Unsupervised Segmentation of Medical Images using DCT Coefficients

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Abstract

Image segmentation is a prerequisite process for image content understanding and visual object recognition in medical images for the development of a computer aided diagnosis(CAD) system. An unsupervised segmentation method is proposed which uses discrete cosine transform(DCT) coefficients for extraction of feature vectors and the Fisher Discriminant K-means (FDK) technique for clustering image pixels. In this study, the parenchymal region in HRCT lung images is separated first and then feature vectors using the deviation in local variance in DCT coefficients are determined for each pixels of parenchyma regions. The extracted feature vectors are used for selection of the best feature sets by reducing the dimensionality of the feature vector. The reduced feature vector is used for unsupervised classification using the K-means clustering algorithm which is guided by Fisher linear discriminant parameters for determining number of distinguishable regions in the image.

Keywords: HRCT image segmentation; Discrete Cosine Transform; K-means clustering; Fisher's linear discriminant

1 Introduction

Medical images are used as an important tool for determination of pathological condition of the vital organs of the body like lung, brain, etc. In this study our focus is on lung images. The density of lung tissues are measured as Hounsfield Units(HU) in High Resolution Computed Tomography (HRCT) technique which is directly transformed to pixel values in HRCT images (Chiu & Sowmya 2001). These HRCT image pixels reflect different gray scale variation and textural patterns in the image and able to present the macroscopic appearances of pathological specimens (Hansell 2000).

Segmentation is first step towards automatic processing for analysis and evaluation of medical images. Image segmentation is the technique which partitions an image into units which are homogeneous with respect to one or more characteristics. Texture is one of the important characteristics used in identifying an object or a region of interest(ROI) in an image (Nadler & Smith 1993). Robust segmentation results generally require both the gray scale/color and textural information simultaneously (Manduchi 1999). The statistical image segmentation technique is a feature based classification method which operates on a feature vector field that is result of the application of a vector operator on an input image. A statistical analysis based segmentation can be seen as a two step process - identifying an appropriate feature vector set for mapping the patterns and further obtaining a classifier which can classify pixels of the image, using feature vectors.

Feature extraction is one of the important step of an image segmentation algorithm. Several feature extraction strategies are proposed in the literature. Normally, in signal processing approaches the textured images are submitted to a linear transform, filter or bank of filters, followed by some energy measure. Discrete cosine transform (DCT) is one of the best filters for feature extraction (Feng & Jiang 2003) in the spatial frequency domain. Furthermore, DCT preserves useful properties such as energy compacting, and image data correlation. In this study we use DCT as a filter. The transformed DCT coefficients are further used for calculation of feature vectors. The extracted feature vectors are then submitted to a feature map classifier.

Many clustering procedures have been developed for unsupervised segmentation. The most commonly used algorithms for image segmentation are self organizing maps, K-means, and EM (Expectation Maximization). Different versions of the K-means algorithm have been proposed for processing the feature vectors of textural images. In this study Fisher Discriminant K-means(FDK) clustering technique is used.

The rest of the paper is organized as follows: in Section II we review the application of DCT for image segmentation and classification. DCT based feature computation is described in Section III. In Section IV, Fisher Discriminant K-means(FDK) algorithm is described. Section V describes the segmentation algorithm at length. In Section VI, the experimental results are presented with discussion. The paper is concluded in Section VII with some remarks.

2 RELATED WORK

Several researchers have explored the use of DCT in segmentation and classification of texture patterns. Chaddha et.al (Chaddha, Sharama, Agrawal & Gupta 1994) compared four algorithms for discrimination of textures and concluded that DCT based algorithms were most accurate and the most robust. In (Dokur & Olmez 2002) feature vectors were extracted using 2D-DCT of 4x4 pixel blocks for segmentation of ultrasound images by using a hybrid neural network. Won (Won 1999) has presented an algorithm for segmentation of textures using octave-band multi-resolution features derived from 2x2 DCT coefficients. Several algorithms based on 8x8 DCT coefficients have also been proposed for detection and classification of color and texture in images (Song, Kittler & Petrou 1996).

Reeves et.al (Reeves, Kubik & Osberger 1997) proposed a method for segmentation of texture blocks of aerial images using first eight AC coefficients of 8x8 DCT blocks. Their feature vectors are based on the measure of local variance of the DCT coefficients. Ng et.al (Ng, Tan & Kittler 1992) report on using the local variance of DCT coefficients to segment images. Their method involves generating a 3x3 DCT at each pixel location, using the surrounding points. The local variance of each DCT coefficient is then computed using 15x15 sliding window. The changes in local variance are used to segment the image. They do not use DC coefficient in their segmentation algorithm.

Our algorithm is similar to the recently proposed algorithm for image segmentation by Jie Wei (Wei 2002) using a DCT descriptor for each pixel of the image. An adaptive K-means clustering algorithm is used for assignment of labels to each pixel. The algorithm has produced promising results but has some restrictions.

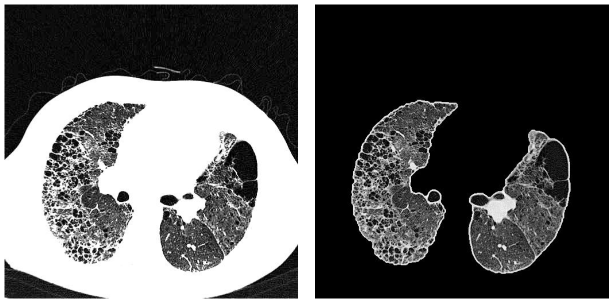
- In the feature set the spatial coordinates of each pixel after multiplication with scalar number are used. This feature set were well in the images which have very clear and well placed blocks of individual textural and gray scale regions. These spatial coordinates in the feature set may confuse the classification method if similar regions are spread over the different locations in the image (Clausi 2002).

- An adaptive K-means clustering algorithm is used for grouping pixels of a similar nature. The K-means algorithm is an efficient and robust technique for segmentation but it requires an explicitly defined value for the number of clusters. Jie Wei (Wei 2002) did some adjustments to get the appropriate number of clusters in the proposed algorithm. In this algorithm clusters of size less than one percent of the number of pixels in the image are removed. This approach may remove small clusters which may have importance in medical applications. Besides, in medical domains it is quite difficult to know apriori the number of classes in an image.

This paper addresses these limitations using the local variance in DCT coefficients as a feature vector and K-means Iterative Fisher binary hierarchical clustering algorithm for segmentation of HRCT lung images.

3 FEATURE EXTRACTION BASED ON DCT

For performing segmentation of an image one needs to calculate features on a pixel by pixel basis. Then these features are used in the pattern recognition algorithm for appropriate classification in order to achieve segmentation. In this section, we explain the methods used for extraction of features for segmentation of HRCT lung images. First we identified the parenchymal lung region. Then we calculated DCT coefficients for each 8x8 block centered on each pixel of parenchymal region. After that, the normalized local variance of each DCT coefficients is computed using a 16x16 sliding window centered on each pixel.



(a) (b)

Figure 1: (a) Original Image (b) Parenchyma Region Image

3.1 Separation of Parenchymal Region

The objective of this preprocessing step is to separate the lung region within the HRCT image from other background and rest of the body region. It is considered that the parenchyma region of lung HRCT images is useful for medical diagnosis and other applications. It is noticed that the parameter representing the density of tissue in terms of Hounsfield Units(HU) is distinct for lung tissues from its surrounding body tissues. Thus, the boundary of lung regions can be detected using binary thresholds on HU, but these HU values are changed in certain diseased lungs. In this study we use the algorithm and software proposed in (Chiu et al. 2001). For detecting the boundary and for segmentation of lung parenchymal region a set of thresholding, filtering and Mathematical Morphology operators are used.

Initially, we created a mask based on the boundary detected using a particular HU value as threshold and subsequently, filter, erosion, and dilation operations are performed for smoothing the boundary regions. The mask created is used with the original image to filter out the non-parenchymal regions of the HRCT images, see Fig.1.

3.2 Positional DCT Calculation

Our feature is based on a measure of the local energy deviation of DCT coefficients. We generate DCT coefficients for 8x8 size block centered at each pixel, in the parenchymal region. The 64 DCT coefficients giving the nature of surrounding gray level and textural energy for each pixel.

The equation used for the DCT calculation for each pixel of parenchymal regions is given as follows:

$$C(u,v) = \alpha(u)\alpha(v)\frac{2}{n}\sum_{y=0}^{n-1}\sum_{x=0}^{n-1} f(x,y)\times$$

$$cos\left(\frac{(2x+1)u\pi}{2n}\right) \times cos\left(\frac{(2y+1)v\pi}{2n}\right)$$

where f(x,y) is the gray scale value at the (x,y) coordinate position in the image, n is the size of window, C(u,v) is DCT domain representation of f(x,y) image. u, v represent vertical and horizontal frequencies. x,y,u,v have values from 0 to 7, n=8 and

$$\alpha(u) = \begin{cases} 1/\sqrt{2} & \text{if } u = 0 \\ 1 & \text{otherwise} \end{cases}$$

The DCT coefficients reflect the compact energy of different frequencies. The first coefficient C(0,0), called DC, is the mean of visual gray scale value of pixels of a block. The AC coefficients of upper left corner of a block represent visual information of lower frequencies, whereas the higher frequency information are gathered at right lower corner of the block. Most of the higher frequency coefficients are small and they become negligible after scalar quantization using the JPEG standard quantization matrix (Wei 2002). To enforce the discriminative impact of the coefficients of different frequencies in texture features, we apply this quantization on DCT coefficients. After quantization, most information required for differentiating the meaningful variations in texture and/or gray scale were found in lower order coefficients. So, we use first 10 low frequency coefficients, say C(0,0), C(0,1), C(1,0), C(2,0), C(1,1), C(0,2), C(0,3), C(1,2), C(2,1), and C(3,0) in our study.

The features derived from the DCT computation is limited to an array of summed spectral energies within a block in frequency domain. There is some textural information in DCT coefficients but more can be derived using some statistical derivatives of the coefficients.

3.3 Normalized Energy in local DCT Coefficients

In our approach we derive additional discriminatory information about textural distribution of the spatial frequency components within regions in frequency domain by calculating local energy coefficients of the DCT of a sub-image. To obtain a feature set containing additional information of textures, the derived local energy is normalized using global standard deviation of respective energy coefficient.
global mean:

$$GM_i = \frac{1}{w \times h} \sum_{u=0}^{w} \sum_{v=0}^{h} C_i(u, v) \quad (1)$$

global standard deviation for each coefficients:

$$GSD_i = \sqrt{\frac{\sum_{u=0}^{w} \sum_{v=0}^{h} (C_i(u, v) - GM_i)^2}{w \times h}} \quad (2)$$

local mean in the window of size NxN is:

$$M_i = \frac{1}{N^2} \sum_{u=0}^{N} \sum_{v=0}^{N} C_i(u, v) \quad (3)$$

local coefficient variance VC_i,

$$VC_i(u, v) = \frac{\sum_{u=0}^{N} \sum_{v=0}^{N} (C_i(u, v) - M_i)^2}{N^2} \quad (4)$$

where, w and h are the number of pixels in horizontal and vertical directions, respectively, in parenchymal region of the image, i = 0 to 9, N = 2n (=16), and the normalized $NVC_i(u, v)$ for each pixel is calculated as follows:

$$NVC_i(u, v) = \frac{VC_i(u, v)}{GSD_i} \quad (5)$$

The relative deviation in local coefficient in the region NxN window is computed for each pixel of the parenchyma region of the HRCT image. In our experiment we use the above calculated relative deviation values of the first 10 lower frequencies DCT of a 8x8 block, which yields a vector of 10 features for each point of the parenchyma region of the image.

4 CLUSTERING THE PIXELS

In this section the extracted features are used for clustering from the point of view of creating segments in the image based on separable gray scale and texture regions. The features obtained at different points in the image are not identical and they can form a cluster in the multi-dimensional feature space. It is believed that if two points in an image are of coherent gray scale and texture, the distance between their corresponding feature vectors should be of small magnitude.

A well known clustering procedure is the adaptive K-means algorithm (Wei 2002, Pappas 1992). This is an appropriate algorithm for clustering data within hyper-spheroidal distribution in clusters. On the other hand, this algorithm is inappropriate for the medical image segmentation problem due to unclear separation and non hyper-spherical nature of clusters of such domain. The clustering problem of such data becomes more complex once the number of clusters in the data is not known beforehand. The algorithm we use here is Fisher Discriminant K-means(FDK) algorithm, similar to recently proposed binary hierarchical K-means Iterative Fisher(KIF) algorithm by Clausi (Clausi 2002).

4.1 Fisher Discriminant K-means (FDK) Clustering

Similar to Clausi's constraints we assume that there is no apriori knowledge about cluster distribution, number of samples belong to each cluster, and actual number of clusters. In this approach fast adaptive K-means clustering is applied to generate clusters followed by iterative Fisher Linear Discriminant (FLD) which improves the classification by obtaining appropriate separable cluster number K using the estimated cluster covariances.

4.1.1 Fast adaptive K-means

The fast adaptive K-means proposed by Darken and Moody (**?**) as an extension of MacQueen's adaptive K-means algorithm is used for generating centroid of K clusters. This is and iterative algorithm. In the first pass the algorithm randomly selects K centres from the data set and those centers are updated until the respective difference in adjacent iterations is not less than the threshold ∂ (<0.0001) or the given number (25) of iterations has been consumed. After each iteration the center value for each cluster is updated according to the following:

$$\Delta K_{closest} = \frac{1}{N_{closest}^{1/2}} (X_i - K_{closest}), \quad (6)$$

where $N_{closest}$ is the total number of data values which have been assigned to the cluster having $K_{closest}$ centroid.

4.1.2 Fisher Linear Discriminant Factor

The adaptive K-means clustering generates two class clusters using minimum Euclidean distance function but the separation of classes is dependent on the distribution of samples. The Euclidean distance assumes the distribution of samples are hyperspherical, whereas it is seldom to satisfy this assumption in real data sets. The approach of Fisher Linear Discriminant (FLD) can generate a more appropriately separated classes using the estimated covariances of each class.

The FDK measures the separation between two projected n-dimensional cluster classes on one dimensional vectors. This provides the optimal separation of two clusters. To find the best direction to maximize the classification accuracy, the FDK criterion written as follows, in terms of within class and between class matrices should be optimized.

$$J(w) = \frac{w^t S_B w}{w^t S_w w} \tag{7}$$

where S_B and S_w are the between and within class scatter matrices. The notation t denotes the transpose operator. These class matrices are defined as follows.

$$S_i = \frac{1}{n_i} \sum_{X \epsilon D_i} (X - m_i)(X - m_i)^t$$

$$S_w = S_1 + S_2$$

$$S_B = (m_1 - m_2)(m_1 - m_2)^t$$

The class scatter matrices (S_i) are weighted by the number of class samples in the FLD criterion equation in order to correct the inequality of class sizes. The solution for the w that optimizes J(.) is

$$w = S_w^{-1}(m_1 - m_2)$$

where m_1 and m_2 are within class means and calculated as follows:

$$m_i = \frac{1}{n_i} \sum_{X \epsilon D_i} X$$

The FLD is a promising non-parametric technique for calculation of class separability and it does not assume any kind of distribution among the class samples (Clausi 2002). Since FLD uses the projection of n-dimensional feature based clusters on one-dimensional vector to determine the separability of classes, only two classes can be compared at a time. Therefore, for comparing the C classes we need to create a matrix based on $\binom{C}{2}$ comparisons.

4.1.3 FDK algorithm

This is a method to determine the correct number of classes in the data set. We use hierarchical divisive Iterative Fisher Discriminant K-means algorithm for getting appropriate number of clusters similar to proposed in (Clausi 2002). Initially entire set of feature vectors are divided into two clusters using adaptive K-means and further Fisher linear discriminant determines the distance between these clusters. If the Fisher distance between clusters are more than explicitly set threshold $\bar{\delta}$ then these

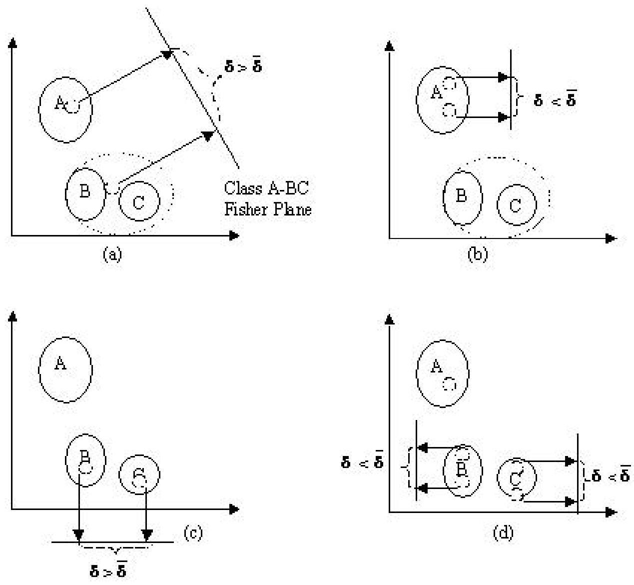


Figure 2: Fisher Discriminant K-means Clustering (a) Initial partitioning of entire feature set into two classes A and BC (b) Splitting of class A into two classes which has low Fisher criterion, so cannot be subdivided into two distinct classes (c) Class BC can be divided into two distinct classes B and c as the generated Fisher criterion δ is greater than the threshold $\bar{\delta}$ (d) Classes B and C cannot subdivided further as the generated Fisher criterion are low and less than threshold $\bar{\delta}$.

clusters are separable set of classes, otherwise they are the part of single cluster.

Furthermore, each separated clusters are divided into two separate clusters using the above mentioned K-means technique and then the separability is tested using Fisher linear test. This process is iteratively performed on each clusters until there is no separable set of clusters is emerging. In this algorithm we need to set the threshold parameter $\bar{\delta}$ which is based on the quality of the feature vectors and the type of imagery being analyzed.

Demonstration of hierarchical FDK clustering in Fig.2. is derived from the paper by Clausi (Clausi 2002). Consider that there are three distinct classes in the features vector set, represented in two dimensional space (Fig.2.). In the beginning two separate classes A and BC from the entire features set are derived using adaptive K-means method. Since BC is a combined class so the Fisher linear discriminant the distance between class A and combined class BC. The Fisher criterion generate projection of these classes which is larger than the assigned threshold value $\bar{\delta}$ and that allow the existence of two classes A and BC distinct. Further, K-means are applied to each separated class in order to split them into two clusters. The splitting of class A produces two clusters whose Fisher criterion are very low and less than the threshold value. Therefore, class A is left as a single class without further division. Whereas, class BC is separated easily due to larger Fisher criterion among the divided parts B and C of class BC. Here, further splitting can be performed on two separated classes B and C. The Fisher criterion for B and C generates low value which is less than the threshold, so they are left as individual classes. The Final set of classes produced by the algorithm is A, B and C.

5 AUTOMATIC SEGMENTATION ALGORITHM

The unsupervised algorithm for segmentation of HRCT lung images which uses features vector based on a measure of the local variation in the DCT coefficients and adaptive clustering alongwith the Fisher linear discriminant is summed up as follows:

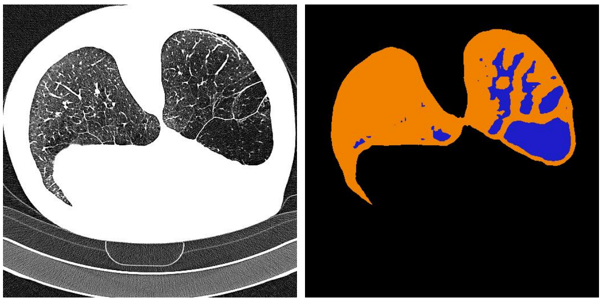
- *Step 1. Parenchyma region separation:* First the lung parenchymal boundary is detected. The detected boundary are used to pick the parenchymal region from the image. Those pixels falling within the boundary are considered the pixels of interest and taken in the resultant image as its original gray scale value and rest pixels are set to zero.
- *Step 2. DCT coefficients calculation:* DCT coefficients for a 8x8 window centered at each pixel of the Parenchymal region is calculated. This method produces a set of 64 DCT coefficients for each pixel. The coefficient values are quantized using JPEG standard scalar quantization matrix. First 10 lower frequency coefficients after quantization are selected for further processing.
- *Step 3. Normalized variance computation:* The global mean value of whole parenchymal region for each 10 coefficients are calculated. The global mean are used for computation of global standard deviation (SD) value. For local mean and variance (VC) a window of 16x16 is used. Local mean and local VC of each 10 DCT coefficients for each pixel of parenchymal region is computed. The local VC of each 10 DCT coefficients is normalized by global SD of corresponding DCT coefficients. For instance, the local VC of DC coefficient of pixel, say p, is normalized by global SD of DC coefficient. The resultant of above computation is packed as a features vector for each pixel of the parenchymal region.
- *Step 4. Adaptive K-means Clustering:* Apply adaptive K-means clustering technique for splitting the given class into two clusters. It implies that the value for number of clusters K is set to 2. Initially the set of entire feature vectors is considered single class. Thus, in the first pass two clusters are generated in the feature vectors set.
- *Step 5. Fisher Criterion:* The Fisher linear discriminant (FLD) based method is adopted in our implementation for arriving the optimal number of clusters. The steps applied are as follows: (i) Fisher criterion δ is computed between two clusters, which are obtained from the split of single class using step 4. (ii) If the value of δ is lower than the threshold $\bar{\delta}$ value then the above split is representing the split of single class and split is ignored. Otherwise, these two clusters are treated as two distinct classes. (iii) If single class is successfully divided into two distinct class based on the test conducted in (ii), each of them are passed to step 4 for further split. (iv) To avoid the infinite loop of the splitting due to poor value of threshold $\bar{\delta}$ we set the a maximum number M of this iterations of step 4 and 5, considering that the maximum number M of clusters can appeared in the data set of the domain. In our experiment we set M=4 and $\bar{\delta}$=6.
- *Step 6. Labelling:* The labelling of clustered regions is an essential step for visual separation of segmented regions. The labelled regions are assumed to be a homogeneous segment in the image and that can be selected for further processing using automatic or semiautomatic method. We use labelling algorithm to label each pixel falling in one class with single color even if they are in spatially isolated regions.

6 EXPERIMENTAL RESULTS AND DISCUSSION

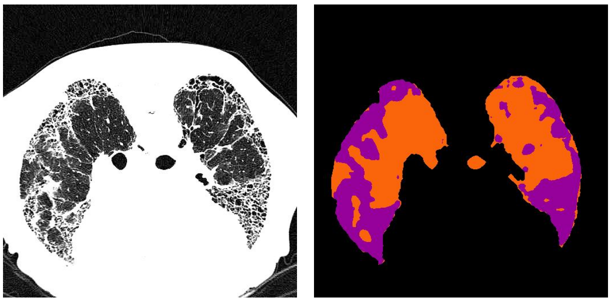
In this section, we apply the proposed segmentation algorithm as described in section V, on HRCT lung images. The HRCT images we use are high resolution gray scale images of 512 by 512 pixels. In our experiment we use 59 labelled lung images collected from 29 patients. Four types of abnormal tissue patterns as well as normal pattern have been labelled in these images by three radiologists. These abnormal patterns are Emphysema, Consolidation, Honey Combing, and Irregular Linear Opacities. Most of the images contains one normal and one abnormal patterns. Few images are containing more than one abnormal patterns. For segmentation of these images, first we separated the parenchymal region from the rest part of the image and then calculated DCT coefficients using 8x8 window. Only first 10 low frequency DCT coefficients after standard quantization are taken for further computation of local variance-based feature vector.

The HRCT lung images are gray scale images. We use gray scale intensity for extraction of the elementary boundary of the parenchymal region. For this we set a threshold of τ=600 which provides satisfactory results in boundary detection. The detected boundary is smoothed using mathematical morphology and filter operators. We use a JPEG standard block size of 8x8 for calculating DCT coefficients. However, we tested other block sizes of 4x4, 12x12, and 16x16 and found that the standard 8x8 block size provides better results. The resultant DCT coefficients for each pixel are used for calculation of the local variance factor in a sliding window of 16x16. We noticed that the smaller window size looses smoothness while a bigger size penalizes small regions and sometimes it increases the shape of the region beyond its actual size. Fig.3 illustrates the results of segmentation of HRCT images having only one type of abnormal patterns. In Fig.4. we presented a set of images having more than one type of abnormal patterns. The illustrated segments are achieved using the FDK clustering algorithm. The feature vector computed using DCT coefficients are used in FDK algorithm for clustering where the threshold is $\bar{\delta}$=6. The threshold $\bar{\delta}$ is sensitive to the feature vector but we use same threshold for all images we segmented in our experiment.

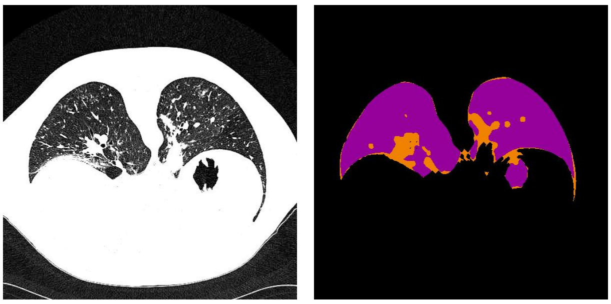
For comparison, we conducted the experiment on the images using the Situational DCT Descriptor(SDD) (Wei 2002) as feature vector. We use the adaptive K-means clustering method for segmentation without any tuning or post processing. For SDD computation we use a block size of 16x16. First 10 low frequency coefficients are used in our feature vector. We use two sets of SDD feature vectors one with location value and other without location value. The results of this algorithm are presented in Fig.4 and Fig.5. The method we have proposed provides clearly better segmentation. Although we have only presented some images, the segmentation of the 59 is of similar quality. These results were evaluated by a radiologist.



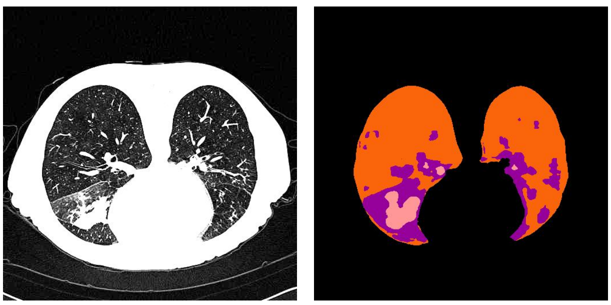
(a) (b)



(c) (d)

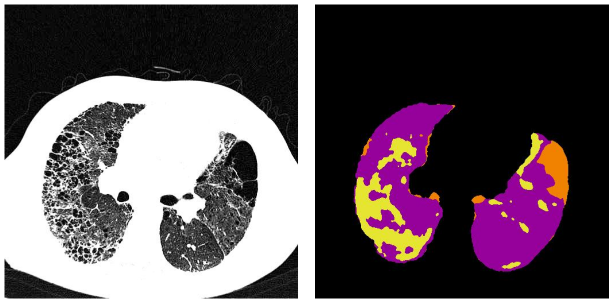


(e) (f)

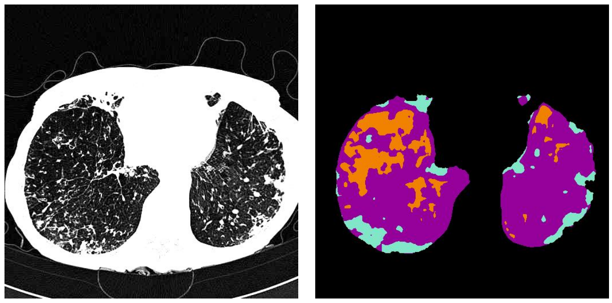


(g) (h)

Figure 3: Original images of (a)Emphysema (c)Honey Combing (e)Irregular Linear Opacities pattern and (g)Consolidation; Segmented image with single patterns right to each original image (b)(d)(f) and (h)

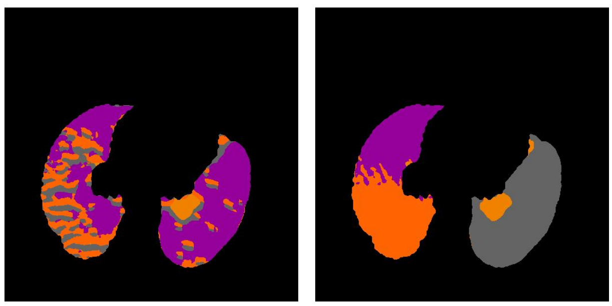


(a) (b)



(c) (d)

Figure 4: Original image having multiple patterns (a)Emphysema and Honey combing pattern (c) Emphysema and consolidation; Segmented images with multiple patterns (b) and (d)



(a) (b)

Figure 5: Segmentation of original image presented in section (a) of Fig.4 using (a)SDD without Location coordinate parameter (b)SDD with location coordinate parameter

7 CONCLUSION

In this paper, we proposed a method for successful segmentation of HRCT lung images. In this work, a feature vector for each pixel of the parenchymal part of the HRCT lung images is computed. The feature based on the local variance of the DCT coefficients appears useful in capturing the gray scale as well as texture characteristics of the image for effective segmentation. This method of feature extraction, however, is computationally intensive and suitable to an off-line segmentation process. Further research could look into the simplification of the feature extraction method.

One important factor in HRCT images is non-availability of apriori knowledge about the number of classes. The appearance of patterns in medical images depends on the pathological conditions of the imagery object. The images subject to the segmentation process may contain several patterns or only one. Under such circumstances we need a robust clustering algorithm which should evolve the appropriate number of present clusters or classes in the sample data. Using adaptive K-means along with iterative class pair-wise the Fisher linear discriminant technique for clustering the image feature vectors appears to be an appropriate unsupervised segmentation solution for images when the number of classes in the sample data is not known.

In this algorithm we need to set the threshold $\bar{\delta}$ that represents the weighted distance between two clusters in the feature space. This parameter has direct relationship with the visual distinctiveness of clusters in the image. Based on our experiment we found a common value of $\bar{\delta} = 6$ was appropriate for fully unsupervised segmentation of HRCT images. However, we should note that this value was derived considering all the images, rather than setting it for some control images and taking the others as test images. But it is important to note that a single value was appropriate for both two and three class images. Whether this is true for images with more than three class remains to be seen. We expect in this domain the identification of three classes is adequate for medical diagnosis.

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