Modified Particle Swarm Optimization Approach applied to MRI Brain Image Clustering

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***Abstract*—This paper proposes a Particle Swarm Optimization Algorithm for Image Clustering, with modified updating mechanisms for particle position. Confinement, wind dispersion and their combination are introduced, compared against standard PSO based clustering and applied on a set of gray-level MRI Brain images. Experimental results show that the PSO-based image clustering with modified updating position performs better than the standard PSO by engendering more compact and well separated clusters.**

Keywords—Particle Swarm Optimization, Image Clustering, Confinement, Wind dispersion.

I. Introduction

In image processing and computer vision, image segmentation is a fundamental problem aiming to partition an image into several sub regions with homogeneous properties such as intensity, color or texture. Several survey papers related to image segmentation techniques exist in the literature [1-2]. Nevertheless, there is no universal segmentation method that can be applied for all images and the elaboration of an image segmentation algorithm depends on the type of image and the application field.

Data clustering is an attractive approach to find similarities between data and bring them closer into same groups. Clustering partitions a data set into a number of groups such that the similarity within a group is bigger than that between others. The proposal of data grouping, or clustering, is straightforward in its reasoning and analogous to the human thoughts who tend to summarize information in smaller collections for further analysis [3]. Clustering algorithms have been used in diverse applications of image processing, among them segmentation techniques.

Indeed, image segmentation could be seen as a clustering problem where the features describing each pixel correspond to a pattern, and each image region corresponds to a cluster [4-5].

Recent developments in applied and heuristic optimization have been strongly inspired by biological and natural system, such as genetic algorithms, evolution strategies and socio-biological optimization techniques: among them, particle swarm optimization (*PSO*).

PSO is a simple but efficient stochastic, adaptive and population-based optimization technique proposed by Kennedy and Eberhart [6].

The advantages of modeling optimization problems using this ethological paradigm are multiple: The model is less complex, it achieves inherently better in multidimensional metric and the convergence rate to optimal solution is faster [7].

Since the inception of *PSO* technique, various developments have been reported in the literature. Omran, Engelbrecht and Salman are pioneers in applying PSO to image clustering [8-9]. It has been shown that *PSO*-based image clustering can have better performance than common clustering methods as k-means by generating more compact clusters and larger inter-cluster separation.

The philosophy of *PSO* approach is about maintaining a population of individuals. Each one is a potential solution of the optimization problem, in multidimensional search space. The particle moves through this space, by updating its position based on its distance from bests positions found by itself or other (neighboring) particles in the swarm. Therefore, the updated position of the particle is a new potential solution to the considered problem. This result is calculated through a fitness function that gives a quantitative rate of the solution efficiency [10].

In this paper, an improvement of *PSO* is used as clustering technique in medical images segmentation. The confinement mechanism [11] combined to the wind dispersion [7] as proposed in [12] are tested with various images to achieve image clustering. Furthermore, a comparison is made between the proposed approach and the *standard PSO* presented in [9].

To achieve this, an overview of *PSO* is presented in Section II. Section III describes the related works in PSO-based image clustering. The proposed approach is described in Section IV. Experimental results, on a database of images, are provided in Section V. Section VI concludes the paper and gives future directions.

II. Particle Swarm Optimization (PSO)

PSO starts with the random distribution of a swarm of particles in the n-dimensional search space (n represents the dimension of problem). Each particle represents a potential solution to the optimization problem. The particle flies over search space, and has its own velocity (v_i), its own best value which is the best position achieved so far (*pbest*) and the best value of its neighbors [6]. When the neighborhood of a particle is the whole swarm, the best position is referred to as the global best solution (*gbest*). For local best position, the population is divided into overlapping neighborhoods of particles and for each of them, a best particle is determined (*lbest*).

In combination, the particles personal experience "Personal best (*pbest*)" and its global best neighbor's experience (*gbest*) influence the movement of each particle through the search space.

In n-dimensional search space, the position and velocity of each particle i are represented as the vectors $Xi = (x_{i1},......,x_{in})$ and $Vi = (v_{i1},......,v_{in})$, respectively. In searching the optimum solution of the problem, the particle's velocity and position are updated as follows:

$$V_i^{k+1} = \omega V_i^k + c_1 r_1\left(Pbest_i^k - X_i^k\right) + c_2 r_2 (Gbest_i^k - X_i^k) \quad (1a)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (2a)$$

where c_1 et c_2 are acceleration factors known as cognitive and social parameters that pick the degree of the attractions in the direction of *pbest* and *gbest*; r_1 and r_2 are two random numbers produced by a uniform distribution in the interval [0,1]; k is iteration index; ω is inertia weight.

The Linear Decreasing of Inertia Weight PSO (*LDIW-PSO*) was introduced into the standard PSO algorithm by Shi and Eberhart in [13]. By employing adapting strategy for adjusting the inertia weight, the performance of PSO has been greatly improved.

$$w^k = w_{max} + (w_{max} - w_{min}) * \frac{k}{K_{max}} \quad (3)$$

where w_{max} is set to 0.9 and w_{min} to 0.4 are the values generally used [14]; k is the current iteration number and k_{max} is the maximum iteration number.

It is common that the velocity of each particle in the swarm, is maintained in the range of v_{max} and v_{min} , to prevent it from exploding, thus causing premature convergence [10]. The velocity clamping is given by the following equation:

$$V_i^{k+1} = MIN\left(MAX\left(V_i^{k+1}, v_{min}\right), v_{max}\right) \quad (1b)$$

PSO algorithm performs repetitive updating of the above equation to certain reached iteration, or until the change in velocity is close to zero. Quality is measured by using a particle fitness function which reflects the optimized solution.

The *PSO* algorithm is shown in the following pseudo code (extracted from [17]):

Begin PSO Algorithm
Input: function to optimize, f
swarm size, p_s
problem dimension, d
velocity range $[v_{min}, v_{max}]$
Output: X^{Ψ}: the best value found
Initialize: for all particle in problem space
$X_i = (x_{i1},........x_{in})$
$V_i = (v_{i1},.......,v_{in})$,
Evaluate $f(X_i)$ in d variables and get $pbest_i$, (i = 1,...p_s)
gbest ← best of *pbest*,
Repeat
Calculate w based on eq. (3)
Update v_i for all particles using (1a)
Limit the velocity to the range $[v_{min}, v_{max}]$ by eq(1b)
Update X_i for all particles using eq.(2)
evaluate $f(X_i)$ in d variables and get $pbest_i$, (i=1,...p_s)
if $f(X_i)$ is better than pbest then *pbest* ← X_i
if the best of *pbest*, is better than *gbest* then
gbest ← best of *pbest*,
Until Stopping criteria (e.g. maximum iteration or tolerance is reached)
X^{Ψ} ← *gbest*
return X^{Ψ}
End PSO Algorithm

The particle fitness function $f(X_i)$ plays an essential role in any evolutionary algorithm; since it quantifies how good a solution is.

III. PSO- based Image Clustering and Related work

One of the pioneering works in the field is the algorithm proposed in [8]. The authors used gbest *PSO* algorithm with a fixed number of clusters:

The following notations are used:

- N_p denotes the number of image pixels to be clustered
- N_c denotes the number of clusters to be formed
- Z_p denotes the p-th pixel
- m_j denotes the mean of cluster j
- C_j denotes the subset of pixel vectors that form cluster j
- $|C_j|$ denotes the number of pixels in cluster j.

A particle represents the N_c cluster centroids, encoded in vector: $X_i = (m_{i1},........,m_{in})$. The value of each particle is considered by the fitness function. The *PSO*-based image clustering can be summarized in the following pseudocode:

Begin PSO-based image clustering Algorithm
Input: fitness function, f
swarm size, p_s
velocity range, $[v_{min}, v_{max}]$
Output: x^{Ψ} : the best value found
Initialize: for all particle in problem space
$X_i = (m_{i1},........m_{in})$
$V_i = (v_{i1},.......,v_{in})$,
Evaluate $f(X_i)$ in d variables and get $pbest_i$, (i = 1,......*ps*)
gbest ← best of *pbest*,

Repeat
for each particle i
for each pixel Z_p
Calculate d(Z_p,m_{ij}) for all clusters C_{ij}
Assign Z_p to C_{ij} where
$d(Z_p, m_{ij}) = min_{\forall c=1,\ldots;N_c}\left(d(Z_p, m_{ic})\right)$
Calculate the fitness function f(X_i^k, Z)
Calculate w based on eq. (3)
Update v_i for all particles using (1a)
Limit the velocity value by eq. (1b)
Update the cluster centroids using eq (2a)
evaluate $f(x_i)$ in d variables and get $pbest_i$, (i=1,...ps)
if $f(x_i)$ is better than pbest then $pbest \leftarrow x_i$
if the best of $pbest$, is better than $gbest$ then
$gbest \leftarrow$ best of $pbest$,
Until maximum number of iteration is reached
$x^{\Psi} \leftarrow gbest$
return x^{Ψ}
End PSO-based image clustering Algorithm

In the context of image clustering problem, the clusters reached are image elements. These image components can be pixels, regions, line elements, etc. Different measures can be used to express the quality of obtained clusters.

The most common performance measurement is quantization error J_e is defined below:

$$J_e = \frac{\sum_{j=1}^{N_c}\left[\sum_{\forall Z_p \in C_j} d(Z_p, m_j)\right]/|C_j|}{N_c} \tag{4}$$

where:

$$d\left(Z_p, m_j = \sqrt{\sum_{k=1}^{N_p}(Z_{pk} - m_{jk})^2}\right) \tag{5}$$

$d(Z_p, m_j)$ is the Euclidean distance.

The intra-cluster distance $\bar{d}_{max}$ is the average of maximum Euclidean distance of particle to its associated class, and is defined as:

$$\bar{d}_{max}(Z, X_i) = max_{\forall j=1,\ldots N_c}\left\{\sum_{\forall Z_p \in C_{ij}} d(Z_p, m_{ij})/|C_{ij}|\right\} \tag{6}$$

$\bar{d}_{max}$ with smaller value, means that the clusters are more compact.
A further measure of quality is the inter-cluster separation. It is calculated by the minimum Euclidean distance between any couple of clusters and is defined below:

$$d_{min} = min_{\forall j1, j2, j1 \neq j2}\{d(m_{j1}, m_{j2})\} \tag{7}$$

d_{min} the more its value is great, more the clusters are well separated.

The above three criteria have been used by [9] to express the fitness function as shown in eq. 8:

$$f_1(X_i, Z) = w_1\bar{d}_{max}(Z, X_i) + w_2(z_{max} - d_{min}(X_i)) + w_3 J_e \tag{8}$$

where w_1 , w_2 ,w_3 are user defined constants that establish the relative weights of intra-cluster distance ($\bar{d}_{max}$), inter-cluster separation (d_{min}) and quantization error (J_e) in the fitness function. z_{max} is the maximum pixel value in the image set, which is 255 for 8-bit grayscale image used in this work. Z is a matrix representing the assignment of pixels to clusters of particle i.

The objective of the fitness function defined in eq. 8 is to minimize the intra-cluster distance ($\bar{d}_{max}$), and the quantization error (J_e) while maximize the inter-cluster separation (d_{min}).

Authors in [9], applied the PSO to clustering image and obtained better performance than other clustering algorithms. Wong and Yeh. in [17], proposed an image clustering algorithm using PSO with two improved fitness functions and their conclusions corroborated with conclusions in [9]. Lahmiri and Boukadoum. [18] compared the segmentation performance of *PSO*, the fractional-order Darwinian particle swarm optimization and Darwinian particle swarm optimization against fuzzy c-means algorithm and Otsu segmentation technique. They showed that PSO based algorithms outperformed other segmentation techniques. More recently, authors in [19] proposed a new initialization approach for the fuzzy C-means algorithm based on Fuzzy Particle swarm optimization and was evaluated on several MR brain images. The proposed approach improves segmentation results.

IV. PSO-CW IMAGE CLUSTERING

From the literature, the *standard PSO* algorithm, is known to have a shortcoming of premature convergence in solving complex problems, due to lack of enough momentum for particles to do exploitation as the algorithm approaches its terminal point [15].

In standard PSO, the particle swarm frequently gets attracted by suboptimal solutions, causing premature convergence of the algorithm and swarm stagnation. Once the particles have been attracted to to stable points that are not necessarily global optima, they continue the search process within a minuscule region of the solution space, and escaping from this local optimum may be difficult.

Once the particles have converged prematurely, they continue converging within extremely close proximity of one another so that the global best and all personal bests are within one minuscule region of the search space, limiting the algorithm exploration[16].

Several approaches have been proposed in the literature aiming to improve the exploratory capabilities of the swarm. Among them, three mechanisms are presented in this paper.

Confinement mechanism proceeds by restraining position changes to an interval [11], the following equation illustrates that:

$$X_{d,i}^{k+1} = MIN\left(MAX\left(X_{d,i}^{k} + V_{d,i}^{k}, x_{min}\right), x_{max}\right) \quad (2b)$$

where x_{min} and x_{max} are de search space range.

If any change are made then $V_{d,i}^{k} = 0$ (9)

Used for a classification task in [12], replacing equation (2a) by equation (2b) could led to a spectacular improvement of the classification accuracy.

The second modification is the introduction of the wind dispersion. As described in [7], the classical PSO doesn't consider the dynamics of the nature. To model the biological atmosphere for position update of the particles, a reproduction of wind speed and wind direction have been made. The subsequent equations represent the introduction of wind component:

$$V_{w}^{k+1} = V_{w}^{k} + v_{op} * rand() + v_{su} * rand() \quad (10)$$

The position update equation becomes:

$$X_{i}^{k+1} = X_{i}^{k} + V_{i}^{k} + V_{w}^{k} \quad (2c)$$

where v_w is the wind velocity, v_{op} is the opposing direction sets to -1 and v_{su} is the supporting direction sets to 1. The influence of the wind speed in the movement of the particles can be summarized in two points the opposing or supporting effects. The opposing effect slows down the particle to attempt the group global best solution, where the supporting effect increases the particle velocity in reaching in global best solution. Therefore, that lets particles to experiment different dynamics of atmosphere. In the case of equality of opposing and supporting direction wind velocity values, a statistic atmosphere is reproduced.

Once combining this with confinement, the following equation is obtained for updating position, as proposed in [12]:

$$X_{i}^{k+1} = MIN\left(MAX\left(X_{i}^{k} + V_{i}^{k} + V_{i}^{k}, x_{min}\right), x_{max}\right) \quad (2d)$$

The initial values of wind speed along the direction plays an important role in determining the final convergence of the particles in the optimal solution [7].

A. *Data set:*

In the present work, the *standard PSO* and the proposed approach *PSO* with Confinement and Wind (*PSO-CW)* for image clustering, have been applied to a proprietary database of sixty-three view of brain magnetic resonances images (MRI), an example is shown in Figure (1).

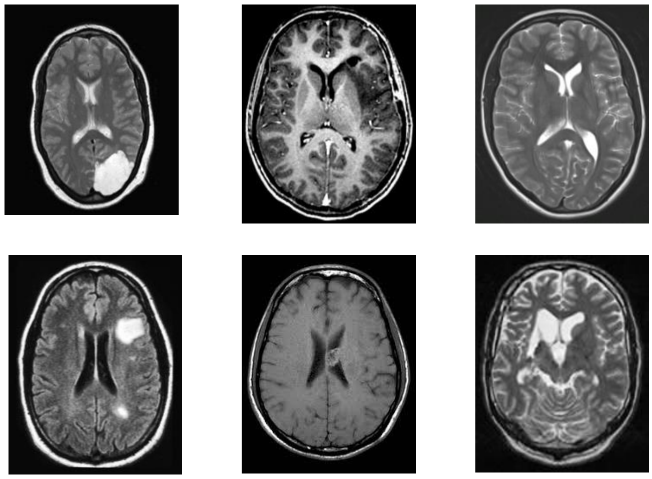

Fig. 1. Examples of MRI images from the used database.

In order to study the robustness and effectiveness of the modified update position, whole images are used without any preprocessing step.

B. *Parameter values*

Table I provides the parameter values used to perform standard PSO and PSO-CW searches. In this work, the number of particles used, the number of iterations, the initial velocity wind and the weights of fitness functions have been set empirically, after multiple experiments.

TABLE I. INITIAL PARAMETERS

Parameter	***Standard PSO***	***PSO-CW***
Number of iterations	150	150
Population	50	50
w_s	0.9	0.9
w_e	0.4	0.4
V_{min}	-5	-5
V_{max}	5	5
X_{min}		0
X_{max}		255
V_w		0
C_1	2	2
C_2	2	2
Number of cluster	8	8
W_1	0.1	0.1
W_2	0.1	0.1
W_3	0.8	0.8

V. RESULTS AND DISCUSSION

A. *Evaluation Metrics*

Performance comparison is following three aspects:

1) Compactness: measures the density of the created clusters, how compact are these clusters, since data on the same cluster should be similar. This is made by the intra-cluster distance, $(\bar{d}_{max})$.

2) Separation: the clusters should be as far as possible of each other. For this purpose, the inter-distance is used, (d_{min}).

3) quantization error :(J_e) is the average distance between a sample x and its representation mj to be minimized.

The number of clusters is chosen to be 8 for both *PSO* clustering to allow a fair comparison of their performance as proposed in [9].

The number of particles used is problem-dependent. The common choice of number of particles varies from 20 to 50 [20].

The settings of acceleration constants C_1, C_2 and the inertia weight are based on the recommendation made in [15].

the relative weights w1, w2, w3 in the fitness function and the min, max values of the velocity are those used by Omran in [9].

Since *PSO* algorithms are stochastic models, all experiments are performed twenty-five independent runs on each image and average of the intra-cluster, inter-cluster and quantization error obtained, are reported as evaluation criteria, with standard deviations to indicate the range of values to which the algorithms converge.

B. Results

Based on the algorithm described in the section III, modified by mechanisms presented in section IV, the average and standard deviation of intra-cluster distance, quantization error and inter-cluster distance are summarized in Table II for both approaches and the best values are shown in bold. The standard deviation for each index is given to check the stability of algorithms.

It is observed from the table II that *PSO-CW* performs well in comparison with standard PSO. The average inter-cluster distances are reported with the maximum value in almost MRI image clustering experiments in comparison with the standard PSO. This indicates that the clusters are well separated and the frontiers between them are well defined. Also, the average intra-clusters distances are presented with the minimum values in most experiments comparatively to the standard algorithm. This performance index indicates that the patterns of a cluster in proposed PSO-CW are very close and compact around the cluster center. The lower value of the average quantization error index indicates that the samples are better assigned to their– respective clusters than in standard PSO results.

Additionally, the *PSO-CW* algorithm is more stable and robust compared with *standard PSO* shown by low values of standard deviation.

Although, the investigation in the convergence of the two approaches, are made over a large number of images. In Figure (2) the obtained clusters for only two images from those presented in Figure (1). Visually, the proposed algorithm achieves a good clustering effect and provides more details than standard PSO, specially to surround a specific area as suspicious region and tumors. For better visualization, the clusters are displayed in false color map.

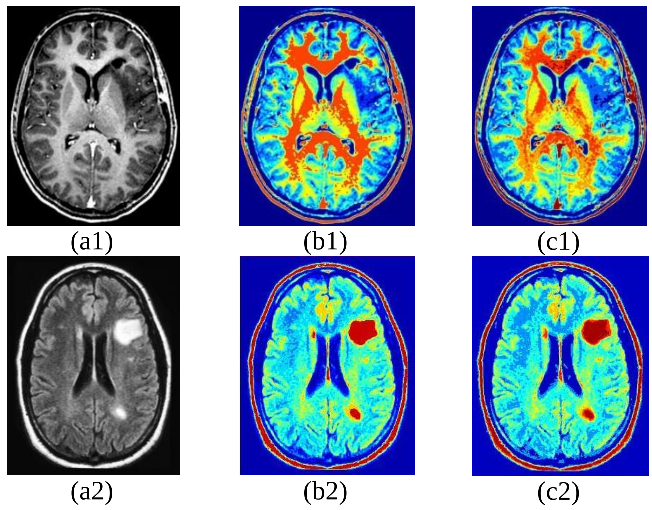

Fig. 2. (a1) Original MRI normal image, (a2) Original MRI image containing a mass, (b1) Standard PSO-based image clustering using only weighted quantization error, inter-cluster distance & intra-cluster distance (8 clusters) applied to image (a1), (b2) Standard PSO-based image clustering using only weighted quantization error, inter-cluster distance & intra-cluster distance (8 clusters) applied to image (a2), (c1) PSO-based image Clustering using weighted quantization error, inter-cluster distance & intra-cluster distance with the modified updating position (8 clusters) applied to image (a1), (c2) PSO-based image Clustering using weighted quantization error, inter-cluster distance & intra-cluster distance with the modified updating position (8 clusters) applied to image (a2).

TABLE II. COMPARAISON OF *STANDARD PSO* AND THE PROPOSED APPROACH *PSO-CW*

MRI	*Standard PSO*			*PSO-CW*		
	Je	*d_max*	*d_min*	*Je*	*d_max*	*d_min*
1	**7,5482±0,2291**	12,7575±3,3270	27,8714±4,5002	7,5960±0,1297	**10,7971±0,9527**	**30,3742±3,2804**
2	6,3992±0,3972	9,4738±1,7013	21,9747±4,6395	**6,2872±0,3911**	**8,6994±1,7656**	**23,3389±3,6565**
3	7,4477±0,1873	11,9595±3,2428	29,3781±4,6362	**7,3535±0,1333**	**10,9085±1,7270**	**29,8667±4,0106**
4	7,4935±0,1823	10,6994±1,3457	**27,7823±3,5578**	**7,4648±0,1513**	**10,6839±1,5946**	27,4629±4,5040
5	7,8268±0,1559	10,5336±1,7422	31,3422±2,4129	**7,5959±0,0466**	**8,9659±0,5762**	**31,8105±2,2582**
6	5,6731±0,6261	9,1671±0,2262	17,6492±4,2403	**5,5464±0,3986**	**9,1537±0,5448**	**18,3936±3,8482**
7	6,9568±0,1841	10,9478±2,2451	**25,7916±2,4416**	**6,5494±0,1521**	**8,7266±1,7629**	24,6547±2,9677

8	7,4191±0,4731	10,5693±3,3651	26,4262±5,2580	**7,2744±0,2773**	**8,9774±1,1359**	**26,9938±4,0404**
9	5,9324±0,2688	8,7298±0,7683	**22,9216±3,2196**	**5,8073±0,1311**	**8,7212±0,7783**	21,8475±2,8578
10	7,2203±0,2399	11,3975±2,0042	26,1275±3,5620	**7,0787±0,2237**	**9,8949±1,5807**	**27,4548±2,6936**
11	7,3770±0,2801	**10,4218±1,1067**	**28,7442±3,1910**	**7,1662±0,2528**	10,6025±1,4905	27,2815±3,7650
12	**7,3231±0,2675**	10,4838±2,1152	30,4022±3,5529	7,3425±0,1151	**9,5460±0,7286**	**31,4999±2,9254**
13	7,4301±0,1631	11,2585±1,5872	27,6897±2,8058	**7,3414±0,1170**	**10,7387±0,9888**	**27,9539±4,1928**
14	7,0036±0,4412	10,8147±1,9387	**26,0512±4,9072**	**6,9546±0,4615**	**10,7074±1,6313**	24,8450±5,5932
15	7,1970±0,2151	9,6828±0,9952	28,1733±2,9994	**7,0722±0,2524**	**8,8641±0,2212**	**30,6734±1,6395**
16	5,4983±0,2102	7,2870±0,7080	**20,6208±2,3770**	**5,4140±0,1789**	**6,7902±0,3606**	20,5269±2,2099
17	**6,4201±0,2333**	8,7298±1,3383	27,7917±2,1001	6,4511±0,1359	**7,8418±0,6001**	**28,0172±1,4641**
18	6,7490±0,3649	9,2809±1,7551	26,7910±2,4101	**6,6256±0,2607**	**8,4755±1,1534**	**26,8223±2,3601**
19	**5,4194±0,2925**	9,1821±0,2860	16,4870±3,2661	5,5145±0,5024	**9,0856±0,1929**	**16,7307±4,1322**
20	7,4901±0,3113	**10,5908±1,1381**	**26,9961±4,2615**	**7,2822±0,2319**	10,5973±1,0935	25,3028±3,1663
21	**5,5958±0,5438**	12,4838±0,9562	19,1492±5,7360	6,3180±0,2277	**11,2008±1,2675**	**25,3586±4,6402**
22	6,6517±0,5670	12,0464±2,4716	25,7473±6,4841	**6,5077±0,6101**	**10,8431±2,2615**	**26,0459±8,0797**
23	5,7747±0,5859	11,0716±1,1836	21,3454±6,1682	**6,1194±0,7563**	**10,9585±1,5301**	**24,6516±4,8385**
24	**6,3405±0,7053**	11,2169±1,9552	21,9803±8,2259	6,3983±0,5584	**10,2354±0,9195**	**23,1720±7,0955**
25	5,5034±0,2150	7,1202±0,8335	**20,7251±1,8199**	**5,3876±0,1631**	**6,7817±0,3646**	20,2778±1,4027
26	7,1464±0,3404	9,7753±1,7187	28,0930±2,8618	**6,9475±0,1584**	**8,2120±0,4092**	**30,0999±0,9588**
27	5,6865±0,2598	7,5776±1,3296	22,9155±1,8185	**5,5628±0,2647**	**6,3758±0,5381**	24,2649±1,3326
28	7,2258±0,2469	10,3890±1,4071	**25,7505±4,2856**	**7,0668±0,2594**	**10,0564±1,4410**	24,7555±4,5457
29	6,7609±0,2544	**8,6348±1,6759**	**25,7498±2,1893**	**6,6676±0,1691**	8,6357±2,0580	25,7032±1,9070
30	7,1952±0,2927	8,8899±1,5983	**30,1008±1,3055**	**6,9730±0,1520**	**8,0868±0,4904**	29,6910±1,2053
31	7,3460±0,2920	10,2752±1,4329	**26,3453±3,7946**	**7,0349±0,7992**	**10,1781±1,9596**	25,8959±5,8313
32	7,1560±0,3332	9,8043±1,0569	**26,2379±3,8705**	**7,0147±0,3946**	**9,5955±0,8145**	24,6815±4,8839
33	**6,6382±1,1908**	12,4253±1,4518	21,0493±9,0016	6,6722±1,1881	**11,2118±1,7034**	**23,2030±8,5198**
34	**5,3448±0,1838**	9,1785±0,4105	15,1232±2,3795	5,5145±0,5024	**9,0856±0,1929**	**16,7307±4,1322**
35	7,5982±0,2887	11,0136±1,6258	**29,3692±3,8428**	**7,3654±0,3439**	**10,5639±1,8299**	27,7320±5,7820
36	6,8042±0,2118	8,9398±0,7912	24,9681±2,5260	**6,7963±0,2026**	**8,8779±0,8119**	**25,2982±4,6350**
37	7,0719±0,2964	12,7609±2,1315	**24,3417±6,1258**	**6,8796±0,2534**	**11,9417±2,1983**	24,1931±4,9703
38	**7,1673±0,4892**	13,2383±2,9515	24,1580±5,3761	7,2010±0,1547	**10,9140±1,5851**	**26,2760±3,6311**
39	7,6885±0,4353	10,6266±1,5727	**25,8613±3,1732**	**7,4807±0,2561**	**10,1606±0,4182**	25,6637±2,4019
40	7,5218±0,2487	11,9308±3,4229	**28,8663±4,4029**	**7,3758±0,2653**	**11,5113±2,8298**	28,0676±4,5225
41	6,3794±0,1640	10,1623±1,8188	23,0369±4,4105	**6,3764±0,1521**	**8,5343±0,6826**	**26,0335±2,0515**
42	**6,8633±0,1004**	9,7650±1,6655	27,6332±3,1031	6,9981±0,0749	**9,0124±1,5920**	**29,2074±2,5166**
43	**6,7917±0,2252**	10,7018±2,5387	28,8152±4,4490	7,3671±0,1249	**10,0039±0,9873**	**29,7406±3,3709**
44	**6,2927±0,2607**	10,5446±1,0979	23,0224±3,0542	6,3517±0,3036	**9,1081±1,4173**	**24,8693±4,9781**
45	7,4381±0,3396	10,1639±2,3989	30,2255±3,4473	**7,2910±0,0853**	**8,9827±0,5756**	**31,7280±2,2411**
46	7,1043±0,2936	10,2315±1,7325	**25,8964±4,1149**	**6,9727±0,2912**	**9,8781±1,1037**	25,3845±3,3764
47	6,7179±0,3066	9,1220±1,6353	**28,0246±2,8100**	**6,5685±0,2282**	**8,4579±1,5183**	26,7018±2,7787
48	7,2377±0,0666	9,7571±1,2338	29,4922±3,8294	**7,1688±0,0569**	**9,0623±0,7526**	**31,3446±2,3954**
49	5,9032±0,3747	**8,1081±0,7198**	**22,4454±3,4473**	**5,8534±0,4731**	8,1312±1,1902	21,3884±2,9815
50	**6,4352±0,1894**	8,6374±1,2415	27,9624±2,1361	6,4963±0,1925	**7,8705±0,6715**	**28,0936±2,1350**
51	**6,6690±0,2145**	11,8828±0,9721	23,4031±4,5914	6,8541±0,2332	**11,0998±1,0987**	**26,6217±4,1061**
52	5,8944±0,5498	**8,8702±2,3492**	**20,4454±3,9179**	**5,6235±0,5703**	10,6342±3,3021	17,2649±4,1926
53	5,9328±0,2745	9,4142±1,6372	**21,7375±4,6657**	**5,8322±0,2484**	**8,7972±1,5587**	21,6016±4,3008
54	7,3642±0,1651	10,1359±1,0589	28,5975±2,5749	**7,2725±0,1343**	**9,4556±0,7891**	**29,5885±2,4517**
55	6,6651±0,2121	**8,3597±1,0172**	**25,4069±2,4026**	**6,5432±0,2123**	8,4749±0,8671	24,1519±2,5635
56	6,6858±0,9305	**10,6206±1,7222**	**25,4715±6,7978**	**6,3600±0,9489**	10,9956±1,8414	23,6118±7,3234
57	**4,3830±0,2192**	6,3854±0,4292	16,6693±1,9510	4,4280±0,2469	**6,1083±0,3918**	**17,6254±2,3805**
58	7,3542±0,1512	11,1682±1,6643	28,1523±3,5166	**7,2616±0,1745**	**9,9932±2,2932**	**30,6373±3,4375**
59	**7,0389±0,3969**	11,3168±1,1255	26,8633±5,0477	7,1713±0,2081	**10,6876±0,6871**	**29,3346±3,2508**
60	**6,9854±0,3671**	12,7145±3,5600	27,1905±7,0116	7,1795±0,2708	**10,1867±1,8684**	**30,4345±3,2375**
61	7,4194±0,2301	11,7990±1,8529	30,2898±3,7296	**7,3177±0,2758**	**11,3760±2,3393**	**30,8690±4,5609**
62	**7,0656±0,2797**	11,0205±3,4809	**26,7020±2,9996**	7,0569±0,2575	**10,5915±2,3314**	26,6133±3,8458
63	6,8927±0,2880	9,6855±1,6401	26,6029±2,8076	**6,6956±0,1314**	**8,9096±0,6362**	**27,6049±1,7556**

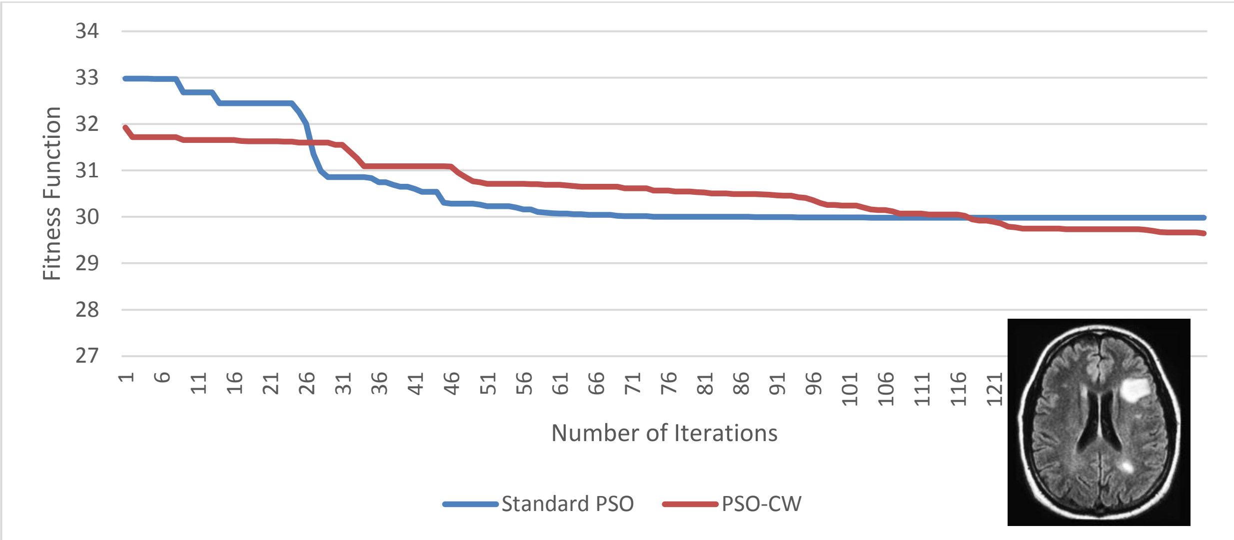

Fig. 3. the convergence behavior of the objective function for the standard PSO and PSO-CW for the MRI image.

Figure (3) illustrates the convergence behavior of the algorithms for the MRI image shown in Figure (2a). The *standard PSO* exhibited a faster, but premature convergence and stagnation in sub-set solution with a large quantization error, while the *PSO-CW* algorithms had slower convergence without stagnation, and better solution with lower quantization errors. This is due to the wind dispersion mechanism which incorporates random procedure for enhancing the PSO search process and diversifies the search directions of the particles.

VI. Conclusions

This paper presented a modified particle swarm optimisation for MRI brain Image Clustering (*PSO-CW*). The quality of the obtained clusters is evalueted by how much the quantization error and intra-distance are minimized and simultaneously the inter-cluster distance is maximised.

The proposed approach is based on a modified updating positions of particles. The combination of two mecanisms : confinement and wind dispertion are introduced in the updating process of the particle's position.

While, confiment mecanism limits the positions of particles to be in a spefic range, the wind dispersion allows particle to explore more by modeling a nature's phenomenon.

Sixty-three whole MRI brain images are used to compare the efficiency of the proposed enhancement.

Experimental results show that *PSO* with the modified updating position (*PSO-CW*) based image clustering have generated more compact clusters and well-separated when compared to standard PSO and also better convergence to lower quantization errors. Moreover, their standard deviations respectively are less than those obtained in standard *PSO*. This indicates that *PSO-CW* is more stable than standard PSO.

For future research, an automatic *PSO*-based clustering algorithm will be elaborated that can find the optimum number of regions of the image and determine the locations of their centoids.

More investigations will be done in medical images segmentation for detecting and extracting suspicious regions and identifying tumors aiming to build an efficient Computer Aided Detection.

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