Medical Image Segmentation using Fuzzy Clustering Techniques

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ABSTRACT

There are many variants of FCM proposed in the literature, but most of these methods don't give satisfactory results for images containing noise. Some methods don't handle noise, but most of the methods that do handle noise, do so by simply smoothing the image. So, we have used the SNI (Spatial Neighborhood Information) term to handle the noise without over smoothing the image. The advantage of SNI is that it uses the information derived in the previous step (specifically membership matrix) to compute the neighborhood information. We haven't simply just added this value to the membership values, but we have included this term in the objective functions of the existing algorithms and derived the formula for membership matrix and cluster centroids using Lagrange's method. We have compared the modified methods with other relevant methods, and concluded that our modified methods give more robust results even in the presence of noise.

Keywords

Fuzzy set, Intuitionistic fuzzy set, clustering, image segmentation, Magnetic resonance imaging

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Chapter 1

Introduction

1.1 Introduction

In computer vision, image segmentation is the task of segmenting or partitioning of the image in various regions of interest. In the medical image, segmentation of these regions of interest may be organs, tissues, tumors, or any other relevant biological structure. Medical image segmentation is the first step of any medical image analysis, and its performance affects the accuracy of the whole process. There are various medical imaging modalities such as CT, X-rays, MRI, and many others, and in literature, there are classes of methods being proposed for segmenting images obtained from the mentioned imaging modalities. But, out of all these different classes of techniques, we are going to focus on clustering only. Clustering is based on the similarity between data points as the criterion for the class division. Clustering has been demonstrated to give good results for segmenting MR Images. In this thesis, new techniques based on clustering has been discussed for MR Image segmentation.

1.2 Motivation

There is an acute shortage of trained radiologists all over the world. Due to this, radiologists are overburdened with work, which has caused lesser time spent by radiologists for image analysis, which in turn causes many medical conditions to go undetected. By automating some of the radiologists' work, we can potentially save many lives, and it has the potential to help in detecting medical abnormalities early. In the literature, numerous methods have been proposed for MR image segmentation. But, a satisfactory level of efficiency and accuracy has not been attained. A robust medical image analysis system requires an efficient and accurate image segmentation method.

Chapter 2

Magnetic Resonance Imagining and Brain Anatomy

2.1 Medical Imaging Modalities

The introduction of advanced imaging techniques has significantly improved patient care. Medical modalities, for example, include MRI, X-rays, CT, PET, etc., helps doctors in accurately diagnosing the diseases and also helps in monitoring the progress of the treatment. Usually, due to different underlying principles of imaging, different modalities react differently to various properties of tissues. Therefore, the information provided by different modalities is often complementary but useful information. X-ray and CT can detect regions of reduced transmissions; thus, these can identify dense areas such as bones and calcification easily, whereas soft tissue structures have the best contrast in the case of MRI. Information provided by the mentioned methods is only anatomical, but these don't offer any functional information. PET can detect metabolic changes by tracing blood flow but poorly delineate anatomy. Therefore, each modality has its own unique use case, and by using the information captured by different modalities in conjecture, a more detailed map can be obtained for better treatment.

2.2 Working Principle of MRI

NMR (Nuclear Magnetic Resonance) spectroscopy and MRI have the same underlying principle, which is to establish the identity of a compound by measuring the resonant properties, i.e., the jiggling of the protons, present in the molecule.

The human body is mostly (60 %) made up of water. Lymph nodes, blood vessels, and even bones contain water molecules, and every water molecule comprises of two hydrogen atoms and one oxygen atom. These hydrogen atoms have a single proton as their nucleus, which can be thought of as a tiny magnet with 'north' and 'south' poles. Just like the magnet whose north and south poles align to the earth's magnetic poles, the protons get aligned to the external magnetic field. Then, short bursts of low-energy

RF (radio frequency) waves are fired, which knock out these protons and change their alignment or polarity. In the absence of RF waves, the protons start to realign with the magnetic field, and this realignment generates RF signals, which are picked up by the receiver. The no. of RF photons and the time is taken for realignment depends on the hardness and thickness of the tissues where the water molecules are present. Therefore, by carefully detecting the emitted RF photons, allows us to calculate the locations and shapes of different tissues present in the body.
Steps for obtaining an MRI scan of a patient are:

1. The patient is placed in the machine, in which powerful magnets generate a uniform magnetic field.

2. Different parameters for the scan, such as RF waveforms and its timings, and shape of the gradients, are controlled using a computer. This information is passed to the RF generator which sent them to the coil for amplification.

3. When RF radiations are turned off, then the excited nuclei emit RF radiations as they come back to the ground state. The emitted waves are picked up by the receiver coil. The analog signals from the receiver are transformed into a digital signal using an analog into a digital converter. The image processor converts the digital signal to an image.

2.3 MRI Imagining and its Artifacts

MRI is one of the most used medical imaging techniques, which can be attributed to its high resolution and high soft-tissue contrast, which makes it perfect for analyzing the soft tissues. Unlike ionizing radiations in CT and X-ray, MRI's magnetic field doesn't harm the tissues. MRI can extract valuable and abundant information about the healthy tissues, which has made it a useful tool for medical image diagnosis. Usually, a contrast is given to the subject to facilitate the MRI machine in getting better scans. MR angiogram (MRA) is a type of MRI scan in which the contrast agent (gadolinium) is injected into the bloodstream. Without gadolinium, standard MRI can't detect moving fluids like blood in veins and arteries, and the fluids will appear as black patches (also called "flow voids"). Gadolinium facilitates in detecting the veins and arteries. There are other contrasts that help in detecting tumors. Extracting valuable information from MR images has proved to be a very time consuming and labor-intensive task and this why this task is well suited for computers. Computers can help in analyzing MR images at a much faster pace. But, due to the presence of image artifacts, automated image analysis becomes very difficult. There are three main types of artifacts that affect MR images:

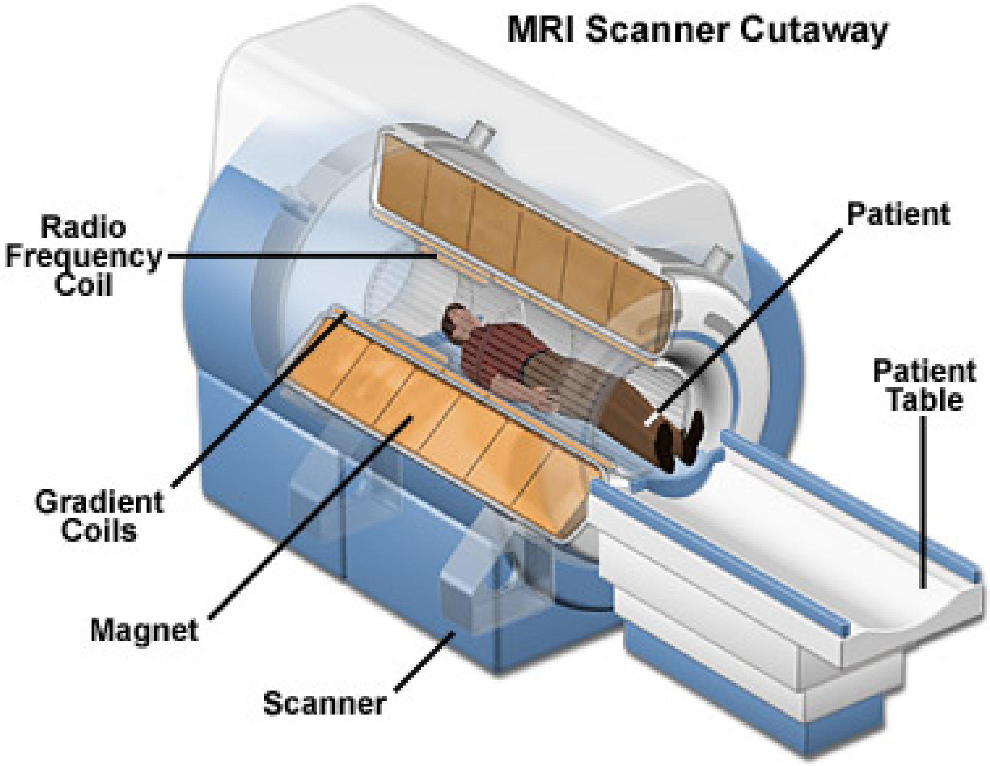

Figure 2.1: MRI Scanner cutaway figure

1. **Noise**: It is the most common artifacts in medical imaging (and even in computer vision). Noise affects the sharpness of the image and can cover up any vital ROI and can reduce the visibility of the image. This makes image analysis tough, even for Radiologists. In MRI, noise is usually caused by equipment (like RF coil, low bandwidth receiver, etc.), environment or even, due to the operator's performance.

2. **Intensity Inhomogeneity**: Intensity inhomogeneity can be defined as a smoothly varying function. It can alter the intensities of the MRI pixels, and it especially affects the middle MRI region the most and causes them to be darker. It causes the originally homogeneous regions to be inhomogeneous. It is caused by the bias field signal, which a very smooth and low-frequency signal that corrupts MR images.

3. **Partial volume effect**: Partial volume effect is the existence of more than one type of tissue in a pixel, and it occurs due to finite spatial resolution. The partial volume effect is more prominent in extreme slices. The partial volume effect can be decreased by increasing the resolution of the MR images, but due to technical reasons, it is not possible to increase the resolution too much.

2.4 Tissue Contrast

When the RF signals are stopped, then the excited protons start to return to the equilibrium position through T1 recovery. Thus, T1 is a longitudinal relaxation time which determines the rate of recovery of proton back to the equilibrium position. Alternatively, it is the time taken by the spinning proton to realign with the external magnetic field. Along with the T1 (or longitudinal) recovery, there is a decline in traversal magnetism through the T2 mechanism. Thus, T2 is traversal relaxation (or decay) time, which decay rate of excited protons to go out of phase with each other. Alternatively, it is the time taken by the spinning protons to lose phase coherence among the nucleus with the spin perpendicular to the external field. Different T1 and T2 values are observed for different tissues. If we compare T1 and T2 values for fat and water, then fat tissues show faster longitudinal relaxation, i.e., shorter T1 and faster latitudinal decay, i.e. shorter T2. Proton density of tissue is just the average number of protons per unit area.

In the case of MRI, different tissues have differences in tissue contrast on images, which can be attributed to different values of T1, T2, and PD for different tissues. The two most important parameters that introduce differences in image contrasts for different images are – repetition time (TR) and echo time (TE). The amount of time taken for registering the peak echo signal after the delivery of the RF pulse is called Time to Echo (TE). Repetition Time (TR) is the length of the time interval between successive RF pulse sequences applied to the same slice.

Different types of images (or different contrasts) are obtained by varying the TE and TR values because different tissues are sensitive to these parameters. For shorter TRs, longitudinal magnetization recovers slowly in water than in fats. Thus fats and water can be differentiated by their relaxation times; for longer TRs, no such differentiating phenomenon is observed. Thus, TR relates to T1 and thereby affects the contrast for T1 weighted images. Similarly, longer TEs can differentiate fats and water, but no such differentiating phenomenon is observed for shorter TEs. Thus, TE relates to T2 and thereby affects the contrast of the T2 weighted image.

For long TR and short TE, the differentiating factors, that are, longitudinal magnetization recovery and latitudinal magnetization decay, are not observed. Thus, the contrast observed in the MRI can be attributed to the varying levels of proton density between fats and water. In this case, the intensity signal depends on the proton density, i.e., the higher intensity is observed for the regions with higher proton density, and lower intensity is observed for the regions with lower proton density.

TR, TE, and PD are the parameters that can alter the tissue contrast of an MR image. Out of these three parameters, only TR and TE are adjustable, and these two can be adjusted to the desired contrast. By changing TR and TE values, we get different MR sequences, which are nothing but MR images with different types of contrasts. There are many

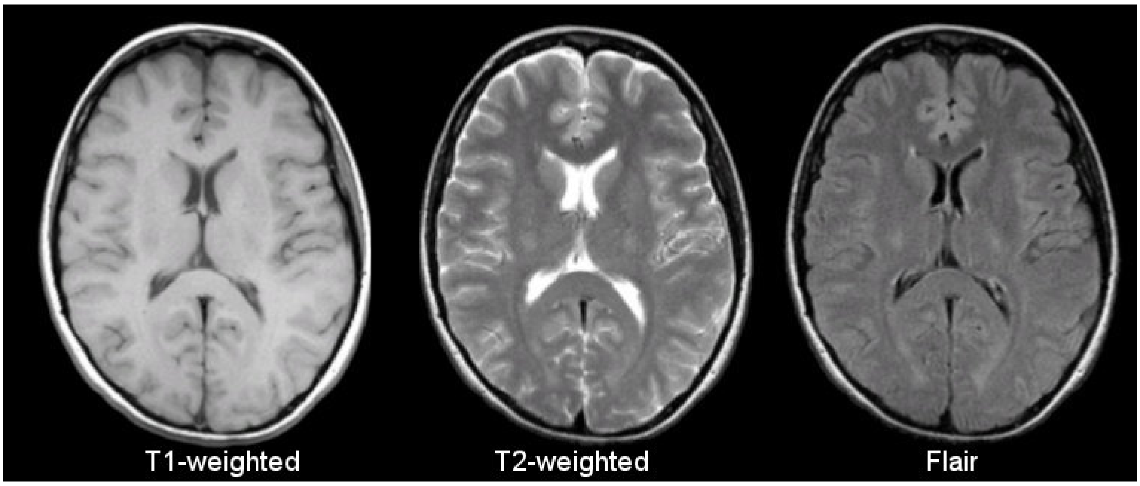

Figure 2.2: MRI T1 vs. T2 vs. FLAIR difference

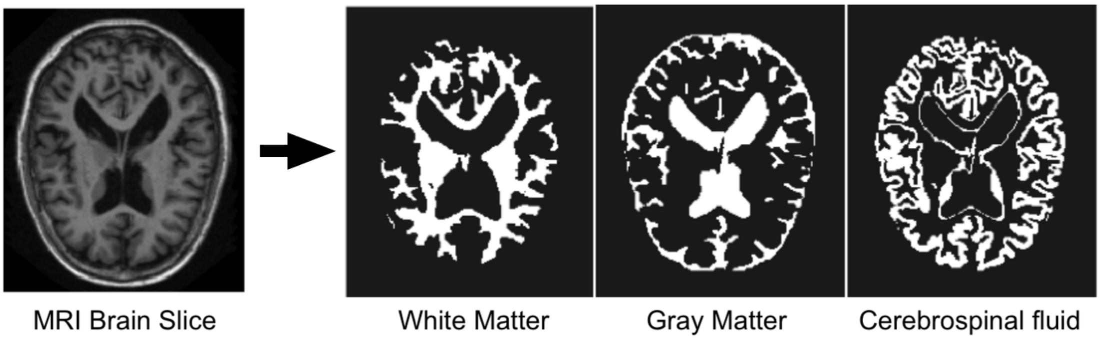

Figure 2.3: MRI Image segmentation into WM, GM and CSF

different MR sequences, but the three most important sequences are – T1 weighted (T1W) image, T2 weighted (T2W) image, and PD weighted image. In the T1 weighted image, T1 contrast is accentuated, and this achieved by having low TE and TR values. Tissues with fluid-like CSF and water appear dark and, fat, slow-moving blood, hematomas, and gadolinium-based MR contrast seems bright. In the T1 weighted MR image. So, T1W is the best sequence to study brain anatomy. In the T2 weighted image, T2 contrast is accentuated, and this achieved by having long TE and TR. Tissues and fluids with high water content appear bright in the T2 weighted image. Thus, T2W is the best sequence for disease detection because of the high water concentration of tissues involved in the pathological process. In PD weighted image, PD contrast is accentuated, and this achieved by having short TE and long TR. Areas with high proton density such as fats and fluid-like CSF appear bright. In the T1 weighted MR image. So, PDW show both the disease entity and brain anatomy.

2.5 Segmentation of Brain MRI

Soft tissues such as brains are captured in great detail by the MRI. Cerebrospinal fluid and bones don't contain water, so these appear black. The intensity of regions such as blood and soft tissues varies from black to white, depending on the water content of the tissues. Here, the task at hand is to segment Brain MRI into three regions, namely – white matter (WM), grey matter (GM), and cerebrospinal fluid (CSF). Segmentation helps in easy detection of conditions such as Parkinson's disease, Alzheimer's disease, traumatic brain injury, developmental anomalies, multiple sclerosis lesion, blockages of the blood vessels, multiple sclerosis, infection, stroke, dementia, etc.

Chapter 3

Related literature works

3.1 Introduction

The MR Images are often found corrupted by various imaging artifacts such as noise, intensity in-homogeneity and partial volume effect. These artifacts arises during the image acquisition due to human errors, technical inconsistency and uneven radio frequencies which ultimately results in making manual medical image segmentation inconsistent. These artifacts induces out-of-distribution like cases while analysis and deviates the decision making of image segmentation. The most common artifact affecting the MR Images is noise which adds some additive deviation in the original signal[1, 2]. To handle the noise, several modified FCM version have been proposed in the literature. Most of these works focuses on integrating neighbour pixel's information in the cost function which tries to solve the problem by incorporating available neighbourhood spatial information instead of just concentrating on a single central pixel. In this chapter, we present an theoretical comparison between different noise segmentation methods.

3.2 Related Works

One of the major problem associated with medical image segmentation is the non-robust performance in the presence of noise corruption in images. The noise corruptions are additive disturbances which deviates the real pixel intensities and makes the segmentation inconsistent. In order to solve this problem several methods have been proposed in the literature which rely upon the neighborhood spatial information. These methods focuses over the improvements in objective function, distance metrics and fuzzy sets to solve different noise related problems associated with image segmentation algorithms using neighborhood information. This section presents an overview of these methods.

Ahmad et al. [3] proposed a modified Fuzzy C-means namely FCM_S to suppress the outliers. They assumed that the intensity distribution of a noise free image would be homogeneous in a pixel's neighborhood and hence, included an additional term in the optimization problem consisting of the immediate neighbor pixels distance from the centroid intensities. The neighborhood information acts like a regularizer and facilitates the optimization towards piece wise homogeneous labeling of pixels. This method is found to be highly dependent on the input spatial parameter alpha which is responsible for controlling the extent of neighbour influence. Optimization of alpha usually takes a lot of time as it involves grid-search for finding optimal value. Furthermore the computational efficiency per iteration was also poor since the neighbour information, over the given local window was incorporated in each optimization step. Chen and zheng [4] proposed FCM_S1 and FCM_S2 where a statistical approximation of mean and median over the neighbours was used respectively, inorder to reduce the time complexity. Although it achieved a better time complexity, yet the methods were not found to be effective as their performance was not up to the mark for a lot of noises especially for Salt pepper and Mix noise.

The above methods used the Euclidean distance to measure the distance between pixel intensity values. The noise induced in an image usually act like an irregularity and the Euclidean distance become incapable in recognizing patterns behind these irregularities as they turn more complex. Therefore, an alternative to eucledian distance i.e. kernel distance metric was employed in KFCM_S [4], which was found to be more efficient in handling noises in comparison to Euclidean distance. Szilgayi et al. [5] proposed Enhanced Fuzzy C-means (ENFCM) which proved to be a major breakout in making the segmentation faster. The method proposed two novelties i.e. first the spatial information was incorporated with the original image in advance by adding the weighted sum of the immediate neighbor pixels intensity and second the whole image was represented by the grey level histogram on the basis of which clustering was done to get the final segmentation.

One major drawback associated with the FCM_S, FCM_S1, FCM_S2 and EnFCM was the use of the same value of the spatial parameter alpha throughout the whole image. The different regions of image were often found to be affected by different noise levels and therefore the performance was not found to be consistent. To overcome this problem, cai et al. [6] proposed FGFCM algorithm containing an adaptive varying spatial parameter alpha which depended on the local statistics in a given window. This adaptive parameter alpha was calculated by using the differences between the spatial and grey level of the pixels lying in a local window. The computation of adaptive varying spatial parameter depends on two input parameter i.e. λ_s and λ_g. Similar to FGFCM, Guo et al. [7] also proposed a Noise detecting Fuzzy C means (NDFCM) focusing on the problem of inhomogeneous noise distribution. NDFCM is able to efficiently suppress the noise and also preserve the sharp image details. Compared to FGFCM it contained less input parameters and hence was time efficient.

Most of the above methods are dependent upon some input parameters, which are required to be fine tuned for getting the optimal results. Krindis et al. [8] proposed a parameter free method named as Fuzzy Local Information C-means Algorithm (FLICM) which consisted of a spatial distance weighted neighborhood information term. FLICM gave good segmentation results along with preserved shapes. Gong et al. [9] further introduced kernel metric in FLICM instead of euclidean distance along with weighted Fuzzy tradeoff factor, which was proficient in capturing the irregularities due to the noise. However both FLICM and KWFLICM were not found to be stable during optimization as the objective function was not found to be converging. Kang et al. [10] proposed Fuzzy C means with Spatially weighted Information (FCMSWI). The method is parameter free and tackled the problem of varying noise distribution throughout the image. The weight coefficients in FCMSWI are calculated using the neighbour pixels intensity. Lin et al. [11] introduced a novel membership constraint in FCM clustering, named as Generalised Fuzzy Clustering with improved partition, which helped in the rapid convergence. To improve robustness against noise Zhao et al.[12] extended the GIFP to kernelized version with spatial information i.e. KGFCM .

Recently Lei et al.[13] proposed a Fast and Robust fuzzy C-means algorithm (FRFCM) which gave impressive results with considerably low time complexity. The method employed a morphological reconstruction operation as a pre-processing step which made it more robust to a variety of noises. To avoid the heavy computation which calculating distance between the neighbor pixels and centroids, the method used membership filtering as a post processing step. Although, the method was robust to a variety of noises, but it was not able to perform well on high noise samples. When encountered with high noise samples, FRFCM was not able to preserve the sharp edges and shapes. Another research work [14], termed as DSFCM_N, modelled the deviation between the original pixel values and measured noisy pixels value as residual and used this value in optimization function. They considered the residual term to be sparse matrix and used the l1 norm measure in objective function as a constraint over residuals. However DSFCM_N did not show reliable performances when tested with higher noise samples. Further, Wang et. al. proposed Weighted Residual Fuzzy C-means (WRFCM) which used weighted l2-norm fidelity for making the residual estimation more reliable and showed better results compared to the previous works [15]

In real life data, there is always some uncertainty associated with the data due to imprecise measurement and noise, hence relying only on the membership value makes clustering a bit imprecise. To handle the vagueness associated in data Atanassov [16] proposed the Intuitionistic Fuzzy Set Theory(IFS). IFS consisted of one additional factor namely hesitancy degree which helped in better representation of data which further resulted in a better decision making. In recent years, some authors have incorporated several advancements with IFS theory to handle the noisy image segmentation. Verma et al.[17] proposed an Improved Intuitionistic Fuzzy C means (IIFCM) which incorporated the spatial and gray scale information over the local window. The algorithm is effective for dealing with a wide variety of noises, but was found to be inefficient w.r.t. to time. Kumar et al. [18] proposed Intuitionistic Fuzzy C means with Spatial Neighborhood Information (IFCMSNI). IFCMSNI consisted of a membership weighted neighbor's deviation from centroids in the objective function. The method was insensitive to the varying noise distribution in image and hence was able to preserve sharp edges and other details

Further an extension on IFS was presented by cuong et al. [19] namely PFS consisting of additional refusal and neutrality degree to make the decision making more realistic. PFS's application in Image Segmentation have shown to be effective compared to previous Fuzzy counterparts. Another work proposed Improved Picture Fuzzy Clustering Algorithm (IPFCM) [20] which considered the spatial information in the framework of Picture Fuzzy Clustering. IPFCM was dependent on the input spatial weighting parameter and was sensitive to the strength of noise, hence the parameter had to be fine tuned for getting the results which further extended the processing time. Further Wu et al. [21]proposed Adaptive Improved Picture Fuzzy Clustering Algorithm (AIPFCM) which resolved the problem of fine tuning the parameter and also worked upon updating the parameter adaptively while optimizing the weighing parameter.

Research work also proposed an Adaptive entropy weighted weighted Picture Fuzzy Clustering Algorithm with spatial Information (APFCMS) which included a novel spatial information function that modified the membership degree using the neighbours membership values resulting in robustness to noise and outliers.

Chapter 4

Approach

4.1 Clustering

Clustering is an unsupervised learning technique used to group data points without label on the basis of some similarity measures. This technique is generally used to find the meaningful patterns and further any associated relationships behind various observations and data points. Clustering has recently gained a lot of popularity due to its immense applicability in the areas of data mining, image segmentation, document classification, data compression, problems in the field of bio-informatics and many other research domains. Clustering is of various types Connectivity Based Clustering (Hierarchical Clustering), Density based Clustering (Model-based Methods), Distribution Based Clustering and Centroid Based Clustering. Centroid based clustering can be further divided into Hard clustering and Soft Clustering.

In Hard C-Means (HCM), each data point either belongs to a cluster completely or not. The HCM tries to assign clusters to each data point by computing membership values i.e. [0,1] , 0 for not being a member of the respective cluster and 1 for being the member of the respective cluster. The HCM doesnt leave room for considering other possibilities therefore to tackle this problem the concept of Soft Clustering is used. In soft clustering, instead of putting each data point into a separate cluster, a probability or likelihood of that data point to be in those clusters is computed. J.C. Dunn in 1973 introduced a fuzzy set theory based soft clustering method termed as fuzzy c-means. Fuzzy C Means is one of the widely used soft clustering technique in a variety of problems. The concept of FCM revolves around assigning a quantified degree to data-points corresponding to multiple clusters in the form of a belongingness metric. It assigns membership values to a data point with respect to the clusters on the basis of its proximity to the center of different clusters. The membership value generally lies in the range of 0-1 and also for a given data point sum of all the membership is 1.

4.2 Fuzzy Sets

Definition 1. Fuzzy set: A Fuzzy set is a set in which each member element will have the fractional membership via a membership function $\mu_A : X \rightarrow [0,1]$ which gives the degree of belongingness [22]. If A is a fuzzy set defined over a set X, it can be represented as:

$$A = \{(x, \mu_A(x)) : x \in X\}$$

4.3 Fuzzy C-Means Clustering

FCM is a soft clustering technique in which a data point can belong to more than one cluster with different membership values [23]. The algorithm was first proposed by Dunn and subsequently improved by Bezdek.

Let $X = \{x_1, x_2, x_3, ..., x_n\}$ be the image vector with n pixels that are to be partitioned into $1 \leq c \leq n$ cluster centers. The algorithm iteratively optimizes the given objective function:

$$J_{FCM} = \sum_{i=1}^{n} \sum_{j=1}^{c} u_{ij}^{m} ||x_i - v_j||^2 \tag{4.1}$$

$$subject \;\; to \quad \sum_{j=1}^{c} u_{ij} = 1, \qquad 1 \leq i \leq n$$

where x_i represents the i^{th} data point, v_j is the j^{th} cluster center and u_{ij} gives the membership of the i^{th} pixel to the j^{th} cluster center. The constant m controls the degree of fuzziness. The membership values u_{ij} and cluster center v_j are updated as follows:

$$u_{ij} = \frac{\left(||x_i - v_j||\right)^{\frac{-2}{m-1}}}{\sum\limits_{k=1}^{c} \left(||x_k - v_j||\right)^{\frac{-2}{m-1}}} \tag{4.2}$$

and

$$v_j = \frac{\sum\limits_{i=1}^{n} u_{ij}^{m} x_i}{\sum\limits_{i=1}^{n} u_{ij}^{m}} \tag{4.3}$$

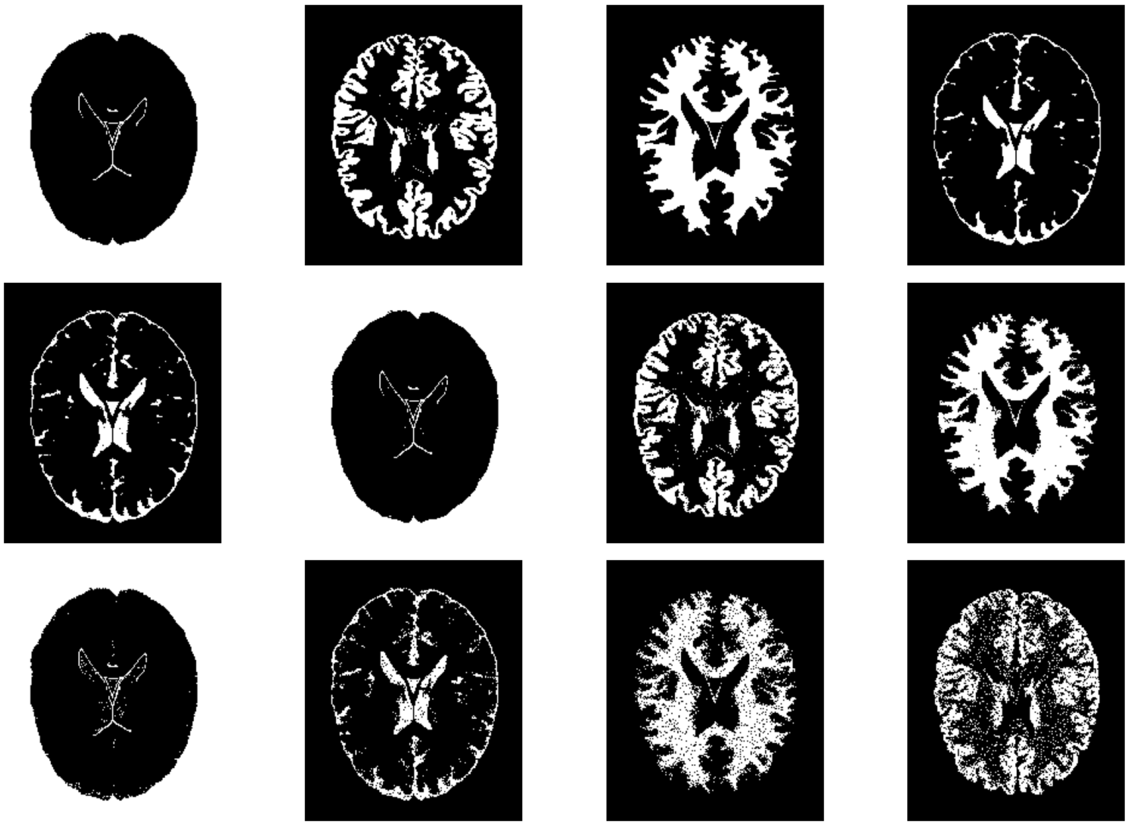

Figure 4.1: FCM results with 1% (top) 5% (middle) and 9% (bottom) noise levels

4.4 Fuzzy C-Means Clustering with Spatial Information

Improving the basic Fuzzy C-Means (FCM) involves adding a spatial neighborhood factor. This means that a pixel's label isn't just determined by its own characteristics, but also by its nearby pixels. This helps make the segmentation smoother, especially when dealing with noisy scans. Think of it like adding a rule that encourages neighboring pixels to have similar labels. This tweak makes a big difference, especially when there's salt and pepper noise in the scans. So, the new objective function looks something like this:

$$J_{FCM} = \sum_{i=1}^{n}\sum_{j=1}^{c} u_{ij}^{m}||x_i - v_j||^2 + (\alpha/N_R) * \sum_{i=1}^{n}\sum_{j=1}^{c} u_{ij}^{m}(\sum_{x_r \in N_R} ||x_r - v_j||^2) \tag{4.4}$$

$$subject \;\; to \quad \sum_{j=1}^{c} u_{ij} = 1, \qquad 1 \leq i \leq n$$

where x_i represents the i^{th} data point, v_j is the j^{th} cluster center and u_{ij} gives the membership of the i^{th} pixel to the j^{th} cluster center. N_R is the set containing neighbor pixel and α weights the regularization term in the complete objective function. The constant m controls the degree of fuzziness. The membership values u_{ij} and cluster center v_j are updated as follows:

$$u_{ij} = \frac{(D_{ik} + (\alpha/N_R) * \gamma_i)^{\frac{-1}{m-1}}}{\sum\limits_{k=1}^{c} \left(||x_k - v_j||\right)^{\frac{-2}{m-1}}} \tag{4.5}$$

and

$$v_j = \frac{\sum\limits_{i=1}^{n} u_{ij}^m x_i}{\sum\limits_{i=1}^{n} u_{ij}^m} \tag{4.6}$$

where,

$$D_{ik} = ||x_i - v_j||^2 \tag{4.7}$$

and,

$$\gamma_i = (\sum_{x_r \in N_R} ||x_r - v_j||^2) \tag{4.8}$$

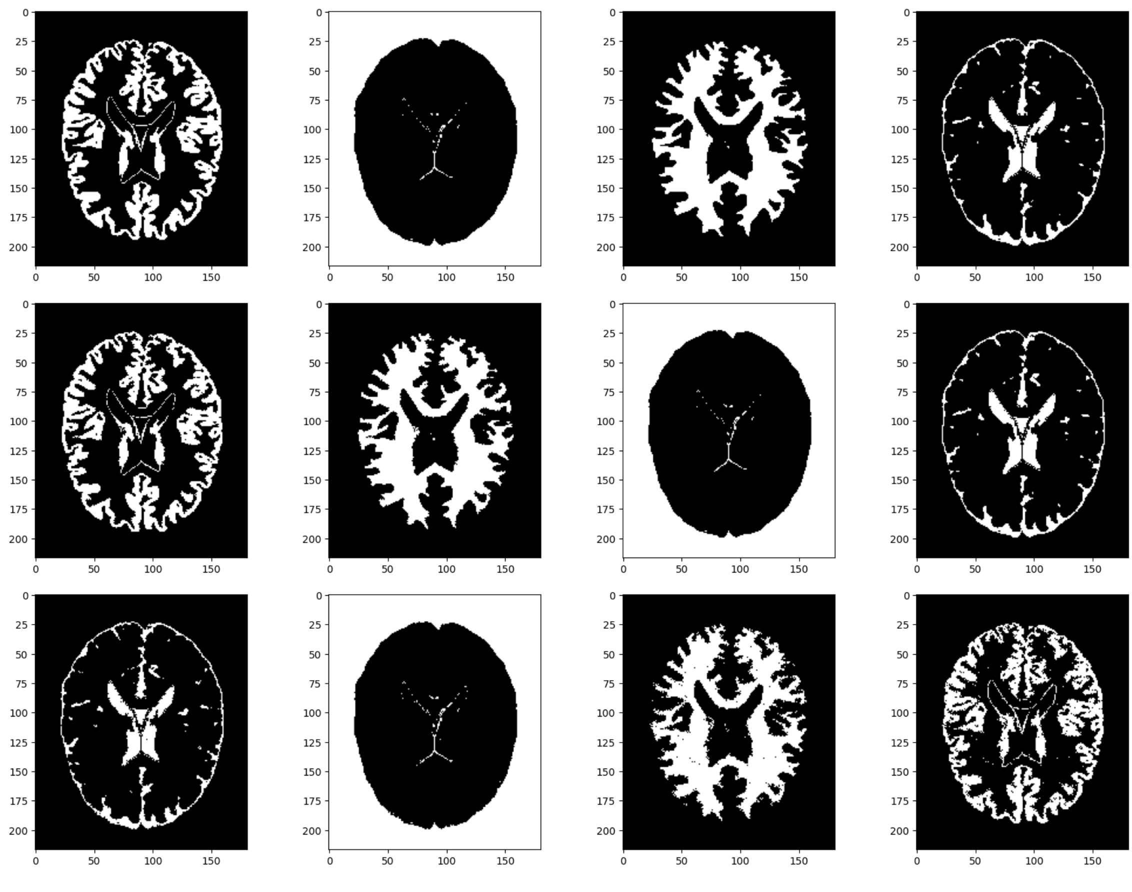

Figure 4.2: FCM with spatial information results with 1% (top) 5% (middle) and 9% (bottom) noise levels

4.5 Fuzzy C-Means Clustering with Spatial Information approximated by Mean and Median Filtering

The standard Fuzzy C-Means with Spatial Information (FCM_S) algorithm can become computationally intensive as it calculates distances involving each pixel's neighbors for every iteration. This significantly slows down the process, thereby limiting the algorithm's scalability and practicality, particularly for large datasets typical in medical imaging.

To address these challenges, we propose integrating spatial filters such as mean and median filters within the FCM_S framework. By applying these filters to the image preprocessing stage, we can simplify the spatial complexity by reducing noise and smoothing the data before segmentation. This preprocessing reduces the computational overhead during the clustering iterations. The filters help maintain the integrity of spatial information by considering aggregate information from neighbors, thus enhancing the segmentation accuracy without the need for intensive computations for each pixel's neighborhood.

This method is anticipated to maintain or even enhance segmentation quality while significantly speeding up the algorithm. By incorporating spatial filters in the FCM_S algorithm, we aim to achieve more efficient and accurate segmentation, making it more suitable for large-scale medical imaging datasets.

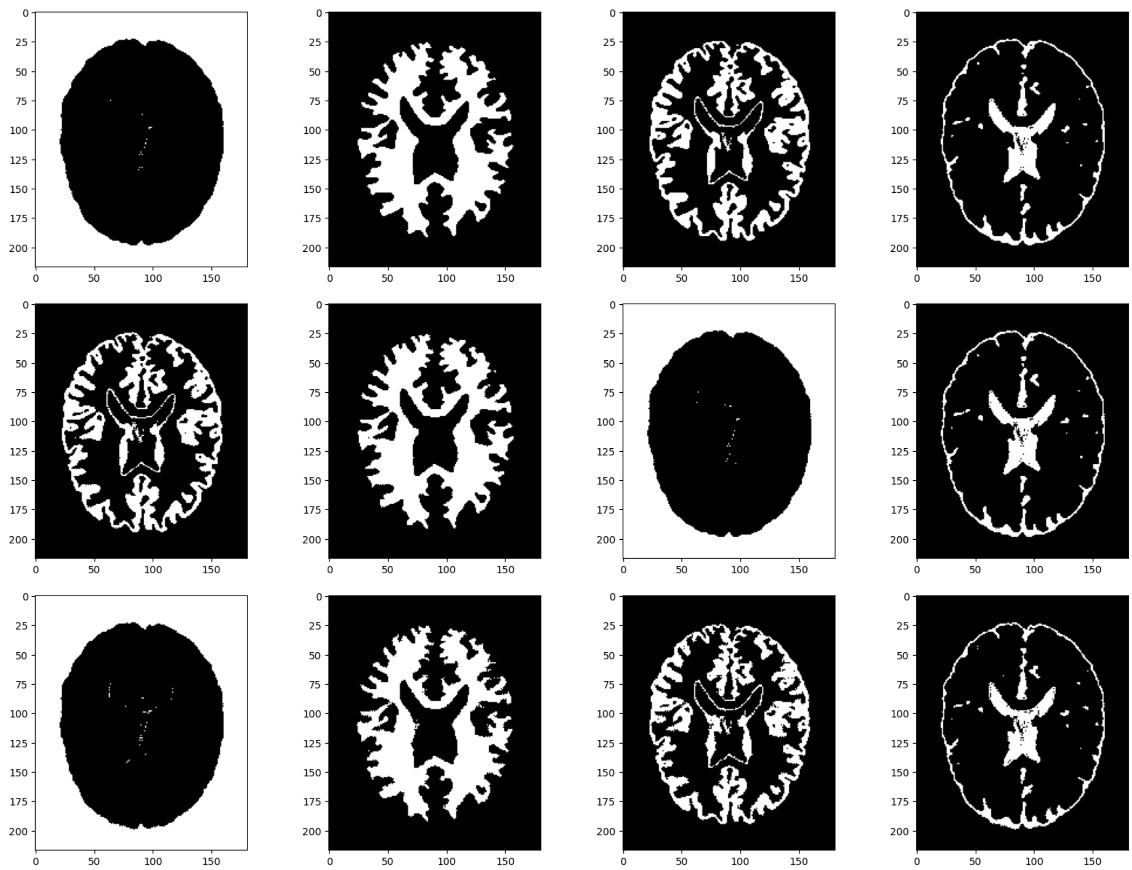

Figure 4.3: FCM with spatial information approximated by mean results with 1% (top) 5% (middle) and 9% (bottom) noise levels

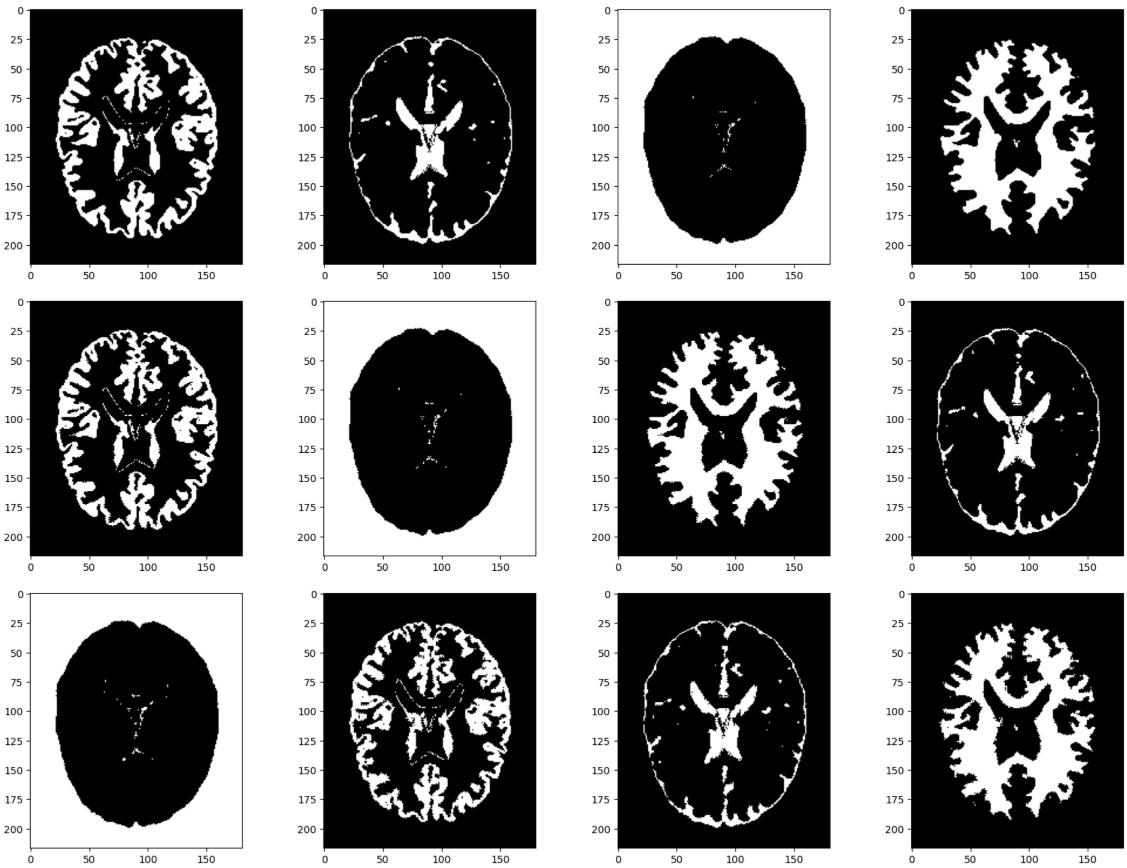

Figure 4.4: FCM with spatial information approximated by median results with 1% (top) 5% (middle) and 9% (bottom) noise levels

Chapter 5

Dataset, Performance metrics and Segmentation Pipeline

5.1 Dataset

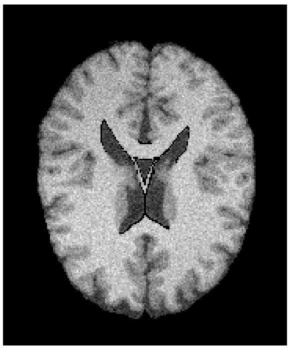

Figure 5.1: Brain Web MRI image corrupted with 9% noise.

To validate the performance of the different approaches, we use BrainWeb simulated MRI brain volumes, a publicly available dataset[1] from the McConnell Brain Imaging Center of the Montreal Neurological Institute, McGill University [24] consist of several simulated T1-weighted brain volume data with different intensity inhomogeneity (0%, 20% and 40%) and noise (1%, 3%, 5%, 7% and 9%) of resolution $1 \times 1 \times 1mm$ with $181 \times 217 \times 181$ dimension.

5.2 Performance Metrics

Different approaches were compared on the basis of performance metrics such as average segmentation accuracy (ASA) and Dice score (DS) [13, 40, 52], which are respectively given as:

[1] BrainWeb [online], available: http://www.brainweb.bic.mni.mcgill.ca/brainweb.

$$ASA = \sum_{i=1}^{c} \frac{|X_i \cap Y_i|}{\sum_{j=1}^{c} |X_j|} \tag{5.1}$$

$$DS = \frac{2|X_i \cap Y_i|}{|X_i| + |Y_i|} \tag{5.2}$$

where number of cluster is represented by c, X_i stands for the pixels which lies in the manual segmented image or also known as ground truth corresponding to the i^{th} region, the pixels being part of the experimental segmented image are represented by Y_i and the cardinality of X_i is represented by $|X_i|$. The values of ASA depicts the overall segmentation performance of a given method and its values lies in range [0,1]. Further, the region wise segmentation performance is evaluated using the DS values which again lies in range [0,1]. The higher value of both ASA and DS corresponding to given method on show the superior performance.

5.3 Segmentation pipeline

Figure 5.2 shows the flow diagram for evaluating the qualitative and quantitative segmentation using the clustering approach. First of all the image is loaded and then pre-processing is done if any required. For MR images skull stripping and tisue extraction is done in pre-processing. After pre-processing, clustering algorithm is initialised and image is passed to it. The clustering of the pixel intensity values produces fuzzy partition matrix which is then defuzzified to get a crisp label for each pixel. The final assignment of a given pixel intensity value to a segmented region is based on the maximum membership values for obtaining the quantitative performance of the related methods. Further, the fuzzy partition matrix can be retained for qualitative evaluation and quantification of different tissues in case of medical image analysis.

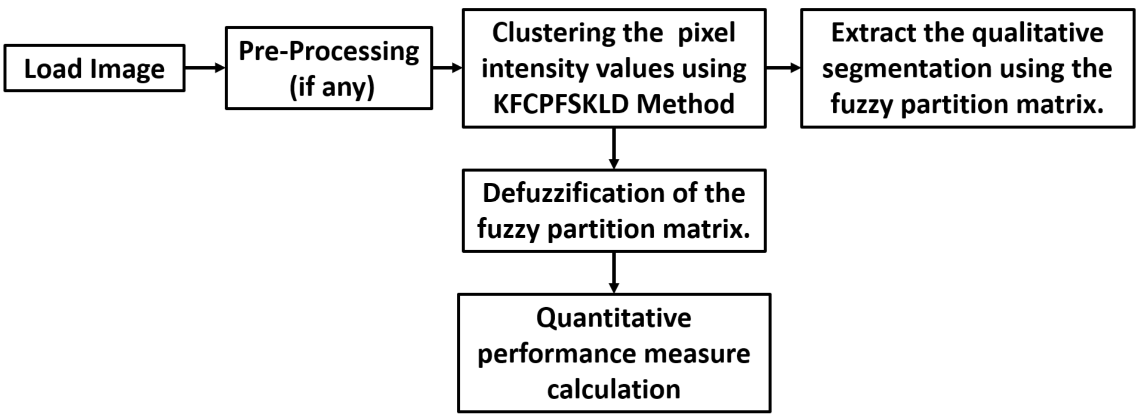

Figure 5.2: Flow diagram for evaluating the clustering approach.

5.4 Results

Average Segmentation Accuracy

Noise	FCM	FCM_S	FCM_S1	FCM_S2
1%	99.2	97.94	95.59	96.41
5%	97.38	97.17	95.54	96.10
9%	92.44	95.69	94.64	95.07

Cerebrospinal Fluid

Noise	FCM	FCM_S	FCM_S1	FCM_S2
1%	97.88	93.82	85.21	86.82
5%	94.72	92.66	85.20	86.96
9%	85.16	90.17	83.58	84.97

Gray Matter

Noise	FCM	FCM_S	FCM_S1	FCM_S2
1%	97.72	95.22	90.36	92.41
5%	92.65	93.01	89.89	91.43
9%	80.16	88.95	87.77	88.48

White Matter

Noise	FCM	FCM_S	FCM_S1	FCM_S2
1%	99.00	97.66	95.59	96.77
5%	96.22	96.45	95.28	96.15
9%	88.42	94.16	94.12	94.67

The tables summarize the performance of various fuzzy clustering methods under different noise levels. Generally, the FCM algorithm exhibits higher average segmentation accuracy across noise levels, especially for low noise (1%). FCM_S shows improvement at higher noise levels, particularly for Gray Matter and Cerebrospinal Fluid. FCM_S1 and FCM_S2, which incorporate spatial information, also demonstrate better noise robustness, improving performance in high-noise scenarios (9%). However, they tend to underperform at lower noise levels compared to FCM. This implies that introducing spatial information helps in more noisy scenarios, but its impact is less beneficial when noise is minimal.

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