DISTANCE EVALUATED SIMULATED KALMAN FILTER 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, a new distance evaluated approach is proposed and combined with SKF. The performance of the proposed distance evaluated SKF (DESKF) 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 DESKF. Based on the analysis of experimental results, we found that the proposed AMSKF is as competitive as BGSA but the BPSO is superior than the both DESKF and BGSA.

Keywords: Simulated Kalman Filter, Distance Evaluated, Combinatorial, Traveling Salesman Problems

INTRODUCTION

In solving discrete optimization problems, algorithms such genetic algorithm (GA) [1] 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 [2]. 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 [3]. The purpose of the mapping function is translate the velocity of PSO into probabilistic value. A random number is generated and compared with the probabilistic value in order to update the position of agent in binary search space.

The objective of this research is to modify SKF algorithm for solving discrete optimization problem. However, mapping function can not be integrated in SKF because there is no specific variable in SKF can be used as the input to mapping function. However, the distance between an agent and the best agent can be exploited to let SKF operates in binary search space. This new approach is introduced in this paper and it is called distance evaluated approach SKF (DESKF). An interesting characteristic of this distance evaluated is that it 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 distance evaluated SKF (DESKF) algorithm. Experimental set up will be explained and 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 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 $\{\boldsymbol{X}_1(0), \boldsymbol{X}_2(0), \boldsymbol{X}_3(0), \ldots, \boldsymbol{X}_{n\text{-}2}(0), \boldsymbol{X}_{n\text{-}1}(0), \boldsymbol{X}_n(0)\}$. 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,

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

whereas, for function maximization problem,

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

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

$$\boldsymbol{X}_{\boldsymbol{i}}(t|t-1) = \boldsymbol{X}_{\boldsymbol{i}}(t-1) \tag{3}$$

$$P(t|t-1) = P(t-1) + Q \tag{4}$$

where $\boldsymbol{X}_i(t-1)$ and $\boldsymbol{X}_i(t|t-1)$ are the previous state and transition/predicted state, respectively, and $P(t-1)$ and $P(t-1)$ are previous error covariant estimate and transition error covariant estimate, respectively. Note that the error covariant estimate is influenced by the process noise, Q.

The next step is measurement, which is a feedback to estimation process. Measurement is modelled such that its output may take any value from the predicted