Melanoma Diagnosis by the Use of Wavelet Analysis based on Morphological Operators

Nima Fassihi, Jamshid Shanbehzadeh, Abdolhossein Sarafzadeh, Elham Ghasemi

Abstract—**Skin melanoma is the most dangerous type of skin cancer which is curable if diagnosed at the right time. Drawing distinction between melanoma and mole is a difficult task and needs detailed laboratory tests. Utilizing morphologic operators in segmenting and wavelet analysis in order to extract the features has culminated in better result in melanoma diagnosis. This paper employs coefficients of wavelet decomposition to extract image's features. Melanoma classification is carried out by using the variance and mean of wavelet coefficients of images as the inputs of neural network. Results show 90% ability in distinction between benign and malignant lesions.**

***Index Terms*—Feature Extraction, Skin Melanoma, Segmentation, Wavelet Transform.**

I. Introduction

Skin cancer is a disease in which malignant cells appear on the outer skin layers. Melanoma is a skin disease in which malignant cancer cells exist in the skin coloring cells (i.e. melanocytes). Skin melanoma is a fatal type of skin cancer which kills thousands of people every year. If diagnosed at the right time, this disease is curable, otherwise, it causes death. Melanoma diagnosis is difficult and needs sampling and laboratory tests. Melanoma can spread out to all parts of the body through lymphatic system or blood. The main problem to be considered dealing with melanoma is that, the first affliction of the disease can pave the way for future ones. Laboratory sampling often causes the inflammation or even spread of lesion. So, there has always been lack of less dangerous and time-consuming methods. Machine vision can improve the speed of skin cancer diagnosis which works according to the disease symptoms. The similarities among skin lesions make the diagnosis of malignant cells a difficult task. But, there are some symptoms of skin cancer, such as: A (asymmetry), B (border irregularity), C (color variation) and D (dermoscopic structure) [6].

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Experts, using these symptoms (known as ABCD rule), can diagnose melanoma. To calculate the ABCD score, the criteria are assessed semi-quantitatively. Each of the criteria is then multiplied by a given weight factor to yield a total dermoscopy score. The ABCD rule works properly for thin melanocytic lesions. As the used features in ABCD offer, the superficial aspects of moles change while progressing toward melanoma. These rules have 59% to 88% accuracy in diagnosing melanoma, but biopsy is needed for more precise diagnosis [4][7].

This paper presents a novel and accurate method to draw distinction between melanoma and skin lesion. This method is based on segmenting by the use of morphologic operators and features extraction by the use of wavelet transform. Figure 1 shows the block diagram of the proposed algorithm. The first block preprocesses the input image by artifact reduction and enhancement. The second block segments the image by morphological operators. The third block performs image transformation and extracts the features by the use of wavelet coefficients for the recognition phase which is performed by three layer neural network in the final step.

The rest of this paper is organized as follow. Section 2 presents a summary of pre-processing step. Section 3 shows the image segmentation. Section 4 is dedicated to features extraction based on the wavelet transform. Section 5 considers the recognition phase based on neural network and finally Section 6 deals with the experimental results. These results are obtained for a set of images. Section 7 concludes the paper and outlines areas for future research.

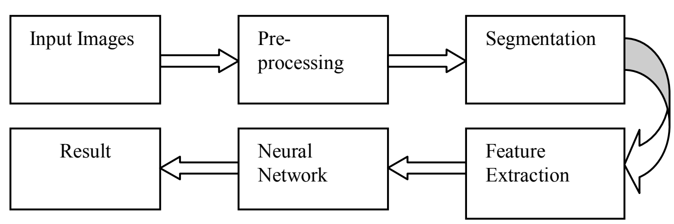

Fig. 1. Block diagram of the proposed system.

II. Pre Processing

Our dataset consists of 91 images, gathered from hospitals and websites, which include both melanoma and benign images. The preprocessing step removes the undesirable parts, enhances the image, corrects the image skew and removes noise from the image [8]. Noise is one of the problems of the melanoma and benign images. Among different filters, the mean filter was chosen because of its

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efficiency [5] and a 3x3 mean filter was employed as the filter mask. Of course, we can perform more sophisticated algorithms in noise removal depending on the source of noise but, as we collected our data set from various sources and there were different sources of noise depending on the devices and conditions, we left more sophisticated algorithms for further research. Fig. 2 shows the result of applying mean filter on a sample image [16]. The figure in the left side is the original image and the left side is result after applying mean filter.

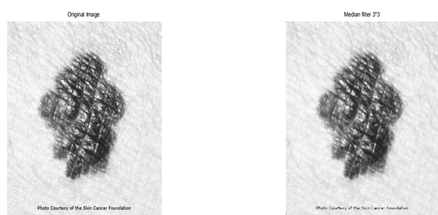

Fig. 2. The left side image is skin melanoma [16], and on the right side one is the denoised image by mean filter.

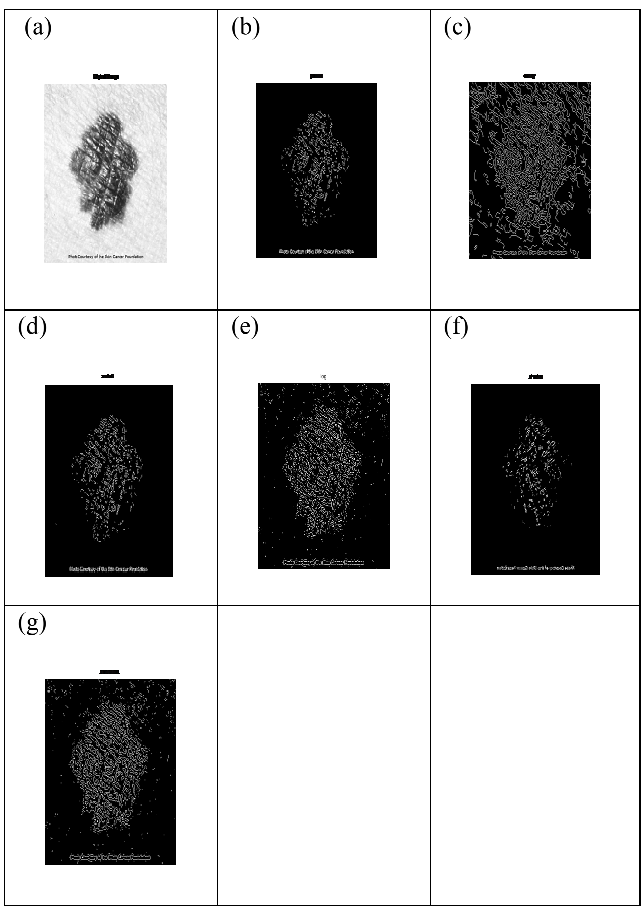

Fig. 3. Results of segmentation by other algorithms: (a)original image; (b)Prewitt; (c)Canny; (d)Sobel; (e)Log; (f)Roberts; (g)Zerocross.

III. Segmentation

Segmentation is one of the difficult processes and the final result depends on this section. The quality of subdivisions depends on segmentation [3]. The boundaries of images segmented by the new algorithm are definable. We can employ Prewitt (Fig 3.b), Canny (Fig 3.c), Sobel (Fig 3.d) and other filters (Fig 3.e to Fig 3.g) in the segmentation phase [1]. We received undesirable results on our database by the mentioned algorithms.

We employed a new algorithm by morphologic operators. Figure 4 shows the steps of the algorithm by morphological image processing. At first the input image is spread out (Fig 4.b), then the result is refined (Fig 4.c). The refined image is reconstructed and extended (Fig 4.d and 4.e). We reconstruct the extended image and complete it and binarize the complete version (Fig 4.f to Fig 4.h).

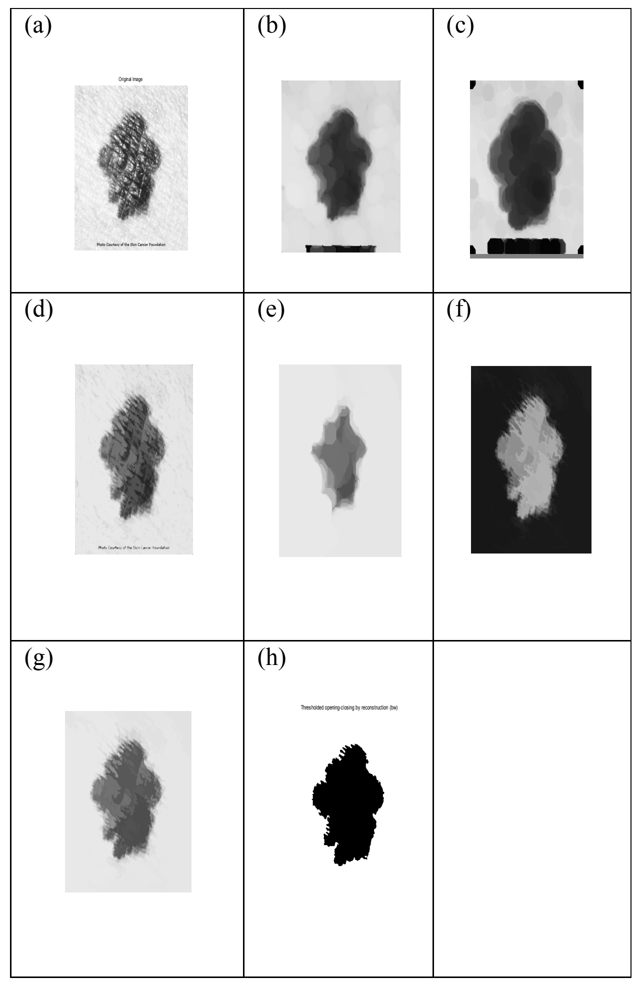

Fig. 4. Results of segmentation by our method: (a)original image; (b)spread out image; (c)refined image; (d)reconstructed image; (e)extended image; (f)reconstructed image; (g)completed image; (h)binary image.

IV. Feature Extraction

At this stage, we determine the eminent and important features of image data. It makes the raw data more useful in processing. By extracting features, we narrow down the image data to a set of features which should be robust against factors such as lighting, camera position, noise and lack of transparency. At this stage, the extracted features should be both representatives of samples and detailed enough to be classified [8][13].

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We employed wavelet in feature extraction. We employed different wavelets and three steps of decomposition. The results of the second step were more detailed to be used in production of final results. At each step of decomposition, the wavelet of primary image is divided into an approximate and three detailed images which show the basic information and vertical, horizontal and diagonal details, respectively. During next steps, the approximate image is employed instead of the original image and is decomposed into sub-images. Figures 5 and 6 present the results of two steps of applying wavelet on the image.

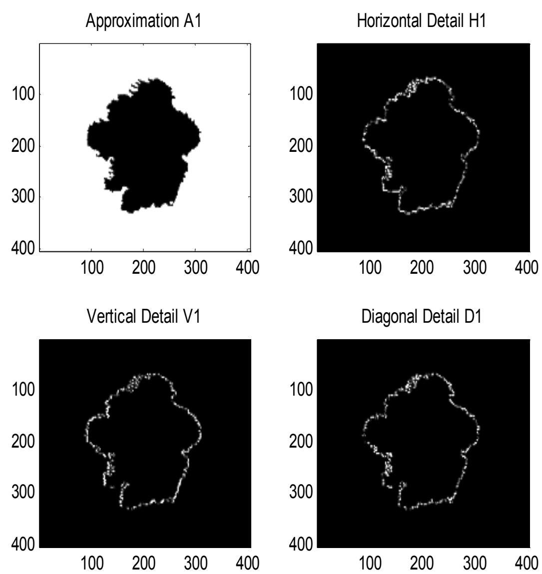

Fig. 5. Results produced after the first step of decomposition of wavelet.

The mean and variance of decomposition coefficients of the second step are utilized to produce the features. Each step of decomposition produces coefficients for approximation and details. There are four mean and four variance features. So, there are totally eight coefficients at each step of wavelet decomposition. We normalize the results and write them in the range of 0 to 1.

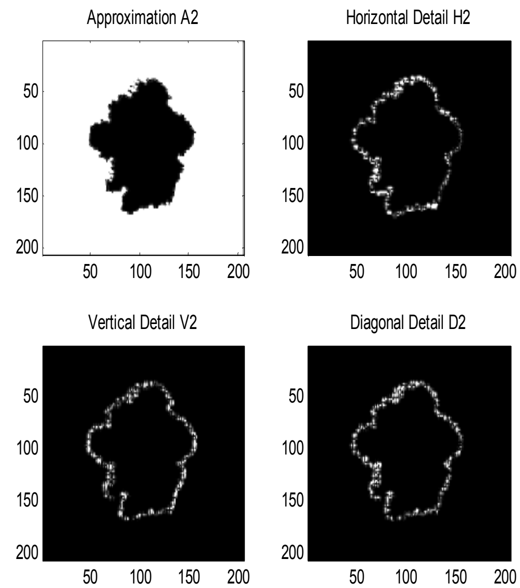

Fig. 6. Results produced after the second step of decomposition of wavelet.

V. Classification based on Neural Network

During the neural network phase, images are divided into training, testing and validation data. The network, after the first round, replaces the subdivisions of training and testing, so that the whole data would be considered as the testing subdivision. Finally the network is fed with the validation data and produces the final results. The purpose of the neural network is, eventually, to make distinction between melanoma and skin lesion images [11][12]. Neural network, regarding its structure, provides desirable results with 90% accuracy in distinction between images. The simulations found 71 images out of 91 to be melanoma and 20 images to be moles. The input of the neural network was 73 images as training and testing and18 images as validation. This neural network has 8 inputs and 1 output and also 3 middle layers.

VI. Simulation Results and discussion

Unlike Fourier transform which uses fixed functions as the basis, wavelet transform permits different wavelet functions to be employed. Wavelets from different families have aspects which are useful for special purposes. This paper considers the effect of several groups of wavelets on the classification. Among all the results in the sequential repetition, regardless of the wavelets family, the accuracy of distinction of this program is about 90 percent. (The training and testing subdivisions have been replaced in rotation). The examined neural network has three middle layers and produces desirable results. The wavelet decomposition was carried out in several steps; among them the results of the second step are more precise. The more the layers are, the less the accuracy in depiction is. Table 1 presents the three results of some different decomposition. These results are accuracy, false positive and false negative. False positive refers to those incorrect results that we find them correct and false negative refers to those correct results that we find them incorrect.

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All the researches in this field have reported the accuracy of 60 to 92 percent. A device called "Solarscan" has the highest degree of accuracy and, it is because this device produces images with high quality which improves the accuracy of feature extraction. Solarscan has a complicated structure and uses different algorithms in segmentation, therefore provides more detailed results [14]. Of course, it is worth-mentioning that in this article, the depiction is performed by the use of wavelet only and there would be the probability of more detailed results if other structures are used as well.

VII. Conclusion

This paper presented an algorithm to improve the diagnoses of melanoma by the use of image processing and machine vision. This algorithm consisted of preprocessing, image segmentation, feature extraction and classification. The results showed 90 percents accuracy, 4.2 to 7.2 percents false positive and 4.3 to 5.9 percents false negative. The variation of false positive and false negative depended on the features extracted by the different wavelet functions.

There are several points that we can leave for further research. The first point is a suitable data set based on specific condition and device to construct a suitable preprocessing step. The second step is the feature extraction and selecting more suitable features by the use of wavelet function and finding the suitable wavelet.

TABLE 1: Result produced by the use of different wavelet functions.

Wavelet function	Accuracy(%)	False positive(%)	False negative(%)
Daubechies 2	90.103	5.489	4.398
Daubechies 6	88.545	7.158	4.298
Symlet 2	90.103	4.246	5.638
Symlet 4	90.103	4.760	5.134
Coiflet 1	88.545	5.538	5.803
Coiflet 3	91.236	6.632	2.102
Biorsplines 1.5	88.545	5.564	5.883
Biorsplines 3.1	90.103	6.338	3.469

References

[1] M. Emre celebi, Hitoshi Iyatomi, Gerald Schaefer, William V. Stoecker, "Lesion border detection in dermoscopy images" computerized Medical Imaging and Graphics 33 (2009) 148-153 Elsevier.
[2] Xiaojing Yuan, Ning Situ, George Zouridakis, " A narrow band graph partitioning method for skin lesion segmentation" Pattern Recognition 42 (2009) 1017-1028 Elsevier.
[3] Jinshan Tang, Raj Rangayyan, Jianhua Yao, Yongyi Yang, "Digital image processing and pattern recognition techniques for the detection of cancer" 6 (2009) 1015-1016 Elsevier.
[4] Sachin V; Patwardhan; Shuangshuang Dai; Atam P. Dhawan. "Multi-spectral image analysis and classification of melanoma using fuzzy membership based partitions". Computerized Medical Imaging and Graphics 29 (2005) 287–296 elsevier.
[5] Delgado D, Butakoff C, Ersboll BK, Stoecker WV. "Independent histogram pursuit for segmentation of skin lesions". IEEE Trans on Biomedical Engineering 2008;55(1):157–61.
[6] Vincent T.Y. Ng; Benny Y.M. Fung; Tim K.Lee "Determining the asymmetry of skin lesion with fuzzy borders" Computers in Biology and Medicine 35 (2005) 103–120.
[7] SachinV.Patwardhan,Atam P.Dhawn,Patricia A.Relue, "classification of melanoma using tree structured wavelet transforms" Computer Methods and Programs in Biomedicine 72 (2003) 223-239 Elsevier.
[8] Sonka M, Hlavac V, Boyle R. "Image processing, analysis, and machine vision". Cengage-Engineering 2007.
[9] Erkol B,Moss RH, Stanley RJ, StoeckerWV, Hvatum E. "Automatic lesion boundary detection in dermoscopy images using gradient vector flow snakes". Skin Research and Technology 2005;11(1):17–26.
[10] R. P. Braun, L. E. French, J.-H. Saurat. Dermoscopy of pigmented lesions: a valuable tool in the diagnosis of melanoma. SWISS MED WKLY 2004;134:83–90.
[11] N. Cascinelli, M. Ferrario, R. Bufalino, S. Zurrida, V. Galimberti, L. Mascheroni, C. Bartoli, and C. Clemente, "Results obtained by using a computerized image analysis system designed as an aid to diagnosis of cutaneous melanoma," Melanoma Res., vol. 2,pp. 163–170, 1992.
[12] Mads Hintz-Madsen, Lars Kai Hansen, and Jan Larsen. "Detecting Malignant Melanoma using Neural Classifiers". Proceedings of International Conference on Engineering Applications with Neural Networks. June 1996.
[13] Philippe Schmid-Saugeon, Joel Guillod, Jean-Philippe Thiran. "Towards a computeraided diagnosis system for pigmented skin lesions". Computerized Medical Imaging and Graphics 27 (2003) 65-78.
[14] Solarscan http://extra.cmis.csiro.au/IA/ryanl/melanoma_technical.pdf (last accessed4/23/08).
[15] John Silkorski."Identification of malignant melanoma by wavelet analysis" Proceedings of Student/Faculty Research Day, CSIS, Pace University, May 7th, 2004.
[16] Melanoma http://www.abiaunion.com/?p=5 (last accessed7/12/10).

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