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ADAPTIVE DETECTION OF PULMONARY NODULES IN CT IMAGES BY SEGMENTATION AND CLASSIFICATION USING MATLAB

Karthika.K*[1], Sandhya.P[2], T.Thaj Mary Delsy[3]
Final year Student, B.E (EIE), Sathyabama University, Chennai- 600119.
Email: karthikakaruna26@gmail.com

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Abstract

The presence of solitary pulmonary nodules in human lungs in the form of benign or malignant determines the gravity of lung ailment. In this paper, a new method for lung nodule detection, segmentation and classification using computed tomography (CT) images is presented. One of the most common noises in CT imaging is an impulse noise which is caused by unstable voltage. In this paper, a new decision based technique called new adaptive median filter is presented which shows better performance than those already being used. The CT slices are initially preprocessed to remove the Gaussian noise by using Gaussian filter. Otsu thresholding is applied to extract the region of Interest (ROI). We have the different classifications about the nodules in the lung. The nodules in the lung have different classifications that is followed by the methods such as segmentation, detection and classification techniques. The nodules are being classified for the treatment processes in the lung named as malignant cell. Previously, the nodule candidate images are being separated into nodules and non-nodules. The feature vectors of the objects are being extracted in the selected blocks. Lastly, the support vector machine (SVM) is applied to separate the extracted feature vectors. The images are now classified into normal or abnormal only after the SVM is being applied which is based on the second order gray level co-occurrence matrix features.

Keywords: CT, SVM, ROI, Gaussian filter, malignant cell, Otsu thersholding.

I. Introduction

Computer aided diagnosis of lung CT image has been a radical step in the early process diagnosing of lung diseases. The best way of enforcing computer aided diagnosis for medical image analysis is first used to preprocess the image in order and accordingly segment it.

The major part in computer aided diagnosis of lung computed tomography of patient image is to generally segment the region of interest, in the case of lung, and then analyze the area obtained separately, for a tumor, cancer, node detection or other pathology for diagnosis. This is method is much easier approach, because the area used for locating the right diagnosis, is obtained smaller with the process of segmentation, so that the radiologist can particularly focus his observation only on specific data inside the unique region. In this paper we proposed lung segmentation technique to accurately section the lung parenchyma of lung CT images, which can help radiologist in early diagnosing lung diseases, the algorithm referred, can also be used for early diagnosing for other benign or malignant pathologies that occurs in other organs, such as liver, brain or spine.

In this paper, a knowledge-based, fully reflexive method for identifying lung regions in digital CT lung image has been described. The method used an object-oriented knowledge model to appropriately allow the anatomical knowledge and image processing routines in lung detection. Lung cancer considerably varies in size, density, and shape, and can attach to bordered anatomic structures such as chest wall. The lesions poses a challenge in the automatic segmentation. This work communicates a new 2-dimensional algorithm for the segmentation of a wide variety of lung cancer, ranging from tumors found in patients with advanced lung cancer to the small node can observed in lung cancer screening programs.

II. Proposed System

In this proposed method, we are presenting a non-rigid registration-driven robust lung segmentation method in which edge based patient specific adaptive lung models are used that detects lung boundaries, surpassing state-of-the-art performance. This method consists of mainly three stages: 1) lung image preprocessing with hybrid median filter 2) image enhancement of lung using adaptive mean adjustment for contrast stretching 3) Lung image cancer segmentation using active shape model.

1. **New Adaptive Median filter:** The CT image contains impulse noise of voltage of the CT image scanners. This noise can be eliminated using New Adaptive Median Filter. The Hybrid Median filtering is similar to an averaging filter, in which apiece output pixel is set to an average of the pixel values in the neighborhood of the accompanying input pixel. Yet, with median filtering, the value of an output pixel is determined by the median of the contiguous pixels, rather than the mean. The median is much less sensitive than the mean to extreme values (called outliers). New Adaptive Median filtering is therefore better able to remove these outliers without reducing the sharpness of the image.

2. **Image enhancement using Mean Adjustment:** In Image enhancement, the histogram is cut at some threshold and then equalization is applied. Contrast Image enhancement with mean adjustment is an adaptive contrast

histogram equalization method, where the contrast of an image is been raised by applying the algorithm on small data regions called tiles rather than the full image. The resulting neigh-boring tiles are then stitched back seamlessly using bilinear interpolation. The contrastive images in the homogeneous region can be limited so that noise amplification can be avoided.

3. **Heuristic Approach for Lung Nodule Segmentation**:

Heuristic approach is used extensively for lung image segmentation and processing applications, particularly to locate cancer boundaries. Heuristic approach is regarded as promising and vigorously systematic model-based approach to computer assisted medical image analysis.

A Heuristic approach segmentation scheme is presented that is guided by optimal local features, contrary to normalized first order derivative profiles, as in the original formulation. A nonlinear classifier is used, instead of the linear Mahalanobis distance, to find optimal displacements for landmarks. For each of the landmarks that depicts the shape, at each resolution level is taken into account during the segmentation optimization procedure, a distinguishable set of optimal features is decided. The selection of features is automatic, using the training images and forward and backward selection of sequential feature.

The image space is divided into unlike cluster regions with similar intensity image values that involves the process segmentation of imaging data. The most medical images always present imbricates gray-scale intensities for different tissues. Therefore, fuzzy clustering methods are particularly adapted for the segmentation of medical images. There are many FCM clustering applications in the lung segmentation. The Fuzzy c-means (FCM) can be seen as the indistinct version of the k-means algorithm. It is a method of clustering that allows one piece of data to belong to two or more clusters. This method is often used in pattern recognition. The algorithm is an reiterative clustering method that produces an optimal c partition by reducing the weighted within group sum of squared error objective function.

4. Classification using SVM

This project proposes an intelligent classification technique to identify normal and abnormal slices of lung CT data. The visual examination of tumor slices in the manual version is done by radiologist/physician may lead to missing diagnosis when a large number of CTs are analyzed. To avoid the human error, an automated intelligent classification system is suggested which provide the need for classification of image slices after identifying abnormal CT volume, for tumor identification. In this work, advanced classification techniques based on Least Squares Support Vector Machines (LS-SVM) are proposed and applied to CT image slices classification using features derived from slices.

III Block Diagram and Description

The CT images are given as the input and it is first Filtered using the adaptive median filter the median filter is used to remove Gaussian noise and salt and pepper noise.

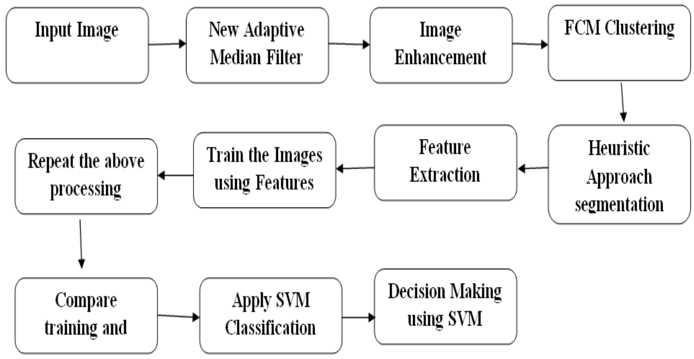


Figure 1. Block diagram.

After the filtration process image enhancement is done it is used to enhance the quality of the image this is followed by the clustering process clustering refers to grouping when grouping is completed heuristic approach is done for the images it is the approach which is used to locate the cancer boundaries as the cancer boundaries are detected from the rest of the image feature extraction is done by grey level co-occurrence matrix and the images are now being trained and compared after which SVM(SUPPORT VECTOR MACHINE) classification is applied and the result is produced using SVM.

IV Results and Discussion

The proposed system was tested on a set of 965 slices taken from 96 CT scans (around 10 slices per CT scan). The number of slices used to form the training dataset are 479 and in which 435 slices were used to test the system. The CT scans were taken from

Table 1. Dataset.

Class Type	Training	Testing	Validation
Normal	130	117	15
Other Slices	118	105	13
PE Slices	126	113	11
PT Slices	105	100	12
Total Slices	479	435	51

Patients who are affected by pleural effusion, pneumothorax, normal lung and by other chest diseases. Table 1 consists the details of total dataset considered. The segmentation process and the ROI extraction are illustrated for pleural effusion, pneumothorax and other slices in figure 2 to figure 17.

The segmentation technique for pleural effusion is first applied to all the slices. The application of the segmentation technique is followed for pneumothorax. Similarly the ROI extraction technique for pleural effusion is first employed to all the segmented lung slices followed by the ROI extraction of pneumothorax. The grayscale CT slices of an input image is and the process is applied shown below

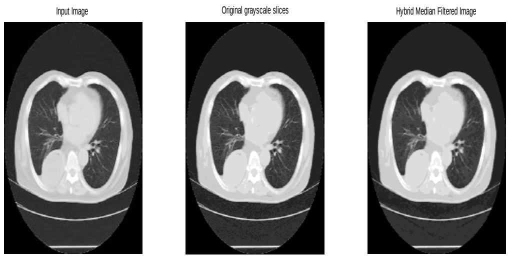


Figure 2. Original gray scale images and hybrid median filter is applied.

Figure 3. Canny edge detection.

Figure 4. Otsu thresholding and segmented lung.

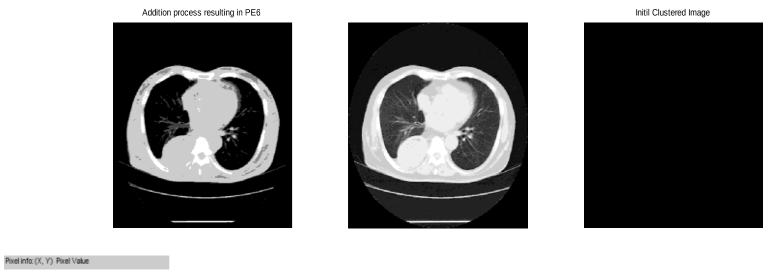
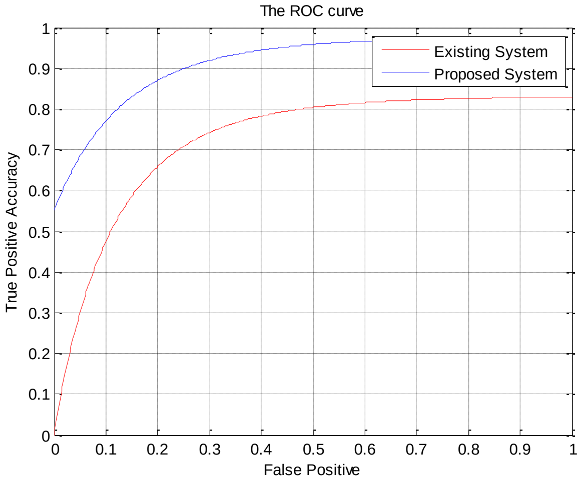


Figure 5. Additional process resulting inPE6.

Figure 6. Final segmented image.



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Corresponding Author:

Karthika.K*,

Email: *karthikakaruna26@gmail.com*