Effect of Lesion Segmentation in Melanoma Diagnosis for a Mobile Health Application

Nasim Alamdari¹, Nicholas MacKinnon², Fartash Vasefi²,³, Reza Fazel-Rezai¹, Minhal Alhashim¹, Alireza Akbardeh¹, Daniel L. Farkas², and Kouhyar Tavakolian¹

Department of Electrical Engineering, University of North Dakota¹
Spectral Molecular Imaging Inc., Sherman Oaks, CA²
School of Medicine, University of North Dakota³
Medical School, Johns Hopkins University⁴
eTreat Medical Diagnostics, Vancouver, Canada⁵

1 Introduction

In 2016, more than 76,380 new melanoma cases were diagnosed and 10,130 people were expected to die from skin cancer in the United States (one death per hour) [1]. A recent study demonstrates that the economic burden of skin cancer treatment is substantial and, in the United States, the cost was increased from $3.6 billion in 2002–2006 to $8.1 billion in 2007–2011 [2].

Monitoring moderate and high-risk patients and identifying melanoma in the earliest stage of disease should save lives and greatly diminish the cost of treatment. In this project, we are focused on detection and monitoring of new potential melanoma sites with medium/high risk patients. We believe those patients have a serious need and they need to be motivated to be engaged in their treatment plan. High-risk patients are more likely to be engaged with their skin health and their health care providers (physicians). Considering the high morbidity and mortality of melanoma, these patients are motivated to spend money on low-cost mobile device technology, either from their own pocket or through their health care provider if it helps reduce their risk with early detection and treatment. We believe that there is a role for mobile device imaging tools in the management of melanoma risk, if they are based on clinically validated technology that supports the existing needs of patients and the health care system.

In a study issued in the British Journal of Dermatology [2] of 39 melanoma apps [2], five requested to do risk assessment, while nine mentioned images for expert review. The rest fell into the documentation and education categories. This seems like to be reliable with other dermatology apps available on the market. In a study at University of Pittsburgh [3], Ferris et al. established 4 apps with 188 clinically validated skin lesions images. From images, 60 of them were melanomas. Three of four apps tested misclassified >30% of melanomas as benign. The fourth app was more accurate and it depended on dermatologist interpretation. These results raise questions about proper use of smartphones in diagnosis and treatment of the patients and how dermatologists can effectively involve with these tools.

In this study, we used a MATLAB (The MathWorks Inc., Natick, MA) based image processing algorithm that uses an RGB color dermoscopy image as an input and classifies malignant melanoma versus benign lesions based on prior training data using the AdaBoost classifier [5]. We compared the classifier accuracy when lesion boundaries are detected using supervised and unsupervised segmentation. We have found that improving the lesion boundary detection accuracy provides significant improvement on melanoma classification outcome in the patient data.

2 Methods

• Data Collection

The images of skin lesions, used in this project, were provided by the International Skin Imaging Collaboration (ISIC): Melanoma Project [6]. From the ISIC archive, we selected the melanocytic lesion pictures where the borders of the lesion are within the field of view in the dermoscopy image. We used 15 benign and 15 malignant melanoma dermoscopy images. All lesions were confirmed by histopathological analysis at Memorial Sloan Kettering Cancer Center.

• Lesion Segmentation

In the unsupervised segmentation method, RGB images input. The dermoscopy image was coarsely represented using 5 color bins. Coarse representation uses the spatial information from a histogram based windowing process [7]. We assigned the window size to 9. Then, a k-means clustering method was used to cluster the coarse image.

In the supervised segmentation technique, the image was processed using the Image Segmenter App available in MATLAB where the coarse boundary of the lesion is drawn freehand on the digital image that provides the input to an active contour function that uses an iterative process to detect the lesion boundary.

• Feature extraction and classification

In the feature extraction step, 22 different shape, size and color features were computed. These features include minimum value of saturation, maximum of hue, histogram of hue, minimum of red color channel, maximum values in HSV color space, wavelet variance, and some lesion size and shape features.

In the next stage, known images were used to train the classifier to identify either benign or malignant lesions. We used the Adaboost classification algorithm [5], adaptive boosting, to build a strong classifier. The same classifier was validated using leave-one-out cross validation on Zagrouba's image dataset (95 images of benign nevi and 25 images of malignant melanoma) [8]. Figure 1 shows overall flowchart of the melanoma classification.

AdaBoost can provide good results regardless of the possibility that the base classifiers are just somewhat superior to the chance level. Base classifiers that are weak learners are trained in sequence and depending on their previous performance, points will be assigned a different weight. Points misclassified by the previous weak classifier, will have more prominent weight in the next classifier. Then, the result of all weak learners will be combined based on a weighted majority voting scheme [9].

3 Results

Figure 2 shows an example of a melanoma image and its supervised and unsupervised segmentation masks. In some images, the existence of hairs surrounding the skin lesion, and poor color contrast relative to the surrounding skin cause inaccurate lesion boundary determination, resulting
in inaccurate feature measurement and lesion classification. Thirty melanocytic lesion images (15 benign and 15 malignant images) were classified using AdaBoost and leave-one-out cross validation. Table 1 shows the sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) of melanoma classification using supervised segmentation and automatic segmentation methods. True positive (TP) is the number of correct malignant predictions, true negative (TN) is the number of correct benign predictions, false positive (FP) is the number of benign images wrongly predicted as malignant, and false negative (FN) is the number of malignant images that wrongly predicted as benign.

Figure 2. (a) Dermoscopy images of melanocytic lesions and lesion segmentation using (b) the supervised method, and (c) the unsupervised method.

<table>
<thead>
<tr>
<th>Statistical Parameter</th>
<th>Supervised Segmentation</th>
<th>Unsupervised Segmentation</th>
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<tbody>
<tr>
<td>Sensitivity</td>
<td>100%</td>
<td>83.67%</td>
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<tr>
<td>Specificity</td>
<td>93.33%</td>
<td>80.39%</td>
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<tr>
<td>PPV</td>
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</tr>
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<td>NPV</td>
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4 Interpretation

In this paper, the feasibility of segmenting melanocytic lesions and categorizing them to either malignant melanoma or benign was investigated. Results confirmed that by applying more accurate segmentation methods, the melanoma lesions can be classified more accurately, in this limited sample case with sensitivity of 100%, specificity of over 93%.

One of the reasons for poor lesion segmentation is the limited spectral selectivity of Bayer filters in color cameras. A system comprising only the three wavelength bands from the Bayer filter does not provide effective tissue component decomposition to assist lesion segmentation.

In future work, we will analyze a larger population to identify the source of segmentation inaccuracy. We plan to compare smartphone imaging of melanocytic lesions using an optical attachment. We will measure the same lesions with a reference hyperspectral imaging system and identify possible spectral selection strategies from hyperspectral data to optimize lesion segmentation using an optical attachment in combination with the Bayer filter. This will help us to redesign the optical attachment with specific spectral selectivity for more accurate lesion border detection and morphological assessment prior to the classification.

References