Computer aided diagnosis of melanoma using Computer Vision and Machine Learning

Jabeer Ahmed
Biomedical Engineering
Oregon Health & Science University

This paper presents a computer-aided analysis of pigmented skin lesions following the ABCD guidelines used by Dermatologists. There are 3 steps to this process: image segmentation, feature analysis and machine learning. The most important and foundational step is image segmentation. In this paper we present 3 lesion segmentation algorithms: Radial Search, Region Growing Search using Flood Fill technique and Statistical Region Growing algorithm. We also present detailed description of the algorithms used to extract asymmetry, border irregularity, color variegation and diametric features. The aforementioned segmentation and feature extraction algorithms were tested on 350 test cases consisting of malignant melanocytic lesions, atypical nevus, superficial spreading, seborrhoeic keratosis, non-melanocytic lesions and benign lesions. An Artificial Neural Network (ANN) was trained using the lesion features with 80% accuracy.

INTRODUCTION

Melanoma is a type of skin cancer caused by irregular growth in melanocytic cells. It is the most frequent and the most malignant skin tumor. Every year about 55,000 people are diagnosed with melanoma in the US alone. It has the highest occurrence rate in fair skinned people and about 51% chance of occurrence in people above 60 years old. One feature of melanoma is that they are well contained in their early stages. If diagnosed in time the entire cancerous lesion can be surgically removed and the patient can be fully cured. Since melanoma can develop from normal pigmented lesions like birthmarks, regular moles and atypical nevi, which are quite normal and can stay dormant for decades, they have a tendency to be remained unnoticed until they are at a late stage. Hence, a computer aided diagnostic tool can of great help for suspecting patients to get a quick, free, +assessment of their lesions and a score of the risk factor.

The distinction between malignant melanocytes and benign or atypical nevi can be very subtle. The standard guideline currently used for superficial examination by dermatologist is the ABCD method. This method checks for 4 negative features. These features are:

Asymmetry – Normal lesions with no irregularity will have a fairly symmetric shape, meaning one side can be folded on to the other with almost complete overlap. As lesions become malignant they tend to have an irregular radial growth, giving rise to the asymmetry in the lesion shape. One way to quantize the asymmetry observed is to determine the centroid of the lesion. With the centroid determined it is possible to calculate the major axis, the minor axis and the angular orientation of the lesion. The lesion is then folded along the major and minor axes and the respective overlapping areas are divided by the total area of the lesion to get a percentage score of the asymmetric index along the major and minor axes. An asymmetric index of 50% is a perfectly symmetric case.

Border – An irregular border is an indicator of malignancy. If a border is abrupt it is a

strong indication that the lesion is malignant and a dark demarcated border with also a fading boundary and jagged edges are features of malignant lesions too. Border irregularity is measured as

$$I = P^2/(4*pi*A);$$

where, P is the perimeter and A is the area of the lesion. Therefore a circle will get an irregularity index of 1 and higher the value more the irregularity of the structure.

Color – Color and network pattern features are the most important discriminatory features of all when differentiating between atypical structures and malignant [1]. These colors vary between black, dark brown, gray, tan, steel blue, purple, yellow, white and red. Statistical color analysis can reveal the color variegation. In this study difference between average skin color and lesion color was used normalize the lesion color [2]. In this study for most cases RGB color values were used while other studies have shown that spherical coordinate system for color yields better results than RGB color values. Color space L*a*b* can be used for better classification [3].

Diameter – Typically a healthy lesion will be less than 5mm in diameter.

IMAGE SEGMENTATION

A toolbox was written in Matlab for image filtering and segmentation. Various filters were applied for noise reduction but median filter produced the best results. A hair removal algorithm was also developed in L*a*b* color space using morphological closing. All the image segmentation and filtering algorithms are described below in this section.

Hair Removal – The RGB colored image is first converted to L*a*b* scales and then it under goes a morphological closing. The morphed image is subtracted from the original L*a*b* image then a threshold is applied to the resultant image. If the pixel value is above the threshold the pixel in the original image is replaced with the pixel from the morphed image. Figure (1) and (2) shows the original and hair removed image respectively.

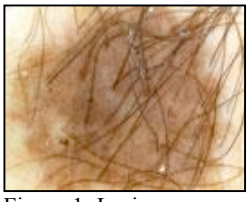

Figure 1: Lesion with hair

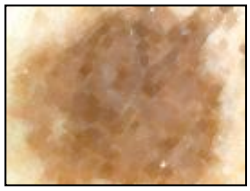

Figure 2: Image after hair removal

Border Detection –
The first step is to extract the tumor from the background. This is the most critical step since all of the other steps to follow will deep on knowing the exact shape and location of the lesion. Due to the variegated color of melanoma it was found that thresholding was not the optimum method for segmentation. It yielded good results for lesions that had strong color contrast with the background but failed to segment lesions with white or reddish white colored segments, which are similar to skin inside the lesion, which are similar in color to the background skin. Three other techniques were applied for border detection: radial search algorithm, region-growing and statistical region-growing algorithm. Each had its pros and cons and one was picked on a case-by-case basis.

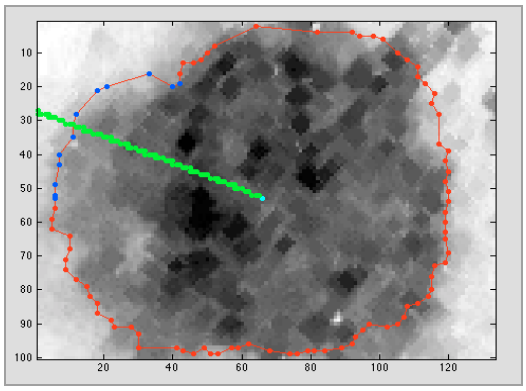

Figure 3: Radial search

Radial Search: A region where, a sharp change in luminance, followed by a sufficiently long period of steady luminance, along a radial path from the center of the

lesion is chosen as a border point. In the first version of this method, an automated center detection algorithm was applied. Although the algorithm was able to detect the center of the lesion for fairly symmetric lesions quite accurately, its detection inaccuracy got larger as the lesion shapes got more irregular and more irregular the shape of the lesion more necessary it is for the radial search algorithm to search from the true center of the lesion. Hence, the fully automated border detection approach was compromised for accurate detection by requiring a user to select an approximate center.

As a variance to the standard technique, the radial search algorithm applied in this study formed better when searching inwards towards the center instead of outwards away from the center as described in [4]. This is because in some highly malignant lesion large patches of multi colors can be seen, which are detected as false borders. Since it is more important to locate the furthest border for complete and accurate analysis, this variance performed better in most cases.

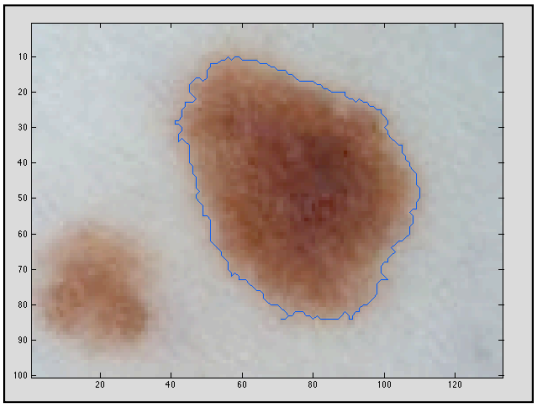

Figure 4: Region Growing Algorithm

Region Growing Algorithm: In this algorithm given a center threshold value the algorithm uses a flood fill technique to find connecting neighbors with variation in intensity less then the threshold value. Once the neighbors are found those neighbors will now look for connecting neighbors with under the same parameter. This process continues until no more neighbors can be found. This technique produced the best results in most cases but for some light pigmented lesions with highly variegated colors and scattered island like pigmented networks it left holes inside. Another similar algorithm, described below, was applied to resolve this issue.

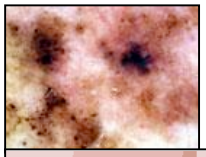
Figure 5a: Irregular shape and border, highly variegated color

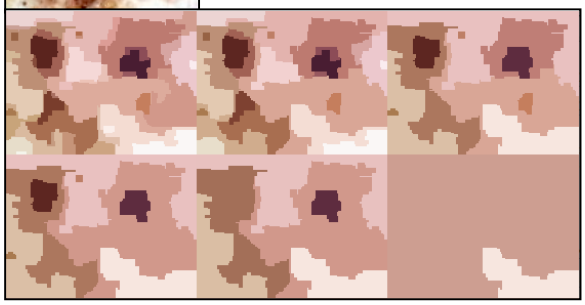
Figure 5b: Segmented image using SRM algorithm

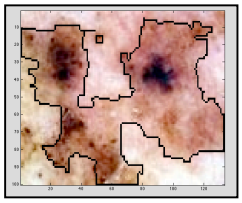
Figure 5c: Segmented legion using SRM algorithm

Statistical Region Merging – This algorithm is similar to the region-growing algorithm discussed earlier, but instead of using luminance images it segments colored images and does not use a user defined threshold value. It uses statistical analysis to determine multiple threshold values from the RGB color spectrum, and then segments the image using region-growing technique using each threshold value. Notice, that in the first image of figure (5b) there more colored segmented region than the following ones. This is because the algorithm decomposes the image for varying degree of threshold bandwidth of the color spectrum. Because of its multi level adaptive segmentation approach, performed fairly well in situations where the regular region-growing algorithm failed. Figure (5a) shows such a case. The lesion is quite spread out with no distinct border. It does not have a

distinct center, instead looks like multiple lesions branching out and merging with one another. It is extremely variegated in color with some non-pigmented regions inside. This algorithm can segment out multiple parts for different colors, and then it is up to the user to choose the correct segments and then merge them together to form the entire lesion.

FEATURE EXTRACTION

Asymmetry Index –

After determining the lesion border the true centroid of the lesion was calculated along with the major axis, minor axis and the orientation of the lesion (figure (6)).

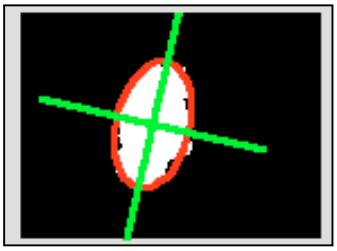

Figure 6: Centroid, major axis and minor axis detection and

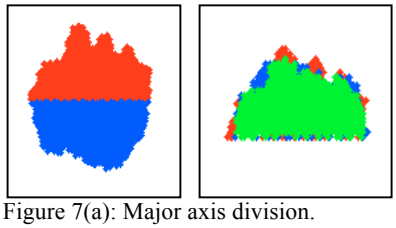

Figure 7(a): Major axis division.

Figure 7(b): Overlapping region in Green

Figure (7b) shows the overlapping region in green after folding the lesion along the major axis. The asymmetry index is:

$$AsymIndx = (\Delta Area / Total\ Area) * 100\%$$

where, ΔArea is the overlapping region along one axis. The asymmetric index was calculated for both the axes and used as image feature. It was found that 35 – 45% asymmetric index was common for benign lesions and lower for malignant with large variation between the major and minor axis.

Border Irregularity index –

$$irrgIndx = P^2/(4\pi A^2)$$

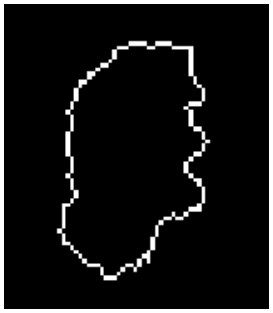

Figure 8: Lesion border

Border irregularity index was computed using the equation shown above. It was found that benign lesions had irregularity index from 1.2 to 1.9, while malignant lesion had value ranging from 1.6 – 5.

Entropy Index –

In order to extract texture features entropy was calculated within a smaller 5x5 window. Entropy is the measure of randomness. This was used to quantify the local texture pattern. For textured regions with globule pattern and cobblestone pattern the local entropy value was found to be quite high around 5, while other pattern were within the range $3.5 < E < 5$.

Color Analysis:

Color analysis is the most discriminatory feature and the hardest to extract. In this study the lesion color was first normalized with respect to the background skin. This gave a relative color value of the lesion, which accounted for the contribution of the photographic artifacts such as saturated image, reflectance, flash etc. The mean, standard deviation and variance of the normalized color values calculated for each color channel.

ARTIFICIAL NEURAL NETWORK

A dataset of 350 test cases consisting of malignant melanocytic lesions, atypical nevus, superficial spreading, seborrhoeic keratosis, non-melanocytic lesions and benign lesions were analyzed and a feature matrix was created along with the respective target value. The target values ranged from -0.9 to +0.9, negative values denoting the probability score of malignancy and positive denoting probability score of benign.

The neural network used was a feed forward multi layer network. The network had 14 input neurons (9 color features, 2 asymmetric feature, 1 border feature, fractal dimension and entropy), 20 hidden layer neurons and 1 output layer neuron. The training function used was Scaled Conjugate Gradient descent back-propagation and Log-Sigmoid transfer function was used. 300 images where used training testing and validation phase. After multiple training configurations the best accuracy rate reached was 80%.

DISCUSSION / CONCLUSION

The trained network was able to distinguish between non-malignant and malignant tumors, but it was not as accurate in distinguishing between benign lesions, which weren't malignant yet but were highly probable cases to become malignant in time, from atypical lesions. The differences between them are quite subtle and in practice doctors always rely on biopsy for final resolution. These differences are in pigment network and color variation. Presence of uniform pigment network around the border indicates a benign lesion while two or more patterns indicate that it is malignant. In a lot of cases, border and asymmetric scores of benign and malignant tumors are similar and the pattern and the color variation is the deciding factor. The Total Dermoscopy Score is the final ABCD score determined by

$$TDS = 1.3*A + 0.1*B + 0.5*C + 0.5*D$$

In TDS A is asymmetry, which is given the most weight while B, the border, is given the least weight, while C (color) and D (dermoscopic structure, meaning the pigmented network) are weighted evenly. A and B values can be easily extracted and quantified, while C and D values are quite difficult and do not always correlate with current quantification techniques. The weight distribution of TDS tells us that about 60% of the cases can be determined just by using accurate A and B values while the other 40% of the cases will require accurate measurement of C and D features. The feature analysis used in this study was fairly accurate in determining the A and B scores and lacked accurate determination of C and D scores hence the 80% success rate. In order to make accurate assessment emphasis needs to put on accurate determination of color variegation and pigment network.

It is essential to notice that computer aided diagnosis can only get better results by being able to classify relevant features correctly. An artificial learning machine will only be as responsive as the quality of the input feature vectors. The inputs and the outputs must be relevant, accurate and correlated. Hence it is important to focus on the missing parts – color and pattern analysis.

Pattern analysis and recognition using wavelet decomposition is currently being researched quite extensively [6][7][8][9][10]. It is also being used to classify and recognize other forms of cancer.

The aim of this paper is create a single toolbox with which one can do all the basic analysis. Future participants are encouraged to use the downloadable toolbox written in Matlab and investigate new techniques the analysis and quantification of new features for accurate characterization.

1. http://dermnetnz.org/doctors/dermoscopy-course/. DermNet New Zealand

2. Fikret Ercal, Senior Member, IEEE Anurag Chawla, William V. Stoecker, Hsi-Chieh Lee, and Randy H. Moss, "Neural Network Diagnosis of Malignant Melanoma From Color Images", IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING. VOL. 41, NO. 9, SEYIEMBER1994.

3. Karen Cheung, "Image Processing for Skin Cancer Detection: Malignant Melanoma Recognition", Masters Thesis, (ECE, University of Toronto) ,1997.

4. Zhao Zhang, William V. Stoecker, and Randy H. Moss, "Border Detection on Digitized Skin Tumor Images", IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 19, NO. 11, NOVEMBER 2000

5. Nock. R, Nielsen. F, "Statistical Region Merge", IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 26, NO. 11, NOVEMBER 2004

6. Nikita V. Orlov, John Delaney, D. Mark Eckley, Lior Shamir, and Ilya G. Goldberg, "Pattern Recognition for Biomedical Imaging and Image-Guided Diagnosis".

7. Chang. T, Kuo. C. C. J., "Texture Analysis and Classification with Tree-Structured Wavelet Transform.

8. Sachin V. Patwardhan, Atam P. Dhawan, Patricia A. Relue, "Classification of Melanoma using tree structured wavelet transform", Computer Methods and Programs in Biomedicine 72 (2003) 223 239