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ANFIS Classifier Based Lung Tumor Severity Diagnosis

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Abstract

Analysis of primary lung tumors and disease in regional lymph nodes is important for lung cancer staging, and an automated system that can detect both types of abnormalities will be helpful for clinical routine. In this paper, we present a new method to automatically detect both tumors and abnormal lymph nodes simultaneously in Computerized tomography(CT) thoracic images. We perform the detection in a multistage approach, by first detecting all potential abnormalities, then differentiate between tumors and lymph nodes. Then lung tumors are classified as benign and maligant using ANFIS by measuring the parameters like Precision, Recall, and Sensitivity.

Keywords

CT, lung tumors, thoracic, ANFIS

I. Introduction

Lung cancer is the most common cause of cancer-related death in men and women, and is responsible for 1.3 million deaths annually, as of 2008 [1]. In particular, non small cell lung cancer (NSCLC) is the most prevalent type of lung cancer, accounting for about 80% of all cases [2]. Staging, which assesses the degree of spread of the cancer from its original source, is the most important factor affecting the prognosis and potential treatment of lung cancer. For NSCLC, the tumor node metastasis (TNM) staging is the internationally agreed system, which involves analysis of the primary lung tumor, regional lymph nodes and distant metastases [2]. The size and spatial extent of Positron emission tomography—computed tomography (PET-CT) with F-fluoro-deoxy-glucose (FDG) tracer is now accepted as the best imaging technique for non-invasive staging [3]. While the CT scan provides anatomical information, it has relatively low soft tissue contrast causing difficulties in separating abnormalities from the surrounding tissues. On the other hand, the PET scan has high contrast and reveals increased metabolism in structures with rapidly growing cancer cells, but their localization is limited by the low spatial resolution in PET images. The integrated PET and CT scan thus provides complementary pathological and anatomical information. In current clinical routine, the localization and characterization of abnormalities need to be performed manually by examining all PET-CT slice pairs. To assist this time-consuming process and potentially provide a second opinion to the reading physicians, an automated system that can provide fast and robust detection is highly desirable. In this work, our objective is to design a fully automatic methodology for simultaneous detection of primary lung tumors and disease in regional lymph nodes from PET-CT thoracic images. The problem exhibits two main challenges. First, although PET indicates areas with high uptake activities, it can also highlight nonpathological areas (e.g., in myocardium), and the standard uptake value (SUV), which is a semi-quantitative measure of normalized radioactivity concentration, normally exhibits high inter-patient variances. Second, separations between lung tumors and abnormal lymph nodes are difficult. Although they may be differentiated by segmenting the lung fields from CT images, if tumors extent to the surrounding organs especially the mediastinum, such segmentations may not be reliable. For complex cases involving tumors invasion into the mediastinum or lymph nodes abutting the lung field, the ability to differentiate between the two types of abnormalities are more challenging.

II. Literature Survey

The need for convenient and reliable growth estimation in the context of lung cancer screening has resulted in the development of a multitude of algorithms for the segmentation of small nodules, an assortment of which will be discussed in the following. It should be noted that the comparison of the performance of algorithms is currently made difficult by the lack of suitable evaluation data that is publicly available. This lack results in the present, unfortunate situation of every publication presenting its own kind of statistics on a private set of data. A standardization of the evaluations and thereby, a fair quantitative comparison of algorithms will eventually become possible when initiatives such as the Lung Image Database Consortium (LIDC) [18] have succeeded in providing a sufficiently large, publicly accessible set of dual-scan data for reproducibility studies, or at least of single scan data comprising some sort of ground truth. Another alternative would be making the methods themselves publicly accessible. The increased availability of open-source software (such as the Image Segmentation and Registration Toolkit (ITK) [19]) is an encouraging movement in that direction. Okada et al. presented an automated method to approximate solid nodules as well as ground glass opacities by ellipsoids using anisotropic Gaussian fitting. The volume of the nodule was estimated by the volume of the ellipsoid. The approach by Kostis et al. [16] was designed for small pulmonary nodules and uses a semi-automatic classification of the target nodule into one of four nodule models, the most important ones representing solitary, vascularized, and juxtapleural nodules. Fetita et al. [23] presented a complete computer-aided detection (CAD) system, which also included the segmentation of detected nodules. This system is also specifically designed for small nodules and also uses initial thresholding followed by morphological methods for segmentation.

III. Proposed System Model

A. Preprocessing

Preprocessing is used to remove the noises from the MRI Brain image. It is also used to convert heterogeneous image in to homogeneous image. Anisotropic diffusion filter is used in lung image preprocessing.

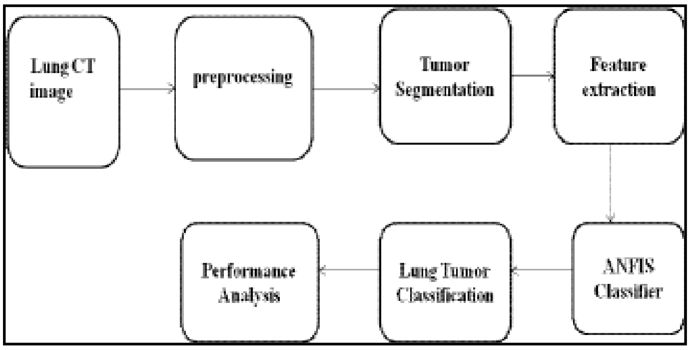

Fig. 1: Lung Tumor Detection System

B. Lung Tumor Segmentation

After enhancing the Lung CT image, the next step of our proposed technique is to segment the Lung tumor region from Lung CT image. Segmentation is done to separate the image in to two or more sub module regions.Segmenting an image also saves the processing time for further operations which has to be applied to the image.We use segmentation using a global threshold in order to segment the tumor region from Lung CT image.

1. Thresholding

Select a global threshold value for the whole CT Lung image. Apply the threshold value to the preprocessed image to convert the image to binary and the thresholded image is obtained.

2. Morphological Closing Operation

Morphological close operation is applied on the thresholded image to fill in holes and small gaps in the image.Reserve the block whose area is the biggest and set the others to zero using 8-connected neighbors.The binary lung mask is obtained using the above step Extract the lung boundary by setting a pixel to 0 if its 4-connected neighbors are all 1's, thus leaving only boundary pixels.Multiply the original Lung CT image with the lung masked image to obtain the final segmented lung region with gray level values as those of original image.

C. Feature Extraction

1. Haralick' texture features

The most commonly used measures of texture, in particular of random texture, are the statistical measures proposed by Haralick. Unlike Laws' texture energy measures, some of Haralick's measures may not be directly related to the intersecting structures, spiculaions, and node-like patterns of architectural distortion, but they may provide useful information regarding the statistical properties of the given ROI or image. Haralick's texture measures are based upon the moments of a joint probability density function (PDF) that is estimated using the joint occurrence or co-occurrence of gray levels, known as the gray-level co-occurrence matrix (GCM), and may be computed for various directions and distances. GCMs were computed with unit pixel distance for the angles of 0 , 45 , 90 , and 135.

2. Local Binary Pattern (LBP)

The local binary pattern (LBP) feature has emerged as a silver lining in the field of texture classification and retrieval. Ojala et al. proposed LBPs , which are converted to a rotational invariant version for texture classification. Various extensions of the LBP, such as LBP variance with global matching, dominant LBPs, completed LBPs, joint distribution of local patterns with Gaussian mixtures, etc., are proposed for rotational invariant texture classification.

The LBP operator on facial expression analysis and recognition is successful. Xi Li et al. pro-posed a multiscale heat-kernel-based face representation as heat kernels is known to perform well in characterizing the topological structural information of face appearance. Furthermore, the LBP descriptor is incorporated into multiscale heat-kernel face representation for the purpose of capturing texture information of the face appearance.

The Lung image is divided into several regions from which the LBP feature distributions are extracted and concatenated into an enhanced feature vector to be used as a image feature descriptor.

3. GLCM features

A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element P (i, j | Δx, Δy) is the relative frequency with which two pixels, separated by a pixel distance (Δx, Δy), occur within a given neighborhood, one with intensity 'i' and the other with intensity 'j'. The matrix element P (i, j | d, ɵ) contains the second order statistical probability values for changes between gray levels 'i' and 'j' at a particular displacement distance d and at a particular angle (ɵ).

Using a large number of intensity levels G implies storing a lot of temporary data, i.e. a G × G matrix for each combination of (Δx, Δy) or (d, ɵ). Due to their large dimensionality, the GLCM's are very sensitive to the size of the texture samples on which they are estimated. Thus, the number of gray levels is often reduced. GLCM matrix formulation can be explained with the example illustrated in fig 2.1 for four different gray levels. Here one pixel offset is used (a reference pixel and its immediate neighbour). If the window is large enough, using a larger offset is possible. The top left cell will be filled with the number of times the combination 0,0 occurs, i.e. how many time within the image area a pixel with grey level 0 (neighbour pixel) falls to the right of another pixel with grey level 0(reference pixel).

4. Discrete Wavelet Transform

A discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over fourier transform is temporal resolution: it captures both frequency and location information (location in time). The DWT transforms or decompose the images in to 4 bands namely LL,LH,HL,HH.

D. ANFIS Classifier

ANFIS uses a hybrid learning algorithm to identify the membership function parameters of single-output, Sugeno type fuzzy inference systems (FIS). A combination of least-squares and back propagation gradient descent methods are used for training FIS membership function parameters to model a given set of input/output data. An Automated classification and detection of tumors in different medical images demands high accuracy since it deals with human life. Different approaches that can produce medical images must be studied. Also, the technique that produces those images is very important in order to know what to apply to a certain medical image in order to get better results. A lot of methods have been proposed in the literature for CT (Computed Tomography), such as scans, different types of X-rays, MRI images and other

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radiological techniques. The problem is that it is not very easy to obtain such results. The idea is to reduce human error as much as possible by assisting physicians and radiologists with some software that could lead to better results. This is important since it involve saving human lives. The automated classification of lung CT by using some prior knowledge like pixel intensity and some anatomical features is proposed. Since currently there are no widely accepted methods, therefore automatic and reliable methods for tumor detection are of great need and interest. The application of neuro fuzzy systems in the classification and detection of data for MR images problems are not fully utilized yet. These include the clustering and classification techniques especially for MR images problems with huge scale of data which consumes time and energy if done manually. Thus, classification or clustering techniques is essential to the developments of neuro fuzzy systems particularly in medical-related problems.

IV. Results and Discussions

To evaluate our method, we first analyze the effects of each component design over the basis techniques, such as the standard LBP and HOG descriptors and sparse-based classifiers. Various settings of the major parameters are also experimented. Furthermore, we compare our proposed method with more standard approaches for both feature extraction and classification, and with the state-of-the-art results reported for the same dataset as well. The performance of tissue classification is measured by recall, precision and F-score

$$\text{precision} = \frac{\text{tp}}{\text{fn} + \text{tp}}$$

$$\text{Recall} = \frac{\text{tp}}{\text{tp} + \text{fp}}$$

$$\text{fscore} = \frac{2\text{tp}}{2\text{tp} + \text{fn} - \text{fp}}$$

Finally, ANFIS classifier has been developed to classify benign and malign. We evaluate the performance of the classifier in terms of sensitivity (also called recall in some fields), specificity and accuracy. The three terms are defined as follows: Sensitivity (true positive fraction) is the probability that a diagnostic test is positive, given that the person has the ischemic stroke disease. Specificity (true negative fraction) is the probability that a diagnostic test is negative, given that the person does not have the disease.

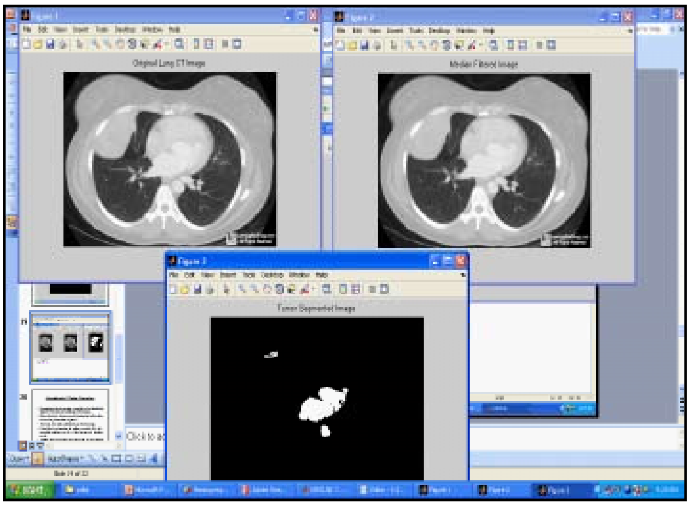

Fig. 2: Simulation Result for Tumor Segmented Image

Table 1: Results of Performance Analysis Using ANFIS Classifier

Performance Evaluation Parameters	ANFIS Classifier
Sensitivity	0.548558
Precision	0.997035
Recall	0.908731
F-Score	0.984175
Accuracy	0.981773

TABLE 2: PERFORMANCE COMPARISION OF ANFIS CLASSIFIER AND PASA ALGORITHM

Performance Evaluation Parameters	ANFIS Classifier	PASA Algorithm
Precision	0.997035	0.807
Recall	0.908731	0.876
F-Score	0.984175	0.84

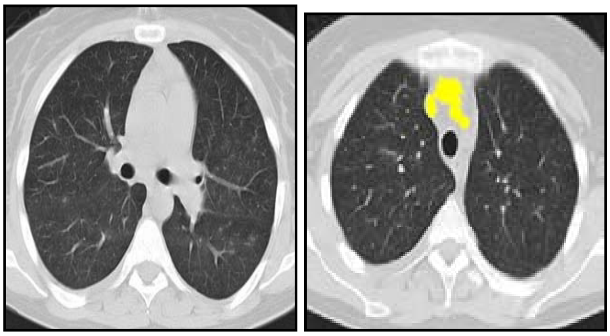

Fig. 3: Normal and Proposed Lung Image

V. Conclusion and Future Work

The lung tumor diagnosis is an important criteria in medical field. In this project, we detect and segment the tumor area from the lung CT image. The segmented lung tumor can be diagnosed using ANFIS classifier. Then the lung tumor are classified as benign or malignant. The performance analysis is carried out in terms of sensitivity, specificity, positive predictive value, negative predictive value and Accuracy. The average accuracy achieved is 98% for tumor region in accordance with ground truth images.

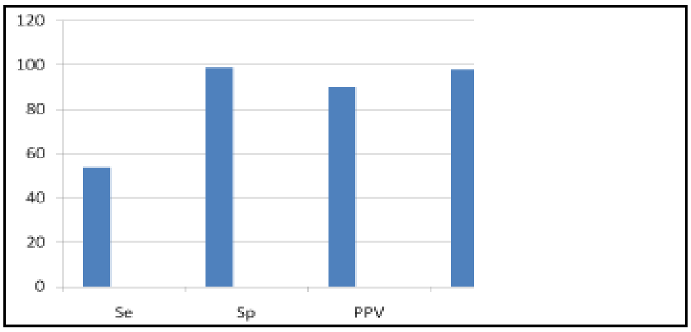

Fig. 4: Performance Analysis (ANFIS)

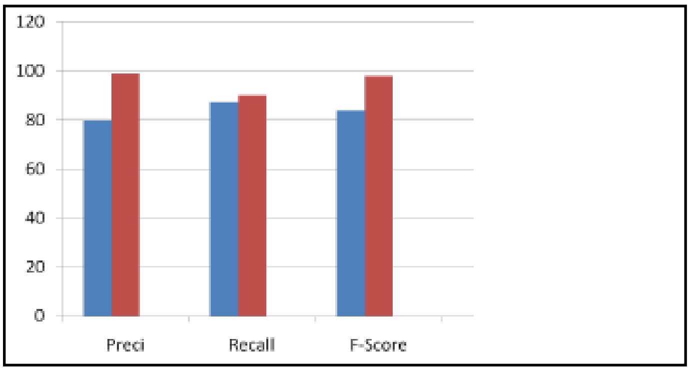

Fig. 5: Performance Comparison.

Even though the accuracy and precision is high in ANFIS system, the sensitivity value for tumor detection in lung image is low. To increase such sensitivity value in higher. To overcome such drawbacks, we propose genetic algorithm based ANFIS classifier for the detection of lung tumors.

VI. Acknowledgement

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