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Segmentation of Brain Magnetic Resonance Images (MRIs): A Review

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Abstract

MR imaging modality has assumed an important position in studying the characteristics of soft tissues. Generally, images acquired by using this modality are found to be affected by noise, partial volume effect (PVE) and intensity non-uniformity (INU). The presence of these factors degrades the quality of the image. As a result of which, it becomes hard to precisely distinguish between different neighboring regions constituting an image. To address this problem, various methods have been proposed. To study the nature of various proposed state-of-the-art medical image segmentation methods, a review was carried out. This paper presents a brief summary of this review and attempts to analyze the strength and weaknesses of the proposed methods. The review concludes that unfortunately, none of the proposed methods has been able to independently address the problem of precise segmentation in its entirety. The paper strongly favors the use of some module for restoring pixel intensity value along with a segmentation method to produce efficient results.

***Keywords**:* Magnetic Resonance Images (MRI), PVE, INU, Brain MRI Segmentation.

1 Introduction

This is well known fact that brain is one the complex organs in human body. The true diagnostic of any neurological disorder depends upon strength and suitability of the method employed for examining the acquired brain data. The area of image segmentation has received major attention due to the sensitivity of the examination task and due to the acute demand for minimizing the risk of re-growth of some of neurological disorder, [1]. This area starts with the critical study of the existing methods and on the basis of gaps found in these methods, it creates an opportunity for introducing best suited new state-of-the-art automatic or semi automatic brain MR image segmentation method(s).

Generally, the segmentation methods are divided into two broad classes, i.e. semi automatic methods and fully automatics methods. Regarding fully automatic methods, the question that up to how much extent this method eliminates the involvement of the operator / expert still remains to be answered. For example if it is an Artificial Neural Network based method the training and testing data are prepared by human expert, if it's a clustering based approach then the selection of number of clusters depends upon expert. Finally, when it comes to verification and validation of the results produced by any of the chosen automatic image segmentation method, then the elimination of human expert becomes impossible. Now, how precisely the verification of the results has been carried out, how much accurate the training and the testing data sets were prepared and how much accurate the number of clusters in clustering based approaches were chosen depends upon the professional strength of the expert. Indeed, this quality of MRI data examination varies from expert to expert. As a result of which, the chances for some percentage of undesired variation in the results cannot be completely ruled out. According to Warfield and Kikinis's [110] investigation, 15% variability in the results was found when the MRI dataset was examined by five different experts. In another study, Kaus *et al* [109] also reached to the conclusion that from 15% to 22% variation was there when MRI dataset was investigated by different experts. In reality, this much variation is un-affordable for the patients suffering from neurological disorders.

On the other hand, the performance of automatic segmentation methods is also not that much encouraging. The results produced by using these methods were investigated by taking into considerations manually prepared ground truth by a human expert. It was found that these results vary from 82% to 94%. In addition to it, it was also observed that, some of these methods are computationally expensive either in terms of resources utilization or in terms of execution time [2][111][112].

Coming back to our actual discussion, i.e. the type of segmentation methods: fully automatic and semi automatic. Unlike fully automatic methods, semi automatic methods share responsibility with human expert for completing the process. For example, region growing method is regarded as semi automatic method. The services of a human expert are required at two stages. First, for the selection of different seed points representing different structures of the image and second, for the verification and validation of the results when the process is completed. In the light of aforementioned information supplied by Warfiled and Kikinis and Kaus *et al* the likelihood for picking up different seed points for the same region is very much there. This possibility most likely brings certain range of dissimilarity in the results. Apart from that, another important reason that can cause variation in the results is the poor quality of the image(s). Generally, this poor quality is because of noise, intensity non-uniformity (INU) and partial volume effect (PVE). It is generally observed that in medical imaging, these impeding factors cannot be completely eliminated [3]. Due to one or the other reason, they are there in some proportion, thereby influencing the image quality. As a result of which precise segmentation of brain MRIs becomes hard to achieve [4][5][6]. From these given set of problems, the case of noise is comparatively straight forward and it can be reduced or eliminated with the help of some good noise removing filter. But the case of intensity non uniformity and / or partial volume effect is comparatively harder to address. Both of these factors are able to draw significant effect on subsequent processing of the data. For example, PVE, which is in fact combination of more than one pixel, is likely to produce an error rate of 30%, 40% and 60% in white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF) if only one pixel is displaced from its original position in every single slice [7]. Due to this much error rate, the pattern of INU and PVE were critically analyzed. On the basis of this analysis, certain solutions were extended. Certainly, these solutions contributed for fixing the problem, but still some more improvement is required to raise the preciseness level closer to the desired level. The case of INU is not different from PVE. In this problem, an image pixel fails in strictly maintaining its intensity value and it keeps on changing the intensity value for the same pixel in the image domain. Occasionally, INU is treated as multiplicative noise but in actual practice both of these things are entirely different from each other [9]. Important sources of INU include geometry, placement and orientation of the object, specific magnetic field permeability and dielectric properties of the object and the strength of the magnetic field. Besides, the presence of some disease like multiple sclerosis [10] and last but not least, the performance of the imaging device itself [8] too contribute in introducing INU in an image. All these impeding factors, i.e. noise, INU and PVE influence post processing / segmentation of medical images. Therefore, in past few years valuable research work has been carried out in order to address these issues. This research resulted in the introduction of important segmentation methods. These methods can be categorized into two main sections. One is supervised methods and the other is un-supervised method. Supervised segmentation methods are believed to be engaging human experts whereas; un-supervised segmentation approach tries its best to eliminate the human involvement as much as possible [11]. The remaining portion of the paper briefly reviews some of the important segmentation methods.

2 Thresholding

Segmenting a medical image by using thresholding is the simplest and straight forward method [102]. It can also be seen as two class clustering procedure, which divides the image into two regions. Pixel values which are lower than the threshold value, make one region. Whereas, the pixel values above than the threshold value, form another region. The method works fine with the uniform intensity values and the segmentation task gets complicated whenever there is a problem of improper contrast, asymmetric illuminations and non stationery noise

[12]. Sezgin and Sunkur [13] have conducted an extensive survey on thresholding methods. They have grouped thresholding methods in to six different classes. However, it may be noted that brain is a complex structured organ and it has varying intensity distribution. Due to which segmentation of brain MRI [105] by straightforward employment of this method is likely to produce un-reliable results. On the other hand, the combination of this method with some other method is expected to produce appreciative results [14].

3 Region Based Segmentation Method

Region based method has received an appreciative level of popularity for addressing image segmentation problems. In this context, Mumford and Shah Model [15] has been frequently applied for image segmentation. This model divides the image into its constituent regions within the bounded open set Ω and these constituent regions are separated by smooth edges. The model introduces the following energy function to achieve the desired objective.

$$F^{MS} = \int_{\Omega} (I-u)^2 \, dxdy + v\int_{\Omega \setminus C} \left| \nabla u \right|^2 dxdy + v\left| C \right| \qquad (1)$$

According to the above mentioned equation, the length of the contour surrounding a specific region is $\left| C \right|$. The equation further suggests that an image can be segmented by minimizing the above functional over all contours and fitting function *'u'*. However, the minimization of this energy functional becomes a challenging job due to dissimilar nature of the contour and the fitting function. On top of it, the non convexity of the functional further complicates the segmentation problem. In order to improve the short comings substantial modifications have been introduced [16]. For example, An and Chen [17] introduced a two phased model to address this problem. Besides, another image segmentation model proposed by [17], works on region intensity information. A region based model introduced by Chan *et al* [18] was able to work in the presence of noise but it lacked the quality for segmenting more than two regions. Vese and Chan [19] improved the model and generalized its application for segmenting more than two regions by utilizing minimal number of level set function and at the same time guaranteeing distinctive segmentation of the regions, i.e. no chances for overlap and no chances for leaving vacuum areas. The description of the model was done in two forms, i.e. piece wise constant case and piece wise smooth case. For piece wise smoothness, one dimension and two dimension cases were taken under consideration. In one dimension case, the representation of any signal with any number of segments by relying on one level set function was made possible. Whereas, in two dimension case, the generalization of piece wise constant model to piece wise smooth model was achieved with a distinctive characteristic of employing only one level set function and at the same time creating a higher degree of possibility for segmenting an image into its constituent regions on the basis of its intensity values. In order to provide a stable performance in varying intensities Li *et al* [16] has proposed a local binary fitting (LBF) model. Primarily, definition of local binary fitting energy was established in variational formulation. This step enables to extract local intensity information which can be integrated into the proposed model. The important achievement of the model is that; it needs no re-initialization for including local binary fitting energy functional into variational level set formulation. Additionally, we can see that “Snakes” is a well known region based (deformable) method that was employed for segmentation of images. The method was introduced by Kass *et al* [20] [21]. According to Li *et al* [22] the proposed model had few weaknesses, for example, on one hand it had small capture range, whereas, on the other hand it was not efficient to accommodate the topological changes. To remove these shortcomings, some important methods were introduced. For example, potential force, pressure force, Gradient Vector Flow (GVF) etc. Out of all these methods, GVF had the ability to attract the evolving contour from a substantially large distance along with its capability for pushing the contour into object cavities. However, in spite of the versatility of the parametric snake method GVF, lack the qualification for becoming a fully automatic method that can effectively deal with the topological changes. However, with the help of geometric active contour models, the topological inflexibility of GVF was removed by Malladi *et al* [23] and Caselles *et al* [24]. Though the geometric active contour models provided the best possible solution for fixing the problems of GVF, but still they suffered from drawbacks. For example, this is too difficult in their proposed method to indirectly bring the evolving curve under some topological constraint through the higher dimensional hyper-surface. Besides, the introduction of user defined external forces was another challenging job. On top of it the geometric active contour model produced un-reliable performance in case of noisy images with significant boundary gaps.

3 Hybridized Segmentation Method

In order to improve the performance of automatic segmentation system researchers have also introduced hybridized systems or the systems with slight modifications. For example, El-Zehiry and Elmaghraby [25] combined graphs cut method and deformable model in order to guarantee maximum optimization both in terms of computational resources and intensity non uniformity. Anquez *et al* [26] proposed a deformable model for the segmentation of medical images by focusing gray level statistical distribution of the region of interest. Probabilistic deformable model offers the extent of un-certainty of the probable shape parameters after the model is fitted to the image data [27]. According to Stough *et al* [28] in Bayesian based image segmentation, the curve deforms itself according to the geometrical shape of the region of interest under the influence of geometric shape parameters. This approach revolves around the optimization of objective function for achieving the best possible segmentation results. It is important to note that in deformable models [21], the segmentation problem assumes the status of optimization problem and the optimization is generally achieved by employing well known gradient decent method. This gradient decent method is efficient only in locating local minima of the equivalent energy function. Subsequent optimization techniques, for example, dynamic programmings, are restricted to two dimensional applications and a path cannot be drawn for displaying boundaries of object of interest in a three dimensional volume. In order to control these shortcomings, Zouqi and Samarabandu [29] have employed graph cuts [30][31][32][33][34][35][36][37][38][39][40] method for image segmentation.

4. Level Set Based Segmentation Method

The method was initially proposed by Osher and Sethian [41]. The method describes an implicit representation of evolving curves and surfaces. The most important achievement of the proposed method was its ability to change topology for adopting itself according to shape of the object of interest. Besides, the curve can also merge or break itself for sticking with the boundaries of the objects of interest. Primarily, the attraction of the method lies in various important features [23], for example the moving curve enjoys the flexibility of changing its topology, breaking itself or merging itself to adjust according to the geometry of the target object. From a specific level set of the surface, it becomes very easy to define and extract geometric properties of the curve. For example, it can be done by finding the curvature of the curve and the method enables the evolution of the curve beyond two dimensions.

According to Li *et al* [42], a major weakness in the traditional level set method is its tendency for developing shocks, sharp and / or flat shapes during the evolution process. This naturally results in wrong computations. In order to control this weakness, the level set function was required to be initialized as a signed distance function before the evolution process takes place and then periodic re-initialization of this level set function as a signed distance function was considered mandatory during the whole process. Therefore, the structure of level set method without re-initialization was supposed to be incomplete. This re-initialization process used to be carried out by employing the following mathematical relation.

$$\frac{\partial \phi}{\partial x} = sign\ (\phi_o)\ (1 - |\nabla \phi|) \qquad (2)$$

Where ϕ_o represents the function that requires re-initialization and $sign\ (\phi)$ is the sign function that takes the responsibly for deciding the location of the point within or outside the sub-region. The apparent disadvantage of this method is that; if ϕ_o lacks the smoothness or if there is an imbalance in the steepness on either side of the interface then the zero level set of the resulting function ϕ may make an incorrect progress when seen in comparison to the actual function. Besides, when there is a substantial distance between level set function and signed distance function then the re-initialization of level set function to the signed distance function may not be fully guaranteed. On top of it, the deviation chances for evolving level set function from its value as signed distance function in fewer numbers of iterations becomes brighter, especially when time stamps are carelessly chosen. Additionally, this is quite difficult to define the most suitable time and method with which the re-initialization of level set function to the signed distance function can be achieved. Therefore, Li *et al* [42] proposed the following energy equation to solve the problem.

$$\varepsilon(\phi) = \mu\rho(\phi) + \varepsilon_{g,\lambda,v}(\phi) \qquad (3)$$

The term $\varepsilon_{g,\lambda,v}(\phi)$ represents the external energy which facilitates the zero level set in approaching the object boundaries. Whereas, the internal energy which is represented by the term $\mu\rho(\phi)$ safeguards any possible deviation of ϕ from the signed distance function and guarantees smooth evolution of the curve.

4. Segmentation through Active Contours without Edges

The model described above i.e., Level Set Method uses an edge stopping function. For doing so, it uses the image gradient. However, it may be noted that the discrete gradients are bounded due to which the edge stopping function fails to get zero value at the edges thereby creating maximum chance for the evolving curve to crossover the edges of the structure of interest [43]. On the other hand, this possibility cannot be ruled out that generally medical images are blurry and noisy which creates difficulty in extracting the crucial information. In this situation, the applied smoothing function is supposed to be strong enough for distinctively smoothing the boundaries of targeted region [43]. Therefore, to meet this requirement, Chan and Vese [43] proposed a new active contour model that produced appreciative performance. The most attractive feature of the model was, it didn't use edge stopping function and at the same time maintained the reliability of segmentation procedure. Considering Ω as whole image domain and an image $I(x, y)$ over this domain, the authors suggested for minimizing the following energy functional.

$$E^{CV}(C, c_1, c_2) = \lambda_1 \int_{in(C)} |I(x) - c_1|^2 dx + \lambda_2 \int_{out(C)} |I(x) - c_2|^2 dx + v|C| \qquad (4)$$

Where C represents the contour, $in(C)$ and $out(C)$ points to the region inside or out side of the contour. The image intensity in the aforementioned two regions (i.e. inside and out side) is approximated with the help of constants c_1 and c_2.The global binary fitting energy which can be characterized through level set formulation is represented with the help of first two terms in the above mentioned energy functional. This is how energy minimization problem is transformed into level set evolution problem In this model, the fitting of image intensities, both within and out side the contour is carried out through the constants c_1 and c_2

respectively. It may be noted that this global fitting will produce desirable results only when there is no intensity problem and the image intensity in both these regions (i.e. inside and out side) carries uniformity. Therefore, with this observation the performance of their proposed model becomes questionable [16].

5 Segmentation by Region Growing Method

In this approach a region is defined on the basis of certain criteria, for example intensity of the pixels constituting a specific region. These pixels can be grouped together for executing any subsequent image processing operation. Alternatively, it can be said that an object's gray values are found to be falling within a certain range around a mean value. Therefore, a region is likely to expand after the inclusion of a new voxel, if its (voxel's) existing mean value and standard deviation is found lying close to the region's mean value. Mean value and standard deviation is regularly required to be updated during the expansion process [44]. Since its inception, a lot of work has been done for achieving optimized results. For example, an adaptive region growing approach has been introduced by Modayur *et al* [108] for dealing with neurological images. According to this approach, the decision function possesses the capability for adapting itself according to region's size [44]. However, regarding extraction of various regions of interest, the region growing [45] algorithm can be applied to segment multiple regions of interest from a single image. To achieve this objective, the algorithm needs some seed points. On the basis of those seed points the neighboring pixels are examined, if they fulfill the criteria they are grouped together. The process keeps on executing it self until it reaches the boundaries of all regions. Finally, all the regions found through this method are grouped together to produce a full segmented image.

5 Segmentation through Edge Tracing Method

Generally, the boundaries of regions of interest are found by employing the edge tracing method [46] [47] [103]. The method relies on the information extracted by finding the peak value in gradient of an image. A well known edge tracing method that received a lot of attention is introduced by Canny [48]. The method makes use of two threshold values, over the basis of which image segments are obtained. Chen *et al* [49] employed neural network for finding edges constituting different regions and eventually got these regions segmented on the basis of this information.

6 Segmentation through Artificial Neural Network (ANN) and Its Variants

Artificial Neural Network (ANN) and its variants are well researched and well established techniques and their contributions in the field of medical imaging cannot be underestimated [50][51]. Due to versatility of the technique, ANN has been employed to solve a wide range of brain MR imaging problems. For example, to mention a few, Magnotta *et al* [52] employed ANN for doing volumetric analysis of brain structures, Dawant *et al* [53] and Hall *et al* [54] used them for segmenting brain MRIs for the extraction of GM, WM, CSF etc. and Li *et al* [55] used them for extracting tumorous region after segmenting brain MR image. There are various interesting reasons due to which the ANNs have invited frequent attention for solving complex problems. For example, they bear an appreciative level of learning capacity [56], they are totally indifferent in considering any assumption about underlying probability density functions thereby maintain the consistency when data significantly departs from normality [56][57], they excellently display the ability for combining morphometric techniques along with larger volume parallel computations [58] and more importantly, the ANNs are flexible enough to be integrated into other frameworks [56]. Radial Basis Function (RBF) is an important variant of ANN. Li *et al* [59] performed the segmentation of brain MR images by using fully tuned RBF network. It was found that unlike Fuzzy C-Means (FCM), RBF can handle the intensity variation. Kondo and Ueno [60] employed Radial Basis Function Group Method of Data Handling (RBF GMDH) type neural network for recognizing medical images. The approach distinguishes it self by keeping the original data intact and eliminate the necessity for grouping the data into training sets and testing sets because prediction sum of squares (PSS) can be employed as the test errors. This approach utilizes heuristic self organization for automatically fitting the complexity of medical images [61]. Enhanced Neural Networks (ENN) proposed by Mingo *et al* [62] for medical image segmentation and 3D re-construction are another important forms of ANN. An important feature of ENN's architecture is that it allows to estimate any data set using n-degree polynomial depending on the number of hidden layers. Hopfield Neural Networks (HNN) had also made significant contribution in segmenting brain MR images [63]. It may be noted that the performance of HNN depends upon the choice of energy function. Appreciative segmentation results are obtained when the energy function is derived from the sum of the squares errors as a cost-term and when the noise term is added to excite the network for detecting and avoiding local minima and adjusting itself closer to global minimum [64] [65]. However, ANN do have certain demerits. For example, it has slow training speed. Due to the unavailability of any standardized rule, it becomes difficult to define suitable parameters and chances of its occasional inability to achieve convergence [56] are increased.

7 Atlas Based Segmentation Method

The transformation of brain MR image segmentation procedures from human experts to fully automatic or semiautomatic methods can be witnessed by exploring the atlas based methods. These atlases are generally prepared by taking into consideration the brain MR images of normal subjects followed by manual delineation of structural details from them [66] [67][68]. The atlas is supposed to discharge two important responsibilities: first, it serves as a source for providing spatial prior probabilities and second, it is also supposed to estimate the parameters which are responsible for initial intensity distribution while addressing the normal tissue classes [66]. Zhou and Bai [69] proposed a fully automatic brain MRI segmentation method by combining together atlas based registration, in which registration of pre- segmented atlas was carried out onto MR images via rigid registration method. Fuzzy connectedness (FC) segmentation method, used for initial segmentation of MR image. Parametric bias filed correction (PABIC) used for correcting INU artifacts, and finally, these corrected images were again segmented by FC method. However, the method was proposed for the environments where there are minimum chances for intensity overlapping. Therefore, the method is likely to produce unreliable results in a situation where the chances for intensity overlapping are higher. Prastawa *et al* [66] has proposed model based segmentation method. This method relies upon the availability of spatial prior of a statistical healthy human brain atlas with a strong feature of drawing individual information drawn from patient's dataset. The distinctive features of the approach are its efficiency and capability to complete segmentation of MR images. Although this method is fully automatic but due to the limited number of test cases, the complete avoidance of manual raters cannot be claimed. Cuadra *et al* [70] proposed a method for deformable brain atlas. The deformable brain atlas has the capability to elastically get it self transformed according to the anatomy of the individual brain by using non rigid registration method [71]. The proposed method by Cuadra *et al* [70] is used for segmenting larger pathological regions. The method utilizes a priori model which has produced encouraging results especially in the situation where the brain structures underwent deformation due to abundance of abnormal cells. Kyriacou *et al* [72] proposed a method for modeling the deformations observed in the normal brain tissues which is generally caused due to the growth of tumor cells. Their approach relies on modeling of INU and non-linearity, existing in the soft tissues' elastic behavior, on the limitations imposed either by the skull tentorium and the falx, or the ventricular deformations caused by the tumors. In their proposed method, they got the normal atlas adjusted with a tumor affected brain in four steps. To begin with, they contracted the tumor to extremely small mass to obtain approximation of the brain in its original, i.e. in its un-deformed state. In the second step, intensity non-uniformity was corrected. In the third step, the registration of the atlas was done and for this purpose they employed normal–to–normal deformable registration method and in the final step, the tumor growth was modeled by on the labeled patient image by utilizing a regression scheme. With the completion of these three steps, their approach concludes with the deformation of the atlas labeled anatomy and consequently to a label of patient's deformed anatomy. However, their proposed method for tumor growth had some restrictions. First, their model can deal with the uniform form of growth of tumor; however, in actual practice the case may not be generalized because naturally, this growth can be expected in the directions offering minimal stress. Secondly, the tumor infiltration situation had not been taken under consideration, this infiltration process do not press the normal tissues to create space for itself. The method proposed by Dawant *et al* [73] doesn't need either segmentation or any fundamental mathematical model due to which the proposed method is efficient. Their method guarantees the consistent deformation with the help of a smoothing filter. Besides, selecting suitable values aids in modifying the algorithm due to which the exact deformations, both over normal and abnormal regions, become possible. Finally, the approach implicitly constrains symmetric movement in the neighboring pixels.

Practically atlas based segmentation methods and classifiers are identical. The only difference that distinguishes atlas based approaches from clustering approach is the mode of their implementation, i.e. unlike clustering which is implemented in feature space, atlas based approaches are implemented in spatial domain. An obvious advantage of atlas based segmentation method is that it guarantees the possibility for receiving both, the labels and the segmented anatomical regions. Besides, the approach also facilitates in standardizing the ethics for exploring morphometric properties. The weakness of the approach stems from anatomical variability where it fails in successfully marking the boundary of region of interest.

8 Segmentation through Clustering

Clustering holds an important position in the area of image segmentation. It is of two types, i.e. supervised or un-supervised. Supervised. Supervised approach works fine when the number of data clusters is known a priori. Fuzzy K-Means algorithm is an example of supervised segmentation method. Whereas, fuzzy C-Means (FCM) is an example of un-supervised segmentation method. Typically an FCM algorithm works on the assumption that similar data points in feature space should be grouped together to form one cluster. The procedure is noise sensitive. Therefore, the chances for misclassification in the presence of noise are likely. This is an iterative process which specifically takes care for minimizing the cost function. Cost function represents the distance of pixel whose fate is to be decided for grouping it with a certain group, from the cluster centers. The pixels through which various regions of the image are composed are naturally interconnected. Therefore, more or less, the neighboring pixels exhibit same feature data. This characteristic makes spatial relationship among neighboring pixels an important source of information for dealing with image segmentation problem. Traditional boundary tracing approaches excellently utilize this spatial information for segmenting regions of interest. However, various variants of conventional FCM have been researched upon which addressed the image segmentation problem but they simply relied upon single feature input [74]. Although FCM, has the ability to cluster large data sets [75], but it fails to handle INU problem [76]. Moreover, it assumes that centroids of the image are spatially invariant which is not considered a valid argument, specially in a case when the underlying image is affected by noise and INU [76]. However, generally, the FCM algorithm is considered to be an efficient approach which enjoys the luxury of automatically adjusting itself during the execution process meant for clustering and segmentation. The approach played significant role in carrying out un-supervised segmentation of brain images [74]. Clustering facilitates in determining the optimum number of clusters after qualifying the eligibility criteria in a given dataset. Usually, clustering algorithm is executed by considering only two clusters. This much number of clusters may or may not be able to solve the problem. Therefore, there is a need for introducing a clustering technique that can dynamically increase the number of clusters on the basis of instant requirement subject to the constraint of satisfying the validity criteria. However, choosing the center for the subsequent clusters is the most sensitive piece of job, otherwise, the method may produce faulty results.

9 Fuzzy Connected Based Segmentation

The fuzzy connectedness method was proposed by Dawant *et al* [77]. It describes image pixels mutual relationship in spatial domain. According to Rosenfeld [78], the fuzziness in image voxels can be attributed to inbuilt object material heterogeneity and artifacts caused due to imaging device. These artifacts may include blurring, imposed noise and back ground variation. This mode of segmentation initiates with the fact that: naturally the images are blurry [69][79]. The objects in an image are displayed in non binary sequential order which is drawn from object's material heterogeneity and from blurring, noise and surroundings variations which are introduced by image acquisition appliance. Despite the complex structured image object, radiologist comfortably distinguishes them during the process of visual inspection. The logic of fuzzy connectedness works on the assumption that a relation between two voxels v1 and v2 exists and this relationship is established by exploring all possibilities for linking v1 and v2 in 3D space. The strength of these linking possibilities is examined by evaluating the successive pairs of voxels along the path. The neighboring voxels are strongly bonded together due to their spatial closeness [80] and due to the uniformity in their pixel intensity characteristics. This bonding force also describes the strength with which the voxels hold them together in the same object. The strength of connectedness [81] between two points v1 and v2 can be realized by determining the strongest of all available possibilities for approaching v2 from v1. An overall fuzzy connected object can be obtained by knowing that how strongly the possible pairs of voxels are tied together [2].

This is worth mentioning that the method is applied to solve wide range of problems. For example, quantification of lesions and tissues constituting different anatomical structures of brain, segmentation of vessels with MR angiography and artery-vein division, volumetric analysis of sub glandular tissue with mammography for the estimation of breast cancer threat and 3 D visualization of muscles with CT for craniomaxillo facial surgery planning [2]. However, the apparent disadvantage of the method is that it is not fully automatic and does require human interaction for selecting the seed points in the regions to be segmented [2]. Improper selection of the seed points will badly affect the performance of the method. Besides, this method is sensitive to intensity non uniformity problem; therefore, it strongly needs some intensity correction mechanism for producing the desired accuracy [69]**.** However, the positive feature of the method is that it was able to receive wide range of attention especially fuzzy connectedness and fuzzy clustering were frequently applied for solving clustering related issues. Besides, the method was extensively researched upon due to which its variants were introduced and were applied for carrying out segmentation process. As an example, these variants include fuzzy adaptive thresholding [82], fuzzy region growing [83], fuzzy thresholding [84] [85], fuzzy markov random field [86], fuzzy rule based approach [87] and fuzzy region based method [88].

10 Segmentation through Statistical Methods

Due to higher degree of complexity, it is always difficult to extract different regions of interest on the basis of their texture. Due to the intensity variations, there is no possibility for getting a single edge representing the whole region nor there is any possibility for extracting the region by employing region based methods on a specific texture, because in the latter case, a number of small regions are likely to be extracted instead of a region representing the whole area of interest. A solution to this problem has been proposed in the form of supervised and un-supervised segmentation method. Since, supervised segmentation methods are operator dependent whereas, un-supervised segmentation methods [107] can perform independently. Therefore, an un-supervised technique, because of having an edge over supervised technique, is recommended for segmenting complex textured brain MR images [89]. This approach relies on the probability density function (PDF) of the tissue intensity for various tissue classes. Generally. this PDF is parametrically modeled [90] [91] as a mixture of Gaussians in which all the tissue classes are represented by independent Gaussians. For the segmentation purposes, this is quite natural that we need to know about the contextual dependencies so that boundaries of regions can be marked appropriately. This information about neighboring voxels can be drawn by utilizing Markov Random Filed (MRF) model [92][101].

The main objective of applying statistical based approaches is to make certain prediction about the data on the basis of few well defined criterions [104]. These methods can be applied to multi spectral MR data. In this context, Bayesian classification system holds basic importance. This method works on the fundamental assumption that the overall range of image intensities can be modeled as sum of Gaussian distribution which is called Gaussian mixture model (GMM) [93][94]. In parametric mode of image segmentation, the input images are illustrated by distinguishing them on the basis of their behavior observed by employing a limited set of parameters. Expectation Maximization (EM) is a good strong example of parametric models [95][96]. It works on labeling of pixels [106]. As EM is an iterative process, therefore, the set of parameters are supposed to be updated on the basis of some estimated values computed during each iteration. However, this is important to note that EM algorithm produces an appreciative performance even when the mixture models are not neatly separated from each other. Secondly, it has the ability to simultaneously perform segmentation along with the creation of mixture models. But the dormant side of the algorithm is that, inherently it takes no botheration for preserving and presenting the spatial information [97][98]. However, subsequently, it extracts the spatial information with the help of MRF along with the presence of one important concern; that, MRF classification methods are not fully automatic and they need supervised learning and a priori information [99]. Along with that, the EM algorithm is expected to get itself hooked up with local minima. Finally, this is also not clear that, how the algorithm deals with pixels with insignificant expectation. On contrary, the case of non parametric segmentation methods is comparatively straight forward. It deals the images on the bases of their pragmatic behavior by taking into considerations the dimensions either from the candidate image or from a group of specimen images reserved for training the algorithm [100].

11. Conclusions

This paper has presented various methods meant for segmenting medical images. Unfortunately, none of the proposed methods was able to completely address the problem of precise segmentation. The issues of impreciseness are still highlighted. This characteristic leads us to the conclusion that brain MRI segmentation is not fully developed area of medical image processing. This attribute makes segmentation of medical images an active area of research.

Generally, noise, PVE and INU which are inherently found in MRIs, degrade the quality of an image. This degradation considerably influences the precise quantification of constituent regions in an image. Therefore, the elimination of these image degrading factors for achieving the desired results is strongly advocated.

A subsequent lesson learnt from this survey is that, even an efficient segmentation method is not going to produce desired results unless it is joined with some modules meant for restoring the original intensity values of pixels representing certain specific regions in an image. These original intensity values can be restored by bringing under complete control the issues of PVE, INU and noise. Besides, the survey comparatively favors the employment of statistical based approaches for dealing with the problems found when processing a medical image. A straightforward and an understandable feature that distinguishes statistical based methods from rest of the methods is their strong and inflexible ability to model noise, INU and PVE. Besides, this mode of modeling method becomes indifferent to the size of the data and maintains its performance, no matter whether a single image is tested or a few hundred images.

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