Asynchronous and stochastic dimension updating PSO and its application to Parameter Estimation for Frequency Modulated (FM) Sound Waves

Yanxia Sun
Department of Electrical and Electronic Engineering Science
University of Johannesburg
Johannesburg 2006, South Africa
sunyanxia@gmail.com

Zenghui Wang
Department of Electrical and Mining Engineering
University of South Africa
Florida 1710, South Africa
wangzengh@gmail.com

Abstract— **The particle velocity and position updating plays very important role for achieving good optimization performance for Particle Swarm Optimization (PSO). This paper analyzed the performance of asynchronously updating PSO and synchronously updating PSO by simulation and found that the asynchronously updating way can achieve better optimization performance than the synchronously updating way. Moreover, the convergence of asynchronously PSO is faster than the synchronously PSO, which means there is spare time to achieve better optimization performance based on some techniques. Here we proposed stochastic dimension updating technique which means only some dimensions of position will be updated. Several benchmark functions have been used to validate the proposed method and the proposed method is also applied to the parameter estimation for frequency modulated Sound Waves.**

Keywords-Particle swarm optimization; asynchronous updating; stochastic dimension updating; parameter estimation

I. INTRODUCTION

Particle swarm optimization as one of the swarm intelligent algorithms has attracted a lot of attention [1-4]. PSO simulates the movement of organisms in a bird flock or fish school. This algorithm has few or no assumptions about the problems being optimized and can search very large spaces of the candidate solutions [5].

The PSO algorithm and its variations have been successfully applied in many areas [6], such as human tremor analysis for biomedical engineering [7, 8], electric power and voltage management [9], machine scheduling [10], robotics [11], and VLSI circuit design [12]. To improve the optimization performance of PSO many methods or techniques have been proposed such as change the inertia weight and constriction factor [13, 14].

In general, the global (local) best experiences of particles are updated once after all the particle positions are updated which is called synchronous updating. There is another kind of updating, which is called asynchronous updating and the global (local) best experiences is to be checked and updated after the position of each particle is updated. This paper focuses on the updating methods and tries to improve the optimization performance of PSO.

The remaining parts of the paper are organized as follows. In section II, the particle swarm optimization is briefly described. The synchronous and asychronous updating methods of particle swarm optimization are analyzed based on simulations in section III. The stochastic dimension position updating of particle swarm optimization is proposed based on the asynchronous updating method in section IV. The proposed method is applied to the parameter estimation for frequency modulated (FM) sound wave in section V. The conclusions are summarized in section VI.

II. BRIEF DESCRIPTION OF PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) was developed by Kennedy and Eberhart [15]. This algorithm is inspired by the social behavior of a flock of migrating birds trying to reach an unknown destination. All members obey a set of simple rules that model the communication within the flock, between the flocks and the environment. Each solution is a "bird" in the flock and is referred to as a "particle". PSO has attracted a lot of attention as it makes few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions [16-18]. The formula of PSO is realized by two update functions:

$$V_i(t+1) = \omega V_i(t) + c_1 R_1 (P_i - X_i(t)) + c_2 R_2 (P_g - X_i(t)), \quad (1)$$

$$X_i(t+1) = X_i(t) + V_i(t+1). \quad (2)$$

Here $V_i = \left[v_i^1, v_i^2, \cdots v_i^n\right]$ is the velocity of particle i ; $X_i = \left[x_i^1, x_i^2, \cdots x_i^n\right]$ represents the position of particle i ; P_i represents the best previous position of particle i (indicating the best discoveries or previous experience of particle i); P_g represents the best previous position among all particles (indicating the best discovery or previous experience of the social swarm); ω is the inertia weight that controls the impact of the previous velocity of the particle on its current velocity and is sometimes adaptive. R_1 and R_2 are two random weights whose components r_1^j and r_2^j $(j = 1, 2 \cdots, n,)$ are chosen uniformly within the interval

[0,1] which might not guarantee the convergence of the particle trajectory; c_1 and c_2 are the positive constant parameters. Generally the value of each component in V_i should be clamped to the range $[-v_{\max}, v_{\max}]$ to control excessive roaming of particles outside the search space.

III. ANAYSIS OF SYNCHRONOUS AND ASYCHRONOUS UPDATING OF PARTICLE SWARM OPTIMIZATION

To analyze the effects of the synchronous updating and asynchronous updating of particle swarm optimization, five famous benchmark functions were chosen and listed in Table I. As can been seen from Table I, for these benchmark functions, some of them are unimodal type and some of them are multimodal. Moreover, the step function is discrete optimization problem.

TABLE I. BENCHMARK FUNCTIONS

Name of the benchmark function	**Equation and its parameters**		
	Equation	***n***	***Variable range***
Sphere	$f_1(X) = \sum_{i=1}^{n} x_i^2$	20	$-100 \le x_i \le 100$
Rastrigin	$f_2(X) = 10n + \sum_{i=1}^{n}[x_i^2 - 10\cos(2\pi x_i)]$	20	$-100 \le x_i \le 100$
Step	$f_3(X) = \sum_{i=1}^{n}[\,floor(x_i + 0.5)^2\,]$ where B = floor(y) rounds the elements of y to the nearest integers less than or equal to y.	20	$-100 \le x_i \le 100$
Rosenbrock	$f_4(X) = \sum_{i=1}^{n}[100(x_{i+1} - x_i^2)^2 + (1 - x_i)^2]$	20	$-100 \le x_i \le 100$
Griewank	$f_5(X) = 1 + \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}})$	20	$-100 \le x_i \le 100$

Here the number of particles is 30 and $\omega = 1/(2*\log(2))$; $c_1 = 0.5 + \log(2)$; $c_2 = c_1$; and the velocity Vmax set to the dynamic range of the particle in each dimension. The maximum number of function evaluations is 30000 for these two methods with 100 independent runs. The optimization statistical analysis of these two algorithms is reported in Table II. The evolutionary curves of these two updating methods were drawn in Fig. 1 which is similar with other benchmark functions.

TABLE II. COMPARISON BETWEEN SYNCHRONOUS UPDATING AND ASYNCHRONOUS UPDATING OF PARTICLE SWARM OPTIMIZATION

Problem	Method	best	Mean	Std.dev	Worst
Sphere	Synchronous updating	0	200	1414	10000
Sphere	Asynchronous updating	0.21	2.72	2.98	12.85
Rastrigin	Synchronous updating	45.77	551.87	1962.80	10081.60
Rastrigin	Asynchronous updating	34.82	12.16	57.94	293.50
Step	Synchronous updating	0	21.40	36.63	208.00
Step	Asynchronous updating	0	13.26	27.41	127.00
Rosenbrock	Synchronous updating	9.105	1.60e+5	3.70e+5	1.00e+6
Rosenbrock	Asynchronous updating	0.05	1.00e+5	3.03e+5	1.00e+6
Griewank	Synchronous updating	0	0.09	0.36	2.58
Griewank	Asynchronous updating	0	0.03	0.04	0.24

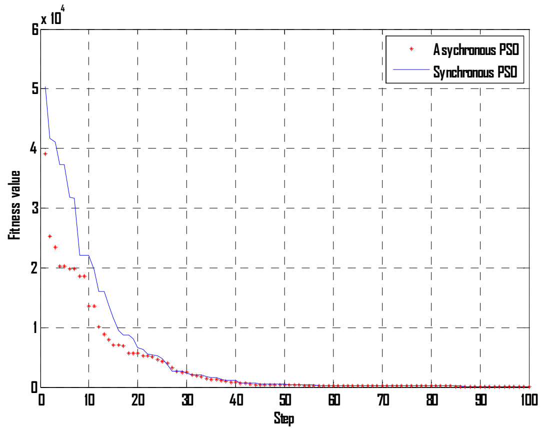

Figure 1 Comparison for Rastrigin function

As can been seen from Table II, in general the asynchronous updating PSO can achieve better optimization performance than the synchronous updating PSO. As typical evolutionary curves shown in Fig. 1, we can find the convergence is faster than the synchronous updating PSO than the asynchronous updating PSO due to the global (local) best experiences are updated timely. Moreover, because the synchronous updating PSO only updates the global (local) best experiences after all the positions of the particles are updated and all the particles are attracted to the same global (local) best experiences, it can make the synchronous updating PSO be premature.

IV. STOCASTICAL DIMENTION POSITION UPDATING OF PARTICLE SWARM OPTIMIZATION

According to the simulations in Section III, the asynchronous updating can achieve better optimization performance than the synchronous updating. Moreover, the convergence of the asynchronous updating is faster than the synchronous updating which gives us time to achieve better optimization performance in a certain number of function evaluations. Here we propose a stochastic dimension position updating method based on the asynchronous updating.

A. Stochastic dimension position updating

This method does not change the velocity updating formula and only change the position updating formula. The position updating (2) can be changed to

$$X_i(t+1) = X_i(t) + \mathrm{ceil}(R_3 - \alpha)V_i(t+1) \quad (3)$$

where ceil(Y) rounds the elements of Y to the nearest integers greater than or equal to Y; R_3 is a rand vector with a range of [0, 1] and $0 \le \alpha < 1$. The term $\mathrm{ceil}(R_3 - \alpha)$ means that if the elements of R_3 is less than α the corresponding elements of the position at the same dimensions will not be changed.

B. Simulations

The same parameters are used except $\alpha = 0.2$. Using the asynchronous stochastic dimension position updating method, the simulation results are shown in Table III. The evolutionary curves of these methods were drawn in Fig. 1. Comparing Table II and Table III, it can be found the proposed method can achieve better optimization performance. Fig. 1 shows that the proposed stochastic dimension position updating method can help reduce the convergence time and achieve better optimization performance.

TABLE III. SIMULATION RESULTS OF ASYNCHRONOUS STOCHASTIC DIMENSION POSITION UPDATING PARTICLE SWARM OPTIMIZATION

Problem	best	Mean	Std.dev	Worst
Sphere	0	0	0	0
Rastrigin	21.89	55.00	28.16	180.08
Step	0	2.28	11.66	81.00
Rosenbrock	0	8.03e+4	2.74e+5	1.00e+6
Griewank	0	0.02	0.02	0.10

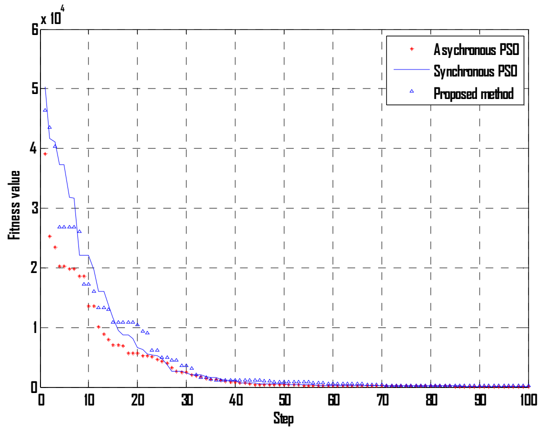

Figure 2 Comparison for Rastrigin function

V. PARAMETER ESTIMATION FOR FREQUENCY MODULATED (FM) SOUND WAVE

The real world optimization problem is taken from CEC2011 competition on testing evolutionary algorithms on real world optimization problems [19] and it is about parameter estimation for frequency-modulated (FM) sound wave. Frequency-Modulated (FM) sound wave synthesis has an important role in several modern music systems and to optimize the parameter of an FM synthesizer is a six dimensional optimization problem where the vector to be optimized is $X = \{a_1, \omega_1, a_2, \omega_2, a_3, \omega_3\}$ of the sound wave given in eqn. (v1). The problem is to generate a sound (v1) similar to target sound (v2). **This problem is a highly complex multimodal one having strong epistasis**, with minimum value $f(\vec{X}_{sol}) = 0$. The expressions for the estimated sound and the target sound waves are given as

$$y(t) = a_1.\sin\left(\omega_1.t.\theta + a_2.\sin\left(\omega_2.t.\theta + a_3.\sin\left(\omega_3.t.\theta\right)\right)\right) \quad \text{(v1)}$$

$$y_0(t) = (1.0).\sin\left((5.0).t.\theta - (1.5).\sin\left((4.8).t.\theta + (2.0).\sin\left((4.9).t.\theta\right)\right)\right) \quad \text{(v2)}$$

respectively, where θ = 2π/100 and the parameters are defined in the range [−6.4, 6.35]. The fitness function is the summation of square errors between the estimated wave (v1) and the target wave (v2) as follows: [v1]

$$f(\vec{X}) = \sum_{t=0}^{100} \left(y(t) - y_0(t) \right)^2 \quad \text{(v3)}$$

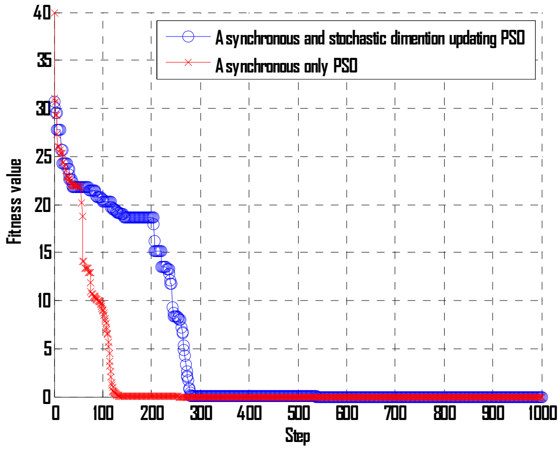

Figure 3 Optimization of FM sound wave with the optimal value

In the simulation, the parameters of PSO are same with the ones in Section IV except the number of particles is 50 since this problem is highly complex. The optimization was shown in Fig. 3. According to the simulations, the asynchronous PSO can only achieve the the global best result 2 times within 50 runs, but the proposed method can achieve 5 times within 50 runs.

VI. CONCLUSION

The synchronous updating PSO and asynchronous updating PSO were analyzed and it was found the asynchronous PSO can achieve better and faster optimization performance than the synchronous PSO. A stochastic dimension position updating method was proposed. The simulation results showed that the proposed method can achieve good optimization performance.

ACKNOWLEDGMENT

This work was supported by China/South Africa Research Cooperation Program (No. 78673), South African National Research Foundation Incentive Grants (No. 81705 and 95687).

REFERENCES

[1] M. Bonyadi, Z. Michalewicz, "An analysis of the velocity updating rule of the particle swarm optimization algorithm". *Journal of Heuristics* **20** (4): 417–452, 2014.

[2] R. Roy, S. Dehuri, S. B. Cho, "A Novel Particle Swarm Optimization Algorithm for Multi-Objective Combinatorial Optimization Problem". 'International Journal of Applied Metaheuristic Computing, 2(4), 41-57, 2012.

[3] W. Chen, J. Zhang, Jun, "A novel set-based particle swarm optimization method for discrete optimization problem". *IEEE Transactions on Evolutionary Computation* **14** (2): 278–300, 2010.

[4] M. Lovbjerg, T. Krink, "Extending Particle Swarm Optimisers with Self-Organized Criticality". *Proceedings of the Fourth Congress on Evolutionary Computation (CEC)* **2**. pp. 1588–1593, 2002.

[5] Kennedy, J.; Eberhart, R.C. (2001). Swarm Intelligence. Morgan Kaufmann. ISBN 1-55860-595-9.

[6] Nor Azlina Ab Aziz, MarizanMubin,Mohd Saberi Mohamad, and Kamarulzaman Ab Aziz, A Synchronous-Asynchronous Particle Swarm Optimisation Algorithm, Nor The Scientific World Journal Volume 2014, Article ID 123019, 17 pages

[7] R. C. Eberhart and X. Hu, "Human tremor analysis using particle swarm optimization," Proceedings of the Congress on Evolutionary Computation (CEC '99), pp. 1927–1930, 1999, Cat.no. 99TH8406.

[8] Z. Ibrahim, N. K. Khalid, J. A. A. Mukred et al., "A DNA sequence design for DNA computation based on binary vector evaluated particle swarmoptimization," International Journal of Unconventional Computing, vol. 8, no. 2, pp. 119–137, 2012.

[9] J. Hazra and A. K. Sinha, "Congestion management using multiobjective particle swarmoptimization," IEEE Transactions on Power Systems, vol. 22, no. 4, pp. 1726–1734, 2007.

[10] M. F. Tasgetiren, Y. Liang, M. Sevkli, and G. Gencyilmaz,"Particle swarmoptimization algorithmfor singlemachine total weighted tardiness problem," in Proceedings of the Congress on Evolutionary Computation (CEC '04), pp. 1412–1419, June 2004.

[11] A. Adam, A. F. Zainal Abidin, Z. Ibrahim, A. R. Husain, Z.Md Yusof, and I. Ibrahim, "A particle swarm optimization approach to Robotic Drill route optimization," in Proceedings of the 4th International Conference on Mathematical Modelling and Computer Simulation (AMS '10), pp. 60–64, May 2010.

[12] M. N. Ayob, Z. M. Yusof, A. Adam et al., "A particle swarm optimization approach for routing in VLSI," in Proceedings of the 2nd International Conference on Computational Intelligence,Communication Systems and Networks (CICSyN '10), pp. 49–53,Liverpool, UK, July 2010.

[13] Y. Shi and R. Eberhart, "A modified particle swarm optimizer,"in Proceedings of the IEEE International Conference on Evolutionary Computation and IEEE World Congress on Computational Intelligence, (Cat. No.98TH8360), pp. 69–73,Anchorage, Alaska, USA, May 1998.

[14] M. Clerc and J. Kennedy, "The particle swarm-explosion, stability,and convergence in a multidimensional complex space,"IEEE Transactions on Evolutionary Computation, vol. 6, no. 1, pp. 58–73, 2002.

[15] J. Kennedy, R. C. Eberhart, "Particle Swarm Optimization". In Proceedings of IEEE International Conference Neural Networks, pp. 1942--1948. Perth, Australia (1995).

[16] X. Hu, Y. Shi, R. Eberhart, "Recent advances in particle swarm". Congress on Evolutionary Computation, pp. 90--97. (2004)

[17] Huang, C.M, Huang C.J., Wang M.L.: A Particle Swarm Optimization to Identifying the ARMAX Model for Short term Load Forecasting. IEEE Transactions on Power Systems. 20, 1126--1133 (2005).

[18] Nedjah, N., Mourelle, L.D.M.: Systems Engineering Using Particle Swarm Optimization, Nova Science Publishers (2007).

[19] S. Das and P. N. Suganthan, Problem Definitions and Evaluation Criteria for CEC 2011 Competition on Testing Evolutionary Algorithms on Real World Optimization Problems, 2011.