2010 2nd International Conference on Education Technology and Computer (ICETC)

Opposition based PSO and Mutation Operators

(OPSO with Power Mutation)

Muhammad Imran, Hajira Jabeen, Mubashir Ahmad, Qamar Abbas,Waqas Bangyal, Qamar Abbas
Department of Computer Science
Iqra University, Islamabad,
Pakistan
Malik_imran@live.com, hajira@iqraisb.edu.pk , Mubahar_ahmad@live.com, qamar.bhk@gmail.com,
waqas_bangyal@hotmail.com, itinformations@gmail.com

***Abstract*—Particle Swarm Optimization (PSO) algorithm has shown good performance in many optimization problems, but PSO suffers from the problem of early convergence into a local minima. Introduction of opposition based initialization and mutation operators have played an important role to overcome the convergence problem in function optimization. In this study we have reviewed different variants of PSO for function optimization. Researchers have proposed different modifications in PSO to prevent it from getting stuck in local optima. At the end, we have proposed a variant of PSO for better conversion.**

Keywords-PSO;Opposition;Mutation;Survey;Function optimization

I. INTRODUCTION

PSO is a population based optimization method purposed by Kennedy and Eberhart. The algorithm simulates the behavior of bird flock flying together in multi dimensional space in search of some optimum place, adjusting their movements and distances for better search [7].

PSO Is A Population Based Algorithm Inspired By The Animal Behavior, Such As Fish Schooling, Bird Flocking [1, 2]. PSO Is A Combination Of Two Approaches, One Is Cognition Model That Is Based On Self Expression And The Other Is Social Model, Which Incorporates The Expressions Of Neighbors. The Algorithm Mimics A Particle Flying In The Search Space And Moving Towards the Global optimum. All the particles are initialized with random positions having random velocity [1] The particles move towards the new position based on their own experience and with neighborhood experience.

Each particle in PSO maintainins two important positions called p_{best} and g_{best} where p_{best} is the particle's own best position and g_{best} is the global best position among all the particles.

The equation used to update a particle's velocity and position are the following.

$$V_i(t+1) = V_i(t) + c_1 * r_1 * (p_{best} - n_i(b)) + c_2 * r_2 * (g_{best} - x_i(t)) \quad \text{(i)}$$

$$X_i(t+1) = x_i(t) + v_i(t+1) \quad \text{(ii)}$$

Where x_i is the position, v_i is the velocity and P_{best} is the personal best position and g_{best} is the global best position for PSO where r_1 and r_2 are two random numbers where range is chosen from [0,1] and C_1 and c_2 are learning factors specifically the cognition and cognition component influential respectively.

II. PSO ALGORITHM

The PSO consist of following steps.

i. Initialize 'n' particles with random velocities and positions

ii. While(termination condition not true)

- Evaluate the fitness of every particle.
- Update global best position
- Update the velocity of each particle.
- Update position of every particle.

iii. Repeat

iv. Output best particle.

Where 'n' is the number of particles (potential solutions) exploring the search space and termination condition is usually set to desired number of iterations or until some desired fitness value is achieved.

III. LITERATURE REVIEW

Wang [14] proposed a new cauchy mutation operator. This operator is applied to perform local search around the global best particle. The motivation for using such a mutation operator is to increase the probability of escaping from a local optimum. [17] several benchmark functions have been used to test the performance of this new operator and better results were achieved.

Initialization of population plays an important role in the evolutionary and swarm based algorithms, in case of bad initialization, the algorithm may search in unwanted areas and may be unable to search for the optimal solution.

Jabeen et al [7] proposed opposition based initialization which calculates opposition of randomly initialized

978-1-4244-6370-1/$26.00 © 2010 IEEE

population and selects better among random and opposition as initial population. This population is provided as an input for traditional PSO algorithm. The proposed modification has been applied on several benchmark functions and found successful.

Wang [16] proposed opposition based initialization in PSO coupled with application of cauchy mutation operator. Cauchy mutation operator is used on the global best particle if newly created global best is better after application of mutation operator then global best is replaced. The proposed modification did not perform realistically well for multimodal functions.

Shahzad et al [11] proposed another variant of OPSO with velocity clamping (OVCPSO). The authors control the velocity by velocity clamping to speed up convergence and to stay away from impulsive convergence. Velocity clamping changes the search direction of particles. Linearly decreasing inertia weight between 0.4 and 0.9 has been used. The proposed algorithms has been tested on various benchmark functions and results revealed its success.

Omran et al [18] used an opposition based learning to improve the performance of PSO. In each iteration, the particle with lowest strength of fitness is replaced by it opposite, the speed and individual experience of the anti-particle are reset. After that a global best solution is updated. They have not introduced any new parameter to PSO. The only modification is the use of opposition based learning to enhance the performance of PSO.

Tang et al [19] proposed an enhance opposition based PSO, called EOPSO. According to the authors opposite point is closer to global optima then current point. This provides more chances to get close to global optima. The enhanced opposition of a population is calculated based on opposition probability and best among original and enhanced population are selected for further exploration of the search space using traditional PSO. Prominent results have been achieved using the proposed modification to traditional PSO.

Zhang et al [20] proposed an enhanced version of opposition based PSO called quasi-oppositional comprehensive learning PSO (QCLPSO). Instead of calculating traditional opposite of a point, the proposed modification calculates qausi opposite particle, which is generated from the interval between median and opposite position of the particle. According to authors the qausi opposite particles have higher chances of being closer to global optima then opposite particle calculated without apriori information.

Wu et al [21] proposed a new variant of PSO called power mutation based PSO (PMPSO), which employs a power mutation operator. The core plan of AMPSO is to apply power mutation on the fittest particle of current swarm. Purpose of power mutation is help particles to jump out from the local optima. The algorithm has been compared with several other PSO variants and better results have been achieved on most of the benchmark functions.

Lovbjerg et al [10] proposed a new hybrid PSO variant which combines the PSO with breeding operators. The authors have also introduced the use of subpopulation for inter and intra population breeding. Some members of a population are marked for breeding in each iteration using the breeding probability and a weighted crossover is performed between these marked particles. In case of subpopulations, inter population breeding is performed using the probability of same subpopulation breeding. Each subpopulation is evolved using its own global best particle. The performance of this new variant has been compared with traditional PSO and Genetic algorithm and results are found outstanding.

PSO has been applied for constrained non linear optimization problem [12]. Feasibility study has been used to deal with constraints, and feasibility function is used to check the satisfaction of all the constraints. Initial population is a group of feasible solutions that satisfy all the constraints. All particles keep feasible solution in their memory. The proposed modified algorithm has successfully solved problems with nonlinear inequality constraints.

In [3] predator pray optimization technique is used for function optimization. New particles known as predators are introduced in the technique to avoid the premature convergence. The particles in the swarm are repelled by the predator particles and attracted towards the best positions of the swarm. This repulsive mechanism ensures the presence of diversity in the swarm and eliminates the phenomenon of premature convergence.

In [23] Brits proposed another variant of PSO which intended to locate multiple best possible solution in a multimodal problems by using subswarms and the convergent subswarms algorithm . Niching algorithms find and track various solutions via fitness based principle to discover and mark particle solution. However there are still some issues that need to be solved.

Ppant el al [25] introduced the new mutation operator for improving the Qantum Particle Swarm Optimization algorithm. The muatation operator uses the qausi random sobol sequence an dis called is a sobol mutation (SOM)operator. Author proposed two version using SOM in one they mutate the best particle and in other they mutate worst particle. The proposed technique is comapred with BPSO,QPSO and two more varients of QPSO, also they comapre both varients to eachother.

In [15] Pant has introduced new variants of the PSO as AMPSO1 and AMPSO2. AMPSO1 mutates the local best position and AMPSO2 mutates the global best position of the swarm. This adaptive mutation is performed by using an adaptive mutation probability and the mutation is a function of beta distribution and normally distributed random numbers. The proposed modified PSO variants have been

tested on various benchmark functions and better results were found when compared to evolutionary programming.

IV. PROPOSED TECHNIQUE

In above study we have seen that opposition based initialization and mutation operators have played a vital role for function optimization problems using PSO. OPSO with Cauchy mutation operator has performed well for unimodal functions. On the other hand, power mutation has ability to perform better for multimodal functions but it has not been explored with opposition based initialization.

We want to explore the use of efficient opposition based initialization with power mutation. The power mutation is based on the power distribution where higher values of power introduce more diversity.

V. CONCLUSION

Many researchers have proposed different variants of PSO, but which we think play a better role is the opposition based techniques. The other good approach is using the mutation operator to mutate the global best particle to perform a local search for better exploration. Power mutation is better for uni-modal functions and Cauchy mutation operator is good for multi-modal functions. To get the good and efficient results we should combine both Cauchy and power mutation.

If we use power mutation operator with the opposition based PSO, then it is the probability to get the good results rather than using mutation operator on the simple PSO. Opposite particles have more chance to get closer to the global optima, so our goal is to implement an opposition based PSO with power mutation.

VI. FUTURE WORK

Regardless of the above mentioned contributions our research effort has some limitations. As our work gets evolve, we are hopeful in overcoming these problems. Steps for the new algorithm need to be defined for experimental setup. The proposed technique must to be compared with other variants to test its feasibility.

REFERENCES

[1] J. Kennedy and R. Eberhart, Particle Swarm Optimization, IEEE International Conference on Neural Networks, Perth, Australia. 1995.

[2] F. Shahzad et al, Opposition Based Particle Swarm Optimization with velocity Clamping

[3] A, Silva, A. Neves and E.Costa. Chasing The Swarm: A Predator Pray Approach to Function Optimization. In Proceedings of MENDEL 2002, 8th International Conference on Soft Computing , Brno, Czech Republic. 2002.

[4] J. Blondon, Particle Swarm Optimiztion, A tutorial September, 4, 2009

[5] Fran Van Den Bergh, An Analysis of Particle Swarm Optimizations, Phd Thesis of Pretoria, 2001

[6] GF. Van den Bergh and A. P. Englbereht, A Cooperative Approach to Particle Swarm Optimization, IEEE, Transaction on evolutionary Computation, Vol 8, No. 3, June 2004

[7] H. Jabeen et al, Opposition Based Initialization in Particle Swarm Optimization, 2009

[8] X. Shiand and R.C. Eberhart. A modified Particle Swarm Optimizer, In Proceeding of IEEE congress of Evolutionary computation, 1998,69-73.

[9] V, Shi, R.C. Eberthart, Particle Swarm Optimization with Fuzy adoption inertia weight, In proceeding workshop, Particle Swarm Optimization, Indiana Polise, IN, 2007.

[10] M. Lovbjerg et al. Hybrid Particle Optimizer with breeding and subpopulation, citseer, 2001.

[11] F. Shahzad et al. Opposition Based Particle Swarm Optimization with velocity clamping, advaced in computational Intells, Springer, 339-348,2009.

[12] X.Hu and R. Eberhart, Solving Constrait non-linear optimization problems with Partilcle Swarm Optimization.

[13] M. Løvbjerg 'Hybrid Particle Swarm Optimizer with Breeding and Subpopulations'

[14] H, Wang. 'A Hybrid Particle Swarm Algorithm with Cauchy Mutation' China University of Geosciences.

[15] M, Pant et al. 'Particle Swarm Optimization Using Adaptive Mutation', Norwegian University of Science and Technology, Norway

[16] H. Wang, Y. Liu, C. Li, S. Zeng "Opposition-based Particle Swarm Algorithm with Cauchy Mutation," IEEE CEC, 4750 - 4756, 2007.

[17] X. Yao, Y. Liu and G. Lin, Evolutionary Programming Made Faster, IEEE Transactions on Evolutionary Computation, vol. 3, 82-102, July 1999.

[18] Mahamed G. H. Omran and Salah al-Sharhan Using Opposition-based Learning to improve the Performance of Particle Swarm Optimization 2008 IEEE Swarm Intelligence Symposium St. Louis MO USA, September 21-23, 2008

[19] Jun Tang and Xiaojuan Zhao An Enhanced Opposition-based Particle Swarm Optimization Global Congress on Intelligent Systems.

[20] Chang Z , Zhiwei N, Wu Lichuan, A Novel Swarm Model With Quasi-Oppositional Particle, 2009 International Forum on Information Technology and Applications.

[21] Xiaoling Wu, Xiaojuan Zhao Particle Swarm Optimization with Adaptive Mutation, 2009 WASE International Conference on Information Engineering

[22] K. Deep, and M. Thakur, "A new mutation operator for real coded genetic algorithms", Applied mathematics and Computation 193, 2007, pp. 211-230.

[23] R.BritsA.P. Engelbrecht, F. v. A NICHING PARTICLE SWARM OPTIMIZER..

[24] LU Zhen-su, H. Z.-r. (2006). Particle Swarm Optimization with Adaptive Mutation. Springer-Verlag , 99–104.

[25] Millie Pant, R. T. (2009). Sobol Mutated Quantum Particle Swarm Optimization. International Journal of Recent Trends in Engineering , Vol. 1 Issue. 1 , 95-99.