International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 3 Issue 4, April - 2014

MRI Brain Tumor Segmentation using Kernel Weighted Fuzzy Clustering

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Abstract-The **process of segmentation plays a vital role in medical application because segmentation is the first step in image analysis. In order to identify any variation, the segmentation in medical images should be clear. Nowadays, segmentation of brain tumor is a difficult task in medical images. This paper proposes a novel approach to detect and segment the brain tumor tissues in MRI images. In this approach a method trade-off weighted fuzzy factor is used to segment the tumor region from the MRI images and kernel metric is used to increase the performance of segmentation results. Finally experimental results of the proposed framework gives better efficiency and provides higher accuracy than other compared existing approaches.**

Keyword: Brain Segmentation, Fuzzy, Weighting factor, Tumor tissues, Kernel metrics.

I INTRODUCTION

A brain tumor [1, 2] or tumor is an intracranial solid neoplasm which is formed by an abnormal and uncontrolled cell division, usually in the brain itself. It is also present in tissues of lymphatic, cranial nerve blood vessels and brain envelopes. It is also developed from cancer and it is present in each organ. Tumor it is formed by high pressure and some damaged nerves in brain. Presence of the tumor in the brain in a particular location is decided by the type of symptoms. Because, several brain parts are controlled by various functions. Only for expectation cases tumors spread to the central nervous system, that includes the brain and spinal cord [3].

The most and chief important task in the image analysis is image segmentation. Even though efficient algorithm for segmentation is very challenging purpose. Several techniques was developed for segmentation of object detection, feature extraction and it is explained in [4, 5]

MRI is a medical imaging technique, and radiologists use it for visualization of the internal structure of the body. MRI can provide plentiful of information about human soft tissues anatomy as well as helps diagnosis of brain tumor. MR images are used to analyse and study behaviour of the brain. A powerful magnetic field is used to align the nuclear magnetization of hydrogen atoms (or protons) of water in the body. In the presence of RF (Radio Frequency) electromagnetic fields, hydrogen nuclei produce a rotating magnetic field which is detectable by the scanner. The transmitter coil functions in the following way: first, it produces electromagnetic waves and transmits these waves inside the brain, and then a receiver coil measures the intensity of the emitted electromagnetic waves. Moreover, an additional gradient coil is used for spatial localization of the signal. The recorded signals (or electromagnetic waves) are reconstructed into an image.

Normally, medical image segmentation is extremely complicated one because of noisy images and poorly sampled and their structures have complex shapes. Several approaches are used for brain tumor segmentation such as Markov Random Fields [7] and Conditional Random Field [8] based machine learning techniques have been applied in tumor segmentation tasks as well. Some other better performances are handled for brain tumor segmentation such as methods like Discriminative Random Fields [9], Support Vector Random Fields [10], and Pseudo-Conditional Random Field [11]. Other supervised statistical machine learning approaches include using fractal features [12], alignment features [13], one-class support vector machine [14], using Bayesian classifier [15], tumor localization using diagonal nearest-neighbours [17], segmentation by outliers [16], and high-dimensional features with level-set [18].

II RELATED WORK

Various approaches are considered for brain tumor segmentation. One novel technique such as vector quantization was implemented to identify the cancerous mass from MRI images [19]. To improve the performance of brain image segmentation, an approach was implemented in [20] here the author used the technique of FCM and it is simulated by Non-Local (NL) framework.

In [21] combination of SOM and FCM was implemented to segment the brain tumor. Here the author is taken the segmentation approach in two phases. In first phase noise is removed and the second phase is used to identify and segment the brain tumor accurately

A Simple algorithm and traditional method was proposed in [22] to detect the shape and range of the tumor in brain cells. Here the author used the K-Means segmentation approach accurately and effectively. Before that segmentation noise was improved by using median filter. Another approach for noise removal for medical image using kernel factor was implemented in [24].

A Technique was implemented in [23] to differentiate the abnormal brain images. In this paper brain tumor classification was used by modified Probabilistic Neural Network. This approach produces the effective result with better accuracy.

The proposed approach describes the brain tumor segmentation by using Kernel Weighted Fuzzy Local Information C Means.

Comparing this proposed approach with Fuzzy Local Information C Means (FLICM) [23], improving the FLICM method by using kernel metrics are termed as Kernel Fuzzy Local Information C Means (KFLICM) and introducing the weighting factor is termed as Weighted Fuzzy Local Information C Means (WFLICM). Proposed framework is the combination of kernel metrics and weighting factor on FLICM is termed as KWFLICM that provides better and effective brain tumor segmentation results.

III Brian Tumor Segmentation

A. General framework

In Kernel Weighted Fuzzy Local Information C-Means (KWFLICM), the objective function is defined as follow

$$J_m = \sum_{i=1}^{N}\sum_{k=1}^{C} u_{ki}^{m}\left(1 - k(x_i, v_k)\right) + G_{ki}^{'} \qquad (1)$$

While the reformulated fuzzy factor is written as follow

$$G_{ki}^{'} = \sum_{i=1}^{N}\sum_{K=1}^{c} u_{ki}^{m} \sum_{\substack{1 \neq j \\ j \varepsilon N_i}} w_{ij}\,(1 - u_{ki})^{m}\left(1 - k(x_j, v_k)\right)$$

(2)

Where N_i stands for the set of neighbors in a window around x_i, w_{ij} is the trade-off weighted fuzzy factor of jth in a local window around $x_i, 1 - K(x_i, v_k)$ represents a non-Euclidean distance measure based on kernel method, $(1 - u_{ki})^m$ is a penalty which can accelerate the iterative convergence to some extent. $\{v_k\}_{k|=1}^{C}$ is the centers or prototypes of the clusters and the array $\{u_{ki}\}$ represents a membership matrix which also must satisfy the Equation 2.

The two updating formulas for minimizing J_m, with respect to u_{ki} and v_k is obtained as follow,

$$u_{ki} = \frac{1}{\sum_{i=1}^{C}\left(\frac{\left(1-K(x_i,v_k)\right)+\sum_{\substack{j \in N_i \\ j \neq i}} w_{ij}\left(1-u_{kj}\right)^{m}\left(1-K(x_j,v_k)\right)}{(1-)+\sum_{\substack{j \in N_i \\ j \neq i}} w_{ij}\left(1-u_{kj}\right)^{m}\left(1-K(x_j,v_l)\right)}\right)^{1/(m-1)}} \qquad (3)$$

$$v_k = \frac{\sum_{i=1}^{N}\left(u_{ki}^{m} K(x_i,v_k)x_i\right)}{\sum_{i=1}^{N}\left(u_{kl}^{m} K(x_i,v_k)\right)} \qquad (4)$$

Thus, the proposed algorithm can be summarized as follow:

Step 1: Set the number c of the cluster prototypes, fuzzification parameter m, and window size Ni and the stopping condition ε.

Step 2: Initialize randomly the fuzzy cluster prototypes.

Step 3: Set the loop counter b = 0.

Step 4: Calculate the trade-off weighted fuzzy factor w_{ij} and the modified distance measurement D_{ik}^2, as described in next section.

Step 5: Update the partition matrix using in Equation 3.

Step 6: Update the cluster prototypes using in equation 4.

Step 7: If $\max|V_{new} - V_{old}| < \varepsilon$ then stop, otherwise, set $b = b + 1$ and go to step 4.

Here $V = [v_1, v_2, \ldots, v_C]$ are the vectors of the cluster prototypes. When the algorithm has converged, a defuzzification process takes place to convert the fuzzy image to the crisp segmented image.

B. Trade-off Weighted Fuzzy Factor

The noise resistance property of the proposed KWFLICM mainly relies on the fuzzy factor $G_{ki}^{'}$, and it is given in Equation (2).

The adaptive trade-off weighted fuzzy factor depends on the local spatial constraint and local gray-level constraint.

For each pixel x_i with coordinate (p_i, q_i) the spatial constraint reflects the damping extent of the neighbors with the spatial distance from the central pixel and defined as

$$w_{sc} = 1/\left(d_{ij} + 1\right) \qquad (5)$$

Where the ith pixel is the center of the local window N_i and the jth pixel represents the set of the neighbors falling into the window around the i th pixel, d_{ij} is the spatial Euclidean distance between the jth pixel in neighbors and the central pixel. The definition of the spatial component makes the influence of the pixels within the local window change flexibly according to their distance from the central pixel and thus more local information can be used. Let us take 3 × 3 window with noise and the damping extent of the neighbours. In which that the window as taken as noise in the Central pixel and also the central pixel is not corrupted by the noise. By introducing the fuzzy factor $G_{ki}^{'}$, membership values are changed. From this clearly get that the corresponding membership values of the noisy, as well as of the no-noisy pixels gradually tend to a similar value after iteration by iteration, ignoring the noisy pixels. And after five iterations the algorithm converges. In such case, the gray level values of the noisy pixels are different from the other pixels within the window, while the fuzzy factor $G_{ki}^{'}$ balances their membership values. Thus, all pixels within the window belong to one cluster. Therefore, the combination of the spatial and the gray level constraints incorporated in the factor $G_{ki}^{'}$ suppress the influence of the noisy pixels. Moreover, the factor $G_{ki}^{'}$ is automatically determined rather than artificially set, even in the absence of any prior noise knowledge. Hence, the algorithm becomes more robust to the outliers.

After that, we get the local coefficient of variation C_j for each pixel j as follow

$$C_j = \frac{var\,(x)}{(\bar{x})^2} \qquad (6)$$

Where var (x) and $\bar{x}$ are the intensity variance and mean in a local window of the image, respectively. Next we project C_j into kernel space. Then, the weights are normalized. Due to the fast decay of the exponential kernel, large distance between C_j and the mean of these local coefficients of variation will lead to nearly zero weights. Finally, according to comparing C_j with $\bar{C}$ (the mean of C_j in local window), we give a varying compensation to C_j, which can enlarge the discrepancy of damping extent in neighborhood.

$$\bar{C} = \frac{\sum_{j \in N_i} C_j}{n_i} \qquad (7)$$

$$\xi_{ij} = exp\left[-\left(C_j - \bar{C}\right)\right], j \in N_i \qquad (8)$$

$$\eta_{ij} = \frac{\xi_{ij}}{\sum_{k \in N_i} \xi_{ik}} \qquad (9)$$

$$w_{gc} = \begin{cases} 2 + n_{ij} & C_j < \bar{C} \\ 2 - n_{ij} & C_j \geq \bar{C} \end{cases} \qquad (10)$$

Where the i th pixel is the center of the local window Ni , the j th pixel represents the set of the neighbours falling into the window around the ith pixel. The constant 2 guarantees the weight w_{gc} be non-negative. C_j represents the local coefficient of variation, which explain the local distribution of the jth pixel, $\bar{C}$ is the mean value of C_j that located in a local window and n_i is its local cardinality.

Therefore, the trade-off weighted fuzzy factor is written as

$$w_{ij} = w_{sc}.w_{gc} \qquad (11)$$

The value of C_j reflects gray value homogeneity degree of the local window. It exhibits high values at edges or in the area corrupted by noise and produces low values in homogeneous regions. The damping extent of the neighbours with local coefficient of variation is measured by the areal type of the neighbour pixels located. If the neighbour pixels and the central pixel are located in the same region, such as homogeneous region or the area corrupted by noise, the results of local coefficient of variation obtained by them will be very close, and vice versa. In addition, it helps to exploit more local context information since the local coefficient of variation of each pixel is computed in its local window. Furthermore, the weight of the neighbouring pixel will be increased to suppress the influence of outlier after transformed into the kernel space and added the spatial constraint.

C. Non-Euclidean Distance Based on Kernel Metric

The objective function in KWFLICM is

$$J_m = \sum_{i=1}^{N}\sum_{k=1}^{C} u_{ki}^{m}\|\phi(x_i) - \phi(v_k)\|^2 + G_{ki}' \qquad (12)$$

Where $\phi(.)$ is an implicit nonlinear map. The inner product between $\phi(x_i)$ and $\phi(v_k)$in the feature space is $\phi(x_i)^T\phi(v_k) = K(x_i, v_k)$

Then, through the kernel substitution, we have

$$\begin{aligned}\|\phi(x_i) - \phi(v_k)\|^2 &= \left(\phi(x_i) - \phi(v_k)\right)^T\left(\phi(x_i) - \phi(v_k)\right)\\ &= \phi(x_i)^T\phi(x_i) - \phi(v_k)^T\phi(x_i)\\ &\quad -\phi(x_i)^T\phi(v_k) + \phi(v_k)^T\phi(v_k)\\ &= K(x_i, x_i) + K(v_k, v_k) - 2K(x_i, v_k) \qquad (13)\end{aligned}$$

In this way, a new class of non-Euclidean distance measures in original data space is obtained. Because of $K(x, x) = 1$ for all x and the GRBF kernels, then equation (12) can be rewritten.

$$J_m = \sum_{i=1}^{N}\sum_{k=1}^{C} u_{ki}^{m}\left(1 - K(x_i, v_k)\right) + G_{ki}' \qquad (14)$$

Where

$$K(x_i, v_k) = exp\left(-\frac{\|x_i - v_k\|^2}{\sigma}\right) \qquad (15)$$

Here the parameter σ is the bandwidth. The bandwidth setting rule based on the distance variance of all data points is defined as follows.

Given the distance$\Omega = \{x_1, x_2, \dots, x_N\}$, then the data center of dataset Ω is given by

$$\bar{x} = \frac{\sum_{i=1}^{N} x_i}{N} \qquad (16)$$

Let $d_i = \|x_i - \bar{x}\|$ be the distance from data point x_i to the data center $\bar{x}$. The mean distance of d_i is then calculated by

$$\bar{d} = \frac{\sum_{i=1}^{N} d_i}{N} \qquad (17)$$

The bandwidth is set to the variance of d_i show as follow

$$\sigma = \left(\frac{1}{N-1}\sum_{i=1}^{N}\left(d_i - \bar{d}\right)^2\right)^{\frac{1}{2}} \qquad (18)$$

The distance metric based on kernel method can be transformed as

$$D_{ik}^2 = 1 - K(x_i, v_k) = 1 - exp\left(-\frac{\|x_i - v_k\|^2}{\sigma}\right) \qquad (19)$$

From the above descriptions, see that the trade-off weighted fuzzy factor and the kernel distance measure are both free of the empirically adjusted parameters which can be incorporated into other fuzzy c-means algorithms easily.

IV EXPERIMENTAL RESULT

The experimental results are carried on medical images using MATLB. Testing and comparing the efficiency of the proposed framework of KWFLICM using some parameters. The result of the proposed framework is compared with FLICM, KFLICM and WFLICM. Performance metrics are handled by some parameters they are tumor detection area, solidity, Equivalent Diameter, Perimeter, Entropy, Segmentation accuracy and Elapsed Time. These parameters are calculated by using region props. Here two images are taken for performance evaluation and the images are collected from the open source and it is evaluated by MATLAB.

TABLE I:

COMPARISON OF EXISTING AND PROPOSED FRAMEWORK FOR IMAGE 1

PARAMETERS	FLICM	KFLICM	WFLICM	KWFLICM
AREA	432	440	719	440
SOLIDITY	0.95	0.87	0.51	0.87
EQUIVALENT DIAMETER	23.45	23.66	30.25	23.66
PERIMETER	83.01	95.74	269.66	95.74
ENTROPY	0.56	0.55	0.47	0.55
SEGMENTATION ACCUIRCY	89.26	89.41	82.75	90
ELAPSED TIME	4.22	9.9	9.52	9.49

TABLE II:

COMPARISON OF EXISTING AND PROPOSED FRAMEWORK FOR IMAGE 2

PARAMETERS	FLICM	KFLICM	WFLICM	KWFLICM
AREA	226	503	2849	503
SOLIDITY	0.25	0.03	0.76	0.02
EQUIVALENT DIAMETER	16.96	25.30	60.22	25.30
PERIMETER	250.02	636.15	339.26	636.15
ENTROPY	0.97	0.73	0.68	0.73
SEGMENTATION ACCUIRCY	30.15	82.75	87.92	92.85
ELAPSED TIME	7.43	9.7	9.20	9.00

Table I and II gives the value for seven parameters they are area, solidity, equivalent diameter, perimeter, entropy, segmentation accuracy and elapsed time for image 1 and image 2.The seven parameters are evaluated by techniques such as FLICM, KFLICM, WFLICM and KWFLICM.

The below figure 1 illustrates the segmentation result of brain tumor segmentation. Original image is shown in figure 1.a. The original image is segmented by using existing approaches like FLICM, KFLICM, WFLICM and proposed approach KWFLICM. From the figure it is clearly observed that the proposed method of KWFLICM gives better segmentation than other approaches.

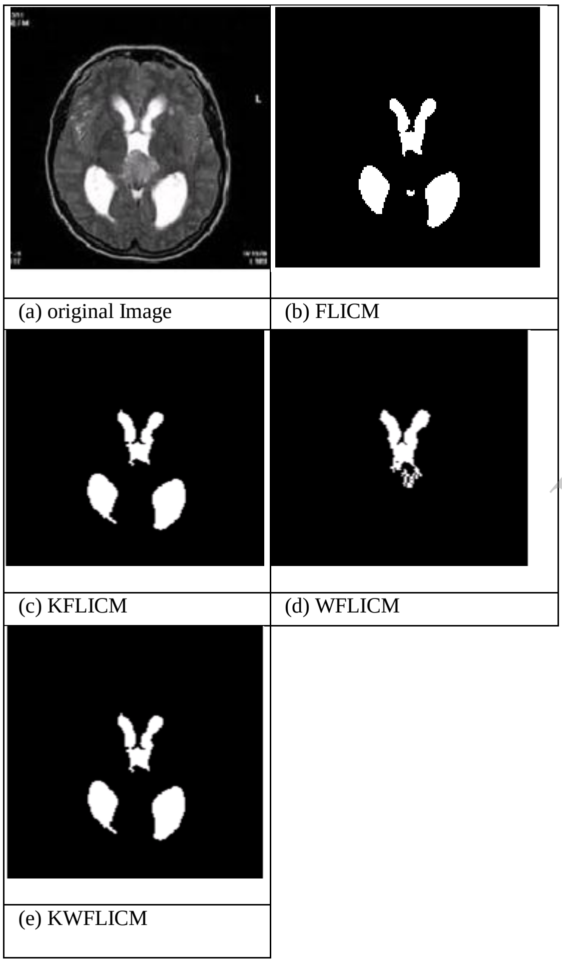

Fig. 1: Brain Tumor Segmentation results for Image 1 (a) Original Image (b) FLICM Segmentation Result (c) KFLICM Segmentation Result (d) WFLICM Segmentation Result and (e)) KWFLICM Segmentation Result

The below figure 2 illustrates the segmentation result of brain tumor segmentation. Original image is shown in figure 2.a. The original image is segmented by using existing FLICM, KFLICM, WFLICM and proposed KWFLICM. From the figure clearly observed that the proposed method of KWFLICM gives better segmentation than other approaches.

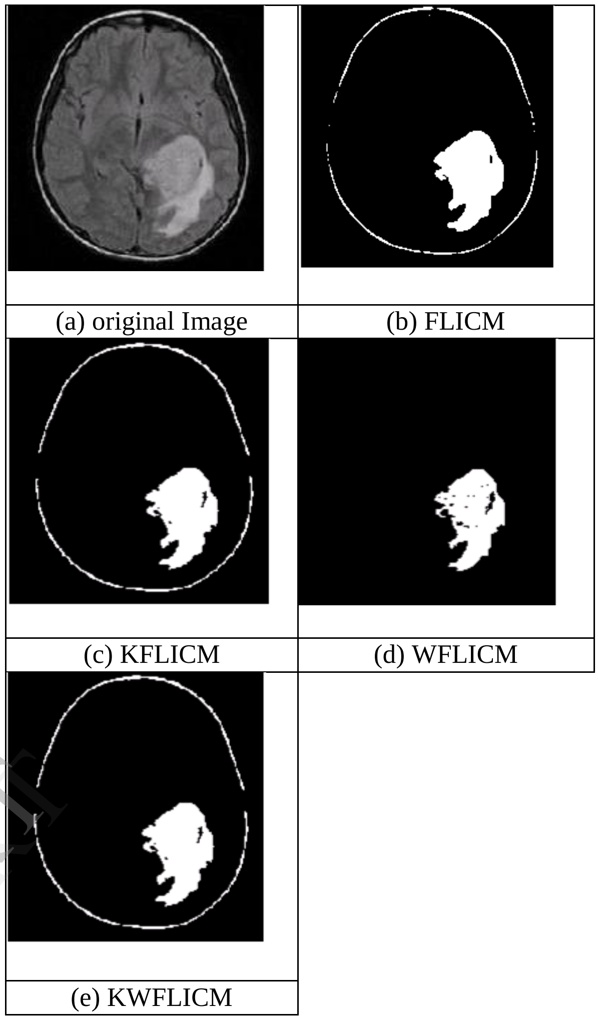

Fig. 2: Brain Tumor Segmentation for Image 2 (a) Original Image (b) FLICM Segmentation Result (c) KFLICM Segmentation Result (d)WFLICM Segmentation Result and (e) KWFLICM Segmentation Result.

TABLE III

COMPARISON OF SEGMENTATION ACCURACY

Techniques	**Segmentation Accuracy**	
	Image 1	**Image 2**
FLICM	89.26	30.15
KFLICM	89.41	82.75
WFLICM	82.75	87.92
KWFLICM	90	92.85

The above table III gives the comparison of segmentation accuracy for image 1 and 2 for the four following techniques FLICM, KFLICM, WFLICM and KWFLICM. From the table it is observed that the proposed method KWFLICM gives better segmentation accuracy.

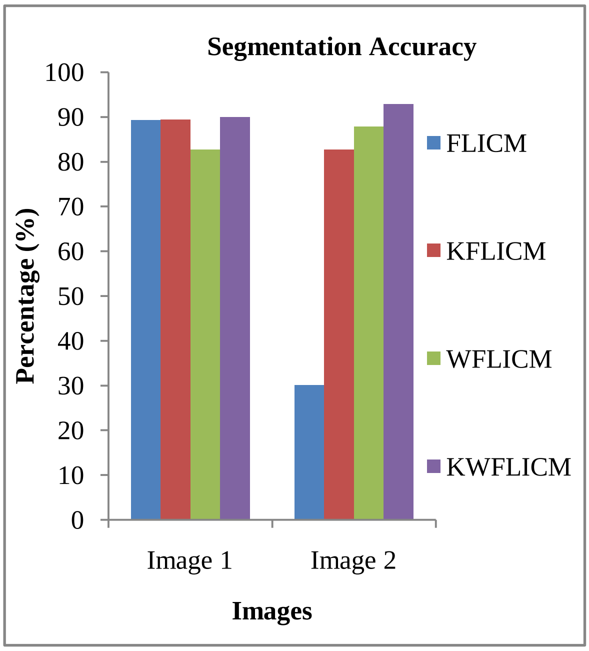

Fig. 3: Comparison of Segmentation Accuracy

The above figure 3 gives the comparison of accuracy for image 1 and 2 for four techniques such as FLICM, KFLICM, WFLICM and KWFLICM. From the figure it is clearly observed that the proposed method of KWFLICM gives better segmentation accuracy. The proposed method KWFLICM gives the segmentation accuracy for image 1 is 90 and for image 2 are 92.85.

V CONCLUSION

This paper provides the segmentation approach for brain tumor in MRI images. This paper uses the method of kernel metrics and weighted trade-off fuzzy factor for brain tumor segmentation. This proposed method uses the combination of both kernel metrics and weighted trade off fuzzy factor mechanism and provides better segmentation accuracy. In table 1 and 2 given some parameter values, in that less elapsed time is given by FLICM, because it is simple algorithm of Fuzzy C Means. But comparing the other three techniques WFLICM, KFLICM and proposed KWFLICM, which is the combination of weighted trade-off fuzzy factor and kernel. From the comparison it is evident that the proposed approach KWFLICM gives less elapsed time also, proposed approach gives better segmentation accuracy than other approaches .In future this paper can extended to find out the types of disease in brain from CT-scan.

ACKNOWLEDGEMENT

I am extremely indebted to prof.M.Vartharaj, HOD and Prof. V.Muralidharan for their guidance and commitment throughout and for the much needed crucial assistance.

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