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Survey of Image Segmentation Algorithm for Medical Images: Challenges and Methodologies.

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ABSTRACT

Due to the tremendous increase in the usage of computer technologies, image-processing techniques have become one among the most important and rapidly used technique in a wide variety of applications. The basic idea of the medical images is to improve the different imaging content with respect to the images. Image segmentation is the basic step for any image processing technique in medical field. Hence several image segmentation techniques were introduced to segment an image before recognition which is the only small part that is more useful out of the whole image. A typical and medical imaging system is composed of four main processing steps such as image acquisition, segmentation, feature extraction and classification. In this paper the survey on existing medical image segmentation algorithms is given. In addition the paper addressed several challenges of the existing medical image segmentation techniques that a researcher can face during the implementation and outline of the strength and weaknesses of the existing segmentation algorithm.

Keywords: Image processing, segmentation, recognition, feature extraction, classification.

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INTRODUCTION

Segmentation is considered as the major step in diagnosing diseases using medical images. Image segmentation is generally used to discover objects and boundaries, i.e., lines, curves, etc. These also play the most important role while analyzing the abnormalities in human body. Identification and analysis of abnormalities will become difficult with naked eye in the absence of image processing techniques. Hence so many diseases are identified in their earlier stages itself with the advancement of imaging techniques in medical field. For capturing of such images a variety of specialized devices were being used for example scanners. Medical images are nothing but the images used for medical diagnosing of human body. The technique used to process such images for clinical purpose is called medical imaging.

It has become both challenging and necessary that categorization of image segmentation based on availability of abundance of literature. Over the past few decades in medical imaging the compression schemes that too mainly in lossless are given more importance because of the property of no information loss. In this paper the approach of categorization is supplementary based on the previous review paper [1,2]. Mostly the image segmentation techniques are categorized[1] as i) edge based ii) pixel based iii) region based iv) hybrid . From paper [3] we can say some authors have also been categorized them based on their color and also texture. However in paper [4] they have the top-down (model-driven) approach and bottom-up (image-driven) approach [5] are specifically used for general categorization based approaches in image analysis.

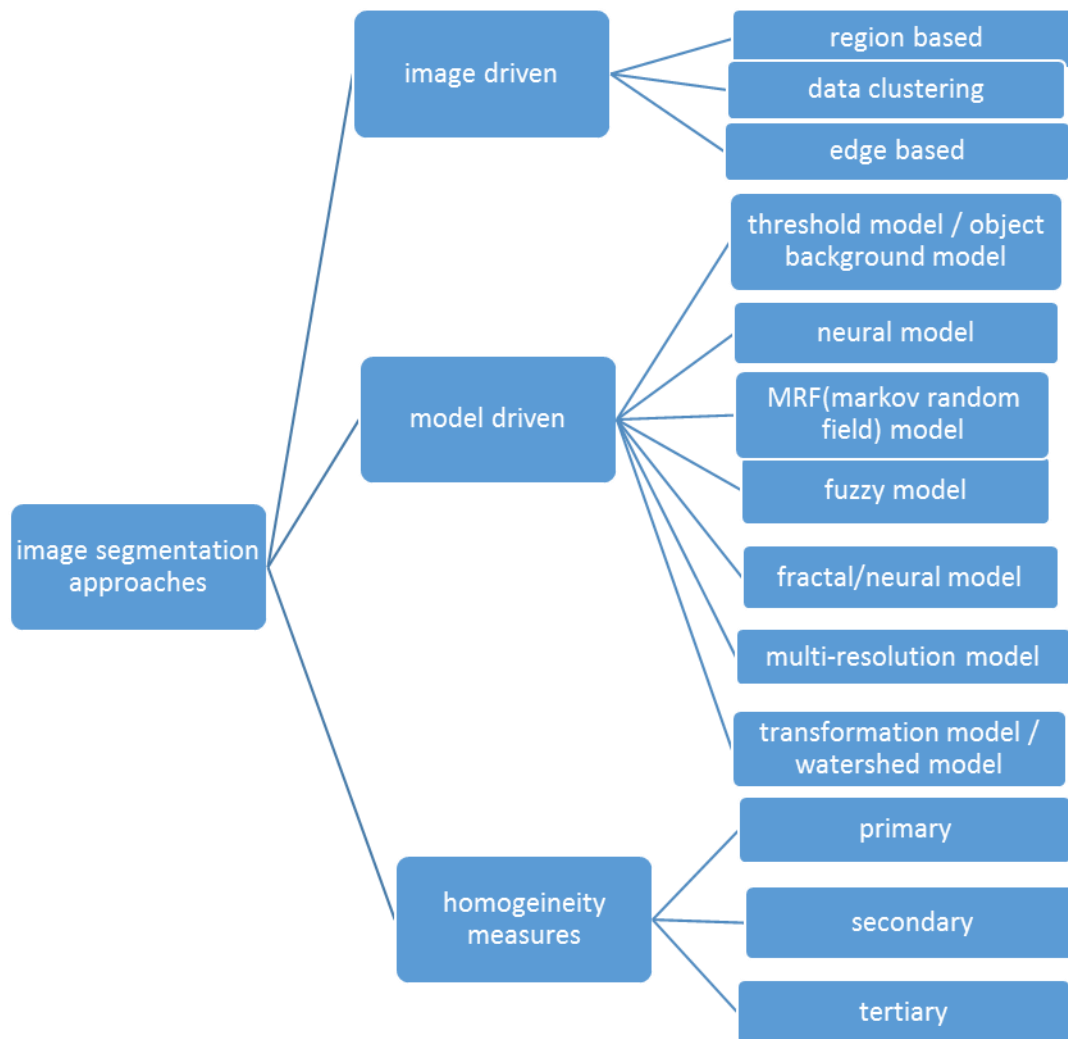


Fig. 1 Traditional approaches in image segmentation

Although there are many definitions generally these approaches refers to the segmentation hierarchy according to the developer software's. As we know as mentioned in fig:1 we will be forming the objects by combining or merging the group of pixels in so called bottom-up approach, and we will split the entire image into its objects on the criteria of heterogeneity in top-down approach. The general features as well as homogeneity measure based approach which are used for delineate the image objects points to the next stage of categorization. And the next former stage will be used for generating the image objects which are based on different operations on image. Sometimes based on supervised and unsupervised approaches also the categorization of images can be done. The clustering and proximity to feature extraction would be holded by unsupervised segmentation approach where as supervised holds accuracy in addition to unsupervised approach and the same is clearly explained in the Fig.1

Medical imaging is the idea to improve the content of the images taken from different imaging modalities like Magnetic Resonance Imaging (MRI), Computed Tomography (CT), X-Rays, Ultrasound, Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT), etc. The various types of Medical images used in latest papers, the advantages of the techniques used and their disadvantages of medical images and their characteristics were discussed in this paper as per the present existing papers. The process of capturing image in this field mostly depends upon the requirements of the doctor and the type of the disease and the area where the disease is affected. There are different varieties of devices used for capturing of images of the particular region inside or outside the human body. The following are the different types of medical images used for various purposes. The most commonly used technique among them was:

1. Tomography: imaging an organ in a single plane (slice) is the basic method used in Tomography. Various forms of Tomography are X-Rays, Computed Tomography (CT) or Computed Axial Tomography (CAT), Ortho Pan Tomography (OPT), Positron Emission Tomography used in conjunction with CT (PET-CT) and MRI (Magnetic Resonance Imaging) called PET-MRI.
2. Magnetic Resonance Imaging (MRI): MRI scanners use a powerful magnetic field and radiofrequency pulses to generate detailed images of the body's internal structures as cross-sectional images or slices. It does not emit any ionizing radiation. MRI is used for identifying tumors in brain and inflammation in the spine to slipped discs, assessing blood flow and functioning of the heart
3. Sonography (Ultrasound): Sonography (Ultrasound Imaging) is a type of imaging which uses the high-frequency sound waves to produce dynamic visual images of organs, tissues or blood flow inside the body. The sound waves are transmitted to the area to be examined and the returning echoes are captured. When ultrasound is used to image the heart it is referred to as an echocardiogram. Echocardiography allows detailed structures of the heart, including chamber size, heart function, the valves of the heart, as well as the pericardium
4. Elastography: Elastography is a new emerging modality. It maps the elastic properties of soft tissues. This uses Ultrasound, MRI and Tactile Imaging. This modality emerged in the last two decades. Elastography is useful in medical diagnoses, as elasticity can discern healthy from unhealthy tissue for specific organs/growths.
5. Thermography: This is the Digital Infrared Imaging technique basically used for breast imaging in which visible or near infrared light is scattered across areas where the density of tissues is high. These digital infrared imaging thermo graphic techniques are based on the principle that metabolic activity and vascular circulation in both pre-cancerous tissue and the area surrounding a developing breast cancer is almost always higher than in normal breast tissue.

Fusion of magnetic resonance imaging (MRI) and positron emission tomography (PET) images, and fusion of MRI and computerized tomography (CT) images. The major advantage of MRI images is that it is able to capture the soft tissue structures in organs such as brain, heart and eyes. Different from MRI imaging, the CT imaging is able to capture the bone structures in the human body with high spatial resolutions. The PET imaging is a useful type of nuclear medicine imaging, while the captured images usually has a low spatial resolution

It has become both challenging and necessary that categorization of image segmentation based on availability of abundance of literature. Over the past few decades in medical imaging the compression schemes that too mainly in lossless are given more importance because of the property of no information loss. In this paper the approach of categorization is supplementary based on the previous review paper[Priyansh Sharma

and Jenkin Suji , V. Dey a , Y. Zhang , M. Zhong]. Mostly the image segmentation techniques are categorized [Guo, D., Atluri, V. and Adam...] as i) edge based ii) pixel based iii) region based iv) hybrid. From paper [Guo, D., Atluri, V. and Adam..] we can say some authors have also been categorized them based on their colour and also texture . however in paper [Maxwell, T. and Zhang..] they have the top-down(model-driven) approach and bottom–up(image-driven) approach[Guindon, B] are specifically used for general categorization based approaches in image analysis. the general flow of work with respect to the medical imaging can be obtained as in Fig 2.

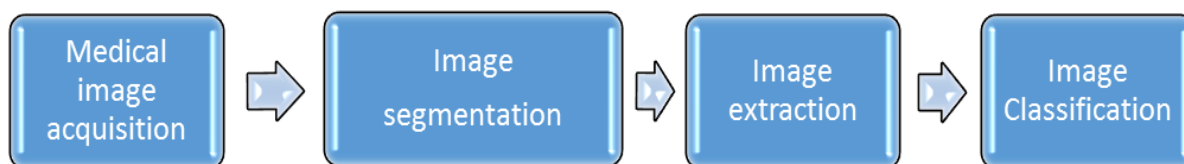


Fig 2 : Work flow of image processing techniques in medical imaging

Sijie Niu et al.,[6] a novel region-based active contour model via local similarity factor algorithm is developed and have showed the promising results of segmenting objects of different nature and characteristics in images of different nature at higher values of noise level, where other known methods seem to fail. This is achieved by incorporating a local spatial distance and intensity difference factors.

Advantages in this method seems to be more robust to higher noise levels and provides outlines of sufficient detail preservation, similarly to many traditional region-based active contour models, the RLSF model is sensitive to the active contour initialization

Xiao-Liang Jiang, ea tl.,[7] an algorithm with a robust level set model for images segmentation by taking the local correntropy-based fuzzy c-means clustering with spatial constraints into consideration and then simplified it, to corresponding robust version LCFCM_S1. These models have efficiently utilized the advantages of fuzzy clustering with spatial constraints and the correntropy criterion, which can reduce the effects of noise and outliers. Hence, advantages of these models can handle images caused by noise, low contrast and intensity inhomogeneity, and are more accurate image segmentation than several state-of-the-art level set methods do. Disadvantages here in this model are cannot segment images with different tissue types, such as brain MRI or tumor PET images.

Intuitionistic fuzzy sets and rough sets are widely used for medical image segmentation, and recently combined together to deal with uncertainty and vagueness in medical images. Yogita K. eat l.,[8] A rough set based intuitionistic fuzzy c-means clustering algorithm is presented for segmentation of MR images corrupted by intensity in-homogeneities and noise. They have proposed a new automated method to determine initial values of centroids using intuitionistic fuzzy roughness index. To address intensity in-homogeneities and noise in brain MR images, intuitionistic fuzzy image representation using proposed intuitionistic fuzzy complement function is used. Advantages here are robust to intensity , inhomogeneity and noise

Abhirup Banerjee, ea tl.,[9] the major contribution lies in developing a methodology for segmentation of images. It integrates the merit of SN distribution and the concept of lower approximation and boundary region of rough sets. This formulation is geared towards maximizing the utility of rough-probabilistic clustering with respect to image segmentation tasks. The main advantage of SN distribution is to introduce the concept of uniform lower approximation region around mean, which provides better representation of image classes and its disadvantage is the estimates of the parameters of the distribution do not have a closed form and must be obtained numerically.

N. Garijo, ea tl.,[10] they proposed a methodology that combines the images with bone remodelling simulations and artificial neural networks. To test the capability of this novel technique, they have quantified the personalized forces for five subject specific tibias using our technique and a gait analysis. Advantages of

this work has great potential for estimating the main forces that define the mechanical behavior of subject-specific bone. Disadvantages are more computational cost and need of only small sample set.

Badri Narayan Subudhi *et al.*, [11] a novel MRI segmentation technique using a combination of region growing and parcel based statistical fusion scheme is introduced. Advantages are to provide good result even for an MRI with intensity inhomogeneity, regional smoothness and surface reflection.

Stefan Matla, *et al.*, [12] they have contributed to a better differentiation of vessel registration techniques by analyzing relevant literature in a flexible way. Advantages in this method is that it does not require a certain differentiation and users can create their individual trees according to their Specific needs.

Deep Gupta, *et al.*, [13] two hybrid segmentation approaches were proposed based on edge based active contour method using the DRLS evolution model and the KFCM X, KFCM S1 and KFCM S2 clustering approach to provide accurate segmentation of the ultrasound medical images. These proposed approaches initiate with the result of KFCM X method that is also responsible for successfully extracting the estimated object boundaries by initializing the curve during the DRLS evolution and evaluating the several controlling parameters automatically. Advantages are it eliminates the manual requirement and also decreases the processing time.

R.J. Kuo, *et al.*, [14] they have introduced the study proposes with three novel clustering ensembles algorithm which integrate meta-heuristic algorithms and clustering ensemble. advantage here is that it is easy to implement and understand. Disadvantages are high computational time, especially for a large dataset.

Ailing De, *et al.*, [15] they have developed a set of parallel algorithms for the SOM-based VQ segmentation method. These parallel algorithms are implemented on GPU programmed with Open CL language and have been successfully applied on segmenting the human brain MRI images. Advantages of the experimental results conducted in that work have shown that these parallel algorithms can provide a significant improvement on the computation efficiency with overall speedup ratios increasing from 28.81 to 89.12 as image sizes increasing from 128x128 to 1024x1024 on average while the segmentation performance is kept unchanged, compared with the original serial algorithm implemented on CPU. disadvantage is that the cpu computation speed decreases as more effort needs to be made to increase the parallel data throughputs of the process,

Sergi Valverde *et al.*, [16] they have proposed the Multiple Sclerosis segmentation pipeline (MSSEG), a new MRI brain tissue segmentation method designed to deal with images containing lesions. They proposed approach incorporates a robust partial volume tissue segmentation with outlier rejection and filling, combining intensity and probabilistic and morphological prior maps in a novel-way.

Wu Qiu *et al.*, [17] proposed an automatic segmentation approach is proposed to delineate lateral ventricles of preterm neonates from 3D US images. The proposed segmentation approach makes use of phase congruency map, multi-atlas initialization technique, atlas selection strategy, and a multiphase geodesic level-sets (MGLS) evolution combined with a spatial shape prior derived from multiple pre-segmented atlases.

Ian J. Gerard *et al.*, [18] they did a review on the research evaluating the causes, measurements and correction methods of brain shift in neuro navigation with a newly proposed taxonomy for classifying the different types of studies were proposed. With the increasingly ubiquitous use of neuro navigation systems in neuro surgical interventions, the need for highly accurate information has become utmost importance.

Mohammad Havaeie *et al.*, [19] they presented an automatic brain tumor segmentation method based on deep convolutional neural networks. They have considered different architectures and investigated their impact on the performance. Advantages in this technique is it improves accuracy and speed.

Engin Akar *et al.*, [20] they have investigated the effects of two noise elimination techniques (median filtering and bilateral filtering) on complexity analyses of sub-cerebellar tissues in CM-I patients and controls to understand the importance of preprocessing in MRI data analysis.

KorsukSirinukunwattana, ea tl.,[21] they presented a summary of the Gland Segmentation in Colon Histology Images (GlaS) Challenge Contest which was held in conjunction with the 18th International Conference on Medical Image Computing and Computer Assisted Interventions (MICCAI’2015). Details of the challenge, including organization, data set and evaluation criteria, are presented, along with the method descriptions and evaluation results from the top performing methods.

Wei yang ea tl.,[22] they presented an effective deep learning method for bone suppression in single conventional CXR using deep convolutional neural networks(Conv Nets) as basic prediction units. The deep Conv Nets were adapted to learn the mapping between the gradients of the CXRs and the corresponding bone images.

Tian ming Zhan ea tl.,[23] they proposed a novel method integrating the multi-sequence and spatial information in a Bayesian framework for WM lesion detection from multi-sequence human brain magnetic resonance images (MRIs). The entire framework is based on a three-step approach: First, a multinomial logistic regression (MLR) algorithm is used to assess the conditional probability distributions of intensities in WM lesions and brain tissues from training data. Second, the spatial information previously given by a Markov random field (MRF) prior is integrated with multimodal information in the Bayesian framework to strengthen the spatial constraint.the algorithm agrees well with manual expert labelling and indicate that our multimodal spatial-based method offers a significant advantage over other approaches

Table 1: review of different methods and modalities used in latest papers.

| Ref no | Authors | Methods used | Modalities | Advantages | Limitations |
|--------|--|--|----------------------|---|--|
| 6 | Sijie Niu, Qiang Chen, Luis de Sisternes, Zexuan Ji, Zeming Zhou, Daniel L. Rubin. | region-based active contour model via local similarity factor algorithm | MRI of blood vessels | more robust to higher noise levels and provides outlines of sufficient detail preservation | sensitive to the active contour initialization |
| 7 | Xiao-Liang Jiang, Qiang Wang, Biao He, Shao-Jie Chen, Bai-Lin Li | Set image segmentation algorithm and c-means clustering | X ray of hand | Reduce the effects of noise and outliers. more accurate | cannot segment images with different tissue types |
| 8 | Yogita K. Dubey, Miind M. Mushrifa, Kajal Mitra | intuitionistic fuzzy c-means clustering algorithm | MRI of brain | robust to intensity , inhomogeneity and noise ³ | Little noise is still present and intensity inhomogeneity occurs |
| 9 | Abhirup Banerjee, Pradipta Maji. | integrates the merit of SN distribution and the concept of lower approximation and boundary region of rough sets | MRI of brain | Provides better representation of image classes | the estimates of the parameters of the distribution do not have a closed form and must be obtained numerically |
| 10 | N. Garijo, N. Verdonshot, K. Engelborghs, J.M. García-Aznar, M.A. Pe´rez | Combines bone remodelling simulations and artificial neural networks | CT of bone | has great potential for estimating the main forces that define the mechanical behavior of subject-specific bone | more computational cost and need of only small sample set |
| 11 | Badri Narayan Subudhi, | Combination of | MRI of skull | Robust to noise , | Not accurate, can |

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|----|---|--|--|---|--|
| | Veerakumar Thangaraj, Esakkirajan Sankaralingam, Ashish Ghosh | region growing and parcel based statistical fusion scheme | | surface reflection and shading | improve if used some other techniques like Bayesian ,fuzzy set based region growing process |
| 12 | StefanMatla, RichardBrosig, MaximilianBaust, NassirNavab, StefanieDemirci | vessel registration techniques | Vascular images | does not require a certain differentiation and provides flexible adaptation | Computational Time is more |
| 13 | Deep Guptaa, R.S. Anand | edge based active contour method and clustering technique | ultrasound image of left ventricle | it eliminates the manual requirement and also decreases the processing time | Implementation is difficult |
| 14 | R.J. Kuo, C.H. Mei, F.E. Zulvia, C.Y. Tsai | clustering ensembles algorithm | CT and MRI of brain and skull | easy to implement and understand | high computational time, especially for a large dataset |
| 15 | Ailing De, Yuan Zhang, Chengan Guo | Parallel algorithms for segmentation technique | MRI of human brain | improvement on the computation efficiency with overall speedup ratios increasing | cpu computation speed decreases |
| 16 | SergiValverde, ArnauOliver, EloyRoura, SandraGonzález-Villà, DeborahPareto, Joan C.Vilanova, Lluís Ramió-Torrentà, | tissue segmentation method | MRI of brain | incorporates a robust partial volume tissue segmentation without liar rejection and filling | Implementation is little bit complex |
| 17 | WuQiu, YiminChen, Jessica Kishimoto, Sandrine de Ribaupierre, Bernard Chiu AaronFenster, Jing Yuan | automatic segmentation approach | ultra sound images of ventricles | Accurate result is obtained using this method | Computational time is more |
| 18 | Ian J. Gerard , MartaKersten-Oertel, KevinPetrecca, DenisSirhan, Jeffery A. Hallb, D.Louis Collins. | a review on the research evaluating the causes, measurements and correction methods of brain shift in neuro navigation | MRI of brain | highly accurate | Implementation is difficult |
| 19 | Mohammad Havaeia, Axel Davy, David Warde-Farleyc, Antoine Biard, Aaron Courville, Yoshua Bengio, Chris Pal, Pierre-Marc Jodoin, Hugo Larochelle | deep convolutional neural networks | MRI of brain | improves accuracy and speed | As cascaded model implementation is little bit tough |
| 20 | Engin Akar, Sadık Kara, | noise elimination techniques | MRI of cerebrum | Noise is completely | Needs more computational time |

| | | | | | |
|----|---|--|-------------------------|--|---|
| | Hidayet Akdemir, Adem Kırıs | | | eliminated | |
| 21 | KorsukSirinukunwattan Josien P.W.Pluim, HaoChen, XiaojuanQi, Pheng-AnnHengc, YunBoGuo, LiYangWangd, BogdanJ. Matuszewskid, EliaBruni, UrkoSanchez, Ea tl., | a summary of the Gland Segmentation in Colon Histology Images | MRI of glands | More Accurate when compared to previous methods | |
| 22 | WeiYang, YingyinChen, YunbiLiu, LimingZhong, GenggengQin, Zhentailu, QianjinFeng WufanChen | Deep convolutional neural networks algorithm | chest cardiographs | can produce high- quality and high- resolution bone and soft- tissue images | Needs complicated contrast normalization procedure at input which increases complexity |
| 23 | Tianming Zhan, Renping Yu, Yu Zheng, Yongzhao Zhan, Liang Xiao, Zhihui Wei | integrates the multi-sequence and spatial information in a Bayesian | MRI of brain | agrees well with manual expert labelling and indicate that our multimodal spatial-based method offers a significant advantage over other approaches | Implementation is bit difficult |
| 24 | Ahmad Jalal, Yeon-Ho Kim, Yong-Joong Kim, Shaharyar Kamal, Daijin Kim. | multi-fused features for online human activity recognition algorithm | 3d images and videos | extracts the spatiotemporal multi-fused features that concatenate four skeleton joint features and one body shape feature | Difficult to implement |
| 25 | Salim lahmiri | Particle swarm optimization technique | MRI of brain | Accuracy is high , processing time is low | Difficult to implement |

Ahmad Jalal ea tl.,[24] here they have proposed a novel multi-fused features for online human activity recognition (HAR) system that recognizes human activities from continuous sequences of depth map. The proposed online HAR system segments human depth silhouettes using temporal human motion information as well as it obtains human skeleton joints using spatiotemporal human body information. Then, it extracts the spatiotemporal multi-fused features that concatenate four skeleton joint features and one body shape feature.

Salim lahmiri[25] have explained about their new algorithm. To detect the gioma presence in brain magnetic resonance images(MRI), they have compared 3 automated diagnosis systems. they have used particle swarm optimization (PSO), directional spectral distribution (DSD), multi-fractals of the computed DSD , classification of the obtained multi-fractal features were obtained and were found to be better compared to previous methods. advantages of this method are high accuracy and low processing time. But due to the usage of different methods implementation is little difficult this is the only disadvantage in this technique.All this papers content can be obtained precisely from the above given Table.1

CONCLUSION

Several challenges and aspects have been facing for segmentation techniques in different medical imaging processes. And basic techniques like fusion of magnetic resonance imaging (MRI) and positron emission tomography (PET) images, and fusion of MRI and computerized tomography (CT) images. The major advantage of MRI images is that it is able to capture the soft tissue structures in organs such as brain, heart and eyes. Different from MRI imaging, the CT imaging is able to capture the bone structures in the human body with high spatial resolutions. The PET imaging is a useful type of nuclear medicine imaging, while the captured images usually has a low spatial resolution.

CHALLENGES

Even though many recent advances have been occurred in this medical image segmentation field, still the existing problem in image segmentation algorithm is to extract accurate region of interest for example the images with noise, high computational time, more information loss, not fully automatic segmentation algorithm, Accuracy and less implementation complexity.

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