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A Novel Fuzzy Rule Based Hybrid Technique for Image Segmentation

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Abstract: Image segmentation is the process of partitioning a digital image into multiple segments to simplify its representation and converting it into something that is more meaningful and easier to analyze. Main goal of this paper is to segment a medical image using hybrid and fuzzy techniques to target the part that is to be diagnosed. It is difficult to analyze a medical image because of very similar grey levels or intensity values. Fuzzy is combined with hybrid segmentation technique to resolve ambiguities in the presence of insignificant data. The proposed algorithm uses different rules to resolve the regions which have similar edges. The results are evaluated on the basis of time, variation and accuracy of the segmented image. Efficiency achieved is satisfactory.

Index Terms: Hybrid Segmentation, KFCM, FCM, Fuzzy Rule Based Segmentation.

I. INTRODUCTION

Image Segmentation

Image segmentation is used to segment the parts from an image for further processing. It is a fundamental step in medical diagrams, surgical planning and treatment. Medical images cannot be directly analyzed as they are inefficient and unrealistic. The adjacent regions are very difficult to study as edge detection and differentiation is quite difficult because of similar pixel intensity. To study these images further processing and extraction of region of interest is required. In this paper, an image segmented using Hybrid and multilevel technique is being compared with an image segmented using Hybrid and Fuzzy Rule Based Segmentation technique. The results are evaluated using the three parameters termed as Random Index, Variation and Global Index Error and total time taken by the processes to segment a particular image. The rest of the work will be grouped into the following sections. Section two comprises of the related work and section three will explain the workflow. Section four and five will respectively discuss the results and conclusion and future scope.

II. RELATED WORK

Hameed et al [1] have explained hybrid and multilevel segmentation technique which aims at producing accurate and fast segmentation of medical images or any other image with many regions of indistinguishable boundaries. Hybrid technique include Multiple thresholding and correlation matching techniques for the extraction of region of interest and then edge detection is done at multiple levels to generate the object of interest.

Kaur and Kaur [2] have compared many segmentation techniques and concluded that thresholding is the simplest of the various methods for segmentation. Further they have explained that thresholding methods are based on the histogram peaks of the image to find particular threshold values. In this technique there is no need of previous information. But it is highly dependent on peaks of the histogram. In thresholding spatial details are not considered

Y. J. Zhang [3] has explained thresholding as a method that divides the image pixels with respect to their intensity level. This method is used over images having lighter objects than background. The selection of threshold values is based on prior knowledge or information of image features. There are multiple threshold values in Multiple Thresholding like T0 and T1. By using these output image can be computed as:

$$q(x,y) = \begin{cases} m \text{ } if \text{ } P(x,y) > T1 \\ n \text{ } if \text{ } P(x,y) \leq T1 \\ o \text{ } if \text{ } P(x,y) \leq T0 \end{cases}$$

Nawaz et al [4] has exhibited a segmentation method that is based on combined color with temporal features like motion vectors. Earlier segmentation methods for region of interest coding were only based on one feature such as motion color or luminance. But the method explained by the authors is based on two features there by combining the strengths of each separate segmentation technique.

Herkand Kooy [5] have described how image correlation is required to utilize the complementary information in CT, MRI and SPECT. A practical method for automatic image correlation in three dimensions (3D) based on chamfer matching is explained. The performance of the method listed was quantified in terms of accuracy, capture range and reliability. The best results were obtained with the cost function based on the mean distance and the simplex optimization method.

Fabijańskaet al [6] has explained that correlation matching must be used where it is difficult to visually differentiate between the edges because of the similar intensity levels. Authors used a filter of known characteristics is used through which an image was passed. The points where the image template matches well with the filter are places of high correlation [9]. It is given as follows:

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$$c(x,y) = \frac{\left(\sum_x \sum_y w(x,y) f(x+i,y+j)\right)^2}{\sum x \sum y\,(w(x,y))^2 \sum x \sum y\,(f(x+i,y+j))^2} \forall_{i,j}$$

Where: c(x, y) - correlation coefficient,
W(x, y) - the template,
F (x, y) - segmented image.
Ideal match between template and image appears when c(x, y) = 1.

Karmakar and Dooley [7] have explained the importance of fuzzy in segmentation. Authors claimed that various other segmentation techniques do not perform well in the presence of vague data.. Fuzzy when combined with these techniques gives much more accurate results. In such circumstances, the processing of images that resolve ambiguities is better performed using fuzzy segmentation techniques, which are more adept at dealing with estimated data.

Chang et al [8] have described a fuzzy rule based automated system which generates membership functions automatically based on the rules formed. Further they have explained how this technique can integrate expert knowledge and is less expensive. It is able to interpret linguistic as well as numeric variables.

Chi, Z & Yan, H have listed that the performance of fuzzy rule based segmentation in many applications is sensitive to both the structure of the membership functions and associated parameters used in each membership function. For example, the fuzzy rule based segmentation technique for geographic map images, intuitively defined the structure of the membership functions with the related parameters being automatically determined,

Sasaki et al [10] used an approach that was used for segmenting the menisci region from MRI slices, with the structure of the membership functions defined from the anatomical knowledge of the knee and the parameters being taken from actual MRI device data.

Park et al [11]s used a new technique which used perceptually selected structures and parameters for the membership functions, in the segmentation of intrathoracic airways trees in computer tomography (CT) images. Validation on a phantom concluded that sub voxel accuracy was achieved for all airway sizes and airway orientations.

Karmkar et al. [12]presented a contemporary review of fuzzy rule based image segmentation techniques, and confirmed that despite being used in a wide range of applications, both the structure of membership functions and derivation of their relevant parameters were still very much application domain and image dependent.

Khokher et al [13] worked on the segmentation of a gray scale, color and texture images using graph cuts. From the input image, a graph was constructed using intensity, color and texture profiles of the image simultaneously. Based on nature of the image, a fuzzy rule based system was designed to find the weight that should be given to a specific image feature during graph development. The graph obtained from fuzzy rule based weighted average of different image features is further used in normalized graph cuts framework. The graph was iteratively bi-partitioned through the normalized graph cuts to get optimum partitions resulting in segmented image. It is concluded that the presented segmentation method provides effective results for most type of the images.

Balafar [14]: The author explained new method for image segmentation based on dominant grey level of image and fuzzy C-mean (FCM). In this the color image is converted to grey level image and stationary wavelet was applied to decrease noise and the image was clustered using ordinary FCM, afterwards, clusters with error more than a threshold were divided to two sub clusters. This process continued until there remain no such, erroneous, clusters. The dominant connected component of each cluster was obtained - if existed. In obtained dominant connected components, the 'N' biggest connected components were selected. 'N' is specified based upon considered number of clusters. Averages of grey levels of 'n' selected components, in grey level image, were considered as dominant grey levels. Dominant grey levels were used as cluster centers. Eventually, the image was clustered using specified cluster centers.

Harini [15]: the author has explained the formation of kernel for the medical images by performing the deviation of mapped image data within the scope of each region from the piecewise constant model and based on the regularization term based on the function of indices value of the region. The functional objective minimization was carried out by two steps minimization in image segmentation using graph cut methods, and minimization with respect to region parameters using constant point computation. Nearest neighbor classifiers were introduced to the benchmarked image data segmented portions. Among the different methods in supervised statistical pattern recognition, the nearest neighbor rule resulted in achieving high performance.

III. PROPOSED ALGORITHM AND WORKFLOW

Algorithm
1st phase: In the very first phase, an image is selected by the user from the dataset.

2nd phase: In the second phase Multi Thresholding is being performed. It is the transformation of an input image (I) into regions of pixels with graylevels from a set A and otherwise background B. These are represented in the equation (i) to (iv).

$$B(x,y) = \begin{cases} 1\ for\ I(x,y) \geq T(foreground) \\ 0\ for\ I(x,y) < T(background) \end{cases} \text{..... (i)}$$

T is threshold, B(x, y) is output pixel, and I(x, y) input pixel intensity value.

$$g(i,j) = \begin{cases} 1\ for\ f(i,j) \mathcal{E}\ A \\ 0\ for\ f(i,j) \mathcal{E}\ B \end{cases} \text{..... (ii)}$$

Since A is a set we divide A into n subsets as:

$$A = \cup_{i=1}^{n} A_i \quad \text{.....(iii)}$$

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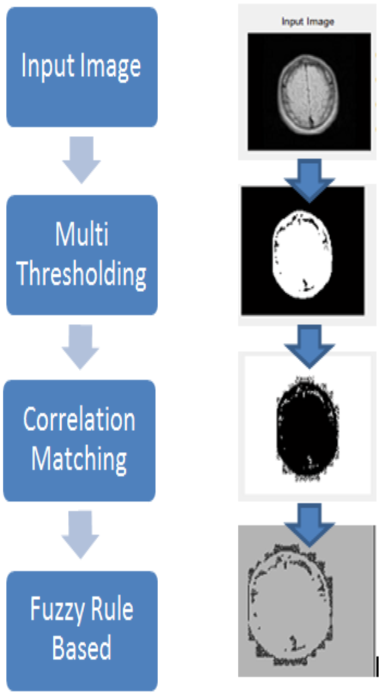

Such that equation (iv) becomes;

$$g(i,j) = \begin{cases} 1 \; for \; f(i,j) \mathcal{E} A1 \\ 2 \; for \; f(i,j) \mathcal{E} A2 \ldots\ldots \quad \text{(iv)} \\ 0 \; for \; f(i,j) \mathcal{E} B \end{cases}$$

Thus equation (iv) represents multiple thresholding.

The threshold values are selected using the peaks of the histogram computed.

3rd Phase: The points of highest correlation between an image template and filter are linked together to form an edge.

$$d = \sum_{i=1}^{n} (x_i - y_i)^2$$

It is a true metric, as it satisfies the triangle inequality, and is the most widely used distance measure of all available. In this formula, the expression data x_i and y_i are subtracted directly from each other.

Unlike the correlation-based distance functions, the Euclidean distance takes the magnitude of the expression data into account. It, therefore, preserves more information about the data.

$$\sum_{t=1}^{N} [\boldsymbol{F(t) - I(x+t)}]^{2} = \sum_{t=N}^{N} \left(\boldsymbol{F^2(t) + I^2(x+t)} - \boldsymbol{2F(t)I(x+t)} \right) = \sum_{t=N}^{N} \left(\boldsymbol{F^2(t)} \right) + \sum_{t=N}^{N} \boldsymbol{I^2(x+t)}) - \boldsymbol{2} \sum_{t=N}^{N} \boldsymbol{F(t)I(x+t)}) \ldots . (\boldsymbol{v})$$

I(x+i) =Image Template centered at x. To be correlated with the filter F (i).

- The first part of equation (v) depends on the filter
- The sum of the square of pixel value that overlap the filter formed the second part, and
- Negated magnitude that is twice the correlation between images and filter forms the third part.

The Euclidean distance between the image and filter decreases as the correlation by the two increases. This is the approach applied in this work except that a 2D (3-by-3) filter is constructed around a single image pixel and this is correlated with the boundary pixels of the regions bordering the image pixel. A basic equation for a square filter is given in equation (vi)

$$F_{corr} I(x,y) = \sum_{i=-N}^{N} \sum_{j=-N}^{N} F(i,j) I(x+t, y+t) \ldots . (vi)$$

Our approach is that 3-by-3 filters are formed around a pixel of interest (P) while the two threshold valued pixels represent the visual limits of two adjacent regions are used successively to correlate the 3-by-3 filter. The sum of the square of difference between each element of the filter and each boundary pixels are formed. The two numbers are compared and the bigger belongs to the region that produces it.

$$PFcorrl1 = \sum_{j=1} \sum_{t=1}^{n} (PF(\mathrm{t,j}) - I_1)^2 \ldots . . (vii)$$

$$PFcorrl2 = \sum_{j=1} \sum_{t=1}^{n} (PF(\mathrm{t}) - I_2)^2 \ldots . . (viii)$$

- if $PFcorrl_1 > PFcorrl_2$, pixel P belongs to region I1
- If $PFcorrl_1$is $< PFcorrl_2$, pixel P belongs to region I2.
- However, if the two are equal in magnitude, the distance between pixel P and pixels I1 and I2 are measured, then, pixel P is made part of the region where a shorter distance is measured.

4th phase: fuzzy rule based segmentation define sealing factor on the basis of class of an image is applied in this phase.

We find convolution between the 2 images and then according to the results obtained rules are created.

In the proposed work,

$$G_x = [-1,1] \ldots . \text{(i)}$$
$$G_y = G_x \ldots .. \text{(ii)}$$

After computing the relation between the two regions, on the basis of G_x and G_y, the following rules of I_x and I_y are formed.

✓If I_x =0 and I_y=0 then $I_{output}$is white
✓If $I_x \neq 0 \; and \; I_y \neq 0 \; then \; I_{output}$ is black.

On the basis of these formulated rules the image is segmented.

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IV. RESULTS & DISCUSSIONS

The hybrid (multiple thresholding and correlation matching) and fuzzy rule based were all implemented using MATLAB. In order to evaluate the performance of the proposed algorithm, a variety of different image were processed. Fifteen images are used for demonstration and numerical evaluation.

The parameters used for evaluation are as follows:

a) Random Index: The value lies between 0 and 1. 0 values indicate that 2 clusters do no correlate at any point while 1 indicates that the clusters are exactly the same.

b) Global Consistency Error: It encodes refinement in one direction only. It is symmetric.

c) Variations: It is related to the conditional entropies between the class label distributions of the segmentations.

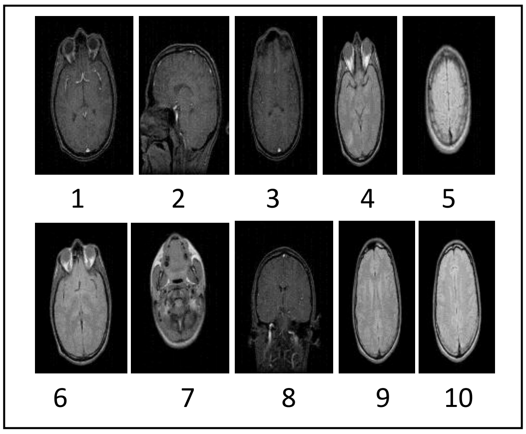

Fig 4.1 Medical images used for segmentation

This figure represents the images that have been used for image segmentation. These images are captured from various body parts. The hidden information from these images has to be extracted.

Image	Hybrid	FCM	KFCM	Proposed
1	0.268887	0.29987	0.42436	0.52438
2	0.264088	0.343402	0.43197	0.52197
3	0.278093	0.29819	0.422419	0.532419
4	0.299809	0.25786	0.382341	0.582332
5	0.247746	0.39988	0.430174	0.530194
6	0.29988	0.384290	0.414302	0.584301
7	0.272466	0.30571	0.449556	0.549579
8	0.343406	0.39980	0.472152	0.532162
9	0.29818	0.38126	0.482665	0.582695
10	0.295719	0.38124	0.476978	0.576989

Table 4.1 Comparison table for Random Index

This table represents the value for Random Index using fuzzy and template matching segmentation approaches for various 10 images. Higher the values for random index better the performance of the approach. Range of random index is between [0 1].

Image	Hybrid	FCM	KFCM	Proposed
1	0.167494	0.142392	0.128484	0.088408
2	0.190437	0.137012	0.012755	0.032968
3	0.174649	0.155888	0.105514	0.095511
4	0.146586	0.13265	0.051724	0.079717
5	0.098214	0.078213	0.132383	0.046328
6	0.142295	0.242394	0.157842	0.078822
7	0.136977	0.036572	0.136922	0.068952
8	0.198794	0.395395	0.01395	0.11791
9	0.140968	0.312966	0.04265	0.081298
10	0.145889	0.213881	0.395959	0.078184

Table 4.2 Comparison table for GCE

This table represents the value for Global Consistency Error using fuzzy and template matching segmentation approaches for various 10 images.

Image.	Hybrid	FCM	KFCM	Proposed
1	5.87904	5.87612	5.3566	5.0976
2	6.47578	5.43478	5.56800	5.35902
3	5.60181	5.09883	4.7362	4.8332
4	5.4997	5.0685	4.72866	4.73146
5	4.76662	4.56360	4.99862	4.73146
6	5.45582	5.29987	4.89754	4.69803
7	5.24317	5.33914	4.73788	4.45328
8	5.70503	5.42803	5.21398	5.02648
9	5.22803	5.31909	4.99567	4.49498
10	5.31517	5.20817	4.65882	4.55019

Table 4.3 Comparison table for Variance

This table represents the value Variance using fuzzy and template matching segmentation approaches for various 10 images

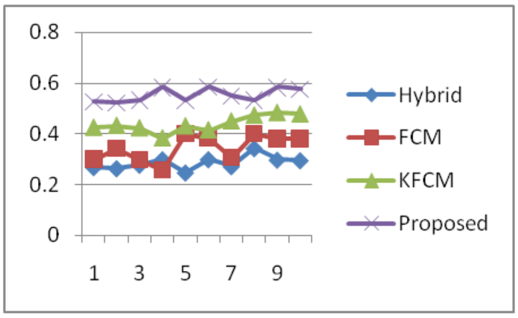

Fig 4.2 Graph for Random Index

This graph represents the difference between values of random index between hybrid, FCM, KFCM k and proposed work. Values near to 1 will provide better results.

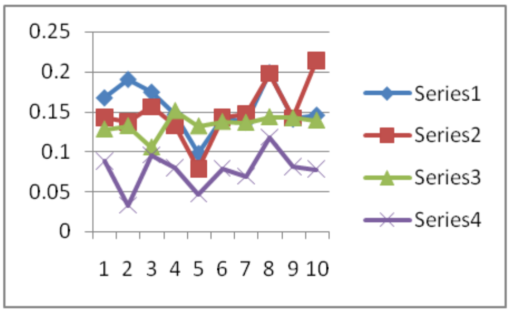

Fig 4.3 Graph for GCE

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This graph represents the difference between values of GCE between hybrid, FCM, KFCM and proposed work. Lower the GCE better the performance.

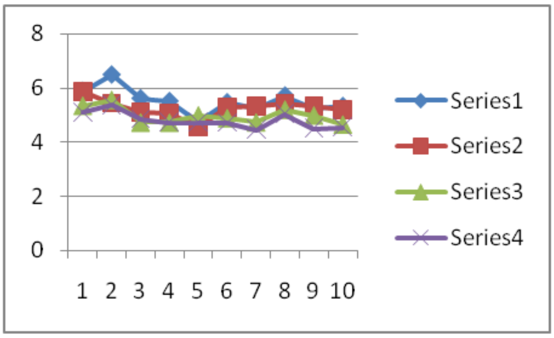

Fig 4.4 Graph for Variance

This graph represents the difference between values of Variance between hybrid, FCM, KFCM and proposed work. Value of variance should be less amongst all the techniques.

For performance evaluation of proposed algorithm, this approach is implemented on 50 different medical images available in the dataset. Parameters have been computed for both previous and proposed work. The average value is computed for all the three parameters used for performance evaluation. This average represents that proposed work provide better results as compare to previous one.

Parameters	Hybrid	FCM	KFCM	Proposed
Random Index	0.295595	0.323321	0.374525	0.567406
GCE	0.149451	0.152462	0.142561	0.075687
Variance	5.287112	5.223111	5.200130	4.510934

Time is also one of the important factor for computing the efficiency of any algorithm therefore total time taken by each technique is computed and listed below:

Hybrid	FCM	KFCM	Proposed
0.0439208	18.4185	18.5234	0.437791

V. CONCLUSION AND FUTURE SCOPE

From the above discussions it is concluded that the proposed technique is less prone to errors and segments the image accurately. And the time taken to calculate the region of interest is also less as compared with FCM and KFCM. In future, different rules with respect to the pixel region can be formed or different threshold values can be used to enhance the segmentation process.

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