An Assessment of Algorithms Utilized in the Lattice Boltzmann Methods Approach for Medical Image Segmentation: A Review

Rashmi Bhardwaj[1*] and Divisha Kansal[2]

[1]Fellow of Institute of Mathematics and Applications (UK), Professor of Mathematics, Head, Non-Linear Research Dynamics Research Lab, University School of Basic and Applied Sciences (USBAS), Guru Gobind Singh Indraprastha University (GGSIPU), Dwarka, Delhi, India

[2]Research Scholar, USBAS, GGSIPU, Delhi, India

(*Corresponding author) E-mail: rashmib@ipu.ac.in

Abstract: In the realm of computational fluid dynamics (CFD), Lattice Boltzmann Method (LBM) is introduced as a research and development tool; nevertheless, its ultimate significance resides in a variety of industrial and academic applications. Several time-dependent fluid dynamic problems can be addressed using LBM. Navier-Stokes equations are indirectly resolved by this numerical technique in a weakly compressible condition, permitting the propagation of acoustic waves. Here is a summary of statistical mechanics and segmentation of medical image methods. LBM, an unconditional methodology, is the main foundation of this method. The enhanced computation frequency of LBM, in accordance with the medical picture segmentation approach, with accuracy and specificity of more than 95% in comparison to conventional strategies, is what makes it so beautiful. A concise assessment of scientific picture separation methods, mostly built upon threshold, total neighborhood, assembly, fragment detection, model- based, and radical methodology approaches to LBM, is presented here in this paper. While certain segmentation strategies for scientific photos have been discussed in this article, it is emphasized that all these algorithms still require major improvements and that none of these issues have been resolved to the satisfaction of the authors. It is anticipated that LBM will become a focal point for future image processing research due to its advantages over modeling in terms of speed and flexibility, which guarantee amazing, remarkable picture processing using a manageable amount of computer resources.

Keywords: *Radiation Therapy, Radiotherapy treatment planning systems, Segmentation, Computed Tomography (CT), Medical Physics, Lattice Boltzmann Methods, Magnetic Resonance Imaging (MRI).*

Introduction: A growingly popular technique for CFD is LBM. Researchers from various fields are drawn to it because of its intriguing features, which include using grid or lattice for its simplified domain representation, its approach based on modeling mesoscopic molecular interaction, its implementation which is relatively simple (similar to Finite Differences algorithms) and its parallelization possibilities (which allow the use of multiple processors or GPUs to reduce the computational time).With advanced methods and tools, image processing techniques have grown in importance across a broad range of applications. A prime example of an image processing topic is image segmentation, which is also a center of attention in the methods of image processing. Breaking up of an image into its individual parts is known as image segmentation. The resulting segments are astonishingly uniform in features and allow for the extraction of some important information. In image analysis, image segmentation holds a somewhat prominent place. Because the diagnosis and treatment plan are influenced by the image quality, medical imaging plays a part in healthcare. Segmentation plays a crucial role in the analysis of medical image by extracting specific details from the images. High-level visual understanding can be achieved using those pictures.

According to science, segmentation is, as figure [1] roughly illustrates, an imaginary task involving a vision which is at middle level between the cortical areas that are at two levels, low and high. The goal of segmenting clinical photographs is to recognize structures that are anatomical and show the limits of those structures on a source that is digital. Important component of the treatment regimen is imaging, particularly in radiotherapy (RT), as it utilized to identify the therapeutic target as well as common structures to prevent radiation exposure. Hence, anatomical data must be displayed on CT scans in order for radiotherapy treatment planning systems (RTPS) to function. Clinicians use CT scans to physically display the therapy target and normal anatomy. Clinical images that have been segmented are moved to an RTPS in order to determine the dose of the radiation. Therefore, accurate segmentation is essential to the outcome of the patient's treatment. Segmentation quality takes into account dosage computation accuracy and spatial precession for radiation treatment purposes, which are closely associated [2, 3]. The goal of segmentation of an image is to segment a medical picture into constituent elements or items with dependable and comparable characteristics. These include intensity, color associated with tumors, features that are anatomical, etc. No general principle of segmentation of an image exists; rather, degree of division varies depending on application. In the literature, numerous segmentation methods or algorithms have been proposed. The mentioned methods overcome specific restrictions associated with techniques of medical segmentation that are traditional. Choosing one method or algorithm over another is based on the kind and nature of images in the challenge. Reviews of recent developments in image segmentation algorithms are common [4, 5]. Classifying the methods used to process pixel and its data and their uses in the diagnosis and planning of treatment is the driving force behind these review articles. Nevertheless, despite the methods' practical application, a clear shortcoming remains: computational speed. Using thresholding, region-based, clustering, edge detection, model-based, and the novel LBM to increase the speed of computation—which is predicted on how the macroscopic physical process is described at the microscopic level. An overview for the segmentation of medical pictures is given in brief in this study. Since there isn't a literature on findings of LB method, this article offers an analysis to raise awareness of the various approaches to medical image segmentation and the innovative LB method. It also serves to stimulate interest in further research and exploration into this area.

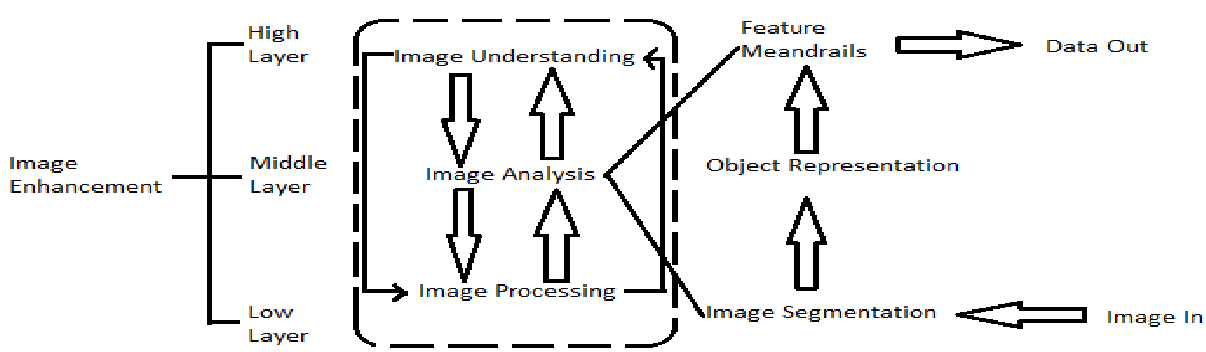


Figure 1. Geometry and segmentation of an image [1]

Soft Computing Techniques: It is possible to combine LBM and soft computing methods to create precise and effective computational models for a range of engineering issues. Control strategies for LBM can be optimized by the application of soft computing approaches. For instance, the best parameters for LBM, like the viscosity coefficient and time step size, can be determined using fuzzy logic. Multi scale simulations and the identification of the best model parameters for a specific task can be accomplished with artificial neural networks (ANNs). Genetic algorithms can be applied to automate the selection process of model and optimize the LBM's parameters. Particle swarm optimization is another tool that may be applied to raise the precision of the LBM's solutions. For a variety of engineering issues, effective and precise simulation models can be created by combining LBM and soft computing approaches.

Image Segmentation technique: Process of dividing an image into a collection of parts with lots of pixels, each of which can be represented by a mask or a labeled image is called segmentation of an image. A picture can be processed in segments such that only the crucial parts need to be treated, rather than the complete image. Finding sharp gap in pixel values, which usually defines a region by showing its edges, is a regular technique. Comparing different areas of an image is another popular method. Recently, a number of initiatives have focused on the process of segmentation. These strategies overcome certain constraints associated with medical division techniques that are traditional. However, no single strategy can be deemed superior for all types of photographs; rather, several strategies are only appropriate for specific types of photos and applications. The following categories comprise image division techniques:

[6] clustering, edge detection, thresholding, region expanding and merging and splitting, and model-based methods. Two fundamental factors that affect all segmentation approaches are resemblance and discontinuity, as well as intensity values. The discontinuity moves on to segment the image according to a sudden shift in the image's greyscale levels or intensity levels. We are primarily interested in the identification of isolated sites in this technique. The second method uses pixels that, according to predetermined criteria used to split images, are comparable in a certain range. These pixels include approaches like region splitting and merging, thresholding and region growing.

Thresholding technique: A straightforward technique for dividing a picture into a background and foreground is image thresholding. By transforming grayscale photos into binary images, this image analysis method separates objects by image segmentation. High contrast photos are the best candidates for this technique. The main technique for segmenting the images is thresholding, in which a grayscale image is converted into binary image using a single threshold value. The selection of the threshold value (T), pixels whose intensity is greater than or equal to the threshold value of the foreground region, and all the other pixels that lie in the background region are crucial steps in this process [7]. Several well-known tactics employed in the field include Otsu's method (maximum) variance [9] and "The maximum entropy method" [8]. In this context, K-means clustering [9] is also useful. Thresholding segmentation is influenced by hazy borders and noise, and it works best crisp edges images [9].

Region based methods

Region growing: When the regions of interest in a picture have roughly uniform or gradually fluctuating intensity, region expanding is a straightforward but effective method for image segmentation. The fundamental principle of region growing is to take a set of seed points and use adjacent pixels that satisfy certain similarity criteria to grow these seeds into larger regions. Frequently, characteristics like intensity, color, or texture are the basis for this resemblance.

Split and Merge Approach: In order to provide a more homogenous segmentation, the region split and merge method separates and merges sections repeatedly. The entire image is first treated as a single region in the procedure. If a condition for homogeneity is not met, the region is divided into four quadrants (or more, depending on the splitting approach). This standard may be determined by attributes such as texture, color, or intensity. Until every region satisfies the homogeneity requirement, the splitting procedure is done recursively to the recently created sub-regions. Reducing over-segmentation involves merging adjacent regions that share sufficient similarities. The difference in mean intensities, texture, or other properties might serve as the basis for the merger criterion. Recursive application of the merging method is used until no further merges are possible. Iteratively, the splitting and merging stages go on until a halting condition is satisfied. This criterion may be based on a predetermined threshold for region homogeneity, the number of repetitions, or the size of the regions.

Watershed approach: The Watershed method is another strategy that varies according on the geography. It sees the picture as a surface that is topographic. The theory is that high-intensity pixels seem as hills or peaks, while low-intensity pixels are perceived as surface troughs [12]. The procedure starts by filling up the valleys from local minima if we have seeds that are sources of water. Water of different colors can be used to dye each seed. They are then utilized to deluge such local minimum in order to elevate the water content in each place. Lines of watershed are a barrier that was constructed where various colored water meets in order to keep them from blending together from one area to another [13]. The collection of water in what are known as catchment basins, which are close to the local lowest points. The greyscale pictures' pixels are similar to beads of water, and image's area that results from the catchment basins is where the pixels in that image belong to the same class. To handle the image utilizing watershed, there are two fundamental algorithmic processes: (a) floods and (b) rainfall. The rainfall algorithm neighborhood approach establishes the lowest value over the entire image. Each neighborhood lowest is assigned a unique marking, and nearby neighborhoods lowest are connected with this marking. Every unmarked pixel contains fictitious drop of water. Drop moves forward with its insignificant neighbor until and unless it reaches a marked pixel, at that point it assumes a marked worth. Single theoretical pixels are maintained at each neighborhood lowest during the flooding process. The neighboring pixel at the neighborhood lowest is still submerged in an ocean of pixels. In the event of pixel flood, pixels that are not required are eliminated, making the next pixel faster than the preceding one. But still, it is not appropriate for segmentation of images with fragile boundaries. Standard watershed methods are prone to excess segmentation when there is noise in the image or when the objects themselves have a low signal to noise ratio. [14]. By choosing an appropriate filtering method, one can reduce excessive segmentation by removing the irrelevant neighborhood lowest [15, 16]. The optimal result is obtained by algorithms of power watershed under regular watershed algorithms [17]. Incorporating advantages of morphological watershed segmentation and unsupervised neural network (NN) classification to precisely identify breast tumor shapes from ultrasound images [18]. To improve the selected contour's accuracy, the updated stochastic watershed variation was used [19]. To adjust the optimal parameters of the method, training is utilized. They were then used on various data sets, and the outcome indicate that it is reliable instrument for segmenting the liver automtically when contrasted to alternative techniques. Using unique feature combinations and marker-controlled watershed algorithms, tumors were extracted from brain MR images [20].

Grouping Approach: Process of organizing identical data into groups as per the analogy criteria is clustering. K-means clustering (hard clustering) is one of the common approach for clustering, in which each component of the dataset is associated with a single cluster at a time. The value of the fuzzy community function, ranging fuzzy community function value, which varies from 0 to 1, is the deciding factor in whether a pixel fits in with a group in soft clustering approach (FCM), where a pixel may be a part of more than one group. The position of the pixel is unusually close to centroid, and it's possible that the class of the community function value that it belongs to is one. The aim function is the sum of the squares of the Euclidean separations that connect to every input sample and relate distances of the cluster center to the fuzzy community[21]. Grayscale and color images are divided with the help of FCM algorithm, where the number of groups can be chosen. Any deviation from the expected value could be useful in identifying segmentation flaws. The objective function in FCM can be extended and balanced in accordance with the requirements. FCM works well with a variety of image kinds because of the goal function's convenient adaptability. Because the FCM algorithm itself has the ability to measure validity, it minimizes computational effort and produces acceptable results. The FCM algorithm was being refined in real life. Outcome of the standard FCM is sensitive to unwanted sound when it comes to adjusting for the intensity heterogeneities in MR images. Kernelized fuzzy C-means (KFCM), a kernel-induced separation, takes the place of Euclidean separation[22]. The objective function now included the dimensional penalty. introduced Fast Generalized Fuzzy C-Means (FGFCM) clustering technique, which suppresses noise and preserves information in an image by combining local spatial and gray data [23]. Some improvements were made to the standard FCM algorithms. These algorithms were tested using a bacterium picture to isolate the bacteria from the background and to identify the locations of abnormality. They came to the conclusion that T2FCM (TYPE-II.FUZZY C-MEANS) effectively eliminated the unwanted sound at an expense of magnifying the object's size. Compared to other techniques, IFCM (INTUITIONIST FUZZY C-MEANS) proved effective at image segmenting suggested "Fuzzy. based artificial bee colony (FABC)", combining "FCM" and "Artificial bee colony optimization (ABC)"[24]. They evaluated on artificial and medical images, utilizing the function of the fuzzy community to find best cluster center using ABC; the efficiency results were displayed in comparison to the other approaches. With the use of regularized kernel adaptability, the suggested ARKFCM, a configurable kernel-based technique for MRI segmentation of brain, improves the resilience to maintain picture subtlety [26].

Side detection: It is the most established approach for identifying anomalies in an image. Edge refers to the division that exists between two regions of varying grey levels or intensities. The edges are outstanding for all applications and image enhancement to bring out the intricacies in the picture. The Edge's presence in an image is determined using derivative operations, mainly a convolution function applied to a picture with a suitable mask [11]. Using the gradient extent threshold to identify the potential Edge, canny is an effective side detector that strengthens Edge. By using hysteresis thresholding and non- maximal suppression systems, it suppresses them [27].Unwanted sound in the image has a huge influence on edge detections, which means that the edges that are detected may be insufficient or irregular due to discontinuous pixel identification. For this reason, the picture must first be adjusted using the Gaussian operator. Preprocessing the pictures can eliminate multi-resolution edge identification and edge tracing methods, which in the past may have resulted in erroneous edge detection [28].

Primarily Model Based Approach: It has been established that model-based approaches are most likely the most effective methods for image analysis in conjunction with a model. Detail regarding the future shape and presence of the structure is contained in this model. Compared to conventional methods, this technique is more resilient against the artifacts associated with the photos.

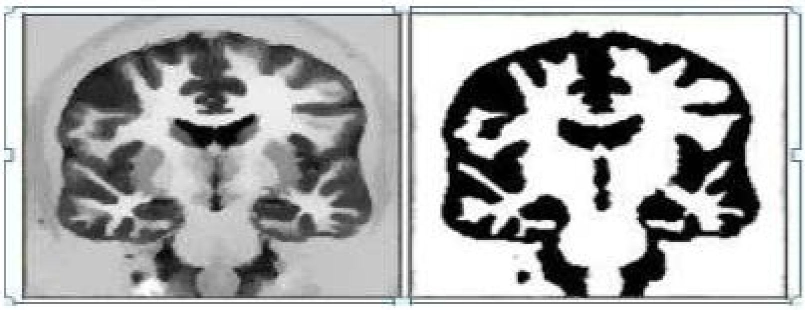
Markov Random.field models: It is a straightforward stochastic procedure where the allocation of the further state depends solely on the present state, not on the way of how it got there. Inspired by the Ising model [29], a sequence of arbitrary order with the Markov attribute if its current situation determines its allocation is referred to as a Markov random field (MRF). Due of its ability to safeguard edges through parameter approximation, MRF algorithms have been broadly used for picture revamping as well as segmentation [30]. Introduced Hidden Markov random field (HMRF) [31], that is based on a random process generated by the MRF model whose arrangement state may be observed through analysis and not directly. The opulent version of "HMRF model" is "FM model" as demonstrated analytically. Correlation experiments using the "FM model-based segmentation" demonstrated accurate and robust segmentation obtained by combining the HMRF model and a "Expectation- maximization (EM)" algorithm into a "HMRF-EM framework" examined how adding geographic limitations to the SOFM (self-organizing feature map) and MRF combination enhances smoothness of region partitioning [32]. Talked about mass breast segmentation using the "Unsupervised MRF model" known as Proclaimed PRF (Pickard random fields). It was found that, in terms of computational complexity, the PRF model was more productive than the standard MRF [33].

Atlas-based approach: Anatomical details are included in the photos of the Atlas to link it with previous data for division and result modifications based on specifics of the Atlas. An atlas is advanced by using the informative indexes of both normal people and clinically disabled subjects. It can be a physically annotated picture that is closely associated to the picture that has to be divided. An important task is performed by the image enrolment, and the partition precession is improved by several atlases [34]. To precisely partition the earmark item in the image enrolment course, a mapping approach commonly referred to as "LABEL PROPAGATION" was applied to the physically marked Atlas. Enrollment accuracy is crucial as mistakes could happen if the difference between examination subject and Atlas exists. [35]. Selecting the source photos for an Atlas creation involved determining the true mean of the population or gathering a sample that was closer to the mean. The bias effect of the development of atlas may be reduced by varied number of algorithms that are iterative, depending on a number of characteristics. A vast database is needed due to the several atlas partitions, and it is necessary to choose the appropriate atlas of the query image [36]. Labels of. Atlas for the earmark portrayal were limited by altering the weights of the fusion in a dimension-wise manner, derived from the neighborhood assessment of the enrollment activity [37]. The preferable result beyond aortic segmentation and an individual atlas- based method of heart in images of CT scan was the average-shape atlas-based segmentation strategy that they presented [37]. To automatically remove the ribs of the patients from a conventional chest x-ray (CXR), rib-bone atlases was used by author, by using bone pictures obtained from a dual-energy x-ray equipment in addition to physically interacting with models imitated from CT scans [38]. In the enrollment process, they use the regional similarities between x-rays of the model as well as patient to calculate the transformation mapping, which they then apply to the rib masks. The patient-X-ray rib bone likelihood map is determined by averaging the enrolled models.

Artificial neural networks: Representing neurons mathematically that is modeled after biological neural networks, much like human brain cells. Copy of a neuron is a node, that can be used along with particular operational divisions. Synaptic weights serve as communication channels between these nodes. With the assistance of the activation function, these synaptic weight's inputs are further processed to identify or classify item [39]. Neural networks have two main characteristics: learning and training. With the use of the Wavelet or Curvelet transform, Neural Networks are geared up with statistical feature like kurtosis, standard deviation, skewness, mean or transfer, depending upon the feature. Neural networks go through an initial phase known as speculating phase during the training phase, which continues until the study state is reached. Additionally, the better the training of neural networks, the more favorable result in relation to test picture. Learning is an adaptable process whereby the interlinking neurons' weights are adjusted to provide relevant input. Neural networks classified as supervised as well as unsupervised learning are used in the learning process [40]. Determining the number of layers, architecture, type, network size, type, architecture, and geographical locations is a major challenge for neural network algorithms. The selection of the aforementioned elements has an impact on how the problem is presented."Group Method of Data Handling (GMDH)" [41] provided instructions for identifying the lungs from the clinical photographs. Better segmentation results are produced by fuzzy neural networks, which are noise-insensitive [42] suggested separation metrics that the SVM classifier used and looked into the significance of choosing the right hyper parameters [43]. This approach shown that the segmentation accuracy is good in addition to using less handling memory and time. labored on segmenting liver cancer from MR pictures by combining the 3D fast marching algorithm along with the "Single hidden layer" feed-forward neural network. The results are compared to those that a radiologist physically delineates and uses as ground truth [44]. Other semi-automated segmentation strategies resulted in exact conclusions and a significant reduction in time unpredictability [44].To detect glioblastomas in the brain MR pictures, a deep convolutional neural network (DCNN) has been employed [45].

Graph cut approach: The fundamental idea behind this approach is to use graph theory tools to separate the image into foreground and background. According to graph theory, each and every pixel is a node where as edges represent connections between the nodes. The likelihood of a node being in the background or foreground connecting the sink or source is known as a connecting link. The weight of the edge is associated with the probability. The weight that encourages comparable pixels to remain in the same segment and encourages distinct pixels to separate into separate segments [46]. Once the graph has been constructed, divide it by making the smallest, least complicated cut possible to separate the foreground from the background. Cost function symbolizes region and boundary properties that are thought of as soft restrictions for the segmentation, together with a few hard constraints. The global optimization is recomputed when the cost function is mentioned and the hard constraints are modified to reflect the new constraints. The nodes in the graph are represented by cut pixels, while the weighted connecting nodes are represented by edges. They use the global optimal minimal cut computation to extract the image's background and object. They used medical image processing, video editing, and photo editing to show this technique [46]. In order to reduce the function of the energy, that is follows the graph cuts, they presented two strategies. The labeling in the first example is done among an arbitrary group of pixels in order to decrease energy through movement among the marked pixels. Smoothing is needed for algorithm number two. Three energy functions were employed that were quadratic. The one at the first place has a reduced quadratic energy function. Outcomes are compared with the various annealing variations, and the energy functions at the last and second last place matches Potts model and reduced gap as smoothness fine.[47]. With prior knowledge of the shape of the foreground, the graph cut method produces a better result than the traditional graph cut techniques. Partition of the multi regional graph cut is carried out by kernel mapping of data of the image, and original data is included in the objective function to evaluate the altered picture's deflection. Fixed point iterations as well as graph cut optimization for updating the parameter of the region were the two successive processes that the optimization method iterated. This approach takes help of computing benefits of images by graph-cut and offers a potent alternative to the intricate modeling of the original data. Using synthetic, real-world, and medical images, this method was quantified and compared to validation. When it comes to partition of multi-region of brain MR images, kernel mapping produces good results [48].

Lattice Boltzmann method (LBM): These are extremely accurate and potent procedures. One such method that simulates relies on microscopic explanation of physical process that is macroscopic is the LBM, that has been extensively used in theory of kinetics to model a variety of systems [49]. By focusing on behavior of collection of particles which are expected to act in same manner and not as the behavior of particle that is single, the motive of LBM is to reduce the distance between the microscopic and macroscopic scales. Each of these particle collections is provided as a distributive function, which serves as a representation of the particle collection. The solution region is divided into lattices in LBM. The dispersal of particles is located at each lattice node. Some of the particles move toward neighboring junction in a particular regulation. The alignment of lattices determines the quantity of directions and connectivity. The traditional term used in this method is DnQm, which refers to size of the problem, 'n' to the number of interconnections, and 'm' to the speed model. Key component of LBM is the function that is equilibrium distributive with time of relaxation (τ) determining type of problem that needs to be solved. For the purpose of solving partial differential equations, LBM offers an alternative tool to traditional mathematical techniques (PDE). Because LBM takes into account the dispersion of particles rather than tagging each particle, it is quicker, simpler, and capable of assimilating huge concurrent computing. It also has the advantage of using less memory during simulations. The two stages of the generic LBM are streaming and collision stage. In first stage particles travel across a lattice from one junction to another, and in second stage particles (or its densities) rearrange themselves at every node [50]. Particle movement in the two phases is determined by the LBM evolution equation, which takes into account the source term (α) and parameter relaxation time (τ). Because the particles move along the linkages, which are governed by lattice number and speed of the lattice , every node's current state is exclusively determined by the states of the nodes that surround it. Techniques of analysing the image like (a) smoothening of image [51–53], (b) image in painting [54], (c) segmentation of image [55–60] etc. can all benefit from the efficient application of LBM. Each pixel value in an image is regarded as a particle density in image processing, and variations in values of pixel can be viewed as a reallocation of particles determined by source term (α) time of relaxation (τ), which contains embedded information of an image such as curvature, gradient. Image processing is carried out using LBM, which is easily applied to complicated domains and has the potential to support multiphase and multi component flows. A model based on LBM, picture division anisotropic diffusion model, was presented and this model illustrated the accuracy of computing the medical images [55], [61–65]. Suggested a novel LBM technique for the segmentation of MR and clinical images utilizing the D2Q19 lattice arrangement model. This technique is comparable to the anisotropic diffusion, cab be seen in figure2 [56], [66-71].



(a) MR image (b) LBM

Figure 2: Segmentation of MR image by LBM

They proposed solving the Level Set Equation (LSE) with LBM and recommending a stop function based on regions [71–76]. At weakly occluded edges, Unsigned Pressure Force (UPF) can satisfactorily halt the contour based on regional attributes [57]. They solved the LSE with the help of parallelizable LBM. Because this method unravels in graphic space in place of the domain of pixel, it is faster [77–81]. Because there are typically far fewer grey levels than there are pixels in the picture, the time issue is greatly reduced. Compared to strategies that rely on the LSM, this one is more productive, profoundly parallelizable, and faster [58]. The Lattice Boltzmann Anisotropic Diffusion Model (LBADM) can be used to determine the edge of object division, and it has been shown that the diffusion and convection conditions can be accurately understood by its computation [59]. This approach drastically reduces the division calculation. They computed entropy for LBM's D2Q9 model and conditions for the multiphase level set, and they suggested a novel variation multiphase level set strategy to clinical segmentation [60]. Their approach for MR breast imaging has been demonstrated to be faster and more efficient [81–84]. The pixel-based algorithmic nature of the LBM is a plus. It works with particles, and since pixels are copies of particles, we can fine-tune the method at any resolution by utilizing different types of lattice points. Computational load will rise along with the number of lattice points, which could be a disadvantage of the LBM from a computation standpoint. All of the macro parameters can be changed because in the domain of microscopic all the parameters are based on particle; however, because LBM is involved, density needs to be defined in a regular structure. It can have the LBM's demerit because it is very difficult to get a regular structure in a medical image.

Conclusion: In order to stimulate interest in further research and inquiry into medical image segmentation, this work provides an overview explaining the various approaches to segmentation for medical images as well as a novel LB method. Stress that there is still work to be done in all of these problem areas and that there is room for widespread improvement in all of the methods shown. In real-time applications such as radiotherapy treatment and diagnosis, medical image segmentation is a challenging problem. Although segmentation algorithms can recognize the various tissues surrounding the tumor site and its boundaries, more creative work is now needed to increase computational speed. With a fair number of computer resources, LBM can offer high image processing quality thanks to its speed and modeling versatility. In image processing, the LBM has a clear physical definition. Changes in value of pixel value can be interpreted as the redistribution of particles, and the image's pixel value is equivalent to density of particle. The same is determined by time of relaxation, that also determines problem type that requires solution, also adding term of source is simple. We anticipate that the field of LB technique research will grow into a new hotspot because of the expected comprehension of the large dimensionality and computing speed of picture segmentation using LBM with more lattice vectors.

References

1. Zhang, Y. J, "An overview of Image and Video Segmentation,". Beijing, China, IGI Global; 2006.chapter-1, An overview of Image and Video Segmentation in the last40 years; p.1-16.
2. Gregory Sharo, Karl D Fritscher, Vladimir Pekar, Marta Peroni, Nadya Shusharina, Harini Veeraraghavan and Jinzhong yang, “Vision 20/20: Perspectives on automated image segmentation for radio therapy,”. Med. Phys. 2014; 41(5): p.050902-13.
3. Najeeb Chowdhury, Robert Toth, Jonathan Chappelow, Sung Kim, Sabin Motwani, Salman Punekar, Haibolin, Stefan Both, Neha Vapliwala, Stephen Hahn and Anant Madabhushi, "Concurrent segmentation of the prostate on MRI and CT via linked statistical shape models for radiotherapy planning,”. Med. Phys. 2012; 39(4): 2214-28 .
4. Nida M Zaitoun, Musbah J.Aqel, "Survey on Image Segmentation Techniques," Procedia Computer Science. 2015; 65: p.797 – 806.
5. Kumar S N, Lenin Fred A, Muthu kumar S, Ajay Kumar Hand Sebastian Varghese P, "A Voyage on Medical Image Segmentation Algorithms,” Biomedical Research. 2017; Special Issue, Res.p.1-12.
6. D. L. Pham, C. Xu, and J. L. Prince, "Current methods in medical image segmentation," Annual Review of Biomedical Engineering. 2000; vol.2: pp.315-337.
7. W. X. Kang, Q. Q. Yang, R. R. Liang, "The Comparative Researchon Image Segmentation Algorithms,”. IEEE Conference on ETCS. 2009; pp. 703-707.
8. R.C. Gonzalez and R.E. Woods, "Digital image processing,” 2-ed .NewYork: Prentice Hall; 2002. 1-813.
9. R.M Haralick and L.G .Shapiro, “Image Segmentation Techniques,”. Computer Vision, Graphics, and Image processing .1985; Vol-29, Issue 1, p.100-132.
10. Wu J, Skip P, Michael DN, Marked VK. “Texture feature- based automated seeded region growing in abdominal MRI segmentation," .Proc IEEE international conference Biomedical Engineering and Informatics,27-30 May 2008, Sanya, China, IEEE, 2008; 2:263-267.
11. Thakur A Radhey SA. "A local statistics based region growing segmentation method for ultrasound medical images". World Academy Science Engineering and Technology, Int J Med Health Biomed, Boeing Pharm Eng.2007;1:564-56.
12. T. Pavlidis, "Algorithms for Graphics and Image Processing," Computer science press, Rockville, MD,1982.
13. Belaid LJ, Walid M. "Image segmentation: a water shed transformation algorithm,". Image Analysis Stereology.2009; 28:93-102.
14. Hanbury A. "mage segmentation by Region-based and watershed algorithms,". Wiley Comp Sci Eng. 2009; 543-1552.

15. Biernacki W . “Over segmentation avoidness in water shed based algorithms for color images,". Proc IEEE International Conference Modern Problems Radio Eng Tele communi CompSci, 28 Feb.2004, Lviv-Slavsko Ukraine,IEEE, 30 Dec 2004;169-172.
16. Grau V Mewes AUJ, Alcaniz M, Ron K Simon KW."Improved watershed transformfor medical image segmentation using prior information," .IEEE Transactions Medical imaging..2004;23:2606-2614.
17. Hamid R.Arabnia, "Advances in computational biology". Springer Science Business Media, 2010;4-18.
18. Huang YL, Dar RC." Watershed segmentation for breast tumour in 2D sonography,". Ultrasound Med Biol.2004;30:625-632.
19. Lopez MF, Valery N, Jesus A, Alcaniz M Luna L ."Liver segmentation in MRI: A fully automatic method based on stochastic partitions,". Comp Methods Prog Biomed.2014;114,11- 28.
20. Benson CC, Lajish VL, Kumar R." Brain tumour extraction from MRI brain images using marker-based watershed algorithm,". International Conference Advances Comp Communications Informatics (ICACCI).2015;318-323.
21. Ahmed M N, Sameh MY, NevinM, AlyAf, Thomas M. "A modified fuzzy c-means algorithm for bias field estimation of Segmentation of MRI data,". IEEE Trans Med Imaging.2002;21:193-199.
22. Zhang DQ, Song CC. "A novel kernelized fuzzy c-means algorithm with application in medical image segmentation,". Artificial Intel Medicine. 2004; 32:37-50.
23. Cai W SongeanC, Daoqiang Z ."Fast and robust fuzzy c- means clustering algorithms in corporating local information for image segmentation,". Pattern Recogn.2007;40:825-838.
24. Anjea D, Tarun KR. "Fuzzy Clustering algorithms for effective medical image segmentation,". Int J Intel SysAppl.2013;5:55.
25. AnkitaB, Kalyani M "Fuzzy-based artificial bee colony optimization for grey image segmentation,". Signal and Video Proc.2016;10:1089-1096.
26. Ahmed E, Changmiao W, Fucang J, Jianhuang W, Guanglin L Qingmao H ."segmentation of brain tissues from MRI images using adaptively regularized Fuzzy c-Means Clustering,".Hindawi Publishing Corporation Computational Mathematical Methods Medicine. 2015;1-12.
27. Nadeem M, Asadullauhnjgb S, AdamuA, Ahafia KSyed BZ. "Image segmentation methods and edge detection: an application to knee joint articular cartilage edge detection, ".J Theor Appl Inform Technol. 2015;71.
28. Lopez-MolinaC, DeBates B, BustinceH, SanzJ, Barreneche E. “Multiscale edge detection based on Gaussian smoothing and edge tracking,". Knowledge-Based Systems. 2013; 44:101- 111.
29. Kindermann, Ross; Snell, J. Laurie."Markov Random Fields and their applications,".1-ed. Providance, Rhode island, American Mathematical Society.1980.1-147.
30. Held K Rota KE, Bernd JK, William MW, Ron K, Muller Gartner HW." Markov random field segmentation of brain MR images,". IEEE Trans Medical Imaging. 1997;16:878-886.
31. Zhang Y, Brady M, Smith S. "Segmentation of brain MR images through a hidden markov random field model and expectation-maximization algorithm,". IEEE Trans Med Imaging .2001;20.
32. Li Y, ZheruC ." MR Brain image segmentation based on self -organizing map network,". Int J Inform Technol.2005;11:45-53.

33. Segbed ji RTJG, YvesG, HichemM. "Unsupervised malignant mammographic breast mass segmentation algorithm based on Pickard Markov random field,". IEEEInt Conference Image Proc,.2016;156-164.
34. Hyunjin P, Peyton HB Charles RM," Construction of an abdominalprobabilistic atlas and its applicationin segmentation ".IEEE Trans Med Imaging .2003;22:483-492.
35. Kang WX, Qing QY, Run PL ." The comparative research on image segmentation algorithms,".Proc First Int Workshop Education Technology Computer Science.2009;1:703-707.
36. Cauadra MB, Claudio P, Anton B, Olivier C, Villemure JG, ThiranJP." Atlas-based Segmentation of pathological MR brain images using a model of lesion growth ".IEEE TransMed Imaging .2004;23:1301-1314.
37. Ivana I, Marius S, Annenarieke R, Mathias P Max AV,Bram van G "Multi -atlas-based segmentation with local decision fusion application to cardiac and aortic segmentation in CT scans,".IEEE Trans Med Imaging.2009;28:1000-1011.
38. Sema C,Stefan J ,Sameer A UlasB,Les RF, Ziyue X, GeorgeT." Atlas based rib-bone detection in chest x-rays,". CompMed Imaging Graphics. 2016;51:32-39.
39. Dayhoff JE, DeL, James M," Artificial neural networks". Cancer John Wiley Sons Inc.2001;91:1615-1635.
40. Egmont P, Michael, Heinz H ."Image processing with neural networks -a review,".Pattrecogn.2002;35:2279-2301.
41. Tadashi K AbhijitSP, Jack MZ. "GMDH type neural networks and their application to the medical image recognition of the lungs". Proc38th SICE Annual Conference;30-30 July 1999; Morioka, Japan.Japan:IEEE;1991;1:1181-1186.
42. Wongchomphu P, Narissara E . "Enhance neuro-fuzzy system for classification using dynamic Clustering,". Proc 4th Joint international Conference Information communication Technology Electronics and Electrical Engineering; 5-8 March 2014; Chiang Rai, Thailand: IEEE;2014;1-6.
43. Mohmmad H Hugo L, Phillippe P. "Within Brain classification for brain tumour segmentation,". International Journal of Computer Assisted Radiology and Surgery. 2015;11:777-788.
44. Trong –Ngoc L, Pham The B, HieuTH," Liver tumor segmentation from MR images using 3D fast marching algorithm and single hidden layer feed word neural network,".Hindawi Publ Corp Bio Med Research Int.2016;1-8.
45. Mohammad H Axel D, David WF, Antoine B Aaron C, Yoshua B, Chris P, Pierre-MJ, HugoL." Brain tumor segmentation with deep neural networks,". Medical Image Analysis. 2017;35:18-31.
46. Boykov YY, Jolly MP," Interactive graph cuts for optimal boundary and region segmentation of objects in ND images,". Proc Eighth IEEE International Conference Computer Vision. 2001;1:105-112.
47. Boykov Y Olga V, Ramin Z. "Fast approximate energy minimization via graph cuts,".IEEE Trans Patt Anal MacIntel .2001;23:1222-1239.
48. Ben Salah M, Mitiche A, Ben AyedI." Multiregional image segmentation by parametric kernel graph cuts". IEEE Trans Image Process. 2011;20:545-557.
49. D.Grunall, S.Chen and K. Eggert." A Lattice Boltzmann model for multi-phase fluid flows,".PhysFluids.1993;5:2557-2562.
50. A.A. Mohamad "Lattice Boltzmann method: Fundamentals and Engineering Applications with Computer codes, "Springer–Verlg London Limited: Springer;2011.1-73.

51. B Jawerth, P Lin and Sinzinger E "Lattice Boltzmann models for anisotropic diffusion of images,". Journal of Mathematical Imaging and Vision. 1999;11:231-237.
52. Y Chen, Z.Z.Yan and Y.H. Qian, "An Anistropic Difussion Model for Medical Image smoothing by using the Lattice Boltzmann method,".7th Asian-Pacific Conference on Medical and Biological Engineering. IFMBE Proceeding of APCMBE;22-25 April 2008; Beijing, China. China: Springer; 2008. 255-259.
53. Wenchuan Zhang, Baochang Shi," Application of Lattice Boltzmann method to Image filtering ", Mathematical Imaging and Vision. 2012; 43:135-142.
54. Y Chen" A lattice-Boltzmann method for Image inpainting", 3rd international congress on image and signal processing(CISP) ;Yantai, China.China:IEEE;2010.vol 3,pp.1222-1225.
55. Y Chen, Z Yan and Shi J, "Application of Lattice Boltzmann method to image segmentation", 29th Annual international conference of the IEEE engineering in medicine and biology society;22-26 Aug. 2007; Lyon,France.France:IEEE;2007.pp.6561-6564.
56. Y Chen, Z.Z.Yan and Y.H. Qian," Lattice Boltzmann Method based Medical Image Segmentation.".2009 2nd International Congress on Image and Signal Processing;17-19 Oct .2009; Tianjin, China. China:IEEE;2009.pp.1-5.
57. S Balla-Arabe, B Wang and X Gao," Level set region- based image segmentation using lattice Boltzmann method,".Seventh International Conference on computational intelligence and security(CIS);3-4 Dec.2011; Hainan, China. China: IEEE;2011.pp,1159-1163.
58. S Balla-Arabe, X Gao," Image multi-thresholding by combining the lattice Boltzmann model and a localized level set algorithm,". Neuro computing.2012; 93:106-114.
59. Q Wu, Y Chen and G Teng, "Lecture Notes on Electrical Engineering 107 ".Computer, informatics, cybernetics and applications,1-ed.Berlin: Springer. Chapter61," Lattice Boltzmann anisotropic diffusion model-based image segmentation;p.577-589.
60. S Balla-Arabe, Wang B and X Gao, "A Multi phase entropy-based level set algorithm for MR breast image segmentation using lattice Boltzmann model". Intelligence science and intelligent data engineering,2013;7751:8-16.
61. Barot, V., Kapadia, V., & Pandya, S., QoS Enabled IoT Based Low Cost Air Quality Monitoring System with Power Consumption Optimization, Cybernetics and Information Technologies,2020, 20(2), 122-140. doi:https://doi.org/10.2478/cait-2020-0021.
62. Sur, A., Sah, R., Pandya, S., Milk storage system for remote areas using solar thermal energy and adsorption cooling, Materials Today, Volume 28, Part 3, 2020, Elsevier, Pages 1764-1770,ISSN2214-7853,https://doi.org/10.1016/j.matpr.2020.05.170.
63. H. Ghayvat, Pandya, S., and A. Patel, "Deep Learning Model for Acoustics Signal Based Preventive Healthcare Monitoring and Activity of Daily Living," 2nd International Conference on Data, Engineering and Applications (IDEA),Bhopal, India, 2020,pp.1-7,
64. Pandya,S., Shah,J., Joshi,N., Ghayvat,H., Mukhopadhyay, S.C. and Yap, M.H., 2016, November. A novel hybrid based recommendation system based on clustering and association mining. In Sensing Technology(ICST), 2016 10th International Conference on (pp. 1-6). IEEE.
65. Pandya, S., W. Patel, H. Ghayvat, “NXTGeUH: Ubiquitous Health care System for Vital Signs Monitoring & Falls Detection”, IEEE International Conference, Symbiosis International University, December 2018.
66. Ghayvat, H., Pandya, S., “Wellness Sensor Network for modeling Activity of Daily Livings Proposal and Off-Line Preliminary Analysis” IEEE International Conference, Galgotias University, New Delhi, December 2018.

67. Mehta, P., Pandya, S., A review on sentiment analysis methodologies, practices and applications, International Journal of Scientific and Technology Research, 2020, 9(2),pp. 601– 609
68. Shah, J., Pandya, S., N. Joshi, K. Kotecha, D. B. Choksi,Load Balancing in Cloud Computing: Methodological Survey on Different Types of Load Balancing Algorithms‖, IEEE International Conference on Trends in Electronis and Informatics, Tamil Nadu, India, May 2017.
69. D.S. Hooda and D.K. Sharma (2008), Generalized R-Norm information Measures-Journal of Appl. Math, Statistics & informatics (JAMSI), Vol. 4No.2 , 153-168.
70. Ravi Manne, Snigdha Kantheti, Sneha Kantheti,(2020),"Classification of Skin cancer using deep learning, Convolutional Neural Networks- Opportunities and vulnerabilities- A systematic Review", International Journal Of Modern Trends in Science and Technology, ISSN:2455-3778,Vol.06,Issue11,pp.101- 108.https://doi.org/10.46501/IJMTST061118
71. Dilip Kumar Sharma, "Some Generalized Information Measures: Their characterization and Applications", Lambert Academic Publishing, Germany, 2010. ISBN:978-3838386041.
72. S. Suman Rajest, D.K. Sharma, R. Regin and Bhopendra Singh, "Extracting Related Images from E-commerce Utilizing Supervised Learning", Innovations in Information and Communication Technology Series, pp. 033-045, 28 February, 2021.
73. Ganguli S., Kaur G., Sarkar P., Rajest S.S. (2020) An Algorithmic Approach to System Identification in the Delta Domain Using FAdFPA Algorithm. In: Haldorai A., RamuA., Khan S. (eds) Business Intelligence for Enterprise Internet of Things. EAI/Springer Innovations in Communication and Computing. Springer, Cham
74. Singla M.K., Gupta J., Nijhawan P., Ganguli S., Rajest S.S.(2020) Development of an Efficient, Cheap, and Flexible IoT-Based Wind Turbine Emulator. In: Haldorai A., RamuA., Khan S. (eds) Business Intelligence for Enterprise Internet of Things. EAI/ Springer Innovations in Communication and Computing. Springer, Cham
75. Rao, A. N., Vijayapriya, P., Kowsalya, M., & Rajest, S. S.(2020).Computer Tools for Energy Systems. In International Conference on Communication, Computing and Electronics Systems (pp.475-484).Springer, Singapore.
76. R. Arulmurugan and H. Anandakumar, "Region-based seed point cell segmentation and detection for biomedical image analysis," International Journal of Biomedical Engineering and Technology, vol. 27, no. 4, p. 273, 2018.
77. Dr.S. Suman Rajest Dr. Bhopendra Singh, P. Kavitha, R.Regin, Dr.K. Praghash, S. Sujatha, "Optimized Node Clustering based on Received Signal Strength with Particle Ordered-filter Routing Used in VANET" Webology,Vol.17, No.2, pp. 262-277, 2020.
78. D Datta, S Mishra, SS Rajest, (2020) "Quantification of tolerance limits of engineering system using uncertainty modeling for sustainable energy" International Journal of Intelligent Networks, Vol.1,2020,pp.1-8,
79. Leo Willyanto Santoso, Bhopendra Singh, S. Suman Rajest, R.Regin, Karrar Hameed Kadhim (2021), "A Genetic Programming Approach to Binary Classification Problem" EAI Endorsed Transactions on Energy, Vol.8, no. 31, pp. 1-8.DOI: 10.4108/eai.13-7-2018.165523
80. Dr. Laxmi Lidiya. S. Suman, Rajest, "Correlative Study and Analysis for Hidden Patterns in Text Analytics Unstructured Data using Supervised and Unsupervised Learning techniques" in International Journal of Cloud Computing, International Journal of Cloud Computing(IJCC), Vol. 9, No. 2/3, 2020.
81. Haldorai, A. Ramu, and S. Murugan, "Social Aware Cognitive Radio Networks," Social Network Analytics for Contemporary Business Organizations, pp. 188–202.doi:10.4018/978-1-5225-5097-6.ch010

82. M. Suganya and H. Ananda kumar, "Handover based spectrum allocation in cognitive radio networks," 2013 International Conference on Green Computing, Communication and Conservation of Energy (ICGCE), Dec.2013.doi:10.1109/icgce.2013.6823431.doi:10.4018/978- 1-5225-5246-8.ch012
83. A. J. Obaid, "Critical Research on the Novel Progressive,JOKER an Opportunistic Routing Protocol Technology for Enhancing the Network Performance for Multimedia Communications ," in Research in Intelligent and Computing in Engineering. Advances in Intelligent Systems and Computing, vol 1254. Springer, Singapore., Springer, Singapore, 2021, pp. 369-378.
84. S. Sharma and A.J. Obaid, "Mathematical modelling, analysis and design of fuzzy logic controller for the control of ventilation systems using MATLAB fuzzy logic tool box," Journal of Inter disciplinary Mathematics, vol. 23,no. 4, pp. 843-849, 2020.

About the Author:

Prof. Rashmi Bhardwaj, Fellow of Institute of Mathematics & Applications (FIMA, UK); Assessor, National Assessment and Accreditation Council (NAAC), UGC, Government of India; Fellow of Indian Society for Mathematical Modelling and Computer Simulation (FISMMACS), under IIT Kanpur, India and working as Professor of Mathematics & Head of Nonlinear Dynamics Research Lab, University School of Basic & Applied Sciences (USBAS), Guru Gobind Singh Indraprastha University (GGSIPU), New Delhi, India. Recipient of Government of India, India Meteorological Department (IMD) 27th Biennial MAUSM Award. Visiting Associate of Inter University Center for Astronomy & Astrophysics (IUCAA) Pune, Young Scientist Award of All India Council for Technical Education (AICTE), Government of India. Best Researcher Award of GGSIPU (3 consecutive years.) Topper of University of Delhi with 100% marks in Integral equation & Boundary value problem. Also, the topper of Zakir Husain college University of Delhi in M.Sc. (Mathematics) and B. Sc (Hons.) (Mathematics) examination. She has about 28 years teaching experience in Mathematics for PhD, Postgraduate and Graduate level. She Supervised Sixteen candidates for Ph.D. Degree and six are presently working for Ph.D. Degree. She has published 4 patents, 10 Books, 200 research papers published in Journals of International / National repute and Conferences. Subject Reviewer for many International Journals of repute. Life member of several international organizations in the sphere of Mathematical Sciences including Indian National Science Congress. Attended/ delivered talks and Chaired Technical Sessions at reputed academic conferences/ workshops across the world Established Nonlinear Dynamics Research Lab and Mathematics Lab in GGSIPU.

Ms. Divisha Kansal is a research scholar working in Nonlinear Dynamics Research lab under the supervision of Prof Rashmi Bhardwaj