

PORTR For MRI Brain Image Segmentation and Classification Using Adaptive Mean Shift Algorithm and Classification

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Abstract

An automated scheme for MRI image brain segmentation is used. Adaptive mean shift methodology is utilized in order to brain voxels into three main tissue types they are gray matter, white matter, cerebrospinal fluid. MRI image represented in high dimensional feature space that includes multi level intensity and special features. Tissue segmentation is obtained by a follow up phase of intensity based mode clustering into three tissue types. The main idea of an adaptive mean shift algorithm in which clusters the joint special intensity feature space called as modes. This paper applied adaptive mean shift algorithm in real MRI data and performance compared with other clustering methods like fuzzy k means and fuzzy c means clustering. It also proposes intelligent classification methods to identify normal and abnormal slices of brain MRI data. In research work advanced classification technique based on least square support vector machine are proposed and applied to MRI data.

Index Terms: Magnetic Resonance Imaging (MRI), Adaptive mean shift algorithm, Classification, Least Squares Support Vector Machine (LS-SVM)

Introduction

Magnetic Resonance Imaging (MRI) is a widely used medical imaging modality that provides rich information about the human tissue anatomy and pathology. Being a non-invasive and safest one and having many advantages over many other imaging techniques enabling it to provide images with high contrast between the three basic

brain tissues, Cerebro-Spinal Fluid (CSF), Gray Matter (GM) and White Matter (WM). Also, it provides a plethora of path physiological tissue information that assists the clinician in diagnosis, therapy design/monitoring and surgery. Manual delineation of brain tissues by a human expert is still considered as the reference and most acceptable method, but unfortunately it is too time consuming, especially in cases where large amounts of data need to be analyzed. In addition manual segmentations by the clinicians have been reported to be prone to large intra- and inter observer variability, fact that stresses out the need of objective and reproducible computer segmentation techniques for the brain in order to perform a number of computational medicine tasks including morphological measurements.

This thesis proposes an automated brain structures segmentation algorithm based on the adaptive mean-shift theory. The MRI image space is used to compute a three-dimensional feature space that includes intensity features as well as spatial features, in particular pixel's coordinates. An adaptive mean-shift algorithm clusters the joint spatial-intensity and feature space of high-density points within the feature space, otherwise known as modes. Because of its adaptive mean-shift can deal successfully with no convex clusters and produce convergence modes that are better candidates for intensity based classification than the initial pixels. All pixels are then classified to these modes according to the Euclidean distance from them. Then, an intensity only feature space is used to merge the remaining modes, to further reduce the remaining number of clusters. Finally, pixels are assigned to the three desired clusters (CSF, GM and WM), according to the fuzzy k-means clustering algorithm. The effectiveness of this algorithm in the automatic detection of brain abnormalities in brain images is also investigated in the following way: Instead of three, four clusters are used and after identifying the cluster with the higher mean value, (since most likely it includes the tumour region), the tumour area is labelled as the largest connected component of that cluster. The output of the algorithm is not only a segmentation map for all the pixels of the dataset but also a membership matrix for each cluster which includes the probability of each pixel to belong to this category.

The proposed method is validated on both simulated and real MRI data. The algorithm was also assessed for various different parameters values in order to check their effect in algorithm's performance and ensure that the proposed segmentation method is reproducible and reliable. Finally, it was compared with a number of well-known brain tissues segmentation algorithms by using a pre segmented atlas dataset. The results indicate that the mean-shift algorithm outperforms these methods.

Statistical parameters approaches used in the unsupervised nonparametric schemes. The main important one is the mean shift algorithm. First we have to detect the local maxima of large density feature space using adaptive gradient ascent. Data points are associated with local maxima, or modes, thereby denote the clusters. In mean shift algorithm there is no need to require initial cluster position. Mean-shift has been used for image segmentation of image, object tracking and medical image analysis and application. In the current work, the objective is to utilize the mean-shift formalism to provide a robust segmentation framework for brain tissues in MRI that integrates spatial information in a simple way without requiring the use of a statistical brain atlas or HMRF modelling. The developed framework, initially proposed in, is based on a

variation of the mean-shift algorithm defined as adaptive mean-shift algorithm. By assigning a regular bandwidth to each data point, it for increased sensitivity to local data structure even in a higher dimensional feature space corresponding to multimodal MRI.

Brain Tumor

A. Brain Tumour Definition

A brain tumour is an abnormal growth of cells within the brain or the central spinal canal. Brain tumours include all tumours .That is created by an abnormal and uncontrolled cell division. The brain envelopes skull or spread from cancers primarily located in other organs. Any brain tumour is inherently serious and life-threatening because of its invasive and infiltrative character in the limited space of the intracranial cavity. However, brain tumours do not automatically cause death. Brain tumours or intracranial neoplasm's can be cancerous or non-cancerous, however, the definitions of malignant commonly used in other types of cancerous or non-cancerous in the body. Threat level depends on the type of tumour its location, tumour size and its state of development. Because the skull was protect the brain. Usually detection occurs in advanced stages when the presence of the tumour has side effects that cause unexplained symptoms.

Image Preprocessing

A. Image Preprocessing – Image Restoration

Preprocessing is a common name for operations with images at the lowest level of abstraction both input and output are intensity images. The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing. Image pre-processing methods used first step of the segmentation. Neighboring pixels corresponding to one object in real MRI image have similar brightness value. Distorted pixel can often be restored as an average value of neighboring pixels.

a. Image Denoising Using Adaptive Median Filtering

The goal of impulse noise removal is to suppress the noise by preserving the integrity of edges and detail information. In this project, a new filter called Adaptive Median Filter is proposed. The adaptive window size is selected using the output image produced by this filter with least mean square error is considered as input image to AMF (Adaptive Median Filter) filter where impulse detection mechanism is taken. In this mechanism, the noise is detected by estimating the values of noisy pixels with a switch based median filter applied exclusively to those neighbourhood pixels not labelled as noisy.

b. Advantages of Proposed System

The contrast does not reduction across step. The output values consist only present values in neighbourhood (no averages).

- Median filtering does not have boundaries as can happen with conventional smoothing filters (a contrast dependent problem).
- The median is less sensitive than the mean value to extreme values (outliers), those extreme values are more effectively removed.

c. Impulse Noise Detection

In an image contaminated by random-valued impulse noise, detect noisy pixel is more difficult in comparison with fixed valued impulse noise, the gray value of noisy pixel may not be substantially larger or smaller than those of its neighbour pixel. So the conventional median-based impulse detection methods do not perform well in case of random valued impulse noise. To overcome this problem, we use a non linear function to transform the pixel values within the filter window $W(x)$ in a progressive manner. This operation widens the gap between noisy pixel $x(i,j)$ and the other pixels in the window $W(x)$ (i, j). In the beginning of each iteration, the central pixel $x(i,j)$ of each window is subtracted from all the pixels in the window and normalized absolute differences are obtained.

$$d(m,n) = |x(m,n) - x(i,j)| \quad (2.1)$$

$$/255: x(m,n) \in W^{(x)}(i,j)$$

The absolute differences are then transformed by a nonlinear function to increase the gap between the differences corresponding to noisy pixels and those due to noise-free Pixels.

$$d^{(t)}(m,n) = e^{K \cdot d(m,n)} - 1 \quad (2.2)$$

$$m = i-L, \dots, i+L, n = j-L, \dots, j+L$$

Where $d(m,n)$ denote the transform value is $d^{(t)}(m,n)$ and K is a constant which varies with iterations. The transformed values $d^{(t)}(m,n)$ are sorted as $\{d^{(t)}(1) \leq d^{(t)}(2) \leq \dots \leq d^{(t)}(9)\}$ in ascending order where $\{d^{(t)}(1), d^{(t)}(2), \dots, d^{(t)}(9)\}$ are the transformed values $\{d(m, n)\}$ of . Now, the central pixel is considered noisy for a filtering window of size 3×3 if . The output of the detector is represented by a binary flag image $\{f(I, j)\}$, where $f(i, j) = 1$ indicates that the pixel (i, j) is noisy, for noiseless pixel, $f(i, j) = 0$.

A. Adaptive Noise Detection

In order to determine whether the pixel is corrupted or not, an 11×11 window is imposed centered around the current pixel to be detected. The noise density within the imposed window is calculated using the equation (6). If the calculated noise density is in between 30% and 50% then the window size is increased by one pixel outwards on all the four sides and if the noise density is greater than 50% then the window size is decreased by one pixel inwards on all the four sides. If the noise density is less than 30% then the AMF window size is used for detection. However, the noise density is

calculated for each time the window size is changed and compared. Thus, depending on the noise density, the window size is made adaptive.

The maximum detection window size is limited to 21x21 and the minimum size is limited to 5x5. Once the window size is determined all the pixels within the determined window centered on the considered pixel will be grouped into three clusters. Hence two boundaries b_1 and b_2 are determined. For each pixel $X_{i,j}$ being considered, if the pixel will be assigned to lower intensity level; otherwise to the medium intensity level for or to the higher intensity level for. Obviously, if the center pixel being considered falls onto the middle cluster it is treated as “uncorrupted”, since its intensity value is neither relatively low nor relatively high. Otherwise, it is very likely that the pixel has been corrupted by impulse noise.

This algorithm is applied to each pixel of the noisy image in order to identify whether it is “uncorrupted” or “corrupted”. After such an application to the entire image, a two-dimensional binary decision map is formed at the end of the adaptive noise detection stage, with ‘0’ indicating the positions of “uncorrupted” pixels, and ‘1’ for those “corrupted” ones.

In summary the steps of proposed method are:

1. Impose a window of size 11x11, which is centered on the current pixel.
2. Calculate the noise density within this window using the Probability Density Function equation given.
3. If the noise density is greater than the threshold, window size is reduced by one pixel inward in all the four sides of the window, Else if the density is lesser than the threshold the window size is extended by one pixel outward in all the four sides of the window. Thus the window size is made adaptive based on the noise density within the window.
4. Sort the pixels in the determined window according to the ascending order and find the median, med of the sorted vector V_o .
5. Compute the intensity difference between each pair of adjacent pixels across the sorted vector V_o and obtain the difference vector V_d .
6. For the pixel intensities between 0 and med in the V_o , find the maximum intensity difference in the V_d of the AMF range and mark its corresponding pixel in the V_o as the boundary b_1 .
7. Likewise the boundary is identified for pixel intensities between med and 255, three clusters are thus formed.
8. If the pixel belongs to the middle cluster, it is classified as “uncorrupted” pixel, and the classification process stops else the second iteration will be invoked.
9. Impose a 3x3 window, being centered on the concerned pixel and repeat Steps (4)–(7).
10. If the pixel under consideration belongs to the middle cluster, it is classified as “uncorrupted” pixel otherwise, “corrupted” pixel.

B. Adaptive Noise Filtering

The major contributions of making the entire switching median filter being noise-adaptive come from the impulse-noise detection as described in the previous section.

In order to determine the window size of the filtering window, the limit of the maximum window size requires being determined first. Based on the binary decision map, “no filtering” is applied to those “uncorrupted” pixels, while the SM filter with an adaptively determined window size is applied to each “corrupted” one.

The maximum window size is limited to 7x7 in order to avoid severe blurring of image details at high noise density cases (i.e., $p > 50\%$). In AMF starting with Window Factor (WF)=3 the filtering window iteratively extends outward by one pixel in all the four sides of the window, provided that the number of uncorrupted pixels is less than half of the total number of pixels within the filtering window. But, it is hard to obtain this condition with small windows in cases of high noise densities. The direct impact on increasing the window size is the possible loss of correlation between the pixel values inside the filtering window. This directly affects the value that replaces the noisy pixel, which may lead to blurring.

The proposed algorithm by comparing the number of uncorrupted pixels noise is less than $\frac{1}{2}(1-P)N$. The term $(1-P)$ basically is the percentage of uncorrupted pixels that is expected to be found in the filtering window. Incorporating this term in the condition makes it adaptive to the noise density. In other words, when the noise density increases, the condition is loosened since the expected number of uncorrupted pixels decreases.

The second modification made in modified AMF is to consider the spatial relation between the noisy pixel and the uncorrupted pixels in the window and the relation between the values in V_u and the Y_{ij} . Thus the value of pixel to be replaced is modified as,

$$Z_{ij} = Y_{ij} + \frac{1}{D} \sum_{k=1}^{N_c} \frac{(V_u(k) - Y_{ij})}{d(k)} \quad (2.4)$$

With $S(k)$ and $T(k)$ are the row and column indices of that pixel. Such approach in expanding the filtering window could be useful in providing a better estimate for the value of the noisy pixel. However, the strict condition of requiring the number of uncorrupted pixels to be greater than half the number of pixels in the window is easily violated under high noise densities. Thus, with high noise densities the filtering window is expected to be expanded and most likely it will reach the size. The direct strong effect on increasing the window size is the possible loss of correlation between the pixel values inside the filtering window. This may directly affect the value that replaces the noisy pixel, which may lead to blurring and unnecessary distortion in the filtered image.

C. Adaptive Median Filtering

Therefore the adaptive median filtering has been applied widely as an advanced method compared with standard median filtering method. The Adaptive Median Filter performs spatial domain processing to determine which pixels in an image have been affected by the noise. The Median Filter classifies pixels as the noise by comparing each pixel in the image to its surrounding neighbour pixels. The size of the neighbourhood is adjustable, as well as the threshold value for the comparison. A pixel that is different from the neighbours, as well as being not structurally aligned with those pixels to which it is similar, is labelled as impulse noise. These noise pixels

are then replaced by the median pixel value of the pixels in the neighbourhood that have passed the noise labelling test.

Image Enhancement

A. Image Enhancement Using Pca Algorithm

Various enhancement schemes are used for enhancing an image which includes gray scale manipulation, filtering and Histogram Equalization (HE). The main technique in the image enhancement is Histogram Equalization. It became a popular technique for contrast enhancement because this method is simple and effective. In latter case, preserving the input brightness of the image is required to avoid the generation of non-existing artefacts in the enhancement output image. These methods along with the contrast enhancement preserve the brightness of the output image and give the enhanced image. The gray levels of an image to be remapped using the HE method. HE methods also introduce some different artefacts and not natural enhancement. This problem reduced by using different brightness technique.

B. Contrast

The difference between lowest and highest intensity level is called contrast. Increase the contrast value means more difference between lowest and highest intensity level.

C. Adaptive Histogram Equalization Method

The traditional Histogram Equalization is defined as the adaptive Histogram Equalization Method. Image contrast to be enhanced by changes the values of the intensity image. Histogram equalization operates on small data regions (tiles), rather than the entire image. Each data region contrast is enhanced, so that the output region of histogram approximately matches the specified histogram. The neighbouring tiles are combined by using the bilinear interpolation in order to eliminate artificially creating boundaries. Especially in homogeneous areas, contrast can be limited in order to avoid amplifying the noise which might be present in the image. Deep valleys a good threshold can be selected which leads to an efficient segmentation. Therefore the shape of the histogram should be enhanced which is possible by the use of boundary characteristics of an image. The shape of the histogram can be improved by considering only the pixels that lie on near the edges between objects and the background. This makes the histogram less dependent on the relative sizes of objects and the background. In histogram improvement it is assumed that the edges between object and background known. The main problem is that in actual case this detail is not available during segmentation.

D. Contrast Limited Adaptive Histogram Equalization Method

a. Algorithm Steps:

1. Obtain all the inputs: The region is specified in row and column direction. In histogram building the image transform using number of bins. (Dynamic range), Clip limit for contrast limiting (normalized from 0 to 1)
2. Pre-process the inputs: Determine real clip limit from the normalized value if necessary, soft the image before splitting it into small regions.
3. Interpolate gray level mappings in order to assemble final CLAHE image: Four mapping function are extracted cluster means image region partially processed. Each mapping tiles to be overlapped and extract a single pixel this will be applied in four mapping pixel, the output pixel, and repeat over the entire image. Suppose image X is segmented by a section with gray level of $X = X_e$.

The mean-shift implementation which uses an adaptive h value instead of a constant h is called Adaptive Mean Shift (AMS) algorithm and it is the basis of the proposed algorithm. In high dimensional feature spaces, adaptive mean-shift clustering has been shown to produce better results than the fixed bandwidth algorithm. Several methods have been proposed to determine an adaptive window size for the AMS algorithm. Although the window size can be also simply defined as the distance h_i between x_i and its k -nearest neighbour:

The neighbours of x_i are sorted by order of increasing distance to x_i . Following the ordering process, x_i , k is the k^{th} distant neighbour from x_i , and h_i is its distance to x_i . The number of neighbours considered for, should be chosen large enough to ensure that there is an increase in density within the support of most kernels.

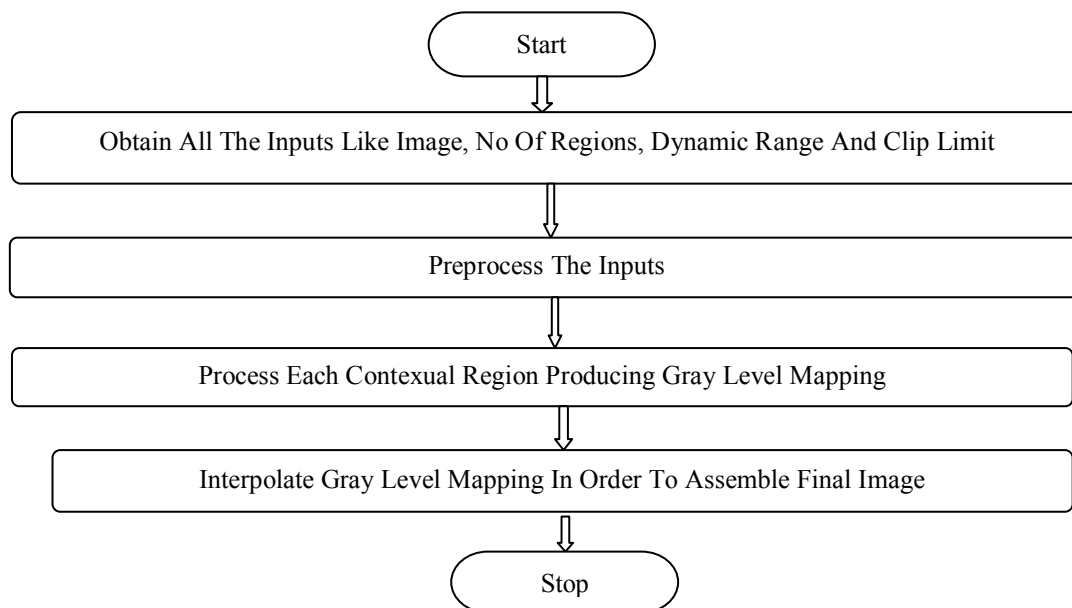


Figure 3.1: Histogram Equalization

It is obvious that sub image X_L is composed by gray level of $\{X_0, X_1, \dots, X_{e-1}\}$, while sub image X_u is composed of $\{X_e, X_{e+1}, \dots, X_{l-1}\}$. The aggregation of the original images gray level distribution probability is decomposed into $\{p_0, p_1, \dots, p_{e-1}\}$ and $\{p_e, p_{e+1}, \dots, p_{l-1}\}$ correspondingly. The corresponding cumulative distribution function will be the transform functions of the two sub images histogram are equalized below.

At last result of dualistic sub image histogram is obtained after the two equalized sub images are composed into one image. Moreover, in order to avoid under segmentation, caused by a single value that is locally too large, it is necessary to choose a bandwidth value that is small enough to avoid over smoothing anywhere in the dataset region. This results in the mean-shift output and requires further merging in the form of an iterative repetition of transitive closure on the region adjacency graph followed by a union-find algorithm, before the final tissue classification is obtained. In a subsequent paper the same group recognized the superiority of the adaptive mean-shift for the segmentation of data that exhibits multistage patterns as is the case with MRI of the brain. The quality of a kernel density estimator can be measured by the mean of the square error between the density and the estimated value is integrated over the domain.

In practice however only an asymptotic approximation of this measure to be computed. Finding the modes of the underlying density $f(x)$ is the first step in the analysis of a feature space. The modes are located among the zeros of the gradient $\nabla f(x)=0$ and the mean shift procedure is an elegant way to locate these zeros without estimating the density. The mean shift vector thus always points towards the direction of maximum increase in density. Mean shift steps are small and the analysis more refined. The regions of low density values are of no interest for the feature space analysis and in such regions the mean shift steps are large.

Image Segmentation And K-Means Algorithm

Image segmentation is the major research topic for many digital image processing researchers. The reasons are effective and applications are endless one. Most computer vision and image analysis problems require a segmentation stage in order to detect objects or divide the image into regions which can be considered homogeneous according to a given criterion such as motion, texture, etc.

Search for distinct groups in the feature space is cluster. These groups have different structures and all that clearly differentiated. The number of data to be separated into partitions using clustering task that is volumes in the n dimensional feature space. Hard limit between the groups is defined by partitions. It also depends on the functions used to model the data distribution.

b. Image Segmentation:

In humans an image is not just a random collection of pixels it is a meaningful arrangement of regions and objects. There also exists a variety of images are nature images, etc. In these images large variations in the pixel and humans do not interrupt the images.

Image segmentation is the first step in image analysis. Critical and essential component of image analysis system is image segmentation and it, is the most difficult tasks in image processing technique, and determines the quality of the image. Image segmentation is the process of dividing an image into different regions such that each region is homogeneous. Image segmentation methods can be categorized as follows (this is not an exhaustive list):

- **Histogram thresholding:** Consider that images are composed of regions with different gray or colour ranges, and separates it into a number of peaks, each corresponding to one region.
- **Edge-based approaches:** Use edge detection operators such as Sobel and Laplacian operators used in edge detection. For example connecting the resulting region may not be connected and hence edges need to be joined.
- **Region-based approaches:** It is defined by a similarity of regional image data some of the more widely used approaches in this category are: Thresholding, Clustering, Region growing, Splitting and merging.
- **Hybrid:** Assumes all the edges and regions.

This project is done using Image Segmentation by Clustering. It is based on Colour image segmentation using Mahalanobis distance. Euclidean distance is also used for comparing between the quality of segmentation between the Mahalanobis and Euclidean distance.

B. Image Segmentation By Clustering

Clustering is a grouping technique. The N vector measurement is given and defining each pixel or group of pixels (i.e., region) in an image, a similarity of the measurement vectors and therefore their clustering in the N-dimensional measurement space implies similarity of the corresponding pixels or pixel groups. Therefore clustering may be used for segmentation purposes.

The vector of measurements describes some useful image feature and thus is also known as a feature space vector. Difference between image regions or pixels implies clustering (small separation distances) in the feature space. Clustering is the very basic technique to data segmentation techniques to be developed. Volumetric analysis of different parts of the brain is extremely useful in assessing the progress of remission of different diseases that is, multiple sclerosis and schizophrenia. The process of partitioning a biomedical brain image, into three segments, as the number of brain tissues, Cerebral-Spinal Fluid (CSF), Gray Matter (GM), White Matter (WM) is called brain tissues segmentation. Segmentation of brain tissues is a challenging problem due to the complexity of the images, as well as the not present of models of the anatomy that fully capture the possible deformations in each brain. For the segmentation task, numerous methods have been proposed. In this project demonstrate some basic techniques that were used in the past, some of them even in nowadays, in order to provide a reliable segmentation algorithm.

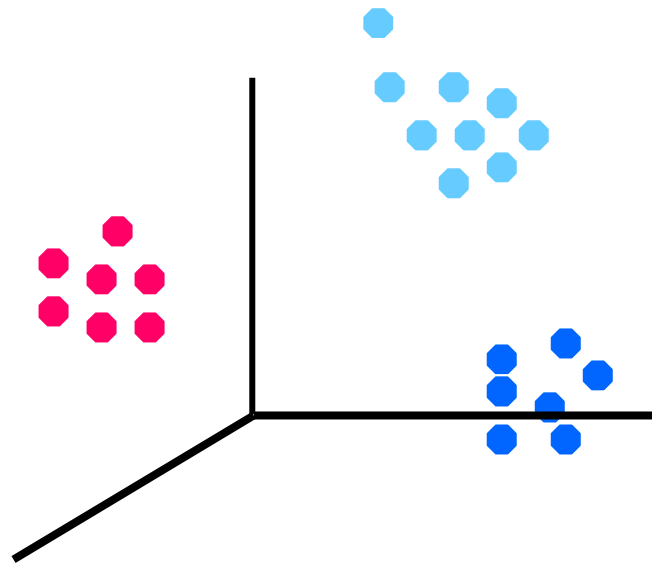


Figure 4.1: Cluster representation

C. Clustering Algorithm

There are many other algorithms used for clustering-means algorithm was used in the project and the distances were calculated using Mahalanobis and Euclidean distances. The main algorithms are given below.

- **K-means**
- **FCM(Fuzzy C- Means)**

D. K-Means Clustering Overview

K-Means clustering generates a specific number of disjoint, flat (non-hierarchical) clusters. It is well fitted to generating shape of clusters.

a. K-Means Algorithm Properties

- There are always K clusters.
- In each cluster they have one cluster.
- The clusters do not overlap.
- In cluster the member is closer to its cluster than any other cluster because closeness does not always involve the center of clusters.

b. K-Means Algorithm Process

- Every dataset is divided into K clusters and the data points are randomly assigned to the clusters resulting in clusters that have roughly the same number of data points.
- For each data point.
- Calculate the distance (Mahalanobis or Euclidean) from the data point to each cluster.
- If the data point is nearest to its own cluster, leave it where it is done.

- Repeat the above step until a complete pass through all the data point's results in no data point moving from one cluster to another cluster. In this point the clusters are stable and the clustering process ends.
- The initial partition can mainly affect the final clusters that result, in terms of inter-cluster and intra-cluster distances and cohesion.

C. Adaptive Mean Shift Clustering For Tumor Detection And Segmentation

The most popular technique k-means clustering however two inherent limitations, the clusters have is constrained to be spherically symmetric and their number has to be known. The amount of computation becomes prohibitively large as the dimension of the space increases. The goal of feature space analysis is to reduce the data to a few significant features through a procedure known under many different names, clustering, unsupervised learning or vector quantization. The inputs are the brain pre-processed image. Each pixel consisted of thirty one bands in the visual spectrum. In the experiments only the photometric data were used. The x-y coordinates of the pixels were discarded. As in the previous experiments the number of clusters recovered by the mean shift clustering was used as the value of k for the k-Means clustering.

Structures of interest include organs or parts such as cardiac ventricles or kidneys, abnormalities such as tumours as well as other structures such as vessels, brain structures etc. The main objective of such methods is referred to as computer-aided diagnosis they are used for helping doctors in evaluating medical imaginary or in recognizing abnormal findings in a medical image. In contrast to generic segmentation methods, used for medical image segmentation are often application oriented they can make use of prior knowledge for the particular objects of interest and other expected or possible structures in the image. This has direct to the improving of a wide range of segmentation methods addressing specific problems in medical applications.

Some methods proposed in the literature are extensions of methods originally proposed for generic image segmentation. The watershed transforms to be modified and it is proposed for knee cartilage and gray matter white matter segmentation in magnetic resonance images. This introduces prior information in the watershed method via the use of a previous probability calculation for the classes present in the image and via the combination of the watershed transform with atlas registration for the automatic generation of markers.

Segmentation tools are developed for use in the study of the function of the brain, for example the classification of the brain areas using functional magnetic resonance imaging data. Clustering method performs segmentation based on intensity of histogram augmented with adaptive spatial regularization using Markov random fields. The end contributes to improved segmentation as compared to non-spatial models, while not requiring the heuristic fine-tuning that is necessary for non-adaptive spatial regularization previously proposed.

Another important application of segmentation tools is in the study of the function of the heart. In detection algorithm based on a radial edge-detection filter is developed for cardiac echo graphic images. Objective of this algorithm is to define a region of

interest in which measurements (e.g. image intensity) can lead, after appropriate interrupt action, to the estimation of mainly cardio vascular parameters without the need for invasive techniques.

D. Image Enhancement Using Contrast Limited Adaptive Histogram Equalization

Some image enhancement operations are performed to enhance the image by each layer. In this contrast enhancement techniques are applied using Contrast Limited Adaptive Histogram Equalization Algorithm. That is extension to the traditional Histogram Equalization technique. Contrast enhancement of the images is performed by transforming the values in the intensity image. It operates on tiles (small data regions), rather than the entire image, unlike histogram equalization. Contrast Enhancement is performed on each tile, to match the histogram of the output region approximately with specified histogram. To eliminate artificially induced boundaries bilinear interpolation is used to combine the neighboring tiles. To avoid the noise which might be present in the image, the contrast, especially in homogeneous areas can be limited.

E. The Mean-Shift Procedure

a. Constant-Adaptive Mean-Shift

Parzen window density estimation (or kernel density) is considered to be the most popular density estimation method. Given n data points, $x_i, i=1, \dots, n$ in the d-dimensional feature space R^d , the multivariate kernel density estimator with kernel $K(x)$ and a symmetric positive definite $d \times d$ bandwidth matrix H and computed in the point x ,

$$f^{\wedge}(x) = \frac{1}{n} \sum_{i=1}^n KH(x - x_i) \tag{5.1}$$

$$KH(x) = |H|^{-1/2} K(H^{-1/2}x) \tag{5.2}$$

$$K^s(x) = a_{k,d} K_1(\|x\|)$$

$$K^p(x) = \prod_{i=1}^d K_1(x_i) \tag{5.3}$$

Where $K^s(x)$ is obtained from rotating $K_1(x)$ in R^d , i.e., $K^s(x)$ is radically symmetric. The constant $a_{(k,d)}^{-1} = \int_{R(d)} K_1(\|x\|) dx$ assures that $K^s(x)$ integrates to one. On the other hand, $K^p(x)$ is obtained from the product of univariate kernels. Either type of multivariate kernel obeys Eq. 4.19, but, for our purposes, the radically symmetric kernels satisfy:

$$K(x) = c_{k,d} k(\|x\|^2) \tag{5.4}$$

In this case, it suffices to define the function $k(x)$, called the main part of the kernel, only for $x \geq 0$. Moreover, in order to avoid under-segmentation, caused by a single value that is locally too large, it is necessary to choose a bandwidth value that is small enough to avoid over-smoothing anywhere in the dataset. This results splitting in the mean-shift output and requires further merging in the form of an iterative repetition of transitive closure on the region adjacency graph.

A. Preprocessing Step

a. Brain Extraction

First of all, for all the images of the dataset, we must remove the scalp and skull pixels, in order to guarantee that the rest of the procedure will not classify pixels that do not belong to any tissue category. There is a great variety of appropriate brain extraction tools (BET) available, although neither of which remove completely all the scalp and skull pixels. The only parameter that we have to choose in BET is a “crop edges” threshold values, that regulates the program crop based on the pixel. It takes values from 0 to 1. Close to zero values means that the program is going to crop few pixels from the MRI image, and as a result plenty skull pixels will still remain, leading to misclassification. On the other hand, close to 1 values means that the program is going to crop plenty pixels from the MRI image, and as a result pixels that belong to brain tissues will be mistakenly cropped. As a conclusion much caution is needed with the use of this tool and in every occasion, we must check the resulting image. In this work observed that the best way to remove scalp and skull pixels is to apply BET one to two times with threshold value 0.4 to 0.6 max. Afterwards, the remaining scalp and skull pixels are removed manually. The basic idea is to apply BET carefully with threshold values 0.4 to 0.6, even though it may needs to be applied more than one time, so as to guarantee that scalp and skull pixels are completely removed and brain tissue pixels have not been cropped. BET procedure is of paramount importance, especially in locating cancer pixels (tumour or edema), that appear hyperintense (in T1 and T2 MRI modality respectively), an intensity value very close to brain skull pixels intensity, and if we don't remove them appropriately, we will end up to misclassification of brain cancer pixels.

b. Median Filter

After having extracted the skull and scalp pixels, now we apply a median filter in order to remove the additive noise. The next step is the intensity normalization via linear histogram stretching based on the darkest and brightest percentage point values. The darkest percent of pixels to zero and rescales the brightest percent to 4095 set by normalization set. This step is necessary in order to guarantee that all the images of any MRI scan will have the same treatment and also to obtain similar dynamic ranges for all the three brain tissues. The last step of the pre-processing step is to estimate the background of every image, by performing a morphological opening operation. After the estimation of the background, we remove it from the images and store only the brain tissue pixels in a matrix. This is done in order to perform the mean-shift algorithm using only the brain tissue pixels (if we were using the background pixels in the mean-shift procedure this would lead to a completely wrong processing of data in mean-shift clustering step and finally misclassification of the brain tissue pixels).

C. Mean-Shift Clustering Step

In this paper suppose that each brain tissue pixel of the MRI slice is a unique category. The feature space of our problem is both spatial (x and y pixel's coordinates) and intensity, for an overall dimensionality of three. So, we have to estimate the

unknown probability density function (PDF) for each category, according to its neighbourhood of pixels that act as samples. As already mentioned in Section 4.1, the most common way to estimate an unknown pdf, is the Parzen Windows method. According to Parzen Windows, an unknown pdf can be estimated by the following equation:

$$f^{\wedge}K(x) = \frac{1}{n} \sum_{i=1}^n \frac{1}{h_i^d} k\left(\left\|\frac{x - x_i}{h_i}\right\|^2\right)$$

where d is the dimension of the feature space, in our case 3 as already mentioned, x is the feature vector of the pixel-category that we want to estimate its pdf, n is the number of neighbourhood pixels-samples considered for the estimation of the pdf, x_i is the feature vector of a pixel-sample that belongs to the neighbourhood of x , h_i is the windows radius that we are taking into consideration (not all pixels of the neighbourhood participate in the estimation of the pdf) and function k is named Kernel Profile and is actually an equation where the similarity of the characteristics between each pixel-sample of the neighbourhood and the pixel that we want to estimate its pdf is taking into account. Pixels-samples that have similarly characteristics with the pixel that we want to estimate its pdf participate more than the pixels-samples that aren't so relative with the current pixel-category.

$$f^{\wedge}K(x) = \frac{1}{n} \sum_{i=1}^n \frac{1}{h_i^3} \exp\left(-\left\|\frac{x-x_i}{h_i}\right\|^2\right) \tag{5.5}$$

A. Block Diagram

In this section, the main idea used in the proposed technique is described. The proposed system has mainly seven modules. They are pre-processing, image segmentation, image feature extraction, training and testing, stage detection, accuracy comparison, graph generation. In Pre processing Median filtering is performed on the MR image. Advanced K-mean, Adaptive mean shift and EM algorithms are used in segmentation work. Gray level Co-Occurrence Matrix is used for feature extraction. And then SVM classifier is applied to detect whether the given image is Normal or Abnormal. Stage detection step is used to find out the stage of tumour which is marked as abnormal in previous step. Then we compare the accuracy of the proposed system with previous one.

B. Description

In pre processing step the image is converted according to the need of the noise removal. Filtering of noise and other artefacts are performed on the image. Median filtering is used to reduce the salt-and-pepper or impulsive noise. Noise arrival possibilities in modern MRI scan are very less but due to the thermal effect it may appear. The main aim of this project is tumour detection, tumour stage detection and comparison of accuracy with previous techniques. But for the better result, it needs the process of noise removal.

For this purpose Adaptive Median Filtering is proposed. Spatial processing is performed by the Adaptive Median Filter to find out those pixels in an image which

have been affected by impulse noise. The AMF classifies pixels as noise by comparing each image pixel to its neighbor pixels. The size of the neighborhood and the threshold for the comparison is adjustable. Impulse noise is labeled as a pixel which is different from its majority of neighbors, also being structurally unaligned with the pixels same to impulse noise. The pixels in the neighborhood by which the noise labeling test have passed then replaces these noise pixels.

The normalization sets the darkest percent of pixels to zero and rescales the brightest percent to 4095. This step is necessary in order to guarantee that all the images of any MRI scan will have the same treatment and also to obtain similar dynamic ranges for all the three brain tissues. The last step of the preprocessing step is to estimate the background of every image, by performing a morphological opening operation. After the estimation of the background, we remove it from the images and store only the brain tissue pixels in a matrix.

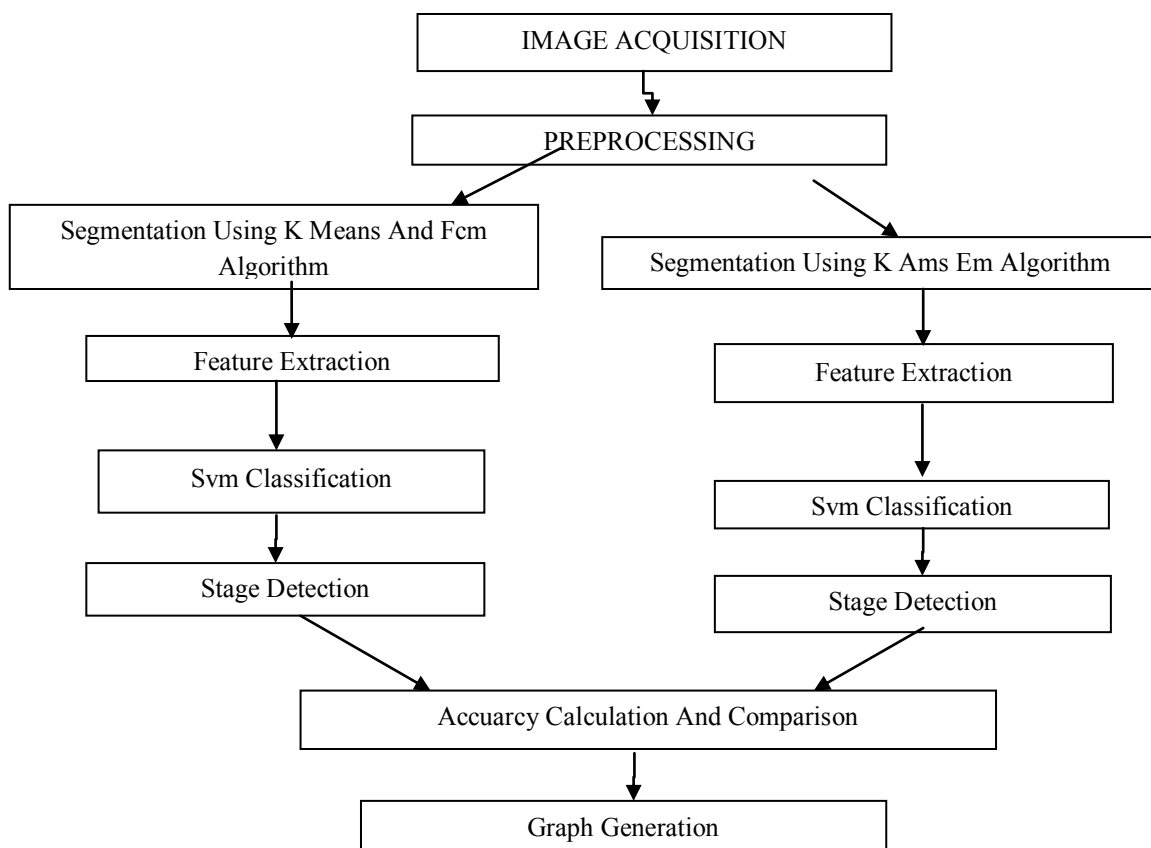


Figure 6.1: Block diagram of image acquisition

C. Existing System

To segment the medical image using K Means clustering algorithm. To propose an algorithm that can be better for large datasets and to find initial centroid to compare the performance. An algorithm is described for segmenting MR brain image into K different tissue types, which include gray matter, white matter and Cerebro Spinal Fluid, and maybe other abnormal tissues types. MR images assumed can be either scale or multivalve images. Each scale-valued image is modelled as a collection of regions with slowly varying intensity plus a white Gaussian noise.

a. Disadvantages Of Existing System

- The FCM segmentation is not preferred for its limited range of applications and automatic features are not having accurate values.
- Pre-processing experiments are needed to find which type of filtering will be more beneficial. This increases the effect of the speckle noise and Gaussian noise the ultrasound, mammogram images and MRI Images.
- The desired cancer area is selected from the segmented image to calculate the volume. The volume of the desired cancer area is greater than the original cancer area. The region growing algorithm will segment not only the tumour area but also the non tumor area which has high intensity ratio.
- This algorithm fully depends on the intensity of the image not the shape and texture. So the accuracy and sensitivity is low.

D. Proposed System

1. MRI Brain image segmentation using Adaptive Mean Shift algorithm
2. Feature Extraction using Gray level co-occurrence Matrix
3. Classification using Support Vector Machine

a. MRI Brain Image Segmentation Using Adaptive Mean Shift Algorithm

An automated scheme for Magnetic Resonance Imaging (MRI) brain image segmentation is proposed. An adaptive mean-shift methodology is useful in order to classify brain voxels into one of three main tissue types: gray, white and Cerebro-spinal fluid. The MRI image space is defined by a high-dimensional feature space that includes multimodal intensity features as well as spatial features.

b. Feature Extraction Using Gray Level Co-occurrence Matrix

It is a statistical method that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial support matrix. By that, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but it can specify other spatial relationships between the two pixels. Each element (I, J) in the resultant GLCM is simply the sum of the number of times that the pixel with value I occurred in the specified spatial relationship to a pixel with value J in the input image.

C. Classification Using Svm

This project proposes an intelligent classification technique to identify normal and abnormal slices of brain MRI data images. The manual interrupt of tumour slices based on visual examination by radiologist or physician may lead to missing diagnosis when a large number of MRIs are analyzed using this method. An automated intelligent classification system is proposed because of human error which caters the need for classification of image slices after identifying abnormal images of MRI volume, for identify tumour. In this work, advanced classification techniques based on Least Squares Support Vector Machines (LS-SVM) are proposed and applied to brain image slices classification using features derived from slices.

Locating the local maximum points with the mean-shift vector for each pixel-category, we are now searching in small neighbour hoods for the maximum of these local maximum points, defining in this way the modes. How small a neighbourhood that we are going to search is, is subjectively. This factor has also major affect in the final results, as it affects the producing modes of the mean-shift procedure. Small neighbourhood will lead to numerous modes (even > 2000) while large neighbourhood will lead to few tens of modes (<100). Both facts lead to misclassification, because in the first case the mean-shift's procedure resulting modes are too many and as a result, the mean-shift procedure doesn't have significant effect in the procedure of segmentation.

D. Advantages Of Proposed System

- It is good for convergence of gradients of the image pixels.
- It is the fastest algorithm when compared to the k means algorithm and Fuzzy C Means algorithm.
- The AMS algorithm can have linear convergence and the speed is based on how many information is lost.
- AMS algorithm is applicable for RGB color space images.
- The convergence rate of EM algorithm is the convergence rate of the E-step. That is to say, if the maximum value in M-step can be easily obtained, the convergence rate will be very fast to converge.
- The exact segmentation of the tumor of MRI is possible.

A.Output:

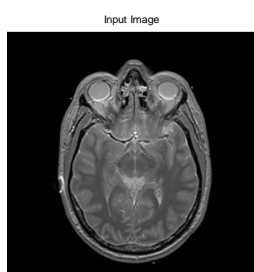


Figure 7.1: Input image

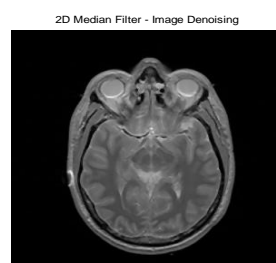


Figure 7.2: Median filter using denoising



Figure 7.3: Noise level



Fig.7.4. Contrast enhancement using mean shift

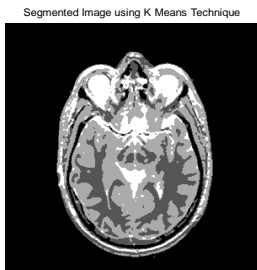


Figure 7.5: segmented image using k means

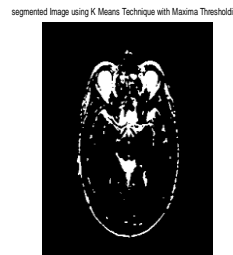


Figure 7.6: K-means using max threshold

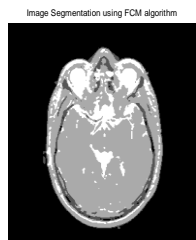


Fig.7.7.Segmentation using FCM

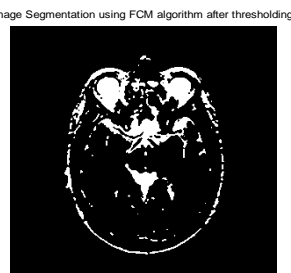


Figure 7.8: Segmentation using FCM after thresholding

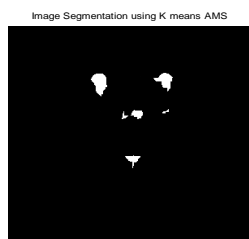


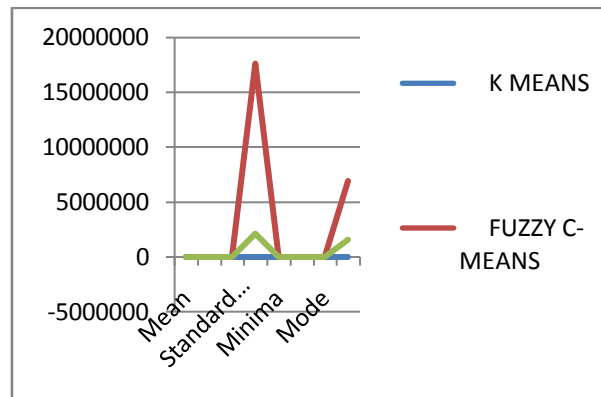
Figure 7.9: Image segmentation using K means AMS

Result

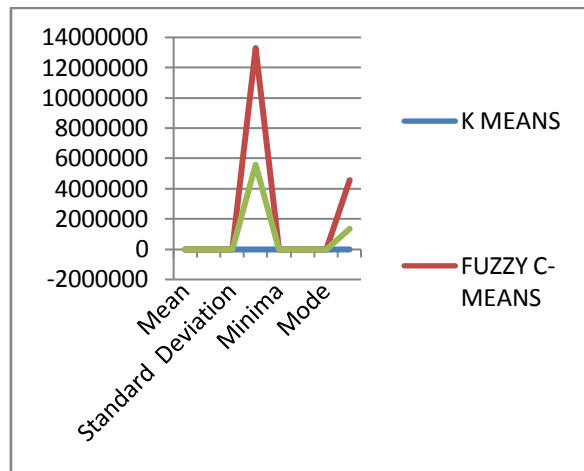
- Peak Signal to Noise Ratio using 2D Median Filter = 48.7725
- Mean Square Error using 2D Median Filter = 0.2368

Table A: First order feature extraction comparisons

First Order Features	K Means	Fuzzy Means	C-	K-Adaptive Mean Shift
Mean	0.2073	19.2928		0.8122
Median	0	0		-1.9995
Standard Deviation	0.4853	42.6316		22.9422
Variance	0.3032	1.7621e+007		2.1455e+006
Minima	0	0		-1.9995
Maxima	3	255		252.0005
Mode	0	0		-1.9995
Covariance	0.1238	6.9267e+006		1.6140e+006

Graph:**Table B: Modified first order features**

First Order Features	K Means	Fuzzy Means	C-	K-Adaptive Mean Shift
Mean	0.1577	15.7554		0.1210
Median	0	0		-1.9995
Standard Deviation	0.4424	39.4888		20.3812
Variance	0.2262	1.3300e+007		5.5979e+006
Minima	0	0		-1.9995
Maxima	3	255		252.0005
Mode	0	0		-1.9995
Covariance	0.1062	4.5900e+006		1.3568e+006



Conclusion

The accurate results of Adaptive Mean Shift Segmentation algorithm effectively extract the tumour region from brain MRI brain images. The AMS segmentation is used because of its simplicity and it is also preferred for faster clustering. Image segmentation is an important issue in digital image processing and finds extensive application in many fields. By using this segmentation method centroid point can be located easy and will give more accurate and high resolution result. This method was successful in detecting the tumour region and extracted hence this work can be extended for more abnormality condition in the brain.

Future Work

The transformation of an image into its set of features is known as feature extraction. Useful image features are extracted from the image for classification purpose. It is a challenging goal to extract good feature set for classification. There are many techniques for feature extraction e.g. texture Features, Gabor features, principal component analysis. Support vector machine (SVM) is one of the techniques used for the classification purpose. SVM classification applied on different real time world problems such as face recognition, text categorization, cancer diagnosis, glaucoma diagnosis, microarray gene expression data analysis. The Proposed system used SVM for binary classification of brain MR image as normal or tumor affected areas. SVM basically divide the given data into decision surface. Decision surface is a hyper plane which divides the data into two classes. Training points are the supporting vector which defines the hyper plane. The basic theme of SVM is to maximize the margins between two classes of the hyper plane.

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