Particle Swarm Optimization with Random Sampling in Variable Neighbourhoods for Solving Global Minimization Problems

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Particle Swarm Optimization (PSO) is a bio-inspired evolutionary meta-heuristic that simulates the social behaviour observed in groups of biological individuals [4]. In standard PSO, the particle swarm is often attracted by sub-optimal solutions when solving complex multimodal problems, causing premature convergence of the algorithm and swarm stagnation [5]. Once particles have converged prematurely, they continue converging to 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. This paper presents a modified variant of constricted PSO [1] that uses random samples in variable neighbourhoods for dispersing the swarm whenever a premature convergence state is detected, offering an escaping alternative from local optima.

PSO-RSVN Algorithm

The Variable Neighbourhood Search (VNS) is a simple and effective meta-heuristic for combinatorial problems and global optimization [2] which is based on the systematic change of the neighbourhood in the search process. Inspired by this idea, we present a procedure called Random Sampling in Variable Neighbourhoods (RSVN) which aims to disperse the swarm when it detects the premature convergence state. The main idea of this procedure is to restructure the particle swarm from the selection of random samples uniformly distributed in several neighbourhoods generated around the global best particle of the swarm. In this procedure m neighbourhoods with parameters $\xi_j \in (0, 1]$ are computed; where the neighbourhood factor ξ_j is used for controlling the j-th neighbourhood proportion to the size of the search space. After collecting the samples in each partition, a selection process of the particles takes place. These agents will form the new swarm as shown below:

$$\beta = \Phi_1 \cup \Phi_2 \cup ... \cup \Phi_m = \bigcup_{j=1}^{m} \Phi_j | \Phi_j \subseteq \Psi_j, \forall j \quad . \tag{1}$$

where β represents the particle swarm and Φ_j is a subset of good enough particles compared to all samples Ψ_j using an elitist criterion. In this procedure each generated particle is a candidate to replace the best global particle, which

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complements the swarm dispersion process. The diversity introduced by the dispersion mechanism ensures the exploration of new areas of the solution space, increasing the possibility of escape from sub-optimal solutions. Moreover, due to the elitist replacement, simplicity and low computational cost the RSVN procedure could be adapted and integrated into several evolutionary paradigms.

Performance Study

We compared PSO-RSVN against five approaches evaluated in [3]: constricted PSO, Gaussian Mutation based PSO (GMPSO), Hybrid PSO and Simulated Annealing (HPSO-SA), Quadratic Interpolation based PSO (QIPSO), and Attraction Repulsion based PSO (ATREPSO) by using nine well-known benchmark function taken from [3]. These functions are minimization problems including unimodal, multimodal and noisy functions that helps in deciding the credibility of an optimization algorithm. In each simulation we used 30 particles and 300.000 objective function evaluations in a 20-dimensional search space. In addition, we used two variable neighbourhoods with factors $\xi_1 = 0.05$ and $\xi_2 = 0.1$. Finally, the fitness value for each algorithm was averaged over 30 independent trials.

From the numerical results of the experiments some conclusions came out: PSO-RSVN always finds the global optimum satisfactorily for Sphere, Rastrigin, Griewank, Himmelblau and Shubert functions, whereas for Rosenbrock and Quartic it provides acceptable estimations. For Schwefel function, HPSO-SA locates the best solutions; however, PSO-RSVN finds better approximations than the others. Finally, QIPSO has the best results reported for Ackley function, followed by PSO-RSVN. These results reveal that PSO-RSVN is a competitive and very promising approach for solving global optimization problems. Future work will incorporate a more rigorous statistical analysis to explore significantly differences among these approaches and there will be studied the algorithm performance using other well-known benchmark functions.

References

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