoma recognition," IEEE Transactions on Medical Imaging, vol. 20, pp. 233–239, 2001.

[12] M. Hintz-madsen, L. K. Hansen, J. Larsen, and K. T. Drzewiecki, "A probabilistic neural network framework for detection of malignant melanoma," in Artificial Neural Networks in Cancer Diagnosis, Prognosis, and Patient Management. CRC Press, 1999, pp. 141–183.

[13] M. Silveira, J. Nascimento, J. Marques, A. Marcal, T. Mendonca, S. Yamauchi, J. Maeda, and J. Rozeira, "Comparison of segmentation methods for melanoma diagnosis in dermoscopy images," Selected Topics in Signal Processing, IEEE Journal of, vol. 3, no. 1, pp. 35 –45, feb. 2009.

[14] B. Erkol, R. Moss, R. Stanley, W. Stoecker, and E. Hvatum, "Automatic lesion boundary detection in dermoscopy images using gradient vector flow snakes," Skin Res. Technol., vol. 11, no. 1, pp. 17–26, 2005.

[15] M. Celebi, H. Iyatomi, G. Schaefer, and W. V. Stoecker, "Lesion border detection in dermoscopy images," Computerized Medical Imaging and Graphics, vol. 33, no. 2, pp. 148 – 153, 2009.

[16] T. Lee, V. Ng, R. Gallagher, A. Coldman, and D. McLean, "Dullrazor: A software approach to hair removal from images," Computers in Biology and Medicine, vol. 27, no. 6, pp. 533–543, November 1997.

[17] P. G. Cavalcanti, J. Scharcanski, and C. B. O. Lopes, "Shading attenuation in human skin color images," in Proc. 6th. International Symposium on Visual Computing (ISVC 2010), in press, 2010.

[18] N. Otsu, "A threshold selection method from gray-level histograms," IEEE Transactions on Systems, Man and Cybernetics, vol. 9, no. 1, pp. 62–66, January 1979.

[19] Dermnet skin disease image atlas. [Online]. Available: http://www.dermnet.com