

Segmentation and Classification Using Artificial Neural Network Of Cervical Cancer In Magnetic Resonance Image

S.Jagadeeswari¹, S.Malarkhodi²

¹Department of ECE, KSR College of Technology, Tamilnadu, India, jagdeeswari@gmail.com

² Department of ECE, KSR College of Technology, Tamilnadu, India, malarsekar@rediffmail.com

Abstract—External beam radiation therapy for the treatment of cancer make likely correct placement of radiation dosage on the cancerous region. Still, the deformation of soft tissue through the progress of treatment, such as in cervical cancer, presents important challenges for the outlining of the target volume and other structures. The segmentation of cervical cancer Magnetic Resonance Image is done by using Expectation maximization segmentation algorithm. The tumor region is selected and the feature are extracted and finally the images are classified by using an Artificial Neural Network to identify the normal and abnormal tumor images.

Keywords—External beam radiation therapy (EBRT), Artificial Neural Network (ANN), Expectation Maximization Segmentation (EM).

Introduction

According to the world health organization (WHO) cervical cancer is said to be the world's second deadly cancer with an estimate of about 493,243 women diagnosed with it and 273,505 dying from it per year. Cervical cancer is frequent among women between 15 and 44 years of age. The cervix is located in the lower part of the uterus also called uterine cervix, it connects the body of the uterus by the cervix part called endocervix to the birth canal by the part named exocervix. Cells covering the cervix are referred to as squamous cells and the glandular. The various stages of cervical cancer Stage I- Outside pelvis Stage I (40%) - confined to cervix, Stage II (30%) - beyond cervix, not to pelvic side wall, Stage III (25%) - to side wall, lower 1/3 pelvic side wall, Stage IV (5%) - involving bladder. A cervical cancer is a cancer malignant of the cervix or within the cervical area. It may form in the interior lining of the cervix, junction of the vagina and the uterus. Cervical cancer begins to develop in the cells around the cervix. Pre-cancerous cells which are described as cervical intraepithelial neoplasia (CIN), squamous intraepithelial lesion (SIL) and dysplasia. The pre-cancerous cells cancer can fully grow into cancer. There are two main forms of cervical cancer namely squamous cell carcinoma and adenocarcinoma, of these types 80% to 90% of the cervical cancers are due to the squamous cell carcinoma which begin where the exocervix joins the endocervix. Cervical adenocarcinoma develops from the mucus-producing gland cells of the endocervix. In some cases some of the cancers can be as a result of a combination of both squamous cells carcinoma and adenocarcinoma, the carcinoma is known as adeno squamous carcinoma or mixed carcinoma. In some women precancerous cells go away with no treatment whatsoever while others turn into true invasive cancers. There are a variety of stages of cervical cancer that identify the extent and site of infection. The first stage is stage 0 which is also in another name known as cervical carcinoma in situ, it is located at the top layer of cells along the cervix line. Carcinoma in situ is not considered as a cancer but in some cases it may develop into cancer if left untreated. Due to this cervical cancer has remained to be the second leading concern of death among the women of this community and the third highest behind Asian and Caucasian women by C. Lopez. [1], [2], [3]. In this paper cervical cancer MRI image is adept of concurrently explaining deformable detection of tumor, segmentation of the organ, constrained non-rigid registration using pixel value. External beam radiation therapy (EBRT), the source of the radiation is outside the body, and the area to be treated is designed carefully to limit the amount of radiation directed at healthy tissue.

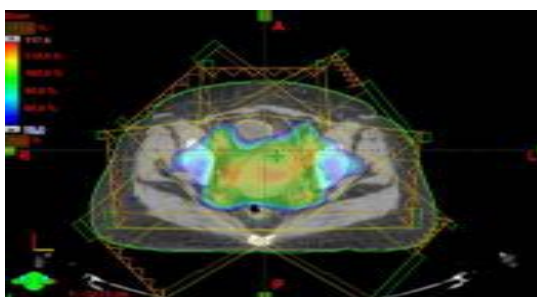
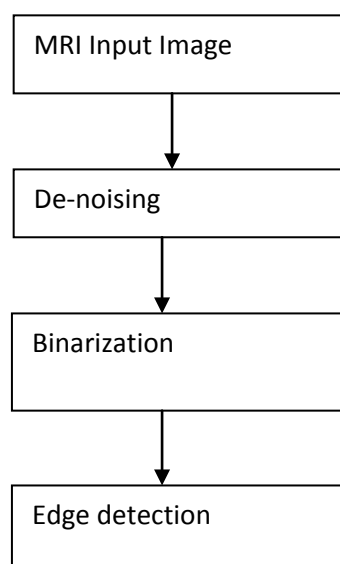


Fig.1.3D view of cervical cancer by applying EBRT with tumor in red, bladder outlined in yellow, and rectum outlined in green.

During EBRT, your body is positioned beneath the x-ray machine in the same way every day, and the radiation field is exposed to the radiation beam for a few seconds once per day, five days per week for five to six weeks. This is done as an outpatient, and you can usually continue your normal daily activities during treatment. by Chao Lu [4]. Level set method is used for segmentation by Chunming Li [5]

2. PROPOSED METHOD

External beam radiation therapy for the treatment of cancer make likely correct placement of radiation dosage on the cancerous region. Still, the deformation of soft tissue through the progress of treatment, such as in cervical cancer, presents important challenges for the outlining of the target volume and other structures. In preprocessing step, image denoising is used to removal of noise and the noise quality of the parameters, such as the signal-to-noise ratio (SNR), the peak signal-to-noise ratio (PSNR), the mean squared error (MSE), and mean absolute error (MAE) represent the quality indicators of the denoising process . Otsu's method involves iterating through all the possible threshold values and calculating a measure of spread for the pixel levels each side of the threshold, the pixels that either falls in foreground or background. The segmentation of cervical cancer Magnetic Resonance Image is done by using EM segmentation algorithm. The tumor region is selected and the feature are extracted and finally the images are classified by using an Artificial Neural Network to identify the normal and abnormal tumor images. The flow diagram of the proposed method is shown in figure 2.]



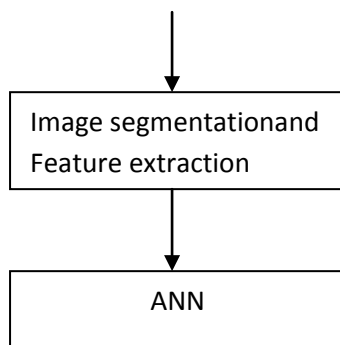


Fig.2.Flow diagram of the proposed method

A. Image Preprocessing

MRI data has a high resolution and high soft tissue contrast, while magnetic resonance (MR) imaging is able to characterize deformable structure with superior visualization and differentiation of normal soft tissue as well as tumor-infiltrated soft tissue.

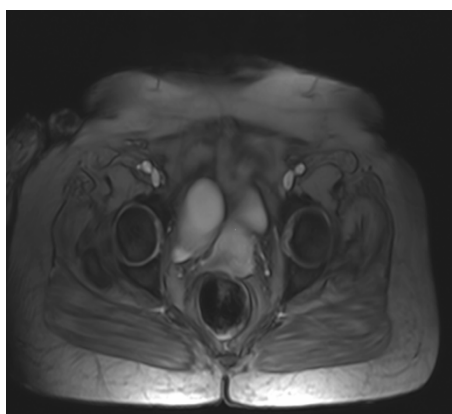
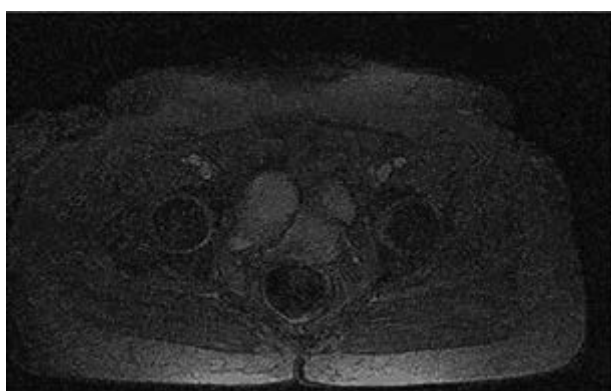


Fig.3. Input MRI Cervical Cancer

B. De-noising

An efficient method for accurate noise filtration of the images is based on the Fourier transform (FT) and Gaussian low-pass filter (GLPF). Here, the image processing is a three-step process: Fourier Transform is performed, filtering the frequency components by using the GLPF and the inverse FT is computed. Smoothing is achieved in the frequency domain by dropping out the high-frequency components.



C. Binarization

Otsu's thresholding method involves iterating through all the possible threshold values and calculating a measure of spread for the pixel levels each side of the threshold, the pixels that either falls in foreground or background. The aim is to find the threshold value where the sum of foreground and background spreads is at its minimum.

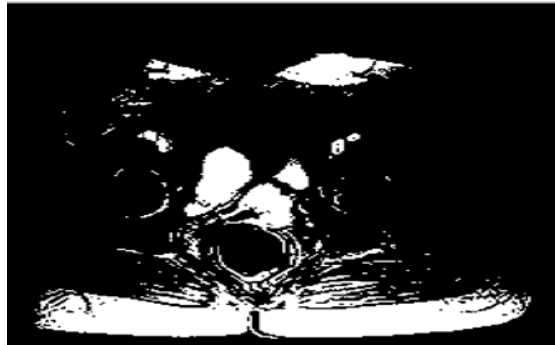


Fig.5. OTSU's Binarization method Output

D. Edge detection

This method divides an image on the basis of boundaries. Numbers of edge detecting operators based on gradient function are available. For cervical cancer detection various edge detection operators are used which are canny edge detection operator. After Binarization edge of Binarization output are detected. The edge detection output is show in figure 6



Fig.6. Edge detection

E. Image segmentation and Feature extraction

The Expectation Step consider the single pixel in the block and calculate the probability of the pixels to be a tumour cell. Finally the log likelihood function value for the pixel is calculate. Maximization step consider the whole block and calculate the probability value of the block likely to be a tumour. The contour of the tumour is shown in figure 7. Final tumour area is detected by using the EM algorithm. The output is shown in figure 8.

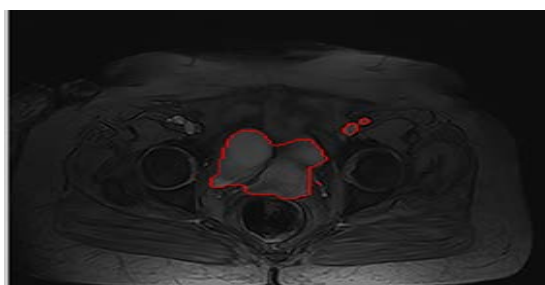


Fig.7.The Contour of the Tumour



Fig.8. Tumour Detection

E. Feature Extraction and Classification

Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. Feature Extraction is a method of capturing visual content of images for indexing & retrieval. Primitive or low level image features can be either general features, such as extraction of color, texture and shape or domain specific features. Artificial Neural Network to identify the normal and abnormal tumor images.

Table 1 Computation of Features

Feature	Formula
Contrast	$\sum_{i,j} i - j ^2 p(i, j)$
Correlation	$\sum_{i,j} \frac{(i - \mu_i)(j - \mu_j)p(i, j)}{\sigma_i \sigma_j}$
Energy	$\sum_{i,j} p(i, j)^2$

F. Artificial Neural Network

Many modern scientists believe the human brain is a large collection of interconnected neurons. These neurons are connected to both sensory and motor nerves. Scientists believe, that neurons in the brain fire by emitting an electrical impulse across the synapse to other neurons, which then fire or don't depending on certain conditions.

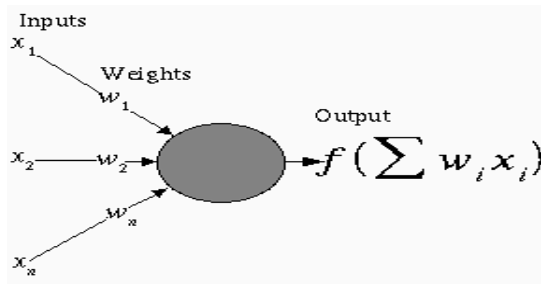


Fig8. Structure of a single neuron

Neuron is given in Figure 8. The Artificial neural network [8] is basically having three layers namely input layer, hidden layer and output layer. There will be one or more hidden layers depending upon the number of dimensions of the training samples. Neural network structure used in our experiment is consist of only two hidden layers having 7 neurons in the input layer and 1 neuron in the output layer as shown in Figure 9.

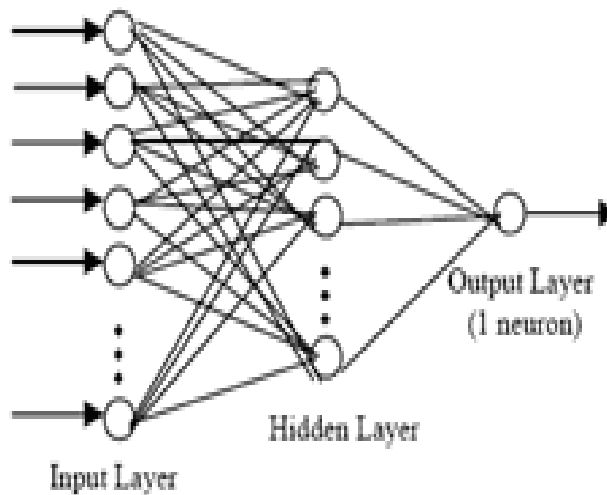


Fig 9.Simple Neural network Structure

A learning problem with binary outputs (yes / no or 1 / 0) is referred to as binary classification problem whose output layer has only oneneuron.

Table.1. Features are extracted

Feature	Normal image	Abnormal image
Contrast	0.3172	0.4144

Correlation	0.9026	0.9160
Energy	0.9799	0.9843
Skewness	0.9698	0.9725
Mean	0.1016	0.0874
Peak Signal-to-Noise Ratio	-1.7956	-0.5060
Mean Squared Error	0.0286	0.0261
Mean Absolute Error	9.2216	2.1145

3. CONCLUSION

Segmentation using EM algorithm is calculate pixel and the probability distribution function and likelihood function in the block and maximize the values estimated in the E step by considering the whole block then calculate the mean, variance and standard deviation. Compare pdf values are equal then the particular block is tumour free. If not equal then the region is affected by tumour .Features are extracted for classification using Artificial Neural Network .

ACKNOWLEDGEMENT

We thank Dr, Madhumathi Lawrence for helpful comments and fruitful discussions. We also thank Dr.Subhashree for providing Images.

4. REFERENCES

1. C. Lopez and S. Chakravarti, 'Imaging of cervical cancer' ,Imaging,vol. 18, no. 1, pp. 10–19, 2006.
2. How many women get cancer of the cervix? Atlanta, GA, Am. Cancer Soc., 2010.
3. Jemal, F. Bray, M. M. Center, J. Ferlay, E. Ward, and D. Forman, "Global cancer statistics," CA: A Cancer J. Clinicians, vol. 61, no. 2, pp. 69–90, 2011.
4. Chao Lu, SudhakarChelikani, David A. Jaffray, Michael F. Milosevic, Lawrence H. Staib, and James S. Duncan , 'Simultaneous Non rigid Registration, Segmentation, and Tumor Detection in MRI Guided Cervical Cancer Radiation Therapy' , IEEE Transactions On Medical Imaging, Vol. 31, No. 6, June 2012.
5. Chunming Li, Rui Huang, Zhaohua Ding, J. Chris Gatenby, Dimitris N. Metaxas, , and John C. Gore, 'A Level Set Method for Image Segmentation in the Presence of Intensity In homogeneities With Application to MRI' , IEEE Transactions On Image Processing, Vol. 20, No. 7, July 2011.
6. R. Potter, J. Dimopoulos, P. Georg, C. S. Lang, Waldhausl, N. Wachter-Gerstner, H. Weitmann, A. Reinthaller, T. H. Knocke, S. Wachter, and C. Kirisits, 'Clinical impact of MRI assisted dose volume adaptation and dose escalation in brachytherapy of locallyadvanced cervix cancer,' Radiotherapy Oncology., vol. 83, no. 2, pp. 148–155, 2007.
7. W. H. Greene, S. Chelikani, K. Purushothaman, Z. Chen, X. Papademetris,L. H. Staib, and J. S. Duncan, 'Constrained non-rigid registration for use in image-guided adaptive radiotherapy,'Med.Image Anal., vol. 13, no. 5, pp. 809–817, 2009.
8. Devendram V, HemalathaThiagarajan, "Texturebased Scene Categorization using ArtificialNeural Networks and Support Vector Machines:A Comparative Study", ICGST-GVIP, ISSN 1687-398X, Volume (8), Issue (IV), December 2008.
9. C. Kirkby, K. Stanescu, S. Rathee, M. Carlone, B. Murray, and B.G. Fallone, 'Patient dosimetry for hybrid MRI-radiotherapy systems',Med. Phys., vol. 35, no. 3, pp. 1019–1027, Mar. 2008.

10. Jaffray, M. Carlone, C. Menard, and S. Breen, 'Image-guided radiation therapy: Emergence of MR-guided radiation treatment (MRgRT) systems', *Med. Imag.*, 2010; *Phys. Med. Imag.*, vol. 7622, pp. 1–12, 2010.
11. Lu, S. Chelikani, X. Papademetris, J. P. Knisely, M. F. Milosevic, Z. Chen, D. A. Jaffray, L. H. Staib, and J. S. Duncan, 'An integrated approach to segmentation and nonrigid registration for application in image-guided pelvic radiotherapy', *Med. Image Anal.*, 2011.
12. L. van de Bunt, U. A. van der Heide, M. Ketelaars, G. A. P. de Kort, and I. M. Jurgenliemk-Schulz, 'Conventional conformal, and intensity-modulated radiation therapy treatment planning of external beam radiotherapy for cervical cancer: The impact of tumor regression', *Int.J. Radiat. Oncol. Biol. Phys.*, vol. 64, no. 1, pp. 189–196, 2006.
13. C. Lu, S. Chelikani, and J. S. Duncan, G. Szekely and H. K. Hahn, Eds., 'A unified framework for joint segmentation, nonrigid registration and tumor detection: Application of MR-guided radiotherapy', in *Information Processing in Medical Imaging*, New York, 2011.
14. Chunming Li, Chenyang Xu, Changfeng Gui, and Martin D. Fox, 'Distance Regularized Level Set Evolution and Its Application to Image Segmentation' *IEEE Transactions On Image Processing*, Vol. 19, No. 12, December 2010.
15. Yegnanarayana B., 'Artificial Neural Networks', Prentice Hall of India Private Ltd, New Delhi, 1999.
16. Dorin Bibicu and Luminita Moraru 'Cardiac Cycle Phase Estimation in 2-D Echocardiographic Images Using an Artificial Neural Network' *IEEE Transactions on Biomedical Engineering*, Vol. 60, No. 5, May 2013.
17. P.D. Wasserman 'Neural computing theory and practice' Van Nostrand Reinhold, 1989.
18. W. Hai-Yang, P. De-Lu, and X. De-Shen, 'A Fast Algorithm for Two Dimensional Otsu Adaptive Threshold Algorithm', Vol. 33, 2007.

BIOGRAPHIES



S. Jagadeeswari Received her B.E in Electronics and Communication Engineering from Mahendra Engineering College For Womens, Namakkal in 2012 and Currently doing Master of Engineering in VLSI Design from K.S Rangasamy College of Technology (Autonomous), Tiruchengode,



Dr. S. Malarkhodi, M.Tech, Ph.D is working as Professor in K.S. Rangasamy College of Technology (Autonomous), Tiruchengode Tamil Nadu. Her field of interest is Medical Image processing. Emailid: malarsekar@rediffmail.com