An Automated Hybrid Approach for Multimodal Tumor Segmentation

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Abstract. For the past few years many people in the entire universe lost their lives due to cancer diseases like breast cancer, brain tumor, lung cancer and skin cancer etc. Many modalities like US, mammogram, CT are used to analyze the masses of cancer but its radiation effects the health for this reason MRI imaging is used for analyzing the anatomy behavior of tumors in terms of size of tumor, growth and location in detail. An automated hybrid approach with adaptive kernel fuzzy C Means with PSO is used to segment the tumor part in efficient manner. Using BRATS and RIDER MRI datasets are used for validation. Our proposed methods yields 97.1% segmentation accuracy and compared with various existing approaches like K Means and Adaptive K Means.

Keywords: Image segmentation, adaptive kernel fuzzy c means, PSO optimization, evaluation metrics

1. Introduction

Image segmentation plays a vital role in real time medical application and aids the radiologist to detect the tumor growth and able to predict its severity in advance using diagnosis and many researchers focused various soft computing approaches to segment the tumor part with less span of time. Region based, threshold based and edge based segmentation methods are used for analyzing and extracting the tumors for MRI brain and breast images. Due to high radiation and heavy dose US, PET, CT are nor preferable, MRI scanning is used to analyze the tumors in details and enhance the perception of tumors in brain and breast images with various sequences like T1-Weighted, T2-Weighted, T1 and T2 Axial images for brain and diffused weighted for breast images. Whole breast segmentation is performed with two deep learning models like U net and Segnet and compared its efficiency with dice coefficient values. With 98 images are collected for 4 datasets and they proved the models segmentation accuracy with ground truth images and with experienced radiologist [1]. MRI Breast tumor is segmented using the integration of adaptive wiener filtering with K Means clustering technique [2] for preserving the edges and reduce the noise information and with active contour based level set method heart area is excluded and with the combination of morphological operations and local adaptive thresholding breast tumors are extracted. 1350 breast images collected from private datasets and proved its sufficiency with computational time comparison. Using adaptive K means clustering [3] breast tumor are segmented and its segmentation accuracy is compared with K means clustering technique with standard segmentation performance measures. With MRI CAD system breast lesion segmentation [4] is performed using multi scale morphological sitting with T1, T2 DCE images and classification is done using random under sampling boost method with 141 images and
obtained 0.90 true positive rate and 0.72 dice similarity index. Ostu thresholding [5] is used to extract the region of interest of MRI breast images with 150 images collected from RIDER and proved that segmentation accuracy yields 97.33%. Integration of adaptive particle swarm optimization and OTSU optimal thresholding [6] is used to segment the tumor and classify the same using CNN and yield 98% classification accuracy MRI brain tumor is extracted using Shift-Invariant Shearlet Transform (SIST) [7] and classify the images into normal and abnormal by applying CANFIS algorithm and obtained 98.1 accuracy.

Limitation for the existing approaches are:
- Ostu with PSO leads high computational time
- Single sequences of images are used for validation

The main goal of this automated hybrid approach is to combine two multimodal images with various sequences like T1, T2-Weighted and T1, T2-Axial images. The flow diagram of hybrid approach is figured in figure 1.

### 2. Materials and Methods

#### 2.1 Image Datasets:

MRI brain and MRI breast images are collected from BRATS 2018, RIDER and few from clinical database. Various image sequences like T1-Weighted, T1-Axial, which are focused in various angle and get the detailed features like edges and size of tumor in detail.

#### 2.2 Adaptive K means clustering

It is one of the best partition based clustering approach for finding the best initial cluster based on the nearest distance, its advantage is the value of k is known in advance for estimating the measures[8]. This method contain two phase such as initialization and segmentation. In initialization cluster point is chosen and number of iterations is fixed as 20 and distance is calculated using equation 1:

$$ F = \frac{4 \times \pi \times A}{p^2} \quad (1) $$

Where A and P are perimeters, goodness can be calculated using equation 2.
goodness = \frac{\sum_{i=1}^{M} F_i A_i}{\sum_{i=1}^{M} A_i} \quad (2)

Where F is the circularity ratio of ith object and Ai is the area of the ith object.

The second phase of adaptive k means clustering is integrated with PSO to find the centroid and to ensure the optimal solution is obtained based on the swarm behaviour, fitness function can be calculated using velocity and random position

\[ y_i(t + 1) = \begin{cases} y_i(t) & \text{if } x_i(t + 1) \geq f(y_i(t)) \\ x_i(t + 1) & \text{if } x_i(t + 1) < f(y_i(t)) \end{cases} \quad (3) \]

To find the gbest \( \hat{y} \) using the following equation

\[ \hat{y}(t) \in \{ y_1, y_2, ..., y_p \} = \min \{ f(y_1(t)), f(y_2(t)), ......, f(y_p(t)) \} \quad (4) \]

From eqn (4) next best position of the particle is calculated as

\[ v_i(t + 1) = w v_i(t) + c_1 r_1(t) (y_i(t) - x_i) + c_2 r_2(t) (\hat{y}(t) - x_i) \quad (5) \]

\[ x_i(t + 1) = x_i(t) + v_i(t + 1) \quad (6) \]

Where \( i \) vary from 1 to \( p \) and \( c \) is fixed as 2 with 40 as number of iterations and initialize \( \text{c1} = 0.5 \) and \( \text{c2} = 1.5 \) and its weights are defined with \( \text{wmax} \) as 0.9 and \( \text{wmin} \) as 0.4 with \( p = 25 \)

2.3 Evaluation Metrics

2.3.1 Jaccard Index

Jaccard index is highly used in all medical images for measures the similarity of pixels in original with expected result

\[ J(A, B) = \frac{\text{SIM}(A \cap B)}{\text{SIM}(A \cup B)} \quad (7) \]

2.3.2 MSE (Mean Square Error)

MSE calculates the estimation of average mean square error between input image \( S(i,j) \) and segmented output image \( T(i,j) \) with \( x \) rows and \( y \) column.

\[ \text{MSE} = \frac{1}{xy} \sum_{i=0}^{x-1} \sum_{j=0}^{y-1} [S(i,j) - T(i,j)]^2 \quad (8) \]

2.3.3 Peak Signal to Noise Ratio (PSNR)

It ensures the quality of segmented image in terms of noise level between input and output images, it always depends on MSE value, PSNR is defined as

\[ \text{PSNR} = 10 \times \log_{10} \left( \frac{255}{\sqrt{\text{MSE}}} \right) \quad (9) \]

2.3.4 Precision, Recall and accuracy

Precision and recall measures are computed to ensure the segmentation accuracy between the given input and segmented output matching with similar pixels

\[ \text{Precision} = \frac{TP}{TP + FN} \quad (10) \]

\[ \text{Recall} = \frac{TN + TP}{TN + FP} \quad (11) \]

\[ \text{Accuracy} = \frac{TN + TP}{TN + FP + FN} \quad (12) \]
3. Results and Discussion

Our automated hybrid approach segments the tumor of MRI brain and breast using adaptive k means with PSO optimization, which is highly aids the radiologist for accurate segmentation. The output obtained from our approach shows that the combination of adaptive k means with PSO is suitable for multimodal image segmentation with less time. Figure 2 contains T2 and T1 weighted MRI brain images collected from BRATS and segmented output is validated with ground truth images and experience radiologist for ensuring the correct tumor extraction.

![Figure 2a input image](image1) ![2b) Adaptive K means with PSO segmentation](image2)

Figure 2a) input image and 2b) Adaptive K means with PSO segmentation

![Figure 3a) MRI breast Image](image3) ![3b) Adaptive K Means with PSO segmentation](image4)

Figure 3a) MRI breast Image 3b) Adaptive K Means with PSO segmentation

Figure 3 contains MR breast of Post processed image collected from RIDER dataset Figure 3a input image and 3b Adaptive K Means with PSO segmentation output. From figure 2 and 3, it is
observed that our method is highly helpful for the radiologist to segment the brain breast tumor in accuracy.

![Jaccard Coefficient Comparison](image1)

**Figure 4**: Jaccard value comparison chart

Figure 4 ensures that the proposed method jaccard coefficient value is comfortably good for providing vital information about the commonality among input and segmented output images. Our approach yields average of 0.93% whereas K means yields 0.91% and adaptive K means produces 0.92%

MSE and PSNR values for all images are mentioned in Figure 5. It was observed that our proposed method produces less MSE value and normal PSNR value (average range 47-50) from the Obtained PSNR values it proved its segmentation quality in terms of noise.

![MSE and PSNR Comparison](image2)

**Figure 5**: MSE and PSNR comparison

Figure 6 represents the segmentation accuracy in terms of precision, recall and accuracy measures compared with existing approaches like K means yields 95.2%, adaptive K means 96.4% and our proposed method produces 97.1%
Computational time is compared with K means, Adaptive K means and our proposed method, among all the existing [3-4, 6] our proposed segments the tumor in less time shown in figure 7

4. Conclusion:

Our automated hybrid approach with the integration of adaptive K means with PSO produces efficient segmentation for all multimodal images like MRI brain and MRI breast images with 97.1% segmentation accuracy, and computational time is compared with various existing techniques like K means with PSO and Adaptive K means with morphological filters and FCMPSO etc. The major limitation using this hybrid approach is Jaccard index need to be improved, computational time need to be reduced and also classify the tumor using various machine learning techniques.

Conflict of interest: No.
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