

Performance and Analysis of Ground-Glass Pattern Detection in Lung Disease based on High-Resolution Computed Tomography

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Abstract

Background/Aim: The aim of this work is to perform and analyze the Ground glass pattern Detection in Lung Disease based on High Resolution Computed Tomography (HRCT). **Methods:** The algorithm incorporates Gabor filter bank which is based on frequency spectrum analysis of image. Gabor filter banks assist in the frequency extraction process. This method when applied to HRCT images will help doctors to extract more information than from the CT images. This method is accomplished in three steps: Extraction of Preliminary mask formation, Extraction of Peripheral mask formation and finally post processing. By applying these methods, higher sensitivity and selectivity may be attained with fast processing time. In the post processing, binary noise removal technique is applied to remove noise from the detection mask. **Findings:** While interpreting the HRCT images we have to consider the blood being distributed to the dependent portions of the lungs. On the basis of the ground glass opacities, the bleeding site is determined as the area having more attenuation. In homogeneous attenuation, the bleeding site is determined as the upper lobes. Therefore, the bleeding site was thus determined keeping all the abnormalities (mass or clot or lesion) in mind. **Application:** The HRCT has also been used to guide and to provide information regarding an optimum site for open lung surgery. HRCT provides additional useful information to the CXR and directly influence the clinical management of pediatric patients with pulmonary disease, especially in detecting post-infection or post bone marrow transplant sequelae, bronchiectasis and in evaluating patients with nonspecific CXR findings.

Key words: Computed Tomography (CT), Chest Radiograph (CXR), CXR Findings, Discrete Wavelet Transform (DWT), Gabor Filter, Multi-Detector (MDCT), Threshold (T), Post Processing, Preliminary Mask

1. Introduction

High Resolution Computer Tomography (HRCT) is capable of producing anatomic information similar to that obtained from pathologic examination of lung sections. The technique of HRCT was fitted with slow CT scanners, that did not use the Multi-Detector (MDCT) technology. The parameters such as scan duration, z-axis resolution and coverage were dependant on each other. For a chest CT scan to cover the chest in a reasonable time period, it was essential to use 10mm thick sections in order to

ensure continuous coverage. As thin sections would require extended scan time, HRCT examination was therefore implemented with widely spread out sections.

Localization by HRCT was demarcated as ground-glass opacities and/or alveolar amalgamation; the abnormalities were considered to replicate the filling of the alveolar lumen with blood. When the alveolar filling was not present, separate cavitations and/or a mass were taken into consideration to be localizing lesions. Research shows that HRCT is superior to the Chest Radiograph (CXR) for early detection and characteristics of a variety

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of lung disease. Further speaking, the level of the disease contribution is shown more accurately on HRCT thus helping to accurately diagnose the lung disease. Using multislice CT scanner for HRCT method of the chest in children delivers images of high diagnostic quality due to the short period available for imaging.

Ground Glass Nodules (GGNs) are, for example, radiographic appearances of obscure lung opacities not connected with an obscuration of underlying vessels¹. GGNs come in two forms, “pure” and “mixed”. Pure GGNs do not consist of any solid components, whereas mixed GGNs consist of some solid components. GGNs are more clearly shown in High Resolution Computed Tomographic (HRCT) images than plain radiographs. GGNs also appear differently than solid nodules in HRCT images because solid nodules have a higher contrast and well defined boundaries. In addition, the appearance of GGNs in HRCT images is an important result as they indicate the presence of an active and treatable process such as bronchioalveolar carcinomas or invasive adenocarcinoma. Because GGNs are naturally associated with the presence of an active lung disease. Thus, a computer-based segmentation can be of assistance to medical experts for diagnosis and treatment of certain types of lung disease. Accordingly, there is a need for a system and method of computer-based segmentation that can be used to accurately and consistently segment GGNs for quick diagnosis. Furthermore, the extent of the disease involvement is shown more accurately on HRCT thus raising the level of confidence for diagnosis of infiltrative lung disease. The HRCT has also been used to guide and to provide information regarding an optimum site for open lung surgery. HRCT provides additional useful information to the CXR and directly influence the clinical management of pediatric patients with pulmonary disease, especially in detecting post-infection or post bone marrow transplant sequelae, bronchiectasis and in evaluating patients with nonspecific CXR findings. Use of the sub second multislice CT scanner for HRCT of the chest in children provides images of diagnostic quality due to the short imaging time²⁻⁵.

Gabor filters: Gabor filters are very good band-pass filters that can be applied to one-dimensional signals such as speech signals. Gabor filters are employed in image representation, texture segmentation, edge detection, retina identification, image coding and image retrieval in decades⁶⁻¹². This Gabor filters are preferred for medical image processing and for signal processing applications

owing to their sharp cutoffs. So, the noise level is on the decrease as the cutoff of the filter smoothes. Those filters are also linear shift independent and orientation based filters. This can achieve the minimum constraint for concurrent localization in both spatial and frequency domains. A benefit of this kind of filters is that they satisfy the minimum space-bandwidth product according to the uncertainty principle. Hence, they provide concurrent optimal resolution in both of the spatial-frequency and space domains. This filter is a linear type of filter used in digital image processing for edge detection. Its impulse response is the product of a harmonic function and a Gaussian function. As per the Convolution theorem, the Fourier transform of the filter's impulse response is the convolution of the Fourier transform of the harmonic function and that of the Gaussian function.

This type of filters is applied to get parts of the image frequency spectrum:

$$G(x, y) = \frac{1}{2\pi\sigma_x \times \sigma_y} \exp[-1/2(x^2/\sigma_x^2 + y^2/\sigma_y^2) + j2\pi(xU + yV)] \quad (1)$$

Where, σ_x and σ_y are the standard deviations of the Gaussian functions. (U, V) is the centre frequency of this filter. The center frequency of each filter was chosen to relate to a peak in the texture power spectrum and it also determined the filter bandwidths. These filters are directly associated to their wavelets, since they can be modeled for a number of rotations and dilations. The method of extracting the preliminary mask information is shown in Figure 1.

Gabor wavelets cannot be expanded because their calculation involves biorthogonal wavelets which consumes large amount of time. So, we will consider a filter having many scales and rotations. Then, these signals are made to undergo convolution with the respective signals which results in Gabor space. This is similar to the primary visual cortex. When a sinusoidal signal is modulated with a Gaussian then the Gabor filter is obtained. Sinusoidal signals of the corresponding dimensions are modulated with the Gaussian to obtain the needed filter. They find their applications in computer vision, image processing, psychophysics and neuroscience. The function defining the filter is $G(x, y, \theta, \phi)$, where θ is the spatial frequency and ϕ is the orientation.

Gabor filter bank: This filter bank includes all the needed frequencies and orientations. The Gabor functions

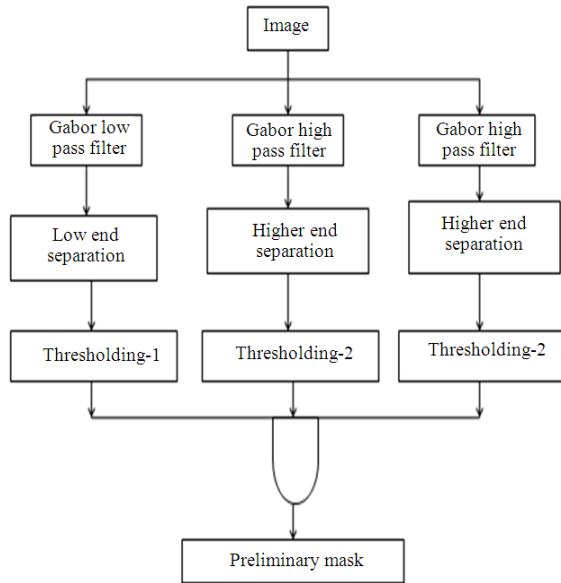


Figure 1. Preliminary mask information.

form a non-orthogonal basic set. The term $G(x,y)$ refers to a modulating Gaussian:

$$G(x,y) = \exp \frac{(-x^2 + \gamma^2 y^2)}{2\sigma^2} \cos[2\pi(x/\lambda) + \phi] \quad (2)$$

$$x' = x \cos\theta + y \sin\theta \quad (3)$$

$$y' = -x \sin\theta + y \cos\theta \quad (4)$$

In the above equations, σ and λ represent variance of the Gaussian function and wavelength of the sinusoidal function respectively. γ represents the spatial aspect ratio and by altering this value, the filter output is changed. We can obtain the outputs as low pass and high pass filter outputs by modifying this spatial aspect ratio. The coordinates are rotated by an angle θ . Information loss can be reduced by applying the knowledge of the interface¹³. The aspect ratio can be changed by the Gaussian envelope of the filters.

Wavelength (λ): The wavelength is the cosine factor of the kernel of the filter. The preferred wavelength of this filter is a valid real number equal to or greater than 2. The phase offset is -90 or 90 . The sampling process is done with zero crossings. The wavelength should be smaller than $1/5^{\text{th}}$ of the image size. Therefore, we can prevent the undesirable effects at the borders of the image.

Phase offset(s) (ϕ): The phase offset ϕ is the argument of the cosine factor of the Gabor function whose unit is degrees. Its permissible values are real numbers and they are between -180 and 180 . The values, 0 , 180 , 90 and 90

correspond to centreon, centreoff and antisymmetric functions. All the others are asymmetric functions.

Aspect ratio (γ): This is called spatial aspect ratio, which refers to the ellipticity of the Gabor function. If $\gamma = 1$, the shape is circular. If $\gamma < 1$ the shape is elongated in alignment of the parallel stripes of the function. Its default value is chosen to be $\gamma = 0.5$.

Bandwidth (b): The bandwidth (b) of a Gabor filter is related to the ratio σ/λ , where σ and λ are the standard deviation and the preferred wavelength, respectively.

Ground glass opacity disease: Ground-glass refers to the HRCT appearance of a obscure opacity that does not obscure the accompanying pulmonary vessels¹⁴⁻¹⁷. This obscure appearance results from the abnormalities in parenchyma. This opacity can be seen with alveolar wall thickening or with partial air-space filling.

Ground glass opacity is a type of frequent finding on CT scans of the lungs. The abnormality that is inside is different; any condition that decreases the air content of the lungs without totally eliminating the alveoli can produce ground glass opacity. These processes are not visible on CT scans. However, in precise clinical settings, the data provided by the CT is acceptable when the structural distribution changes are analyzed.

The ground glass opacity is regarded by a slight increase in lung density, with insistent perceptibility of the bronchial walls and vascular structures. If the vessels are concealed, then this kind of pulmonary opacity, which is in the form of a patch was re-evaluated. This kind of opacity is found in patients with pulmonary infiltrative diseases, which is very significant. In particular, it refers to some diseases such as sarcoidosis and idiopathic pulmonary fibrosis.

Ground glass opacity is detected when the thickening of the alveolar walls minimal. The level of increased lung opacity is not sufficient to obscure pulmonary vessels, as would be the case in true consolidation. This kind of opacity is reversible with proper therapy, if it is treated early, because none of the changes in the lungs are permanent. Some of the processes include pulmonary edema;

This kind of Ground glass opacity can be seen as a result of increased capillary blood in the distribution of blood flow. Although it is a non precise finding, it propounds a precise diagnosis in certain clinical conditions or indicate a possibly treatable disease. Therefore, correct detection and diagnosis of the ground glass opacity are very important. The presently available lung disease recognition algorithms are all based on statistical learning.

Significance of ground glass opacity: In sarcoidosis and fibrosing alveoliis, the appearance of ground glass opacity associates with disease activity, as shown by biopsy or bronchioalveolar lavage or gallium lungs scans. These areas with ground-glass opacities have been revealed to relate to regions of active alveolitis and honey-combing. The ground-glass opacity can also be related with receiving steroids. CT Scans, therefore, ought to be used to assist biopsies in the areas of ground-glass opacity.

Anatomic distribution of ground glass opacity: An early air-space accumulation indicates that there is a centilobular distribution which occurs due to the bronchial dissemination of the blood. The centilobular ground-glass opacity is also manifested as Hypersensitivity pneumonid and desquarmative interstitial pneumonitis. The nodular opacities in diameter from a millimeter to a centimeter are termed as air-space in the CT scans.

When the ground-glass opacity is distributed pan lobularly indicates a diseased secondary pulmonary lobule. If they are diseases, then the boundaries between normal and abnormal areas will be indistinct. If the ground-glass is a large area then the diagnosis may be excluded because the diseases normally progress to accumulation. This may result in liquid pneumonia, pneumocystis carinii pneumonia, alveolar proteinosis, dug toxicity and sarcoidosis. Sometimes, ground-glass opacity is also manifested as hemorrhages.

1.1 Ground glass detection masking

Preliminary mask formation: In the process of extracting preliminary mask formation, the output from the filters are extracted from the bank of Gabor filter. Low pass filter uses the local average intensity information alone. In this manner, the lower frequency spectrum is obtained from Gabor filters.

$$G(x, y) = \frac{x + y}{2\pi\sigma} \exp[-1/2((x^2 + y^2)/\sigma^2)] \quad (5)$$

Considering the low pass filter, all the portions cannot be differentiated but as far as high pass filter is concerned, it can filter all the opacity patterns. Gabor filters as already stated they are the band pass filters that can be utilized to separate the frequencies of lower range and higher range. Their appearance is as rectangular pulses and it cannot be filtered because they have a large frequency spectrum sink. In the low pass filter, this problem can be solved by thresholding.

The method of thresholding is imposed to the images of diverse frequencies and it is therefore performed on the images to acquire the preliminary mask, but still the images are not clear, it is filled with some noise. So binary noise removal method is incorporated in the next section to remove the noise completely.

1.2 Steps Involved

Thresholding: Partitioning of images based on intensity values is called thresholding. While performing the thresholding process, separable pixels in an image are represented as “object” pixels if their value is greater than “background” pixels. There are two threshold values one inside and the other outside. If the object pixel is given as “1”, then the background pixel is given as “0”. Finally, based on the pixel label a binary image is created by coloring each pixel as white or black.

Adaptive thresholding: Adaptive thresholding refers to the method where a different threshold is applied for different regions in the image. This may also refer to local or dynamic thresholding. The important factor to be considered in this process is the threshold value. This can be done by simply choosing the mean or median as the threshold. This will not suit to all the cases. In other cases, a threshold can be chosen by creating a histogram of the pixel intensities. Again, this doesn't apply to all the cases and are computationally expensive. Therefore, a simple method that doesn't require any specific knowledge of the image is the iterative method.

An initial Threshold (T) is selected; this can be accomplished indiscriminately or according to any other method preferred. The image is separated into object and background pixels as mentioned above, creating two sets such as:

$$G_1 = \{f(m, n) : f(m, n) > T\} \text{ referring to the object pixels.}$$

$$G_2 = \{f(m, n) : f(m, n) \leq T\} \text{ referring to the background pixels. Where, } f(m, n) \text{ denotes the pixel located in the } m^{\text{th}} \text{ column and } n^{\text{th}} \text{ row.}$$

Each set has its average computed as follows:

$$m_1 = \text{corresponds to the average value of } G_1$$

$$m_2 = \text{corresponds to the average value of } G_2$$

A new threshold value is thus calculated that is the average of m_1 and m_2 :

$$T' = (m_1 + m_2)/2$$

This procedure has to be repeated so that a convergence is achieved. Thus a special one-dimensional case of the

algorithm is exploited to achieve a local minimum which means a different threshold in the beginning can cause a different result at the end.

Categorizing thresholding methods: Thresholding methods can be classified into the following six types based on the information the algorithm manipulates.

Histogram shape-based methods in which the valleys, peaks and curvatures of the smoothed histogram are evaluated. **Clustering-based methods**, where the gray-level samples are grouped into two parts as background pixels and foreground pixels, or alternately are exhibited as a combination of two Entropy –based Gaussians methods resulting in algorithms that use the entropy of the background and foreground regions, which is the cross-entropy between the original and binary image. **Object attributed methods** seek a measure of similar information between the gray-level image and the binary images. The **Spatial methods** use correlation between pixels to identify them. Other methods utilize the threshold value on every pixel to exploit the local image characteristics.

Multiband thresholding: The thresholding process can be applied on Color images also. One approach is to label a distinct threshold for each of the RGB components present in the image and then unite them together with an AND operation. This replicates the way the camera performs and how the data is kept in storage in the computer, but it does not relate to the way that people identify color. Hence, the HSV and CMYK color models are more often used.

In histology, color images are given the value as 2. Color deconvolution can be applied to establish the contributions. By measuring the 3 RGB components of the image, Absorption is defined as per the Beer's Law. This is solved with the help of a computer software solving three linear equations for every pixel of the image. The resultant image is used for image analysis of immunohistochemical stains.

Edge detection: Edge detection is a fundamental tool used in most image processing applications to obtain the needed data from the frames as a predecessor step to the extraction of the features and object segmentation. This process spots the outlines of an object and borders between objects and the original background in the image. An edge-detection filter can also be employed to recover the appearance of blurred video streams.

There are many disadvantages in the traditional statistical approaches for the detection of texture edges. The problem with them is that they do not consider multi-channel of the human vision system. Discrete

Wavelet Transform and Gabor filter are the two band pass filters that resemble the human visual system. Gabor filters are specifically regulated to fragment images with bipartite textures.

One of the important preprocessing steps is Edge Detection. There are many edge detection techniques present including CLAP algorithm based detection, wavelet based detection. Wavelet based detection is found to be the superior method;

The basic operator used for edge-detection is a matrix area gradient operation that decides the level of variance between different pixels available in the image. This operator is calculated by forming a matrix whose centre is the center of the matrix area. If this matrix has a threshold, then the middle pixel is categorized as an edge. Examples of such type of edge detectors are Prewitt, Roberts and Sobel operators. All these algorithms have kernel operators that compute the strength in orthogonal directions. Later, they are combined to give the total value of the edge strength.

Based on the noise features of the image or video, the edge detection results will vary. Prewitt filter, which is a gradient based algorithm is very sensitive to noise. The size of the filter's kernel and the corresponding coefficients are fixed and cannot be changed to any given image. To differentiate between the image contents from visual artifacts, an adaptive edge-detection algorithm is necessary.

1.3 Calculating Accuracy

Sensitivity: Sensitivity of the applied algorithm is calculated by taking into account each separate diseased region characterized by the radiologists as the ground glass pattern.

$$\text{Sensitivity} = \text{FP} / (\text{FP} + \text{LN})$$

Where,

- **Final Positive (FP):** They are the regions identified by the radiologists as well as recognized by Ground-Glass Detection Algorithm.
- **Last positive (LP):** They are the regions recognized by Ground-Glass Detection Algorithm but not identified by the radiologists.
- **Last Negative (LN):** They are the regions identified by the radiologists but not recognized by Ground-Glass Detection Algorithm.
- **Final Negative (FN):** They are the regions neither identified by the radiologists nor recognized by the Ground-Glass Detection Algorithm.

Specificity: The specificity of the algorithm, which is one minus the probability of a slice being labeled as ground glass when there is no ground glass present, can be calculated as follows and values are shown in table.

2. Materials and Methods

In this study ground glass pattern detection of HRCT images is done for better visualization and their analysis. For this we have taken the HRCT images of lungs from Ground glass opacity patients. These are basically RGB images and these are converted to GRAY SCALE images for making further process easy. Then preliminary mask is obtained using Gabor high pass and Gabor low pass filters. Thresholding and Morphological operations such as erosion and dilation are performed to obtain peripheral mask. This peripheral mask contains noise which appears as tiny dots and they are often few pixels wide. For getting accuracy, we are going for post processing technique in which the noise is removed by median filters. This may assist doctors for making decisions for better and quick treatment. The results obtained from the above steps are shown in the following Figures 2–7.

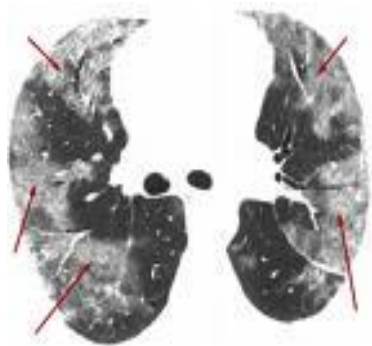


Figure 2. Original image.

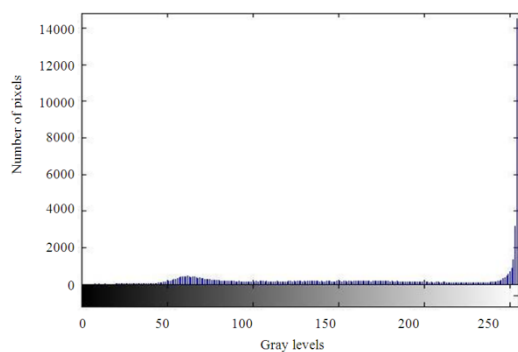


Figure 3. Histogram of original image.



Figure 4. Input image.

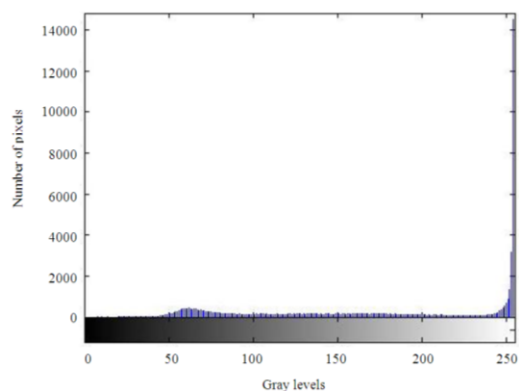


Figure 5. Histogram of input image.



Figure 6. Preliminary mask output.

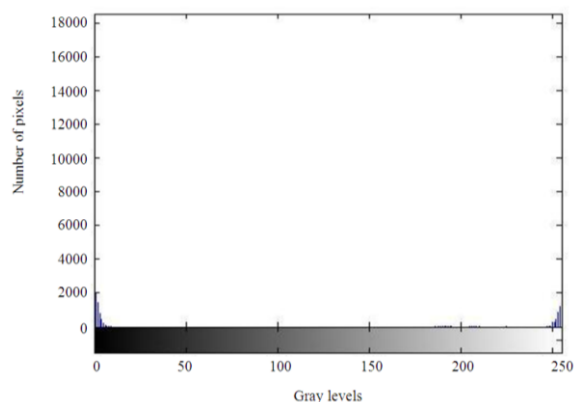


Figure 7. Histogram of preliminary mask

3. Conclusion

By this method of Ground glass detection, the banks of the Gabor filter were designed and the corresponding masks were formed. In this manner, the pattern was identified with the frequency spectrum analysis. This method therefore exhibits high sensitivity and high specificity with very less time consumption.

4. Future Scope

The future work lies in exploring other filter techniques that can be employed to remove the noise. This work can be extended to other diseases like consolidation and reticular emphysema. The sensitivity can also be increased by applying various other methods.

5. References

1. Yamaguchi T, Ashizawa K, Nagaoki K, Hayashi K, High resolution CT evaluation of ground glass opacity in diffuse lung disease. *Acta Med Nagasaki*. 1998; 43(1-2):1–11.
2. You I-G, Lim C-H, Joo Y-C. A study on the of justification of low dose chest computed tomography during health examinations. *Indian Journal of Science and Technology*. 2015; 8(S1):231–5.
3. Rahmat MF, Isa MD, Jusoff K, Hussin TA, Rozali SMd. Image reconstruction algorithm for electrical charge tomography system. *Am J Applied Sci*. 2010; 7(9):1254–63.
4. Noor M, Isa M, Mashor MY, Othman NH, Zamli KZ, et al. Automatic glass-slide capturing system for cervical cancer pre-screening program. *Am Journal Applied Sci*. 2008; 5(5):461–7.
5. Benamrane N, Freville A, Nekkache R. A hybrid fuzzy neural networks for the detection of tumors in medical images. *Am J Applied Sci*. 2005; 2(4):892–6.
6. Murad SAZ, Ismail W. Design of active integrated antenna for dual frequency image rejection. *Am J Applied Sci*. 2006; 3(6):1890–4.
7. Desai SR. High resolution computed tomography of the lung. *CME Radiology*. 2001; 2:126–33.
8. Fukumoto T, Nitta N, Tsudagawa M. Detection of ground glass opacities in lung CT images using Gabor filters and neural networks. *Proceedings of the IEEE Instrumentation and Measurement Technology Conference, IMTC'05; Ottawa, ON*. 2005. p. 251–6.
9. Hoffman EA, Clough AV. The comprehensive imaging based analysis of the lung. *Am. Radiol*. 2004; 11(12): 1370–80.
10. Bennet MA, Sankaranarayanan S, Babu GS. Performance and analysis of effective iris recognition system using independent component analysis. *Journal of Chemical and Pharmaceutical Sciences*. 2015; 8(3):571–6.
11. Bennet MA, Suresh R, Sulaiman SM. Performance and analysis of automated removal of head movement artifacts in EEG using brain computer interface. *Journal of Chemical and Pharmaceutical Research*. 2015; 7(8):291–9.
12. Bennet MA, Raglend J. Performance analysis of filtering schedule using deblocking filter for the reduction of block artifacts from mpeg compressed document images. *Journal of Computer Science*. 2012; 8(9):1447–54.
13. Manjunath BS, Ma WY. Texture features for browsing and retrieval of image data. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 2006; 18(8):837–42.
14. Rizon M, Hashim MF, Saad P, Yaacob S. Face recognition using eigenfaces and neural networks. *Am J Applied Sci*. 2006; 3(6):1872–5.
15. Uppaluri R, Sonka M, Hartley PG, Hunninghake GW, Lennan GM. Computer recognition of regional lung disease patterns. *American Journal of Respiratory Critical Care Medicine*. 1999; 160(2):648–54.
16. Bennet MA, Babu GS, Natarajan S. Reverse room techniques for irreversible data hiding. *Journal of Chemical and Pharmaceutical Sciences*. 2015; 8(3):469–75.
17. Dharmarajan A, Velmurugan T. Lung cancer data analysis by k-means and farthest first clustering algorithms. *Indian Journal of Science and Technology*. 2015; 8(15):1–8.