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Estimation of Objects in Computer Tomography Lung Images Using Supervised Contextual Clustering

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Abstract: Image segmentation plays a vital role in medical imaging applications. Image processing techniques provide a good tool for improving the manual screening of CT samples of lung. Developing a robust and efficient algorithm for medical image segmentation has been a demanding area of growing research of interest during the last two decades. This research reports on Estimation of objects by segmenting Computer Tomography (CT) lung images using supervised contextual clustering method. Matlab Software regionprops function has been used as one of the criteria to show the performance of Contextual Clustering (CC). The CC segmentation shows more segmented objects with least discontinuity within the objects in the CT lung image. The segmented results are compared with the conventional algorithms such as Sobel, Prewitt, Roberts, Log and Zero crossing. The results obtained from the experiments show that the proposed approach is found to be efficient and robust against segmentation faults when compared to the existing methods.

Key words: Contextual clustering, segmentation performance, area, CT lung image, screening, India

INTRODUCTION

Image segmentation is a process of partitioning an image into non-overlapped and consistent regions that are homogeneous in nature with respect to some characteristics like intensity, color, tone or texture (Dong and Xie, 2005). Image segmentation plays an important role in many applications such as robot vision, object recognition, remote sensing and medical imaging. A thorough research has been reported in the literature, regarding the development of various techniques specifically for segmenting the lung fields. Computed Tomography (CT) is the most effectively used diagnostic imaging examination for chest diseases such as lung cancer, tuberculosis, pneumonia and pulmonary emphysema. The lung segmentation plays a crucial role in pulmonary nodule detection by increasing reliability and accuracy mean while decreasing computational cost of detection.

Lung nodules indicate lung abnormalities. Early detection of nodules can help in saving lung patients. Lung nodules can be detected by radiologists through examining lung images. Lung Nodule Detection (LND) in the Computer Tomography (CT) images is still a challenging task. Inspite of lot of mathematical algorithms that have been developed over the period of years and implemented as Automatic LND (ALND) still intervention and suggestions by a good radiologist is a must.

Related work: Lung segmentation must be done accurately because nodules may be on the boundary of the lung parenchyma. If the entire lung is not segmented accurately such lung nodules will be lost and it reduces the detection accuracy. Main goal of lung extraction is to separating the voxels corresponding to lung tissue from the voxels corresponding to the surrounding anatomy.

First hand assessment of lung affected patients for radiologic diagnosis is done by Hansell (2000) by using cross-sectional and projectional imaging techniques such as chest radiography.

CT imaging provides better identification, localization and quantification of small lung nodules (Way *et al*., 2010, Ye *et al*., 2007; Golosio, 2009). Computer Aided Detection (CAD) of lung nodules increases sensitivity and specificity (Yao *et al*., 2011). The performance of CAD is based on its capability in detecting LN (Giger *et al*., 2008). CAD can be used for identifying and diagnosing infectious pulmonary diseases; segmentation and registration of pulmonary anatomical structures, detection and classification using texture and shape analysis for respiratory tract infections (Bagci *et al*., 2012).

Nodules and nodular patterns are seen both in chest radiographs and in CT scans. A single nodule has the appearance of a rounded or irregular opacity which may be well or poorly defined; solid, non-solid or partly solid and of soft tissue or GGO usually with a diameter <3 cm (Hansell *et al*., 2008).

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The existing problem in CT Lung image segmentation is to have continuity inside each segmented objects. Many methods have been used for segmentation of CT lung images. An accurate segmentation procedure called a multi level thresholding was proposed.

Kanazawa *et al*. (1998) proposed an analytical and diagnostic procedure by combining the thresholding and morphology operations to extract the lung regions in CT images. Fuzzy clustering algorithm was used to extract the lung and the pulmonary blood vessel regions.

Zhao *et al*. (1999) used the nodule gradient and sphere occupancy measurements in order to improve the shape-based segmentation scheme. The shape criterion which was included to the algorithm effectively prevents the high density surrounding structures such as blood vessels from being falsely segmented as nodule.

Armato and Sensakovic (2004) identifies the ROI in Computer aided diagnosis of lung nodule detection. 5-17% of the lung nodules was missed in their nodule detection scheme due to the preprocessing segmentation.

Kim *et al*. (2003) developed a novel segmentation method to segment the lung region in CT images by combining the thresholding, region filling and deformable model. The segmented results are further compared with thresholding based method. The difference between true nodules and false nodules can be identified by selecting the discriminating features such as size, solid shape, average, standard deviation and correlation coefficient.

The purpose and the contribution of this study is to propose contextual clustering segmentation that guarantees continuity inside each segmented objects of the CT Lung image.

Difference in the parameters considered in forming the methods including the properties of the training and test datasets, performance evaluation methods and characteristics of the targeted nodule plays dominant role in comparing the performance of Nodule Detection Methods (Lee *et al*., 2012).

The existing methods for LND have used different stages of image processing according to the user requirements. Segmentation detection methods have been discussed by Diciotti *et al*. (2008). Classification detection methods appear in 2007 (Ochs *et al*., 2007). The segmentation-template detection methods appear in 2006 (Ozekes and Camurcu, 2006). The Segmentation-Classification Detection Methods appear in 2007 (Kim *et al*., 2007).

MATERIALS AND METHODS

The primary objective of this research is to develop a computer aided system for segmentation of lung region from the chest Computer Tomography (CT) images. The proposed method does not affects the objects present in the lung image. The main advantage of this approach is that researchers can get the holes and objects present in the original image after segmentation without any change in its size and shape.

Contextual clustering based segmentation: Image segmentation plays an important role in image analysis and computer vision and it is considered as one of the major obstruction in the development of image processing technology. Recently there has been considerable interest among researchers in statistical clustering techniques in image segmentation was inspired by the methods of statistical physics. These methods were developed to study the equilibrium properties of large, lattice based systems consisting of interacting components as identical. In a clustering technique for image segmentation, each pixel is associated with one of the finite number of categories to form disjoint regions.

The contextual clustering based algorithms are assumed to be drawn from standard normal distribution. It segments a data into category 1 (ω_0) and category 2 (ω_1).

The following are the steps adopted for implementing the contextual clustering algorithm for segmenting the lung region from LIDC CT images:

- Define decision parameter T_{cc} (positive) and weight of neighborhood information β (positive). Let N_n be the total number of data in the neighborhood. Let Z_i be the data itself, i

This proposed approach has two main sections namely: Segmentation based on contextual clustering and objects detection and estimation based on Matlab region properties:

- Classify data with $z_i>T_\alpha$ to ω_1 and data to ω_0. Store the classification to C_0 and C_1
- For each data i, count the number of data u_i belonging to class ω_1 in the neighborhood of data i. Assume that the data outside the range belong to ω_0
- Classify data with:

$$z_i + \frac{\beta}{T_{cc}}(u_i - \frac{N_n}{2}) > T_\alpha$$

to ω_1 and other data to ω_0. Store the classification to variable C_2

- If $C_2 \neq C_1$ and $C_2 \neq C_0$, copy C_1 to C_0, C_2 to C_1 and return to step iii otherwise stop and return to C_2

The contextual clustering implementation is as follows:

Step 1: Read a pattern (lung image feature).

Step 2: Sort the values of the pattern.

Step 3: Find the median of the pattern cm.

Step 4: Find the number of values greater than the median values, U_m.

Step 5: Calculate CC using C_m + (beta/Tcc)×(U_m−(bs/2)).

Step 6: Assign CC as the segmented values.

Figure 1 shows a steady increase in the error as the beta value changes from 0.1-1. Hence, lower beta value is preferred for better estimation by CC. Figure 2 shows a steady decrease in the error as the threshold value changes from 10-100. Hence, higher threshold value is preferred for better estimation by CC.

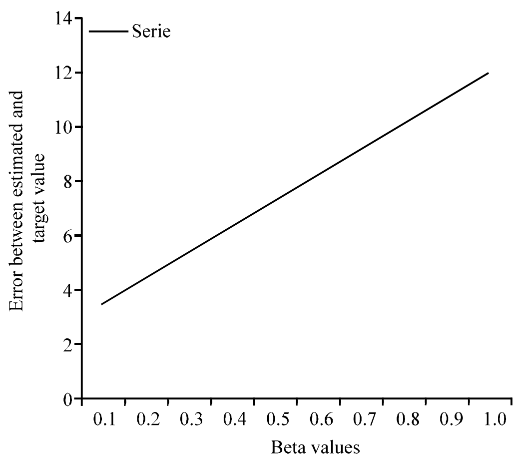

Fig. 1: Impact of Beta value in CC estimation

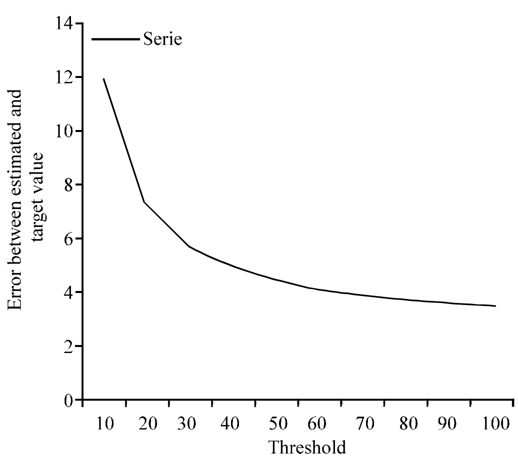

Fig. 2: Impact of Threshold value in CC estimation

RESULTS AND DISCUSSION

LIDC images have been considered in this presentation. Images of the patient 1.3.6.1.4.1.9328.50.3.68 which contains 123 dicom images have been considered. The CC segmented images takes as thumbnail in the windows explorer has been shown in Fig. 3 (Images from 1-45th slice) and Fig. 4 (Images from 46-90th slice). Remaining slices have not been presented for want of space.

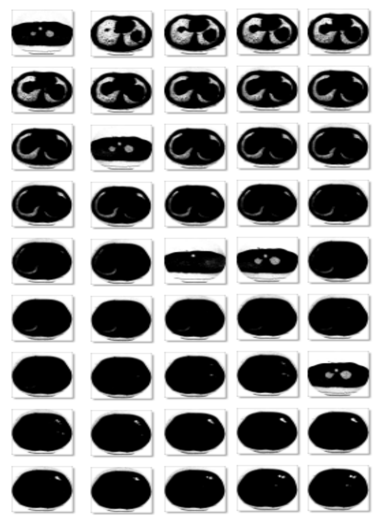

Fig. 3: Lung image slice 1-45

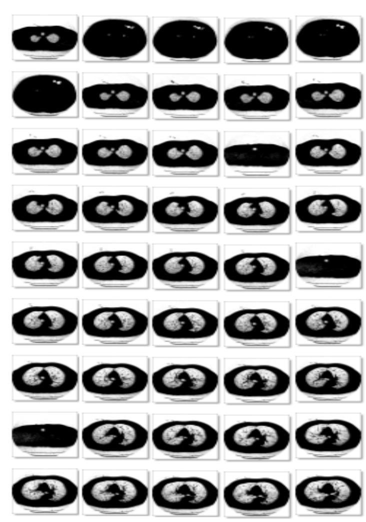

Fig. 4: Lung image slice 46-90

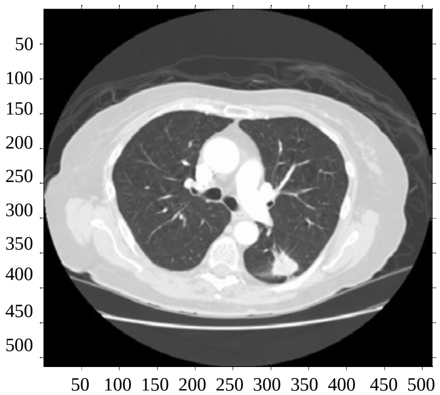

Fig. 5: Sample lung LIDC CT image

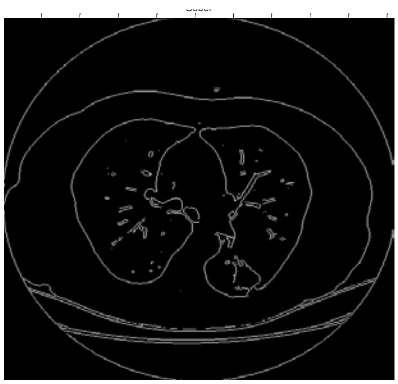

Fig. 6: Segmentation by Sobel

Fig. 7: Segmentation by Perwitt Method

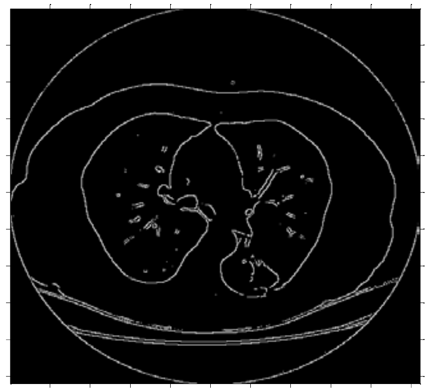

Fig. 8: Segmentation by Roberts Method

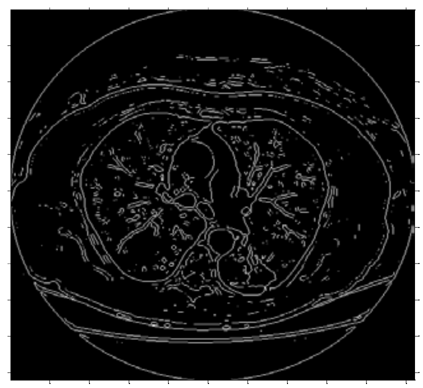

Fig. 9: Segmentation by Log Method

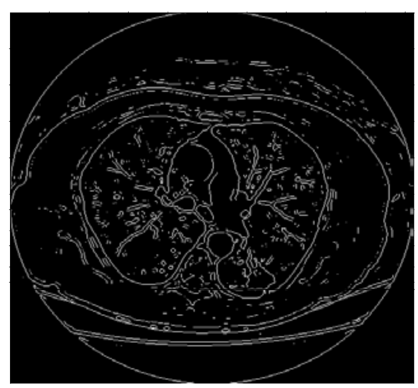

Fig. 10: Segmentation by Zero Crossing Method

Many of the image slices in Fig. 3 show less information and many of the images in Fig. 5 show more information. Figure 4 shows one of the CT lung slice. Figures 5-13 show the segmentation by Sobel, Prewitt, Roberts, Log, Zero crossing, Canny and CC Methods.

Except CC Method, in all other segmentation methods, the number of objects are more and there are some objects segmented are not clear. Matlab bwlabel function has been used and the number objects for each method is shown in Table 1. In addition to bwlabel, the Regionprops command has been used to find out correct number of segmented objects.

Earlier researchers had used different metrics to evaluate the segmentation accuracy. In this study,

Fig. 11: Segmented by CC

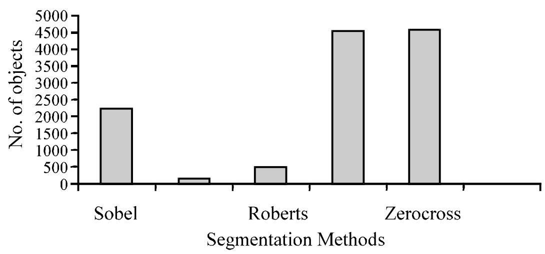

Fig. 12: Comparison of number of objects in each Segmentation Methods

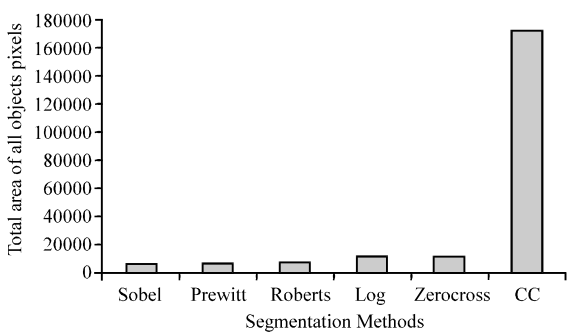

Fig. 13: Comparison of total area of pixels in each Segmentation Methods

Table 1: Number of objects in each Segmentation Methods

Method	Objects detected
Sobel	2270
Prewitt	184
Robertz	527
Log	4580
Zerocross	4580
Contextual clustering	25

researchers have used bwlabel and Regionprops to evaluate the accuracy of segmentation and it has been found that CC segmentation is much better when compared to that of remaining segmentation methods mentioned in this study.

CONCLUSION

In this study, researchers have proposed a new method for segmenting lung images based on supervised contextual clustering method. The main purpose of proposing contextual clustering method is to improve the segmentation accuracy by reducing the false segmentation. The proposed approach has been found more efficient when compared with other conventional segmentation algorithms. Matlab predefined function bwlabel is used for the estimation of the objects present in the CT lung image.

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