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Fast Fuzzy C Means Clustering and Adaptive Mean Shift Threshold Segmentation for Lung Cancer on CT Images

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Abstract

The accurate identification of lung cancer on the CT scan is essential for the early diagnosis of it, which enables the patient with better treatment. The clustering technique has been used for presenting under computer visual impairment, but there are many challenges which continuous in detecting lung cancer because of the inadequate database. In this research, Computer Tomography the CT scan is used to scan the human organs, and to visually represent the issues that occurs in the human body. The CT scans are mostly used for detecting lung cancer and tumor, and the tracking of it is so detailed. In this research a new methodology is proposed for segmentation and classification of lung cancer using the CT scans. The CT scan images are less radiant when compared to those of MRI (magnetic resonance imaging). The result of the CT images is sometimes poor and is highly disorder due to the noise created in it. But it can be removed using the preprocessing method used in the CT scan, which also improves the quality in terms of contrast and its brightness. The 2D Adaptive Gabor Diffusion Filter (2D-AGDF) algorithm is proposed to remove various types of noises. The Edge Preserved Contrast Limited Adaptive Histogram Equalization (EP-CLAHE) algorithm is used for improving the contrast and brightness of the image from the CT scan.

The Fast-Fuzzy C Means is a hybrid clustering approach applied for the clustering of the CT image to group the CT lung cancer region. The Adaptive Mean Shift Threshold (AMST) is the methodology applied for the threshold lung cancer region in order to segment the lung cancer portion. The Experimental result demonstrates the proposed methodology is providing with improved accuracy and efficiency.

Keywords: *Fast-Fuzzy C Means, Adaptive Mean Shift Threshold, Adaptive Gabor Diffusion Filter, CT image, Magnetic Resonance Imaging.*

1. Introduction

Pulmonary cancer is an overwhelming irregular lung cells expansion, which is mentioned as swellings, whose exposure in initial stages is extremely important to the efficient control of dis- ease development and therefore potentially improve the endurance rate of the patient. Among various kinds of cancer, pulmonary cancer likewise refers to as lung disease is considered to be one of the highly destructive tumors. In 2015 Global Cancer Statistics demonstrate that lung cancer accounts for roughly 19.5% of cancer-related fatalities each year and 13% of 14.1 mil- lion new cancer cases [1]. In 2018, there were around 2.2

million additional pulmonary cancer cases and nearly 1.8 million passing's in U.S. within a year. Most frequently utilized manual lung nodule description by the radiologist at the high-quality and high-resolution chest Computed Tomography (CT) is complicated, time-consuming and very tedious. [2]. Automated System of pulmonary nodule detection with an efficient and effective CAD (Computer-Assisted Diagnosis) tools enables radiologists in rapid diagnostic and enhances the analytical self-confidence. Among such methodologies, some important challenge in CAD methods for lung cancer is dealt with the morphological changes in the nodules in CT images. Though CADs (computer-aided diagnosis systems) have been utilized to help radiologists in perusing chest CT scans, automatic identification of malignant and benign nodules on chest CTs continues to be difficult because of two causes: the complexity of lung nodule demarcation triggered by a wide variety of nodule form and quality difference and the visual resemblances that are shared with benign and malignant nodules. Therefore, non- specialists can have trouble in dividing them. Generally, such differences are obvious in images with various image modalities like CT or X-ray, PET (Positron Emission Tomography), or M-RI (Magnetic Resonance Imaging), although in situation of lung nodules various morphological differences are existing even though the similar image modality is utilized [3,4]. In recent times, clustering techniques [5,6] have combined both nodules classification process and the hand-designed feature extraction process into a unified computerized training procedure. Clustering methods have shown excellent performance (i.e. decreased number of FP (False Positive) results) in comparison with the characteristic findings described by implementing conventional segmentation methods [7,8].

Early lung cancer exposure consequently provides the best opportunity for medical treatment. The 5-year survival rate for patients who appear with an advanced stage IV lung cancer is not more than 5 %, although it is no less than 60 % if the diagnosis has been done at the be- ginning once the primary cancer is tiny and sooner than it has been spreading [9]. The National Lung Diagnosis Trial [9, 10] demonstrates that diagnosis with CT leads to a 20% decrease in the lung cancer fatalities by identifying the disease early. A "spot on the lung" on a chest CT has been characterized as a lung nodule, and it may be malignant or benign [11]. Nearly all lung cancers occur from tiny malevolent nodules. Radiologists usually understand chest CT scans for malignant nodules on a slice-by-slice basis, and such a method involves a high level of ability and intensity, and is time-consuming, costly, and susceptible to worker bias. Conventional lung nodule segmentation techniques include lung segmentation and the identification and segmentation of a ROI (region of interest) that incorporates the nodule. Such techniques can be usually classified as the histological [12-14], region growing [15], energy optimization [16, 17] and statistical learning-based techniques [18, 19].

Diciotti et al. [12] utilized an automatic correction technique, that is based on a local shape evaluation utilizing three-dimensional geodesic distance map pictures, to a preliminary uneven segmentation of swellings to respond to the trouble in segmentation of nodule is triggered by an attachment among nodules and other pulmonary structures.

Song et al. [15] recommended a narrative TBGA (toboggan based growing automatic seg- mentation approach), that consist of an automated preliminary selection of seed point, multi- constrictions three-dimensional lesion refinement and lesion extraction.

Farag et al. [16] combined the image intensity statistical data in the variation intensity set structure for the segmentation of lung nodule. To enhance the segmentation of nodule limits, Wu et al. [18] utilized a CRF (conditional random field) model which combines consistency, gray-level concentrations, form, and edge cues. Tao et al. [19] produced a multi-

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level statistical learning-based structure for automatic identification and segmentation of GGN (ground glass nodules). Following segmentation, the lung nodule is transformed into a feature vector by feature extraction.

Most widely utilized characteristics consist of texture descriptors, like the GLCM (gray level co-occurrence matrix)-based features [20-22], HOG (histogram of oriented gradients) [20] and LBP (local binary pattern) [23] and shape descriptors like the spherical harmonics [24] and Fourier shape descriptor [25,26]. Then the mined visual characteristics can be prosecuted in order to prepare a classification system, like the random forest [27], BPNN (back propagation neural network) [28, 29], SVM (support vector machine) [30] and KNN (K-nearest neighbor) [31]. In spite of their frequency, those lung CADs response strongly on hand-made classifiers and features.

In recent times, clustering methods have succeeded in achieving tremendous achievement in computer concept, because they offer a standardized feature mining-categorization structure to free consumers from problematic hand-made feature mining [32-39]. This accomplishment has provoked several researchers to hire deep CNNs (convolutional neural networks) in evaluation of medical image. The FCN (fully convolutional network), that includes the up-sampling levels for the segmentation of image to produce the scope of production match that of an input image, offers a new path. Newly, Ronneberger et al. [40] stated a novel FCN termed as U-Net bio-medical image segmentation with the encouraging results. Hua et al. [41] utilized the DBN (deep belief network) and deep CNN for classification of lung nodule, to distinguish between malignant and benign lung nodules and described that clustering accomplished improved dis- crimination. Kumar et al. [42] utilized CNNs and automatic encoders to categorize the lung nodules as benign or malignant, with the 77.52% precision. Shen et al. [43] recommended a multi-scale CNN that encapsulates lung nodule heterogeneities through extricating discriminative features from alternate between stacked layers. Additionally, the author expanded this version to a multi-crop CNN [44] which has the ability to extract automatically prominent nod- ule information through cropping various areas from a convolution feature maps and applying max pooling at differing times. Shafiee et al. [45] leveraged stochastic sequencing, which is composed of three randomly established convolutional layers, to achieve an 84.49% precision. For classification of lung nodule, Hussein et al. [46] utilized an end-to-end trained MV-CNN (multi-view CNN) and Hussein et al. [47] suggested three-dimensional CNN multi-task learning.

2. Proposed Methodology

To increase the accuracy of the CT image the pre-processing measures are applied. The 2D Adaptive Gabor Diffusion Filter (2D-AGDF) is being used to eliminate noise, and to adjust scattered pixels using hexagonal scanned grid. This research explores the use of neighborhood and accessibility attributes of CT image pixels to solve those problems. In this analysis a lot of morphological analysis has been used to remove noise and airways from the lung's CT image. This research provides a new method to enhancing variations in characteristics between healthy and diseased lung so that accurate evaluation can be accomplished. The method is focused on a hybrid dynamic filtering methodology which excludes the pulmonary vessels that occur in the CT boundary-sectional images without influencing the inherent subtle intensity lung detail.

To restore potential functional distortions caused by the hybrid filter, a characteristic localization procedure based on severe feature wavelet restoration is employed. The resultant images are used to delineate region limits of the diseased regions after a contrast improvement and measurement is rendered with regard to the extent of the disorder. The segmentation-based clustering methods Fast Fuzzy C Means (FFCM) and the Adaptive Mean Shift Threshold (AMST) method are most often used for lung cancer segmentation. The automated seed level is chosen using K clustering, and the high intensity gradient is determined by using the FCM approach as a hybrid clustering strategy.

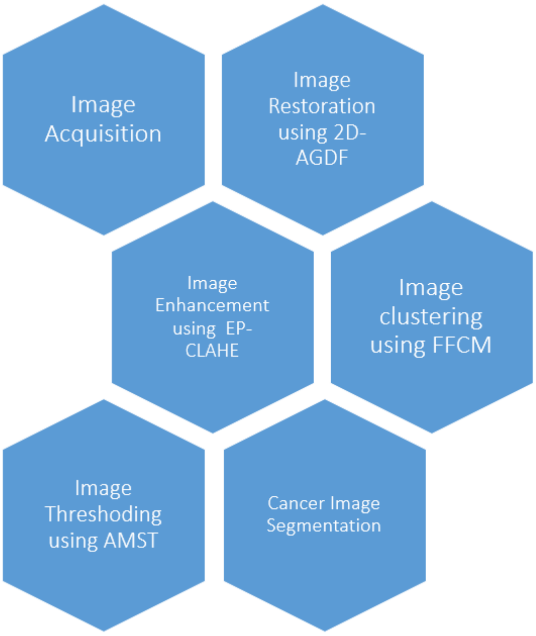

Figure 1 Proposed Method

3. Objective

While CT scan imaging is the strongest imaging tool in the medical world, the understanding and detection of disease from CT scan images is challenging for physicians. Hence computer- aided detection may be helpful for physicians to correctly classify the cancer cells. Some com- puter assisted strategies were investigated and applied using image recognition and machine learning. The key purpose of this work is to compare the different computer-aided approaches, assess the current best methodology to figure out its limitations to weaknesses and eventually suggest the latest approach with changes in the current best approach. The tool used was to arrange and classify the lung cancer identification strategies on the basis of their precision of diagnosis.

4. Existing Methodology

In this research, median filter and Gaussian filter were introduced in the pre-processing level, instead of Gabor Filter. Using watershed segmentation, the captured image is segmented after pre-processing. This provides a defined image of the cancer nodules. In addition to features such as field, perimeter and eccentricity, features such as Centroid, Diameter, and Mean Intensity pixel were extracted for the identified cancer nodules during the feature detection phase. Yet, there has been no enforcement of its designation as benign or malignant. Hence, an additional stage of cancer nodule detection was done using Support Vector Machine. Derived attributes are used as learning attributes and they create a qualified design. This method identifies artifacts or borders that help to obtain the area of image value. To define the relevant content, it divides the image into regions. In diagnosis of lung cancer, the cancer nodule is segmented from the CT scan image.

Watershed segmentation is applied within the suggested layout. Its key trait is that the inter- acting items in the image may be isolated and marked. This functionality assists in appropriate cancer nodule clustering whether it hits certain fake nodules.

4.1 Disadvantages of Existing Methodology

The key disadvantages of deformable model-driven clustering are the extreme susceptibility to activation and the failure of conventional external powers to catch normal in-homogeneity in the lung areas (e.g., centered on borders and gray rates). As a consequence, it is challenging to provide the deformable model with sufficient instructions to obtain the same clustering. The disadvantages to this kind of methodologies are the complexity in distinguish lung partition nodules.

5. Result and Discussion

5.1 Image Restoration using 2D Adaptive Gabor Diffusion Filter (2D-AGDF)

Thus, modifications in conventional diffusion filtering (PM) were suggested to address its staircase effect shortcomings, such as diffusion and nonlinear dynamic diffusion. Much of them, though, operated in a simplistic scale and could have the drawback of maintaining nuanced functionality. The diffusion method is built using the representation of gradient intensity, rather than local gradient values, such that the edges could be well maintained and smoothed while creating an apparent influence of the staircase. The proposed restore filter is a decomposition of the initial image into an image pyramid, such that each stage correlates to a specific image frequency unit.

In our process, the corrupted image (Figure 2) is disintegrated into 3 layers with the estimation image as the highest point. After decomposition, using the Gabor methodology the real noise and usable signal elements of an image would be expressed in various levels. Regarding a deteriorated image, because noise has higher frequency, it often occurs in the lower level of the pyramid. We need to remember, however, that while noise occurs primarily in the lower level, some still occurs in the higher level and should be discarded. Similarly, certain valuable layout details can remain and should be maintained in the lower stage.

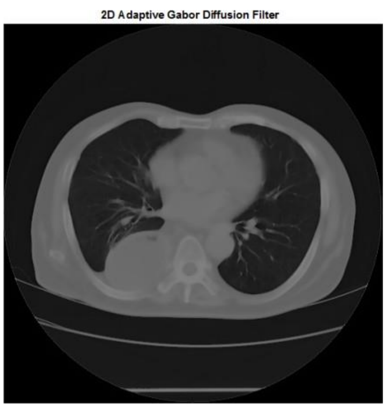

Figure 2 2D Adaptive Gabor Diffusion Filter

Figure 3 Image Enhancement using EPCLAHE

5.2 Image Enhancement using Edge Preserving Contrast Limited Adaptive Histogram Equalization (EP-CLAHE)

This segment introduces an innovative image enhancement approach by integrating the CLAHE (contrast limited adaptive histogram equalization) with control-law transformation in light of low contrast and distorted information of ultrasonic well-logging images. The color image in RGB(red, green, and blue) is first converted into HIS(hue, saturation, and intensity) area and the EP-CLAHE is added only to the image's strength (or luminance) portion (I). This improves local information and eliminates unnecessary light in flat areas and standard areas while preserving the reduced image emission spectra values. After the processing of EP-CLAHE the power-law transformation is then extended to the simulated file.

This maps a broad range of darkened input values into a smaller range of output variables, whereas a narrow band of bright input numbers into a wider range of output principles, further improving the contrast and emphasizing the local data. The result is finally displayed as an RGB image (Figure 3). The efficiency of the proposed methodology is contrasted with histogram equalization and EP-CLAHE approaches focused on quantitative measuring techniques for image quality like MSE(mean square error) that involves contrast luminance (LC), information entropy (IE), and peak signal-to-noise ratio (PSNR).

The Power-Law Conversion Algorithm and EP-CLAHE are given as follows:

- Stage 1: Firstly, the RGB image is converted into HSI space (hue, saturation, and intensity).
- Stage 2: CLAHE is only added to luminance factor I when the components H and S remain unchanged.
- Stage 3: Then control-law transformation is implemented on the basis of CLAHE, and then extended to the transformed luminance variable I in order to convert a large level of dark input values into a smaller range of output variables.
- Stage 4: Lastly, the changed I, H, and S luminance elements are transferred back to the RGB standard and the output is translated back to the RGB image standard. It will also enhance the contrast, highlight local information and avoid over-enhancement of the flat region, and that is of major importance to further increase the precision of image logging information perception. To make the process

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illustrated more comprehensible, we additionally explain the color model transition method, the stages of the CLAHE methodology and control-law transformations.

Figure 4 Segmented Lungs

5.3 Lung cancer segmentation using Fast Fuzzy C Means Clustering (FFCM) with Adaptive Mean Shift Threshold (AMST)

The major aim of clustering and segmentation is to simplify the image recognition into easily analyzed. Adequate contours are obtained and identified for diagnostic assessment. In addition, it should be noted that the hierarchical clustering operates segmentation of the area by arranging the image into pixel clusters which have a greater rate of resemblance with respect to the space of the function. Using fuzzy clustering, members of information can be in more than one cluster and are a group of membership rates associated with each component.

It indicates the resilience of connection between that particular data component and the respective group. Therefore, fuzzy clustering is the mechanism by which certain composition thresholds are consigned to the components and used to assign group more fuzzy clusters. One of the commonly utilized, effective clustering strategies is Fast Fuzzy C Means (FCM). Here, FCM is utilized to properly segment the lung nodule known as cancer. The measures involved in determining effective clustering are obtained.

5.4 Adaptive Mean Shift Threshold (AMST)

The automated algorithm for the threshold is based on the Otsu process. The threshold rule calculation is achieved by using an easy and efficient method to determining the gray scale meaning (t), which allows decrease proportion within-class variance and optimize inter-class heterogeneity with the overarching presumption that the histogram is nonparametric.

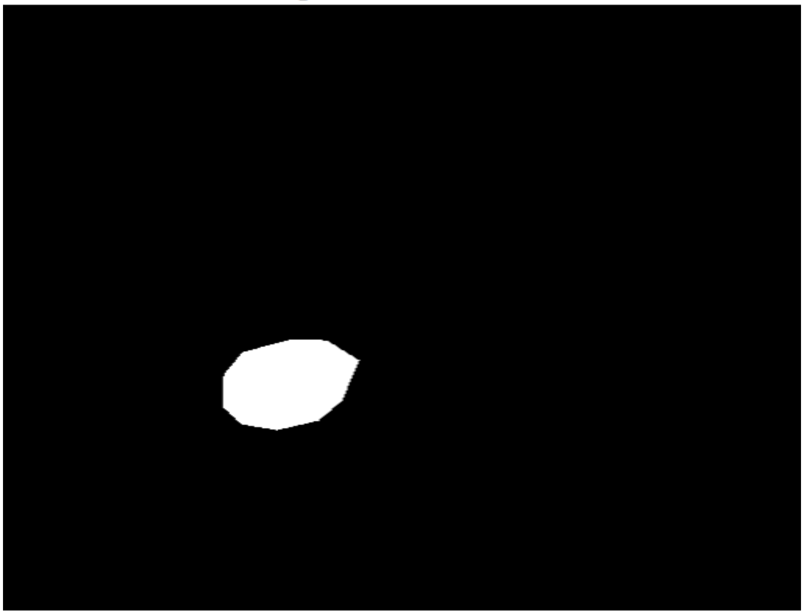

Figure 5 Segmentation of Cancer

Let us say that the pixels are defined in L gray levels [1, 2 ..., L] for any given CT image, and that the normalized histogram increasing be viewed as a spectrum of probabilities. Threshold segmentation is called the threshold process, the easiest form of segmentation of images. This approach is based on a clip-level (or threshold value) to turning a gray-scale image into a binary one.

The trick to this approach is to pick the threshold value (or values while chosen from various levels). The segmentation goal is to reduce and/or alter an image's portrayal into one that is more concrete and simpler to interpret. Image segmentation is usually used in the CT images to identify artifacts and borders (lines, curves, etc.). The product of image segmentation is a collection of pixels that jointly covering the whole image or a collection of feature shapes (edge tracking). With regard to any feature or computational resource, such as color, strength or texture, increasing of the pixels in an area is identical. Adjacent areas vary considerably with regard to a certain characteristic(s).

6. Conclusion

In this research, bio-medical image analysis is carried out for Computer Tomography (CT) lung image. The CT scanning is used to identify lung cancer, since it gives the human body clear sense of the tumor and monitors its enlargement. A novel algorithm is proposed for segmentation for lung cancer based on CT images. The CT image is basically a low quality and noisy source content. The 2D Adaptive Gabor Diffusion filter is applied to filter image adaptively to remove all noise content. The Edge Preservation-Contrast Limited Adaptive Histogram Equalization (EP-CLAHE) is applied to improve contrast and brightness of the image. The Fast-Fuzzy C Means methodology is a hybrid segmentation technique that is introduced to organize CT lung cancer area for segmentation of CT image. To separate the lung cancer part, the Adaptive Mean Shift Threshold (AMST) technique is used to threshold the lung cancer area. The experimental findings indicate that the approach proposed methodology provide better accuracy and efficiency.

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