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Novel Approach for Lung Image Segmentation through Enhanced Fuzzy C-Means Algorithm

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Abstract

Image segmentation is a vital part of image processing. Segmentation has its application widespread in the field of medical images in order to diagnose curiousdiseases. Medical image segmentation is an essential step for most consequent image analysis tasks. Accurate segmentation of abnormal and healthy lungs is very crucial for a steadfast computer-aided disease diagnostics. Although the original FCM algorithm yields good results for segmenting noise free images, it fails to segment images corrupted by noise, outliers and other imaging artifact. This paper presents novel image segmentation approaches for segmentation of the multimodal gray scale lung CT scan using enhanced Fuzzy C-Means (FCM) algorithm. The enhanced FCM algorithm is formulated by modifying the distance measurement of the standard FCM algorithm to permit the labeling of a pixel to be influenced by other pixels and to restrain the noise effect during segmentation. Instead of having one term in the objective function, a second term is included, forcing the membership to be as high as possible without a maximum limit constraint of one. Experiments are conducted on images from Interstitial Lung Disease (ILD) database to investigate the performance of the proposed enhanced FCM technique in segmenting the lung images. Standard FCM and enhanced FCM algorithms are compared to explore the accuracy of proposed approaches. The experimental results illustrate that the proposed method is able to segment the various kinds of complex multimodal medical images precisely.

1. Introduction

Pulmonary diseases and disorders affect the human severely and sometimes lead to death. A radiological imaging method like Computed Tomography (CT) is used in hospitals to detect and diagnose the lung disease. It is also helpful to measure the rigorousness of the disease and to intend the treatment or surgical procedure (Mansoor et al., 2014). As a result of the technical developments in imaging methods, computerized investigation becomes automatic and does not require the effort of human. Several decision support modules are frequently aspired by physicians and radiologists to help out the diagnostic processes. As soon as detecting the lung from the chest CT image, the segment with the disease is identified further using classification process to get accurate results. Since the diagnosis of the lung diseases requires a huge range of measurements, a precise and hasty analysis tool which is economical is required. The attainment of such a tool becomes a great challenge. As studied in paper (Armato and Sensakovic, 2004) the precision degree of lung segmentation process can disturb lung nodules recognition by 17%.

The conventional models, like Markov Gibbs Random Fields (MGRF), demonstrate substantial possibilities in segmentation or noise removal process in multimodal images. The process stipulates a joint probability distribution of images and region of interest to approximate a preferred map for a given image. The image pattern commonly depends on the hypothesis of statistically autonomous image signals with dissimilar marginal probability distributions in every region. A region map obtained after the preliminary pixel-wise classification is then distinguished by optimal statistical estimation of a concealed Markov model of regions. Numerous segmentation techniques have been proposed earlier in literature. Some of them are histogram based technique, edge based techniques, region based techniques, hybrid methods which combine both the edge based and region based methods together, and so on [1]. In recent years image segmentation has been extensively applied in medical field for diagnosing the diseases. Cluster investigation is a process of clustering data set into many classes of analogous entities. In clustering methods the k-means process is the eminent and traditional statistical clustering method which controls each map of the data set to k-clusters (Wu and Yang, 2002). Fuzzy C-Means (FCM) is obtained from K-Means which has improved performance than K-Means. The FCM is dynamic and provide accuracy.

In this paper, novel segmentation technique is presented based on FCM algorithm which specifies the essential features of the multimodal chest image. Performance evaluation of the proposed approach is done on Interstitial Lung Disease (ILD) database entailing various degrees and kinds of abnormalities.The remainder of the paper is organized as follows. Section 2 provides an overview on related research works in lung image segmentation. Section 3 illustrates the standard FCM algorithm and latter the proposed enhanced FCM algorithm is presented. In section 4, experimental results are discussed. Section 5 concludes the paper.

2. Related Work

Appearance-based segmentation method employs texture features to extricate between elements which do not have perfect boundaries. In the paper (Mansoor et al., 2014), an extensive range of lung images with disease are segmented in two stages.Primarily, the lung parenchyma was taken from fuzzy connectedness process, and the variances of the rib-cage from the lung parenchyma volumes were investigated to detect the disease. Wang et al., (2009) presented traditional Haralick's texture features to distinguish the normal and abnormal tissues in chest CT scans and analyzed indistinct boundaries for Inter stage Lung Disease (ILD). Initially, the simple thresholding method was employed to segment normal tissues and moderate ILD pathological tissue from the voxel-wise signals. From the developed segments, the severe ILD tissues are detected and merged with the primarily segmented areas. This method produced an average overlap of 96.7% with the conventional manual based segmentation method on a database consisting of 76 CT scans (31 normal and 45 ILD lungs). In paper (Kockelkorn et al., 2014) the authors separated the chest CT scan into several 3D volumes containing voxels of equal intensities and classified each volume as the lung or local environment. Then, the missed voxels were adjusted through either a cooperative process or a slice-wise supervised classification method. Sluimer et al., (2005) utilized15 chest CT images to develop a probabilistic atlas of normal lung regions and registered a lung scan to the atlas with the intention of segmenting the lungs having severe ILD. In Zhou et al., (2014) an atlas-based segmentation model was implemented to segment lungs with tumors. In Nakagomi et al., (2013) employed a graph-cut segmentation technique which as simulated shape and other details of the adjacent lung regions. By conjoining more than one segmentation methods, hybrid segmentation method is attained to get high accuracies. Korfiatis et al., (2008) segmented lung image, with interstitial pneumonia based on the voxel-wise gray levels. Afterwards the original segmentation was sophisticated by classifying the voxels with the help of a support vector machine classifier. Lassen et al., (2010) employed a series of morphological functions to improve the threshold-based segmentation of the pulmonary spaces. Kockelkorn et al., (2010) performed segmentation of the lung CT images with a k-nearest neighbor classifier, trained on existing erstwhile data.

3. Proposed Approach

3.1. Fuzzy-C-Means Clustering Algorithm

Clustering is the method of separating the data into homogenous units by considering the relationship of objects. The clustering method is the allocation of the feature vectors into N clusters. Every n^{th} cluster has Cn as its center. Fuzzy Clustering is employed in numerous areas such as pattern recognition and Fuzzy detection. Among various kinds of fuzzy clustering methods, Fuzzy C-

Means clustering (FCM) is the extensively used one. FCM utilizes reciprocal distance to determine fuzzy weights. The input of this process is a pre-known number of clusters, N. The mean position of every member of the cluster is identified. The output is the segregating of N clusters on a class of objects. The goal of the FCM cluster is to reduce the total weighted Mean Square Error (MSE). The FCM consents each feature vector to match with several clusters of different fuzzy membership values.The final segmentation is based on the optimum weight of the feature vector over all clusters. The steps involved in the FCM algorithm are given below.

Algorithm: FCM

FCM is an iterative algorithm. The aim of FCM is to find cluster centers (centroids) that minimize a dissimilarity function. To accommodate the introduction of fuzzy partitioning, the membership matrix (U) is randomly initialized according to Equation 1.1

$$\sum_{i=1}^{c} u_{ij} = 1, \forall j = 1,..., n \qquad (1.1)$$

The dissimilarity function which is used in FCM is given Equation 1.2

$$J(U, c_1, c_2, ..., c_c) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}{}^{m} d_{ij}{}^{2} \qquad (1.2)$$

u_{ij} is between 0 and 1;
c_i is the centroid of cluster i;
d_{ij} is the Euclidian distance between i^{th}centroid(c_i) and j^{th} data point;
m ϵ [1,∞] is a weighting exponent.

To reach a minimum of dissimilarity function there are two conditions. These are given in Equation 1.3 and Equation 1.4.

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}{}^{m} x_j}{\sum_{j=1}^{n} u_{ij}{}^{m}} \qquad (1.3)$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}}\right)^{2/(m-1)}} \qquad (1.4)$$

Steps:

Step 1.Randomly initialize the membership matrix (U) that has constraints in Equation 1.1.

Step 2.Calculate centroids(c_i) by using Equation 1.3.

Step 3.Compute dissimilarity between centroids and data points using equation 1.2. Stop if its improvement over previous iteration is below a threshold.

Step 4.Compute a new U using Equation 1.4. Go to Step 2.

By iteratively updating the cluster centers and the membership grades for each data point, FCM iteratively moves the cluster centers to the "right" location within a data set. FCM does not ensure that it converges to an optimal solution. Because of cluster centers (centroids) are initialized using U which is randomly generated using Equation 1.3,performance depends on initial centroids.

3.2. Enhanced Fuzzy C-Means Clustering Technique for Image Segmentation

The most important shortcoming of standard FCM algorithm is that the objective function does not think about the spatial dependence therefore it deal with image as the same as separate points. In order to decrease the noise effect during image segmentation, the proposed method incorporates both the local spatial context and the non-local information into the standard FCM cluster algorithm using a novel dissimilarity index in place of the usual distance metric. Therefore a enhanced FCM algorithm is proposed to segment the image in this paper. The non-local means algorithm [15] [16] tries to take advantage of the high degree of redundancy in an image. The membership value decides the segmentation results and hence the membership value is evaluated by the distance measurement denoted as d_{ki}. Therefore the approach enhances the distance measurement parameter which is readily influenced by local and non-local information.

$$d_{ki}\,(x_j,v_i)=(1-\lambda_j)\,d_l^2\,(x_j,v_i)+\lambda_j\,d_{nl}^2\,(x_j,v_i) \qquad (1.5)$$

where d_l stands for the distance measurement influenced by local information, and d_{nl} stands for the distance measurement influenced by non-local information, λ_j with the range from zero to one, is the weighting factor controlling the tradeoff between them. The distance measurement influenced by the local measurement dl is given by,

$$d_{\mathrm{l}}^2(x_j, v_i) = \frac{\sum_{x_k \in N_j} \omega_{\mathrm{l}}(x_k, x_j)\, d^2(x_k, v_i)}{\sum_{x_k \in N_i} \omega_{\mathrm{l}}(x_k, x_j)} \qquad (1.6)$$

Where $d^2\,(x_j,v_i)$ is the Euclidean distance measurement, $\omega_l\,(x_k, x_j)$ is the weight of each pixel in Ni.

The distance measurement influenced by non-local information d_{nl} is computed as a weighted average of all the pixels in the given image I,

$$d_{\mathrm{nl}}^2(x_j, v_i) = \sum_{x_k \in I} \omega_{\mathrm{nl}}(x_k, x_j)\, d^2(x_k, v_i) \qquad (1.7)$$

Enhanced FCM algorithm goes through the following steps,

1. Set the number of clusters ‘c’ and the index of fuzziness ‘m.’ Also initialize the fuzzy clusterCentroid vector ‘v’ randomly and set as ≥0 to a small value,

2. Set the neighborhood size and the window size includes the evaluation of cluster centersand membership matrix,
3. Evaluate the enhanced distance measurement using the equation mentioned as ki d (xj,vi),
4. Update the membership matrix and the distance measurement.

4. Experimental Results and Discussions

Dataset Used

The public database of ILD in the lung is used for evaluating the results of the proposed method experimentally. The considered database consists of 113 image sets of high-resolution CT (HRCT) images of dimension of 512 x512 pixels per slice.

Implementation

By using the dataset mentioned above, the proposed method is evaluated in MATLAB software. Initially, the left and right lungs are segmented from the chest CT scan available in the set, using FCM segmentation process.

The proposed enhanced FCM algorithm is implemented using MATLAB and tested on images from ILD dataset to explore the segmentation accuracy of the proposed approaches. Performance evaluation of standard FCM and enhanced FCMalgorithms is done against various metrics such as Mean Square Error (MSE), the Peak Signal to Noise Ratio (PSNR) and the FP & FN ratios. These parameters are employed to compare image quality. The MSE signifies the cumulative squared error between the output image and the input image. PSNR denotes a measure of the peak error. For small value of MSE, the error is also less. The PSNR gives the peak signal-to-noise ratio (in decibels (dB)) between two images. This ratio is used as a factor for measuring the quality between the input and output image. For large PSNR value, the improved image quality is obtained. Table 1 and 2 shows the performance comparison of these methods.

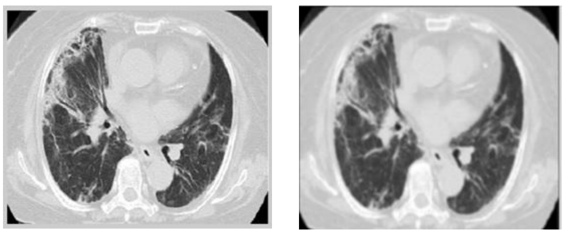

Figure 1&2: Input CT Image and Filtered Image

Figure 3: After Segmentation Using Existing Method (MGRF)

(a) (b) (c)

Figure 4: (a) Actual Image (b) Segmented Image Using Standard FCM (c) Segmented Image Using enhanced FCM

Table 1: Performance Comparison on MSE and PSNR

Parameters	FCM	Enhanced FCM
MSE	0.3664	0.16
PSNR	52.4911	56.0902
Loss percentage	20	8
Accuracy	97	99

Table 2: Performance Comparison on FP and FN Ratios

Approach	Similarity	False Positive Ratio	False Negative Ratio
StandardFCM	86.03	20.15	8.50
Enhanced FCM	89.50	16.50	5.30

The segmentation results of standard FCM and enhanced FCM algorithms are compared against various performance evaluation metrics. The three most important parameters used to determine the accuracy of the proposed algorithm are similarity, false positive (FP) and the false negative(FN) ratios. From Table 2, it is observed that our proposed algorithms performed well ahead of other techniques in segmenting the real medical images. Figure 4 shows the segmentation result of standard FCM and enhanced FCM. The performance evaluation of this approach can be estimated based on sensitivity, specificity andaccuracy

Sensitivity = TP / (TP + FN)

Specificity = TN / (TN + FP)

Accuracy = (TP + TN) / (TP + FP + TN + FN)

The true positives (TPs) identified by this approach was 94 and hence the sensitivity was reported as 76.42% (94/123). The number of false positives (FPs) was 38 and hence the specificity was reported as 78.53 % (139/177). Accuracy was estimated as 77.67% (233/300). The performance of the proposed scheme was evaluated using the following parameters sensitivity, specificity and accuracy. The true positives (TPs) identified by this approach was 102 and hence the sensitivity was reported as 82.93 % (102/123). The number of false positives (FPs) identified was 31 and hence the specificity was reported as 82.48 % (146/177). Accuracy was estimated as 82.67% (248/300). The TPs identified shows that this segmentation method can identify some of the nodules that are greater than or equal to 2mm in size.

The experimental results obtained by employing the FCM and enhanced FCM algorithms revealed that the proposed technique for image segmentation has a better performance over other FCM method. Furthermore, they eliminate the effect of noise greatly. This in turn increased the segmentation accuracy of the proposed image segmentation technique.

5. Conclusion

In computer aided diagnostics of lung image, detection, classification and quantification and segmentation are the vital steps. Existing methods of lung segmentation exploited the difference presenting in the image contrast of the lung area and its adjacent tissues. These methods did not identify the abnormalities in the lung. In general, lung images have some pathologies and abnormalities happened due to experimental environment. EnhancedFCM algorithm is proposed in this paper. In the proposed FCM algorithm, both local and non-local information are incorporated to control the tradeoff between them. The algorithm is formulated by modifying the distance measurement of the standard FCM algorithm to permit the labeling of a pixel to be influenced by other pixels and to restrain the noise effect during segmentation. Experiments were conducted on real medical images to evaluate the performance of the proposed algorithm. The three most important parameters used to determine the accuracy of the proposed algorithm are similarity, false positive and the false negative ratio. The experimental results show that the proposed algorithm performed well than other segmentation algorithms.

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