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Analysis of Cancerous Liver MRI Image using Various Segmentation Methods

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Abstract: The precise and early identification of cancerous regions in liver MRI images is paramount for effective diagnosis and treatment planning. This research work focuses on the analysis of edge detection techniques in the context of cancerous liver MRI image segmentation. Leveraging Region of Interest (ROI) selection and the Chan-Vese segmentation method are the main study which aims to improve the accuracy and efficiency of liver cancer localization. In order to improve the accuracy, two phases are involved in this proposed work. The initial phase involves the meticulous selection of ROIs within liver MRI. The ROI-based approach enhances computational efficiency by narrowing down the area of interest and reduces the processing burden. In the second stage, identify regions that may harbor cancerous lesions, optimizing the subsequent segmentation process. Then, the work investigate the applicability and performance of various edge detection techniques, including classic methods such as Sobel, Canny, and Prewitt. The traditional techniques are essential for extracting meaningful edges and features from the MRI images. The effectiveness of this approach is evaluated concerning their ability to isolate the cancerous areas within the defined ROIs. The Chan-Vese segmentation method, a level set-based active contour approach, is incorporated into the proposed workflow. This method has been recognized mainly for its versatility in handling complex object shapes and variations in intensity, making it a valuable tool for medical image analysis. The comparative analysis is obtained by using Chan-Vese and from traditional edge detection techniques to assess its effectiveness to delineating cancerous liver regions accurately. The evaluation is conducted on a diverse dataset of cancerous liver MRI images, and different performance metrics such as accuracy, sensitivity, feature specification, and the Dice similarity co-efficient are utilized. The research findings of our proposed work highlight the superiority of the Chan-Vese segmentation method when integrated with ROI selection, demonstrating its potential in improving the precision of liver cancer identification. The main goal of this approach is to enhance the accuracy and efficiency of liver cancer diagnosis, contributing to more effective treatment planning and patient care.

Keywords: *Active Contour Segmentation, Cancerous liver MRI image, Edge Detection, Image segmentation ,ROI selection,*

1. Introduction

Edge detection is a fundamental process in image processing that plays a pivotal role in computer vision, pattern recognition, and numerous other applications. It aims to identify abrupt changes in intensity or color within an image, typically representing object boundaries, features, or areas of interest. Segmentation for detecting uterine fibroid areas is also automatically done [11]. The accurate detection of edges is critical for image segmentation, object recognition, and various image analysis tasks. Detection of well-localized thin edges in medical images can also be optimized of edges using genetic algorithm [1]. In this study, we explore three commonly used edge detection techniques: the Sobel operator, the Prewitt operator, and the Roberts operator. These methods are essential tools in the image processing toolbox and are widely employed due to their simplicity and effectiveness.

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The Sobel and Prewitt operators utilize convolution masks to estimate the gradient of the image intensity. They are particularly useful for detecting edges with directionality, making them well-suited for applications like character recognition, where the orientation of edges is crucial. The Roberts operator, on the other hand, uses a pair of 2x2 convolution kernels to approximate the gradient. While it is simpler than Sobel and Prewitt, it can be effective for detecting edges in a broader range of directions.

This study aims to provide a comprehensive evaluation of these three edge detection techniques, comparing their strengths and weaknesses in terms of accuracy, computational efficiency, and robustness to noise. By understanding the nuances of each method, we can better choose the appropriate edge detection approach for specific image processing tasks, contributing to advancements in computer vision and image analysis. Iterative thresholding is the method that performs best for lesions with a range of border irregularity properties [2].

2. Segmentation Techniques for Liver Tumor Segmentation

Tumor segmentation from MRI images is a great component for performing analysis of medical image data [3,12], as it aids in the early diagnosis, treatment plan, and continuous monitor of liver cancer patients. Edge detection is a well-developed field within image processing. Region boundaries and edges are closely related [4]. It is dividing an image into distinct meaningful regions with similar characteristics [6]. Accurate and efficient segmentation is essential for the precise delineation of tumor regions within the liver, which in turn facilitates timely medical interventions. Various segmentation methods have been developed and employed to address this task, with Region of Interest (ROI) selection and the Chan-Vese method being two noteworthy approaches that significantly impact the accuracy and effectiveness of liver tumor segmentation.

2.1. Thresholding-Based Segmentation

One of the simplest segmentation methods is thresholding. It involves setting a specific intensity threshold to separate the tumor region from healthy liver tissue. While thresholding is straightforward, it may not be suitable for all cases, especially when tumors exhibit similar intensities to surrounding tissue.

2.2. Region Growing

Region growing methods start with a seed point within the tumor and expand the region by including neighboring pixels that meet certain criteria. These criteria could be based on intensity, texture, or other image features. Region growing techniques are more adaptive but can be sensitive to the choice of seed points.

2.3. Active Contour Models (Snakes)

Active contour models, commonly known as snakes, use a deformable curve or contour to capture the tumor's boundary. Snakes evolve based on internal forces, such as smoothness, and external forces derived from image features. While powerful, their accuracy can vary depending on initialization and parameter settings.

2.4. Machine Learning-Based Segmentation

Machine learning techniques, including deep learning methods such as convolutional neural networks (CNNs), have gained popularity in liver tumor segmentation. These models are trained on labeled datasets to learn complex patterns and can achieve remarkable accuracy. However, they require extensive training data and computational resources.

2.5. Chan-Vese Segmentation Method

The Chan-Vese segmentation method, a level set-based active contour model, offers several advantages in liver tumor segmentation. It is an energy-minimization technique that partitions an image into regions based on minimizing an energy functional. This method is advantageous because it does not rely on gradient information and is capable of segmenting objects with irregular shapes and inhomogeneous intensities, which are often observed in liver tumors. Chan-Vese is known for its ability to adapt to different tumor characteristics, making it a valuable tool in the context of liver tumor segmentation.

3. Region of Interest (ROI) Selection

Image segmentation is the partitioning of an image into a set of nonoverlapping regions whose union is the entire image [5].The selection of a Region of Interest is a critical preprocessing step in liver tumor segmentation. Rather than analyzing the entire image, ROI selection focuses on a specific area containing the liver, which reduces computational complexity and enhances the segmentation process's efficiency. By localizing the area of interest, the algorithm can dedicate more resources to accurately segment the liver tumor, improving overall accuracy. This is particularly important when working with large, high-resolution MRI images.

The significance of combining ROI selection and the Chan-Vese segmentation method lies in the optimization of the segmentation process. By reducing the computational burden through ROI selection, the algorithm can operate more efficiently, leading to quicker results. Additionally, Chan-Vese is highly adaptable to the variations in tumor intensity and shape that are common in liver tumors, making it an excellent choice for accurate segmentation. The Chan-Vese method is particularly advantageous in cases where liver tumors are ill-defined, have irregular boundaries, or vary in intensity. By actively evolving the contour to minimize the energy functional, Chan-Vese is capable of segmenting these tumors with greater precision than some traditional methods.

In summary, the segmentation of liver tumors from MRI images is a complex and crucial task in medical image analysis. Various methods have been developed to address this challenge, each with its strengths and limitations. Combining ROI selection with the Chan-Vese segmentation method is a promising approach, as it streamlines the process, reduces computational overhead, and enhances the adaptability of the algorithm to diverse tumor characteristics [9, 10]. This combination represents a significant step toward improving the accuracy and efficiency of liver tumor segmentation, ultimately benefiting the diagnosis and treatment of liver cancer patients.

4. Edge Detection Without Segmenting the Region of Interest (ROI)

An MRI image of Liver tumor is taken for analysis is shown below in the Figure 1. Here the Input image shows the actual input image before applying any preprocessing steps.

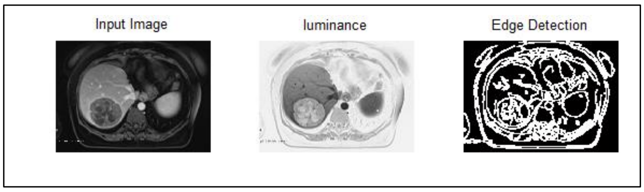

Fig 1: Input image, luminance image and Edge detection

Applied to the input image

The next image is the luminance image of the input image. This gives clear illumination of the tumor present in the image. The edge detection of the image before segmentation gives the third image. It is clearly seen that the edge detection without segmenting does not give any useful information for medical imaging. Hence in the next session segmentation techniques are applied to the input image as preprocessing step.

5. Lesion Detection Using Segmentation Techniques

The Region of interest is segmented using basic intensity based segmentation called as thresholding based segmentation. The input image is also segmented using other segmentation methods like, Chan Vese Active Contour Model or otherwise Active Contour Model(AVC) and Level set segmentation. Threshold with Sobel method is used to removes all edges that are no fixed than the threshold [7, 8].

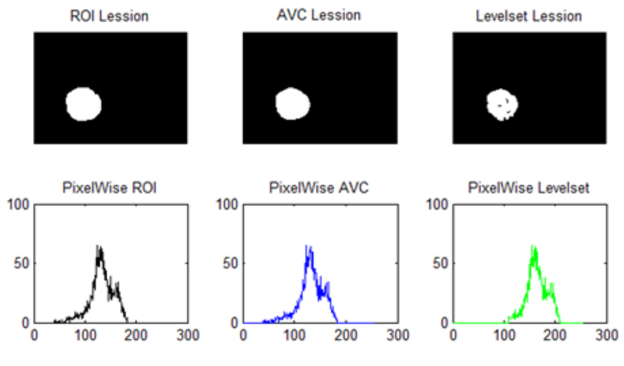

Fig 2. Segmented Lesion using ROI, AVC and Levelset method. Corresponding pixel count with intensity level is shown.

The input image is segmented and the results are shown in figure 2. Each segmentation method is followed by a graph that denotes the pixel count of the lesion with the intensity level. From the MATLAB simulation done the size of segmented region is measures and tabulated below.

Table 1: Size of the segmented region for various methods

Segmentation Method	Lesion Size	Lesion Intensity count
Threshold Method	3078	473180
AVC Method	2755	427544
Level set Method	2842	442104

The table 1 shows the lesion size and lesion intensity count. Here the various segmentation methods are used to segment the input image. The variation in the lesion size can be seen in the tabulated values. Lesion size by using Threshold method gives high value which implies that this basic method gives the gross segmentation. The AVC method seems to give the less lesion size. This also reflects in the lesion intensity count. Intensity count is the total pixel wise intensity value in the segmented area.

The size of the lesion is the prediction accuracy. And the accuracy is very important in case of heat ablations in the tumor region. This allows the heat ablation to take place in efficient manner not affecting the healthy tissue. The high intensity focused radiation used to destroy the tumor tissue is applied with the segmented results[13]. Figure 2 shows a different input image of liver tumor and the preprocessing steps are done. The Region Of Interest area is identified using the Threshold segmentation and finally the border image of healthy and tumor pixel is identified in the simulation results. This final image will be greatly helpful to the radiation therapist to give the thermal radiation to the tumor affected pixels. Thereby the healthy pixels are not unnecessarily treated with heat.

6. Guidelines for Graphics Preparation and Submission

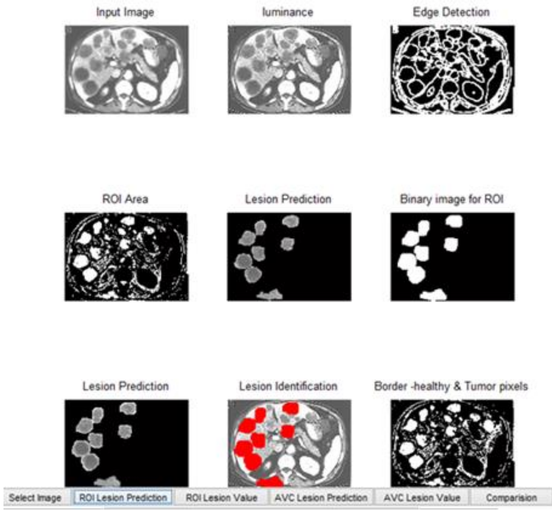

Fig 3. Segmentation, Lesion Prediction and Border prediction

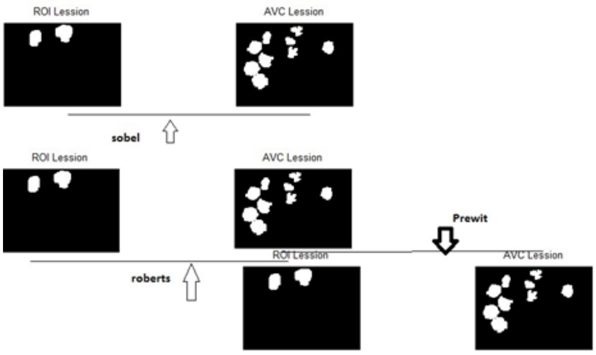

Fig 4: Edge detection using the operators Sobel, Roberts and Prewitt's.

Figure 4 shows the results of edge detection done on the liver tumor MRI images. All three operators segmented the edges in perfect manner.

7. Conclusion and Future Work

In conclusion, the choice of edge detection operator such as Sobel, Roberts, or Prewitt works depend on the specific characteristics of the images being analyzed and the goals of the application. Each operator has its unique advantages, with Sobel excelling in capturing horizontal and vertical edges, Roberts offering simplicity and computational efficiency, and Prewitt providing a balanced approach for both horizontal and vertical edge detection. The selection should be tailored to the specific requirements of the task at hand.

Moreover, the integration of edge detection with active contour segmentation techniques has shown great potential in enhancing segmentation accuracy across a wide range of image processing applications. Active contour models, also known as snakes, leverage the detected edges to efficiently delineate object boundaries, offering more precise and adaptive segmentation results. This fusion of edge detection and active contours paves the way for improved image analysis, object tracking, and computer vision tasks.

In future, researchers can explore the integration of deep learning approaches with traditional edge detection operators to enhance robustness and accuracy. Additionally, efforts should be directed towards optimizing these techniques for real-time applications and extending them to 3D and video data. Investigating interactive image segmentation methods and developing user-friendly software for broader accessibility will be crucial for advancing this field. The synergy between edge detection and active contour segmentation continues to hold great promise for advancing the accuracy and applicability of image segmentation in various domains.

Conflicts of interest

The authors declare no conflicts of interest.

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