Novel Hybrid Approach Combining ANN and MRA for PET Volume Segmentation

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Abstract— **Medical volume segmentation is an essential stage in volume processing. This stage is important for tumour classification and quantification in medical volumes particularly in positron emission tomography (PET) imaging. Analysing PET volumes at early stage of illness is important for radiotherapy planning, tumour diagnosis, and fast recovery. There are many techniques for segmenting medical volumes, in which some of the approaches have poor accuracy and require a lot of time for analysing large medical volumes. In this paper, a novel hybrid approach (HA) combining artificial neural network (ANN) with multiresolution analysis (MRA) for segmenting oncological PET data aiming at providing an accurate quantitative analysis tool is proposed. Proposing artificial intelligence (AI) technologies can provide better accuracy and save decent amount of time. The proposed approach has been evaluated against other medical volume segmentation techniques such as thresholding, clustering, and multiscale Markov random field model. The proposed approach has shown promising results in terms of the detection and quantification of the region of interest (ROI) and tumour, in phantom and clinical PET volumes respectively.**

Keywords— **Multiresolution analysis, artificial neural network, positron emission tomography, tumour.**

I. Introduction

Positron emission tomography (PET) is a tomographic modality which is used to measure physiology and function rather than anatomy. It plays a central role in the management of tumour beside the other main components as diagnosis, staging, treatment, prognosis, and follow-up. Due to its high sensitivity and ability to model function, it is effective in targeting specific functional or metabolic signatures that may be associated with various types of diseases [1, 2]. However PET treatment planning is accompanied with complex procedures need to be developed for accurate delineation of target regions from typical blurred and noisy functional images suffering from many instrumentation- and physics-related factors [3].

Medical volume segmentation is an important stage in medical volume processing. This stage includes significant analysis work by delineating the anatomical structures and discriminating them from volume background [4, 5]. Medical volume segmentation approaches play a vital role in numerous biomedical-imaging applications, such as the quantification of tissue volumes, diagnosis, study of anatomical structure, and radiotherapy treatment planning [6, 7]. Many segmentation systems have been developed utilising different techniques such as thresholding, clustering, deformable models, watershed segmentation using distance transform, and wavelet based segmentation [8, 9, 10]. Each of these techniques has been utilised in different ways to analyse and extract the proper information from the medical volume.

Artificial neural network (ANN) is one of the powerful artificial intelligence (AI) techniques. It has the capability to learn a set of data and construct weight matrices to represent the learning patterns. ANN is a mathematical model which emulates the activity of biological neural networks in the human brain. It consists of two or several layers each one has many interconnected groups of neurons. ANN has a great success in many applications including pattern classification, decision making, forecasting, and adaptive control. Many research studies have been carried out in the medical field for medical image segmentation [11, 12].

The main aim of this paper is to evaluate the robustness and the accuracy of the proposed system against some other existing segmentation techniques including thresholding, and clustering, and multiscale Markov random field approaches to segment the region of interest (ROI) in PET volumes.

This paper is organised as follows. Section II presents a theoretical background for the selected algorithms. The proposed medical volume segmentation system is described in section III. Results and analysis are illustrated in section IV, and finally conclusions and future work are presented in section V.

II. Theoretical Background

A. Hybrid Approach

In this study hybrid approach (HA) combining ANN with MRA is used for medical volume segmentation. MRA is a powerful tool used in a wide range of applications, including image processing, numerical analysis, and telecommunication. The advantage of this methodology over existing transforms such as discrete Fourier transform and discrete cosine transform is that it performs the analysis of a an image with localisation in both time and frequency. It also enables the exploitation of image characteristics associated with a particular resolution level, which may not be detected using other analysis techniques [13, 14]. The wavelet transform for a function *f(t)* (1-D vector) can be defined as follows:

$$X_{\psi(a,b)} = \int_{-\infty}^{\infty} f(t)\psi_{(a,b)}(t)dt \qquad (1)$$

where

$$\psi_{(a,b)}(t) = \frac{1}{\sqrt{a}}\psi(\frac{t-b}{a}) \quad (2)$$

The parameters a, b are called the scaling and shifting parameters, respectively. Haar wavelet transform (HWT) of a two-dimensional image has been used in this study. HWT can be performed using two approaches: the first one which is applied in this study is called standard decomposition of an image, where the one-dimensional HWT is applied to each row of pixel values followed by another one-dimensional HWT on the columns of the processed image. The other approach is called non-standard decomposition, which alternates between the one-dimensional HWT operations on rows and columns. HWT is a matrix-vector based operation and it decomposes the volume and produces the approximation, horizontal, vertical, and diagonal coefficients. The approximation coefficients are considered for PET volume analysis.

These coefficients are fed to ANN, where each neuron in this ANN has a number of inputs (the input vector P [x_1, x_2… x_m] is equal to the approximation coefficients vector) and one output (Y). The input vector elements are multiplied by weights vector W ($w_{1,1}$, $w_{1,2}$..., $w_{1,m}$), for one neuron and m element input vector. The weighted values are fed then to the summing junction. Their sum is simply the dot product ($W.P$) of the single row matrix W and the vector P. The neuron has a bias b, which is summed with the weighted inputs. The transfer function f (tangent sigmoid), Eq. 3, is used as an activation function [15].

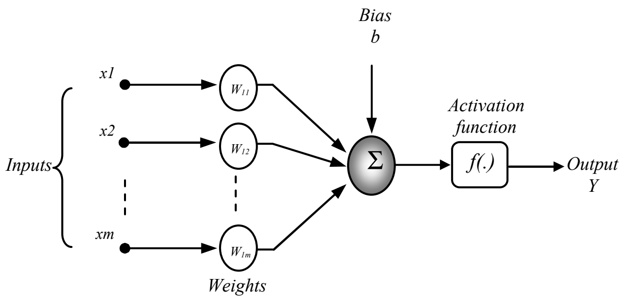

Fig. 1 Abstract model of an artificial neuron.

$$f(x) = \frac{1}{1+e^{-x}} \quad (3)$$

$$Y = f(\sum_{i=1}^{m} w_{1i}\, p_i + b) \quad (4)$$

The inputs are modulated by the neuron synaptic weights, then summed up with an external bias. The total is then fed to an activation function whose output determines the neuron output, as illustrated in Fig.1 and Eq. 4. Network learning consists of adjusting the network connectivity so that a processing unit is capable of adapting its input/output behaviour depending on any possible changes in the inputs. The set of the presented input/output is referred to as a “training set”. Therefore, the weights are adjusted such that the network responds to any input to generate the desired output with an accepted accuracy. As the mean square error is used to estimate the difference between the actual outputs and the desired ones.

B. *Thresholding*

Thresholding is the simplest precursory technique for image segmentation. This methodology attempts to determine an intensity value that can separate the image *g(x,y)* into two parts [9]. All voxels with intensities *f(x,y)* larger than the threshold value T are allocated into one class, and all the others into another class. Thresholding approach does not consider the spatial characteristics of an image; it is sensitive to noise and intensities variation.

$$g(x,y) = \begin{cases} f(x,y), \; if \; f(x,y) > T \\ \quad 0, \; if \;\; f(x,y) < T \end{cases} \quad (5)$$

C. *Clustering*

Clustering technique is aiming to classify each voxel in a volume into the proper cluster, then these clusters are mapped to display the segmented volume. The most commonly used clustering technique is the K-means method, which clusters n voxels into K clusters (K less than n) [16]. This algorithm chooses the number of clusters, K, then randomly generates K clusters and determines the cluster centres. The next step is to assign each point in the volume to the nearest cluster centre, and finally recompute the new cluster centres. The two previous steps are repeated until the minimum variance criterion is achieved. This approach is similar to the expectation-maximization algorithm for Gaussian mixture in which they both attempt to find the centres of clusters in the volume. Its main objective is to achieve a minimum intra-cluster variance V.

$$V = \sum_{i=1}^{K}\sum_{x_j \in S_i}(x_j - \mu_i)^2 \quad (6)$$

where K is the number of clusters, $S=1,2,...K$, and the mean of all voxels in cluster i is μ_i.

III. The Proposed System

The proposed medical volume segmentation system is illustrated in Fig. 2. The 3D PET volume acquired from the scanner goes through the checking block to check each slice; if the slice contains the ROI then it proceeds to the pre-processing stage. At this stage median filter is utilised to enhance the quality of volume features and then most of the noise in the volume is removed. The enhanced volume can be segmented using three approaches, the first processing block is the thresholding which removes the background and reduces the artifacts assigned with PET volume. The second approach is the clustering procedure which is performed using K-means principle. The third segmentation approach is the HA using MRA and ANN, where the volume is transformed into the wavelet domain using HWT at different levels of decomposition. This transform decomposes the volume and produces the approximation, horizontal, vertical, and diagonal features. The best level of decomposition is chosen according to the amount of details required from each coefficient using ANN. The selected approximation features are fed to the ANN for detecting, segmenting, and quantifying the ROI. The generated segmented slices are finally mapped and displayed.

IV. Results and Analysis

The developed system has been tested using two data sets of volumes, the first one contains 66 PET slices (168 x 168) with simulated tumour in it (PET phantom data), and the second data set consists of 178 clinical PET slices (128 x 128) for non-small cell lung tumour patient.

A. PET Phantom Data

The phantom slices are obtained from NEMA IEC image quality body phantom which consists of elliptical water filled cavity with six spherical inserts suspended by plastic rods of volumes 0.5, 1.2, 2.6, 5.6, 11.5, and 26.5 ml. The inner diameters of these spheres are: 10, 13, 17, 22, 28 and 37 mm [17]. The proposed approaches have been used to segment each slice in the phantom data.

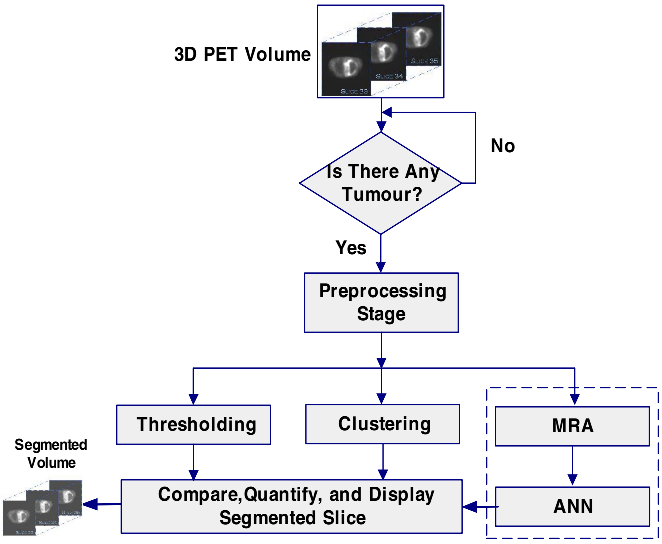

Fig. 2 Proposed system for PET volumes segmentation.

Different threshold values have been used for segmentation. The best threshold value was 6500 and the segmented slices from the thresholding technique are illustrated in Fig. 3.b. Thresholding approach has overestimated all spheres. Table I presents the original diameter (OD), the measured diameter (MD), and the percentage of absolute relative error (ARE%) for thresholded spheres. The utilisation of *K*-means clustering approach underestimates the diameter of all spheres, particularly the small ones. The result of using this technique is illustrated in Fig. 3.c, and Table II shows the MD of all spheres with ARE%.

The designed ANN consists of input layer, one hidden layer, and output layer. The experimental study done for the HA has revealed that the best number of neurons in the hidden layer is 70, and 1000 iterations have been done with backpropagation training algorithm. ANN had a good performance in selecting the best features from the wavelet domain, with a very small mean squared error (MSE), 2.39×10^{-6}. The most suitable features for ANN inputs were the approximation coefficients extracted from the wavelet domain. The features vector represents the detailed information about the slice, and its size is half of the original slice size. The HA has clearly detected all spheres in the slices, and outperformed the other approaches in term of the accuracy of measuring spheres diameters. Table III presents the results obtained for MD, and ARE%, while Fig. 3.d illustrates the outputs of HA. In addition to the objective evaluation for the results obtained through the proposed HA, a comparison with the existing approaches in the literature has been also carried out to evaluate the robustness of the developed approach. In [18] a multiscale Markov random field (MMRF) model has been utilised to segment the ROI in phantom data. The accuracy achieved through the proposed approach is better than the one obtained in [18] particularly for sphere 1 and 2. A comparison between the proposed approaches in term of the measured volume is illustrated in Fig. 4.

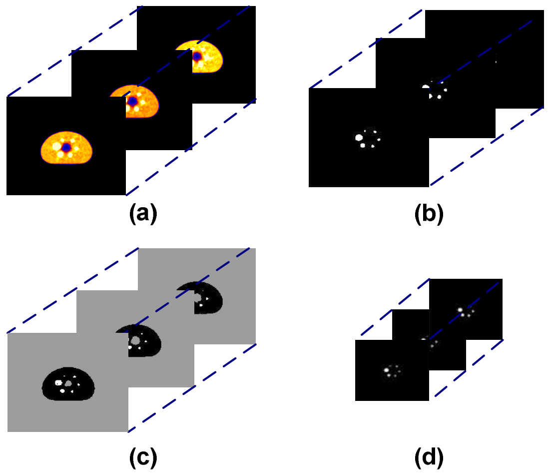

Fig. 3 Phantom data: (a) Original PET volume (168x168x66), (b) thresholded volume (168x168x66), (c) clustered volume (168x168x66), (d) segmented volume (84x84x66) from the HA.

TABLE I
MEASURED SPHERES DIAMETERS USING THRESHOLDING APPROACH

Spheres	1	2	3	4	5	6
OD(mm)	37	28	22	17	13	10
MD(mm)	37.1	28.1	22.5	17.5	13.5	10.5
ARE(%)	0.270	0.357	2.272	2.941	3.846	5.000

TABLE II
MEASURED SPHERES DIAMETERS USING CLUSTERING APPROACH

Spheres	1	2	3	4	5	6
OD(mm)	37	28	22	17	13	10
MD(mm)	36.63	27.6	21.6	16.6	12.55	9.6
ARE(%)	1.000	1.428	1.818	2.352	3.461	4.000

TABLE III
MEASURED SPHERES DIAMETERS USING NOVEL HA

Spheres	1	2	3	4	5	6
OD (mm)	37	28	22	17	13	10
MD (mm)	37.01	28.01	22.07	17.12	12.8	9.8
ARE (%) in HA	0.027	0.035	0.318	0.705	1.538	2.000
ARE(%) in MMRF	0.560	0.600	0.670	0.790	1.034	1.400

B. Performance Evaluation

In the field of artificial intelligence a number of performance metrics can be employed to evaluate the performance of ANN. The confusion matrix for the phantom data set shows that 1 voxel out of 65 ones in the first segmented sphere was misclassified. The other performance checking approach is receiver operating characteristic (ROC). The ROC curve for phantom data set, sphere 1, is located near the perfect point (0, 1) and the false positives rate (FPR) is almost 0. Dice similarity coefficients (DSC) is also used as a validation metric [19]. The proposed approach has performed well in segmenting the ROI, as DSC for phantom data set was 0.9352.

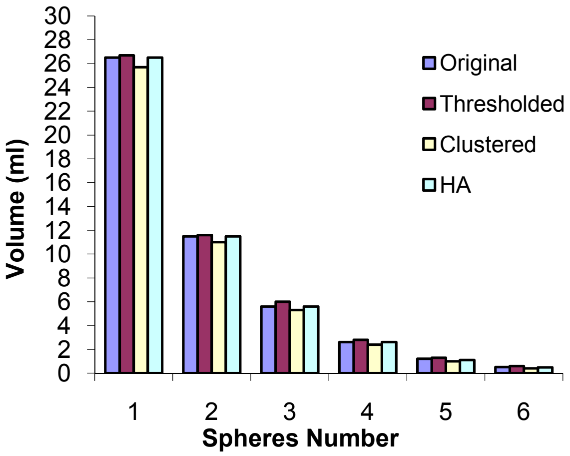

Fig. 4 Comparison between the proposed approaches for measuring different spheres volumes.

C. Clinical Data

The proposed approaches have been also tested on clinical PET volume for non-small cell lung tumour patient. A subjective evaluation based on the clinician knowledge has been carried out for the output of the proposed approaches. The tumour in this volume has a maximum diameter on the y-axis of 90 mm (estimated by histology). The segmented tumour using HA has a diameter of 90.098 mm. The generated volumes using the proposed approaches have clear detection of ROI as illustrated in Fig. 5.

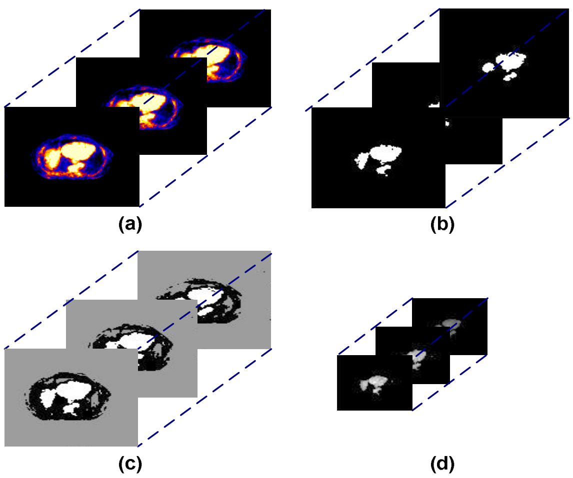

Fig. 5 Clinical PET data: (a) Original PET volume (128x128x178), (b) thresholded volume (128x128x178), (c) clustered volume (128x128x178), (d) segmented volume (64x64x178) from the HA.

V. Conclusions and Future Work

A hybrid approach based on ANN and MRA for 3D medical volume segmentation has been presented and evaluated in this paper. The comparison results have shown that the proposed approach outperforms thresholding, clustering, and other existing techniques. Objective and subjective evaluations for the segmented ROI have been carried out for phantom and clinical PET volumes respectively. Ongoing research is focusing on the exploitation of other AI techniques to validate the performance of the existing solutions.

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