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RESEARCH ARTICLE

Detection of Lung Cancer Tumor Using PET Image

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Abstract- Positron emission tomography (PET) is complimentary to other imaging modalities such as CT and MRI and provides a unique and effective means for detecting tumors in vivo through tissue metabolism measurement. We have developed an image processing method capable of automatically detecting and ranking tumor candidates in the lungs using the whole-body PET images. The intended utility is to visually prompt tumor candidates, assisting the physician to achieve better diagnosis, especially when the candidates appear to be subtle. In this work SWFCM clustering is used to segment the tumor from the lungs. This method is fast in computation and display and thus is suitable for real-time applications using high-end PCs. Our preliminary retrospective study involving nine patients has yielded promising results. We demonstrate that the use of the anatomical priors to restrict the PET data to regions of interest consisting only of lung structures is able to improve the accuracy and reliability of the cluster analysis segmentation of lung tumors in PET images.

Keywords: PET lung image, SWFCM, Super imposed image

I. INTRODUCTION

Medical imaging modalities, such as CT, MRI, and PET, are an integral part of cancer diagnosis [4,12]. They also provide an effective means for assessing cancer treatment efficacy. CT and MRI have already achieved Wide spread clinical use. PET scanners, and more recently integrated PET-CT scanners, are entering hospitals rapidly nationwide. They will become widely available in the near future. Computer image processing technology is critically important, regardless of the modalities; it has been developed mostly for CT and MRI images with various process. Its application to PET images has been considerably less due to relative inaccessibility of the PET equipment. During image acquisition, the PET scanner generates one set of transmission images, one set of uncorrected images, and one set of corrected images that have been corrected to account for attenuation, scattered photons random coincidences, and differing sensitivities of individual imaging planes. Practically speaking, the correction process is not perfect. It can introduce artifacts in the corrected images that look like a tumor. Or, a tumor that is in the uncorrected images can be lost in the correction process and fails to show up in the corrected images. Thus, to achieve the best cancer detection, both the corrected images and the uncorrected images should be inspected by the physician. However, doing so is time consuming and expansive. Consequently, it is a fairly common clinical practice that only the corrected images are read by the physician, which creates a small possibility of misdiagnosis.

The objective of our study is to explore the feasibility of developing an image processing software that can first automatically detect tumor candidates using all the three image sets and then rank them in a clinically sensible way. The clinical utility of the software is to ease the stressful and error-prone work of the image reading of the physician by automatically prompting tumor candidates found by the software so that more accurate cancer diagnosis may be achieved. Due to the wide grey level variation in different portions of the human body in the PET images, it is sensible to develop our method for a certain portion of the body first.

II. ALGORITHM

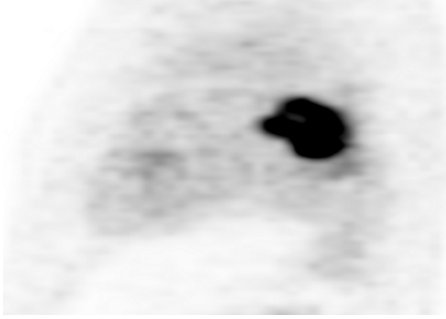
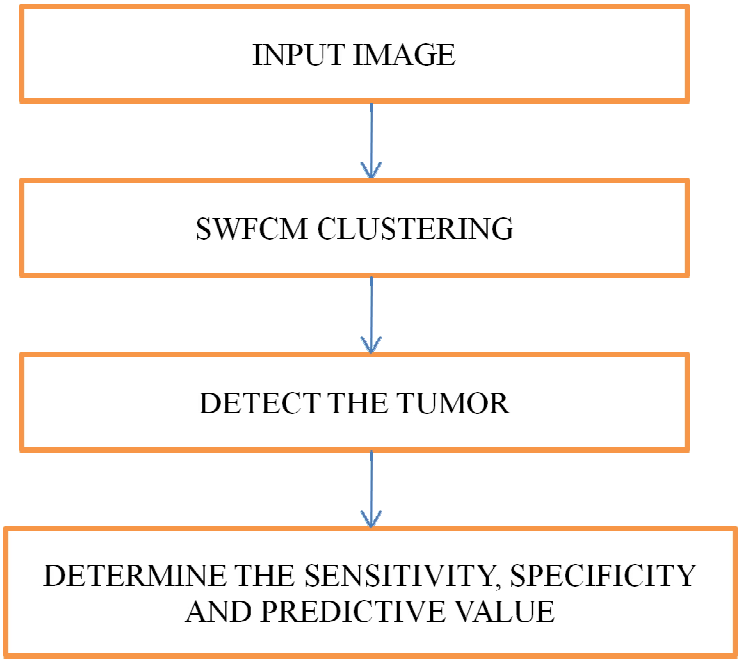


Figure. 1. Shows the input PET RGB Image



III .LUNG CANCER DETECTION USING SPATIALLY WEIGHTED FUZZY C-MEAN ALGORITHM

The standard FCM AkaraSopharak, BunyaritUyyanonvara and Sarah Barman (2009), 'Automatic exudates detection from non-dilated diabetic retinopathy retinal images using fuzzy c-means clustering' does not consider the spatial information of pixels and in turn, the segmentation result is affected. One of the important characteristics of an image is that neighbouring pixels are highly correlated which is considered in spatially weighted fuzzy C-mean (SWFCM) method.

a) Segmentation of Lung Cancer using SWFCM

The SWFCM (V. Ramesh Babu and A.N. Nandakumar (2015))is applied to the PET image. One of the important characteristics of an image is that neighbouring pixels are highly correlated. The spatial relationship is important in clustering, but it is not utilized in a standard FCM algorithm. In SWFCM, to exploit the spatial information, a spatial function is defined as

$$h_{ij} = \sum_{k \in NB(x_j)} u_{ik} \quad (1)$$

where$NB(x_j)$ represents a square window centered on pixel x_j in spatial domain. Larger window size may blur the images and the smaller window size does not remove the noise at high density. Therefore, an optimal window of size 5x5 is used in this work. Just like the membership function, the spatial function h_{ij} represents the probability that the pixels x_j belong to the i^{th}cluster. The spatial function of pixels is large if the majority of its neighbourhood belongs to the same clusters. The spatial function is incorporated into membership function as follows

$$u_{ij}^{'} = \frac{u_{ij}^{p} h_{ij}^{q}}{\sum_{k=1}^{c} u_{kj}^{p} h_{kj}^{q}} \quad (2)$$

Where p and q are the controlling parameters of both functions. The spatial functions simply strengthen the original membership in a homogenous region, but it does not change clustering result. However, this formula reduces the weight of a noisy cluster in noisy pixels by the labels to its neighbouring pixels. As a result, misclassified pixels from noisy region or spurious blobs can easily be corrected. he clustering is a two-pass process at each iteration. The first pass is the same as that in standard FCM to calculate the membership function. In the second pass, the membership information of each pixel is mapped to the spatial domain and the spatial domain function is computed from that. The FCM iteration proceeds with the new membership that is incorporated with spatial function. The iteration is stopped when the maximum difference between two cluster centres at two successive iterations is less than 0.00001. After the convergence, defuzzification is applied to assign each pixel to a specific cluster for which the membership is maximal.

Step 1: Generate the random number with the range from 0 to1 to be the initial memberships. Let us consider the number of cluster is N then calculate V_i using (3)

$$V_i = \frac{\sum_{j=1}^{N} u_{ij}^m x_j}{\sum_{j=1}^{N} u_{ij}^m} \quad (3)$$

Where,
$V_{i=i}^{th}$ cluster center
m = fuzziness parameter m=2

where $u_{ij}$is by using Equation (3)

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\|x_j - v_i\|}{\|x_j - v_k\|}\right)^{2/(m-1)}} \quad (4)$$

Step 2: Map u_{ij} into the pixel position and calculate the modified membership $u_{ij}^{'}$ using (4). Compute objective function J using (5)

$$J = \sum_{j=1}^{N} \sum_{i=1}^{C} u_{ij}^m \, ||x_j - v_i||^2 \quad (5)$$

Step 3: Update the cluster center using (3)

Step 4: Repeat steps 2 to step 4 until the following termination criterion is satisfied:

$$\|J_{new} - J_{old}\| < \varepsilon \quad (6)$$

where
ε=0.00001 which is same as in the FCM method used previously in this work.

Figure 2. Result of SWFCM

The segmented image has three clusters, namely the backgrounds and tumors. From the SWFCM cluster image corner cluster is removed, then from the two cluster it will identify the small cluster size namely tumor.

Figure 3 shows the tumor has detected from the SWFCM output

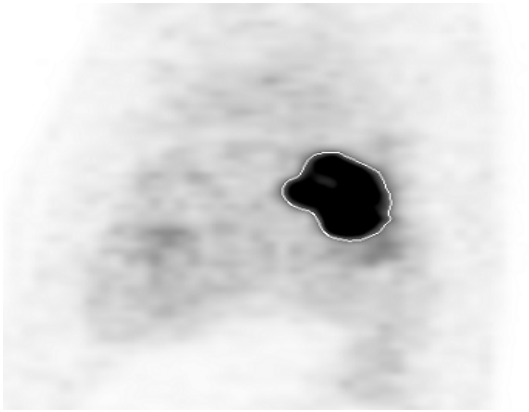


Figure 4 shows the tumor is super imposed with input image

A simple and effective overlap measure of the match between the ground truth region and detected. region(R) by the proposed method is used to measure the accuracy (M) as follows: Kavitha.D and ShenbagaDevi.S (2005).

$$M = \frac{AREA(T \cap R)}{AREA(T \cup R)} \quad (7)$$

The other 2 accuracy measures used are

$$\text{Sensitivity (S)} = \frac{TP}{TP+FN} \quad (8)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (9)$$

Where True positive TP= R n T;
False Positive FP=R - (R n T);
False Negative FN=T - (R n T).

The number of true negatives, i.e. the number of pixels that are not classified as tumor pixels, neither by the grader nor by the algorithm is very high. So the specificity is always near100%. This is not very meaningful. Therefore, alternative is to calculate the Predictive Value as

$$PV = \frac{TP}{TP+FP} \quad (10)$$

PV is the probability that a pixel which has been classified as exudates is really an exudates. Here the specificity, sensitivity and predictive value are 0.8557, 0.9692 and 0.9692.

V. CONCLUSION

This proposed work addresses the image processing techniques to recognize the cancerous nodule from the lung PET images. In this paper, we develop an automatic detection of lung cancer in PET images using spatially weighted FCM clustering technique. The accuracy of the tumor has been calculated and presented.

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