ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 4, Special Issue 19, April 2017

Various Segmentation techniques for lung tumor therapy planning on fused PET/CT images - Survey

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***Abstract*— Image segmentation is the technique by which the image is partition into sub-images and the region of interest is taken separately to be examined, studied and investigated. For radiotherapy treatment planning the fused PET/CT (Positron Emission Tomography/ Computerized Tomography) images find its major applications. The Gross Tumor Volume (GTV) is delineated either automatic or manually by the radiologist on the treatment planning CT images. Image segmentation is one of the challenging areas of research in the field of medical image processing such as visualization and location of the lung tumor in cancer patients. The goal of segmentation is to reduce the amount of radiation to the nearby tissues or normal cells by which the maximum radiation should reach the affected cells. In this paper, the various techniques of segmentation proposed by the authors on PET/CT images are reviewed.**

Keywords
Segmentation, PET/CT images, lung tumor

1.INTRODUCTION

Medical imaging plays a vital role in many applications. Such applications may include the clinical track of events in diagnosis, areas of planning, carrying out surgical and radiotherapy treatment [1]. Structural imaging like CT and MRI are well suited to examine anatomical abnormalities caused by the disease. However structural imaging is not well suited for pathology detection since cellular activity is more significant [2]. The need for functional characterization leads to the development of PET scanners, which provide the molecular activity of diseases. When combined with CT or MRI utilizing both functional and structural activity provides the higher sensitivity and specificity than is achievable using either modality alone [3]. Although the sensitivity of PET scans is higher than structural images, anatomical information from another modality is still needed to localize the radiotracer uptake since the PET images are limited due to low resolution [4]. Recently PET-CT combines the diagnostic information from different imaging modalities into a single imaging device without the need for image registration. These scanning techniques can be used to identify the disease at an earlier diagnosis with the more accurate staging of patients [5]. PET-CT imaging is widely used for diagnosis, staging, treatment planning and therapy follow-up in the field of oncology. Radiation therapy as a common cancer treatment in oncology aims to target the boundary and volume of abnormal tissue and irradiated the targeted area with a high dosage of radiation, intending to eliminate all the cancerous cells. Proper determination of the boundary i.e delineation is necessary to minimize the damage to the healthy tissue but should include the entire extent of the diseased tissue [2].

In this work, we review on various segmentation methods used for PET-CT scan images. Mostly the segmentation techniques can be classified as methods based on thresholding, deformable boundary based models, edge-based approach, shape based methods and clustering techniques. Tumor segmentation in PET and CT images is challenging due to the low spatial resolution in PET and low contrast in CT images.

2. SEGMENTATION TECHNIQUES

2.1 REGION GROWING METHOD OF IMAGE SEGMENTATION

David Jakobsson et al in their paper [6] proposed a method to segment the lung region in the CT and then to achieve a better orientation with the PET image. With the knowledge of which voxels (3D pixels) it is suspected that the tumor lies within or outside the lung region. He used both region growing and thresholding method of segmentation to develop a fully automatic method for segmentation of the lung region. [7] proposed a system in which the cross-diamond search algorithm employs two diamond search patterns (a large and small) and a halfway-stop technique. It finds small motion vectors with fewer search points than the DS algorithm while maintaining similar or even better search quality. The efficient Three Step Search (E3SS) algorithm requires less

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Available online at www.ijartet.com

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computation and performs better in terms of PSNR. Modified objected block-base vector search algorithm (MOBS) fully utilizes the correlations existing in motion vectors to reduce the computations.

Region growing is a recursive algorithm that groups pixels or sub-regions into larger regions. The grouping is based on predefined criteria, for example gray level or color threshold values. The region growing starts with one or several seed points and then recursively add neighboring pixels that fulfill the criteria to the region. The selection of seed points is done with 1D spatial signature. 1D spatial signature of a CT image is done by summarizing the rows or the columns of the image matrix. After selecting the seed point the region growing is done on one slice at a time. The 2D region growing is extended to 3D by using all the pixels from the region of a slice as seed points in the next slice. In this method, there is a risk in the selection of the seed point that is placed just outside the lung.

Vaclav Potesil et al [8] proposed a new method for automated tumor delineation in the whole body by jointly using the information from both PET and diagnosis CT images. A region with high FDG uptake is detected in PET and lesion segmentation in PET is done based on mode seeking region growing segmentation algorithm (MSRG). Mode-seeking deals with finding the voxel locations with local maximum SUV values (SUV_{max}) within the region of interest. Initially, the seed point is taken as a probe on the 4D surface as defined by the spatial coordinates (x,y,z) and the corresponding SUV intensity $I_{SUV}(x,y,z)$. At the probe point the maximum SUV value is found compared to its neighborhood and then the probe is moved to the point with that maximum. The process continues until the probe reaches the intensity mode in the given region of interest. 3D region growing is applied originating from the detected local modes, with a fixed threshold of 40% of the corresponding SUV_{max} value. A conservative segmented lesion mask in PET is produced based on a clinically meaningful threshold that has been utilized in the literature [9]. This method is used to model the tumor appearance and shape in corresponding CT structures. The model provides the basis for classifying each voxel to either lesion or background class. The CT classification is then probabilistically integrated with PET classification using the joint likelihood ratio test technique to derive the final delineation.

Integration of PET and CT segmentation enables automated tumor delineation more robust and accurate compared with PET segmentation. The disadvantage of this algorithm is it requires minimal user interaction.

2.2. IMAGE SEGMENTATION USING OPTIMAL THRESHOLDING ALGORITHM

Jilong Zhang [10] et al proposed the iterative optimal thresholding algorithm to segment the CT image and for PET segmentation the extracted ROI from CT image is mapped to the PET volumes by selecting the corresponding voxels. ROI segmentation on CT is done by iterative optimal threshold algorithm that calculates the threshold value and divides the image volume voxel into the region of interest (ROI) and background.

Optimal Thresholding is the automatic threshold selection method that allows us to accommodate the small variations in tissue density expected across a population of subjects. Assuming the image volume contains the body voxels and non-body voxels, the aim is to separate the body voxels from the non-body voxels. The algorithm involves the segmentation where the threshold value is selected after an iterative process. Let T^i be the threshold at step i. The new threshold is selected by applying T^i to the image to separate the body and non-body voxels. μ_b and μ_n be the mean gray level of the body voxel and non-body voxel respectively. The new threshold is obtained at i+1 step by

$$T^{i+1} = (\mu_b + \mu_n) / 2 \qquad (1)$$

The iterative procedure is repeated until there is no change in the threshold $T^{i+1} = T^i$. The initial threshold T^0 is based on the CT number. The difficulties of this thresholding methods is that the lungs sometimes are connected and sometimes not connected also due to the varying sizes of lungs

Jilong Zhang et al [10] proposed Quantitative texture characterization of lung lesions with co-registered FDG PET/CT images to determine whether texture features can help for differentiation of malignant and benign tissues. Texture features were computed from every segmented region of interest (ROIs) and analyzed according to the classification of ROIs. In their paper, the textural characterization for radiation treatment planning included the calculation of 14 features of PET and CT images that belong to four groups such as first order features, second order features, higher order features and structural features.

In certain cases the SUV value is influenced by pathological type of cancer which led to the misdiagnosis of normal and malignant tumor. The future work is to determine the nature of the lesions in fused PET/CT images combined with SUV value. Texture characterization combined with various features of PET/CT might be the accurate method to discriminate ROIs of tissues.

2.3. TUMOR DELINEATION BASED ON NEW SEGMENTATION ENERGY

The tumor delineation may suffer leakages to the surrounding non-tumor voxels under two cases (i.e) when the

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ISSN 2394-3785 (Online)
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International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 4, Special Issue 19, April 2017

tumor boundaries are not discernible in CT since it involves the chest wall or the mediastinum and when the surrounding non-tumor voxels in PET have similar intensities to the tumor voxels. Cherry Ballangan et al [11] proposed a tumor delineation method with an energy function using information from CT and PET with a downhill cost. A penalty was added to the energy function when a voxel is not part of the downhill region where the energy will be negative of the initial energy.

$$E_D = \begin{cases} -\psi\,|E|, & D(v) = 0 \\ E, & \text{otherwise} \end{cases} \quad (2)$$

The proposed energy is incorporated into a region based active contour where the segmentation is implemented using a localized active contour to focus on the voxels near the tumor without considering all the global intensities. The experiments prove that the downhill cost increases the DSC (Dice Similarity Coefficient) of tumor delineation and the leakage to non-tumor voxels is avoided.

2.4. SEGMENTATION OF GROSS TUMOR VOLUME REGION USING OPTIMUM CONTOUR SELECTION (OCS) METHOD

Ze JIN et al [12] proposed a method to assist the radiation oncologists in the delineation of lung tumor regions during treatment planning of cancer. An automated contouring algorithm based on an optimum contour selection (OCS) method was proposed. The basic concept of optimum contour selection (OCS) is to select a global optimum object contour based on multiple active delineations with a level set method around tumors. Initially, the gross tumor volume (GTV) was identified by thresholding the PET image at a certain standardized uptake value and then initial GTV location was corrected in the region of interest of the planning CT image. Then the contours are selected from the final gross tumor volume regions of the planning CT images using the OCS method. In the OCS method, the level set method (LSM) is employed for searching for the optimum object contour in the relationship between the average speed function value on an evolving curve and the evolution time. The GTV contour and the speed function value obtained by the LSM were recorded at each evolution time from the initial GTV region until the evolution time reached 10000 or the evolving curve reached the edge of the ROI in the planning CT image. The level set function $\phi(x,y,t)$ was updated from the initial GTV region contour by using the following discrete partial differential equation.

$$\phi^{n+1}(x,y,t) = \phi^{n}(x,y,t) - \Delta t F(x,y,t)|\nabla\phi^{n}(x,y,t)|, \quad (3)$$

where n is the evolution number, t is the evolution time, Δt is the evolution time interval, and F(x,y,t) is the speed function. The zero level set of $\phi(x,y,t)$ which corresponds to the contour of the segmented region, moves according to the speed function F(x,y,t) in the 3D level set function. The zero level set function moves according to the speed function F(x,y,t) and is given by

$$F(x,y,t) = b(x,y)\{1 - v_k(x,y,t)\}, \quad (4)$$

$$b(x,y) = \frac{1}{1+|\nabla\{G(x,y)\circledcirc I(x,y)\}|}, \quad (5)$$

where b(x,y) is the edge indicator function, G(x,y) is the Gaussian function, I(x,y) is the planning CT image, © denotes convolution, v is a constant and k(x,y,t) is the curvature. The edge indicator function b(x,y) and speed F(x,y,t) were small around the edges, and the functions b(x,y) and F(x,y,t) would be large in homogenous regions. Then the GTV contour was determined from the optimum contour derived from the LSM by searching for the minimum point in the relationship between the evolution time and the average speed function value, based on the steepest descent method (SDM).

This method can be applied for many types of tumors improving the segmentation accuracy. They are well suited especially for cavity type tumors and for tumors abutting the chest wall.

2.5. ANALYSIS OF FEATURES FOR TUMOR DETECTION AND SEGMENTATION

Punithavathy et al [13] proposed a methodology for automatic detection of lung cancer from PET/CT images. Contrast Limited Adaptive Histogram Equalization (CLAHE) and wiener filtering are the image preprocessing methods performed to remove the artifacts due to contrast variations and noise. Lung region of interest was extracted using morphological operators. Statistical texture features proposed by Haralick et al [14] was extracted from the images that give more texture information from the tumor regions than the visual assessment. The GLCM functions characterize the texture of an image by calculating how often pairs of the pixel with specific values and in a specified spatial relationship occur in an image. Fuzzy C-means (FCM) clustering was chosen to classify the regions as normal or abnormal since it is simple, unsupervised and soft clustering and it retains more information compared to hard clustering method. The performance of this methodology was evaluated by using Receiver Operating Characteristics (ROC) curve and proved to have a better overall accuracy of 92.67%. The accuracy can be improved by considering transform based feature extraction employing supervised classifiers like SVM, ANN, etc.

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ISSN 2394-3785 (Online)
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International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 4, Special Issue 19, April 2017

Hui Cui et al [15] proposed an automated localization and segmentation of lung tumor based on image feature analysis. Based on quantitative analysis of contrast features of PET volume grey-tone difference matrix (NGTDM) takes spatial relationship and probabilities of intensities into consideration which reveals more information than first order features like mean, standard deviation and gradient. The calculation of contrast in PET volume [16] is on a voxel by voxel basis. Three-dimensional (3D) windows surrounding each voxel are defined. Then based on analysis of the surrounding CT features of the initial tumor definition, the decision strategy determines the tumor segmentation from PET or CT. Decision strategy is based on two cases (i.e) simple case and complicated case. By expanding the tumor region with a threshold of 20% of maximum SUV and mapping the PET tumor expansion region onto CT volume the Decision Making Region (DMR) is defined. For the simple case, where the tumor is isolated from the surroundings the final output of segmentation is obtained by fusion with input CT. For complicated case, where the tumor is in a proximity of surrounding structures such as mediastinum or chest wall the final segmentation is obtained by fusion with PET.

This automatic approach effectively utilized the PET and CT image features like SUV, gradients, contrast and CT intensity distribution for decision making and classification of tumors.

2.6. A GRAPH-BASED CO-SEGMENTATION METHOD

Dongfeng Han et al [17] proposed a general framework to use both PET and CT images simultaneously for tumor segmentation. The strength of each modality that is the superior contrast of PET and the superior spatial resolution of CT is utilized. Markov random field (MRF) based segmentation of the image pair with the regularized term that penalizes the segmentation difference between PET and CT is formulated. The task of co-segmenting as a binary labeling of Markov random field (MRF) on a graph corresponding to the input PET and CT images is formulated. They assumed that there is a one to one correspondence between f_p and f_c and denote u' the voxel in the CT image corresponding the voxel u in the PET image. Each label f in f_p and f_c takes a label value from the label set L = {0, 1} indicating the voxel to be in the foreground (f=1) or in the background (f=0). The new energy term $E_{p\text{-}c}(f_{p\text{-}c})$ is introduced into the objective energy function penalizing the segmentation difference between PET and CT images to achieve tumor segmentation simultaneously. The introduced co-segmentation binary variables $f_{p\text{-}c}$ associated with a pair of corresponding voxels (u,u') in the PET and CT images to utilizes the strength of both systems for segmentation. Hence, the problem of PET-CT co-segmentation is to minimize the following energy function [18].

$$E_{PET\text{-}CT} = E_p(f_p) + E_c(f_c) + E_{p\text{-}c}(f_{p\text{-}c}) \qquad (6)$$

Where $E_p(f_p)$ and $E_c(f_c)$ are the MRF energy functions for PET and CT respectively and the energy term $E_{p\text{-}c}(f_{p\text{-}c})$ is used to penalize the segmentation difference between the PET and CT. The co-segmentation energy term $E_{p\text{-}c}(f_{p\text{-}c})$ makes use of the high contrast of PET and the high spatial resolution of CT to link the PET segmentation and the CT segmentation as a co-segmentation process. Segmentation accuracy evaluated using dice similarity coefficient (DSC) and the average median Hausdorff distance (HD) prove the improvement compared to the graph cuts method using PET or CT alone.

Wei Ju et al [19] proposed a method that effectively uses the two modalities by fully using the superior contrast of PET images and superior spatial resolution of CT images. The segmentation problem is solved by integrating Random walk and graph cut method. Random walk method provides the object seeds for graph cut segmentation. The co-segmentation problem is formulated as an energy minimization problem which is solved by max-flow or min-cut method. A graph is constructed including two sub-graphs and a special link, in which one sub-graph is for the PET and another is for CT. This special link encodes a context term that penalizes the difference of the tumor segmentation on the two modalities

The work of using dual modality PET-CT images can be extended using surface context to improve segmentation on CT images. The accuracy can be improved by studying the adaptive parameter selection and to use the atlas based segmentation to reduce the human interaction.

2.7. SEGMENTATION BASED ON MARKOV TREE MODEL

H.Hanzouli et al [20] proposed a method dealt with the use of efficient aspects (multi-observation and multi-resolution) of Hidden Markov Tree (HMT) and Bayesian interference that exploits the joint statistical dependencies between hidden states so as to handle the entire data stack. The framework is applied for PET image denoising taking into consideration simultaneously the wavelets and contourlets transforms through multi-observation capability of the HMT model. The multi-observation aspect of the proposed HMT was exploited to associate both wavelets and contourlet coefficients to each voxel leading to a wavelet contourlet denoising (WCD). The results of wavelet denoising (WD), contourlet denoising (CD), wavelet contourlet denoising (WCD) and Gaussian filtering are compared and the visual analysis demonstrates that the boundaries of the tumor are better preserved in CD and WCD than with WD that led to

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 4, Special Issue 19, April 2017

more loss of structural integrity. But this method was found to be better preserving the original intensities and contrast values with the significant increase in signal to noise ratio were obtained.

In this work, the process of segmentation is automated by exploiting the HMT multiresolution framework to associate high-resolution CT image at the leaf of the tree with low-resolution PET image at the next higher scale in the tree. The future work is focused on using the HMT model for multi tracer information for use of Pairwise Markov Tree (PMT) with evidence theory validating the segmentation on datasets.

2.8. BAYESIAN SPATIOTEMPORAL SEGMENTATION USING BIVARIATE POISSON MIXTURE MODEL

Zacharie Irace et al [21] presented a supervised algorithm for the joint segmentation of 4-D PET-CT images based on Bivariate-Poisson Mixture model to represent the bimodal data. A Bayesian framework is developed to label the voxels as well as jointly estimate the parameters of the mixture model. The image segmentation problem is formulated as maximum a posteriori (MAP) problem:

$$\square = \text{argmax } p(\theta, z/x) \qquad (7)$$

Where θ is an unknown parameter vector and let $z = \{z_1, \ldots\ldots\ldots z_N\}$ be a hidden label variable and x be a 4D PET-CT image. This problem is solved in a Bayesian framework by estimating the posterior and jointly estimating θ and z. Bivariate Poisson mixture has been used to model the PET-CT bimodal data taking into consideration that they are dependent.

Considering the parameter vector θ and z are independent, using Bayes' theorem the posterior distribution of the vector (z, θ) is expressed. A Metropolis within Gibbs sampler is proposed to solve the segmentation problem. Samples are iteratively drawn according to the conditional densities of the posterior and then used to estimate the maximum a posteriori (MAP) [22].

The proposed model works based on two contributions consisting in performing statistical multimodal data fusion and spatiotemporal dynamic images segmentation. This proposed work can be generalized to other modalities and other statistical models. Future work will consider the distribution of heterogeneity within the tumors and more reliable sampling methods.

3. CONCLUSION

In this paper, the survey of different segmentation techniques to segment the target tumor volumes from fused PET/CT images is studied. From the papers reviewed it is the clear that the segmentation of Gross Tumor Volumes from the fused PET/CT images is done either by segmenting both PET and CT image simultaneously or by segmenting the PET image first based on its contrast resolution and then mapping it on treatment planning CT images. Authors have used different algorithms to segment the tumor in which each has its own reliability and accuracy. From the survey done, future work will proceed with graph based segmentation using Markov Tree Model since it is more accurate for treatment planning. Accuracy plays a major role in the evaluation of the tumor for medical applications.

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ISSN 2394-3777 (Print)
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