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ANGLE MODULATED SIMULATED KALMAN FILTER ALGORITHM FOR COMBINATORIAL OPTIMIZATION PROBLEMS

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ABSTRACT

Inspired by the estimation capability of Kalman filter, we have recently introduced a novel estimation-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 and measurement process, every agent estimates the global minimum/maximum. Measurement, 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. However, the SKF is only capable to solve continuous numerical optimization problem. In order to solve discrete optimization problems, the SKF algorithm is combined with an angle modulated approach. The performance of the proposed angle modulated SKF (AMSKF) is compared against two other discrete population-based optimization algorithms, namely, binary particle swarm optimization (BPSO) and binary gravitational search algorithm (BGSA). A set of traveling salesman problems are used to evaluate the performance of the proposed AMSKF. Based on the analysis of experimental results, we found that the proposed AMSKF is as competitive as BGSA but the BPSO is superior to the both AMSKF and BGSA.

Keywords: simulated kalman filter, angle modulated, combinatorial, traveling salesman problems.

INTRODUCTION

There are a lot of discrete optimization problems in literature and real-world applications. Examples of discrete optimization problems are assembly sequence planning [1-2], DNA sequence design [3-4], VLSI routing [5-6], robotics drill route problem [7], and airport gate allocation problem [8].

In solving discrete optimization problems, algorithms such genetic algorithm (GA) [9] has been originally developed to operate in binary search space. However, not all optimization algorithms are originally developed to operate in binary search space. An example of these algorithms is simulated Kalman filter (SKF), which has been recently introduced by Ibrahim *et al.* in 2015 [10]. In order to solve discrete optimization problems with SKF, modification or enhancement is needed. For example, sigmoid function has been employed as a mapping function to let particle swarm optimization (PSO) to operate in binary search space [11].

The objective of this research is to modify SKF algorithm for solving discrete optimization problem. However, mapping function cannot be integrated in SKF because there is no specific variable in SKF can be used as the input to mapping function. Thus, an angle modulated approach [12] is employed in this research. Angle modulated approach is universal, which means that it can be integrated to any optimization algorithm.

This paper is organized as follows. At first, SKF will be briefly reviewed followed by a detail description of the proposed angle modulated SKF (AMSKF) algorithm. Experimental set up will be explained, results will be shown and discussed. Lastly, a conclusion will be provided at the end of this paper.

SIMULATED KALMAN FILTER ALGORITHM

The simulated Kalman filter (SKF) algorithm is illustrated in Figure-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,

$$\boldsymbol{X}_{\mathbf{best}}(t) = \min_{i \in 1,\ldots,n} fit_i(\boldsymbol{X}(t)) \tag{1}$$

whereas, for function maximization problem,

$$\boldsymbol{X}_{\mathbf{best}}(t) = \max_{i \in 1,\ldots,n} fit_i(\boldsymbol{X}(t)) \tag{2}$$

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 (($\boldsymbol{X}_{\mathbf{best}}(t) < \boldsymbol{X}_{\mathbf{true}}$ for minimization problem, or $\boldsymbol{X}_{\mathbf{best}}(t) > \boldsymbol{X}_{\mathbf{true}}$ 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.

$$\boldsymbol{X}_i(t|t) = \boldsymbol{X}_i(t) \tag{3}$$