A NEW HYBRID SIMULATED KALMAN FILTER AND PARTICLE SWARM OPTIMIZATION FOR CONTINUOUS NUMERICAL OPTIMIZATION PROBLEMS

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ABSTRACT

Inspired by the estimation capability of Kalman filter, we have recently introduced a novel population-based optimization algorithm called simulated Kalman filter (SKF). Every agent in SKF is regarded as a Kalman filter. Based on the mechanism of Kalman filtering, which includes prediction, measurement, and estimation, the global minimum/maximum can be estimated. Measurement process, which is required in Kalman filtering, is mathematically modelled and simulated. Agents communicate among them to update and improve the solution during the search process. Inspired by the bird flocking, particle swarm optimization (PSO) has been introduced in 1994. In PSO, a swarm of agent search the global minimum/maximum by velocity and position updates, which are influenced by current position of agent, current position of agent, personal best, and global best of the swarm. In this research, SKF and PSO are hybridized in such a way that PSO is employed as prediction operator in SKF. The performance of the proposed hybrid SKF-PSO algorithm (SKF-PSO) is compared against SKF and PSO using CEC2014 benchmark dataset for continuous numerical optimization problems. Based on the analysis of experimental results, we found that the proposed hybrid SKF-PSO is superior than both SKF and PSO algorithm.

Keywords: Simulated Kalman Filter, Particle Swarm Optimization, CEC2014 Benchmark Problem

INTRODUCTION

The main objective of an optimization problem is to find the best combination of real-valued variables of a fitness function such that the value of the fitness is maximum or minimum. This can be achieved efficiently by employing a population-based optimization algorithm.

The simulated Kalman filter (SKF) and particle swarm optimization (PSO) are examples of population-based optimization algorithms. PSO has been introduced in 1994 by Eberhart and Kennedy [1] while SKF has been recently introduced by Ibrahim *et al.* [2] in 2015. Even though both algorithms are population-based, however, they are inspired differently. In particular, PSO is inspired by bird flocking behaviour while SKF is inspired by the estimation capability of Kalman filter.

In literature, PSO has been subjected to various improvements including hybridization with other optimization algorithms. For example, PSO can be hybridized with gravitational search algorithm [3] and chemical reaction optimization [4].

In this research, hybridization between PSO and a recently introduced SKF is proposed. From the SKF point of view, this is among the first attempt to improve its performance by hybridization with other algorithm such as PSO.

This paper is organized as follows. At first, SKF and PSO algorithms will be reviewed. After that, the new hybrid SKF-PSO will be explained in detail. Experimental procedure will be presented and the superiority of the new hybrid SKF-PSO will be shown and discussed. Lastly, conclusion will be given at the end of this paper.

SIMULATED KALMAN FILTER ALGORITHM

The simulated Kalman filter (SKF) algorithm is illustrated in Fig. 1. Consider n number of agents, SKF algorithm begins with initialization of n agents, in which the states of each agent are given randomly. The maximum number of iterations, t_{max}, is defined. The initial value of error covariance estimate, $P(0)$, the process noise value, Q, and the measurement noise value, R, which are required in Kalman filtering, are also defined during initialization stage. Then, every agent is subjected to fitness evaluation to produce initial solutions $\{\boldsymbol{X}_1(0), \boldsymbol{X}_2(0), \boldsymbol{X}_3(0), \ldots, \boldsymbol{X}_{n-2}(0), \boldsymbol{X}_{n-1}(0), \boldsymbol{X}_n(0)\}$. The fitness values are compared and the agent having the best fitness value at every iteration, t, is registered as $\boldsymbol{X}_{\mathbf{best}}(t)$. For function minimization problem,

$$\boldsymbol{X_{best}}(t) = \min_{i \in 1,\ldots,n} fit_i(\boldsymbol{X}(t)) \qquad (1)$$

whereas, for function maximization problem,

$$\boldsymbol{X_{best}}(t) = \max_{i \in 1,\ldots,n} fit_i\big(\boldsymbol{X}(t)\big) \qquad (2)$$

The-best-so-far solution in SKF is named as $\boldsymbol{X}_{\mathbf{true}}$. The $\boldsymbol{X}_{\mathbf{true}}$ is updated only if the $\boldsymbol{X}_{\mathbf{best}}(t)$ is better (($\boldsymbol{X_{best}}(t) < \boldsymbol{X_{true}}$ for minimization problem, or $\boldsymbol{X_{best}}(t) > \boldsymbol{X_{true}}$ for maximization problem) than the $\boldsymbol{X}_{\mathbf{true}}$.

The subsequent calculations are largely similar to the predict-measure-estimate steps in Kalman filter. In the prediction step, the following time-update equations are computed.