Sindh Univ. Res. Jour. (Sci. Ser.) Vol.49(2) 375-380 (2017)

SINDH UNIVERSITY RESEARCH JOURNAL (SCIENCE SERIES)

Texture Analysis Approach to Quantify and Discriminate Normal and Pathological Human Lung CT- Images

M. S. AHMAD[++], M S. NAWEED*, M. M. WARAICH**, M. NISA***

Computer Science and IT, Govt. Sadiq College Women University Bahawalpur, 63100, Pakistan

Received 22nd August 2016 and Revised 21st March 2017

Abstract: Pulmonary diseases are one of the most attractive area of medical research domain all over the world. Diagnosis of these diseases lack due to subjective interpretation of diagnostic images, even medication has been in effect from decades. Better diagnosis is an essential requirement before prescribing medication. As radiologists learn and differentiate various cases varies among themselves during training and routine practice. The main objective of this research work is to provide some standard pulmonary diseases diagnostic measures. Normal and pulmonary diseased Lung CT images were collected from BVH Hospital. Haralick texture parameters have been computed on the selected Regions of Interest. B11 is used for discrimination and interpretation of various pulmonary diseases. Results of this research work concludes that texture parameters have high degree of reliability to automatically discriminate similar tissue textures when regions are marked correctly

Keywords: Pulmonary Diseases, Lung CT-Images, Texture Analysis, B11 program

1. INTRODUCTION

Pulmonary diseases are one of the major subject in medical research domain all over the world. Diagnosis of these diseases lacks due to non-standard methods, though medication has been in effect from decades but better diagnosis is an essential requirement before proposing medication for these diseases. One of the major factors involved in this issue is the absence of better diagnostic infrastructure at hospitals (Badnjević, *et al.*, 2015). However, with the advancement of computer technology it seems to be possible to develop and implement machine vision diagnostic system for hospitals and health care centres.

Lung cancer is one of the most common causes of death from malignancy. It is common observation that early detection using diagnostic test promises to reduce mortality from lung cancer (Curran *et al.*, 2000; Lee, *et al.*, 2009; Shukla, *et al.*, 2017; Team, 2011). All normally controlled and lung cancer patients are confirmed by biopsy, or by diagnostic imaging, namely by chest radiography, CT and MRI.

In this research work we decided to work on human lung images to analyse and quantify the normal and pathological lung tissue using texture analysis techniques introduced by Haralick (Haralick, *et al.*, 1973) for aerial images and their applications for human body soft tissue proposed by Lerski et al (Lerski *et al.*, 1993). Later followed by Naweed in his esearch work (Naweed, 1997). They concluded that these techniques are very useful and has potential to characterize micro texture (Dennie *et al.*, 2016). Before starting this experimental work on normal and pulmonary diseased Lung computed tomographic (CT) images were collected from department of Radiology, Bahawal Victoria Hospital (BVH), Pakistan. It is necessary to understand the human lung anatomy and pathology in normal and pathological situations.

We as computer vision students already have not enough knowledge of human lung anatomy and pathology and same for human lung CT-images interpretation. For this purpose we managed regular visits to department of Radiology, BVH, Pakistan and managed meetings with expert in lung CT-images interpretation. As for human lung anatomy and pathology in our experimental work concerned cases we studied it from (Kim *et al.*, 2005; *et al.*, 2003; Webb, *et al.*, 2001). The literature demonstrating these situations is presented in the following sections in their true text form with references.

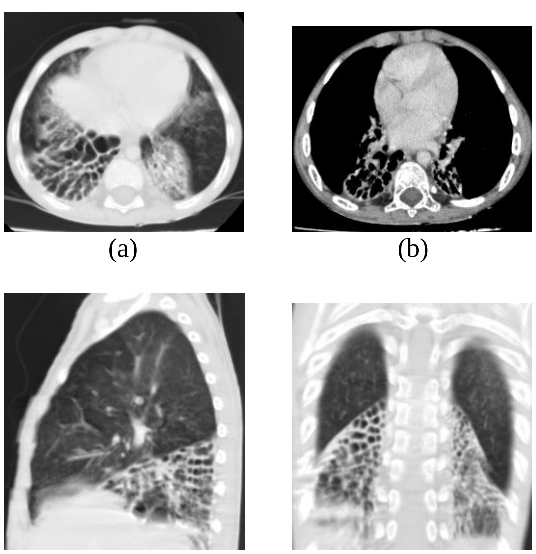
The way radiologists learn to differentiate normal and pathological tissues texture and anatomical structures in different cases is subjective. It is very essential in computer vision approach to know and apply human knowledge in the development of computer vision systems to provide standard diagnostic CT-images interpretation results (Jannette *et al.* 2008).

[++] Correspondence Author: Email: drsaeed@gscwu.edu.pk
*Department of Computer Science, GLIMS Institute, Bahawalpur,
**Head of Radiology (Diagnostics) Deptt. Quid-e-Azam Medical College/BVH, Bahawalpur
*** Department of Physics, GSCWU, Bahawalpur

During the development of subject mentioned system communicating protocols among clinicians and radiologists highlighted by Collins (Jannette and Stern, 2008) have been considered:

1. Air Brochogram Sign
2. Air Crescent Sign
3. Bulging Fissure Sign
4. Continuous diaphragm Sign
5. CT Angiogram Sign
6. Deep Sulcus Sign
7. Fallen lung Sign
8. Flat Waist Sign
9. Finger-in-glove Sign
10. Golden Sign
11. Hallo Sign
12 Hampton Hump Sign
13 Juxtaphrenic Peak Sign
14 Luftsichel Sign
15. Melting Ice Cube Sign
16. Ring around the Artery Sign
17. Silhouette Sign
18. Split Pleura Sign
19. Westermark sign
20. Spine Sign

The following patterns are not always isolated findings on chest radiographs or CT scans et al., 2008). They show combination with other patterns or findings.



(a) (b) (c) (d)

Fig.1 show Honey Comb Sign in three different cross-sections

The more common and useful signs and patterns in X-Ray and CT images of focal and diffuse lung diseases (Collins, 2001) are mentioned below:

- Septal Thickening
- Cystic pattern
- Nodular pattern
- Ground Glass pattern
- Mosaic pattern of lung attenuation
- Tree-in-bud pattern

Lung CT-images included in this research work contains signs labelled by numbers: 1, 2, 3, and 10. In the medical literature, the adverse effect of some of the drugs can cause interstitial lung diseases (Sugiyama, 2001), Individual exposed to fire and smoke inhalation can result in variety of injuries, this can produce direct or indirect pulmonary compromise.

2. TOOLS AND DEFINITIONS

A. Co-Occurrence Matrix and Texture Parameter Computation

In (Haralick et al., 1973) Haralick presented a typical second ordered statistically methods named co-occurrence matrices, to describe the grey tone spatial dependencies. Co-occurrence matrices are a popular representation for the texture in images. The co-occurrence matrix is essentially a two-dimensional histogram of the number of times that pairs of intensity values occur in a given spatial relationship. Thus, it forms a summary of the sub-patterns that could be formed by intensity pairs and the frequency with which they occur (Zucker and Terzopoulos, 1980). In our research work we have constructed co-occurrence matrices from the selected Region of Interest (ROI) of window size 16 x 16 at four angles (0, 45, 90 and 135) and displacement d = 1 then constructed matrices are normalized and their average values are used to compute thirteen Haralick texture parameters (1-13) for each sample and their average values computed for class training step.

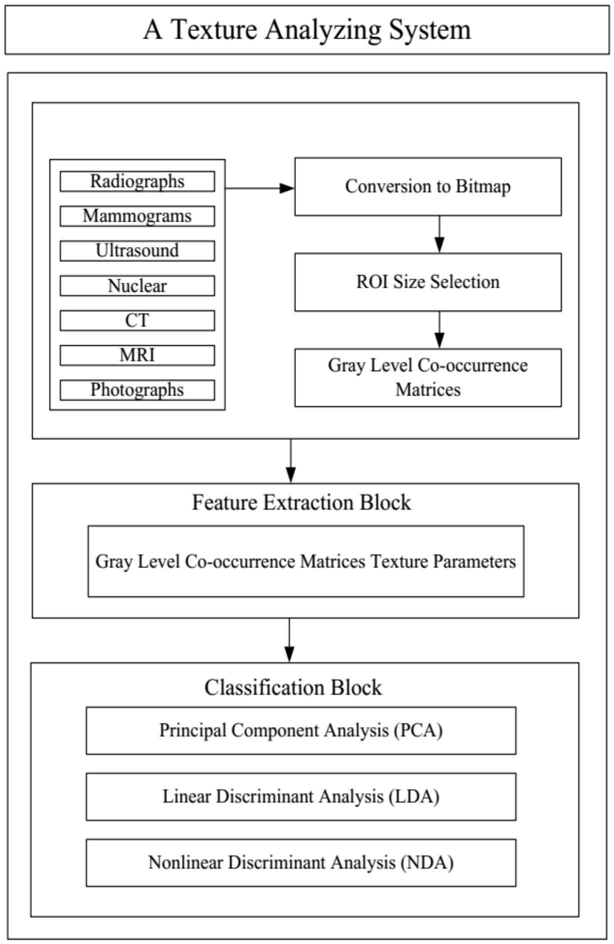
B. Feature Analysis and Classification

B11 is an effective, reliable, and efficient software program for analysis of texture image, feature reduction, and classification. B11 tool for analysis is developed by the COST. Following techniques are implemented in B11 for feature extraction or projection and classification (Hajek, et al., 2006):

- Principal Component Analysis (PCA)
- Linear Discriminant Analysis (LDA)
- Non-Linear Discriminant Analysis
- Nearest Neighbour Classifier (1-NN)
- Artificial Neural Network Classifier (ANN)

B11 also provides visualization of feature distribution of sample data. In this research work we used B11 and the Unscrambler (AS, 2009-2010) for discrimination and interpretation.

C. Texture Analysis System Diagram



3. METHODOLOGY

The research work is performed with the collaboration of BVH Radiology department with CT *and* MRI imaging diagnostic experts as to complete the analysis part of our Texture Analysis System development and also to understand experimental work on the CT-Lung-Images data collected from this department. We have also tested the working of our developed texture analysis system applying on the selected images (Textures for Professionals) having similar texture spread as that of Medical Soft Tissues. Obtaining excellent output in the form of the highest classification results. We followed the same approach here on more than 500 lung CT-images data during experimental work. Images included Steps followed briefly are as under:

(a) Patients data is collected on DVDs
(b) Free downloaded 'DICOM Viewer' is used to retrieve patient's data and then exported to save images in TIF file format, the only option available here in it.
(c) CT-Images are then converted to BMP image file format.
(d) Patient's images are then accessed to compute 13 Haralick texture parameters. These texture parameters can be computed on: 8x8, 16x16, and 32x32 window sized ROIs. It depends on nature of different type of textures. We have opted 16x16 ROI size on CT-Lung images.
(e) We have used 'B11' (Szczypiński, Strzelecki, Materka, *and* Klepaczko, 2009) during Normal *and* Pathological lung-tissue classes training and testing. Final classification task is also performed using the same software.

We have divided lung CT-images into following nine cases to perform research work:

Case 1:
A. Solid Mass and Fluid N. Normal lung
Case 2:
A. Inflammatory mass N. Normal lung
Case 3:
A. Normal Aorta N. Normal lung
Case 4:
A. Mass in Right lung N. Normal lungs
Case 5:
A. Metastasis N. Normal lung
Case 6:
A. Normal spleen N. Normal lung
Case 7:
A. Pleural effusion left-lung N. Normal Lung
Case 8:
A. Pleural effusion Right lung. N. Normal Lung
Case 9:
A1. Pleural effusion, A2. Air pocket, N. Normal Lung

More than 945 samples were taken from the selected data of the clinically verified selected patients for these cases that includes normal lung samples and abnormal lung samples.

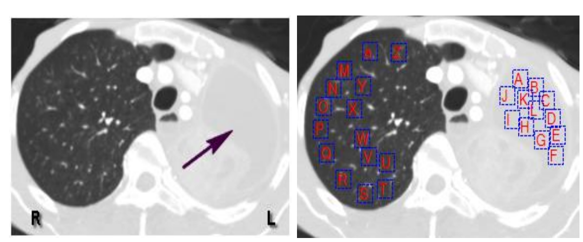


Fig. 2. show how 16 x 16 ROIs are obtained to complete steps d *and* e

Following three figures give graphical display of (a). PCA, (b). LDA, and (c). NDA when applied on data of case no. 9.

1 with dot filed red circle represents Abnormal-1 Samples,

2 with green plus sign represents Normal Samples,
3 blue circle represents Abnormal-2

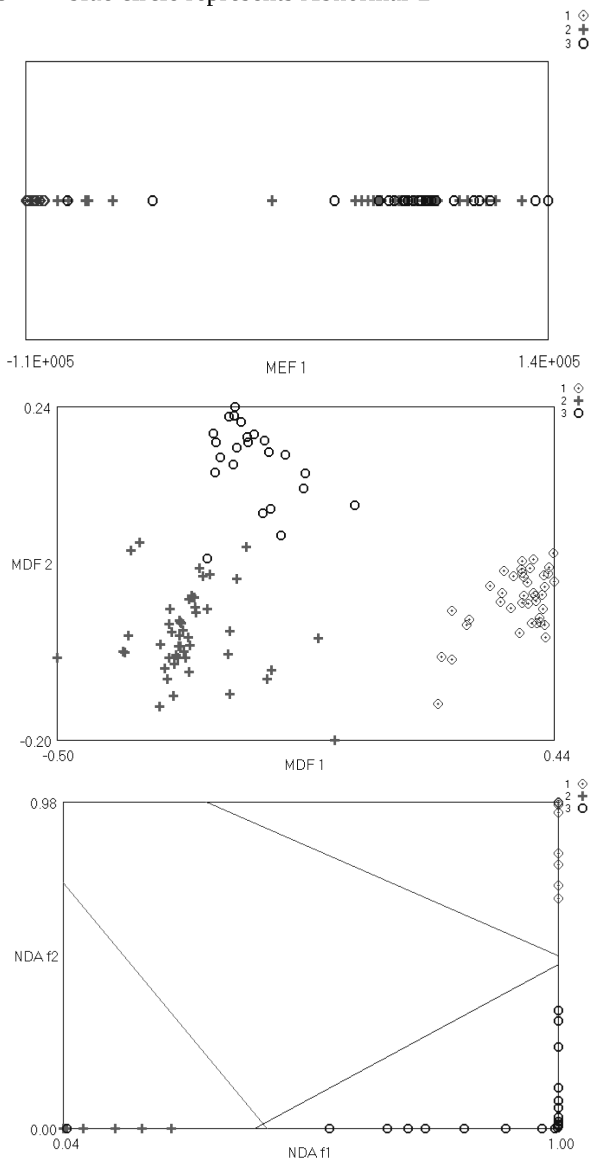


Fig. 3. Show PCA, LDA, and NDA respectively of case 9

4. RESULTS AND DISCUSSION

During this research work several parameters have been computed on the selected region of interests and observed very close correction among obtained results on similar lung tissue textures of normal and various diseased affected selected lung CT-images. That reflects that this method is very successful in similar tissue textures studies. These texture parameters have been used in classification and discrimination of normal and abnormal pulmonary tissue.

The Unscrambler (AS, 2009-2010) and B11 (PCA, LDA, and NDA approaches) are used to test discriminatory strength of the computed texture parameters in the interpretation of medical images during experimental work.

With PCA analysis total 987 lung samples were analysed and 326 predicted true positive, 532 true negative, 47 false positive, and 82 false negative. 372 classified as diseased and 614 normal while in reality 408 samples were diseased affected and 579 were normal.

With LDA analysis total 950 lung samples were analysed and 343 predicted true positive, 545 true negative, 34 false positive, and 28 false negative. 377 classified as diseased and 573 normal while in reality 371 samples were diseased affected and 579 were normal.

With NDA analysis total 946 lung samples were analysed and 350 predicted true positive, 561 true negative, 18 false positive, and 17 false negative. 368 classified as diseased and 578 normal while in reality 367 samples were diseased affected and 579 were normal

Case No	Classification Rate		
	PCA	**LDA**	**NDA**
1	94.78%	90.87%	94.35%
2	78.22%	83.17%	88.12%
3	80%	84.62%	93.85%
4	87.5%	91.67%	91.67%
5	80%	95.38%	100%
6	93.58%	98.17%	100%
7	80.9%	97.75%	100%
8	100%	100%	100%
9	67.86%	99.11%	96.43%

Table: classification performance of PCA, LDA, and NDA on nine cases analysed

Classification performance evaluation of nine cases were analysed during our research work of lung CT-images are as under:

PCA: 100% one 93.58% and above two, 87.5% one, 80% three, 67.86 To 78.22 two.
LDA: 100% One, 90.87 to 99.11 Six, 83.17% to 84.62 Two
NDA: 100% Four 91.67% to 96.43 Four 88.12% One

5. CONCLUSIONS

Highly affective discriminatory information from the lung CT-images using texture analysis methodologies. It particularly incorporated features that are otherwise inaccessible to human observation. Results of this research work concludes that texture parameters have high degree of reliability to automatically discriminate similar tissue textures when regions are marked correctly.

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