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ANFIS Based Lung Tissue Classification on CT Scan Images

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Abstract:
Analysis of primary lung tumors and disease 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 project, present a new method to automatically detect both normal and abnormal tumor, simultaneously in Computerized Tomography(CT) thoracic images and perform the detection in a multistage approach, by first detecting all potential abnormalities, then differentiate between normal and abnormal tumor. Then lung tumors are classified as benign and maligant using ANFIS and evaluate the parameters sensitivity, specificity, precision, recall and accuracy. The proposed method achieve results 98% for malignant tumor region in accordance with ground truth images.

***Key words**: Lung tumors, thoracic, detection, tissue classification*

1. 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. In particular, non small cell lung cancer (NSCLC) is the most prevalent type of lung cancer, accounting for about 80% of all cases. 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. The size and spatial extent of Positron emission tomography computed tomography (PET-CT) with fluro deoxy glucose (FDG) tracer is now accepted as the best imaging technique for non-invasive staging. While the CT scan provides anatomical information, it has relatively low abnormalities from the soft tissue contrast causing difficulties in separating the soft cell 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 to 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 non pathological 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. The Interstitial lung disease (ILD) represents a group of more than 150 disorders of the lung parenchyma. Most of these cause progressive scarring of lung tissues and eventually affect breathing. Determining the specific type of disorder is important for treatment, and in conjunction with other methods, such as blood tests and pulmonary function tests, imaging scans are often used for accurate diagnosis. In particular, CT imaging is quickly becoming the standard practice with its high imaging quality. Different ILDs normally exhibit different combinations of tissue patterns on CT images , and differentiating the tissue patterns is critical to identify the actual type of ILD. However, interpreting the CT images for lung diseases is challenging even for trained radiologists. Patients also have different physical conditions and medical histories, hence even those with the same type of ILD could display quite different tissue patterns. As a consequence, manual interpretation of the images could be error prone, especially when the radiologists are under heavy workload with short time frames. It is thus suggested that an automatic system for differentiating the tissue patterns would be useful to provide initial screening or second opinions..In this study, focus on classification of two categories of lung tissues on benign and malignant which are highly prevalent among the main types of ILDs.

It can be seen that while in general there are perceivable differences between the different categories, the visual distinctions between different categories are sometimes subtle, and the pattern variations within the same tissue category are rather obvious. Therefore, it is quite challenging to design a robust method for automatic classification, accommodating both low inter-class distinctions and high intra-class variations.

1.1. Related Work

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) 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) 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.* 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 juxta pleural nodules. Fetita presented a complete computer-aided detection (CAD) system, which also included the segmentation of detected nodules. This system is also specifically designed for initial thresholding followed by morphological methods for segmentation. It is also quite effective in handling intra-class variations, with classification based on reference samples rather than learned parametric models.

2. Methodology

In this work, propose a new image classification method for lung tissue patterns, based on an fis classifier. 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.

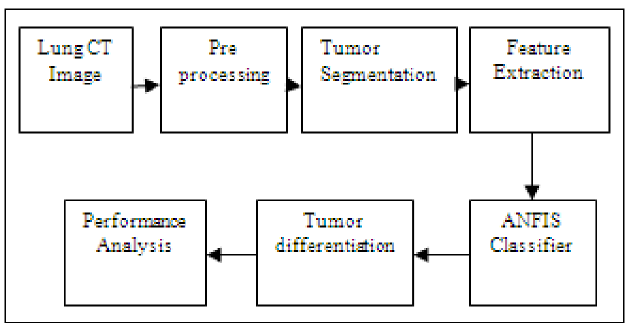

Figure 1: Lung diagnosis system

2.1. Preprocessing

Preprocessing of CT Lung image is the first step in our proposed technique. Preprocessing of an image is done to reduce the noise and to enhance the image for further processing. The purpose of these steps is basically to improve the image and the image quality to get more surety and ease in segmenting the Lung Region alone.

1) Median Filter: In Image processing, it is often desirable to be able to perform some kind of noise reduction on an image or signal. The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical pre-processing step to improve the results of later processing for example, edge detection on an image. Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise.

The main idea of the median filter is to run through the signal entry by entry, replacing each entry with the median of neighboring entries. The pattern of neighbors is called the "window", which slides, entry by entry, over the entire signal.

$$f(x, y) = median[f(x, y) \qquad (1)$$

For 1D signal, the most obvious window is just the first few preceding and following entries, whereas for 2D (or higher-dimensional) signals such as images, more complex window patterns are possible (such as "box" or "cross" patterns). Note that if the window has an odd number of entries, then the median is simple to define. It is just the middle value after all the entries in the window are sorted numerically.

For an even number of entries, there is more than one possible median.

2.2. Segmentation

After enhancing the Lung CT image, the next step of 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. Segmentation using a global threshold in order to segment the tumor region from Lung CT image. Segmentation is local thresholding, global thresholding. Threshold using averaging Gradient Detector, region Growing Split & Merging. *1)Thresholding:* Thresholding is one of the most important approaches to image segmentation. In this method, pixels that are alike in grayscale or some other feature) are grouped together. An image histogram is used to determine the best setting for the thresholds. Some images such as scanned text will tend o be bimodal and a single threshold is suitable. Other images may have multiple modes and multiple thresholds may be helpful. In general multilevel thresholding is less reliable than single level thresholding. Mostly because it is very difficult to determine thresholds that adequately separate objects of interest. In practice, global threshold can be expected to be successful highly controlled environments such as industrial inspection applications, where illumination control is feasible. Note that uniform illumination is required for this method to work, or at least some sort of compensation for non-uniform illumination. Usually a successful segmentation is highly dependent on the choice of thresholds. There are many methods for automatic determination of these thresholds. Morphological processing is constructed with operations on sets of pixels. Binary morphology uses only set membership and is indifferent to the value, Identification, analysis, and description of the structure of the smallest unit of word. Theory and technique for the analysis and processing of geometric structures. Based on set theory, lattice theory, topology, and random functions. Extract image components useful in the representation and description of region shape such as boundaries, skeletons, and convex hull Input in the form of images, output in the form of attributes extracted from those image. Dilation and erosion are basic morphological processing operations. They are defined in terms of more elementary set operations, but are employed as the basic elements of many algorithms. Both dilation and erosion are produced by the interaction of a set called a structuring element with a set of pixels of interest in the image. The structuring element has both a shape and an origin. Let A be a set of pixels and let B be a structuring element. Let B be the reflection of B about its origin and followed by a shift by Opening smoothes the contours of an object, breaks narrow isthmuses, and eliminates thin protrusions.

3. Features Extraction

Features, characteristics of the objects of interest, if selected carefully are representative of the maximum relevant information that the image has to offer for a complete characterization an image. Feature extraction methodologies analyze objects and images to extract the most prominent features that are representative of the various classes of objects. Features are used as inputs to classifiers that assign them to the class that they represent. In this Work Gray Level Co-Occurrence Matrix (GLCM) and Local Binary Pattern (LBP) features are extracted.

3.1. GLCM Features

GLCM is a statistical method that considers the spatial relationship of pixels is the Gray-Level Co-occurrence Matrix (GLCM), also known as the gray-level spatial dependence matrix. By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but you can specify other spatial relationships between the two pixels. Each element (I, J) in the resultant GLCM is simply the sum of the number of times that the pixel with value I occurred in the specified spatial relationship to a pixel with value J in the input image.

A co-occurrence matrix, also referred to as a co occurrence distribution, is defined over an image to be the distribution of co-occurring values at a given offset or represents the distance and angular spatial relationship over an image sub-region of specific. The GLCM is created from a gray-scale image.

The GLCM is calculates how often a pixel with gray-level (grayscale intensity or Tone) value i occurs either horizontally, vertically, or diagonally to adjacent pixels with the value j. Contrast returns a measure of the intensity contrast between a pixel and its neighbor over the whole image.

$$\sum|i-j|\text{^}2, p(I,j) \qquad (2)$$

Energy returns the sum of squared elements in the GLCM.

$$\sum p|I,j|\text{^}2 \qquad (3)$$

Homogeneity returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Correlation returns a measure of how correlated a pixel is to its neighbor over the whole image.

3.2. 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 in-variant 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 multistage 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

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3.3. ANFIS Classifier

Fuzzy theory provides the basis for Adaptive Neuro Fuzzy Inference Systems (ANFIS) which is a useful tool for classifications of data, static and dynamic process modeling and identification, decision making, classification, and control of processes.

The first kind of ANFIS is designed based on the ability of fuzzy logic to model human perception. These ANFIS elaborates fuzzy rules originates from expert knowledge and they are called fuzzy expert system. Expert knowledge was also used prior to FIS to construct expert systems for simulation purposes. These expert systems were based on Boolean algebra and were not well defined to adapt to regressive intrinsic of underlying process phenomena.
The proposed method ANFIS is a kind of neural network that is based on Takagi–Sugeno fuzzy inference system. Since it integrates both neural networks and fuzzy logic principles, it has potential to capture the benefits of both in a single framework. Its inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions. Hence, ANFIS is considered to be a universal estimator. There are two modes in ANFIS, training mode and classification mode.

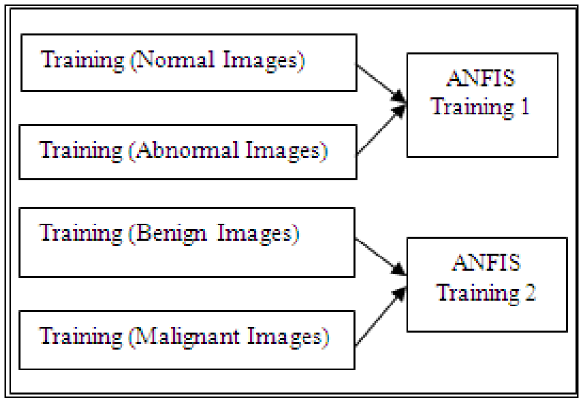


Figure 2: ANFIS in Training Mode

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 .

4. Results and Discussion

4.1. Tumor Classification
First report the classification results using our proposed ANFIS classifier explained earlier that the main difficulties in robust classification of tissue patterns are 1) low inter-class feature distinctions and 2) high intra-class variations. Regarding the first challenge, some tissue categories. In particular, both and appearing quite dark in the overall lung field, the tumor details differentiating these two could be sometimes difficult to perceive even visually. The small increase of tumor in some patches compared to the normal lung also makes them difficult to identify from Tumor. It is also found that if the tumor show relatively high densities, they could look similar to consequently, misclassifications are expected to occur between these two pairs of tissue categories. Regarding the second challenge, within each tissue category, there is normally large degree of feature variations. One common type of variations is the background intensity .For example, the background intensity in and often becomes higher than usual, and can become more difficult to differentiate from the other tissue categories. The more complex types, such as and , contain more irregular local structures and thus exhibit large variations across images of the same category. Especially if considering the patch-level, even the tumor from the same image would display varying visual patterns, with tumor dividing at different places of the image. Such difficulties would thus also affect the classification performances. While the ANFIS classification performs reasonably well.

4.2. Evaluation of Features
To evaluate the feature design, first measure the classification recall and precision based on different parameter settings for computing the feature descriptors GLCM and LBP, for the entire dataset.
The advantage of GLCM and LBP, simple to differentiate benign and malignant.
The lung tumor diagnosis is an important criterion 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 tumors are classified as benign or malignant. Lung tumor identified by GLCM and LBP.
The two benign and malignant images were taken for test.

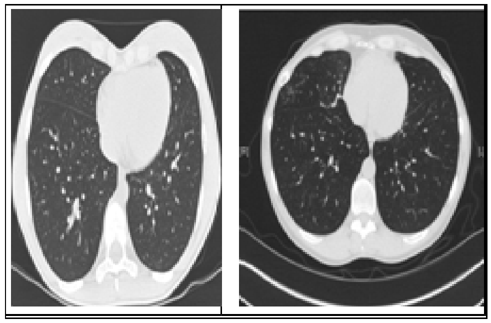


Figure 3: (left) Patient 1benign image; (right) patient 2 benign image.

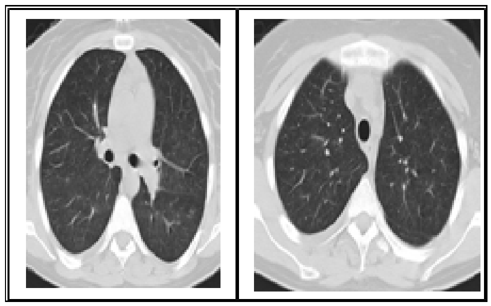


Figure 4: (left) Patient 1malignant image; (right) patient 2 malignant image.

The ground truth image shown below is doctor detected malignant tumor image.

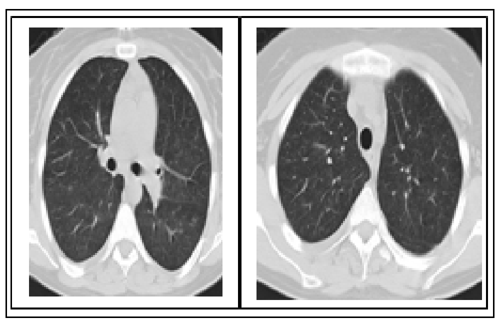


Figure 5: (left) Patient 1ground truth image; (right) patient 2 ground truth image

The proposed method Adaptive Neuro Fuzzy Interference System classifier is identified malignant tumor image shown below accurately than doctor identified

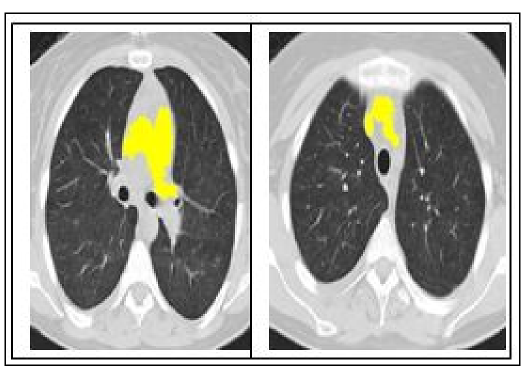


Figure 6: (left) Patient 1 Malignant Image Identified by ANFIS; (right) Patient 2 Malignant Image Identified by ANFIS.

4.3. Performance Analysis

The lung tumor diagnosis is an important criterion 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 tumors 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 malignant tumor region in accordance with ground truth images.

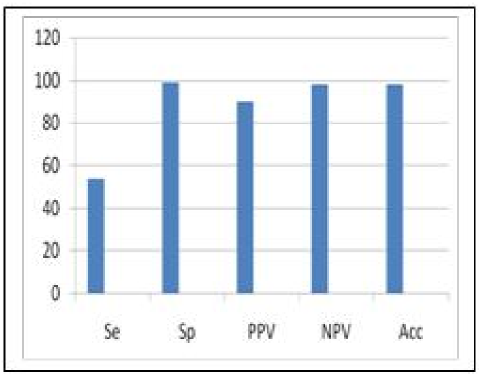
Performance Analysis	Precision	Recall	F-score
ANFIS Classifier	99.7	90.8	98.4

Table 1: Performance Analysis of Anfis

Performance Analysis	Precision	Recall	F-score
ANFIS Classifier	99.7	90.8	98.4
PASA Classifier	80.7	87.6	84

Table 2: Performanc Analysis between Anfis Classifier and PASA

- Table 1 shows sensitivity, precision, recall, accuracy performance of ANFIS is analysed.
- Table 2 shows comparison between ANFIS and
- PASA classifier for the parameters, precision, recall, F-score.



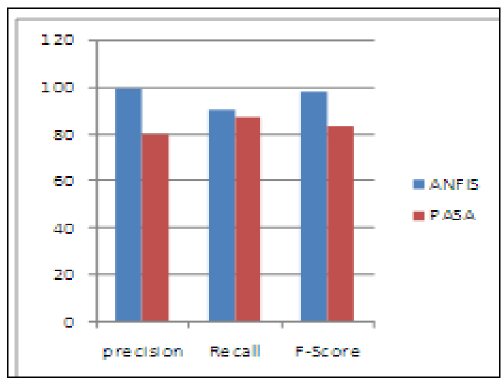


Figure 7: Comparisons of ANFIS Classifier Parameters
Figure 8: Comparisons between ANFIS Classifier and PASA

By comparing with the classification results using RGLBP and MCHOG feature, the advantages of the proposed GLCM and LBP is identify the tumor accurate. The advantage of ANFIS classifier rather than the respective PASA classifier shown in fig.5.The overall results suggest that with GLCM and LBP feature descriptions are more comprehensive and thus very helpful for enhancing the classification performance.
In this paper, from the above results, our proposed method ANFIS achieved better results than PASA method. The average accuracy achieved is 98% for malignant tumor region in accordance with ground truth images.

5. Conclusion and Future Work
An automatic classification method for lung CT images is presented in this paper. Two categories of lung tissues benign and lung tumor that are important for ILD disease diagnosis are the main objects to be differentiated. To tackle the challenges in low inter-class distinctions and high intra-class variations, we have designed an ANFIS classifier based method. First, features are extracted by GLCM and LBP. Then, the image is classified into two categories, using our proposed ANFIS classifier based on reference image. Using a publicly available ILD CT image database, we have conducted extensive experiments to evaluate the overall method design and the proposed features and ANFIS-based classification, and demonstrated promising performance improvements. We also suggest that the proposed method, in its whole or some components, can be easily extensible to other medical imaging domains. In our future work, we will use Genetic algorithm based classifier and achieved better results.

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