VOL. 10, NO. 7, APRIL 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

DETECTION OF MELANOMA SKIN CANCER USING DIGITAL CAMERA IMAGES

V. Jeya Ramya, J. Navarajan, R. Prathipa and L. Ashok Kumar
Department of Electronics and Communication Engineering, Panimalar Institute of Technology, Chennai, India
Email: jeyaramyav@gmail.com

ABSTRACT

Skin cancer is rapidly increasing in western parts of the world. Survival rate of skin cancer is high, if detected early. So an efficient method is necessary to detect skin lesion at the earliest. Since the cost of dermatoscope scan for screening the patient is high, there is a need for an automated system to detect skin lesions captured using a standard digital camera. The main aim of a skin cancer detection system is to reduce the percentage of error by choosing the appropriate method in each stage .In this paper, for pre-processing stage adaptive histogram equalization technique and wiener filter is used. A novel method is proposed for the segmentation and classification of skin lesions.

Keywords: skin lesion, pre -processing, segmentation, GLCM, SVM.

1. INTRODUCTION

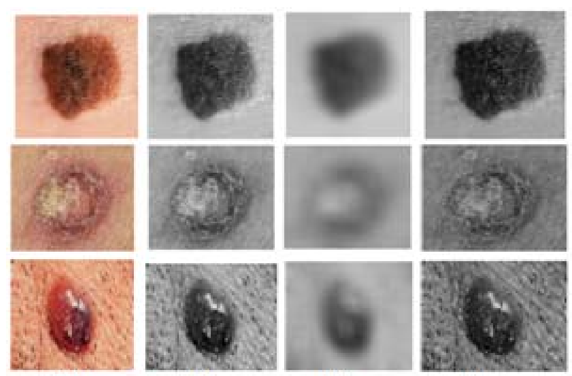
Malignant skin cancer is nowadays one of the leading cancers among many white-skinned populations around the world [1]. Incident of UV-rays and tanning beds are the main reasons for cancer. Recent trends found that incidence rates for non-Hispanic white males and females were increasing at an annual rate of approximately 3%. The curability of skin cancer is nearly 100%, if it is recognized early enough and treated surgically [2]. To reduce costs of screening skin cancer in the general population, development of automated skin cancer screening algorithms have been proposed.

A dermatoscope is a special device for dermatologists to use to look at skin lesions that acts as a filter and magnifier. The most common reasons against using the dermatoscope include a lack of training or interest. Recent work with automated skin cancer screening algorithms tries to adapt the algorithms to analyze images taken by a standard digital camera. Differentiation of skin lesion images demands very fast image processing and feature extraction and classification algorithms.

The proposed method comprises at first Pre-Processing the images. The weiner filter is used for the noise removal. Next the ACM segmentation method is used to extract the lesion from the Digital camera Image. Thirdly, extracting second order statistical textural GLCM features from the segmented skin lesion. Finally classify the lesion as benign or malignant by using SVM classifier. Evaluation of the proposed method is done by calculating accuracy, specificity and sensitivity.

2. PRE-PROCESSING

Preprocessing is the first stage of detection system helps to enhance the quality of an image by noise removal, unwanted illumination and contrast enhancement. The enhanced image is used for feeding the next step. Adaptive Histogram Equalization is used for image enhancement and Wiener filtering for image restoration.[3,4]. Adaptive Histogram Equalization (AHE) technique considers the local contextual region of an image for contrast enhancement. In other words, the value of each pixel is computed based on the rank in local contextual region instead of entire image. It computes several histograms for each section of an image and employs that for redistribution [5, 6]. The preprocessed images are shown in Figure-1.



(a) (b) (c) (d)

Figire-1. (a) Original image (b) Gray scale image (c) Filtered image (d) Contrast enhanced image.

3. SEGMENTATION

The first aim of this paper is to build an efficient robust automatic segmentation tool for skin lesion images. It can be noticed that the lesions have large variations in size as well as in color and contrast to the surrounding skin. In order not to lose any important structures within the lesion, grey-scale morphology is used to derive the segmentation. Active-contours methods have already been used to segment pigmented skin Lesion images. However, usually a conversion to a grayscale image precedes the processing stages. Other approaches are there for color images [7], but these algorithms were designed for dermoscopic images, which have different characteristics.

Active contour model, also called Snakes, is a framework. An active contour model (ACM) is a technique for contour extraction based on the principle of minimization of the energy defined on a closed curve

VOL. 10, NO. 7, APRIL 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

comprising control points. It extracts object at a high contrast against a background and for distinguishing smooth forms. The primary condition for Snake is the initialization of the contour. This significantly influences the final result.

In case of variations in a mass, it is not easy to recognize the size, form, and position of the target, and in such cases, even if it is not desirable, the initial contour must be set up manually. The segmented image is shown in Figure-2.

This model can be used to solve many image processing problems such as detection of edges, lines, contours and object tracking. By providing appropriate energy it is possible that to push the initial contour to the desired solution. Snake is used for semi-automatic image interpretation. So, when no automatic starting mechanism exists, Active contour model can be used there.

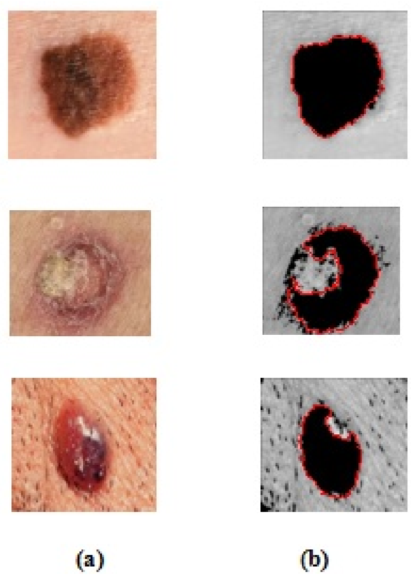


Figure-2. (a) Original image (b) Segmented image

4. FEATURE EXTRACTION

Analysis of texture shows that the features are extracted and decimated into first order, second order and higher order statistics. They are computed from position of the pixels with specified intensities. The Gray Level Co-occurrence Matrix (GLCM) method is a way of extracting second order statistical texture features. The approach has been used in a number of applications, Third and higher order textures consider the relationships among three or more pixels. These are theoretically possible but not commonly implemented due to calculation time and Interpretation difficulty [8].

A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element P (i, j | .x, .y) is the relative frequency with which two pixels, separated by a pixel distance (.x, .y), occur within a given neighborhood, one with intensity 'i' and the other with intensity 'j'. This paper presents an application of gray level co-occurrence matrix (GLCM) to extract Four features namely, Variance, Energy, Correlation, Homogeneity and Entropy[9,10]. The results show that these texture features have fast extraction and high discrimination accuracy. Hence it is used effectively.

a) Entropy

Entropy gives the amount of information of the image that is needed for the image compression as in Equation (1). It measures the loss of information or message in a transmitted signal and also measures the image information.

$$Entropy = \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} - P_{ij} * \log P_{ij} \quad (1)$$

b) Correlation

Correlation measures the linear dependency of grey levels of neighboring pixels as in Equation (2). For accurate 2D and 3D measurements of changes in images.

$$Corr = \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} \frac{(i, j)p(i, j) - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (2)$$

c) Energy

It is the sum of squares of entries in the GLCM as in Equation (3). It measures the image homogeneity. It is high when image has very good homogeneity. Energy is high when image has very good homogeneity or when pixels are very similar.

$$Energy = \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} P_{ij} \quad (3)$$

d) Homogeneity

It measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Homogeneity is one for a diagonal GLCM.

5. CLASSIFICATIONS

SVMs have several advantages over the more classical classifiers such as decision trees and neural networks. The support vector training mainly involves optimization of a convex cost function. Therefore, there is no risk of getting stuck at local minima as in the case of back propagation neural networks. The principle of structural risk minimization is used in SVM which minimizes the upper bound on the generalization error. Therefore, SVMs are less prone to over fitting when compared to algorithms such as back propagation neural networks that implement the ERM (empirical risk minimization principle). Another advantage of SVMs is that they provide a unified framework in which different learning machine architectures (e.g., RBF networks and feed forward neural networks) can be generated through an appropriate choice of kernel .The disadvantage of support vector machines is that the classification result is purely contradiction, and no probability of class membership is given.

a) Accuracy:

The accuracy of the classifier is the percentage of the test samples that are correctly classified by the classifier.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (4)$$

b) Sensitivity

It is also referred as true positive (TP) rate that is the propagation of positive samples that are correctly identified.

$$Sensitivity = \frac{TP}{TP + FN} \quad (5)$$

c) Specificity

It is the true negative (TN) rate that is the proportion of negative samples that are correctly identified.

$$Specifcity = \frac{TN}{TN + FP} \quad (6)$$

6. RESULT

Database consists of 20 digital images, previously diagnosed, 10 of them are benign and 10 are malignant. The active contour segmentation was performed for ten test skin samples .The fig1 shows the results of segmentation for three skin lesion images. GLCM features were used for feature extraction and Support Vector Machine for classification. Required features are extracted and fed to the classifier. Table-1 shows the GLCM features for skin lesion images.

Table-1. GLCM features.

Features	Image 1	Image 2	Image 3
Variance	52.323	25.59	41.44
Entropy	7.024	6.6057	7.0722
Correlation	0.9665	.69193	.8394
Energy	0.243	.20211	.1898
Homogenei ty	0.9307	.8291	.83004
Threshold	.5294	.5333	.4980
Contrast	.1414	.37389	.45577

The performances of the Classifier for different parameters are shown in Table-2.

Table-2. Performance of the SVM Classifier**.**

Parameters	SVM classifier
TP	19
TN	17
FP	03
FN	01
Accuracy	90%
Specificity	95%
Sensitivity	85%

7. CONCLUSIONS

In this paper, an automated system for skin cancer detection was developed with normal and abnormal classes. First, preprocessing of the image was done by the wiener filter. The impressive segmentation performance is achieved by active contour segmentation. The features used in the system are extracted using GLCM.

In a classification approach with two categories (malignant and benign lesions), a sensitivity of 90%, accuracy of 95% and a specificity of 85% is observed. The texture parameters can be included in the feature set to improve the overall performance of the system the lesion boundary as well as texture descriptors are not yet included in the feature set, and might yield a good starting point to improve the discriminative information in the feature set.

REFERENCES

[1] A. Green, N. Martin, G. McKenzie, J. Pfitzner, F. Quintarelli, B. W. Thomas, M. O'Rourke and N. Knight. 1991. "Computer image analysis of pigmented skin lesions," Melanoma Res. Vol. 1, pp. 231–236.

[2] H. Pehamberger, A. Steiner and K.Wolff. 1987. "In vivo epiluminescence microscopy of pigmented skin lesions. I. Pattern analysis of pigmented skin lesions," J. Amer. Acad. Dermatol., vol. 17, no. 4, pp. 571–583, Oct.

[3] S.S. Al-amri, N.V. Kalyankar and S.D. Khamitkar. 2010. "Linear and Non-linear Contrast Enhancement Image", IJCSNS International Journal of Computer Science and Network Security, Vol.10, No.2, pp. 139.

[4] L. R. Lagendijk and J. Biemond. 2005. "Basic Methods for Image Restoration and Identification". Handbook of Image and Video Processing 2nd edition, Elsevier Academic Press, 167-181.

[5] H. Yeganeh, A. Ziaei and A. H. Rezaie. 2008. "A Novel Approach for Contrast Enhancement Based on Histogram Equalization", Proceedings of the

International Conference on Computer and Communication Engineering, 13-15 May, Malaysia.

[6] C.W. Kurak. 1991. “Adaptive histogram equalization: a parallel implementation”, Proceedings of the Fourth Annual IEEE Symposium in Computer-Based Medical Systems, Univ. of North Florida, Jacksonville, FL, USA.

[7]. Silveira M., Nascimento J., Marques J., Marcal A., Mendonca T., Yamauchi S., Maeda J. and Rozeira J. 2009. Comparison of segmentation methods for melanoma diagnosis in dermoscopy images. IEEE J Sel Top Signal Process Vol. 3, pp. 35–45

[8] R. E. Haralick, K. Shanmugam and I. Dinstein. 1973. Textural Features for Image Classification, IEEE Transactions on Systems, Man and Cybernetics. Vol. SMC-3, No.6, November.

[9] R.M. Nishikawa, M.L. Giger, K. Doi, C.J. Vyborny and R.A. Schmidt. 1995. “Computer aided detection of clustered micro calcifications in digital mammograms,” Med. Biol. Eng. Comp. Vol. 33, pp. 174-178.

[10] S. Theodoridis and K. Koutroumbas. 1999. “Pattern Recognition”, Academic Press, San Diego.