AN ANALYSIS OF MEDICAL IMAGE SEGMENTATION ALGORITHMS

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Abstract: Image segmentation in medical field plays a vital role in image analysis to identify the affected tumour. The process of subdividing an image into its constituent parts that are homogeneous in feature is called Image segmentation, and this process concedes to extract some useful information. Numerous image segmentation techniques have been developed, and these techniques conquer different restrictions on conventional medical segmentation techniques as Thresholding, Region-based, Clustering, Edge detection, Model-based.This paper presents a review of medical image segmentation techniques and statistical mechanics based on the novel method named as Lattice Boltzmann method (LBM). The novel LBM is to augment the computational speed in the process of medical image segmentation with an accuracy and specificity of more than 95% compared to traditional methods. As there is not much information on LBM in medical physics, it is intended to present a review of the research progress of LBM.

Keywords: *Segmentation, Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Image processing, Image analysis, Thresholding, Edge detection, Clustering*

I. Introduction

Image segmentation plays a vital role in image processing, particularly in medical imaging, where accurate analysis is critical for diagnosis and treatment. It involves dividing an image into homogeneous regions to extract meaningful information, such as anatomical structures or abnormalities like tumors. In radiotherapy (RT), segmentation is essential to accurately define treatment targets and healthy structures, helping to avoid unnecessary radiation exposure. Clinical images, especially CT scans, are manually segmented by clinicians and imported into Radiotherapy Treatment Planning Systems (RTPS) for precise radiation dose calculations. Therefore, the quality of segmentation directly affects treatment outcomes, requiring high spatial precision and computational accuracy.

Various segmentation methods have been developed, including thresholding, region-based, clustering, edge detection, and model-based techniques. Each method offers unique advantages depending on the nature of the medical image and clinical application. However, limitations such as computational inefficiency persist, especially in practical clinical environments.

To address these challenges, this paper provides a concise review of traditional segmentation methods and introduces a novel approach—the Lattice Boltzmann Method (LBM). LBM is based on a microscopic representation of macroscopic physical processes and shows promise in enhancing computational speed and accuracy in segmentation tasks. Unlike previous reviews, this paper uniquely emphasizes the application of LBM in medical image segmentation, aiming to inspire further research and development in this emerging area. This review serves as a resource for understanding various segmentation techniques and highlights the potential of LBM to improve the efficiency and effectiveness of medical image analysis.

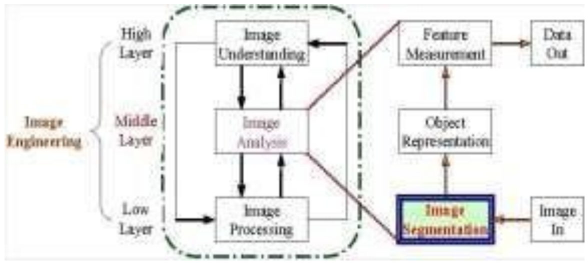


Figure 1. Image Segmentation

II. Segmentation techniques

Recent advancements have focused heavily on the process of image segmentation, particularly in medical imaging. Numerous segmentation methods have been proposed in the literature, each aiming to overcome limitations found in conventional techniques. Though, no single method proves universally superior; rather, each is suited to specific image types and applications. Segmentation techniques are generally categorized into Thresholding, Region Growing & Merging/Splitting, Clustering, Edge Detection, and Model-Based methods. All segmentation approaches rely on two key principles: intensity discontinuity and similarity. Discontinuity-based methods detect sudden changes in pixel intensity or grey levels, often identifying edges or isolated points within an image. In contrast, similarity-based methods group pixels with similar intensity values according to predefined criteria. This includes techniques like Thresholding, Region Growing, and Region Splitting and Merging. Each approach offers distinct advantages, and selecting the appropriate method depends largely on the characteristics of the image and the intended application in medical diagnosis or analysis.

III. Thresholding approach

Thresholding is the primary method of image segmentation, in which one threshold value is used to change a greyscale image into a binary image. This procedure's important thing is to choose the threshold value (T), pixels with intensity over and above the foreground region's threshold value, and all other pixels in the background region [7]. A few famous strategies utilized in the industry are "The maximum entropy method" [8], Otsu's method (maximum) variance [9]. K- means clustering [9] can also be used in this regard. The presence of noise and obscure boundaries influences Thresholding segmentation and performs well for the images with sharp edges [9]. To invalidate the impact of noise on Thresholding smoothing Image and Thresholding with Edge detection are two regular strategies

IV. Region-based methods

There are three essential techniques for Region-based Segmentation of the Image.

a. Region growing

At the region growing algorithms beginning of the specific pixel, the region's growth will be dependent on the connectivity with the neighbouring cells depending on similarity criteria corresponding to the greyscale intensity, shape size, or colour defined by the thresholds to expand the growth [10]. The choice of the seed point and the similarity criteria reflects the segmentation results by region growing. Statistical information and prior knowledge assimilated in algorithms to depend on starting seed points and make the algorithm adaptive [11].

b. Region split and Merge approach

The second method based on the region is the split and merge image segmentation. The said method depends on a quadtree information depiction where splitting of an image takes place into four quadrants with due consideration of the non-uniform feature of the original image segment. If splitting of neighbouring images is discovered as uniform, they are converged by a solitary image made out of the four neighbouring images [11]. The cycle ends when no further merges are conceivable. This technique wipes out the high recurrence artefacts with the seed point selection depend on nearby statistics, utilized for evaluating the breast and cyst mass [11]. These algorithms predominantly depend on the image intensity information to deal with the partial volume effects and control the leakage.

c. Watershed approach

The Watershed method is a region-based image segmentation technique that models an image as a topographic surface, where low-intensity pixels represent valleys and high-intensity pixels represent peaks. Segmentation is achieved by simulating water flooding from local minima, with barriers (watershed lines) formed where different waters meet. These barriers define distinct image regions, known as catchment basins. Two main algorithms are used: rainfall and flooding. In the rainfall approach, each unmarked pixel flows toward the nearest minimum, while in the flooding method, water spreads outward from each local minimum.

Despite its effectiveness, the standard watershed method is prone to over-segmentation, especially in noisy images or those with weak boundaries. This issue can be mitigated through filtering techniques or advanced variants like Power Watershed and stochastic watershed. These incorporate neural network classification or probabilistic methods to improve accuracy. Applications include breast tumour detection in ultrasound and liver and brain tumour segmentation in medical imaging.

V. Clustering approach

Clustering is a technique that groups homogeneous data based on similarity criteria. One common method is K-means clustering, a hard clustering approach where each data point belongs to only one cluster. In contrast, Fuzzy C-Means (FCM) is a soft clustering method that allows pixels to belong to multiple clusters with varying degrees of membership, ranging from 0 to 1. The membership value depends on a pixel's proximity to the cluster centroid, and the algorithm minimizes an objective function based on the weighted Euclidean distance.

FCM is widely used for segmenting both grey and color images, allowing the number of clusters to be predefined. Its adaptability and the ability to modify the objective function make it suitable for various image types. However, standard FCM is sensitive to noise and intensity variations, especially in MR images. To overcome this, variants like Kernelized FCM (KFCM), which replaces Euclidean distance with kernel-induced distance, and Fast Generalized FCM (FGFCM), which incorporates spatial and intensity information, have been developed.Advanced versions such as T2FCM, IFCM, and FABC enhance noise robustness and segmentation accuracy. ARKFCM, a regularized kernel-based FCM, further improves segmentation in brain

MRI by preserving fine details and increasing robustness. These improvements demonstrate FCM's versatility in medical image segmentation.

VI. Edge detection

Edge detection is a traditional method used to identify irregularities in an image by detecting boundaries between regions with distinct intensity or grey levels. Edges play a crucial role in image analysis and enhancement. Derivative operations, particularly convolution with suitable masks, are used to highlight edges. The Canny edge detector is a widely used and efficient method that employs gradient thresholding, non-maximum suppression, and hysteresis thresholding to accurately detect edges. However, edge detection is highly sensitive to image noise, which can result in broken or incomplete edges. To mitigate this, images are typically smoothed using a Gaussian filter before edge detection. Improper pre-processing, however, can lead to incorrect results. Multi-resolution edge detection and edge tracing techniques help address such limitations.

VII. Model-based algorithms

Model-based approaches have been set up as probably the best strategies for picture analysis to go with a model. This model contains information about the look forward of the shape and existence of the structure. This technique is stronger against the artefacts associated with the images than the conventional algorithms.

a. Markov Random field models

Markov Random Fields (MRF) are stochastic models where the future state depends only on the present state, not on the path taken to reach it. Inspired by the using model, MRFs are widely used in image segmentation due to their ability to preserve edges through parameter estimation. The Hidden Markov Random Field (HMRF), an extension where states are not directly observable, enhances segmentation accuracy when combined with the Expectation-Maximization (EM) algorithm in the HMRF-EM framework. Further advancements include integrating MRF with self-organizing feature maps (SOFM) to improve spatial coherence and using Pickard Random Fields (PRF), offering reduced computational complexity for tasks like breast mass segmentation.

b. Atlas-based approach

Atlas-based segmentation uses reference images containing detailed anatomical information to guide image partitioning. These atlases are typically built from labeled images of both healthy and diseased subjects and are closely related to the target image. A crucial step in this method is image registration, which aligns the atlas with the image to be segmented through a process called label propagation. Accurate registration is vital, as topographic differences can lead to segmentation errors. Atlases can be selected based on statistical averages or samples nearest to the population mean to reduce bias. Multi-atlas segmentation improves precision but requires a large database and appropriate atlas selection. Labels are refined using fusion weights based on local registration evaluations. Studies have shown that average-shape atlas strategies outperform single-atlas methods in segmenting cardiac and aortic structures in CT scans. Additionally, rib-bone atlases from CT and dual-energy x-rays have been used for rib segmentation on conventional chest x-rays, enhancing accuracy through model-patient x-ray alignment.

Artificial Neural Networks

Neural networks, inspired by biological brain cells, are mathematical models composed of nodes (representing neurons) connected by synaptic weights. These networks process inputs through activation functions to classify or identify objects. Training and learning are key components: training involves adjusting weights to optimize performance, while learning refines these weights based on feedback. Neural networks are classified into supervised and unsupervised learning, with training attributes such as statistical features or wavelet transforms. Challenges include determining network architecture, size, and layers, all of which affect performance. Fuzzy neural networks offer better segmentation, especially in noisy images. Techniques like the Group Method of Data Handling (GMDH) and Support Vector Machine (SVM) classifiers enhance segmentation accuracy and efficiency. Applications include lung identification in clinical images and liver cancer segmentation using a 3D fast marching algorithm combined with a feed-forward neural network. Additionally, deep convolutional neural networks (DCNN) are used for detecting glioblastomas in brain MR images, demonstrating high accuracy and reduced processing time.

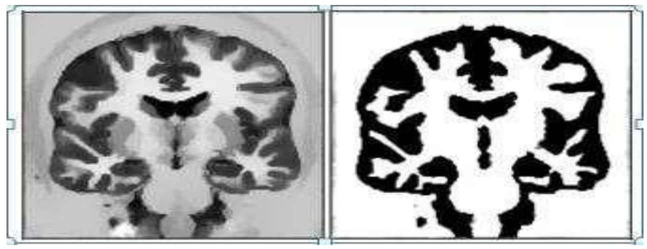
Graph cut approach

The graph cut algorithm uses graph theory to segment an image into foreground and background. Each pixel is treated as a node, and the edges between them represent the probability of a pixel being part of the foreground or background. The edges are weighted to promote similar pixels staying together while separating different pixels. The graph is partitioned by finding a minimal cut that separates the foreground from the background, considering both hard constraints (e.g., boundary) and soft constraints (e.g., region properties). The energy function is minimized to optimize the segmentation. This method has applications in photo, video editing, and medical image processing. The algorithm has two variations: one that labels pixels to minimize energy, and another that smooths the energy function. Multiregional graph cuts further improve segmentation by using kernel mapping for image data, optimizing the partitioning into multiple regions. This approach has been validated with synthetic, natural, and medical images, such as brain MRI scans, achieving excellent results.

Lattice Boltzmann method (LBM)

The Lattice Boltzmann Method (LBM) is a simulation technique used to model macroscopic physical processes by simulating the behavior of particle groups, rather than individual particles. The solution area is divided into lattices, with particles moving along specific directions between nodes. LBM operates in two stages: a streaming stage where particles move between nodes, and a collision stage where particles are reorganized at each node. This method is faster, requires less memory, and supports large parallel computations. It is often preferred over traditional methods for solving partial differential equations (PDEs) due to its efficiency and scalability.

The two stages are governed by the LBM evolution equation, where parameter relaxation time(τ) and source term (α) decide the particles' movement. The state of each node at the next moment is only related to the state of its neighbouring nodes because the particles move along the links, and the lattice number and lattice speed govern the links. LBM can be efficiently used in image analysis techniques such as (i)image smoothening [51-53], (ii) image inpainting [54], (iii) image segmentation [55- 60]etc. In image processing, each pixel value is considered as particle densities, and changes in pixel value can be considered as a redistribution of particles that are decided by relaxation time (τ) source term (α) in which image information such as gradient and curvature are embedded. LBM in image processing is done, which can be applied easily to complex domains and could be used to serve multiphase and multicomponent flows. Introduced an anisotropic diffusion model dependent on LBM for picture division and showed the adequacy of the calculation in clinical pictures [55], [61-65]. Proposed a novel LBM method using the D2Q19 lattice arrangement model for the Segmentation of MR and clinical images, which is similar to anisotropic diffusion as shown in figure 2 [56], [66-71].



(a) MRI Image (b) LBM

Figure 2. Segmentation of MRI image by LBM [56].

Utilized LBM to tackle the Level Set Equation (LSE), they proposed a Region-based stop function [71-76]. Unsigned Pressure Force (UPF) in light of regional attribute can adequately and effectively stop the contour at feeble obscured edges [57]. They utilized the parallelizable lattice Boltzmann method (LBM) to solve the level set equation(LSE). This technique is quicker since it is unravelled in histogram space instead of pixel domain [77-81]. The time problem is extensively diminished since the quantity of grey levels is commonly a lot littler than the size of the picture. The strategy is productive, profoundly parallelizable, and quicker than those dependent on the LSM [58]. Edge of object division can be obtained by the Lattice Boltzmann Anisotropic Diffusion Model (LBADM) and indicated their calculation could precisely fathom the convection and diffusion condition [59]. The algorithm incredibly lessens the calculation of division. They proposed a new variation multiphase level set approach to clinical segmentation, calculated multiphase level set conditions and entropy for the LBM model for D2Q9[60]. Demonstrated their method for MR breast images reveals it is more efficient and faster [81-84]. The LBM's merit is a pixel-based algorithm. It deals with the particles, and the pixels are the replica of particles, therefore at any resolution, we can tune the algorithm using various kinds of lattice points. With the increase of lattice points, computational load also will be increasing, and it may be a demerit of the LBM in the view of computation. Since it is particle- based in the microscopic domain, all the macro parameters can be redefined, but since LBM is dealt with, density has to define in a regular structure. In a medical image, getting a regular structure is very difficult; therefore, it may have the LBM's demerit.

VIII. Conclusion

This paper presents a review to explain the different segmentation for medical images and novel LB method to advance interest for future investigation and exploration in medical image segmentation. Emphasize that none of these problem areas has been acceptably settled, and all of the algorithms depicted are available for broad improvement. Segmentation of medical images is a yet complicated issue in real-time applications like diagnosis and radiotherapy treatment where segmentation algorithm can accurately recognize different tissues encompassing the tumour site and tumour boundaries, henceforth more inventive work is required augment the computational speed. LBM has the benefits of speed and adaptability of modelling to guarantee excellent image processing quality with a reasonable amount of computer resources. The LBM has an exact physical meaning in image processing, the image's pixel value is considered particle densities, and changes in the pixel value can be considered redistribution of particles. It is governed by the relaxation time, which decides the kind of problem needed to be addressed, and the addition of source term is straight forward. The quality of the image segmentation and the computational speed utilizing LBM with high dimensionality and more lattice vectors are expected to comprehend, so we predict that the LB method will become a new research hotspot field Medical image segmentation.

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