A Novel Hybrid Segmentation Method with Particle Swarm Optimization and Fuzzy C-Mean Based On Partitioning the Image for Detecting Lung Cancer

P Kavitha, S Prabakaran

Abstract:
Recently, the medical image processing is extensively used in several areas. In earlier detection and treatment of these diseases is very helpful to find out the abnormality issues in that image. Here there are number of methods available for segmentation to detect the lung nodule of computer tomography (CT) image. The main result of this paper, the earlier detection of lung nodules using Pre-processing techniques of top-hat transform, median and adaptive bilateral filter was compared both filtering methods and proved the adaptive bilateral filter is suitable method for CT images. The proposed segmentation technique uses novel strip method and the image is split into number of strips 3, 4, 5 and 6. A marker- watershed method based on PSO and Fuzzy C-mean Clustering method was proposed method. Firstly, the input image was reduced noise reduction and smoothing and the filter image is using strips method and then the image is segmented by marker watershed method. Secondly, the enhanced PSO technique was used to locate the better accurate value of the clustering centers of Fuzzy C-mean Clustering. Final stage, with the accurate value of centers and the enhanced target function and the small region of the segmented object was clustered by Fuzzy C-mean. In segmentation algorithm presented in this paper gives 95% of accuracy rate to detect lung nodules when strip count is 5.

Index Terms: Adaptive bilateral, Marker Watershed, PSO, Fuzzy C-mean, GLCM, SVM

I. INTRODUCTION
Recently the medical image techniques are most important technology is screening of cancer images. Computer Tomography is a standard modality of detecting and assessing cancer images. The nodules are differentiate benign and malignant. For the present study, pre-processing of original sample image to reduce noise detection and gaussian blur using adaptive bilateral filter, by comparing adaptive bilateral filter is best method to find better accurate rate. Three segmentation techniques are compared and proved the combination of marker based watershed algorithm based on PSO and Fuzzy C-mean was proved best accuracy value measured using the True positive, True negative, False positive and False negative values. It was proved that the combination of adaptive bilateral filter and Marker watershed based on PSO and FCM algorithm has more accurate results among others.

II. LITERATURE REVIEW
Emre Dandl [1] was proposed method to classify the lung nodules. In LUVEM (Lung Volume Extraction Method), using median filter to reduce the noise and to implement LUVEM method to extract the nodules from CT scan image. After that the Self Organizing Method (SOM) is successful detection of early stages. It’s unsupervised neural network method and easily segmented to small nodules on the lung nodules. In feature extraction, first we used shape based method for analyzing lung nodule image and to utilize GLCM and adaptive bilateral filter was compared both filtering methods.

Lavanya M, Muthu Kannan P was proposed comparative analysis of FCM and FLICM algorithm. Pre-processing the input image to reduce noise reduction and histogram equalization is done using median filter and filtering image is using segmentation of Modified Expectation Maximization (MEM) algorithm. This algorithm to initialize the parameter of expectation and maximization and the value is increased step by step. Finally, calculate the new maximization and expectation position. After that the completion of segmentation to extract the nodule is utilized for feature extraction method such area, perimeter and eccentricity. Final steps to classification method to compared better best performance measures of FCM and FLICM. The performance measures of specificity 92%, precision 97%, sensitivity 82% and accuracy 95% [2].

The author is mainly focused to implement soft computing methods. In pre-processing, various filtering methods median, gabor filter and anisotropic filtering are compared and proved anisotropic filter are more suitable for pre-processing.
A Marker based algorithm is used to segment the lung nodule to extract the image. Finally, compared SVM and KNN classification result the KNN classifier to provide better accuracy value of the image and this proposed method was implemented by Shraddha G. Kulkarni, Sahebrao B. Bagal [3].

III. METHODOLOGY

A. Pre-processing

In pre-processing, the input lung CT image is being processed to enhanced image quality. The various pre-processing technique is used to reduced noise effect and blurring effect. The better quality measurements are depends on the various methods.

B. Filtering

Pre-processing techniques of top-hat transform, median and adaptive bilateral filter was compared and the proposed method adaptive bilateral is filter is suitable for pre-processing to CT image.

Top-hat transform

The top-hat transform technique in morphology operation and image processing. In this method, the elements are extracted from original image according to small or narrow features, bright or dark features. It works by computing morphological operation in openings is subtracted for the original image [4]. The filtering function defined as:

\[ \text{SE} = \text{strel}('disk', r) \]
\[ \text{Input} = \text{imtophat}(I, \text{SE}) \]

Median Filter

In this method, to remove salt and pepper noise of original image and retains the sharpness of the image. Each pixel is replaced by the median value from the neighbourhood pixels and a window size 3x3 [5].

Adaptive Bilateral Filter

Original image is converted to gray scale image. Bilateral filter is a non-liner, edge preserving and reducing noise for images. It replaces of each pixel intensity with a weighted average values from neighbourhood pixel. The weight average of pixel value is based on the gaussian blur. Its defined as:

\[ BF[I][p] = \frac{1}{W_p} \sum_{q \in S} G_{\sigma_s}(I_p - q) G_{\sigma_r}(I_p - I_q) I_q \]

Where \( W_p \) is normalization factor:

\[ W_p = \sum_{q \in S} G_{\sigma_s}(I_p - q) G_{\sigma_r}(I_p - I_q) \]

Where,

\( \sigma_s \) and \( \sigma_r \) - compute quantity of filtering input image

\( G_{\sigma_s} \) – To decrease distant pixels

\( G_{\sigma_r} \) – If decrease a gaussian the influence of pixels q with intensity value different from \( I_p \).

When tuning the parameter of \( \sigma_r \) increases, the filter is very closer to gaussian blur because the range gaussian is flatter and the parameter \( \sigma_s \) increases, smoothening larger features

Table 1: The input image values of MSE and PSNR

<table>
<thead>
<tr>
<th>Sample Image</th>
<th>top-hat transform</th>
<th>Median Filter</th>
<th>Adaptive Bilateral Filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Img1</td>
<td>79.218</td>
<td>64.08</td>
<td>62.377</td>
</tr>
<tr>
<td>Img2</td>
<td>80.135</td>
<td>68.374</td>
<td>67.319</td>
</tr>
<tr>
<td>Img3</td>
<td>83.724</td>
<td>61.192</td>
<td>59.427</td>
</tr>
<tr>
<td>Img4</td>
<td>80.239</td>
<td>66.135</td>
<td>65.194</td>
</tr>
<tr>
<td>Img5</td>
<td>82.192</td>
<td>70.493</td>
<td>69.196</td>
</tr>
</tbody>
</table>

Table 2: The input image values of MSE and PSNR

<table>
<thead>
<tr>
<th>Sample Image</th>
<th>top-hat transform</th>
<th>Median Filter</th>
<th>Adaptive Bilateral Filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Img1</td>
<td>79.722</td>
<td>85.483</td>
<td>87.217</td>
</tr>
<tr>
<td>Img2</td>
<td>76.386</td>
<td>80.291</td>
<td>81.394</td>
</tr>
<tr>
<td>Img3</td>
<td>78.331</td>
<td>82.492</td>
<td>82.971</td>
</tr>
<tr>
<td>Img4</td>
<td>77.487</td>
<td>85.742</td>
<td>87.485</td>
</tr>
<tr>
<td>Img5</td>
<td>79.381</td>
<td>84.497</td>
<td>85.941</td>
</tr>
</tbody>
</table>

In this filter technique, the adaptive bilateral filter gives more accurate rate of the original image.
A. Segmentation

In image processing, the segmentation techniques are used to partition a medical image into multiple segments. It's going to find the image locate an object and boundaries like a lines, curves, etc. In this proposed method, the filter image is subdivided into five horizontal equidistance strips. The strips are numbered str1, str2, str3, str4 and str5. The strip str2 is considered for segmentation.

Marker based watershed transform

In this proposed method, the image strip str2 is binarized using Otsu’s thresholding method to perform graythresh() function and the image is converted to binary format. A structuring element is defined based on the original image. Its computing foreground and background markers. Final stage, the watershed transform image is executed.

Fuzzy C-mean based on Particle Swarm Optimization

Traditionally, the fuzzy c-mean clustering method without consideration of neighbour information and the efficiency is low rate [6]. In these proposed techniques, the clustering center are initialized in the particle swarm optimization (PSO) and the traditional fuzzy c-mean clustering is also improved. The algorithm is defined (1) Cluster and Iterations are initializing (2) Parameter

Particle Swarm Optimization (PSO)

The PSO algorithm is given as:

Step1: Cluster and Iterations are initializing
Step2: Parameter $p$, $sc$, $fc$, $numsucc=0$, and $numfail=0$ are initializing
Step3: Identify a fitness function
Step4: To find the fitness of each particle rate
Step5: Update the local best solution.
Step6: Steps 4 and 5 repeat
Step7: Each particle velocity and position are updated
Step8: Execute the selection operator.
Step9: If any local best position $yi$ has changed, and to perform the clustering algorithm.
Step10: End procedure

In this method focuses on the current best position of a new particle, the new particle is considered as the swarm and the velocity update equation for new particle is defined as:

$$vnp(t + 1) = \alpha vnp(t) + pbest(t) + \omega vnp(t) + p(t)(1 - 2r). \quad (1)$$

The gbest position is to improve the random search area around the position. The $r$ and $p(t)$ is random vector and diameter of the search area. The range of the random vector lies between 0 and 1.

The diameter of the search area can be updated using the following equation:

$$\rho(t + 1) = \begin{cases} 
2p(t), & \text{#successes} > sc, \\
\left(\frac{1}{1.5}\right)p(t), & \text{#failures} > fc, \\
p(t), & \text{otherwise},
\end{cases}$$

Where.
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sc and fc - Threshold parameters, the value of sc=15 and fc=5

**Enhanced Fuzzy C-mean**

Enhanced FCM method, the relativity between the gray value of small region and single pixel value is not considered. So a new concept \( h_i \) called gray dissimilarity is proposed method. \( h_i = \text{Average}(i) - x_k \) means the gray dissimilarity between the average gray value and pixel value \( x_k \). In this equation for calculating distance from the pixel \( x_k \) to the clustering center is also redefined as \( d_{hi} = ||x_i - v||^2 \)

The improved clustering function

\[
J(U,V) = \sum_{i=1}^{n} \sum_{h=1}^{c} \mu_{hi}^m h(i) \||x_i - v_h||^2
\]

In this equation, the variation between the typical gray value of the \( i^{th} \) is a small region and the pixel \( x_k \), the more possibility they belong to the equivalent region, vice versa. The proposed method of new iterating equation of the matrix and clustering center are redefined as:

\[
\mu_{ik}^{(t+1)} = \frac{1}{\sum_{j=1}^{n} \left( \frac{h(i) \||x_i - v_j||^2}{h(j) \||x_i - v_j||^2} \right)^{\frac{1}{m-1}}} \sum_{j=1}^{n} \left( \frac{h(i) \||x_i - v_j||^2}{h(j) \||x_i - v_j||^2} \right)^{\frac{1}{m-1}}
\]

The original iterating equation is

\[
\begin{align*}
\mu_{ik}^{(t+1)} &= \sum_{j=1}^{n} \left( \mu_{ik}^{(t)} \right)^m x_k \\
\mu_{ik}^{(t)}) &= \frac{1}{\sum_{j=1}^{n} \left( \frac{d_{ij}^2}{d_{ik}^2} \right)^{1-m}} \sum_{j=1}^{n} \left( \frac{d_{ij}^2}{d_{ik}^2} \right)^{1-m} \\
V_{ik}^{(t+1)} &= \sum_{k=1}^{n} \left( \mu_{ik}^{(t+1)} \right)^n x_k \\
V_{ik}^{(t+1)} &= \sum_{k=1}^{n} \left( \mu_{ik}^{(t+1)} \right)^n
\end{align*}
\]

The above method to improved clustering function in the data aggregation, clustering center aggregation, weight and matrix aggregation to control result of the clustering function. The proposed method of the segmentation is more accurate compared other methods.

![Figure 7: Segmentation of Proposed Method](image)

### Table 2: Accuracy measures Proposed Algorithm

<table>
<thead>
<tr>
<th>Sample Image</th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
<th>Accuracy Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td>92.6128</td>
<td>99.9999</td>
<td>0.0001</td>
<td>9.3942</td>
<td>96.8179</td>
</tr>
<tr>
<td>Image 2</td>
<td>88.8404</td>
<td>99.9999</td>
<td>0.0001</td>
<td>11.1592</td>
<td>94.4204</td>
</tr>
<tr>
<td>Image 3</td>
<td>87.2946</td>
<td>99.9999</td>
<td>0.0001</td>
<td>12.7054</td>
<td>93.6473</td>
</tr>
<tr>
<td>Image 4</td>
<td>87.2946</td>
<td>99.9999</td>
<td>0.0001</td>
<td>12.7054</td>
<td>93.6473</td>
</tr>
<tr>
<td>Image 5</td>
<td>83.9061</td>
<td>99.9999</td>
<td>0.0001</td>
<td>16.0939</td>
<td>91.9531</td>
</tr>
</tbody>
</table>

### Table 3: Comparative Results of segmentation algorithm

<table>
<thead>
<tr>
<th>Sample Image</th>
<th>Marker Watershed</th>
<th>PSO</th>
<th>MWFRM</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td>89.3672</td>
<td>89.0624</td>
<td>88.9813</td>
<td>95.8079</td>
</tr>
<tr>
<td>Image 2</td>
<td>88.5622</td>
<td>88.9689</td>
<td>86.1018</td>
<td>94.4204</td>
</tr>
<tr>
<td>Image 3</td>
<td>79.8186</td>
<td>84.9967</td>
<td>83.0334</td>
<td>93.6473</td>
</tr>
<tr>
<td>Image 4</td>
<td>82.4514</td>
<td>81.8114</td>
<td>83.2876</td>
<td>93.6473</td>
</tr>
<tr>
<td>Image 5</td>
<td>79.9876</td>
<td>82.0954</td>
<td>81.2033</td>
<td>91.9531</td>
</tr>
</tbody>
</table>

![Figure 8: Segmentation of Proposed Method](image)

### IV. IMPLEMENTATION

The above techniques are practically executed by opencv python coding and proposed method results was verified. In the pre-processing, an evaluation of both filter methods was done and measures the performance of top-hat transform filter, median and adaptive bilateral filter.

The MSE and PSNR rate are shown in Table 1 and Figures 2 and 3. From the filtering results, the adaptive bilateral filter has given better accurate rate compared with top-hat transform filter and median filter.

In the proposed method, accuracy was measured using the TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) by comparing the results from the other segmentation algorithm with manual results.
The results of the proposed segmentation method are shown in Table 2 and graphical view of the segmentation accuracy was calculated using the TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) shown in figure 8. Comparative Results algorithm shown in Table 3

V. CONCLUSION

In this paper, different segmentation algorithms have been classified to early detection of lung tumor. The original medical image use to pre-processing the adaptive bilateral filter has given better results by comparing top-hat transform filter and median filter. Analyzing four segmentation techniques, the better accuracy result of the tumor detection is enhanced proposed method with maximum accuracy rate of 95%. The proposed method is more accurate when compared to the existing segmentation algorithm. In future studies, various segmentation algorithm will be integrated and to improve the better accuracy rate.

REFERENCES


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