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INCORPORATION OF THE UNCERTAINTY EVALUATION PROCEDURE INTO PARTICLE SWARM OPTIMIZATION IN A NOISY ENVIRONMENT

Seon Han Choi

Dept. of IT Convergence & Application Engineering
Pukyong National University
Busan, 48513, REPUBLIC OF KOREA

ABSTRACT

This paper incorporates a robust resampling method called the uncertainty evaluation (UE) procedure into particle swarm optimization (PSO) to improve its performance in a noisy environment. The UE procedure allows PSO to find the global best correctly by allocating a limited number of samplings to each particle effectively. In addition, compared with other resampling methods, the high robustness to noise of the UE procedure enhances the performance of PSO in complex problems involving large stochastic noise and many local optima, which is demonstrated in the results of comparative experiments on some benchmarks.

1 INTRODUCTION

Particle swarm optimization (PSO) inspired by the social behavior of swarm is a widely-used metaheuristic algorithm for deterministic optimization. However, many real-life problems involve stochastic noise, so several variants incorporated with a resampling method have been developed to cope with it. That is, they improve the accuracy of fitness evaluations in a noisy environment using the resampling method. Horng et al. (2012) combined the optimal computing budget allocation (OCBA) procedure with PSO to resolve the minimization problem in wafer probe testing. While it applied OCBA procedure to evaluate the fitness for particles' current position, Rada-Vilela et al. (2013) utilized it to estimate the particles' best position more precisely to improve the accuracy of the particles' attractors. Existing variants, including these two works, mainly use OCBA procedure for resampling. Although the OCBA procedure is intuitive and an asymptotic optimal solution, it can be degraded in the presence of large stochastic noise (Choi and Kim 2018). Recently, the higher complexity of modern industrial systems increases the noise in optimization problems. Therefore, this paper proposes a new variant of PSO incorporated with the uncertainty evaluation (UE) procedure that has high robustness to noise by considering the precision of the sample mean neglected by OCBA procedure.

2 PROPOSED VARIANT OF PSO AND EXPERIMENTAL RESULTS

Since the global best has a significant effect on the movement of the entire swarm and is the ultimate goal of PSO, the correct selection of the global best can greatly improve the performance of PSO in a noisy environment. Thus, we applied the UE procedure to select the global best correctly, and Algorithms 1 and 2 represent the proposed variant of PSO. To select the global best more accurately, the proposed variant allocates further samples to the global best as well as particles' current position using the UE procedure, as shown in Algorithm 2. In addition, reusing the previous evaluation data of global best $\boldsymbol{\mathcal{D}}_g^{l-1}$, it minimizes the waste of limited sampling resources.

To demonstrate the improved performance of the proposed variant, comparative experiments on three complex benchmarks with many local minima were conducted, where $\mathcal{N}(0, 5^2)$ was added to each function as a large stochastic noise. We set the parameters of PSO and resampling methods as follows: $m = 50$, $l_{max} = 100$, $c_1 = c_2 = 2.05$, $T^l = 5000 + 100(l - 1)$, $n_0 = 10$, and $\Delta = 100$. As shown in Figure 1, the proposed one presents superior performance to the other variants combined with OCBA or equal allocation (EA). In addition, it converges on a more accurate value for the global minimum of benchmarks in the presence of large stochastic noise by taking advantage of the high robustness to noise of UE procedure.

Algorithm 1 Proposed PSO procedure incorporated with UE procedure

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generate m particles with initial position $\boldsymbol{X}_i^1 = [x_{i1}, \dots, x_{id}]$ and velocity $\boldsymbol{V}_i^1 = [v_{i1}, \dots, v_{id}]$ randomly

for l = 1 to l_{max} **do**, where l_{max} is the maximum number of iterations in PSO

    evaluate the estimated fitness $\bar{f}(\boldsymbol{X}_i^l)$ for each particle $i \in \{1, \dots, m\}$ and **update** the *global best* $\boldsymbol{P}_g^l$ and $\boldsymbol{\mathcal{D}}_g^l$:

$\left[\bar{f}\left(\boldsymbol{X}_{i=1,\dots,m}^l\right), \boldsymbol{P}_g^l, \boldsymbol{\mathcal{D}}_g^l\right]$ = **UE**$\left(\boldsymbol{X}_{i=1,\dots,m}^l, \boldsymbol{P}_g^{l-1}, \boldsymbol{\mathcal{D}}_g^{l-1}, T^l, n_0, \Delta\right)$, where $\boldsymbol{\mathcal{D}}_g^l = \left[\bar{f}\left(\boldsymbol{P}_g^l\right), s_g^2, N_g\right]$ is the evaluation data of $\boldsymbol{P}_g^l$

    update the *personal best* $\boldsymbol{P}_i^l$ for each $i \in \{1, \dots, m\}$: **if** $\bar{f}\left(\boldsymbol{X}_i^l\right) \le \bar{f}\left(\boldsymbol{P}_i^{l-1}\right)$, **then set** $\boldsymbol{P}_i^l \leftarrow \boldsymbol{X}_i^l$; **else set** $\boldsymbol{P}_i^l \leftarrow \boldsymbol{P}_i^{l-1}$

    update $\boldsymbol{V}_i^{l+1}$ and $\boldsymbol{X}_i^{l+1}$: $v_{id}^{l+1} = \chi\left(v_{id}^l + c_1\epsilon_1\left(p_{id}^l - x_{id}^l\right) + c_2\epsilon_2\left(p_{gd}^l - x_{id}^l\right)\right)$ and $x_{id}^{l+1} = x_{id}^l + v_{id}^{l+1}$

return $\boldsymbol{P}_g^l$

Algorithm 2 UE Procedure for PSO$\left(\boldsymbol{X}_{i=1,\dots,m}^l, \boldsymbol{P}_g^{l-1}, \boldsymbol{\mathcal{D}}_g^{l-1}, T^l, n_0, \Delta\right)$

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if $l > 1$, **then load** $\boldsymbol{P}_g^{l-1}$ and $\boldsymbol{\mathcal{D}}_g^{l-1}$ for the additional allocation: **set** $\boldsymbol{X}_{m+1}^l \leftarrow \boldsymbol{P}_g^{l-1}$, $\bar{f}(\boldsymbol{X}_{m+1}^l) \leftarrow \boldsymbol{\mathcal{D}}_g^{l-1}.\bar{f}\left(\boldsymbol{P}_g^{l-1}\right)$, $s_{m+1}^2 = \boldsymbol{\mathcal{D}}_g^{l-1}.s_g^2$, $N_{m+1} \leftarrow \boldsymbol{\mathcal{D}}_g^{l-1}.N_g$, and $k \leftarrow m+1$; **else set** $k \leftarrow m$

collect n_0 samples of $f\left(\boldsymbol{X}_i^l\right)$ for each $i \in \{1, \dots, m\}$ and **calculate** the sample mean $\bar{f}\left(\boldsymbol{X}_i^l\right)$ and sample var. s_i^2

set the number of collected samples $N_i \leftarrow n_0$ for each $i \in \{1, \dots, m\}$, $T^l \leftarrow T^l - mn_0$, and $b \leftarrow \text{argmin}_{i \in \{1,\dots,k\}} \bar{f}\left(\boldsymbol{X}_i^l\right)$

while $T^l \ge 0$ **do**

    evaluate the *uncertainty* ε_i for each $i \in \{1, \dots, k\}$ using the equations (9) and (10) in Choi and Kim (2018)

    allocate the further samples a_i to each $i \in \{1, \dots, k\}$ based on ε_i using the allocation policy (Choi and Kim 2018)

    collect a_i samples of $f\left(\boldsymbol{X}_i^l\right)$ for each $i \in \{1, \dots, k\}$ and **update** $\bar{f}\left(\boldsymbol{X}_i^l\right)$ and s_i^2

    set $N_i \leftarrow N_i + a_i$ for each $i \in \{1, \dots, k\}$, $T^l \leftarrow T^l - \Delta$, and $b \leftarrow \text{argmin}_{i \in \{1,\dots,k\}} \bar{f}\left(\boldsymbol{X}_i^l\right)$

update $\boldsymbol{P}_g^l$ and $\boldsymbol{\mathcal{D}}_g^l$: **set** $P_g^l \leftarrow \boldsymbol{X}_b^l$, $\boldsymbol{\mathcal{D}}_g^l.\bar{f}\left(\boldsymbol{P}_g^l\right) \leftarrow \bar{f}\left(\boldsymbol{X}_b^l\right)$, $\boldsymbol{\mathcal{D}}_g^l.s_g^2 \leftarrow s_b^2$, and $\boldsymbol{\mathcal{D}}_g^l.N_g \leftarrow N_b$

return $\left[\bar{f}\left(\boldsymbol{X}_{i=1,\dots,m}^l\right), \boldsymbol{P}_g^l, \boldsymbol{\mathcal{D}}_g^l\right]$

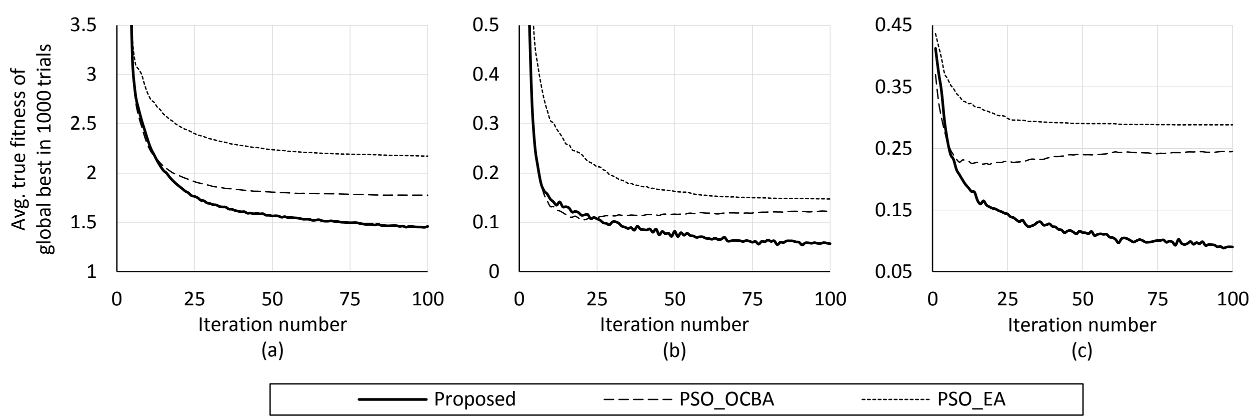

Figure 1: Experimental results of (a) Griewank($d = 30$), (b) Levy N. 13, and (c) Schaffer N.2 functions.

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