Advances in Environmental Biology, 8(11) Special 2014, Pages: 1406-1411

AENSI Journals

Advances in Environmental Biology

ISSN-1995-0756 EISSN-1998-1066

Journal home page: http://www.aensiweb.com/AEB/

Detection of Malignant Cells in Skin Wounds using Image Processing

[1]Maryam Karimi Fard and [2]Farhad Ebrahimi Nezhad Rafsanjani

[1]*Assistant prof., dep.of Internal Education, Rafsanjan university of medical science, Rafsanjan, Iran*
[2] *Islamic Azad University, Rafsanjan branch, Rafsanjan, Iran*

ARTICLE INFO

Article history:
Received 15 April 2014
Received in revised form 22 May 2014
Accepted 25 May 2014
Available online 15 June 2014

Keywords:
Medical image segmentation, texture classification, quantum invasive weed optimization (QIWO).

ABSTRACT

Accurate medical diagnosis needs to exact segmentation of a great deal of medical images. However, manual segmentation makes good results; this process is a costly process in both time consuming and money. Furthermore, automatic segmentation is still challenging in order to low image contrast and improper boundaries.In this article, we propose a fully automated lesion segmentation approach. In this approach, the segmentation process is limited by texture model. This model employs the wavelet packet decomposition to extract the texture features. The new introduced quantum invasive weed optimization (QIWO) is utilized to refine the main segmentation due to the classification approach. In this research, we tested the proposed approach for the segmentation of the lesion images from abdominal CT scans and the achieved results show the performance of the proposed method to accurately delineate the considered objects.

To Cite This Article: Maryam Karimi Fard and Ebrahimi Nezhad Rafsanjani., Detection of Malignant Cells in Skin Wounds using Image Processing. ***Adv. Environ. Biol., 8(11),*** *1406-1411, 2014*

INTRODUCTION

Skin cancer is the most common malignant cancers in the body. Each year more than about one million people are diagnosed as skin cancer patients. Prolonged exposure toward sunlight, medical or repeated exposure to occupational diseases, burns and scars and the line of inheritance which is more common in some families are some of the reasons that cause the skin cancer. Skin ulcers are created from impaired circulation, bacterial, viral, fungal, infection or cancers and they are commonly occurred. Chronic types of ulcers can make the malignant cancers.

Medical images play very essential role in medical diagnosis to assist health care providers to access patients for diagnosis and treatment. Studying medical images relates significantly to the visual description of the radiologists.

However, this is time consuming and typically subjective, relating to the experience of the radiologist. As a result, employing the computer-aided systems becomes very important to overcome these problems. Artificial Intelligence approaches like image processing and machine vision with forming by others like machine learning, fuzzy logic and pattern recognition get so valuable in image methods. This can be divided into three layers: image processing (lower layer), image analysis (middle layer), and image understanding (high layer). Image segmentation is one of the most important tasks of image analysis. Its purpose is that of information derivation (illustrated by data) from an image by image segmentation, object representation, and feature measurement. Results of segmentation have clearly considerable effect over the accuracy of feature measurement [2].

Many researchers try to make the medical image segmentation process automatically and numerous techniques have been proposed for this purpose [3, 4]. The conventional approaches use the intensity changes for extracting the edges and the local features of the considered objects [5] or they begin with a seed point inside the region of interest and then grows the region by utilizing the similarity measures [6, 7]. Despite these approaches are helpful in some states, they have not good performance for medical applications because of noise, parasite, occlusion and the similarity between objects intensity. A large number of methods model the segmentation problem as an optimization of energy function [8]. In these approaches, a closed curve deforms until the balance is achieved between the internal and the external energy. This curve is illustrated as a set of control points [9] or it is contrived as a zero level in a level set function [10]. Although these approaches are so precise than the conventional methods, the confidence to image information is usually not enough. In this

Corresponding Author: Maryam Karimi Fard, Assistant prof., dep.of Internal Education, Rafsanjan university of medical science, Rafsanjan, Iran

Advances in Environmental Biology, 8(11) Special 2014, Pages: 1406-1411

research, we propose an automated medical image segmentation approach based on a new meta-heuristic algorithm. In the proposed method, the desired texture is efficiently modeled by employing the wavelet packet decomposition. The quantum invasive weed optimization (QIWO) is used to optimize the support vector machine (SVM) to classify the lesion images in a high accuracy rate.

MATERIALS AND METHOD

There are numerous approaches based on texture-based image segmentation are proposed by Sonka et al. [11]. Haralick et al. employed co-occurrence matrices to evaluate a set of 14 scalar features, generally known as the Haralick transformbecause of the terrain classification in aerial photographs. Richard et al. utilized genetic algorithm with a particular adaptation, which could include texture analysis as part of its calculation module for medical image segmentation. Here, GA-based optimization algorithm is employed to generate a population of individual sub-images that are analyzed by a quantitative fitness function, ranked using a linear fitness and decrement scheme, and developed by crossover [12]. Here we will illustrate the utilized technique and the instrument used for data acquisition.

1.1. Input Dataset:

Lesion datasets in this work are employed from different references [13- 16]. It includes 68 pairs XLM and TLM images captured by the same Nevoscope system under lighting conditions (notice that there are 40 pairs of melanoma images). All the employed iages from datasets are resized into a spatial resolution of 256×256 pixels to decrease the computational resources required for processing the images. For some lesions two different images including: the TLM and the XLM modality are utilized. However, because of the wide range of lesion shapes and colors and also different skin tones, segmentation step is difficult; fig.1 shows these diversities.

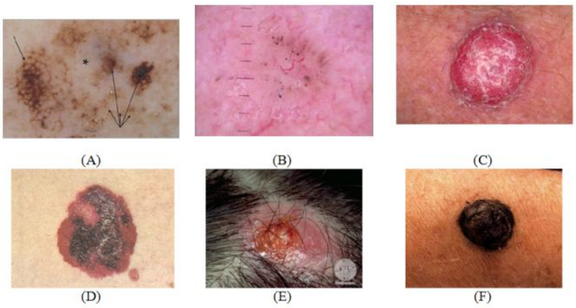

Fig.1: The diversity of dermoscopy images: (A) melanoma, (B) melanoma-associated vascular patterns, (C) squamous cell Carcinoma, (D) melanoma superficial spreading, (E) sebaceous gland Carcinoma, (F) melanoma superficial spreading.

1.2. Preprocessing:

Before beginning the lesion segmentation, we need to remove the hair and artifacts to ease the skin melanoma segmentation. Great deals of works are applied based on a method known as Dull Razor. This approach is explained in below [17]:

a) It characterizes the dark hair parts by a generalized grayscale morphological closing operation.
b) It inquires the shape of the hair pixels as thin and long structure, and replace the verified pixels by a bilinear interpolation.
c) It smoothes the replaced hair pixels with an adaptive median filter.

In [18], a new algorithm is applied and the results show good results. For the pre-processing step, we used this method. The presented method is summarized in below:

a) Median filtering to improve the results of later processing to reduce the effect of small structures
b) Canny edge detection
c) Thicken morphological operation
d) Dilate morphological operation
e) Add to original image

Some cases of artificial removal are shown below:

1.3. Lesion Segmentation:

1.3.1. Discrete wavelet transform (DWT):

DWT is a linear transformation which applies on a data vector, whose length is an integer power of two, transforming it into a numerically various vector of the same length. It divides data into different frequency divisions and then analyzes each divide with resolution matched to its scale. Discrete wavelet transform is computed with a cascade of filtering followed by a factor 2 sub sampling (Fig3).

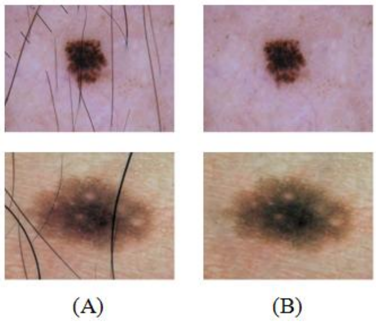

Fig. 2: Artifact Removal Results: (A) original image, (B) image after artifact removal.

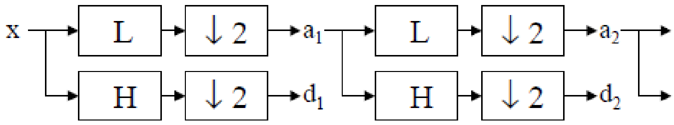

Fig. 3: DWT tree [19].

H and *L* describes high and low-pass filters respectively, ↓2 denotes sub sampling. Outputs of these filters can be illustrated by equations below:

$$a_{j+1}[p] = \sum_{n=-\infty}^{\infty} l[n-2p]a_j[n] \tag{1}$$

$$d_{j+1}[p] = \sum_{n=-\infty}^{\infty} h[n-2p]a_j[n] \tag{2}$$

Elements a_j are employed for next step of the transform and element d_j called wavelet coefficient. It describe output of the transform $l[n]$ and $h[n]$ which characterize the coefficient of low pass filter respectively.

1.3.2. Support vector machine:

Support vector machine (SVM) is a mathematical approach to maximize a specific mathematical function with respect to a given collection of data [20]. SVMs result a unique solution as the optimality problem is convex. This is a profit compared to neural networks that have several solutions associated with local minima and for this reason may not be stable over multiple samples. SVMs employ the results of statistical learning and optimization theories due to their generalization authority maximization for samples. These characteristics make the SVM as a tool which could improve performance on the proposed lesion segmentation. The significant purpose is to find a decision surface that best classifies the data points into two classes. The decision function in SVM can be illustrated as the equation below [20]:

$$y = \mathrm{sgn}\left(\sum_{i=1}^{N} y_i \alpha_i K(x, x_i) + b\right) \tag{3}$$

Where *x* is the vector of a test example in d-dimension, $y \in \{-1,1\}$ is a class label, x_i is the vector for the i^{th} training example, *N* is the number of training examples, $K(x, x_i)$ is a kernel function, $\alpha = \{\alpha_1 \ldots \alpha_N\}$ and *b* are the parameters of the model. α_i Can be leaded from [21].

1.4. Quantum Invasive Weed Optimization (Q-IWO):

Quantum Invasive Weed Optimization (QIWO) is a new meta-heuristic algorithm which is proposed by Razmjooy and Ramezani [22]. QIWO is based on improving the invasive weed optimization algorithm by the quantum computing. It is described by a consideration about quantum seeds and their competition to survive. The most important profit of QIWO is the reaching to the global minimum in less iteration. Therefore, we decided to use this algorithm to optimize the proposed classifier. The pseudo code of the QIWO is presented in below:

1. Start
2. Initialize population
3. Classical state conversion

4. Evaluate objective values
5. Quantum state conversion
6. Fast non-dominated sorting
7. Generate child population via tournament selection and IWO operators
8. Evaluate objective values of child population
9. Combine parent and child population
10. Fast non-dominated sorting
11. Create next generation based on rank and crowding distance
12. Go to 7
13. Classical state conversion
14. end

1.5. QIWO based SVM:

In this study, QIWO algorithm is employed to optimize the precision of the SVM classifier by detecting the subset of best feature and estimating the value for regularization of kernel parameters of SVM model. The QIWO-SVM algorithm is the combination of two machine algorithm. QIWO, like each iterative algorithm starts with n randomly selected members (Q-seeds in QIWO) and searches for the optimal member iteratively.

The proposed QIWO-SVM approach can be briefly written as follows:

Initializing QIWO with q-seed population size, number of quantum plants and quantum seeds, modulation index value, standard deviation values.

Evaluating the fitness of each quantum seed.

Comparing the fitness values and describes the local best and global best quantum seeds.

Updating the quantum plants and quantum seeds till the value of the fitness function converges. After converging, the global best quantum seed is fed to the SVM classifier for training. Training the SVM classifier. The QIWO-SVM takes the advantage of minimum structural risk of SVM and the quick global optimizing ability of QIWO. The principle parameters for QIWO is shown in below:

Table.1: QIWO parameters used for the proposed system.

Symbol	Quantity	Value
N_0	Number of initial population	10
Iter	Maximum number of iterations	100
P_{max}	Maximum number of plant	15
S_{max}	Maximum number of seeds	5
S_{min}	Minimum number of seeds	0
N	Nonlinear modulation index	10
$\delta_{initial}$	Initial value of standard deviation	3
δ_{final}	Final value of standard deviation	0.001

2. *Performance Measurement:*

In this section, the performance is evaluated by three factors; first metric is the correct detection rate **(CDR)** and is given in Equation (4). The false acceptance rate (FAR) is the percentage of identification moments in which false acceptance happens. The false rejection rate (FRR) is the percentage of identification moments in which false rejection happens. The FAR and FRR are expressed in Equations (5) and (6), respectively:

$$CDR = \frac{No.of.Pixels.Correctly.Classified}{Total.Pixels.in.the.Test.Dataset} \tag{4}$$

$$FAR = \frac{No.of.non-Potato.Pixels.Classified.as.Potato.PixelsClassified}{Total.Pixels.in.the.Test.Dataset} \tag{5}$$

$$FRR = \frac{No.of.Potato.Pixels.Classified.as.non-potato.PixelsClassified}{Total.Pixels.in.the.Test.Dataset} \tag{6}$$

3. *Experimental Results and Validation:*

This proposed hybrid method is applied on a real data set consisting of 68 pairs XLM and TLM images captured by the same Nevoscope device under lighting conditions. This had a spatial resolution of 1712×1368 pixels.

The device utilized an optical lens (Nikon, Japan) to obtain a standard 5x magnification and an Olympus C2500 (Olympus, Japan) digital camera for capturing the images. For each lesion two different images were achieved; one in the TLM and one in the XLM modality. We also tried to collect the referred images from the chronic ulcer images which are dubious malignant with complaints of chronic wounds and skin from the skin clinic of the KERMAN province (IRAN) in the years 2012 to 2013. However, segmentation is difficult because of the wide range of lesion shapes, sizes and colors and also different skin tones. We only illustrate the experiments of the lesion segmentation from the described dataset, but this technique can be adapted and implemented for the other organs.

A two zone classification (as lesion and background individually) is employed in this article; we discuss pixel-based lesion diagnosis, which classify each pixel independently from its neighbors. Support vector machine (SVM) has been implemented to different applications such texture classification, as in [24]. In this article, we used an optimized SVM for lesion classification by the features which are extracted from the wavelet characteristics. End-accuracy is equal 10-4. The evolutional situation was quite same as each model. Some of the applied images are given in below.

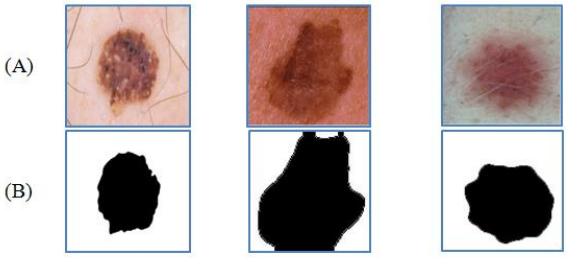

Fig. 4: (a) original image; (b) segmented image with QIWO based SVM.

Fig. 4 demonstrates the use of the described optimal system for segmenting the lesion images. As it can be seen, the proposed method has a good ability to segment lesion images.

Conclusion:

This article proposed an optimized algorithm to improve the diagnoses of lesion using of image processing and machine vision. This algorithm included pre-processing to eliminate hair and scale lines, and after that, lesion images are segmented. The results showed 94 percents accuracy, 4.4 percents FAR and 1.5 percents FAR. The first point is a proper data set based on specific condition and device to construct a suitable pre-processing step. In the second step, pixel based measures on the texture are applied to texture feature extraction and diagnosis the lesion images.

Table 2: Classification accuracy results using the training and testing selected dataset.

	CDR	FAR	FRR
Train (%)	96	2.9	1.5
Test (%)	94	4.4	1.5

REFERENCES

[1] Rastgarpour, M. and J. Shanbehzadeh, 2011. Application of AI Techniques in Medical Image Segmentation and Novel Categorization of Available Methods and Tools, Proceedings of the International MultiConference of Engineers and Computer Scientists, 16-18, Hong Kong.

[2] Zhang, Y.J., 2001. An Overview of Image and Video Segmentation in the last 40 years, Proceedings of the 6th International Symposium on Signal Processing and Its Applications, 144-151.

[3] Bankman, I.N., hand book of medical imaging, processing and analysis, academic press, pp: 67-211.

[4] Dzung, L.P., X. Chenyang and L.P. Jerry, 2000. Current Methods in Medical Image segmentation, Annual Review of Biomedical Engineering, 2(1): 315-337.

[5] Chi, Z. and P. Wang, 2000. A New Method of Color Image Segmentation Based on Intensity and Hue Clustering, icpr, pp: 3617, 15th International Conference on Pattern Recognition (ICPR'00).

[6] Pan, Z. and J. Lu, 2007. A Bayes-Based Region-Growing Algorithm for Medical Image Segmentation, Computing in Science and Engineering, 9(4): 32-38.

[7] Pohle, R. and K.D. Toennies, 2001. Segmentation of medical images using adaptive region growing, SPIE Medical Imaging, 4322: 1337-1346.

[8] McInerney, T. and D. Terzopoulos, 1996. Deformable models in medical image analysis: a survey, Medical image analysis, 1(2): 91-108.

[9] Kass, M., A. Witkin and D. Terzopoulos, 1988. Snakes: Active contour models, international journal of computer vision, 1(4): 321-331.

[10] Osher, S. and R. Fedkiw, 2003. Level Set Methods and Dynamic Implicit Surfaces, Springer-Verlag, New York.

[11] Sonka, M., V. Hlavac and R. Boyle, 1994. Image Processing, Analysis and Machine Vision. London, U.K.: Chapman & Hall.

[12] Cornely, R. and W.S. Kuklinski, 1994. Application of genetic optimization to medical image segmentation, in Proc.20th Annu. Northeast Bioeng. Conf., pp: 76-79.
[13] http://www.cancer.org/index.
[14] http://www.melanomafoundation.org/prevention/abcd.htm
[15] Ganster, H., A. Pinz, R. Rohrer, E. Wildling, M. Binder, H. Kittler, 2001. Automated melanoma recognition, IEEE Trans. on Medical Imaging, 20(3): 233-239.
[16] Zouridakis, G., M. Doshi, N. Mullani, 2004. Early diagnosis of skin cancer based on segmentation and measurement of vascularization and pigmentation in nevoscope images, in: Proceedings of the 26th Annual International Conference of the IEEE EMBS.
[17] Bayro-Corrochano, E. and J.O. Eklundh, 2009. Pigmented Skin Lesions Classification Using Dermatoscopic Images, CIARP, LNCS, 5856: 537-544. Springer-Verlag Berlin Heidelberg.
[18] Razmjooy Navid, 2013. A computer-aided diagnosis system for malignant melanomas, Neural Computing and Applications, 23.7(8): 2059-2071.
[19] Kociolek, M., A. Materka, M. Strzelecki, P. Szczypinski, 2001. Discrete wavelet transform –derived features for digital image texture analysis ,proc. of international confrernce on signal and Electronic System, Lodz, Poland, 163-168.
[20] Razmjooy, Navid, B. Somayeh Mousavi and Fazlollah Soleymani, 2012. A real-time mathematical computer method for potato inspection using machine vision, Computers & Mathematics with Applications, 63(1): 268-279.
[21] Kim, K.I., K. Jung, S.H. Park and H.J. Kim, 2003. Support Vector Machines for texture classification, IEEE Transactions on Pattern Analysis and Machine Intelligence, 24(11): 1542–1550.
[22] Navid Razmjooy and Mehdi Ramezani, 2014. An Improved Quantum Evolutionary Algorithm Based on Invasive Weed Optimization, Indian J.Sci.Res., 4(2): 413-422.
[23] Nevoscope, http://www.nevoscope.com
[24] Nashat, S., A. Abdullah, S. Aramvith, M.Z. Abdullah, 2011. Support vector machine approach to real-time inspection of biscuits on moving conveys or belt, Computers and Electronics in Agriculture, doi: 10.1016/j.compag.2010.10.010.