MRI IMAGE SEGMENTATION – A REVIEW

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Abstract- **The magnetic resonance imaging (MRI) technique has been proven to be a valuable tool in the areas of anatomical, and functional analysis of human brains. The identification of brain structures in magnetic resonance imaging (MRI) is very important in neuroscience and has many application such as: mapping of functional activation onto brain anatomy, and the study of brain development, and the analysis of neuro anatomical variability in normal brain. For real clinical applications, such as diagnosis of abnormalities, visualization of pathology, and quantification of tissue volume, it is important to classify the brain MRI images into several meaningful tissue types. Thus, segmentation of brain tissues into white matter (WM), grey matter (GM), and cerebrospinal fluid (CSF) is an important pre processing step for these clinical applications.[1,5]**

Segmentation is an important tool in medical image processing and it has been useful in many applications which can be used to detect brain tumours, functional mapping, blood cell classification etc.[2,3].

Segmentation of image is basically division of image with respect to various properties of colour and texture. Image segmentation is widely used in exploratory pattern analysis, grouping, decision-making, and machine-learning situations, including data mining, document retrieval and pattern classification. [4]

Clustering is the most popular method for medical image segmentation, with fuzzy c-means (FCM) clustering and expectation–maximization (EM) algorithms being the typical methods. The applications of the EM algorithm to brain MR image segmentation were reported by Wells *et al.* [6] and Leemput *et al.* [7]. A common disadvantage of EM algorithms is that the intensity distribution of brain images is modelled as a normal distribution, which is untrue, especially for noisy images.[8]

The clustering technique can be hard or fuzzy. A hard clustering algorithm allocates each pattern to a single cluster during its operation and in its output. A fuzzy clustering method assigns a degree of membership to each input pattern depending on its association with several clusters.[9].

Among the algorithms, clustering methods based on fuzzy set theory, such as Fuzzy C-means (FCM) algorithm has been widely used for segmentation MRI data. Unfortunately, the conventional intensity based clustering algorithms are usually sensitive to the noise and intensity in homogeneity induced by the imperfection of radio- frequency coil, which can leads to unsatisfactory segmentation results.[10] Practically, due to a great diversity of MRI images from different subjects and imaging settings and due to an aim of reducing the human interactivity in favour of a less labour-intensive and fast segmentation. No prior knowledge of the parameters of FCM is available straight forwardly. However these parameters can be estimated through an initial segmentation which constructs automatically the training set of classified pixels in the original image [11].

Index Terms- **magnetic resonance imaging (MRI), fuzzy c, image segmentation**

I. FUZZY -MEANS CLUSTERING ALGORITHM

FCM was initially developed by Dunn and later Bezdek generalized it .FCM use iteration and is an unsupervised clustering algorithm. It includes minimizing and objective function with respect to fuzzy membership U and set of cluster centroids V

$J_m(U,V) = \sum_{j=1}^{N}\sum_{i=1}^{C} u_{ij}^{m}\, d^2(x_j, v_i)$........ (1)

Where $x = \{x_1, x_2 \ldots\ldots x_j \ldots\ldots x_N\}$is a p × N data matrix in which dimensions of each x_j "feature" vector is represented by p and the number of feature vectors is represented by N. C denotes the number of clusters. u_{ij} c U(p × N × C) which is the membership function of vector $x_j$to the ith cluster satisfying $u_{ij} \epsilon [0,1]$ and $\sum_{i=1}^{C} u_{ij} = 1$, (j = 1,2…, N)

The membership function is expressed as

$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\sum_{j}^{C}\frac{d(x_j, v_i)}{d(x_j, v_k)}\right)^{\frac{2}{m-1}}}$ .... (2)

Where $v = \{v_1, v_2, \ldots\ldots v_c\}$which denotes the cluster feature centre and is a p × C matrix.

$v_i = \frac{\sum_{j=1}^{N}(u_{ij})^m x_j}{\sum_{j=1}^{N}(u_{ij}{}^m)}$ (i = 1,2,3…, C) .... (3)

Here $m\epsilon(1,\infty)$ and it controls the degree of fuzziness.

$d^2 = (x_i, v_i) = \| x_j - v_i \|^2 \ldots\ldots\ldots.(4)$

Euclidean distance or its generalization , for example , Mahalanobis distance defines ‖.‖

The pixel intensities is represented by feature vector X in MR images , so $p = 1$. As we know

FCM uses iteration, so, it optimizes $J_m(U,N)$ with continuous updation of U and V until $|U^{(l+1)} - U^{(l)}| \leq \in$

Where l denotes the no. of iteration .

One drawback of FCM is that any spatial dependence among X is not taken into consideration but it deals with images the same as separate points. Also, the membership function U in eq.(2)is mostly decided by $d^2(x_j\, v_i)$, which is used to measure the similarity between the pixel intensity and the cluster centre.

II. IMPROVED FUZZY-C MEANS CLUSTERING ALGORITHM

Fuzzy-C Means has some drawbacks which need to be circumvented and hence comes the Improved Fuzzy-C Means Algorithm (IFCM).The segmentation result is decided by the membership value of FCM and the value of membership function is determined by the similarity measurement $d^2(x_j\,, v_i)$ in (4).This measurement is the key to success.The difference between intensity of a pixel and the cluster center is measured by $d^2(x_j\,, v_i)$ in FCM and it has no resistance to noise.In IFCM an attraction entitled neighbourhood attraction is considered to exist between neighbouring pixels. Each pixel attempts to attract its neighbouring pixel towards its cluster in the process of clustering.

The pixel intensities or feature attraction and spatial position of neighbour pixels or distance attraction determines the attraction between neighbourhood pixels, which also depends on neighbourhood structure.

Neighbourhood attraction is considered in IFCM by $d^2(x_j\,, v_i)$ directly.

$d^2(x_j\,, v_i) = \parallel x_j - v_i \parallel^2 \left(1 - \lambda H_{ij} - \xi F_{ij}\right)$ .... (5)

Where the feature attraction is represented by H_{ij} and the distance attraction is represented by F_{ij}.

The two parameters λ and ξ in (5)have magnitude between 0 to 1 and they adjust the degree of the two neighbourhood attractions

$H_{ij} = \frac{\sum_{k=1}^{S} u_{ik} g_{ik}}{\sum_{k=1}^{S} g_{ik}}$ .... (6)

where g_{ik} is the intensity between the study pixel and its neighbourhood pixel k , and $g_{ik} = x_j - x_k$

Membership of neighbouring pixel k to the ith cluster is denoted by u_{ik} and the total number of neighbouring pixel is denoted by S.

$F_{ij} = \frac{\sum_{k=1}^{S} u_{ik}{}^2\, q_{jk}{}^2}{\sum_{k=1}^{S} q_{jk}{}^2}$ .... (7)

where q_{ik} is the relative location between pixel j and its neighbourhood pixel k.

The neighbourhood structure is of the form

$K_j = \left\{k \epsilon N | 0 < \left(a_j - a_k\right)^2 + \left(b_j - b_k\right)^2 \leq Q\right\}$ .... (8) where the co-ordinates of pixel j ,k ,Q is a constant , equal to $2^{(L-1)}$ and is denoted by (a_k, b_k), and L is the level of the neighbourhood.

.q_{jk} in (7) can be described as $q_{jk} = \left(a_j - a_k\right)^2 + \left(b_j - b_k\right)^2$

$d^2(x_j\,, v_i)$ is modified in IFCM and initialization of the membership is not created randomly but directly taken from FCM.

The steps involved in IFCM are –

(1) -Determination of the number of clusters C$(2 \leq C \leq N)$ and the degree of fuzziness m , is done.

(2)- FCM is executed completely.

(3)- Final membership of FCM is utilized as the initial membership $u_{ij}{}^{(0)}$ of IFCM.

(4)- Calculation of cluster centre $v_i{}^{(l)}$ $(i = 1,2, \ldots\ldots, C)$, using the membership $u_{ij}{}^{(l)}$ is done at the ith iteration $(l = 0,1,2, \ldots\ldots)$.

(5)- Improved similarity measurement $d^2\left(x_j\,, v_i{}^{(l)}\right)$ is calculated.

(6)- $u_{ij}{}^{(l)}$ is updated with $d^2\left(x_j\,, v_i{}^{(l)}\right)$.

(7)- At last $u_{ij}{}^{(l)}$ and $u_{ij}{}^{(l-1)}$ are compared. If $\left\| u_{ij}{}^{(l)} - u_{ij}{}^{(l-1)} \right\| < \epsilon$, then the process is stopped , else , $l = l + 1$, and the process goes to step 4 and is repeated.

III. K-MEANS ALGORITHM

One of the simplest unsupervised learning algorithms that solve the well known clustering problem is K-means Algorithm. The procedure in it follows a simple and easy way to classify a given data set through a certain number of clusters. the steps involved are

First, K Initial centres are chosen $Z_1(1), Z_2(2)$, which are arbitrary.

Then, at the Kth Iterative Step , Distribution of the sample $\{X\}$ is done among the K Cluster Domain , using the relation $X \in S_i(k)$ if ‖ X-$z_j(k)$‖<‖ $X - z_i(k)$ ‖ , where $s_j(k)$ is the set of samples whose cluster center is $z_j(k)$.

The result in the step 2 is used to calculate the new clusters $z_j(k+1)$, where j = 1,2,3, … , k

$z_j(k+1) = {}^{1}/_{n_j} \sum x\,, x \in S_j(k)$ .... (8)

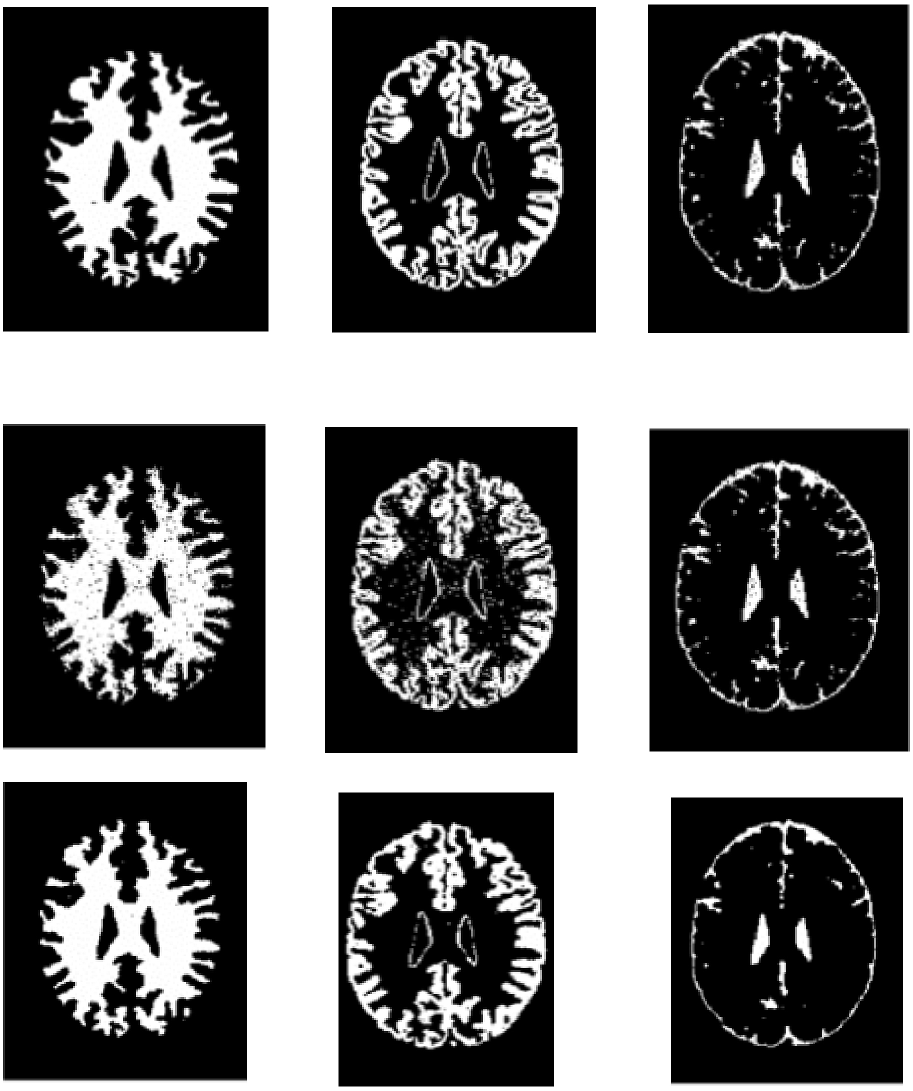
Where $n_j$is the number of samples used in $s_j(k)$ and the updation of cluster centres is sequentially done.

If $z_j(k+1) = z_k(k)$, then the algorithm is said to have converged and the procedure is terminated, or else step -2 is repeated.

One of the major drawback of the K-Means Algorithm is that there is a large number of misclassified data points after the segmentation of image is done.

IV. CONCLUSION

In MR images, the presence of noise or artefacts can change the intensities of some pixels; these may be segmented more appropriately with the help of their neighboring pixels. Instead of modifying the objective function, the measurement of similarity was extended by considering neighborhood attraction. This included feature attraction and distance attraction, which account for feature differences and relative spatial locations between neighboring pixels in the image.



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