*Available online www.jocpr.com*

**Journal of Chemical and Pharmaceutical Research, 2015, 7(3):2529-2531**

**Research Article**

**ISSN : 0975-7384**
**CODEN(USA) : JCPRC5**

# Characterization of Tomography image for lung cancer identification

**R. Pandian and Lalithakumari S.**

*Department of Electronics and Instrumentation, Sathyabama University, Chennai, Tamilnadu, India*

---

**ABSTRACT**

*In this paper, the characterization of Computer Aided Tomography image is proposed to identify the cancer. Even though, many image processing algorithms were proposed recent years, a simple and novel methodology is proposed in this work. Manual interpretation of the CT image is overcome in this proposed work. Various features are extracted from the CT image of normal lung and malignant lung. Variations in the values are taken into account and the detection is automated.*

**Keywords**: CT image, features, gray level co occurrence, Lung, Classification

---

## INTRODUCTION

One of the most severe health problems is cancer and the death rate due to lung cancer is the maximum among the remaining types of cancer. Lung cancer leads to the least survival rate after the diagnosis, with a gradual raise in the number of deaths every. The chances of successful treatment are higher, if the detection is earlier. The CT images of lungs, provides a low noise, compared to scan image and MRI image.[1] So we can take the CT images for detecting the lungs. Computer tomography image give better clarity, low noise and distortion. But, manual interpretation is not reliable always; hence, automatic interpretation technique overcomes this. Many image processing techniques were adopted to automatically interpret the information. Ginneken [2] implemented a classification algorithm, based on the lung regions extraction approaches. Feature based approached have been used in [3]. Features like uniformity, connectivity, and position features were extracted to identify. In [4], the features such as size, circularity, and mean brightness of region of interests (ROIs) were extracted. Area, thickness, circularity, intensity, variance, localization, and distance from the lung wall are the extracted features in [5]. But, in this proposed work, gray level co occurrence matrix features are extracted and used to identify the cancer affected lung. The paper is structured as follows. The image data base is described in chapter 2. The feature extraction techniques are described in chapter 3. The research work is concluded in chapter 4.

## 2. IMAGE DATA BASE

The Computer tomography of a lung image is considered in this work. Computed tomography scan, is used as a diagnostic medical tool, similar to the traditional x-rays, which gives multiple images or pictures of the internal organs of the human. The cross-sectional images, which obtained after conducting the CT scanning, may be formatted in a different manner in terms of multiple planes, and can thus produce three-dimensional images. These three dimensional images are generally be viewed on a monitor, can be printed further on film saved for future reference. These types of CT scans of internal organs, bones, tissue and blood vessels usually provide more detail compared to digitized l x-rays., especially, the soft tissues and blood vessels information are more accurate, in this scanning. The human lung consists of major soft tissues and blood vessels; it is wise to undergo the CT scanning in order to identify the malfunctioning of it. In this work also, the normal lung images and a cancer affected lung images are taken to characterize the cancer in lung. A sample of normal and cancer affected Ct images are shown in figure 1 and 2.

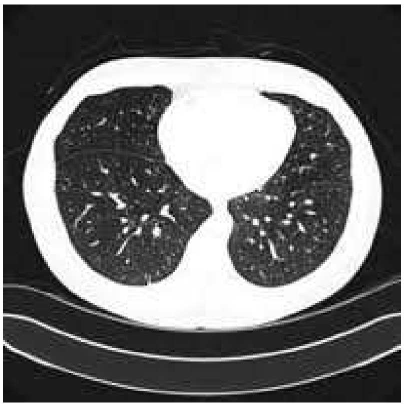

**Figure 1.Normal CT of lung**

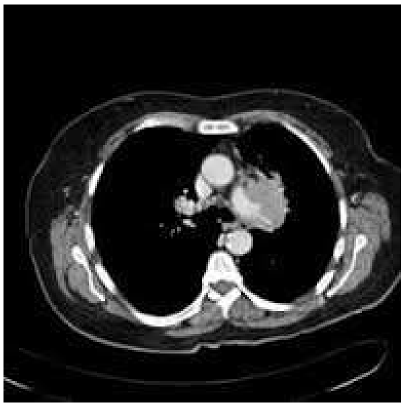

**Figure 1.Cancer affected CT of lung**

**Table 1. Features of the lung images**

| Feature | Normal Image | Cancer Image |
|---|---|---|
| Average or mean value | 32.887 | 102.334 |
| Median | 7.5 | 56 |
| Variance | 3.72E+06 | 7.39E+06 |
| Image Entropy | 0.8967 | 0.0448 |
| Auto Correlation | 37.5389 | 63.459 |
| Contrast | 13.7078 | 0.4721 |
| Correlation | 0.3475 | 1.75E-04 |
| Cluster Prominence | 1.69E+03 | 23.1627 |
| Cluster Shade | 193.8792 | 0.1387 |
| Dissimilarity | 1.9583 | 0.0674 |
| Sum of squares | 44.1928 | 63.4532 |
| Sum average | 11.6428 | 15.9322 |
| Sum variance | 141.8356 | 252.5713 |
| Sum entropy | 0.9879 | 0.0546 |
| Difference variance | 13.7078 | 0.4721 |
| Difference entropy | 0.5927 | 0.0543 |
| Information measure of correlation1 | 0.0941 | 4.83E-07 |
| Information measure of correlation2 | 0.3319 | 1.74E-04 |
| Inverse difference normalized (INN) | 0.8694 | 0.9955 |
| Energy | 0.3698 | 0.9808 |
| Maximum Probability | 0.5489 | 0.9903 |
| Sum of Variance | 44.1928 | 63.4532 |
| Sum of Average | 11.6428 | 15.9322 |
| Entropy | 1.1818 | 0.0613 |
| Homogeneity | 0.7552 | 0.9916 |
| Information Measure of Correlation | 0.3319 | 0.00017357 |
| Inverse Difference Normalization | 0.8694 | 0.9955 |

## 3. FEATURE EXTRACTION

Since, the accuracy of a classification system mainly based on the proper choice of the features, it is necessary to identify a good set of features. In this proposed work, a gray-level co-occurrence matrix (GLCM) is employed, which is a statistical method that utilizes the spatial relationship of pixels. Davis et al [6] initiated the application of gray level co-occurrence matrix (GLCM) in order to find out the features that are to be generated based on a pixel's neighborhood. Davis t al [7]) continued the work of "in such a way of the directional distribution of GLCM features and proposed a set of polarogram statistics which are rotationally invariant. Haralick et al [8] suggested that rotation invariant features could be obtained from co-occurrence matrices by taking the average and range of each feature type over the four angles that is used. The gray-level difference statistics is another texture description method, which is closely related to GLCM, Weszka et al [9]. A co-occurrence matrix, also referred to as co occurrence distribution, is defined over an image to be the distribution of co-occurring values at a given offset. Represents the distance and angular spatial relationship over an image sub-region of specific size. 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.A well-known statistical tool for extracting second-order texture information from images is the grey-level co-occurrence. The GLCM matrix is one of the most popular and effective sources of features in texture analysis. For a region , defined by a user specified window , GLCM is the matrix of those measurements over all grey level pairs .In this method, features are calculated based on the absolute differences between pairs of gray-levels or average gray levels instead of original gray-level pixel values. This approach makes the statistics a little more robust to illumination variations than in the case of GLCM. The gray level co occurrence matrix is extracted from the above mentioned images. The features, extracted from the images are tabulated in table 1.

The deviation in between the two classes clearly indicates that this can be used for identifying the cancer cells. These values are given as inputs to the neural networks for classifying the groups as normal and cancer images.

## CONCLUSION

Gray level Co occurrence matrix based features are extracted in this work, in order to characterize the lung CT images. The difference in between the normal image and cancer image, clearly reveal the ability of this method to classify the normal image from the cancer images. A sophisticated neural network based classifier can be developed in future will lead an automatic classifier for identifying the lung cancer.

## REFERENCES

[1] Disha Sharma, Gagandeep Jindal,Identifying, Lung Cancer Using Image Processing Techniques, **2011**, International Conference on Computational Techniques and Artificial Intelligence .

[2] B.V. Ginneken, B. M. Romeny and M. A. Viergever, Computer-aided diagnosis in chest radiography: a survey, **2001**, IEEE, transactions on medical imaging.

[3] A. El-Baz, A. A. Farag, PH.D., R. Falk, M.D. and R. L. Rocco,M.D,detection, visualization, and identification of lung abnormalities inchest spiral CT scans: phase I,**2002** Information Conference on Biomedical Engineering, Egypt.

[4] K. Kanazawa, Y. Kawata, N. Niki, H. Satoh, H. Ohmatsu, R. Kakinuma, M. Kaneko, N. Moriyama and K. Eguchi, 22(2), **1998**,pp. 157-167. Computer-aided diagnosis for pulmonary nodules based on helicalCT image, Compute. Med. Image Graph.

[5] D. Lin and C. Yan, **2002**-4, Lung nodules identification rules extraction with neural fuzzy network", IEEE, Neural Information Processing.

[6] L Davis, S Johns, J Aggarwal Texture analysis using generalized co-occurrence matrices **1979**,IEEE Transactions on Pattern Analysis and Machine Intelligence

[7] R M Haralick, K Shaunmugam, I Dinstein**,** Textural features for image classification ,**1973** IEEE Transactions on Systems, Man and Cybernetics.

[8] Weszka et al , A comparative study of texture measures for terrain classification,**1996**, SMC 6- 269-285 , IEEE Transactions.