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Automatic Spinal Cord Segmentation From Medical MR Images using Hybrid Algorithms

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Abstract— Medical image processing is the top most research area. There are huge amount of researches found in the medical image analyze, classification and segmentation process. Spinal cord segmentation of MRI images is the challenging process. In the proposed research work, automatic Spinal Cord (SC) segmentation from medical MRI image is performed with various techniques. The proposed work improves the segmentation with less iteration and improved accuracy by adopting improved Weighted Expectation Maximization (WEM) and Strong Fitness Firefly (SFF) algorithms. The proposed work effectively segments the spinal cord by applying effective pre-processing, image enhancement process and clustering with less iterations. Using the combination of different techniques, the proposed system effectively identifies the spinal cord from the MRI image, the experiments performed using Matlab tool. The accuracy is calculated and shown for the proposed system. The result shows, the mixed approach of WEM and SFF increases the segmentation accuracy than using the WEM alone.

Keywords-*Medical image processing; Spinal cord segmentation; MRI Images; Segmentation;Strong Fitness Firefly;Weighted Expectation maximization*

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I. INTRODUCTION

Automatic and accurate segmentation of Magnetic Resonance (MR) spinal cord images is extremely important for medical analysis and interpretation [1]. The segmentation of medical images and analysis is becoming increasingly important in the medical field, since it is crucial for several treatment planning and diagnosing of abnormalities. The MRI scan of spinal cord allows the physicians to assess a patient's spinal anatomy, to measure tissue volume to examine abnormalities growth, to assess inflammation, compression of the spinal and nerves, to detect spinal injury, spine metastasis, tumor and to analyses neurological diseases such as multiple sclerosis.Image segmentation is the partition of a digital image into similar regions to simplify the image representation into something more meaningful and easier to analyze. These image analysis and segmentation techniques [2] are often used to detect the abnormalities in the human bodies through scanned images. Magnetic Resonance imaging scan of spinal is the most common test taken to the analysis and surgical assistance in spinal and other human part. Compared to all the other imaging techniques, MRI is efficient in the application of spinal cord analysis and detection and, due to the high contrast of soft tissues, high spatial resolution, and absence of any harmful radiation. Manual segmentation of magnetic resonance spinal cord abnormalities images is a challenging and time-consuming task. Manual segmentation is highly prone to error due to inter observer variability and human error. As a result, the segmentation results are highly inferior leading to fatal results. So, the proposed system has developed an improved image segmentation method to automatically detect the spinal cord from MRI images [3].

The present work focuses on designing, applying and assessing a tool for the radiologist to accurately segment spinal cord. To promote a medical support system for better decision making which is developed by hybrid WEM clustering and SFF based segmentation, multiple feature set, wrapper/hybrid approach based feature selection combined with new technique to detect the spinal cord regions from the MRI images. The proposed system estimates the performance of the segmentation and the efficiency of its detection accuracy. The works uses multiple features set such as color, texture and shape features from MRI for improving the MRI segmentation accuracies. The proposed work aims to validate and analyze the segmentation results in various MRI images.

II. PROBLEM STATEMENT

Accurate segmentation of MR spinal cord regions from the MRI images is a tedious job in medical imaging and diagnostic radiology [4]. In recent years, researchers from different disciplines ranging from medical to mathematical and computer sciences have combined their knowledge and efforts to better understanding of the disease and find more effective treatments. In recent times, hybrid intelligent MRI image analysis approaches have been explored for computer aided diagnosis to improve the sensitivity and specificity of radiological tests involving medical images. The use of artificial intelligent techniques for instance, Particle Swarm Optimization, Ant Colony Optimization, Artificial Fish Swarm algorithm and Firefly algorithm has shown great potential in this field, further soft computing techniques enhance the interpretation for better decision making.

A number of studies have been done on MRI segmentation. These include techniques using Neural Networks [5]; Fuzzy c Means [6], and very few techniques have used Support Vector Machine (SVM) [7] for image classification, which described abnormalities objects tracking method for MRI images that utilizes color-converted segmentation algorithm with K-means clustering technique [8].

There are several techniques have been proposed in the literature, the process and its merits, demerits have described in [9]. The issue with such a method is that it is highly dependent on the initial state and its arrival at local optimal solution. Also this method relies on intensity-level segmentation, which is susceptible to wrong segmentation. Further, computer aided segmentation to categorize MR spinal cord images with its different types not been developed with WEM and SFF segmentation approach..

III. PROPOSED SYSTEM

By considering the above facts, the proposed system has been developed using hybrid WEM clustering and SFF based segmentation algorithm with wrapper/hybrid feature selection approach to enhance the segmentation accuracy of magnetic resonance spinal cord images. In the present research, three approaches are utilized for segmentation. The proposed system performs the color enhancements for the accurate spinal region identification.

i) Effective pre-processing is proposed.
ii) Weighted Expectation Maximization based clustering algorithm(WEM).
iii) Color converted hybrid WFF (Weighted Fitness Firefly)-WEM clustering segmentation.

The proposed system is designed to effectively segment spinal cord region from T1 images. The MRI spinal cord images cannot be segmented directly without any preprocessing steps. So, it is indispensable to perform pre-processing on the input image, so that the image gets transformed to be relevant for further processing. Segmentation of spinal cord from MRI is a very important task. An image enhancement method is concerned about improving the visual appearance of images from magnetic resonance image .The proposed method consist of three main steps, image selection and pre-processing, feature selection and segmentation.

A. ***T1-weighted MRI:*** A T1 weighted image is one where the contrast depends predominantly on the differences in the T1 times between the tissues for example, fat and water. T1-weighted image provide a lot of anatomical information about the spinal cord. T1-weighted image is particularly useful for identifying lesions; abnormal areas appear as dark spots. T1-weighted images provide good contrast between the gray and white matter. In T1-weighted image, fat appears bright, water and fluids appear dark. T1-weighted images optimally show normal soft-tissue anatomy and fat. Figure 1.0 shows an example of T1-weighted MRI image.

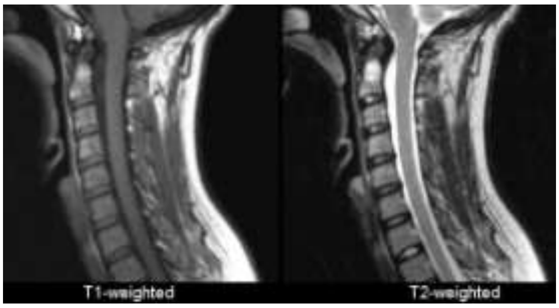

Figure 1.0 T1 and T2-weighted Midsagittal MR Images of the cervical spine

B. ***T2-weighted MRI:*** A T2 weighted image is an image whose contrast is predominantly due to the differences in T2 decay times of tissues.T2 weighted scans use a Spin Echo (SE) sequence, with long TE and long TR. They are particularly well suited to edemas they are sensitive to water content. T2 weighted images offer high sensitivity to most pathologic processes as most pathology has increased water content and is therefore bright on T2 weighted images. In T2-weighted image, fat appears dark, water and fluids appear bright on T2-weighted images. T2-weighted images optimally show fluid and abnormalities.

In this study,T1 weighted MRI of cervical region acquired from hospital. The images got from the MRI of patients ranged from 27 to 55 years. The total number of MRI spinal cord images obtained from the hospital is 40. Another dataset that has been utilized for testing the developed CAD system is taken from the publicly available sources. Grayscale or intensity images are displayed of default size of 512 x 512. A grayscale image can be specified by giving a large matrix. MRI spinal cord image collected from the hospital shown in fig 2.0.

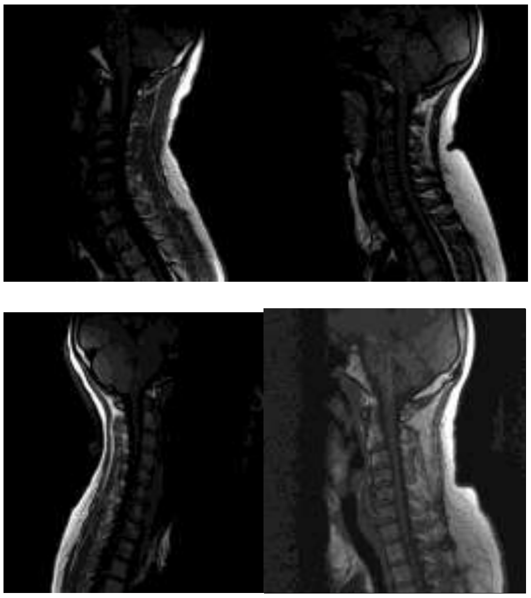

Fig 2.0 MR Images of spinal cord in cervical region collected from the hospital.

Preliminary diagnosing of MRI images from the hospital cannot be relied on because of the chances of occurrence of artifacts resulting in degraded quality of image, while others may be confused with segmentation. Obtained MRI image usually contains limited artifacts. It becomes complex one for doctors in analyzing them. By increasing the contrast of an image, it is easy to analyze. In order to find the spinal cord region efficiently, there is a need for proper image enhancement process. In the proposed system a set of algorithms have been proposed and named as WFF and WEM. The hybridization method allows fast and accurate spinal region segmentation.

The proposed system part is to begin with the feature extraction techniques used for obtaining the content descriptive features. From the segmented image, features are computed to encode the useful diagnostic information. After image segmentation, a feature extraction step reduces the data by measuring certain properties of the labeled objects. The extracted features act as input to classifier by considering the description of relevant properties of the image into feature space. In the present research, statistical features based on gray level co-occurrence matrix, gray level run length features, color and shape features are extracted and used to detect spinal cord. The diagnosis model discussed in the present work is to segment the spinal cord images by employing WEM combined with SFF approaches.

Algorithm: WFF_WEM

Begin

1. *Read the image I, and perform pre-process using G (gabor)*
2. *Initial cluster center and segment the data from the maximum likelihood.*
3. *Initialize the objective function f(x), x= (x1,x2..xn)*
4. *Select the initial population from the WEM centroid xi(1=1,2…n)*
5. *Set Max number of iterations = Max generations=5:*
6. *Initialize algorithm's parameters: number of fireflies (n) =20, α=0.2; y=1.0; β0 = 0.1; Set t=1*
7. *Define absorption coefficient λ, Define centers of cluster from WEM: c←k*

Light intensity of firefly I_i at is determined by value of objective function f ( ) Evaluate the fitness of the population f( ) which is directly proportional to light intensity

While (t<=Max generation)

fori=1: n (for all n fireflies)

for j=1: n (for all n fireflies)

if(Ij>Ii)

Define weight parameters wi: Set $\sum_{i=1}^{N} wi = 1$ *1where wi<wi+1, <wi+2…<wi+n*

Higher fitness firefly is given with more weight and vice versa

Find mean weighted best position between two fireflies and display it

Move firefly i towards j to re fine position of fireflies (clusters center)

End if

Vary attractiveness with distance r

Update new solutions and light intensity with mean weighted best position.

End for j;

End for i;

Rank the fireflies and find the current best cluster result t=t+1

End while

8. *Rank the fireflies and find global best and extract the position of global best Repeat*

Do until predefined iteration

End. [10]

In the proposed weighted firefly algorithm firefly i is moved towards j using equation (2.0). In weighted firefly algorithm numbered size of n fireflies at locations within 2D-dimensional search space is considered. The fitness of population which is directly proportional to light intensity is now evaluated. The fitness score calculation process is given by equation (3.0) which indicates the value of the average distance between the data in matrix D and the cluster centroid to which they belong (ADVDC).

$$\mathbf{N=f(x)=}\sum_{i=1}^{Dc}\{\sum_{j=1}^{ki} d(ci, mij)/ki\ )\ /Dc\} \quad \mathbf{(1.0)}$$

Where m_{ij} denotes the *j*th data in *i*th cluster in matrix D (D be the *a*b** color information+ gabor texture information assigned as a matrix); Ci is the centroid vector; d(ci,mij) is the distance between mij and ci;ki stands for the number of pixels which belong to cluster stands for the number of clusters with maximum likelihood. Now the intensity value of a firefly is compared. If Ij>Ii, the fitness score value is assigned based on intensity, the higher intensity firefly weighs higher and lower intensity firefly weighs less. Now the position of the firefly is multiplied with the fitness score value and the position average of all the fireflies is then taken. This provides the best weighted position. Moving the firefly to a weighted best position rather than best position omits sharp reduction of fitness. Further fitness gradually changes from iteration to iteration and the average distance is very less. Therefore the searching process cannot go farther away from the local minima point. It cannot skip local minima point. This could avoid random movement of firefly. In proposed algorithm movement of the firefly denoted by,

$$\mathbf{Oi^{t+1} = Oi^{t} + \beta\ exp[^{-yr^2}ij](Oj\text{-}Oi)+\alpha[rand\text{-}1/2]*si} \quad \mathbf{(2.0)}$$

Where w is the weight parameter and the summation of fitness score value is 1in this algorithm. The fitness score value is calculated by following equation

Fitness score (s)=fitness(i)-fitness(i-1)/ fitness(i) (3.0)

Congenially, compare all the fireflies and update the movement phase of each firefly by evaluating the light intensity using the fitness function. This procedure is continued till it converges to optimal cluster center. After obtaining optimal cluster centers, the WEM algorithm is initialized with this center. The WEM is then used to cluster the objects into specified number of clusters. Algorithm shows pseudo code of WFF-WEM algorithm. In WFF-WEM algorithm, fitness gradually changes from one iteration to other iteration and after 20 iterations it maintains a stable value. As the average distance value is the lowest, the probability of obtaining local optima is very less and generates the highest clustering compact results than the other methods. Finally, the proposed system is realized and the discrimination capability is assessed with the test images of different categories**.** The proposed system consists of preprocessing, clustering and image segmentation process. In the present system, in addition to color feature vector (colors in and spaces) gabor texture features is added to construct feature vectors for clustering algorithm, texture features in MRI spinal cord images are extracted using Gabor Wavelet Transform, Gabor wavelet features which is a feature vector (texture representation) created using mean and standard deviation as the feature components with a scale of 4 and orientation of 2 can effectively extract the texture frequency and orientation information. Hence, color feature and Gabor texture features are feature vectors, which will be given to the clustering process as an input. Here, WEM algorithm is being used for the clustering purpose. In WFF-WEM algorithm, fitness gradually changes from one to other iteration and after 25 iterations it maintains a stable value. As the average distance value is the lowest, the probability of obtaining local optima is very less and generates the highest clustering compact results than the other methods.

IV. IMPLEMENTATION RESULTS

The proposed system is implemented by using Matlab software with T1 weighted MR images of spinal cord in the cervical region. The segmentation results obtained using real MR spinal cord images is shown in this section. The output of the proposed system is shown in fig 3.0. Validation is performed by comparing the proposed method's output with manually obtained ground truth. For quantitative comparison of the performance of proposed methods with traditional EM, manually obtained ground truth T2 weighted MRI spinal cord datasets from the hospital and radiology center is used. Table 1.0 shows comparisons of the different clustering methods used for segmentation.

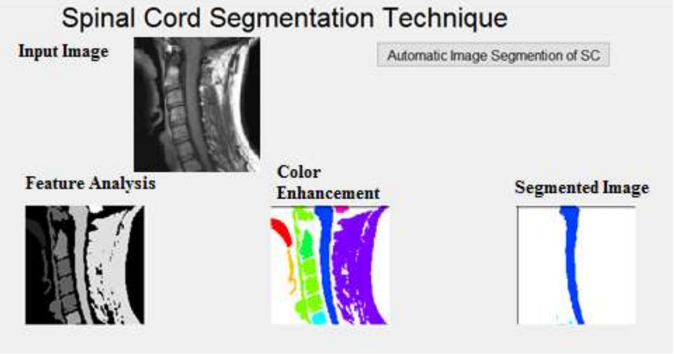

Fig 3.0 Segmentation Performance Comparison chart

The performance analysis of the proposed method is compared in terms of accuracy. The performance of the proposed segmentation algorithm has been validated using the most commonly used validation metric tanimoto's index. From table 1.0 quantitatively, the proposed method has produced low ADVDC (Average distance Data Cluster Centriod), low intra cluster distance, less quantization error and high inter cluster distance compared to other segmentation approaches. The evaluation of segmentation performance is also carried out quantitatively by using sensitivity, specificity, false positive fraction (FPR), false negative fraction (FNR), total misclassification rate and tanimoto's index in the present research. From table 2.0, it shows that the highest value for sensitivity, specificity and low value for FPR, FNR and total misclassification result is obtained by hybrid methods.

Algorithm	ADVDC	Intra Cluster	Inter cluster	Quantization Error
EM	95.321	6.9871	48.32	0.5711
Propseg	94.2897	6.31	50.212	0.4828
WFF_WEM	48.5722	3.1	62.1234	0.0106

Table 1.0Comparison of Clustering Segmentation Performance for the Proposed Hybrid Techniques and Other Works

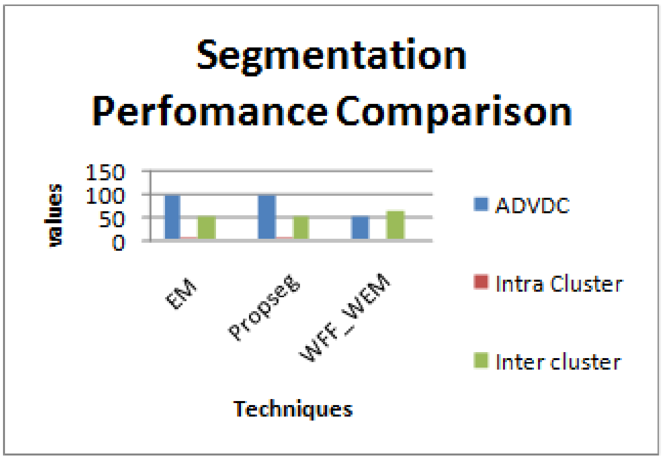

Figure 4.0 Segmentation Performance Comparison chart

Figure 4.0 shows the segmentation performance comparison in terms of intra and inter-cluster, ADVDC between existing and proposed algorithms. It has shown that that the proposed algorithm generates more accurate, robust and better segmentation results than the existing methods. As far the computational complexity is concerned, it is observed that, the proposed WFF-WEM hybrid method reduces the computation time compared to other conventional segmentation techniques. Moreover it is slightly higher than EM and lower than existing techniques. Table 3.0, shows the computational time involved in various methods with the proposed method. The hybrid method achieved convincing results within a reasonably fast computation time.

Accuracy: The results were represented using confusion matrix. The results obtained are as follows:

Accuracy calculation		Predicted	
		Positive	**Negative**
Observed	Positive	TP	FN
	Negative	FP	TN

Table 2.0 Confusion Matrix

True positives (TP) refer to the positive tuples that were correctly labeled by the classifier, while true negatives (TN) are the negative tuples that were correctly labeled by the classifier. False positives (FP) are the negative tuples that were incorrectly labeled. Similarly, false negatives (FN) are the positive tuples that were incorrectly labeled. In the above table 2.0, performance is measured in terms of precision, recall and accuracy and is computed using the confusion matrix.

$$\text{Accuracy} = \frac{tp + tn}{tp + tn + fp + fn}$$

Figure 5.0 accuracy calculation formulas

Method	Accuracy
EM	88
Propseg	92
WFF-WEM	96

Table 3.0 Segmentation Accuracies Obtained with

Proposed method and Other Clustering Segmentation from Literature

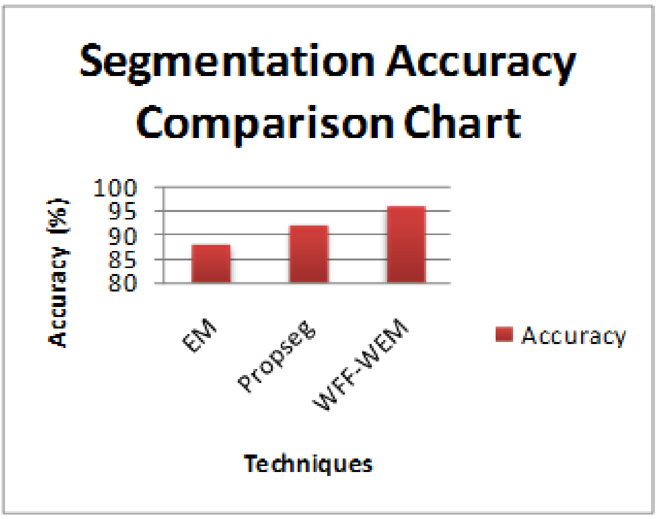

Figure 6.0 segmentation accuracy comparisons

A summary of different clustering segmentation methods together with their reported results in terms of the accuracy is summarized in table 3.0.Comparing to these papers, an effective hybrid clustering algorithm is proposed in the present research which provides a better accuracy. It has shown that that the proposed hybrid algorithms generate more accurate, robust and better clustering results.

CONCLUSIONS

This paper presented a complete and automatic pipeline for segmentation of the spinal cord from real time MRI Images. The methods were anchored on the concept of propagated deformable models, continuously adapting local orientation of mesh structures based on contrast levels in the image. The sensitivity of influential parameters related to the propagation of mesh were thoroughly investigated and further tested on T1 weighted sequences. The effect of the initialization position on spinal cord segmentation accuracy was assessed in this proposal, the proposed system developed a hybrid segmentation method, which is combined the weighted firefly and weighted EM algorithms. The method was combined with an automatic spinal cord detection technique, in order to output useful results.

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