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Brain's MRI Segmentation for Lesion Detection using Clustering with Grammatical Swarm Based-Adaptable Particle Swarm Optimizer

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Abstract: **Magnetic Resonance Image segmentation is an important image analysis task in medical image processing for diagnosis of diseases. Brain MRI segmentation is done for the proper diagnosis of lesions. In this paper, a new segmentation method using partitional clustering algorithm with Grammatical Swarm Based-Adaptable Particle Swarm Optimizer is proposed for lesion detection of brain MR images. Difficulty in use of segmentation occurs due to presence of noise in the MR images. Therefore, noise is removed using non-local means filter. After segmentation of T2-weighted MR images using the proposed clustering method, lesions are extracted from the MR images. A comparative study has been made with PSO based method using quantitative measurement indices. The experimental results show that proposed method performs better than PSO based method.**
Keywords: Magnetic Resonance Imaging, Lesion, Segmentation, Clustering, Grammatical Swarm, Particle Swarm Optimizer

I. Introduction

A. Background

Mutlimodal Magnetic Resonance Imaging (MRI) [1, 2] segmentation is an important image analysis task in medical diagnosis and segmentation of multimodal MRI has become crucial in detection of lesion in the brain. Magnetic resonance imaging provides detailed information about brain tumor anatomy, cellular structure and vascular supply. Therefore, it is an important tool for the effective diagnosis, treatment and monitoring of the brain disease [1]. It is also very important in the progressive transmission [3, 4] of images. In progressive transmission, only the segmented MRI of patients having lesion is transmitted whereas segmented images not having lesions are transmitted only on demand to reduce the effective load of the transmitter as stated in articles [3, 4]. Brain MR images can have maximum seven classes or objects [5]:(i) background, (ii) cerebrospinal fluid(CSF), (iii) white matter, (iv) gray matter,(v) bone, (vi) scalp and (vii) lesion. With different parameters settings, it is possible to obtain three types of brain MRI of same patient: (a) T1-Weighted (b) T2-Weighted (c) Proton density (-weighted) [5]. In this work, only T2-Weighted images are considered for segmentation because of the intrinsically higher soft tissue contrast resolution. Segmentation is a process to make partition the image into different regions or segments or class. The main difficulties in MRI segmentation are (a) noise (b) the bias field (intensity inhomogeneity i.e. smooth intensity change inside originally homogeneous regions) and (c) the partial volume effect i.e. a voxel contributes in multiple tissues [6, 7].

B. Related Works

Brain MRI segmentation is to partition the image into different class of tissues as well as to detect lesion. W. M. Wells et al. [9] proposed an adaptive segmentation of MRI images. This adaptive method used the knowledge of tissue intensity properties and intensity inhomogeneities to correct and segment the MRI image and Expectation-Maximization (EM) algorithm was used to obtain the bias field estimates from nonlinear estimator. A knowledge-based technique for automatic segmentation of brain MRI was presented in article [10]. First, Fuzzy C-Means (FCM) clustering algorithm is used to segment the image in this method. Then an expert system was used with initial FCM segmentation to detect normal or abnormal slice of MRI. S. Saha et al. [11] proposed an automatic segmentation technique of multispectral magnetic resonance image of the brain using new fuzzy point symmetry based genetic clustering technique. Real-coded variable string length genetic fuzzy clustering technique (Fuzzy-VGAPS) was used to evolve the number of clusters present in the Multiple Sclerosis MRI data set automatically. M. Y. Siyal et al. [12] proposed an intelligent modified fuzzy c-means based algorithm for bias (or intensity in-

homogeneity) estimation and segmentation of brain MRI. A. Dasgupta [13] segmented the brain MRI for lesion detection using a modified Fuzzy C-Means algorithm which can filter the image at the time of segmentation of noisy image. A. De et al. [14] proposed masking based segmentation of diseased MRI Images. An entropy based maximization using Particle Swarm Optimizer was used to select the threshold value for brain MRI segmentation to separate the lesions from healthy tissue cells and a variable mask is used to de-noise the image. A. De et al. [3, 4] used hybrid particle swarm optimization with wavelet mutation based segmentation for brain MRI. In these methods entropy based maximization is used to select proper threshold values for segmentation the images. J. Alirezaie et al. [5] used Back-Propagation neural network and Learning Vector Quantization neural network to segment the brain MR images. In the year 2013, S. Sindhumol et al. [15] proposed an automated brain tissue classification by multi-signal wavelet decomposition and independent component analysis. In this method, a multi-signal wavelet analysis is applied on input multispectral data. Signals are reconstructed from detail coefficients were used in conjunction with original input signals to do Independent Component Analysis (ICA). Fuzzy C-Means (FCM) clustering was performed on generated results for segmentation. In article [16], Grammatical Swarm based clustering algorithm is applied on Magnetic Resonance images and mass lesion are separated from the healthy objects in the brain.
In this work, Non-local Means (NLM) filter [8] based denoising method is used in order to remove noise from MRI first. Second, the denoised images are segmented using clustering with Grammatical Swarm based-adaptable Particle Swarm Optimizer (GSPSO) proposed by T. Si et al. [17]. Finally, the lesion regions are extracted from the segmented MR images. Quantitative measurement indices are used to measure the performance of the proposed method and a comparative study is done with existing PSO based method [24].

C. *Contributions of this paper*

The contributions of this paper is summarized as following:

1. A partitional clustering technique with GSPSO algorithm (CGSPSO).
2. Application of CGSPSO algorithm for lesion detection in Brain's MRI.
3. A comparative study with PSO based method.

II. Material & Methods

The outline of the proposed method is as following:

1. MRI data acquisition
2. Denoising
3. Segmentation
4. Lesions extraction

A. *MRI Data Acquisition*

A set of six MRI slices of human brain of same patient have taken for application purposes. For these experiments, Axial T2-Weighted images generated by 1.5-T MRI imaging device are considered. The slice thickness is 5.0 mm and the gap between two slices is 1.5 mm. Each MRI slice is having a resolution of 256×256.

B. *Denoising*

High SNR MR Images contain the Rician distributed noise which are approximated to Gaussian distributed noise [8]. Whereas the backgrounds of the images (i.e. "no signal" regions due to air) contain Raleigh distributed noise. The images are de-noised using Non-Local Means (NLM) Filter. In the real world MR images, the noise level is unknown as there is no "ground truth" available. An average level of noise over all the data from a same scanner is estimated using the noise regions extracted from the backgrounds of MR images by assuming that the noise level is generated by the MRI scanner machine for a given sequence is constant. The details of this method can be obtained from article [8].

C. *Segmentation*

Segmentation of brain's MR images is done using the proposed GSPSO based clustering algorithm. T. Si et al. [17] proposed GSPSO algorithm in which the velocity update rules of particles in PSO are evolved using GS resulting better exploration of the search space which leads to get better quality of solutions. GSPSO algorithm is an hybridization of Grammatical Swarm (GS) and Particle Swarm Optimization (PSO) algorithms.

1) *GSPSO Algorithm*

GSPSO algorithm runs both adaptive PSO and GS algorithms in parallel. The different particles in PSO use different velocity update rules evolved by GS whereas particles in GS use same velocity update rule (i.e Eq.(1)) during all the iterations. There is a *one-to-one correspondence* from particles of GS to particles of PSO based on index.
Particle Swarm Optimization: Particle swarm optimization (PSO) [18] is a population based global optimization algorithm having stochastic nature. Each individual in PSO is called as particle and set of particles is called as swarm. The position y_i of i^{th} particle is represented as $< y_{i1}, y_{i2}, y_{i3}, ..., y_{iD} >$ where D is the dimension of the problem to be optimized by the PSO. Each particle has its own memory to store its personal best y_i^{pbest} found so far. The best of all personal best solution is called the global best y^{gbest} of the swarm. Each particle is accelerated by its velocity V_i and the velocity is updated by the following equation:

$$v_i(t+1) = w \times v_i(t) + c_1 \times r_1 \times (y_i^{pbest}(t) - y_i(t)) + c_2 \times r_2 \times (y^{gbest}(t) - y_i(t)) \quad (1)$$

and position is updated by following equation:

$$y_i(t+1) = y_i(t) + v_i(t+1) \quad (2)$$

In Eq. (1), $w \in (0,1)$ is the inertia weight, c_1 and c_2 are the personal cognizance and social cognizance respectively.

r_1 and r_2 are two uniformly distributed random number in $(0, 1)$.
Y. Shi and R.C Eberhart [19] introduced a linearly decreasing inertia weight with time in the range $(w_{min}, w_{max}) = (0.4, 0.9)$. The corresponding equation is given in below:

$$w = w_{max} - (w_{max} - w_{min}) \times (\frac{t}{t_{max}}) \quad (3)$$

Grammatical Swarm: Grammatical Swarm (GS)[20] algorithm is a variant of Grammatical Evolution (GE) based on PSO and it is used to generate computer programs in any arbitrary language. In Grammatical Swarm, PSO is used as search engine in genotype-to-phenotype mapping process. Each particle's position represents a set of integer valued codon in the range $[0, 255]$. Particle's position represents the genotype which is mapped to phenotype (*fitness* corresponding derived expression). Backus-Naur Form (BNF) of Context-Free Grammar (CFG) is used to generate the computer programs from the codons. The dimension of particle is the number of codons. An example of genotype is given in Fig. 2.
In GSPSO algorithm, GS evolves the velocity update equations for each particle in PSO in order to increase diversity in the population. A *Dual Swarm Space* is used in GSPSO. The search space of GS is denoted as *Grammatical Swarm Space* in which each particle's position represents a genome containing a number of integer codons. On the other side, another *Swarm Space* denotes the problem's search space where particles search the solution of the given problem. *Grammatical Swarm Space* is mapped to *Swarm Space*(i.e Genotype-to-Phenotype *mapping*). Therefore, the number of population in two swarm spaces are equal. The search space range in GS is $[0, 255]$. And search space range of particles in other swarm space is $[y_{min}, y_{max}]$. The block diagram of GSPSO algorithm is given in Fig. 1.

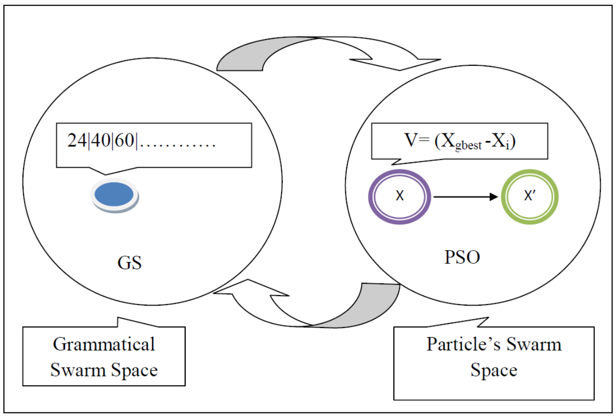


Figure. 1: Block diagram of GSPSO algorithm

In the GSPSO algorithm, individuals in Grammatical Swarm share PSO's *fitness function* i.e *local fitness, pbest* and *gbest* of PSO in solution space.
The velocity update equation for PSO in GSPSO is represented in the following form:

$$v(i)(t + 1) = f(a_j(t)), j = 1, 2, 3, 4 \quad (4)$$

where $a_1 = v_i(t), a_2 = y_i(t), a_3 = y_i^{pbest}(t), a_4 = y_i^{gbest}(t)$. The function set is $F = \{+, -, *, /\}$ and the terminal set is $T = \{a_1, a_2, a_3, a_4, r\}$ where r is random constant in (0, 1).

180	**55**	**153**	**85**	**211**	**177**

Figure. 2: Genotype

The velocity update rules are derived from particle's position i.e codons in GS using the following Backus-Naur Form (BNF) of Context-Free Grammar(CFG):

```
1. <expr> := (<expr><op><expr>) (0)
             | <var> (1)
2. <op> := + (0)  | - (1)  | * (2)  | / (3)
3. <var> := a1 (0)| a2 (1)  | a3 (2)
            | a4 (3)  | r (4)
r represents a random number
in the range (0,1).
```

Rules number and number of corresponding choices are given in Table 1. A *mapping process* is used to map from

Table 1: Rules and their choices

Rule#	Choice#
1	2
2	4
3	5

integer-valued codon to rule number in the derivation of velocity update expression using BNF grammar by the following ways:
rule=(codon integer value) MOD (number of choices for the current non-terminal)
In the derivation process, if the current non-terminal is <expr> , then, the rule number is generated by the following way:
rule number=(180 mod 2)=0
<expr> will be replaced by (<expr><op><expr>)

```
<expr> :=(<expr><op><expr>)(180 mod 2)=0
       :=(<var><op><expr>) ( 55 mod 2)=1
       :=(a4<op><expr>)    (153 mod 5)=3
       :=(a4-<expr>)       ( 85 mod 4)=1
       :=(a4-<var>)        (211 mod 2)=1
       :=(a4-a2)           (177 mod 2)=1
```

The resultant derived expression $(a4 - a2) = (y_i^{gbest}(t) - y_i(t))$.

2) *GSPSO based Clustering*

Clustering is an unsupervised learning technique widely used in bio-medical application like MRI image analysis [21, 22]. Let $\mathcal{X} = \{\vec{x}_1, \vec{x}_2, ..., \vec{x}_\mathcal{N}\}$ is a set of input patterns, $\vec{x}_i = (x_{i1}, x_{i2}, ..., x_{ij}, .., x_{id}) \in \Re^d$ and each x_{ij} is the attribute of input patterns. (Hard) partitional clustering attempts to seek a $\mathcal{K}$-partition of $\mathcal{X}$,$\mathcal{C} = \{\mathcal{C}_1, \mathcal{C}_2, ..., \mathcal{C}_\mathcal{K}\}(\mathcal{K} \leq \mathcal{N})$ such that

1. $\mathcal{C}_k \neq \phi, k = 1, 2, ..., \mathcal{K}$
2. $\bigcup_{k=1}^{\mathcal{K}} C_k = \mathcal{X}$

3. $\mathcal{C}_k \bigcap \mathcal{C}_l = \phi, k, l = 1, 2, ..., \mathcal{K}$ and $k \neq l$

A very popular and widely used partitional clustering algorithm is K-means algorithm [23]. The objective of K-means algorithm is to minimize the intra-cluster spread (ICS) for $\mathcal{K}$ number of clusters and it is defined as following:

$$ICS = \sum_{k=1}^{\mathcal{K}} \sum_{\vec{x}_i \in \mathcal{C}_k} \|\vec{x}_i - \vec{m}_k\|^2 \tag{5}$$

where $\vec{x}_i$ is the pattern in $\mathcal{C}_k$ cluster and $\vec{m}_k$ is the mean of the patterns in the same cluster. In K-means algorithm, $\mathcal{K}$ cluster centroids are initialized by random selection from the data set and each pattern $\vec{x}_i$ in the data set is then assigned to the closest cluster using the following equation:

$$k = \arg \min_{\forall k \in \mathcal{K}} \{\mathcal{D}_{ik}\} \tag{6}$$

Where $\mathcal{D}_{ik}$ is the Euclidean distance between i^{th} pattern $\vec{x}_i$ and k^{th} centroid $\mathcal{C}_k$ and it is calculated using the following equation:

$$\mathcal{D}_{ik} = d(\vec{x}_i, \vec{m}_k) = \left[\sum_{l=1}^{d} (x_{il} - m_{kl})^2 \right]^{\frac{1}{2}} \tag{7}$$

The cluster's centroids are updated by the mean of the associated patterns in the cluster and the algorithm is terminated when the maximum number of iterations reach or there is no performance improvement during some successive iterations. The K-means algorithm is very easy to implement but K-means often leads to converge to suboptimal solutions because it is heavily dependent on the initial cluster's centroids. Clustering technique with Evolutionary Algorithms [21, 22], Differential Evolution [25], PSO [24] performed better than K-means algorithm. Partitional clustering using PSO performed better than K-means algorithm in MR image classification [24]. PSO has faster convergence speed but it gets stuck often due to lacks in diversity. GSPSO algorithm has superiority over PSO in obtaining better quality of solutions. Therefore, in this work, proposed GSPSO based clustering algorithm is used to segment the MR images by using gray level feature values.

Now, in the context of clustering with GSPSO, each i^{th} particle's position y_i represents a set of cluster centers $\mathcal{M}_i = \{\vec{m}_1, \vec{m}_2, ..., \vec{m}_{\mathcal{K}}\}$ where $\mathcal{K}$ is the number of predefined clusters in the images. The dimension of particle's position is $\mathcal{K}$ because dimension of $\vec{m}$ is one as clustering is performed based on gray values of image pixels. First, cluster centers are decoded from the particle's position and the euclidean distance is calculated for each pixel from all centers using the Eq.(6). Second, each pixel is assigned to a cluster by following the Eq.(7). Finally, the quality of clustering solution is measured using multiple objective functions defined in next.

Multiple Objective Functions: In this work, three different objective functions adopted from article [24] are used to perform better clustering of the MR images. The first objective function f_1 is the maximum within-cluster distance which is to be minimized and it is defined by the following equation:

$$f_1 = d_{max}(X, \vec{m}) = \max_{\forall k \in \mathcal{K}} \left\{ \sum_{\forall \vec{x}_i \in \mathcal{C}_k} \frac{d(\vec{x}_i, \vec{m}_k)}{|\mathcal{C}_k|} \right\} \tag{8}$$

where $|\mathcal{C}_k|$ is the number of pixels belong to cluster $\mathcal{C}_k$.
The second objective function f_2 is the minimum inter-class distance which is to be maximized and it is given as following:

$$f_2 = d_{min}(\vec{m}_i, \vec{m}_j) = \min_{\substack{i \neq j \\ i,j \in \mathcal{K}}} \{d(\vec{m}_i, \vec{m}_j)\} \tag{9}$$

The third objective function f_3 is the quantization error which is to be minimized and it is given as follows:

$$f_3 = \frac{1}{\mathcal{K}} \sum_{k=1}^{\mathcal{K}} \sum_{\forall \vec{x}_i \in \mathcal{C}_k} \frac{d(\vec{x}_i, \vec{m}_k)}{|\mathcal{C}_k|} \tag{10}$$

Finally, all three objective functions are converted into a single objective function (f^*) which is to be minimized and it is defined by following equation:

$$f^* = w_1.f_1 + w_2.(x_{max} - f_2) + w_3.f_3 \tag{11}$$

where w_1, w_2, w_3 are the weight values in the range $(0, 1)$ and $\sum_{i=1}^{3} w_i = 1$. The second objective function f_2 is converted into minimization problem by subtracting it from the maximum gray level x_{max}.
The objective function f^* is minimized by GSPSO algorithm and it is also used as fitness function of particles. Putting all together, the CGPSO algorithm is summarized in Table 2.

Table 2: GSPSO Based Clustering Algorithm

Algorithm:CGSPSO	
1.	Initialize the population of PSO and GS in the range $[0, 255]$
2.	Decode the cluster centers m_k from each particle's position y_i in PSO
3.	Calculate the euclidean distance $\mathcal{D}_{jk}$ of each pixel x_j from all centers m_k using the Eq.(6).
4.	Assign each pixel x_j to a cluster k by the following the Eq.(7).
5.	Calculate the fitness of particles using Eq.(11).
6.	Calculate the pbest and gbest
7.	**While** (termination criteria)
8.	**For** each individual
9.	Perform velocity and position update for GS
10.	**If** derived expression from particle of GS is valid
11.	Update the velocity using this new expression and update the position
12.	**Else**
13.	Update the velocity with pbest expression and update the position
11.	**End If**
12.	Do the steps 2,3 and 4
12.	Calculate new fitness
13.	Update pbest and gbest of PSO
14.	Update pbest expression if new expression is valid and gbest velocity updating equation in GS
15.	**End For**
16.	**End**

III. Experiment & Evaluation

A. Parameter Settings

The parameters of GS in GSPSO are set as following: Dimension of GS=100, Number of Wrapping=2, Population Size(NP)=50, $V_{max} = 0.5 \times (X_{max} - X_{min})$, $c_1 = c_2 = 2.05$,$(w_{max}, w_{min}) = (0.9, 0.4)$.
The parameters of PSO in GSPSO are set as following: Dimension$D$=$\mathcal{K}$, Population Size(NP)=50, $v_{max} = 5$.

The parameters of PSO [24] are set as following: Dimension(D)=$\mathcal{K}$, Population Size(NP)=50, $v_{max} = 5$, $c_1 = c_2 = 1.49$,$w = 0.72$.
In both GSPSO and PSO, $w_1 = w_2 = 0.325, w_3 = 0.35$
Both GSPSO and PSO algorithms are allowed maximum 5000 function evaluations(FEs) in each run and this is the termination criteria. Total number of separate runs for each MR images is 30.

B. Quantitative Measurement Indices

The performance of the proposed method along with PSO based segmentation method are measured quantitatively using *Davis-Bouldin (DB) Index* [26] and *Dunn-Index* [27]. These two indices were used by P. Maji and S.K Pal [28] to measure the performance of brain's MRI segmentation. The lower value of *DB-Index* and higher value of *Dunn-Index* indicate good segmentation of the MR images.

1) Davis-Bouldin (DB) Index

DB-Index [26] is a well-known cluster validity index used to measure the performance of clustering algorithm quantitatively. *DB-Index* is a function of the ratio of the sum of intra-cluster scatter to inter-cluster separation. *intra i^{th} cluster scatter* is defined by the following equation:

$$\mathcal{S}_q(\vec{m}_i) = \left[\frac{1}{\mathcal{N}_i}\sum_{\vec{x}\in\mathcal{C}_i}|\vec{x}-\vec{m}_i|^q\right]^{\frac{1}{q}} \tag{12}$$

Inter–cluster distance between i^{th} and j^{th} cluster is defined by the following equation:

$$\mathcal{D}^t_{ij} = \left[\sum_{p=1}^{d}|m_{i,p}-m_{j,p}|^t\right]^{\frac{1}{t}} = \|\vec{m}_i-\vec{m}_j\|^t \tag{13}$$

where $\vec{m_i}$ is the centroid of i^{th} cluster,$q, t \geq 1$, q, t are integer, $\mathcal{N}_i = |\mathcal{C}_i|$ is the number of elements in the i^{th} cluster $\mathcal{C}_i$. q and t are set to 2 in this work. $R_{i,qt}$ is calculated as

$$R_{i,qt} = \max_{\substack{j\in\mathcal{K}\\ j\neq i}}\left\{\frac{\mathcal{S}_q(\vec{m}_i)+\mathcal{S}_q(\vec{m}_j)}{\mathcal{D}^t_{ij}}\right\} \tag{14}$$

Finally, *DB-Index* is measured by the following equation:

$$DB(\mathcal{K}) = \frac{1}{\mathcal{K}}\sum_{i=1}^{\mathcal{K}}R_{i,qt} \tag{15}$$

2) Dunn-Index

Dunn index [27] is designed to identify sets of clusters that are compact as well as well separated. Dunn index is defined as following:

$$Dunn = \min_i\left\{\min_{i\neq j}\left\{\frac{d(\vec{m}_i,\vec{m}_j)}{\max_k \mathcal{S}_q(\vec{m}_k)}\right\}\right\}, \quad 1\leq i,j,k\leq\mathcal{K} \tag{16}$$

C. PC Configuration

System: Windows 7, CPU: AMD FX -8150 Eight-Core 3.6 GHz, RAM: 16 GB, Software: Matlab 2010b

IV. Results & Analysis

The proposed method is applied on six Axial T-2 MR images. First, noises across the MR images are removed by NLM filter based deoising method. The original images and their denoised versions are given in Fig. 3. After that, CGSPSO algorithm is used to segment the denoised MR images with cluster number=4. The segmented images obtained using both proposed method and PSO based method are given in Fig. 4. Finally, the lesions are extracted from the segmented MR images and the images contains lesioned regions are given in Fig. 5. Separate 30 runs are carried out for both GSPSO and PSO methods over all MR images. The performances of the methods are measured using *DB-Index* and *Dunn-Index*. Mean and standard deviation of these measurements over 30 separate runs are tabulated in the Table 3 & 4.
From the visual analysis of the segmented images in Fig. 4 and their extracted lesion images in Fig. 5, it can be said that the proposed method performs better segmentation of the MR images than PSO based method. From the Table 3, it is observed that the proposed method obtains lower *DB-Index* values than that of PSO based method which indicates that the proposed method performs better than PSO based method. It is also observed from the Table 4 that the *Dunn-Index* values of the proposed method are higher than that of PSO based method which signifies again that the proposed method performs better than PSO based method. From the analysis of these two quantitative measurement indices over all MR images, it is seen that the proposed method performs better segmentation of the MR images resulting in better detection of lesions in the brain's MR images. The proposed method performs better than PSO based method because GSPSO has higher exploration ability in the search space leading to CGSPSO algorithm for providing better clustering solutions in terms of cluster centers of the MR images. The extracted lesion images also contain some parts of other objects in the brain because there are similarities in pixel intensities of others objects with the lesions in the MR images. MR images also contain the intensity inhomogeneity i.e smooth intensity changes in originally homogeneous regions for which segmentation faces difficulties.
Overall, the above experimental results with analysis demonstrate that the proposed method performs better segmentation than PSO based method and that resulting the proposed method in better lesions detection in multimodal MR images of brain.

Table 3: Mean and standard deviation of *DB-Index* values over 30 separate runs

MRI#	GSPSO		PSO	
	Mean	Std. Dev.	Mean	Std. Dev.
1	0.1240	0.0132	0.1319	0.0222
2	0.1158	0.0122	0.1282	0.0276
3	0.1215	0.0137	0.1301	0.0183
4	0.1182	0.0098	0.1347	0.0238
5	0.1165	0.0112	0.1299	0.0215
6	0.1231	0.0119	0.1391	0.0258

Table 4: Mean and standard deviation of *Dunn-Index* values over 30 separate runs

MRI#	GSPSO		PSO	
	Mean	Std. Dev.	Mean	Std. Dev.
1	13.1697	1.7836	11.5180	2.4779
2	13.5186	1.7533	11.9542	3.1449
3	13.4013	2.0040	11.9038	2.5638
4	13.5144	1.8531	11.8177	2.4392
5	14.3860	1.5185	12.2854	2.8217
6	13.1453	1.6019	11.3684	2.6149

V. Conclusions

This paper proposes a new segmentation method for lesion detection in brain's MRI. In this proposed method, first multimodal MR images are denoised using NLM filter. Second, MR images are segmented using a new partitional clustering technique with GSPSO algorithm. The key feature of GSPSO algorithm is that different particle updates their velocities using different velocity update rules evolved by GS algorithm. This characteristic of GSPSO algorithm leads to better exploration of the search space than PSO. Finally, the lesions are extracted from the segmented MR images. The experiment results with quantitative measurement indices of segmentation demonstrates that the proposed method performs better than PSO based method. This work can be further extended with the incorporation of different distance measures like kernel distance measure etc. in the proposed CGSPSO algorithm. Intensity inhomogeneity across the MR images effect the segmentation as well as lesion detection. Therefore, the proposed method can be further improved with intensity inhomogeneity correction before the segmentation process of the MR images.

References

[1] Paul M. Parizel , Luc van den Hauwe , Frank De Belder , J. Van Goethem , CarolinVenstermans , Rodrigo Salgado , Maurits Voormolen , and Wim Van Hecke: *Magnetic Resonance Imaging of the Brain*, P. Reimer et al. (eds.): Clinical MR Imaging, Springer-Verlag Berlin Heidelberg,2010.

[2] L. Tonarelli: *Magnetic Resonance Imaging of Brain Tumor*, CEwebsource.com, 2013.

[3] A. De, A. K. Bhattacharjee and C. K. Chanda and B. Maji: Hybrid Particle Swarm Optimization With Wavelet Mutation Based Segmentation and Progressive Transmission Technique For MRI Images, *International Journal of Innovative Computing, Information and Control*, Vol. 8,No. 7(B), pp. 5179-5197, 2012.

[4] A. De, A. K. Bhattacharjee and C. K. Chanda and B. Maji: Entropy Maximization Based Segmentation, Transmission and Wavelet Fusion of MRI Images, *International Journal of Hybrid Intelligent Systems*,IO Press,Vol. 10, pp. 57-69, 2013.

[5] J. Alirezaie, M. E. Jernigan, and C. Nahmias: *Neural Network based Segmentation of Magnetic Resonance Images of the Brain*, IEEE Transactions on Nuclear Science, Vol. 44, Issue 2, pp. 194-198, 1997.

[6] M. A. Balafar, A. R. Ramli, M. I. Saripan and S. Mashohor: Review of brain MRI image segmentation methods, *Artif. Intell. Rev.*,Vol.33 pp. 261–274, 2010.

[7] M. A. Balafar, A. R. Ramli, and S. Mashohor: A new method for MR grayscale inhomogeneity correction, *Artif. Intell. Rev.*,Vol.34 pp. 195–204, 2010.

[8] 9. P. Coupie , J. V. Manjon, E. Gedamu, D. Arnold, M. Robles, D. L. Collins: Robust Rician Noise Estimation for MR Images, *Medical Image Analysis,14(4)*, pp.483–93, 2010.

[9] W. M. Wells et al.: Adaptive Segmentation of MRI Data, *IEEE Transaction on Medical Imaging*, Vol. 15, No. 4, pp. 429-442, 1996.

[10] M. C. Clark, L. O. Hall, D. B. Goldgof, R. Velthuizen, F. R. Murtagh, and M. S. Silbiger: Automatic Tumor Segmentation Using Knowledge-Based Techniques, *IEEE Transaction on Medical Imaging*, Vol.17, No. 2 pp. 187-201, 1998.

[11] S. Saha and S. Bandyopadhyay, MRI Brain Image Segmentation by Fuzzy Symmetry Based Genetic Clustering Technique, *IEEE Congress on Evolutionary Computation*, Singapore pp. 4417-4424, 2007.

[12] M.Y. Siyal and L. Yu: An intelligent modified fuzzy c-means based algorithm for bias estimation and segmentation of brain MRI, *Pattern Recognition Letters*, 26, pp. 2052–2062, 2005.

[13] A. Dasgupta: Demarcation of Brain Tumor Using Modified Fuzzy CMeans, *International Journal of Engineering Research and Applications*,Vol. 2, Issue. 4, pp. 529-533, 2012.

[14] A. De, R. L. Das, A. K. Bhattacharjee and D. Sharma: Masking based Segmentation of Diseased MRI Images, *IEEE International Conference on Information Science and Applications (ICISA)*, Seol, South Korea pp. 1-7, 2010.

[15] S. Sindhumol, Anil Kumar and Balakrishnan Kannan, Automated Brain Tissue Classification by Multisignal Wavelet Decomposition and Independent Component Analysis, *ISRN Biomedical Imaging*, Hindawi Publishing Corporation, Volume 2013, pp.1–10.

[16] T. Si, A. De and A. K. Bhattacharjee: Brain MRI Segmentation for Tumor Detection using Grammatical Swarm Based Clustering Algorithm , *IEEE International Conference on Circuit, Power and Computing Technologies*, Tamilnadu, India, pp.1196–1201, 2014.

[17] T. Si, A. De and A. K. Bhattacharjee: Grammatical Swarm Based-Adaptable Velocity Update Equations in Particle Swarm Optimizer, *In: S.C. Satapathy (eds.),FICTA 2013, Advances in Intelligent Systems and Computing 247*, Springer International Publishing Switzerland 2014, pp. 197–206, 2014. DOI: 10.1007/978-3-319-02931-3_24

[18] J. Kennedy and R. C. Eberhart: Particle swarm optimization, *In proceedings of IEEE International Conference on Neural Networks*, Piscataway, NJ. pp. 1942–1948, 1995

[19] Y. Shi and R. C. Eberhart: A modified particle swarm optimizer. *In Proceedings of the IEEE Congress on Evolutionary Computation (CEC 1998)*, Piscataway, NJ. pp. 69–73, 1998

[20] M. O'Neill, A. Brabazon: Grammatical Swarm: The Generation of Programs by Social Programming, *Natural Computing* 5(4),pp. 443–462.

[21] R. Xu and D. C. Wunsch: Survey of Clustering Algorithms, *IEEE Transaction On Neural Networks*, Vol. 16, No. 3, pp. 645-678, 2005.

[22] R. Xu and D. C. Wunsch: Clustering Algorithms in Biomedical Research: A Review, *IEEE Reviews In Biomedical Engineering*, pp. 120-154, 2010.

[23] J. MacQueen: Some methods for classification and analysis of multivariate observations, *in Proc. 5th Berkeley Symp. Math. Stat. Probability*, 1967, pp. 281–297.

[24] M. G.H. Omran, A. P. Engelbrecht, and A. Salman: Dynamic Clustering using Particle Swarm Optimization with Application in Unsupervised Image Classification, *World Academy of Science, Engineering and Technology*,9, pp. 755-760,2007.

[25] S. Das, A. Abraham and A. Konar: Automatic Clustering Using an Improved Differential Evolution Algorithm, *IEEE Transaction On Systems, Man, and Cybernetics Part A: Systems and Humans*, Vol. 38, No. 1, pp. 218-237, 2008.

[26] D. L. Davies and D. W. Bouldin: A cluster separation measure, *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 1, no. 2, pp. 224–227, Apr. 1979.

[27] J. C. Bezdek and N. R. Pal: Some New Indexes for Cluster Validity, *IEEE Transactions on System, Man, and Cybernetics*, Part B, Vol. 28, 301–315, 2007.

[28] P. Maji and S. K. Pal: Rough Set Based Generalized Fuzzy C-Means Algorithm and Quantitative Indices, *IEEE Trans. On Systems, Man, and Cybernetics–Part B: Cybernetics*, Vol. 37, No. 6, pp. 1529–1540, 2007.

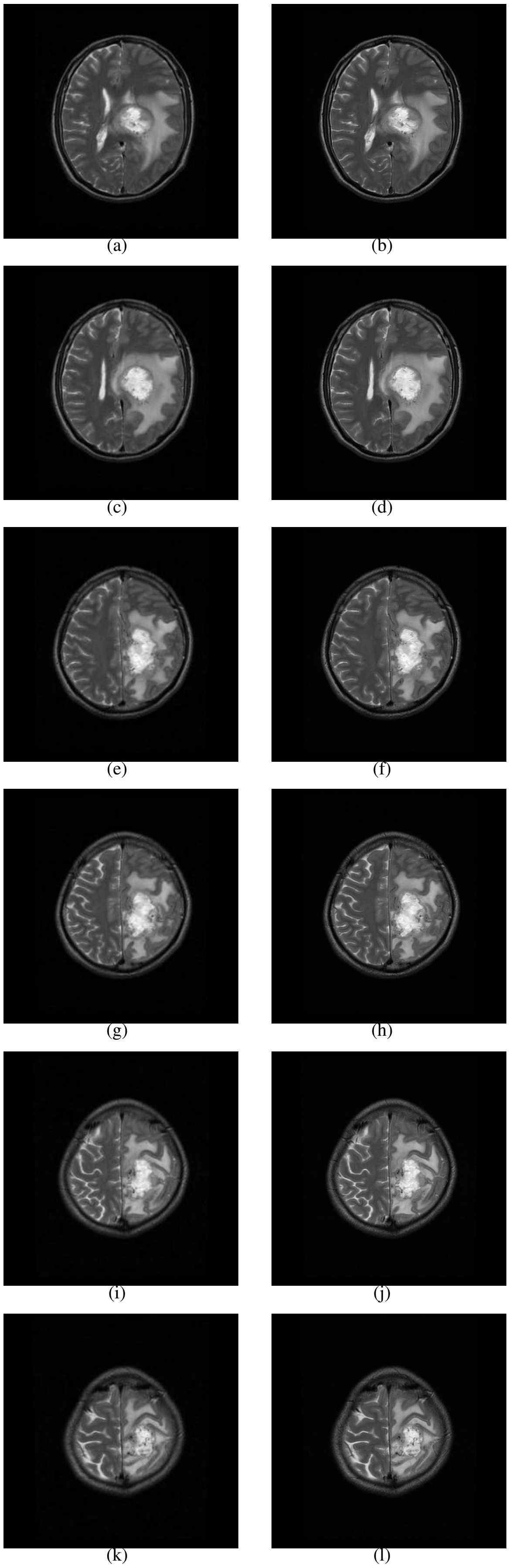
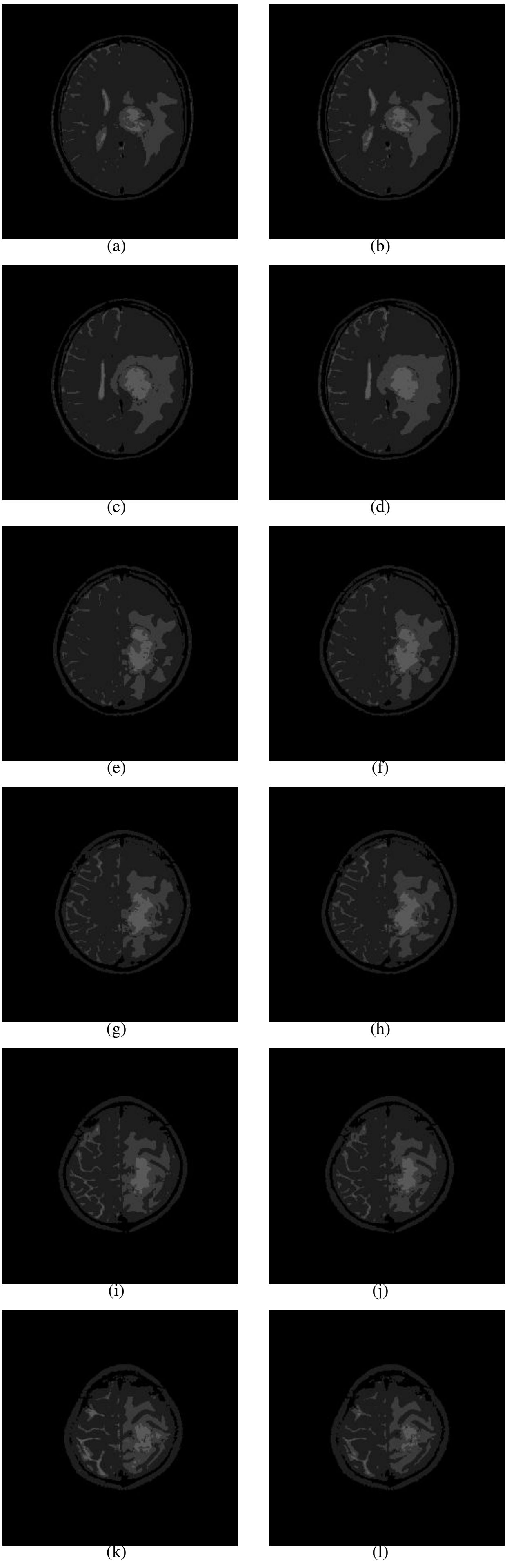


Figure. 3: 1^{st} column: Original MRI, 2^{nd} column: denoised MRI.



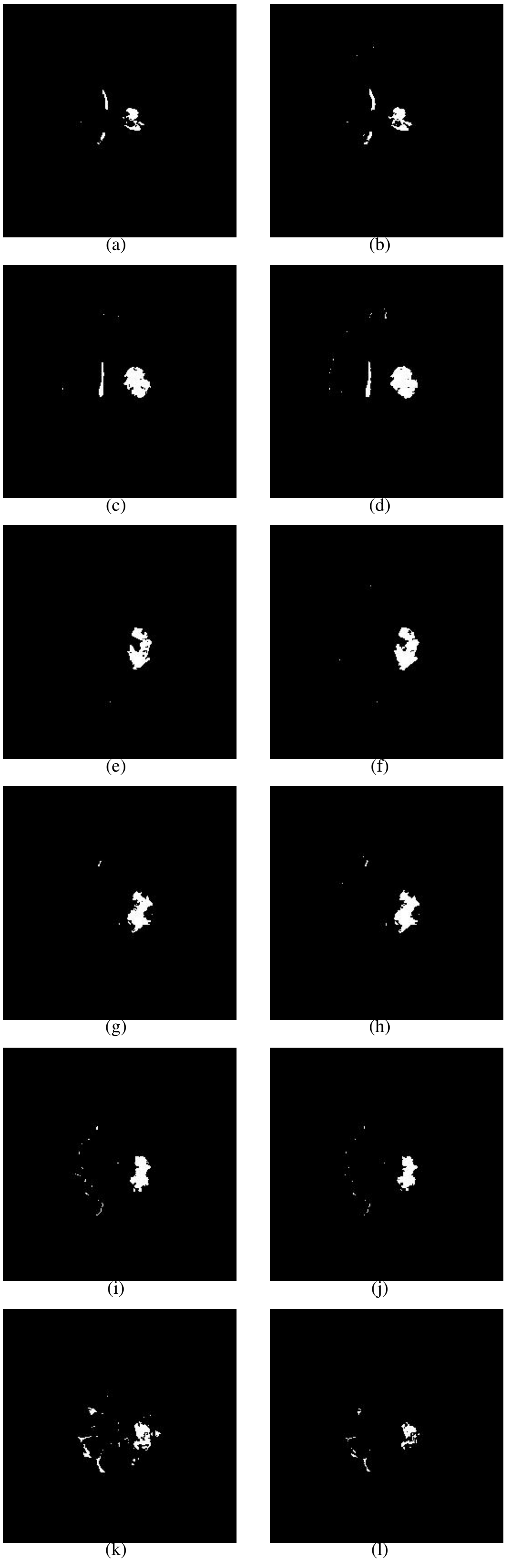


Figure. 5: Extracted lesions,1^{st} column: GSPSO, 2^{nd} column: PSO.

Figure. 4: Segmented MR images, 1^{st} column: GSPSO, 2^{nd}