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CELLULAR ORGANISM BASED PARTICLE SWARM OPTIMIZATION ALGORITHM FOR COMPLEX NON-LINEAR PROBLEMS

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Abstract

Particle Swarm Optimization (PSO) is the global optimization technique that inspires many researchers to solve large scale of non-linear optimization problems. For certain complex scenarios, the premature convergence problem of PSO algorithm cannot find global optimum in dynamic environments. In this paper, a new variant motility factor based Cellular Particle Swarm Optimization (m-CPSO) algorithm is proposed which is developed by the migration behavior observed from fibroblast cellular organism to overcome this problem. The proposed m-CPSO algorithm is modeled in two different social best and individual best models. The *performance of m-CPSO is tested in benchmark and real time data instances and compared with classical PSO. The outcome of experimental results has demonstrated that m-CPSO algorithm produces promising results than classical PSO on all evaluated environments.*

Keywords

Cellular Organism, Computational Model, Moving Peak Benchmark Function, Particle Swarm Optimization (PSO), Optimization, Population Structure

1. Introduction

Particle Swarm Optimization (PSO), developed by Kennedy and Eberhart (1995), is a population based swarm intelligence algorithm inspired by aspects of nature like birds flocking and fish schooling (Riccardo Poli, James Kennedy & Tim Blackwell, 2007). Two key components of the algorithm are velocity and position; the updating factors to enable particles to migrate in n-dimensional problem space. The optimal solution is thereby obtained through a set of parameters such as inertia weight, acceleration factors, constriction co-efficient and random numbers. Also, [-vmax, +vmax] plays a vital parameter which limits the divergence and convergence of the particles to fly in the regions. The algorithm itself infers that if minimum velocity (–vmax) value is too small; the particle may not explore sufficiently, and, if the maximum velocity (+vmax) value is too large; it may deviate from the solution space which leads to infeasible results. Thereby, when the movement of swarm fails in the search space, it directs the particles to be trapped in the local optimum. Therefore, to avoid the misleading search behavior of the algorithm, a novel idea is proposed by introducing the characteristics of cellular organism which leads to improving the quality of the solution.

All living beings are composed of cell, which is the basic unit of life. It helps to carry out different processes of life. The unicellular organism performs vital functions in the body, whereas, the multicellular organism type of cells are grouped together to carry out specific activities like tissue formation (Howard Stebbings, 2001). Fibroblast is an ubiquitous stromal cell, found in animals and mammals connective tissue which is capable of movement from one place to another. The protrusion activity of a cell is unconfined from tissue, where it migrates randomly over their substrate so called collagen in the region. The energy for driving fibroblasts is derived directly from the proton gradient found in the extracellular matrix. The cell then moves forward as a result of traction within the cytoplasm, and the cycling process is terminated by release and retraction of the tail of the cell (PeterRodemann & Hans-Oliver Rennekampff, 2011). This research incorporates the behavioral characteristics of fibroblast in PSO algorithm to avoid the particles converging quickly.

In this work, the functionality of PSO algorithm encompasses a new motility factor (σ) in the velocity and position for updating process. This motility factor acts as an external force for the movement of neighborhood particles for survival of fittest candidate in the swarm. It enables all the particles to actively participate for finding best multiple sub optimal solution located in a problem space. The entire search space gets explored, thus preventing the swarm from settling on a local optimum. Here, the inertia weight (ω) factor is set to change randomly at each step according to the following equation (1), where

$$\omega = 0.5 - \frac{r()}{2} \tag{1}$$

Thus, the trajectory of a particle with inertia weight (ω) converges to a stable point, which is a weighted mean of P_{best}(personal best) and G_{best}(global best). It also correlates with acceleration factors c_1 and c_2 ($\varphi_1 = \varphi_2 = 0.747$) to guarantee the convergence and the value of inertia has been satisfied with the following relation given in equation (2):

$$\omega > \frac{1}{2}(\varphi_1 + \varphi_2) - 1 \tag{2}$$

Another important factor that guarantees the convergence of particles in an equilibrium state is the constriction co-efficient (K) (Ben Niu, Yunlong Zhu, Xiaoxian He & Henry Wu, 2007) which maintains a balance between exploration and exploitation of particle evolution and prevents the speed limit of velocity to move beyond the boundary level. Based on the analysis of population topology, it is clearly identified that many real world optimization problems have dynamic features which often encounter changing environment. Moving Peak Benchmark (MPB) function is used to measure the robustness of optimization algorithm in dynamic situation (Iman Rezazadeh, Mohammad Reza Meybodi & Ahmad Naebi, 2011) (Moser & Chiong, 2013). The comparative results of moving peak benchmark function, with Classical PSO and m-Cellular PSO algorithm, reveal that the proposed work yield better performance than the Classical PSO algorithm. In this research work, the design and development of proposed m-Cellular PSO algorithm is tested with two models, namely, I-best (Individual best) model and S-best (Social best) model. In the I-best model, the particle which interacts with their adjacent particles for displacement in the problem space. With the S-best model, a candidate which follows trajectory to migrate to a new location based on information gained from neighborhood particles in the entire population.

The population structure is a pictorial representation of reciprocal action of particles in the evolutionary space. It is used to investigate the co-operative nature of particles which are survival for fitness solution in the algorithm. The derived population topology from the experimental results reveals that there is a noted improvement in the collaborative behavior of particles in the motility factor based Cellular particle swarm optimization (m-CPSO) algorithm. It is also inferred that the effect of algorithm depends on the interaction of particles in the entire population (James Kennedy & Rui Mendes, 2002) (Aleta Fabregas, Bobby Gerardo, Bartolome & Tanguilig, 2016).

The communication among the neighborhood particles lays a foundation for information sharing within a swarm. The greater interactions within particles have a major impact on finding the high quality results. It is illustrated in the pictorial representation of various social networks which involve star, mesh, ring, pyramid, Von Neumann architecture and so on. Highly connected networks favor faster convergence, but are often stuck in the local optima. Sparsely connected networks converge slower, but sometimes the search space may not be covered sufficiently. It reveals that an interaction among the swarm is much better than structure of Classical PSO algorithm. Information flood through the network is rapid, as each individual particle is easily attracted to the best solution found so far. The population is scattered quickly in the evolutionary region and tend to slow converge. Indeed, all the particles actively participate (survival) in the hyperspace for obtaining best (fitness) candidate solution.

The neighborhood particles often get trapped in local optimum (stagnation) problems adversely affects the probability of finding global optima in the problem space. To overcome this problem, the motility factor involved in fibroblast organism is incorporated into velocity updating equation of classical PSO algorithm. It enforces the particles to exhibit equilibrium state of exploration and exploitation in the problem space. The objective of this study is to evaluate the performance of new variant m-CPSO algorithm in solving benchmark and real time applications and compared with classical PSO.

2. Literature Review

The chronology of PSO evolution and comprehensive PSO based methods surveyed by (Davoud Sedighizadeh & Ellips Masehian, 2009) illustrated that PSO algorithm can be a suitable tool in solving various optimization problems considering its better efficiency in comparison with other evolutionary algorithms such as GA and also its simplicity. (Tanweer, Abdullah Al-Dujaili & Suresh, 2016) proposed human learning principles for performance improvement of PSO algorithm. It was tested on black box optimization testbed in solving selective class of problems under different budget settings and compared with nine different PSO variants. The examined results demonstrate that human learning principles inspired PSO offers significant results than other variants of PSO. (Tanweer, Suresh & Sundararajan, 2015) introduced self-regulating particle swarm optimization (SRPSO) algorithm which has been evaluated using the 25 benchmark function taken from CEC 2005 test suites. The performance of the proposed work was investigated with Bare Bones PSO (BBPSO) and Comprehensive Learning PSO (CLPSO) and the results exemplify that SRPSO achieves 95% significant results compared to other algorithms. (Ben Niu, Yunlong Zhu, Xiaoxian He & Henry Wu, 2007) developed a Multiswarm Cooperative Particle Swarm Optimizer (M-CPSO) algorithm which was inspired by the phenomenon of symbiosis in natural ecosystems. It was investigated on several benchmark functions and the obtained result reveals that the performance of M-CPSO is competitive with standard PSO. The convergence of Particle Swarm Optimization algorithm analyzed by (Fvan den Bergh & AP Engelbrecht, 2010) shown that standard PSO is not guaranteed to the convergence of global optima which causes stagnation problem and suggested a few parameters to be incorporated to elucidate and modify the behavior of standard PSO. (Hesam Izakian, Behrouz TorkLadani, Ajith Abraham &Vaclav Snasel, 2010) applied discrete particle swarm optimization (DPSO) algorithm for grid job scheduling problem. It was tested on 512 jobs and 16 machines and evaluated with popular metaheuristic algorithm such as Genetic Algorithm (GA), Ant Colony Optimization (ACO), Fuzzy Particle Swarm Algorithm (FPSO) and Continuous Particle Swarm Optimization (CPSO). Results illustrate that the proposed method is more efficient than other heuristic approaches. (Vaclav Snasel, PavelKromer & Ajith Abraham, 2013) introduced protoPSO, a new variant Particle Swarm Optimization algorithm by incorporating protozoic behavior inspired from protozoa organism. The fitness evaluation of proposed algorithm was investigated to solve test problem using well known functions. The obtained results have shown that the novel optimization strategies would be able to solve some set of problems. Improved binary PSO (IBPSO) applied for feature selection method to classify the gene expression data was done by (Li-Yeh Chuang, Hsueh-Wei Chang, Chung-JuiTu& Cheng-Hong Yang, 2008). Comparison of results with K-nearest neighbor (K-NN), the proposed IBPSO method attained the highest classification accuracy in the 11 gene expression data test problems.

A study on the potential literature works signifies that variants of PSO paradigms are extensively utilized to solve complex problems, diverse sort of real world applications and the experimental results demonstrated its effectiveness. The remainder of the paper is organized as follows. Section 3 describes the methodology of m-CPSO algorithm. Experimental results are discussed in Section 4 and Section 5 draws the conclusion and future works.

3. Modified Algorithm – Particle Swarm Optimization Using Cellular Organism Behavior

The quick convergence of PSO algorithm cannot find multiple optimal solutions and get trapped in local optima. PSO could not exhibit equilibrium state between divergence and convergence of particles in the n-dimensional problem space. In this work, this intricacy is controlled by incorporating the motility behavior of fibroblast cellular organism (John Dallon & Jonathan Sherratt, 1998) to enhance the behavior of PSO. The motility factor (σ) acts as an energetic force that enables the swarm to proliferate around the entire problem space and the particles are accelerated towards the best candidate solutions which have better fitness values. The functionality of swarm has been progressed with migration factor (σ) which is applied in neighborhood particles that increases the degree of interaction among the population (Howard Stebbings, 2001). Henceforth, the introduced motility factor based Cellular Particle Swarm Optimization (m-CPSO) algorithm enhanced the moving speed of particles in association with the randomly generated collagen and the efficiency of m-CPSO algorithm to obtain optimal solution has been improved.

Algorithm: motility factor based Cellular Particle Swarm Optimization (m-CPSO)

Step 1: Initialize the particles of population size M_i ($i = 1, 2,\ldots, n$) with randomly generated position x_i and velocity v_i in the n-dimensional search space.

Step 2: Repeat

Evaluate the objective function of every particles using standard benchmark function.

Step 3: Compare the fitness value of each particle F (M_i) with the value of individual best P_{best}. If the current value of a particle F (M_i) is better than P_{best}, then the value of M_i is set to P_{best} and then the position of a current particle x_i is assigned to P_i in the problem space.

Step 4: Identify the neighborhood best (G_{best}) particle in the population. If the current value of a particle F (M_i) is better than F (G_{best}), then the value of M_i is set to G_{best}. And the index value of a current particle x_i is assigned to P_g.

Step 5: Update the velocity and position of particle according to the following equation:

I-best model:

$$V_{ij}^{(t+1)} = \omega * K * V_{ij}^{(t)} + \left(\varphi_1 * R_1 * \left(P_{best} - x_p^{(t)}\right)\right) + \sigma * (\varphi_2 * R_2 * (P_g - x_p^{(t)})) \quad (3)$$

$$X_{ij}^{(t+1)} = X_{ij}^{(t)} + V_{ij}^{(t+1)} \quad (4)$$

S-best model:

$$V_{ij}^{(t+1)} = \omega * K * V_{ij}^{(t)} + \left(\varphi_1 * R_1 * \left(G_{best} - x_p^{(t)}\right)\right) + \sigma * (\varphi_2 * R_2 * (P_g - x_p^{(t)})) \quad (5)$$

$$X_{ij}^{(t+1)} = X_{ij}^{(t)} + V_{ij}^{(t+1)} \quad (6)$$

where

$V_{ij}^{(t)}$ = velocity of j^{th} particle in i^{th} iteration at time t
$X_{ij}^{(t)}$ = position of j^{th} particle in i^{th} iteration at time t
σ= motility factor
R_1, R_2 = random numbers lies between 0 and 1
P_{best}= Personal (individual) particle best p
G_{best}= Neighborhood (social) particle best g
x_P ,p_g= Index value of current and neighborhood particle
$\sigma^{(a)} = \psi a^2 e^{-a}/_{asat}$
φ_1,φ_2 = acceleration factors
K = Constriction coefficient

In the proposed m-Cellular PSO algorithm, the moving nature of fibroblast acts as motility factor in the velocity and position updating process. It gives an additional energetic force for the swarm to widely scatter around the problem space and the particles will slowly converge to give optimum solution. It can maintain the right balance of exploration and exploitation which is essential for the success of a given optimization task. This algorithm is designed with both I-best (cognitive) and S-best (social) models. except for the selection of best particle. During convergence, each particle of the swarm adjusts its trajectory according to knowledge gained from its own previous experience and its neighbor's experience making use of the best previous position encountered by itself and its neighborhood particles in the swarm. This idea is realized and recognized by further introducing a new term called motility factor (σ) into the update equation of velocity component in m-Cellular PSO (Ben Niu et al., 2007)(John Dallon & Jonathan Sherratt, 1998)(John Dallon, Jonathan Sherratt, Philip Maini & Mark Ferguson, 2001).

4. Experimental Results and Discussion

The proposed work is tested in two different applications such as prediction of cardiovascular disease in medical database available in the archive (http:/archive.ics.uci.edu/ml/machine-learning-databases/heart-disease/processed.cleveland.data) and noise removal of sign language dataset generated in real time environment (Krishnaveni, Subashini & Dhivyaprabha, 2015). The search process, implemented with most popular test functions, involves rotated ellipse2, schwefel and sphere. The mathematical equation of these benchmark functions are given below and executed with fitness evaluation of 1000 and 5000 iterations under various circumstances.

$$f(x) = {x_1}^2 - x_1 x_2 + x_2^2 \quad (7)$$

$$f(x) = \sum_{i=1}^{D} |x_i| + \pi_{i=1}^{n} |x_i| \quad (8)$$

$$f(x) = \sum_{i=1}^{D} x_i^2 \quad (9)$$

Case 1:

The proposed m-Cellular PSO algorithm is implemented to select the optimal threshold values to be used in Weighted Associative Classifier (WAC) algorithm. It is used to predict the diagnosis of heart disease in five different output classes [0-absence; 1-prerisk; 2-risk; 3-high risk; 4-critical]. Table 4.1 and Table 4.2 present the outcome for standard performance metrics such as accuracy, specificity, false positive rate, sensitivity, false negative rate, precision, error rate, geometric mean and f-measure which are measured, and the analysis of the previous work (Dhivyaprabha & Subashini, 2017) and the proposed model are compared.

The results observed from Table 4.1 and Table 4.2 inferred that both I-best and S-best models yield better solutions for all above mentioned metrics. But, the metric false positive rate gives slightly worse result for S-best model in 1000 iterations. And, sensitivity and specificity rate of I-best model doesn't give improved result than traditional method. Indeed, the evaluation outcome of I-best model in 1000 iterations and S-best model in 5000 iterations give more optimal solutions. It reveals that the motility factor introduced in the proposed work enables adjacent and neighborhood particles to actively participate in the n-dimensional hyperspace. When the iteration gets increased, the swarm consistently scattered throughout the problem space and will eventually converge to the neighborhood best and then to the global best. Thus, the novel m-Cellular PSO algorithm improves swarm diversity and also it avoids the stagnation problem.

Table 4.1 *Result analysis and comparison of classical PSO and m-cellular PSO algorithm for 1000 iterations*

Metrics	Classical PSO	m-Cellular PSO	
		I-best model	***S-best model***
Accuracy	6.94e-01	9.02e-01	7.86e-01
Sensitivity or True Positive Rate	6.05e-01	9.09e-01	9.09e-01
Specificity or True Negative Rate	7.42e-01	9.00e-01	7.28e-01
False Positive Rate	2.57e-01	1.00e-01	2.71e-01
False Negative Rate	3.94e-01	1.09e-02	4.08e-02
Precision	5.60e-01	8.10e-01	6.12e-01
Error Rate	3.05e-01	1.90e-02	2.13e-01
g-mean1	5.82e-01	8.58e-01	7.46e-01
g-mean2	6.70e-01	9.04e-01	8.13e-01
F-measure	5.82e-01	8.57e-01	7.31e-01

Table 4.2 *Result analysis and comparison of classical PSO and m-cellular PSO algorithm for 5000 iterations*

Metrics	Classical PSO	m-Cellular PSO	
		I-best model	***S-best model***
Accuracy	6.69e-01	7.37e-01	9.78e-01
Sensitivity or True Positive Rate	6.06e-01	8.18e-01	9.69e-01
Specificity or True Negative Rate	7.00e-01	7.00e-01	9.71e-01
False Positive Rate	3.00e-01	3.00e-01	2.85e-02
False Negative Rate	3.93e-01	1.81e-01	3.03e-02
Precision	4.87e-01	5.62e-01	9.41e-01
Error Rate	3.30e-01	2.62e-01	2.91e-02
g-mean1	5.43e-01	6.78e-01	9.55e-01
g-mean2	6.51e-01	7.56e-01	9.70e-01
F-measure	5.40e-01	6.66e-01	9.55e-01

Case 2:

Sign language is the most prevailing means of communication and knowledge sharing medium with the hearing impaired children. Acquisition of sign language images contains impulse noise due to various factors. The proposed m-Cellular PSO algorithm is applied to choose optimal weights to be used in Weighted Median Filter algorithm. It is used to suppress impulse noise present in digital images in order to improve the qualitative results. It is tested with three specified benchmark functions with fitness evaluation of 5000 iterations. The performance metrics includes Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Mean Absolute Error (MAE) and Correlation (CORLN) (Krishnaveni, Subashini & Dhivyaprabha, 2015) are used for assess and compared the analysis between the previous work and the proposed model. PSNR is an approximate measurement of visual perception quality in human beings. When the information loss in the image is low, the result of PSNR value is high. The experimental results are presented from Table 4.3 through 4.10 reveals that novel m-Cellular PSO algorithm provide an improved solution than traditional PSO algorithm for different metrics by using standard test functions such as rotated ellipse2, schwefel and sphere. The size of 16 bit sign language images are taken for this experimental study. The range of PSNR value for this type of images are lie between 60 and 80 dB, the higher value is better (Nilesh Loya & Avinash Kesar, 2015)(http://en.wikipedia.org/wiki/Peak_signal-to-noise_ratio).

The mean results shown in Table 4.12 through Table 4.14 illustrate that m-Cellular PSO algorithm yields better solution for most of the scenarios. But it suffers from poor results in a few cases. An assessment of results exhibits that the solutions obtained by using schwefel function is significantly better than Classical PSO algorithm while the solutions given by rotated ellipse2 and sphere functions are comparable or slightly worse when it is analyzed using PSNR and MSE of I-best and S-best models. Analysis reveals that the optimization strategies, inspired by cellular organism, will be a helpful approach to solve highly complex real time problems.

Moving peak benchmark is a fitness function that changes over time. It is widely applied to measure the performance of dynamic complex optimization problems. It consists of a number of peaks changing in height, width and position (Mosen & Chiong, 2013; Yaochu Jin & Jurgen Branke, 2005). Various kinds of parameters such as f(x) denote the fitness function, dim represents dimensionality of landscape, severity describes the distance at which peaks moves to a target and lamda (λ) characterize the degree of correlation between the direction of the previous and current moves of peaks. A set of values used to define the parameters for function definition are presented in Table 4.11 given below. In this work, the fitness function named f(x) is used with the scenario 1 represented as

$$f(x) = h/\left(1 + w\sqrt{\sum_{i=1}^{N}(x_i - p_i)^2}\right) \quad (10)$$

where

h = height
w = width
p = position
x = particle

Table 4.3 *I-best model result analysis and comparison of Classical PSO and m-Cellular PSO based on PSNR*

Rotated Ellipse2			Schwefel			Sphere		
Classical PSO	m-Cellular PSO		Classical PSO	m-Cellular PSO		Classical PSO	m-Cellular PSO	
	Pbest	Gbest		Pbest	Gbest		Pbest	Gbest
67.93	72.48	65.85	63.87	65.85	67.73	63.76	62.76	67.73
67.86	72.44	65.74	63.77	65.74	67.63	63.67	62.67	67.63
67.71	72.37	65.61	63.62	65.61	67.53	63.52	62.52	67.53
68.52	72.65	65.71	64.36	65.71	67.68	64.27	62.65	67.68
67.71	72.37	65.61	63.98	65.61	67.53	63.86	62.52	67.53
68.53	72.52	65.70	64.39	65.70	67.68	64.27	62.67	67.68
67.57	72.11	65.35	63.41	65.35	67.30	63.30	62.27	67.30
67.27	73.14	66.25	63.22	66.25	68.20	63.12	63.19	68.20
68.03	72.54	65.77	63.22	65.77	67.68	63.73	62.70	67.68
68.58	73.00	66.61	63.83	66.61	68.46	64.49	63.53	68.46
67.40	72.01	65.23	64.63	65.23	67.19	63.10	62.19	67.19
68.52	72.96	66.27	64.33	66.27	68.26	64.25	63.24	68.26
66.96	71.66	64.82	62.83	64.82	66.78	62.74	61.74	66.78

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Table 4.4 *I-best model result analysis and comparison of Classical PSO and m-Cellular PSO based on MSE*

Rotated Ellipse2			Schwefel			Sphere		
Classical PSO	m-Cellular PSO		Classical PSO	m-Cellular PSO		Classical PSO	m-Cellular PSO	
	Pbest	Gbest		Pbest	Gbest		Pbest	Gbest
0.10	0.06	0.13	0.16	0.18	0.10	0.10	0.15	0.21
0.10	0.06	0.13	0.16	0.18	0.10	0.10	0.15	0.21
0.11	0.06	0.13	0.16	0.19	0.10	0.11	0.15	0.21
0.09	0.05	0.13	0.15	0.18	0.10	0.15	0.15	0.21
0.10	0.06	0.13	0.16	0.19	0.10	0.16	0.15	0.21
0.09	0.06	0.13	0.15	0.18	0.10	0.15	0.15	0.21
0.10	0.06	0.13	0.17	0.19	0.10	0.17	0.16	0.22
0.11	0.05	0.12	0.17	0.17	0.09	0.17	0.14	0.20
0.10	0.06	0.13	0.17	0.18	0.10	0.16	0.15	0.21
0.09	0.05	0.11	0.16	0.16	0.09	0.15	0.14	0.19
0.10	0.06	0.13	0.14	0.19	0.11	0.17	0.16	0.22
0.09	0.05	0.12	0.15	0.17	0.09	0.15	0.14	0.20
0.11	0.06	0.14	0.18	0.20	0.11	0.18	0.17	0.23

Table 4.5 *I-best model result analysis and comparison of Classical PSO and m-Cellular PSO based on MAE*

Rotated Ellipse2			Schwefel			Sphere		
Classical PSO	m-Cellular PSO		Classical PSO	m-Cellular PSO		Classical PSO	m-Cellular PSO	
	Pbest	Gbest		Pbest	Gbest		Pbest	Gbest
0.09	0.04	0.09	0.12	0.13	0.07	0.07	0.11	0.15
0.09	0.04	0.09	0.12	0.13	0.07	0.99	0.11	0.15
0.09	0.04	0.09	0.12	0.14	0.07	0.07	0.11	0.16
0.08	0.04	0.10	0.11	0.14	0.08	0.11	0.12	0.16
0.09	0.04	0.09	0.11	0.14	0.07	0.12	0.11	0.16
0.09	0.04	0.09	0.12	0.13	0.07	0.12	0.11	0.16
0.09	0.04	0.10	0.13	0.14	0.08	0.12	0.12	0.16
0.10	0.04	0.09	0.13	0.13	0.07	0.13	0.11	0.15
0.09	0.04	0.09	0.13	0.13	0.07	0.12	0.11	0.15
0.08	0.03	0.08	0.12	0.12	0.06	0.11	0.10	0.14
0.10	0.04	0.10	0.15	0.15	0.08	0.14	0.12	0.17
0.08	0.03	0.08	0.11	0.12	0.07	0.11	0.10	0.14
0.99	0.05	0.11	0.13	0.17	0.09	0.15	0.14	0.19

Table 4.6 *I-best model result analysis and comparison of Classical PSO and m-Cellular PSO based on CORLN*

Rotated Ellipse2			Schwefel			Sphere		
Classical PSO	m-Cellular PSO		Classical PSO	m-Cellular PSO		Classical PSO	m-Cellular PSO	
	Pbest	Gbest		Pbest	Gbest		Pbest	Gbest
0.994	0.996	0.995	0.992	0.988	0.996	0.993	0.996	0.997
0.992	0.995	0.995	0.993	0.987	0.996	0.994	0.996	0.996
0.994	0.996	0.994	0.994	0.985	0.995	0.995	0.996	0.996
0.995	0.996	0.996	0.997	0.988	0.996	0.997	0.997	0.997
0.993	0.996	0.994	0.995	0.985	0.995	0.996	0.996	0.996
0.993	0.995	0.996	0.995	0.991	0.997	0.996	0.997	0.997
0.995	0.996	0.996	0.996	0.991	0.997	0.997	0.997	0.997
0.992	0.996	0.997	0.994	0.991	0.997	0.994	0.997	0.997
0.995	0.996	0.996	0.994	0.990	0.997	0.997	0.997	0.997
0.992	0.995	0.995	0.996	0.988	0.996	0.995	0.996	0.996
0.994	0.995	0.996	0.994	0.991	0.997	0.997	0.997	0.997
0.994	0.995	0.996	0.995	0.993	0.997	0.996	0.996	0.997
0.990	0.995	0.993	0.992	0.976	0.992	0.993	0.994	0.996

Table 4.7 *S-best model result analysis and comparison of Classical PSO and m-Cellular PSO based on PSNR*

Rotated Ellipse2			Schwefel			Sphere		
Classical PSO	m-Cellular PSO		Classical PSO	m-Cellular PSO		Classical PSO	m-Cellular PSO	
	Pbest	Gbest		Pbest	Gbest		Pbest	Gbest
67.93	69.25	68.99	63.87	70.57	66.93	63.76	64.34	61.57
67.86	69.15	68.90	63.77	70.63	66.87	63.67	64.26	61.49
67.71	69.06	68.79	63.62	70.43	66.70	63.52	64.13	61.34
68.52	69.27	68.95	64.36	70.84	67.01	64.27	64.24	61.47
67.71	69.06	68.79	63.98	70.43	66.70	63.86	64.13	61.34
68.53	69.25	68.91	64.39	70.91	67.01	64.27	64.25	61.49
67.57	68.81	68.54	63.41	70.28	66.55	63.30	63.85	61.09
67.27	69.81	69.46	63.22	71.34	67.55	63.12	64.77	61.99
68.03	69.28	68.96	63.22	70.90	67.01	63.73	64.29	61.53
68.58	69.90	69.72	63.83	71.15	67.62	64.49	65.09	62.32
67.40	68.74	68.43	64.63	70.30	66.50	63.10	63.76	60.99
68.52	69.71	69.40	64.33	71.30	67.47	64.25	64.80	62.05
66.96	68.38	68.03	62.83	69.90	66.03	62.74	63.34	60.57

Table 4.8 *S-best model result analysis and comparison of Classical PSO and m-Cellular PSO based on MSE*

S.No	Parameter
1.	Number of peaks
2.	Height range
3.	Width range
4.	Peak shape
5.	Number of dimensions
6.	Height severity (minimum)
7.	Width severity (minimum)
8.	dim

Table 4.9 *S-best model result analysis and comparison of Classical PSO and m-Cellular PSO based on MAE*

Rotated Ellipse2			Schwefel			Sphere		
Classical PSO	m-Cellular PSO		Classical PSO	m-Cellular PSO		Classical PSO	m-Cellular PSO	
	Pbest	Gbest		Pbest	Gbest		Pbest	Gbest
0.10	0.06	0.08	0.16	0.07	0.11	0.10	0.07	0.11
0.10	0.06	0.08	0.16	0.07	0.11	0.10	0.07	0.11
0.11	0.06	0.08	0.16	0.07	0.11	0.11	0.07	0.11
0.10	0.06	0.08	0.16	0.07	0.11	0.16	0.07	0.11
0.09	0.06	0.08	0.15	0.07	0.11	0.15	0.07	0.11
0.10	0.06	0.09	0.17	0.07	0.11	0.17	0.07	0.11
0.11	0.05	0.08	0.17	0.06	0.10	0.17	0.06	0.10
0.10	0.06	0.08	0.17	0.07	0.11	0.16	0.07	0.11
0.09	0.05	0.08	0.16	0.07	0.10	0.15	0.07	0.10
0.10	0.06	0.09	0.14	0.07	0.12	0.17	0.07	0.12
0.09	0.05	0.08	0.15	0.06	0.10	0.15	0.06	0.10
0.11	0.06	0.09	0.18	0.08	0.12	0.18	0.08	0.12
0.09	0.08	0.09	0.12	0.05	0.08	0.12	0.05	0.08

Table 4.10 *S-best model result analysis and comparison of Classical PSO and m-Cellular PSO based on CORLN*

Rotated Ellipse2			Schwefel			Sphere		
Classical PSO	m-Cellular PSO		Classical PSO	m-Cellular PSO		Classical PSO	m-Cellular PSO	
	Pbest	Gbest		Pbest	Gbest		Pbest	Gbest
0.09	0.07	0.06	0.12	0.05	0.08	0.07	0.05	0.08
0.09	0.08	0.06	0.12	0.05	0.08	0.99	0.05	0.08
0.09	0.08	0.06	0.12	0.05	0.08	0.07	0.05	0.08
0.08	0.08	0.06	0.11	0.05	0.08	0.11	0.05	0.08
0.09	0.08	0.06	0.11	0.05	0.08	0.12	0.05	0.08
0.09	0.08	0.09	0.12	0.05	0.08	0.12	0.05	0.08
0.09	0.08	0.06	0.13	0.05	0.08	0.12	0.05	0.08
0.10	0.07	0.06	0.13	0.05	0.08	0.13	0.05	0.08
0.09	0.07	0.06	0.13	0.05	0.08	0.12	0.05	0.08
0.08	0.07	0.05	0.12	0.04	0.07	0.11	0.04	0.07
0.10	0.89	0.06	0.15	0.05	0.06	0.14	0.05	0.09
0.08	0.07	0.05	0.11	0.04	0.07	0.11	0.04	0.07
0.99	0.19	0.07	0.13	0.06	0.10	0.15	0.06	0.10

Table 4.11 *Default settings of moving peak benchmark (MPB)*

S.No.	Characteristics	Classical PSO	m-Cellular PSO – I-best model	m-Cellular PSO – S-best model
1.	Movement of swarm	25	77	67
2.	Peaks attained	5	10	10
3.	Divergence of particles in the problem space	Random distribution	Consistent distribution	Harmonized distribution
4.	Convergence speed	High	Moderate	Low
5	Offline error	6.06e-06	2.32e-05	1.93e-05

Offline error is a performance index which is implemented to calculate the efficiency of optimization algorithms in dynamic environment. The optimum solution changing over time, it is not adequate to compare the best solution found so far in the result analysis of chosen problem

(Iman Rezazadeh et al., 2011). An alternative method is to report the adapted offline performance, which averages the best solution found at each step in time. It is defined as follows:

$$offlineerror = 1/T \sum_{t=1}^{T} f(bs) \qquad (11)$$

where

T = maximum number of iterations
bs = best solutions obtained so far

Table 4.12 *Performance analysis of Classical PSO and m-Cellular PSO algorithms with Rotated Ellipse2*

Rotated Ellipse2			Schwefel			Sphere		
Classical PSO	m-Cellular PSO		Classical PSO	m-Cellular PSO		Classical PSO	m-Cellular PSO	
Gbest	Pbest	Gbest	Gbest	Pbest	Gbest	Gbest	Pbest	Gbest
0.994	0.997	0.991	0.992	0.994	0.992	0.993	0.997	0.994
0.992	0.997	0.991	0.993	0.993	0.993	0.994	0.996	0.994
0.994	0.996	0.991	0.994	0.992	0.992	0.995	0.996	0.993
0.995	0.997	0.992	0.997	0.995	0.993	0.997	0.997	0.995
0.993	0.996	0.991	0.995	0.992	0.992	0.996	0.996	0.993
0.993	0.997	0.991	0.995	0.996	0.994	0.996	0.997	0.995
0.995	0.997	0.992	0.996	0.996	0.994	0.997	0.997	0.995
0.992	0.997	0.992	0.994	0.996	0.995	0.994	0.997	0.995
0.995	0.997	0.992	0.994	0.996	0.994	0.997	0.997	0.995
0.992	0.996	0.990	0.996	0.993	0.991	0.995	0.996	0.992
0.994	0.997	0.990	0.994	0.995	0.994	0.997	0.997	0.994
0.994	0.997	0.991	0.995	0.995	0.993	0.996	0.997	0.993
0.990	0.995	0.990	0.992	0.991	0.988	0.993	0.996	0.992

CPSO – Classical PSO; I – Improvement; D – Deterioration;

Table 4.13 *Performance analysis of Classical PSO and m-Cellular PSO algorithms with Schwefel*

S.No.	Characteristics	Classical PS	m-Cellular PSO – I-best model	m-Cellular PSO – S-best model
1	Movement of swarm	60	196	212
2.	Peaks attained	09	20	17
3.	Divergence of particles in the problem space	Uniform distribution	Harmonized distribution	Harmonized distribution
4.	Convergence speed	High	Low	Low
5.	Offline error	0.0106	0.0025	0.0018

Table 4.14 *Performance analysis of Classical PSO and m-Cellular PSO algorithms with Sphere*

Metric	CPSO	I-best model				S-best model			
		m-Cellular PSO							
		Schwefel							
		Pbest	% I/D	Gbest	% I/D	Pbest	% I/D	Gbest	% I/D
PSNR	63.8	65.73	2.98 (I)	67.67	5.89 (I)	70.69	10.79 (I)	66.92	4.89 (I)
MSE	0.16	0.18	11.76 (I)	0.1	46.15 (I)	0.07	56.25 (I)	0.11	31.25 (I)
MAE	0.12	0.14	16.66 (I)	0.07	41.66 (I)	0.05	58.33 (I)	0.08	33.33 (I)
CORLN	0.99	0.99	0.00 (I)	1	1.01 (I)	0.99	0.00 (I)	0.99	0.00 (I)

CPSO – Classical PSO; I – Improvement; D – Deterioration;

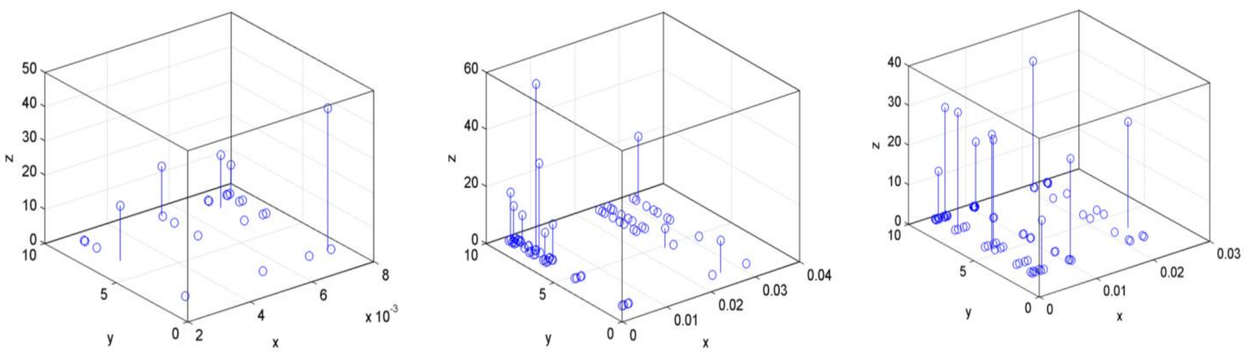
Evolutionary algorithms often have to solve non-linear complicated problems in a wide range of uncertainties such as fitness function is subject to approximation error, the design variables and environmental parameters modify after optimization and the quality of optimal solution may frequently alter in dynamic environment. In this scenario, the optimization algorithm needs to track optimum of the problem continuously over time. In this research work, it can be attained by m-Cellular PSO algorithm using knowledge about previous search space to advance the search process after optimal solution change. The performance of Classical PSO and m-Cellular PSO algorithms in a dynamic environment are measured by using the generation-best for plotting the development of the population as it evolves over time (Mosen & Chiong, 2013)(Yaochu Jin & Jurgen Branke, 2005). From the experimental results shown in Figure 1 and Figure 2, it is inferred that the moving peak benchmark function is capable of tracking the incessant shifting optimal solution over time. In the proposed work, whenever the environment change is detected, the particles are generated, and diversity is appreciably maintained throughout the execution for both 1000 and 5000 iterations with three benchmark functions. The results given in Table 4.15 and Table 4.16 reveal that the m-Cellular PSO algorithm will ultimately improve the quality of the results. Based on the analytical results, it concludes that this proposed work will be best suited to solve problems in dynamic environments. An analysis on the moving peak benchmark function results indicate that rotated ellipse2 with 5000 iteration gives significant results for both models among the others which is considered for analysis.

Table 4.15 *Comparison of Models using MPB function for Processed Cleveland dataset*

Metric	CPSO	I-best model				S-best model			
		m-Cellular PSO							
		Rotated Ellipse2							
		Pbest	% I/D	Gbest	% I/ D	Pbest	% I/D	Gbest	% I/D
PSNR	67.89	72.48	6.54 (I)	65.73	3.23 (D)	69.21	1.94 (I)	68.91	1.5 (D)
MSE	0.1	0.06	50 (I)	0.13	26.87 (D)	0.06	50 (I)	0.08	20 (I)
MAE	0.16	0.04	75 (I)	0.09	43.75 (I)	0.08	50 (I)	0.06	62.5 (I)
CORLN	0.99	1.00	1.01 (I)	1.00	1.01 (I)	1.00	1.01 (I)	0.99	0.00 (I)

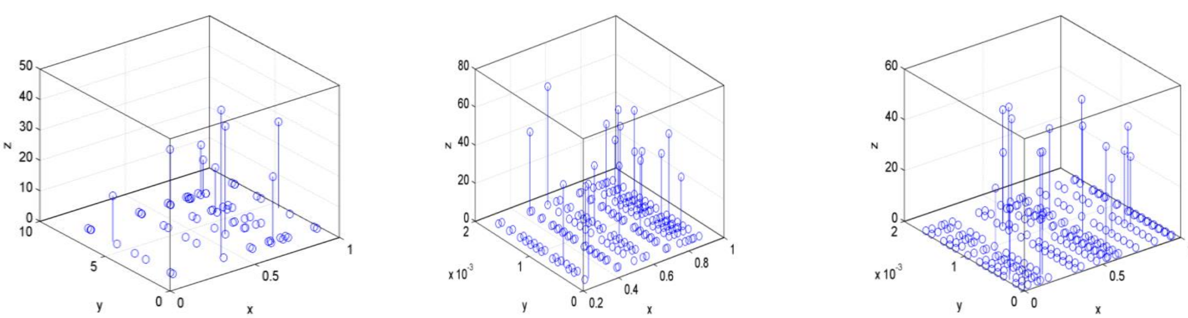
Table 4.16 *Comparison of Models using MPB function for Sign Language dataset*

Metric	CPSO	I-best model				S-best model			
		m-Cellular PSO							
		Sphere							
		Pbest	% I/D	Gbest	% I/D	Pbest	% I/D	Gbest	% I/D
PSNR	63.7	62.67	2.65 (D)	67.67	6.04 (I)	64.25	0.86 (I)	61.48	3.48 (D)
MSE	0.15	0.15	0.00 (I)	0.29	63 (D)	0.07	53.33 (I)	0.11	26.66 (I)
MAE	0.18	0.11	38.88 (I)	0.16	1.1(I)	0.05	72.22 (I)	0.08	55.55 (I)
CORLN	1.00	1.00	0.00 (I)	1.00	0.00 (I)	1.00	0.00 (I)	0.99	1.01 (I)



(a) Classical PSO (b) m-Cellular PSO – I-best model (c) m-Cellular PSO – S-best model

Figure 1: *Moving Peak Benchmark (MPB) results for processed Cleveland dataset*



(a) Classical PSO (b) m-Cellular PSO – I-best model (c) m-Cellular PSO – S-best model

Figure 2: *Moving Peak Benchmark (MPB) results for sign language dataset*

5. Conclusion and Future works

PSO algorithm subjected to no free lunch theorem, also suffers to solve non-linear complex problem due to the degree of premature convergence in some situations. It leads to particles perturbed, when it is introduced in the local optimum in n-dimensional domain space. To overcome this problem, a new variant PSO algorithm, which fuses the behavior of cellular organism inspired from fibroblast, is introduced. It is tested and evaluated in two different dynamic environment based applications. The computational results have revealed that the novel motility factor based m-Cellular PSO algorithm exhibits better solutions, based on various performance metrics, in all the three well known test functions. This high performance results due to motility behavior and optimization strategies of cellular organism helps to recommend the proposed m-Cellular PSO algorithm to solve non-linear complex optimization problems. The topology formation of m-CPSO algorithm can be validated with solving varied sizes of benchmark problems and compared with other variants of PSO algorithms. This study can be further extended to investigate m-CPSO algorithm in solving forecasting/estimation problems, real time applications and evaluate the convergence and robustness of m-CPSO to some extent.

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