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Brain Image Segmentation Using Conditional Random Field Based On Modified Artificial Bee Colony Optimization Algorithm

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***Abstract*—**Tumor is an uncontrolled growth of tissues in any part of the body. Tumors are of different types and they have different characteristics and treatments. Brain tumor is inherently serious and life-threatening because of its character in the limited space of the intracranial cavity (space formed inside the skull). Locating the tumor within MR (magnetic resonance) image of brain is integral part of the treatment of brain tumor. This segmentation task requires classification of each voxel as either tumor or non-tumor, based on the description of the voxel under consideration. Many studies are going on in the medical field using Markov Random Fields (MRF) in segmentation of MR images. Even though the segmentation process is better, computing the probability and estimation of parameters is difficult. In order to overcome the aforementioned issues, Conditional Random Field (CRF) is used in this paper for segmentation, along with the modified artificial bee colony optimization and modified fuzzy possibility c-means (MFPCM) algorithm. This work is mainly focused to reduce the computational complexities, which are found in existing methods and aimed at getting higher accuracy. The efficiency of this work is evaluated using the parameters such as region non-uniformity, correlation and computation time. The experimental results are compared with the existing methods such as MRF with improved Genetic Algorithm (GA) and MRF-Artificial Bee Colony (MRF-ABC) algorithm.

***Keywords*—**Conditional random field, Magnetic resonance, Markov random field, Modified artificial bee colony.

I. Introduction

THERE are two types of MRI Images, namely, MRI high field for producing high quality images and MRI low field for smallest diagnosis conditions. MRI images help the physicians to diagnose tears in injuries to ligaments and even hair line cracks, muscles and other soft tissues. MRI for brain tissue classification is of great importance for clinical studies and research in neurological pathology. The important task in segmentation involves, accurately segmenting the MR images into Gray Matter (GM), White Matter (WM) and Cerebrospinal Fluid (CSF) [16], [18]. It has several advantages over the other imaging techniques, enabling it to provide the three-dimensional (3D) data with a high contrast between soft tissues.

Segmentation techniques are classified into two types: supervised and unsupervised. Supervised methods are also known as semi-automatic since these methods require user interaction. Unsupervised techniques can segment the regions in feature space with a high density and hence it is completely automatic. An unsupervised technique includes K-Means (KM), Fuzzy C-Means (FCM) and Expectation Maximization (EM) methods, which are eminent automatic tools for brain diagnostic system.KM is a hard segmentation process that generates a sharp classification [1], [2]. FCM makes use of fuzzy theory, in which a tissue can be classified into several classes at the same time with different degree [3], [4]. It is considered to be the best method for the anisotropic nature of volumes that are affected by Partial Value Effects (PVE), where multiple tissues contribute to single voxel resulting in the blurring of tissue boundaries. EM algorithm is used to find the mixture of Gaussians that can model the data set, in which there is no prior knowledge about their density distributions on each MRI echo [5]. It is often used in estimation problems where some of the data are missing [6]. In this application, the missing data is knowledge of the tissue class.

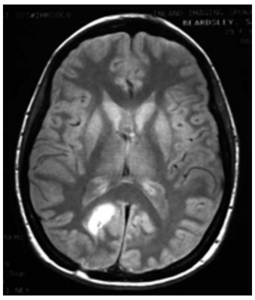

Fig. 1 MR image of human brain

Brain tumor segmentation in multimodal image data plays a major role in different clinical areas such as radiology, radiotherapy and longitudinal studies [17]. Fully automated segmentation methods facilitate the otherwise cumbersome and time consuming manual segmentation process.

There are a number of techniques to segment an image into regions that are homogeneous. Due to the complexity and inaccuracy not all the techniques are suitable for medical image analysis .Optimal selection of features, tissues, brain and non-brain elements are considered to be the key obstacles for brain image segmentation. Accurate segmentation over full field of view is another hindrance [19], [20].

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II. Related Works

Hall et al. proposed a method named Fuzzy C-Means, which is a popular method for medical image segmentation, but it only considers image intensity thereby producing unsatisfactory results in noisy images [7]. A bunch of algorithms were proposed to make FCM robust against noise and homogeneity, but they were still not as perfect as FCM. Firstly, the algorithm selects the initial cluster centers from Self Organization Map (SOM) clustering algorithm. Then, after much iteration, the final result converges to an actual cluster center. As a result, a good set of initial cluster is generated. The winning neural units and their corresponding weight vectors from each layer result in an abstraction tree. The region of the image at a specified level of abstraction is represented by a node of the abstraction tree. Segmentation of image is generated on demand by traversing the abstraction tree in the Breadth First Search (BFS) manner starting from the root node until some criterion is satisfied. The sum of the variances of weight vector divided by size of the weight vector is less than element of weight vector if the size of the abstraction tree (weight vector) is expanded, else the node is labeled as a closed node and none of its descendants are visited. Regions corresponding to the closed nodes constitute a segmented image and the resulting segmented image contains the regions from different abstraction levels.

Ahmed [8] presented algorithm for fuzzy segmentation of magnetic resonance imaging data and estimation of intensity of nom-homogeneities with fuzzy logic. This algorithm is created by changing the objective function of the Fuzzy C-Means algorithm to compensate for non-homogeneities and allows the labeling of a voxel to be influenced by the labels in its immediate neighbourhood, which acts as a regularizer. By adding a neighbourhood averaging term to the objective function, they developed a bias corrected FCM algorithm. BCFCM performed well on both stimulated as well as on real MRI images, compared to FCM and EM algorithms. However, FCM has advantage that it works for vectors of intensities, while bias-corrected FCM algorithms are limited to single-feature inputs. The bias-corrected FCM algorithm gives better results than the EM algorithm in noisy images as it compensates for noise.

Edge detection is a basic step for image segmentation process [9]. It divides an image into object and its background. Edge detection divides the image by observing the change in pixels or intensity of an image. Yu Xiaohan [10] proposed a new image segmentation technique based on edge detection and region growing methods. When both techniques are used in a separate manner, their hybrid method helps the segmentation process to avoid errors. Region growing is used to find the edge pixels in the image, while edge detection technique makes use of second order derivative. Experiments are conducted on 3D MRI image data. Gaussian technique is used for smoothing after edge detection. Results have shown that their technique is better in order to preserve more edge information.

Fuzzy set theory is used in order to analyze the images and provide accurate information of the image. Fuzzification function can be used to remove noise from image as well. Gour Chandra Karmakar [11] introduced a new fuzzy rule based image segmentation technique that can integrate the spatial relationship of the pixels. Three types of membership functions are used, i.e., membership function for region pixel distribution, to measure the closeness of the region and to find the spatial relationship among pixels. There is no need to define parameters in this technique as in FCM algorithm. Fuzzy rules are used above three membership functions and fuzzy IF-THEN rule structure is used to perform segmentation of an image. FCM and this technique are implemented on Matlab 5.3.1 on X-ray image and human vocal tract image.

Brummer et al. used histogram analysis and morphology to generate a 3D brain mask [12]. Using the model of background noise, they first generated a mask of the head automatically and performed intensity correction on the masked volume. Next, an initial brain mask was created using an automatic threshold based on a pre-supposed brain voxel intensity distribution. Then the regions in the brain mask that were too close to the edge of the head were eliminated. Finally, novel morphological operations were used to clean up the resulting mask. The method relies on a priori intensity correction to deal with Radio Frequency (RF) in homogeneity, hence cannot be used retroactively.

Clarke [13] introduced a supervised classification using an Artificial Neural Network (ANN) approach for brain tumor segmentation in MR images. Ozkan et al [14] also made use of ANN classification methods. Their system first uses the patient-specific training of a neural network classifier on a single slice. ANN was used to classify all the pixels in the adjacent slices. These pixels in the adjacent slices were used as a new training set for the neural network classifier used to classify the adjacent slice. Dickson and Thomas [15] presented one of the uncommon supervised methods that do not require patient-specific training. The authors used a set of 50 hand-labeled MR slices from the same area of the head from different patients with acoustic neuromas and learned to automatically label this type of tumor without patient-specific training. The features used in this system included not only the pixel intensities, but also the intensities of neighbouring pixels and the pixel location within the image.

A. Existing Methodologies

1. MRF Based Image Segmentation Using ABC

MRF technique is widely used in medical image processing, mostly for segmentation and the images are categorized with the identity (labels) of the neighbouring elements. The traditional image segmentation methods are classified based on the data identity only and not on the labels of the other elements. The image features such as set of vowels $x = \{x_1,\ldots,x_n\}$ and labels $y: p(x,y) = p(x|y)\,p(y)$are the joint probabilities, due to the generative approach of MRF and it is calculated with the assumptions of the system. The system deduces the likelihood factorized form such as $p(x|y) = \Pi_i\, p(x_i|y_i)$ and it has some restrictions such as independence assumptions and modeling of complex dependencies that are not allowed between features and labels. Usually the set of sites used for segmentation are defined as clique but in MRF model, a clique is defined by a set of sites 's', and the clique in neighbourhood system is defined as $\{C_1, C_2, C_3, C_4, \ldots, C_{nm}\}$.

$$p(x|y) = \frac{1}{z} exp\left[\sum_{i\in S} log\big(p(x_i|y_i)\big) + \sum_{c\in C} V_c(y_c)\right], \qquad (1)$$

where, C is a set of cliques in the neighbourhood (defined here as a set of 8 planar neighbours), $V_c(y)$ is a clique potential function of labels for the clique $c \in C$ and z normalizes over all possible labeling. The Gaussian assumption allows us to use ML parameter estimation.

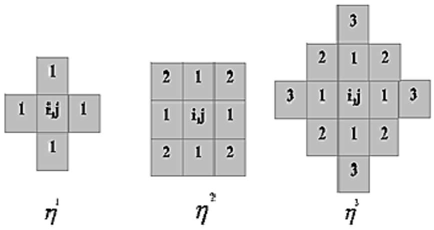

Fig. 2 First, Second and Third Order Cliques

2. Artificial Bee Colony (ABC) Optimization

Karaboga and Basturk in 2006 [21] suggested an efficient multi-objective optimization algorithm based on the natural behaviour of honey bees. The algorithm follows primarily on the two intelligent behaviours specifically, collecting the data about nectar source and abandonment of ants and bees. The search process for food by the cluster of ants or bees is better than the individual search. Honey bees are divided into three groups: employee bees, onlooker bees and scout bees. These parameters are considered important within the artificial bee colony improvement algorithm. The food source data is gathered by the employed bees. The new food sources are found by the scout bees close to the environment. The foods are collected by the onlooker bees from the source through the data shared by the employed bees [24].

In ABC algorithm [25], the onlooker bees concede a random choice scheme based on the nectar (fitness) values associated with the 'roulette wheel selection' as in Genetic algorithm (GA). Mutation process in GA is expounded to the ABC algorithm that also produces the mechanism of neighbor source (solution). Unlike GA, there is no exact crossover in ABC algorithm. On the other hand, the sharing of data between the bees is carried out by the mutation process. In ABC, a food source characterizes a possible solution to the optimization problem. As a result, at the initialization step, a set of food source positions are considered. The nectar quantity of a food source matches with the quality of the solution characterized by that source searched by the bee. Therefore the nectar amounts of the food source obtainable at the initial positions are determined. Alternatively, the standard values of the initial solutions are calculated.

Each employee bee is moved onto her food source area for influencing an alternative food source within the neighbourhood of the current one and then its nectar amount is evaluated. If the nectar amount of the new one is higher, then the bees forget the preceding one and remember the new one. When the employed bees complete their search, they are back to the hive and share their data about the nectar amounts of their food sources with the onlooker bees waiting in the hive. If the nectar quantity of a food source is higher on comparing with other food sources, then the probability of choosing this source by the onlooker will be more. This method is comparable to the natural selection process in evolutionary algorithms. Each onlooker bee determines a neighbour food source surrounded by the neighborhood of the one to which she has been allocated and its nectar amount is evaluated.

B. Limitations

The main disadvantage of MRF-based methods is that, the objective function associated with most non-trivial MRF problems is extremely non-convex and as such the minimization problem is computationally very taxing. Computing the probability and the parameter estimation are difficult tasks in MRF.

The fundamental ABC algorithm is simple, robust, and can be easily controlled. But, as a random optimization technique, ABC has slow convergence features and easily gets stuck on local solutions.

III. Methodology

A. Preprocessing and Enhancement Process

1. Image Acquisition

To access and use the real medical images for carrying out research is a very difficult due to various technical problems. The MRI data for the research is obtained from the Brain Web Database at the McConnell Brain Imaging Center of the Montreal Neurological Institute (MNI), McGill University. Sample T1-weighted images of size 181x217x36 were taken and used for enhancement and segmentation purpose. T1-weighted images show the water content of the brain, darker and the fat content of the brain, brighter. The images were acquired in MINC format, which are then converted to JPEG format before the processing. Fig. 3 shows the MR image immediately after its acquisition.

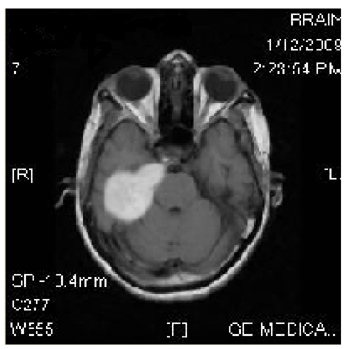

Fig. 3 Acquired T1-weighted MR Image

2. Removal of Film Artifacts and Skull Portions

The acquired MR image of the brain consists of lot of film artifacts and labels, which include patient's name, age and marks for identification on the MRI. These film artifacts were removed using tracking algorithm. The tracking algorithm starts from the first row and first column of the image. The intensity values of the pixels were analyzed using the threshold value of the film artifacts. If the pixel intensity value is greater than that of the threshold value then that pixel intensity was made to zero and removed from MRI. The high intensity values of film artifacts were removed from MR image of the brain. Separate threshold values were set for the labels and the skull region so that the unwanted parts of the MR image of the brain can be removed. Fig. 4 shows the image after removing the artifacts.

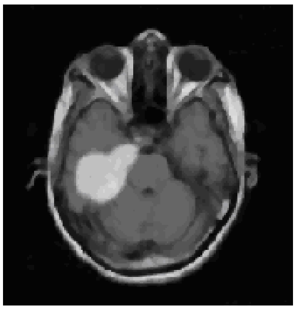

Fig. 4 Image after removing the artifacts

3. MR image enhancement using Histogram Equalization and Center Weighted Median Filter

Image enhancement techniques are used to improve the visual appearance of the MRI, by eliminating high frequency components from the images [22]. Image enhancement can be done by applying various types of filters such as low pass filter, median filter, Gaussian filter, Sobel filter, etc. on the images. The proposed system describes the image enhancement done using Histogram Equalization (HE) and Center Weighted Median (CWM) filter for removing high frequency components such as impulsive noise, salt and pepper noise, etc. The MR image of the brain is histogram equalized and then the center weighted median filter is applied.

The CWM filter is a type of weighted median filter, which gives more weight only to the central pixel of each window. This filter can preserve the fine image details while suppressing additive white and impulsive-type noise. When comparing the properties of the CWM filter with other median filters, it is very clear that the CWM filter along with the HE can outperform other median filters.

B. Image Segmentation

1. Conditional Random field

Conditional Random Fields (CRFs) are undirected graphical models that encode a conditional probability distribution using a given set of features [23]. CRFs are defined as follows.

Let G be an undirected model over sets of random variables y *and* x. As a typical special case, $y = \{y_t\}$ *and* $x = \{x_t\}$ *for* $t = 1,\dots,T$, so that y is a labeling of an observed sequence x. If $C = \{\{y_c, x_c\}\}$ is the set of cliques in G, then CRFs define the conditional probability of a state sequence given the observed sequence as:

$$p_\wedge(y/x) = \frac{1}{Z(x)}\prod_{c\in C}\Phi(y_c, x_c), \qquad (2)$$

where Φ is a potential function and the partition function $Z(x) = \sum_y \prod_{c\in C}\Phi(y_c, x_c)$is a normalization factor over all state sequences for the sequence x. It is assumed that the potentials factorize according to a set of features$\{fk\}$, which are given and fixed, so that

$$\Phi(y_c, x_c) = exp\left(\sum\nolimits_y \lambda_k f_k(y_c, x_c)\right), \qquad (3)$$

The model parameters are a set of real weights $\wedge = \{\lambda_k\}$, one weight for each feature.

The training data is fully observed, i.e., D = {(x,y)}, and for each state sequence, an output sequence pair is independently and identically distributed (IID).

Maximum a posteriori (MAP) estimation is used to maximize the equation. The prior, $p(\wedge)$, encodes some prior knowledge that one might have known about the distribution over parameter values.

The prior is used for smoothing (regularization), such that over-fitting of the training sample is minimized and therefore generalization accuracy is not compromised. When the parameter $\lambda_k$is zero, the corresponding feature f_k, is ignored. When all the parameters are zero, the distribution $p(y|\boldsymbol{x})$ is uniform. Making an a priori assumption of uniformity is a reasonable one and is consistent in nature with the maximum entropy principle, which also maximizes uniformity. The Gaussian probability density function is:

$$p(\lambda_k) = \frac{1}{\sigma_k\sqrt{2\pi}} exp\left(-\frac{(\lambda_k-\mu_k)^2}{2\sigma_k^2}\right), \qquad (4)$$

where,μ_k is the mean for parameter λ_k and $\sigma_k$are the standard deviations. The MAP based on log-likelihood, after excluding constant terms is given in (5).

$$L^{MAP} = L - \frac{1}{2}\sum_k\left(\frac{\lambda_k-\mu_k}{\sigma_k}\right)^2, \qquad (5)$$

2. Maximum a Posteriori Using Modified ABC and FPCM

A. Modified Artificial Bee Colony Optimization

Artificial Bee Colony (ABC) algorithm was proposed by Karaboga [21] for optimizing numerical problems. The algorithm simulates the intelligent foraging behavior of honey bee swarms. The artificial bee colony algorithm is a population-based stochastic optimization algorithm and it is very simple and robust. Compared with those of other well-known modern heuristic algorithms such as genetic algorithm, differential evolution, particle swarm optimization, the performance of artificial bee colony algorithm is better or similar with the advantage of employing fewer control parameters.

In artificial bee colony algorithm, each cycle of the search consists of three steps: first, sending the employee bees onto their food sources and evaluating their nectar amounts; second, after sharing the nectar information of food sources, the selection of food source regions by the onlooker and evaluating the nectar amount of the food sources; third, determining the scout bees and sending them randomly onto possible new food sources.

Based on the above descriptions, an improved artificial bee colony algorithm is proposed to maximize the effective coverage of area: max $\{R_{area}(S)\}$.The fitness value function is defined as $f = R_{area}(S)$. At the first step, the algorithm generates a randomly distributed initial population P of Q solutions, where Q denotes the size of employed bees or onlooker bees. Each solution is a 2N-dimensional vector: $v_i = (x_1^i, y_1^i x_2^i, y_2^i, \ldots, x_N^i, y_N^i), i = 1,2, \ldots, Q,$ where N is the number of sensor nodes, and we define $v_{ij} = (x_j^i, y_j^i)$as the position of node j. After initialization, the population of the positions is subject to repeated cycles of the search processes of the employee bees, the onlooker bees and the scout bees.

An employee bee produces a modification on the position in her memory depending on the local information. In order to produce a candidate position from the old one in memory, the proposed algorithm uses (6).

$$v_{ij} = v_{ij} + \varphi_{ij}(v_{ij} - v_{kj}) \tag{6}$$

where, k∈{1,2,…,Q } and j∈{1,2,…,N} are randomly chosen indexes and $k \neq j$, φ_{ij} is a random number between -1 and 1.

An artificial onlooker bee chooses the position (solution) depending on the probability value associated with it and it will do local search near the position. The probability value p_i of each position is calculated using (7).

$$p_i = \frac{f_i}{\sum_{n=1}^{Q} f n} \tag{7}$$

In the proposed algorithm, each onlooker bee prefers the position with bigger p_i, so it chooses the position v_j based on the pseudo-random proportional rule given by (8).

$$j = \begin{cases} \arg\max\{f_i\}, q \leq q_0 \\ \quad i \in \{1,2, \ldots Q) \\ \quad J, \ Otherwise, \end{cases} \tag{8}$$

where, q is a random variable uniformly distributing between the region 0 and 1; $q_0 (0 \leq q_0 \leq 1)$ is parameter and J is a random variable. The pseudo-random proportional rule can assure that the onlooker bee selects the position with bigger $p_i$with larger possibility and can avoid precocious.

In the proposed algorithm, if a position cannot be improved further through a predetermined number of cycles, then it is assumed to be abandoned. The value of predetermined number of cycles is an important control parameter of the algorithm, which is called "LimitCycle" for abandonment. Assume that the abandoned position is v_l and the scout discovers a new position to be replaced with v_l. This operation can be defined as in (9).

$$v_l = v_{lb} + rand[0,1](v_{up} - v_{lb}) \tag{9}$$

where,v_{lb} is the lower boundary of the position and v_{up} is the upper boundary of the position. In the proposed algorithm, besides abandoning the position with repeat cycles bigger than the LimitCycle, the worst position v_{worst} with minimal fitness value in each cycle will be abandoned. The operation is same as in (9) and given in (10).

$$v_{worst} = v_{lb} + rand[0,1](v_{up} - v_{lb}) \tag{10}$$

After updating v_{worst}, the proposed algorithm can avoid local optimization and speed convergence. Based on the above description, the detailed pseudo-code of improved ABC algorithm is given below:

1. Initialize the population of solution, v_i, i=1,2,…,Q
2. Evaluate the population.
3. cycle=1.
4. *repeat*.
5. produce new solutions v_i for the employee bees by using (6) and evaluate them.
6. calculate the probability values p_i by (7).
7. apply pseudo-random proportional rule for each onlooker bee selecting solution and produce the new solutions with (6).
8. abandon the worst solution v_{worst} and replace it with a new randomly produced solution by (10).
9. if a solution cannot be improved further through *LimitCycle*, replace it with a new randomly produced solution by (9).
10. memorize the best solution achieved so far.
11. cycle=cycle+1.
12. *until* cycle=MaxCycle.

$$J_{MFPCM} = \sum_{i=1}^{c} \sum_{j=1}^{n} (\mu_{ij}^m \, w_{ji}^m d^{2m}(x_j, v) + t_{ij}^\eta w_{ji}^\eta d^{2\eta}(x_j, v_i)), \tag{11}$$

$U = \{\mu_{ij}\}$ represents a fuzzy partition matrix is defined as:

$$u_{ij} = \left[\sum_{k=1}^{c} \left(\frac{d?x_j, v_i}{d?x_j, v_k}\right)^{2m/(m-1)}\right]^{-1} \tag{12}$$

B. Modified Fuzzy Possibilistic c-Means Algorithm (MFPCM)

The objective function of the MFPCM can be formulated as follows:

T=$\{t_{ij}\}$represents a typical partition matrix, is defined as:

$$t_{ij} = \left[\sum_{k=1}^{n} \left(\frac{d?x_j, v_i}{d?x_j, v_k}\right)^{2\eta/(\eta-1)}\right]^{-1} \tag{13}$$

V=$\{v_i\}$ represents c centers of the clusters, is defined as:

$$v_i = \frac{\sum_{j=1}^{n} (\mu_{ij}^m w_{ji}^m + t_{ij}^\eta w_{ji}^\eta) * x_j}{\sum_{j=1}^{n} (\mu_{ij}^m w_{ji}^m + t_{ij}^\eta w_{ji}^\eta)}, \tag{14}$$

$$\alpha = \exp\left(-min \frac{\|v_i - v_k\|^2}{\beta}\right) \tag{15}$$

where β is a normalized term so that we choose βas a sample variance. That is, we define β:

$$\beta = \frac{\sum_{j=1}^{n} \|x_j - \bar{x}\|^2}{n} \text{ Where } \bar{x} = \frac{\sum_{j=n}^{n} x_j}{n}, \quad (16)$$

where α: Membership matrix; β: possibilistic matrix.

$$w_{ij} = \exp\left(-\frac{\|x_j - v_i\|^2}{\sum_{j=1}^{n} \|x_j - \bar{v}\|^2 * c/n}\right), \quad (17)$$

where $w_{ij}$is the weight of the point j in relation to the class i.

This weight is used to modify the fuzzy and typical partitions. All update methods that were discussed in Chapter II are iterative in nature, because it is not possible to optimize any of the objective functions reviewed directly. To classify a data point, cluster centroid has to be closest to the data point and for estimating the centroids, the typicality is used for alleviating the undesirable effect of outliers. The objective function is composed of two expressions: the first is the fuzzy function and uses a fuzziness weighting exponent, the second is possibililstic function and uses a typical weighting exponent, but the two coefficients in the objective function are only used as exhibitor of membership and typicality [23].

C. Algorithm for CRF Based MABC-MFPCM

Step 1. Read the human brain MRI images.

Step 2. Label the pixels with same gray value with same number.

Step 3. For each kernel in the image, calculate the posterior L^{MAP} value using conditional random field using formula.

Step 4. The posterior values of all the kernels are stored in a separate matrix.

Step 5. Modified Artificial bee colony optimization is used to minimize the Maximum a posterior function.

Step 6. Initialize number of iterations (μ), number of bees (φ), initial food position value (v_0), a constant value for food position update (ρ). Store the energy function values in S. Initialize all the food position values with T_0=0.001.

For N times

For each pixel in the image

Calculate the probability value using

$$p_i = \frac{f_i}{\sum_{n=1}^{Q} f_n} \quad (18)$$

For each bee update food position values using the modified equation of artificial bee colony

$$v_{ij} = v_{ij} + \varphi_{ij}\left(v_{ij} - v_{kj}\right), \quad (19)$$

then new position is updated

$$v_{new} = (1-\rho)^* v_{ij} + \rho^* v_{ij} , \quad (20)$$

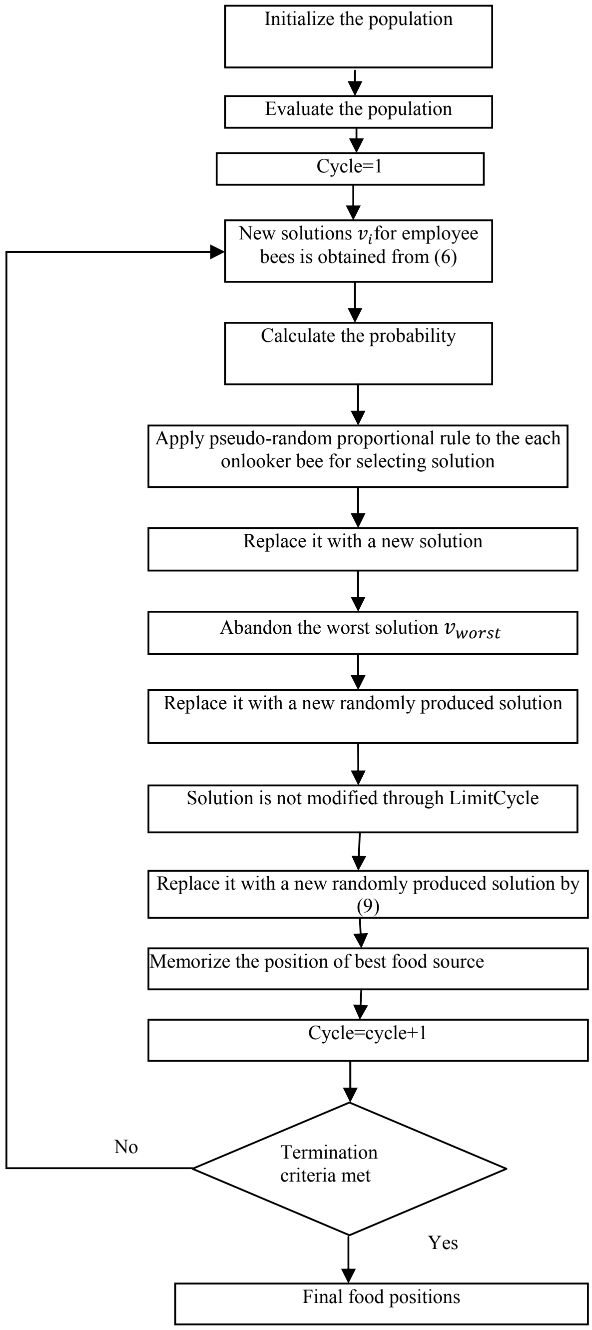

Fig. 5 Flow chart for modified artificial bee colony optimization

End

End

End

If the slave value is less than the master value, then the value is discarded, else, interchanged.

Step 7. Select a random pixel for each bee, which was not selected previously.

Step 8. Update the food position values for the selected pixels by all the bees.

The optimal value of MABC is used to select the initial cluster point.

1. Calculate the cluster center C

$$C = \left(\frac{N}{2}\right) 1/2, \tag{21}$$

2. Compute the Euclidean distance

$$D_{ij} = CC_P - C_n, \tag{22}$$

3. Update the partition matrix

$$\sum_{i=1}^{c} u_{ij} = 1, \forall \in \{1, \dots n\}, \tag{23}$$

$$u_{ij} = \frac{1}{1 + \left[\frac{d^2(x_j, v_i}{\eta_i}\right]^{\frac{1}{m-1}}}, \tag{24}$$

$$v_i = \frac{\sum_{k=1}^{n} (u_{ik}^m + t_{ik}^n) X_k}{\sum_{k=1}^{n} (u_{ik}^m + t_{ik}^n)}, \quad 1 \le i \le c, \tag{25}$$

is the possibilistic typicality value of the training sample $x_j$belonging to the cluster ‘i’. $m\epsilon[1, \infty]$is a weighting factor called the possibilistic parameter.

4. Compute the adaptive threshold using

Adaptive threshold =max (Adaptive threshold, C_i) $i = 1 \dots n$

In the MRI image, the pixels having lower intensity values than the adaptive threshold value are changed to zero. The entire procedure is repeated for any number of times in order to obtain the more approximate value.

D. Detection of the Shape of Brain Tumor

In the approximate reasoning step, the tumor area is calculated using the binarization method. In this method, the image has only two values either black or white (1 or 0). Here the JPEG images have a maximum image size (256x256). The binary image can be represented as a summation of total number of black and white pixels.

$$Image\ I = \sum_{w=0}^{255} \sum_{H=0}^{255} [f(0) + f(1)], \tag{26}$$

where, Pixels = Width (W) X Height (H) = 256 X 256; f (0) = white pixel (digit 0); f (l) = black pixel (digit 1)

$$No\_of\_white\ pixel\ P \sum_{w=0}^{255} \sum_{H=0}^{255} f(0), \tag{27}$$

where,

$$P = number\ of\ white\ pixels\ (width * height)$$
$$1\ Pixel = 0.264\ mm$$

The area calculation formula is

$$Size\_of\_tumour, S = [(\sqrt{P}) * 0.264]\ mm^2, \tag{28}$$

where P= no-of white pixels; W=width; H=height

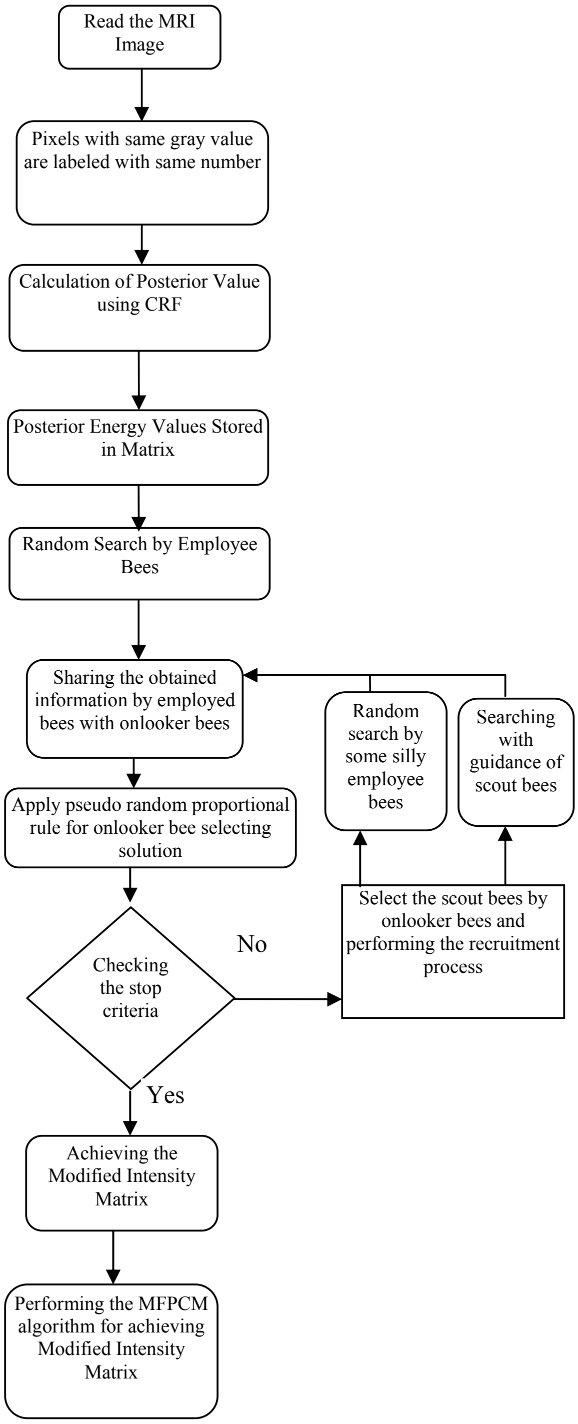

Fig. 6 Proposed CRF-MABC based Algorithm

The edge of the gray scale image

$$Edge_{strength} = \frac{\sum_{p \in edge} p}{N} \tag{29}$$

where (p) represents edge points gradient values which come from the image step for all pixels (p) on the edge between every two regions, and N are the number of edge pixels.

Algorithm

The steps involved for finding the shape of the brain tumorare as follows:

Step 1. Start the process.

Step 2. Get the segmented MR image of human brain obtained from the CRF-MABC given as a input.

Step 3. Check whether the input image is in required format and move to step 4 if no error messages is displayed.

Step 4. Find the edge of the gray scale image.

$$Edge\_strength = \frac{\sum_{p \in edge} p}{N}$$

Step 5. Calculate the number of white points in the image.

$$No\_of\_white\ pixel\ P \sum_{w=0}^{255} \sum_{H=0}^{255} f(0)$$

Step 6. Calculate the size of the tumor using the formula

$$Size\_of\_tumour, S = [(\sqrt{P}) * 0.264]\ mm^2$$

Step 7. Display the size and stage of tumor.

Step 8. Stop the process.

IV. Experimental Results

A. Data Set

For the purpose of study, the details from ten tumor patients were collected. The scanned images were recorded as DICOM and then converted to JPEG format. For segmentation, a total of 100 images (10 images per patient) were taken. The performance of the algorithm was evaluated based on the region non-uniformity, correlation and computation time. The results of this work were compared with the existing algorithms and the efficiency has been measured.

This work is done in MATLAB 7.0 environment.

B. Performance Evaluation

Various techniques are available to estimate the performance of the segmentation algorithms and their results. In this paper, region non-uniformity and correlations of segmented images are the main parameters that were used to evaluate the performance of the algorithm proposed.

C. Region Non-Uniformity

To assess the performance of the segmentation algorithm, the region Non-Uniformity (NU) is defined as,

$$NU = [|F_T| \,/\, |F_T + B_T|] * [\sigma_f{}^2 \,/\, \sigma^2], \tag{30}$$

where σ^2 variance of the whole image; $\sigma_f{}^2$ foreground variance; $F_T$and B_T foreground and background area pixels for the test image

Non-uniformity close to 0 and the worst case corresponds to NU=1.

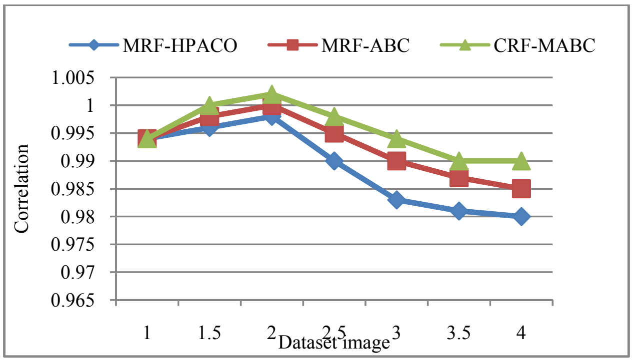

Fig. 7 Average Region of Non-uniformity Comparison

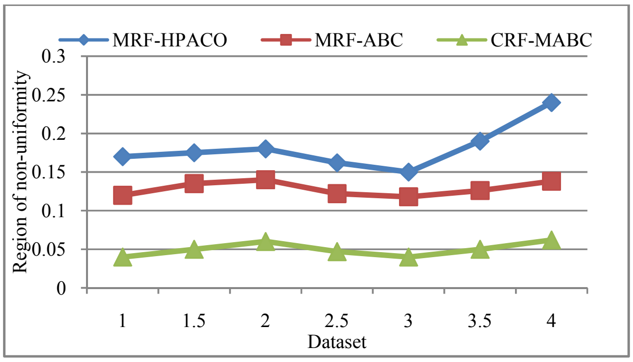

Fig. 8 Average Correlation Comparison

Fig. 7 shows the average region of non-uniformity for the existing and the proposed approaches. From this graph, it is observed that the proposed segmentation approach has lesser region of non-uniformity when compared with the existing approaches.

D. Correlation

A correlation is used to evaluate the performance of image segmentation algorithm and it is done between the segmented image and the ground truth image.

Fig. 8 represents graphically of average correlation value. It is observed from Fig. 8 that the proposed CRF-MABC based segmentation approach provides better results when compared with the existing approach such as MRF –HPACO, MRF-ABC and CRF-MABC.

E. F-measure

The F-measure is defined as the combination and harmonic mean of precision and recall. The F-measure is given by (31).

$$F - measure = \frac{2pr}{r + p}, \tag{31}$$

where p and r denote precision and recall, respectively.
The F-measure is also an important parameter for evaluating the performance.

F. Similarity Index

The quantitative evaluation of the performance of the segmentation process is measured using the similarity index between ground truth and result of the segmentation, as given by (32).

$$D(K) = \frac{2 \cdot V_{p \cap g}(k)}{V_p(k) + V_g(k)}, \quad (32)$$

where $2 \cdot V_{p \cap g}(k)$ is the number of classified pixels in class k with two images (a segmented image and a ground truth image); *D(K)* is the Dice Index.

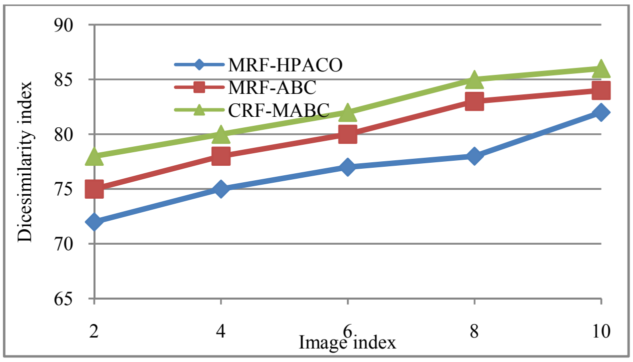

Fig. 9 Dice similarity index for simulated datasets for existing and proposed approach

The graphical representation of the dice index is shown in the Fig. 9. From this graph, it is observed that the similarity index of the proposed approach CRF-MABC is better index than the other existing approach such as MRF-HPACO and MRF-ABC.

Table I shows the comparison of the proposed algorithm with existing algorithm based on the parameters such as correlation, computation time and region of non-uniformity.

TABLE I
PERFORMANCE EVALUATION RESULTS FOR MEDICAL IMAGES

Images	Region non-uniformity			Correlation		
	MRF-HPACO	MRF-ABC	CRF-MABC	MRF-HPACO	MRF-ABC	CRF-MABC
1	0.17	0.04	0.02	0.995	0.996	1
2	0.18	0.05	0.024	0.996	1	1
3	0.15	0.04	0.016	0.984	0.99	1
4	0.24	0.05	0.01	0.98	0.99	1
	Computation time (s)					
For All Images	MRF-HPACO	MRF-ABC		CRF-MABC		
	115	105		85		

The sample images are given in Figs. 10 (a), (along with the statistics.

The statistical parameters of the segmented images in Figs. 10 (a)-(d) are presented in Tables II and III.

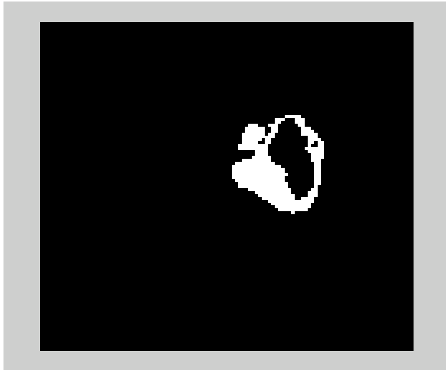

Fig. 10 (a) Segmented Image 1

Fig. 10 (b) Segmented Image 2

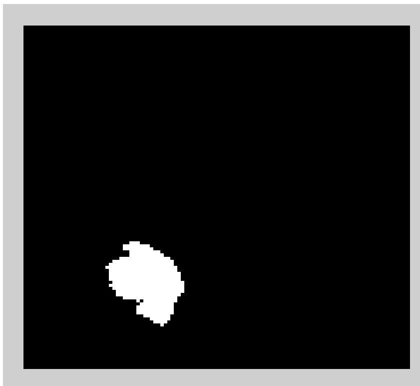

Fig. 10 (c) Segmented Image 3

Fig. 10 (d) Segmented Image 4

TABLE II
STATISTICAL PARAMETERS OF THE SEGMENTED IMAGES

Figure	Correlation	NU	Area	Centroid	Eccentricity
10 (a)	1	0.0279	421	[71.7577 50.4679]	0.5305
10 (b)	1	0.0556	671	[34.4232 33.9076]	0.6041
10 (c)	1	0.0248	387	[36.7235 84.6227]	0.6967
10 (d)	1	0.0504	823	[32.5006 52.1215]	0.6530

TABLE III
STATISTICAL PARAMETERS OF THE SEGMENTED IMAGES

Figure	Orientation	Solidity	Extent	Perimeter	Max. Intensity	Min. Intensity
10 (a)	-77.8275	0.5759	0.4422	117.7401	1	0
10 (b)	79.0683	0.9007	0.7262	123.3970	1	0
10 (c)	-60.6783	0.9042	0.6009	86.0833	1	0
10 (d)	31.4245	0.7495	0.5173	168.2670	1	0

V. DISCUSSION

The statistical parameters of the segmented images in Fig. 10 are represented in Tables II and III. The main reason for adopting the conditional random field is computation probability and statistical parameter estimation is easy when compared to the existing Markov random field process. The segmented image of proposed method is evaluated using the metrics such as correlation, non-uniformity, similarity measure. The performance evaluation of the proposed method is better than the existing methods. The graphical representation of the performance evaluation is shown in the Figs. 7-9. The comparative results of existing and proposed methods are shown in Table I.

VI. CONCLUSION

Brain tumor is inherently serious and life-threatening because of its character in the limited space of the intracranial cavity (space formed inside the skull). A novel algorithm based on the combination of conditional random filed and modified artificial bee colony optimization with modified fuzzy possibility c-means is proposed in this research. Conditional random field is a widely used method for image segmentation. The combination of Modified ABC optimization algorithm with FPCM is used to find out the optimal label that minimizes the posterior energy function to segment the image. The performance of this proposed algorithm has been evaluated by using the methods such as correlation, similarity measure and computational complexity. It is clearly observed from the results that the proposed approach provides significant results for the statistical parameters taken for consideration and it outperforms the existing approaches such as MRF-HPACO and MRF-ABC.

REFERENCES

[1] Bouchet A, Pastore J and Ballarin V, “Segmentation of Medical Images using Fuzzy Mathematical Morphology”, JCS and T, Vol.7, No.3, pp.256-262, October 2007.
[2] N. Senthilkumaran and R. Rajesh, “Edge Detection Techniques for Image Segmentation-A Survey of Soft Computing Approaches”, *International Journal of Recent Trends inEngineering*, Vol.1, No.2, pp.250-254, May 2009.
[3] Dao QiangZhanga and Song Can Chena, “A novel kernelized fuzzy C-means algorithm with application in medical image segmentation”, Artificial Intelligence in Medicine, Vol. 32, pp.37-50, 2004.
[4] Ian Middleton and Robert I. Damper, “Segmentation of magnetic resonance images using a combination of neural networks and active contour models”, Medical Engineering and Physics, Vol.26, pp.71-86, 2004.
[5] M. E. Brummer, “Optimized intensity thresholds for volumetric analysis of magnetic resonance imaging data”, *Proc. SPIE*, Vol.1808, pp. 299-310, 1992.
[6] A. Kundu, “Local segmentation of biomedical images,” *Comput. Med. Imag. Graph.*, Vol. 14, pp. 173-183, 1990.
[7] A.M. Bishop, “Neural Networks for Pattern Recognition”, Oxford, UK: Oxford Univ., 1995.
[8] W. M.Wells, E. L. Grimson, R. Kikinis, and F. A. Jolesz, “Adaptive segmentation of MRI data”, IEEE Trans. Med. Imag., Vol.15, pp. 429–442, Aug. 1996.
[9] R. Guillemaud and J. M. Brady, “Estimating the bias field of MR images”, IEEE Trans. Med. Imag., Vol.16, pp. 238-251, June 1997.
[10] C. Li, D. B. Godlgof, and L. O. Hall, “Knowledge-based classification and tissue labeling of MR images of human brain”, *IEEE Trans. Med.Imag.*, Vol.12, pp. 740-750, Dec.1993.
[11] M. E. Brummer, R. M. Mersereau, R. L. Eisner and R. R. J. Lewine, “Automatic detection of brain contours in MRI data sets”, *IEEE Trans.Med. Imag.*, Vol. 12, pp. 153-166, June 1993.
[12] H. A. Rowley, S. Baluja, and T. Kanade, “Neural Network Based Face Detection”, IEEE Transactions on Pattern Analysis and Machine Intelligence, pp. 23-38, Jan.1998.
[13] S. Geman and D. Geman, “Stochastic relaxation, Gibbs distributions, and the Bayesian restoration of images”, IEEE Trans. Pattern Anal. Machine Intell., No. PAMI-6, pp. 721-741, June 1984.
[14] J. Besag, “On the statistical analysis of dirty pictures (with discussion)”, J. of Royal Statist. Soc., Ser. B, Vol.48, No.3, pp. 259-302, 1986.
[15] S. Z. Li, “Markov Random Field Modeling in Computer Vision”. Berlin, Germany: Springer-Verlag, 1995.
[16] K. Held, E. R. Kops, B. J. Krause,W. M.Wells, and R. Kikinis, “Markov random field segmentation of brain MR images”, IEEE Trans. Med. Imag., Vol.16, pp.878-886, Dec. 1997.
[17] Stefan Bauer1,3, Roland Wiest2, Lutz-P Nolte1 and Mauricio Reyes, “A survey of MRI-based medical image analysis for brain tumor studies”, Phys. Med. Biol. 58 (2013) R97–R129.
[18] Resmi A*,1, Thomas T, Thomas B, “A novel automatic method for extraction of gliomatumour, white matter and grey matter from brain magnetic resonance images”, Biomedical Imaging and Intervention Journal, J 2013; 9(2):e21.
[19] Nelly Gordillo, Eduard Montseny, PilarSobrevilla, “State of the art survey on MRI brain tumor segmentation,” Elisevier. (2013) 1426–1438.
[20] Wedad S. Salem, Ahmed F. Seddik, Hesham F. Ali1, “A Review on Brain MRI Image Segmentation”, Computers and Systems Department, Electronics Research Institute, Cairo, Egypt.
[21] B. Basturk, DervisKaraboga, “An Artificial Bee Colony (ABC) Algorithm for Numeric function Optimization”, *IEEE Swarm Intelligence Symposium,* May, 2006.
[22] E. Ben George, M.Karnan, “MR Brain Image Segmentation using Bacteria Foraging Optimization Algorithm”, *International Journal of Engineering and Technology* (IJET), Vol.4, No.5, Oct.-Nov. 2012.
[23] Lafferty, J., McCallum, A., & Pereira, F, “Conditional random fields: Probabilistic models for segmenting and labeling sequence data”, *Proc. 18th International Conf. on MachineLearning*, 2001.
[24] DusanT,TatjanaD,Milica S “Bee Colony Optimization Overview”, BCO chapter.
[25] Cuevas, E., Sención-Echauri, F., Zaldivar, D., Pérez-Cisneros, M. Multi-circle detection on images using artificial bee colony (ABC) optimization, Soft Computing, 16 (2), (2012), pp. 281-296.

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