Medical Image Segmentation A Review of Recent Techniques, Advancements and a Comprehensive Comparison

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Medical Image Segmentation: A Review of Recent Techniques, Advancements and a Comprehensive Comparison

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***Abstract*—**Image segmentation is the most critical function in image analysis and processing. Results of segmentation fundamentally affect all subsequent image analysis processes such as representation and description of objects, measurement of features, and even higher-level tasks such as classification of objects. Image segmentation is therefore the most essential and crucial process for facilitating the delineation, characterization and visualization of regions of interest in any medical image. The radiologist's manual segmentation of the medical image is not just a tedious and time-consuming technique, also not very accurate, especially with the increasing medical imaging modalities and the unmanageable quantity of medical images that need to be examined. It is therefore necessary to review current image segmentation methodologies using automated algorithms that are accurate and require as little user interaction as possible, especially for medical images. In the segmentation process, it is necessary to delineate and extract the anatomical structure or region of interest so that it can be viewed individually. In this paper, we are projecting the important place of image segmentation in decision-making information extraction and deliberating upon current techniques which are used in medical imaging and discussing about various advancements in this research field.

***Keywords*—**Medical Imaging, Segmentation, Watershed Transform (WT), Expectation Maximization (EM), Level Set Method (LSM), Genetic Algorithms (GA), Artificial Neural Networks (ANN).

I. INTRODUCTION

The recent advancements in imaging have not only led to research, innovation and diversification of its potential application areas but also strived to resolve long pending solution to the existing problems i.e. image-guided interventions. From discovery of X-rays beams by Roentgen in 1895 [01] that penetrate our body and allows production of images of our internal organs to present day application fields i.e. medical, forensics, engineering, agricultural etc. imaging has progressed and impacted every sphere of science. In general, imaging has impacted every field of our lives. Through the use of medical imaging a medical practitioner relies on patient reports and accordingly makes accurate and timely diagnosis about the condition of the patients. [02]

Image segmentation is one of the important, key challenging and primary tasks performed in computer vision. Image segmentation divides an image area into multiple non-overlapping, connected regions which are homogenous and share some common characteristic i.e. tone, colour, brightness, texture, boundary continuity etc. [03]. If an image field is denoted by α then segmentation deals in defining set β C α, whose union is entire domain of α. The sets that represent segmentation have to satisfy the equation:

Where $\beta_i \cap \beta_j \neq \Phi$ for $i \neq j$ and β_t is connected. The advances in imaging have progressed rapidly with increase in computational power of devices, easy availability and reduced cost of storage and transmission devices. The focal point of research in medical imaging field is shifting from procurement of images to post processing and information retrieval. There exists a need to design a proficient system that deals with efficient post-processing of images and improvises clinical diagnosis. The current areas of research mainly focus on image retrieval and post processing as depicted in figure (1):

Image Retrieval: Image retrieval techniques allude to tools utilised for looking a specific image from a set of images that are typically put away in a database. [04] The technique employed is either text based or based on content of the image.

Image Processing: Once the image is retrieved, techniques can be utilized to upgrade, reproduce or permit automatic analysis in order to highlight or bring up regions that may form region of interest (ROI).

Once the ROI is decided upon and located, then selection and application of segmentation algorithms is done. There are various proposed segmentation algorithms that have their corresponding application areas but altogether they help in automatic delineation of anatomical structures. The segmentation algorithms which automate the radiological tasks are referred as medical image segmentation algorithms [05]. The main function that these algorithms perform is pathological localization, anatomical structure study, planning of treatment and computer assisted surgery.

The rest of this paper is organised as follows: Firstly, in section II, we briefly review methods of segmentation for medical imaging. Then, in section III, we focus on methods based upon thresholding, region, edge/boundary, clustering and other features. Then in section IV, we focus on various segmentation technique and a detailed comparison of these techniques is provided. In section V, we propose different imaging modalities for effective segmentation of medical images along with their respective application areas. Finally, in conclusions, we assess the current state-of-the-art features required for effective segmentation and provide future directions for development. So, in general this paper will summarize suitable image segmentation methods to be used for each types of medical images scan.

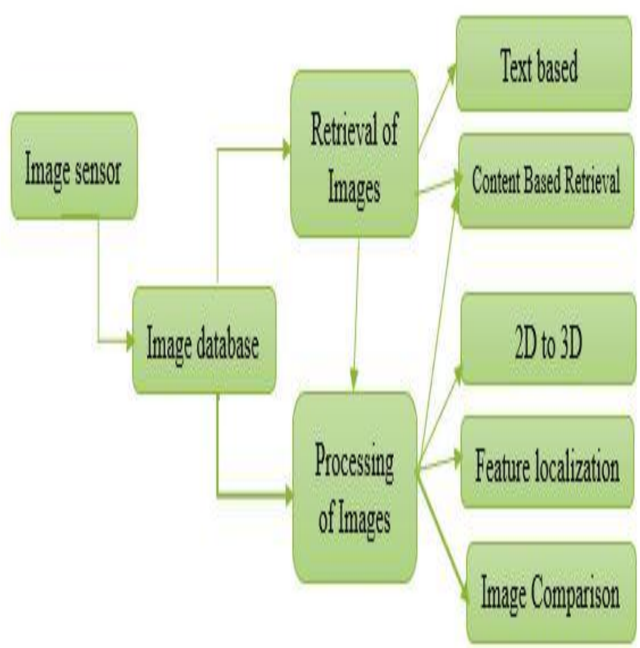

Figure (1): Research areas in Medical Image Processing

II. RELATED WORK

X.Zhang et al proposed a multi-scale 3D Otsu segmentation algorithm based on dimension decomposition [06]. The algorithm takes into consideration spatial information of image and works in multiple iterations. The output of one iteration is fed as input for the other iteration. Firstly, a Laplacian filter is used to obtain multiple scales of image, after that 3D Otsu is applied to generate segmentation maps. The maps are combined to generate a final segmented image. The main advantages with this algorithm are enhanced segmentation of image, reduced noise levels for both bi-level and multi-level thresholding, reduced time complexity as usually seen in other thresholding algorithms.

Han Jie et al proposed multi-threshold segmentation technique using state transition algorithm (STA) [07]. The authors propose that the linear combination of normal distribution functions is used to fit the histogram of normalised image and then optimization, denoising is performed to generate optimised threshold value for segmented image. The authors have compared their results with Otsu, particle swarm optimization (PSO), genetic algorithm (GA) and differential evolution (DA) algorithm and results show competitive performance in optimisation and thresholding.

C. Yang et al proposed a method for lung lesion extraction using toboggan region growing algorithm [08]. The method is stable, automatic, quick-responsive and consists of three phases: seed selection followed by lesion extraction and lesion refining. The method was tested on publicly available (LIDC-IRDI) and clinical dataset. The seed point selection was done using toboggan method and this approach was scaled for 3D lesion segmentation. The lesions were extracted by an automated region growing algorithm with multi-constraints. The proposed method shows that it outperforms over ground-glass opacities and other pre-existing techniques.

M.A. Mohammed et al proposed a method that can assist in detection of nasopharyngeal carcinoma (NPC) by use of computer-based systems as a decision support tool [09]. The technique proposes to reduce FP and FN averages and enhance TP and TN average cases. The proposed methodology works in three phases: image enhancement followed by generation of ROI using empirical domain knowledge of NPC structure and segmentation. The segmentation takes place in two steps: early segmentation of ROI with removal of unwanted objects using geometrical features and modification phase where precise detection of NPC takes place using region growing algorithm. The proposed method achieves segmentation exactness. The study carried out by author shows that the technique is strong and powerful and can greatly assist ENT specialists in detecting NPC. The method is best suitable for detection and identification of ROI for first premature NPC cases.

Y. Li et al proposed an image segmentation technique that improvises the performance parameters of (CCQPSO) algorithm [10]. The CCQPSO algorithm has lesser convergence rate, very slow searching speed and it can fall into local optima. To overcome this, partitioned and cooperative quantum based PSO technique is applied to overcome the above issues. This is done by coupling two techniques for effective segmentation. Firstly, performance and diversity of swarms is improvised by partitioning search spaces followed by applying context vector and cooperation for exploitation of information. This method improvises convergence and avoids trapping into local optima. The proposed technique improvises OSTU segmentation with multiple thresholds.

Rouhi, R., et al proposed a segmentation technique that is used for classifying breast tumours i.e. benign or malignant. The proposed technique uses region growing and CNN segmentation techniques for producing adaptive thresholds and templates for preserving tumour boundaries [11]. Genetic algorithms were used with appropriate features for training and learning purposes to generate CNN templates and classification was performed by classifiers like random forest, SVM, KNN, MLP, Naïve Bayes. The proposed technique was tested on (DDSM and MIAS) databases which are publicly available. The dataset consisted of 219 images in total out of which 93 and 170 were malignant and benign respectively. The results obtained by this technique show that the region growing, CNN and selection of features such as intensity, textual, shape help in effective segmentation of breast tumours. The results from this technique show specificity of 95.94%, accuracy 96.47%, sensitivity 96.87% and AUC to tune of 95.16% was achieved.

Tyan et al compared various image segmentation techniques for effective detection of ischemic stroke or embolus in brain. The author considers an image in frequency-time domain and the applies various operations for detection of emboli in brain [12]. The images obtained were from transcranial doppler (TCD). SM modelling, E+ZCR and STE+STAZCR methods were compared and it was calculated that SM modelling has 84.2% acceptance rate for estimating stroke area precisely. Segmentation was performed on basis of energy levels in signal and three cases were considered: embolus was detected, embolus was missed and embolus was too small to be detected.

M. Nikolic et al proposed a technique that modifies original canny edge algorithm and makes it adaptive for changes in filtering techniques and threshold values [13]. The algorithm was tested for ultra sound images (phantom) in two phases. In the first phase, author adapts SRAD technique to reduce multiplicative noise generation instead of gaussian filter. After performing experiments and deducing results it is shown that SRAD is better instead of canny operator. The technique is able to detect edges in images. In the second phase, the threshold values were changes to calculate optimal threshold values. When T1 and T2 were 0.4 and 1.5, it resulted in false edges, the image area was shown as edge. Upon changing and modifying values for T1 and T2 the optimal values were calculated, depicting optimal threshold is effective in segmenting an image.

[14] proposes a technique for segmenting retinal images in humans. The information contained in retina is vital for diagnosis of various eye-related diseases. The eye-structure i.e. veins in eye are very delicate and small and their segmentation using normal methods is quite difficult. The author proposes technique that segments the eye retina using combination of various filters and unsupervised learning for classification. For enhancement phase Matched filter (MF), Frangi’s filter (FF), Gabor wavelet filter (GF) are used in combination for combination purposes weighted mean and median ranking is used and for segmentation fuzzy c-means, ORSF to optimise threshold is used. MF enhances vascular structures by convolution, GF enhances by calculating eigen values that represent vascular structures, GF enhances small vessels as it is less sensitive to noise.

For combining these filters weighted means approach is followed which assigns weights automatically to GA for calculating threshold. The use of GA gave accuracy of 0.94 whereas fuzzy c-means 0.93. Median ranking shows greater performance then weighted means in fact it outperforms unsupervised learning for the proposed data-set. The weighted mean approach using FCM has better results in terms of accuracy than the ORSF method. The Drive and Starbase databases were used for experiments. This technique showed quite remarkable performance over other techniques.

[15] proposed a segmentation method based on veronoi tessellation model and makes use of fuzziness to design segmentation algorithm. A special CVT (centroidal veronoi tessellation) is used by authors which is a special kind of VT, where the centre of mass of the generator is also the centre of mass of corresponding veronoi regions. The model proposed makes use of fuzzy edge energy in their objective function. The energy of FEWCVT is minimized with each iteration that results in effective enhancement. The authors compare their proposed technique with existing techniques that work on similar principle on use of local spatial information. The proposed method is compared with other existing techniques and it is established that FEWCVT gives F-score of 99.58% which is significantly great over other methods.

[16] propose a method of segmenting medical images using unsupervised learning and calculating local centre of mass of an image signal. In this approach the pixels are grouped into regions based on their centre of mass. The authors have proposed this scheme for 1D where they obtain complexity of O(N) and expand the same scheme to higher dimensions (2D, 3D) by iterating the algorithm for respective cases. They compared their method with other existing techniques like watershed method, SLIC, GMM-HMRF and concluded that their method produces less over segmentation and better boundaries between regions. The proposed method obtained highest optimal-dice score among other techniques and through quantitative and qualitative validation they have proven that their method of segmentation outperforms other unsupervised methods.

III. METHODOLOGY

L Khoon et al [17] proposes four main techniques that can be used to classify various segmentation algorithms. These techniques are classified based upon thresholding, region, edge localization and clustering. Besides these techniques, there are other additional techniques which are being used in segmentation of images like level set method [18], graph-based method [19], genetic algorithms [20], artificial neural networks [21]. All these techniques are depicted in figure (2):

A. Thresholding Based

Thresholding based segmentation method is one of the most widely used and fastest segmentation techniques. The assumption here is that an image is composed of multiple grey level regions. Histogram is used to classify the images based on different values of peaks and valleys. The threshold value differentiates an image into two parts: “foreground (F)”, where pixel value intensities are greater or equal to threshold value and “background (B)” where pixel value intensities are less then threshold value. i.e.

$$g(x,y) = \mathrm{F} \qquad \text{if } f(x,y) \geq \mathrm{T}$$
$$g(x,y) = \mathrm{B} \qquad \text{if } f(x,y) < \mathrm{T}$$

Where are intensity values of pixels with coordinates and T is threshold value. If the selected value of threshold is inappropriate, it leads to poor segmentation results and if there are multiple objects in an image with different grey level intensities, then multiple thresholding can be applied. Thresholding doesn’t take into consideration spatial information in an image, which sometimes results in sensitivity or noise or intensity inhomogeneity, which in turn results in shading affect [22]. This effect can be seen in MRI images, which results in more complex partitioning of an image.

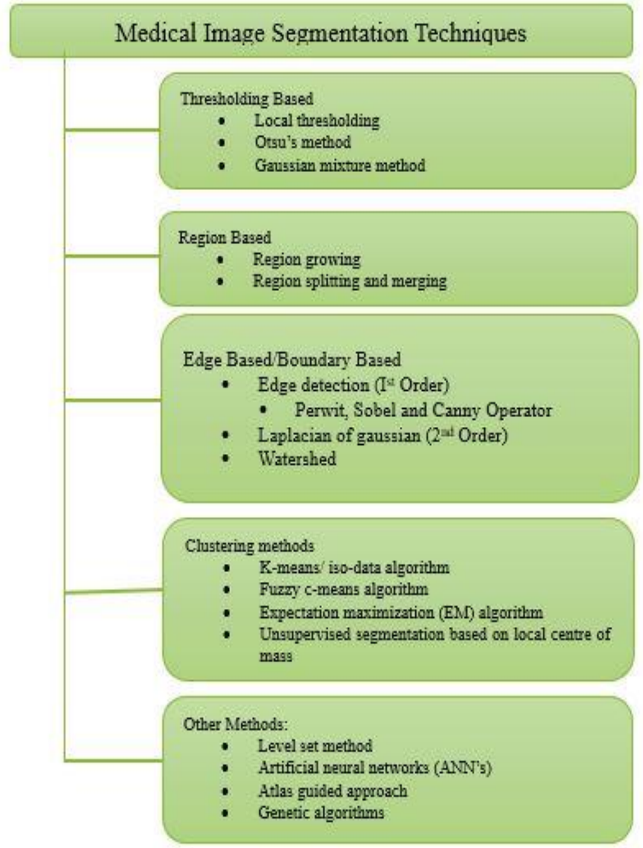

Fig 2: Medical Image segmentation Techniques

1) Local Thresholding:

The images which don’t possess a constant background or contain diversity among the objects can’t be segmented effectively using global thresholding and the results generated won’t be satisfactory, an intra-class variation can be observed in segmenting different regions. For the images with diversity in background and objects, local thresholding is a good option [23]. Local thresholding determines different threshold values of sub-images by dividing an image into multiple sub-images or regions. Once each threshold is calculated, then sub-images are merged together. The division of image is done in vertical and horizontal lines and every part of an image contains background and object. Interpolation is applied to obtain appropriate results. The threshold value is calculated by different statistical methods i.e. mean, standard deviation, combination of mean and standard deviation, mean of maximum and minimum [24]. Although local thresholding is efficient and widely used but in comparison to global thresholding it requires more time for segmenting images.

2) Otsu’s Method:

The method works in determining an optimal value of threshold for segmenting the images. It is akin to calculating global threshold value but Otsu's takes into consideration inter-class and intra-class variation in an image. Otsu considers that an image is bimodal or consists of only two classes. This is done to minimize the intra-class variance or maximise between-class variance in an image [25]. The first or primary step is determination of intra-class variance by calculating weighted sum of variances of each cluster. The weights represent probability of each class. The second step is to determine mean value for each class. The third and final step determines individual class variance. The value that maximises the between-class variation is called as optimal threshold [26]. However, selection of optimal threshold value greatly increases time complexity as the levels of thresholds increase.

3) Gaussian mixture (GM) approach:

In this method of image segmentation, the posterior probability and maximum likelihood is calculated for number of components in an image along with their individual mean, covariance and mixing coefficients. This is done sequentially and it doesn't require any initialization as proposed by [27]. This approach requires an initial seed component (single mixture component) that covers all the data set. It then sequentially splits incrementally during EM steps. The method of GM shows effectiveness only when tested multiple number of times [28].

B. Region Based Segmentation:

This image segmentation technique is used to directly locate regions in an image. It is very convenient and it splits regions of an image based upon similarity [29]. This technique is very much immune to noise.

1) Region Growing:

This is a segmentation technique that is used to extract a specific region from pre-existing image based on some characteristics i.e.: intensity level inhomogeneity or edges in an image. This technique requires prior information for selecting a seed pixel. The seed point or pixel is selected by an operator and then pixels that share a common characteristic property are selected to grow the region [30]. i.e. we can grow a seed pixel in an image till an edge is detected. The region growing technique is never used alone but it is usually associated with set of image processing operations for visualisation of small, simple and delicate regions in tumours and lesions. Sometimes region growing can be sensitive to noise which can result in holes of extracted regions that are continuous [31]. It can also lead to merger of separate regions.

2) Region splitting and merging:

This technique is based upon region generation in an image. This technique first splits a given image into multiple sub-images and then merges them again. This process is fast and efficient with less noise generation or altogether immune to noise [32]. This approach is based on quad-tree generation, consisting of four branches. The branches of quad-tree represent sub-images [33]. The image region is split into four parts or branches and then merged back together till no partitioning or splitting is possible.

C. Edge based/ boundary based:

This method of segmentation deals with identifying and locating boundaries in an image i.e. edges. The edges are sharp discontinuities i.e. intensity values in an image. This technique is helpful in recognition, disclosure and segmentation of image artefacts [34]. The edge detectors are called as 'masks' or 'filters' which are super-imposed over an image to detect discontinuities or boundaries [35]. The change in intensity level values of an image can be calculated by first order filters (Prewitt, Sobel, Canny) that produce thick edges and second order filters (Laplacian, zero crossing) produce finer edges.

1) First Order Operators:

a) Prewitt operator:

This mask was proposed by Prewitt and J.M in 1970. This is a gradient based operator and calculates gradient of image intensity function. It calculates magnitude and direction of edges in image. The Prewitt operator can find only eight directions [36]. Although it is widely used and (3*3) mask the results differ to show its accuracy of estimating direction of edges.

b) Sobel operator:

This (3*3) mask is based upon discrete differentiation and works in vertical and horizontal orientations that makes it quite expensive. This mask possesses better noise suppression which makes it preferable to use. It generates isotropical results for horizontal and vertical edges [37].

c) Canny operator:

This mask was developed in 1986 by John Canny and is a multi-stage algorithm-based edge detector which helps in recognition of wide range of edges and orientations. This mask is adaptable and can be used in wide range of applications. Its parameters can be tuned to meet specific application areas [38].

2) Second Order Operators:

a) Laplacian of Gaussian Operator (LoG):

This filter was proposed by Marr and Hildreth in 1980 and also referred to as Marr-Hildreth operator. It is a combination of Laplacian and gaussian technique and finds its application in machine vision. It is differential and adaptive based operator that can be tuned to adapt application area [39]. It is most widely used to detection of blurry edges and sharply focussed fine details in an image.

b) Watershed Technique:

This technique was proposed by S. Beucler and F. Mayor in 1990. The technique was introduced to overcome the problem of over-segmentation in natural images during image processing. This method uses mathematical morphology in segmentation of images and is used to separate overlapping objects [40] in an image. This technique uses two approaches: watershed transform and homotropy modification. This technique is applied on grey-level images. It is fast, simple, intuitive and helps in global segmentation of an image [41].

D. Clustering/Unsupervised Methods:

This is a technique in which grouping of objects (physical or abstract) is done to form classes and is referred to as clustering. The objects that share similar properties form a cluster. The objects should be similar to one cluster and dissimilar from other one for effective clustering. The objective here is maximisation of intraclass similarity and minimization of interclass similarity [42]. It is a type of unsupervised learning as we don't need to train data. The clustering algorithms don't rely on predefined classes and use unsupervised learning for classification of training data. This is done by increasing iterations [43]. For segmenting an image and characterise its properties, clustering algorithms help themselves in training using available data. The clustering algorithms share similar nature that of classification techniques. This technique is mainly used in data-mining for the analysis of large data-sets, derive meaningful results, effective storage and fast retrieval [44]. There are multiple algorithms and techniques that have been proposed by researchers. The widely used ones are: k-means or iso-data algorithm, fuzzy-c means algorithm, expectation maximization algorithm (EM).

a) K-Means algorithm:

This is one of simplest and popular unsupervised algorithms. It classifies the 'n' datasets into k-clusters iteratively. The mean intensity is calculated for each of the clusters and then the pixels are classified accordingly with closest mean values. K-means clustering approach tries to reduce the number of clusters and cluster variability.[45] It is also referred to as iso-data algorithm as it shares same working principles, the only difference being that the number of clusters are known a priori in k-mean algorithm. It is used for segmentation of MRI images.

b) Fuzzy C-Means algorithm:

generalises k-means algorithm and is based on unsupervised learning, the only difference being that the classification of data into clusters happens on the basis of degree of membership of an object. The advent of fuzzy-c means algorithm dates back to the introduction of fuzzy set theory by Zadeh. This algorithm was proposed in 1981 by Bezdek based on fuzzy set theory of Zadeh that helps in soft segmentation. Its popularity in medical image segmentation is increasing due to its simplicity and ability to derive more information from the data. Since the uncertainty, vagueness and fuzziness [46] are taken into consideration, it can sometimes result in introducing higher order fuzzy set for dealing with hesitation and uncertainty in classification of data.

c) Expectation Maximization (EM) algorithm:

is also one of the unsupervised algorithms that underlies on gaussian mixture model (GMM). The algorithm iterates multiple times for calculating the posterior probabilities and maximum likelihood estimates of the special factors [47]. The special factors are means, covariances and mixing coefficients of GMM. The requirement that of GMM is initial segmentation which results in reduced sensitivity of GMM over K-means algorithm and Fuzzy-C means algorithm. The clustering algorithms don't incorporate spatial modelling, which results in noise generation and intensity inhomogeneity during image processing.

E. Other methods:

a) Level Set Method (LSM):

The LSM was first of all proposed by Osher and Sethian, in 1998. Then later, research on LSM was performed by Mallandi et al. in 1995. LSMs use level sets for numerical analysis of various surfaces and shapes. This technique is employed with regional or edge-based features. One can perform LSM on curves and surfaces that are on a fixed cartesian grid. LSM don't require us to parametrise the objects. The shapes that change topology are most researched by LSMs and where existing algorithms don't perform well. If the training samples vary their shape too much, it leads to non-linear space. LSM have implicit nature and they don't require landmarks [48]. Previously, LSM technique used grey-level images for processing. LSM finds its use in computer vision, hydraulics, optimisation and trajectory planning.

b) Artificial neural network (ANN):

Frank Rosenblatt, in 1958 described ANN's as computational systems that learn on their own [49]. More precisely ANN's are parallel networks that imitate how humans learn. The processing elements are referred to as nodes. The nodes perform computational part and learning is done by adapting by adapting weights which are assigned to connections between nodes. ANN's find their application in wide areas of image processing when a priori information isn't available like image recognition, natural language processing etc. ANN's can perform image segmentation using either supervised or unsupervised learning techniques. Research shows ANN's when combined with Kohenen's Self Organising Maps (KSO), genetic algorithms significantly improvise the result outcome [50]. ANN's had led to a more robust learning called deep learning. The main disadvantages associated with use of ANN's is to decide which best architecture fits the model and black box problem.

c) Atlas guided approaches:

The human organelles vary significantly in shape and size. This variability in population creates difficulty in representation of these images. To account this, variability in images it is crucial to have a standard template which can be achieved through uses of atlases [51]. One or more atlases may be required for a specific model for learning from population images. The learning can be achieved from parent data-set. These atlases contain information such as local image statistics and probability of assigning labels to a particular spatial location. The new images can easily be mapped to these atlases which have been set for specific applications i.e. segmentation. The labelling of images can be done by a clinical expert or a medical specialist. The segmentation problem of new images is akin to extrapolating these labelled images [52]. This method is referred to as atlas-based segmentation. There are two kinds of approaches in atlas guided approaches: parametric and non-parametric. In parametric method new images are combined with trained images to form a single atlas and in non-parametric method all the images are used separately for training purposes. Image registration is an essential step in mapping of atlases [53] to these images. In this way the variability of medical images can be addressed.

d) Genetic algorithms:

John Holland, in 1960 proposed a technique of optimisation that was based on evolutionary biological sciences. J. Holland made use of Darwin's natural selection theory and evolutionary sciences to generate solutions to optimisation problems in computational sciences [54]. The algorithm works in 3 steps referred as operators: mutation, crossover and selection [55]. We start from a group of solutions (initial population), then evaluate the fitness of each individual in the population and repeat on selection of best until termination. The best individuals from the population are then combined to produce the off springs which possess better characteristics. The changes or mutations introduced result in generation of heuristic solutions from the population until the most optimised solution is obtained the process continues. The most researched GA's are based on ant-colony optimisation (ACO) and particle-swarm optimization (PSO) [56]. In image processing GA's have been used for image enhancement, segmentation, feature extraction.

IV. COMPARISON OF VARIOUS MEDICAL IMAGE SEGMENTATION TECHNIQUES:

Table 1: Medical image segmentation techniques and their potential application areas.

	Segmentation Techniques		
	Methodologies	***Advantages***	***Disadvantages***
Thresholding	Local Thresholding	Ease of Implementation No need of prior information	Produces noisy and blurred edges
	Otsu's Method	Minimizes inter-class and intra-class variations. No particular histogram shape considered prior. Extendable to multi-level thresholding.	Creation of binary classes in grey-level images. Increase in complexity with increase in levels of threshold. Regions might get merged or mixed.
	Gaussian Mixture Approach	Used for generalization of histogram-based problems. Minimizes classification error probability. preferred for small size-classes. Iterative model	All histograms don't follow Gaussian model. Resulting intensities that are finite and non-negative. Difficult for flat models. Simplified approach for multi-thresholding
Region-Based	Region Growing	Based on similarity and immune to noise. Convenient and easy computation.	Seed point specification. Generation of holes in sensitive regions. Costly approach.
	Region Merging and Splitting	Splitting an image on demand resolution. Follows quad-tree approach, fast and efficient. Splitting done by calculating mean, variance of segment pixel value. Less noise generation Merging different from splitting technique.	May result in blocky segments.
Edge Based/ Boundary Based	Edge Detection	Selects a large region in an image. Used for images with uneven illumination.	Applicability for simplified backgrounds. May form closed contours all the time.
	Prewitt filter	Calculates edges and their orientations in 8 directions of pixel.	Less accuracy. Sensitive to noise
	Sobel filter	Calculates edges in horizontal and vertical	Expensive

	Segmentation Techniques		
	Methodologies	***Advantages***	***Disadvantages***
		orientations. Better noise suppression Isotropical results	
	Canny filter	Calculates wide range of edges and orientations. Adaptive.	Difficulty in working effectively at curves, corners.
	Laplacian of Gaussian (LoG)	Detection of blurry edges, sharp focused fine detail. Effective detection of edge orientation.	Difficulty in working at corners. Finding orientation by Laplacian filter is difficult
	Watershed	Reduces over-segmentation. Separation of overlapping objects. Fast and reliable output.	Time consuming and gradient based.
Clustering Methods	K-Means/ Iso-data algorithm	Fast and easier to implement. Reduces number of clusters and cluster variability.	We should know a-prior no. of clusters. Sensitive to selection and initialization of centroids.
	Fuzzy C-Means algorithm	Unsupervised & considers vagueness, uncertainty in an image.	Optimal solution is undefined. Initialization is sensitive. Least compatible for noisy images.
	Expectation Maximization (EM) algorithm	Unsupervised Iterative and reduced sensitivity	Results in noise generation & intensity-inhomogeneity. Slow convergence rate. Gets stuck into local optima. High computational cost.
Other Methods	Level Set Method (LSM)	It is efficient, versatile, robust and accurate.	Sensitive, requires considerable design planning for level set function.
	Artificial neural networks (ANN)	Ease of implementation. Applicable to diverse problems.	Selection of architecture. Black-box problem
	Atlas Guided approach	Computationally fast. Suited for structures that are stable over population of study. Labels are	Difficulty in accurate segmentation of complex structures with non-Linear registration methods

	Segmentation Techniques		
	Methodologies	***Advantages***	***Disadvantages***
		transferred during segmentation.	
	Genetic algorithms	Incremental segmentation. Adaptive to user access patterns. Computationally fast.	Choosing number of generations, population size. It doesn’t always result in optimal solution.

V. IMAGING MODALITY

In the diagnosis and treatment of patients, imaging assists radiologists or clinicians to make the diagnosis and treatment efficient. There is a wide range of imaging modalities that are being used for diagnosis and in effective treatment planning currently. The main widely used modalities can be split into two general classes: anatomical and functional. In this paper, we only discuss about the anatomical modality. Images can be represented in 2-D, 3-D and 4-D systems. The elements of an image in 2-D are referred to as pixels, while as in 4-D they are referred to as Voxels. In this paper specific medical imaging modalities are presented and emphasis is mainly focussed on Ultrasound, MRI, CT and X-Ray. Figure (3) can be referred for knowing various imaging modalities, their application areas and recommended methods.

F. CT:

Also referred to as computed tomography, helps in capturing different sectional planes(tomography) which are difficult to process otherwise. It visualises small density gradients i.e. In case of brain, it distinguishes between grey-matter, white-matter and cerebro-spinal-fluid (CSF).

G. Ultrasound:

It is a non-invasive imaging method that uses sound waves to generate computerises images reflected by body organs and interior organs of body. It can also be used for interventional procedures. It doesn't have any known harmful effects on human body in clinical imaging. It is inexpensive technique but it can't visualise all the anatomical regions i.e. Brain

H. MRI:

Uses magnetic fields and radio-frequencies to generate visualisation area of different body organs. The variation in reflected frequencies helps in localization of different body organs with the help of magnetic field. This method is employed to get fine details of organs i.e. brain, liver, chest, pelvis and abdomen.

I. X-Ray:

Is also a non-invasive imaging method and one of the oldest imaging techniques that uses ionizing radiations that are rapid and of shorter duration. This imaging technique is inexpensive as compared to others. It can also be used in interventional procedures for detecting fractures in bones.

Table 2: Medical imaging modalities and their application areas

S.No	Imaging Modality Techniques		
	Technique	***Recommended Methods***	***Application Area***
1.	Thresholding and region-based segmentation	Abdomen, Appendix, Bladder, Brain, Breast, Chest, Cervix, Kidney, Lungs, Pancreas, Esophagus	CT Scan
2.	Watershed and region-growing(3D) Clustering (2D)	Neuro-imaging, Cardiovascular, Musculoskeletal, liver, Gastro-Intestinal, Functional, Oncology, Phase Contrast	MRI
3.	Thresholding Based	Transrectal, Breast, Doppler, Abdominal, Transabdominal, Cranial, Gall-bladder, Spleen	Ultrasound
4.	Edge-Based and watershed	Radiography, Mammography, Fluoroscopy, Contrast-Radiography, Anthography, Discography, Dexa-Scan, Upper GI	X-Ray

VI. CONCLUSION AND FUTURE SCOPE

This paper surveys multiple aspects of image segmentation techniques i.e. Pre-existing and current techniques, their implementation and application areas. The accuracy of segmentation remains most concerning issue for patients with complications i.e. Tumour. Each segmentation method that has been discussed here has its leads and limitations and to set a particular benchmark for comparison is inappropriate. The segmentation of medical images has been broadly categorized in this paper. This paper can be used for reference purposes. Segmentation of delicate areas i.e. brain is difficult and time consuming, but with advancements in segmentation algorithms it can be overcome. The paper presented by aganj et al in [16] shows promising results for segmentation of MR images. The need of the hour is the development of algorithms which don't require any prior information of the image i.e. Intensity, color, texture, homogeneity and many more. The comparison of new segmentation techniques with pre-existing techniques has shown good behaviour. The future work remains in improving accuracy, precision, reduced time complexity of segmentation algorithms and reduction in the amount of manual interaction.

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