Medical Image Segmentation using Enhanced Neuro Fuzzy Classification Algorithm based on Multi-Modal Function of PSO

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***Abstract*—Segmentation is the process of partitioning a digital image into multiple segments. Image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. According to the advanced medical pictures are not invariably delineated victimisation the constant quantity technique with previous likelihood, resulting in the distinction between the particular physical model and also the basic hypothesis of the model, specifically the matter of "model mismatch", the strategy of medical image segmentation supported the multi-modal operate optimisation is projected during this paper. It projected a density model of the statistic orthogonal polynomials for image knowledge, the novel Particle Swarm Optimisation (PSO) technique is employed to resolve the multi-modal operate optimisation downside. On the idea of the heuristic optimisation search, the novel technique was prospering in multi-modal operate optimisation. The FCM cluster formula is employed to section image with native optimum resolution because of the cluster centre.**

Particle swarm optimisation (PSO) is a recent approach that may be used in a very wide selection of applications. It associate in nursing organic process computing technique supported colony ability that could be a higher parallel looking out formula. Image segmentation could be a low level vision task that is applicable in numerous applications like seeing medical imaging, document analysis, simply to call some. PSO itself could be a terribly powerful technique and once combined with alternative machine intelligence technique leads to a really affected approach. During this paper was reviewed however PSO will be combined with numerous alternative methodologies like neural networks, clustering, and thresholding using neuro fuzzy clustering based image segmentation. Thus, the proposed approach increases the accuracy level and reduces the time.

Keywords—Model mismatch, optimization, PSO, FCM, thresholding, neuro fuzzy clustering.

I. Introduction

Image processing is a form of signal processing, in which the input is an image(such as a photograph or video frame), the output of image processing may be either an image or a set of characteristics or parameters related to the image. It usually refers to digital image processing but also it refers optical and analog image processing and it deals with images in bit mapped graphics format that have been scanned in or captured with digital cameras. The acquisition of image is referred to as imaging.

Various techniques have been developed in image processing during the last four to five decades[1][2]. Most of the techniques are developed for enhancing images obtained from unmanned spacecrafts, space probes and military reconnaissance flights. Image processing systems are popular due to easy availability of powerful PC, large memory size devices, graphics software's etc. Image processing is used in various application such as: Remote Sensing, Medical Imaging, Non-destructive Evaluation, Material Science, Military ,Film Industry.

Image segmentation is the important process of image analysis and image understanding.[1] It is defined as the process of partitioning the digital image into different sub regions of homogeneity. The objective of image segmentation is to cluster pixels int o salient image regions i.e., regions corresponding to individual surfaces, objects or natural parts of objects. Segmentation might be used for object recognition, image compression, image editing, etc. The quality of the image segmentation based on digital image. In the case of simple images the segmentation process is clear and effective due to small pixel variation, whereas in the case of complex images, the utility for subsequent processing becomes questionable.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics. When applied to a stack of images, typical in medical, the resulting contours after image segmentation can be used to create 3D reconstruction with the help of interpolation algorithms like marching cubes.

The organization of the paper is as follows. In section II, the detail of existing methods. In section III, explanation about proposed method . The experimental results comparisons are presented in section IV. Finally, section V,

***Manuscript received Dec, 2014*.**
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conclusion and future enhancement of the paper work is noted.

II. EXISTING SYSTEM

The existing system used particle swarm optimization method with FCM segmentation algorithm. The novel method was successful in multi-modal function optimization. The FCM clustering algorithm is used to segment image with local optimal solution as the cluster centre

A.Particle swarm optimization (pso)

The Particle swarm optimization (PSO), first introduced by Kennedy and Beernaert , is a stochastic optimization technique that is similar to the behaviour of a flock of birds or the sociological behaviour of a group of people[5]. Consider a scenario in which a flock of birds are searching for a piece of food in an area. All the birds do not exactly know where the food is, but with each iteration they come to know how far the food is. The best strategy will be to follow the bird which is near to food and also from its own previous best position. This is the basic idea on which PSO works. In PSO algorithm the five essential parameters that are considered are as,

Step 1: Initialisation. The velocity and position of all particles are randomly set to within pre-defined ranges.

Step 2: Velocity Updating. In each iteration, the velocities of all particles are updated according to

$$\vec{v_i} = w\vec{v_i} + c_1R_1(\vec{p}_{i,best}\text{-}\vec{p_i})+c_2R_2(\vec{g}_{i,best}\text{-}\vec{p_i})$$

Where and are the velocity and position of particle I, respectively. and are the position with the 'best' objective value found so far by particle *i* and the entire population respectively; *w* is used to control the convergence behaviour of PSO; R1 and R2 are random variables in the range [0, 1]; c1 and c2 control how far a particle move in single iteration. After updating, velocity should be checked and secured within a pre-specified range to avoid violent random walking.

Step 3: Position Updating. Assuming a unit time interval between successive iterations, the positions of all particles are updated according to.

$$\vec{p_i} = \vec{p_i} + \vec{v_i}$$

After updating, *pi* should be checked and limited to the allowed range.

$$\begin{array}{ll} \vec{p}_{i,best}=\vec{p}_i & \text{if } f(\vec{p}_i) > f(\vec{p}_{i,best}) \\ \vec{g}_{i,best}=\vec{g}_i & \text{if } f(\vec{g}_i) > f(\vec{g}_{i,best}) \end{array}$$

Step 4: Memory Updating: Update and when condition is met

Step 5: Termination Checking. The algorithm repeats Steps 2 to 4 until certain termination conditions are met, such as a pre-defined number of iterations or a failure to make progress for a certain number of iterations. Once terminated, the algorithm reports the values of and f as its solution .

Algorithm: pso-seg algorithm

Assuming the population size of the particle swarm is S, the current location of the ith particle (i = 1, 2, ..., S) in the n-dimension space is xi = (xi1, xi2, ..., xin), and the current flight speed is vi = (vi1, vi2, ..., vin). The location of each particle is a potential solution. We can calculate its fitness value by plugging xi into the objective function and measure its pros and cons according to the size of the fitness value. The best fitness value that each particle has experienced is called the individual best position, it is recorded as pi = (pi1, pi2, ..., pin). The best fitness value that the whole particles experienced is recorded as pg = (pg1, pg2, ...,pgn). As for the iteration of the PSO algorithm, the particle updates its own speed and position through tacking pi and pg dynamically. In the minimization problem, the smaller the objective function value, the better the corresponding fitness. Setting f(x) the minimized objective function, so the individual best position of the particle i is defined as:

$$p_i(n+1) = \begin{cases} p_i(n) & if\ f(x_i(n+1) \geq f(p_i(n))) \\ x_i(n+1) & if\ f(x_i(n+1) < f(y_i(n))) \end{cases}$$

The best fitness value that each particle experienced in the particle swarm is called global best position and it is defined as:

$$\begin{aligned} p_g(n) &= \{p_1(n), p_2(n), ..., p_m(n)\} | f(p_g(n)) \\ &= \min\{f(p_1(n)), f(p_2(n)), ..., f(p_m(n))\} \end{aligned}$$

According to the above definition, the evolution formula of the particle *i*(*i*= 1, 2, ...,*N*) in the *j*th (*i*= 1, 2, ...,*N*) dimension subspace can be described as:

$$v_{ij}(t+1) = \omega v_{ij}(t) + c_1r_1(t)(p_{ij}(t) - x_{ij}(t)) + c_2r_2(t)(p_{gj}(t) - x_{ij}(t))$$
$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1)$$

B.Fuzzy c-means clustering

Because of the advantages of magnetic resonance imaging (MRI) over other diagnostic imaging, the majority of researches in medical image segmentation pertain to its use for MR images, and there are a lot of methods available for MR image segmentation. Among them, fuzzy segmentation methods are of considerable benefits, because they could retain much more information from the original image than hard segmentation methods. In particular, the fuzzy C-means (FCM) algorithm, assign pixels to fuzzy clusters without labels. Unlike the hard clustering methods otherwise known as k-means clustering which force pixels to belong exclusively to one class, FCM allows pixels to belong to multiple clusters with varying degrees of membership. Because of the additional flexibility, The Fuzzy C-means clustering algorithm (FCM) is a soft segmentation method that has been used extensively for segmentation of MR images applications recently. However, its main disadvantages include its computational complexity and the fact that the performance degrades significantly with increased noise (NG and et al, 2006)[4][6].

Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. In other word, each point has a degree of belonging to clusters,

ISSN: 2278 – 1323

as in fuzzy logic, rather than belonging completely to one cluster. Thus, points on the edge of a cluster may be in the cluster to a lesser degree than points in the center of cluster. Fuzzy c-means has been a very important tool for image processing in clustering objects in an image. In the 70's, mathematicians introduced the spatial term into the FCM algorithm to improve the accuracy of clustering under noise. (Wikipedia 2009)

Fuzzy c-means algorithm allows data to belong to two or more clusters with different membership coefficient. Fuzzy C-Means clustering is an iterative process. First, the initial fuzzy partition matrix is generated and the initial fuzzy cluster centers are calculated.

In each step of the iteration, the cluster centers and the membership grade point are updated and the objective function is minimized to find the best location for the clusters. The process stops when the maximum number of iterations is reached, or when the objective function improvement between two consecutive iterations is less than the minimum amount of improvement specified.

Moreover the update in the iteration is done using the membership degree as well as the centre of the cluster that is the two parameter change as the steps are being repeated until a set point called the threshold is reached or the process stops when the maximum number of iterations is reached, or when the objective function improvement between two consecutive iterations is less than the minimum amount of improvement specified. In addition a fuzziness coefficient 'm' is chosen which may be any real number greater than 1.

C.Disadvantage of existing system

Image segmentation is a vital part of image processing. Segmentation has its application widespread in the field of medical images in order to diagnose curious diseases. The same medical images can be segmented manually. But the accuracy of image segmentation using the segmentation algorithms is more when compared with the manual segmentation. In the field of medical diagnosis an extensive diversity of imaging techniques is presently available, such as radiography, computed tomography (CT) and magnetic resonance imaging (MRI). Medical image segmentation is an essential step for most consequent image analysis tasks. Although the original FCM algorithm yields good results for segmenting noise free images, it fails to segment images corrupted by noise, outliers and other imaging artifact.

III PROPOSED METHOD

The work involves the feature extraction of MRI images of brain, dimensionality reduction and finally developing a suitable neuro fuzzy classifier to classify the normal and abnormal brain images. Images of brain are obtained from MRI and the textural features are extracted using principal component analysis (PCA) technique. These features are used to train the neuro fuzzy classifier. The neuro fuzzy classifier is used for classification is the Adaptive Network based Fuzzy Inference system(ANFIS).The developed neuro fuzzy classifier is tested for classification of different brain MRI samples. Thus, the proposed work emphasizes on development of Neural Network and Fuzzy logic based method for the classification of MRI brain images[9][17].

A.Feature extraction

The feature extraction extracts the features of importance for image recognition. The feature extracted gives the property of the text character, which can be used for training the database. The obtained trained feature is compared with the test sample feature obtained and classified as one of the extracted character. The feature extraction is done using principal component analysis (PCA).This technique is mostly used for the image recognition and reduction. It reduces the large dimensionality of the data.The feature extraction of the test image is done. The memory of an MR image recognizer is generally simulated by a training set. The training database is a set of MR images. The task of MR image recognizer is to find the most similar feature vector among the training set image and test image. In the training phase, feature vectors are extracted for each image in the training set. Let_1 be a training image of image 1 which has a pixel resolution of MxN (M rows, N columns). In order to extract PCA features of_1, first convert the image into a pixel vector $\Phi 1$ by concatenating each of M rows into a single vector. The length of the vector $\Phi 1$ will be MxN.

B. Enhanced Neuro fuzzy classifier

A neuro-fuzzy classifier is used to detect the abnormalities in the MRI brain images. Generally the input layer consists of seven neurons corresponding to the seven features. The output layer consist of one neuron indicating whether the MRI is of a normal brain or abnormal and the hidden layer changes according to the number of rules that give best recognition rate for each group of features. Here the neuro-fuzzy classifier used is based on the ANFIS technique. An ANFIS system is a combination of neural network and fuzzy systems in which that neural network is used to determine the parameters of fuzzy system. ANFIS largely removes the requirement for manual optimization of parameters of fuzzy system. The neuro-fuzzy system with the learning capabilities of neural network and with the advantages of the rule-base fuzzy system can improve the performance significantly and neuro-fuzzy system can also provide a mechanism to incorporate past observations into the classification process.In neural network the training essentially builds the system. However, using a neuro-fuzzy technique, the system is built by fuzzy logic definitions and it is then refined with the help of neural network training algorithms. Some advantages of ANFIS systems are:

- It refines if-then rules to describe the behaviour of a complex system.
- It does not require prior human expertise
- It uses membership functions plus desired dataset to approximate.
- It provides greater choice of membership functions to use.
- Very fast convergence time.

The first step of the proposed segmentation method is to automatically locate initial pixels, called seeds, within the defective regions. Once the seeds are determined, they become the input data for FMMIS. The seed locations in the image are determined by an adaptive thresholding method, which is based on certain features of each wood board im-age.

This allows us to take into account the great variability of the wood's color.The features used are the mean color intensity value, and the minimum colour intensity value, of the image for each channel (t=R,G,B).For each color channel of the board image, a cumulative histogram ,is constructed as follows

$$H_t(n) = \sum_{i=\eta_t}^{n} h_t(i) \rightarrow 1$$

For each t=R,G,B.Where in the intensity level (0≤n≤255) and ht is the histogram of the boardimage for channel t . Since h t (i)=0for all i <η t , the sum in Equation [1] starts fromi=t . From the cumulative histo-gram an adaptive intensity level is de-fined as:

$$\Theta_t = \alpha H(\mu_t) \rightarrow 2$$

Where 0≤α≤1 is a user-defined value.Typicallyα≤0.01, since only a few pixels belonging to defective regions are searched for as seeds, and usually the defect areas cover less than 10 percent of the image. If the color intensities were constrained to be betweenH tandθt, only the darker defects would be detected. But usually there are several defects on the same board, some brighter than others. To take into account this fact, an extra color intensity level, ξt, is defined as:

$$\xi_t = \frac{\Theta_t + \mu_t}{2} \rightarrow 3$$

For each board, the seeds are taken from the following intensity range:

$$I_t = \begin{Bmatrix} [\eta_t \Theta_t] \wedge \xi_t & if & \Theta_t < \lambda_t \\ [\eta_t \Theta_t] & if & \Theta_t \geq \lambda_t \end{Bmatrix} \rightarrow 4$$

Where λt is a user-defined threshold for each channel. The rationale underlying this parameter is that when the entire defects in a board image are not too dark.

In proposed method the interest is on making the number of iterations equal to that of the fuzzy c means, and still get an optimum result. This implies that irrespective of the lower number of iteration, we will still get an perfect result.

IV. RESULTS AND DISCUSSION

This section gives the overview of the conducted experiment and presents the obtained result to evaluate the performance of the enhanced neuro fuzzy classification algorithm. The work involves the feature extraction of MRI images of brain, dimensionality reduction and finally developing a suitable neuro fuzzy classifier to classify the normal and abnormal brain images. Images of brain are obtained from MRI and the textural features are extracted. These features are used to train the neuro fuzzy classifier. The neuro fuzzy classifier is used for classification of affected region.The developed neuro fuzzy classifier is tested for classification of different brain MRI samples. Thus, the proposed work emphasizes on development of Neural Network and Fuzzy logic based method for the classification of MRI brain images. Clearly, the proposed algorithm gives remarkable improvement in image segmentation better than existing system. The proposed enhanced neuro fuzzy classifier algorithm efficiently reduces the time and increases the accuracy.

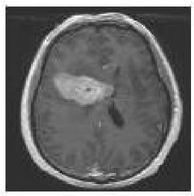


Figure 1: Original Input Image

The figure 1 shows the user selected original input image for performing image segmentation. The input image is collected from online MRI brain image.

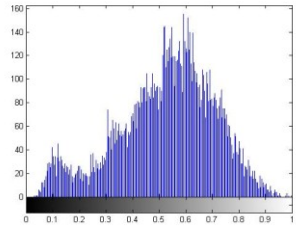


Figure 2: Histogram of the input image

The figure 2 shows the histogram of the original input image of MRI Brain image

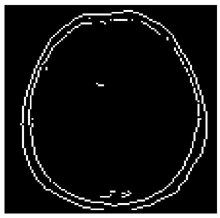


Figure 3: Sobel edge detection image

The figure 3 shows the preprocessing step of edge detection using sobel method.

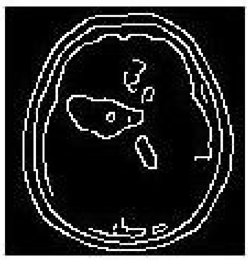


Figure 4: Canny edge detection image

The figure 4 shows the preprocessing step of canny edge detection for the input image.

ISSN: 2278 – 1323

International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)
Volume 3 Issue 12, December 2014

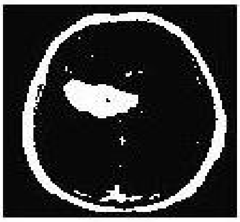


Figure 5: Fuzzy C-Means clustered image

The figure 5 shows the clustered image using Fuzzy C-Means method . It shows the grayscale image into 0 as 1and vice versa.

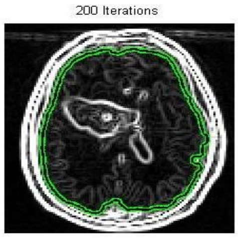


Figure 6: Active counter based image

The figure 6 shows the segmentation of MRI brain image using Active counter based iteration.

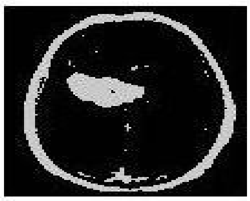


Figure 7: Neuro fuzzy classification image

The figure 7 shows the neuro fuzzy classification image which classify the affected region from unaffected region.

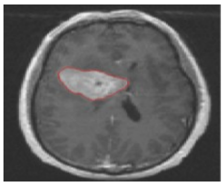
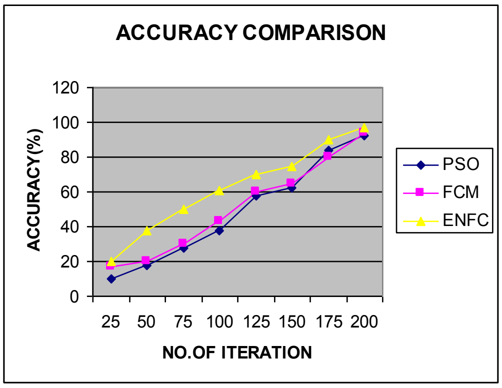


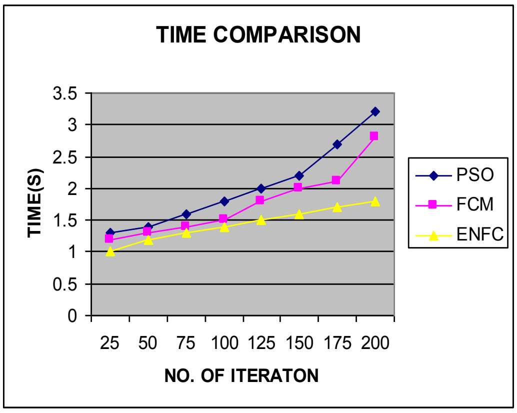
Figure 8: Segmented Output Image

The figure8 shows the segmented output image using the proposed method of ENFC.



Graph 1: Accuracy comparison

The graph1 shows the comparison of accuracy between PSO, FCM and with the proposed method of ENFC.The accuracy of proposed method is improved when comparing eith the existing methods while segmenting the image.



Graph 2: Time comparison

The graph2 shows the comparison of time between PSO, FCM and with the proposed method of ENFC.The proposed method reduces the time while segmenting the image and thus it is more efficient.

TABLE 1. PERFORMANCE TABLE

METHODS/ PARAMETER	PSO	FCM	ENFC
TIME PERIOD(s)	3.2	2.8	1.8
ACCURACY(%)	92.5	93.8	96.7

V. CONCLUSION AND FURTHER RESEARCH

Medical image segmentation is a case study that is fascinating and very important as well. Enhanced neuro fuzzy classification algorithm have been considered so far they have been seen effective in the image segmentation. Time, accuracy, and iterations have been the major focus here. The proposed algorithm is one of the most efficient methods for segmenting the image. This method is easy to use unlike some other methods in existence. There are many algorithms available for image segmentation but the proposed method gives the better accuracy result with less iteration for the image segmentation. The proposed method is mainly used to remove the noisy pixel and improving the accuracy and also reduces the time complexity while doing image segmentation. Enhanced Fuzzy Classification algorithm generating an overlapping results and not being able to segment colored images until they are converted into grey scale. In future, the colored image can be segment by various methods using multi modal function of PSO optimization with less time and more accuracy. And also the future scope of this work is to enhance the ANFIS architecture to achieve high classification accuracy at a lower convergence rate. The convergence time period of ANFIS is ten times better than the neural and the fuzzy classifier.

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ISSN: 2278 – 1323