LAMPIRAN B

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Picture related to the research project

OPPOSITION-BASED LEARNING SIMULATED KALMAN FILTER FOR NUMERICAL OPTIMIZATION PROBLEMS

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ABSTRACT (120 words)

Simulated Kalman Filter (SKF) optimization algorithm is a population-based optimizer operated mainly based on Kalman filtering. The SKF is however subjected to premature convergence problem. In this research, opposition-based learning is employed to solve the premature convergence problem in SKF. The opposition-based learning can be applied either after the solution is updated or as the prediction step in SKF. Using CEC2014 benchmark suite, it is found that the SKF with opposition-based learning outperforms the original SKF algorithm in most cases. The SKF with opposition-based learning is also applied as adaptive beamforming algorithm for adaptive array antenna. In this application, the objective is to maximize the signal to interference plus noise ratio (SINR) and results show that the SKF with opposition-based learning outperforms the existing adaptive mutated Boolean particle swarm optimization (AMBPSO)

1. INTRODUCTION

Applications of optimization are numerous. Most processes have a possibility to be optimized. In fact, there are challenging applications in science and industry that can be regarded as optimization problems. Optimization takes place in the minimization of time, cost, as well as maximization of accuracy and efficiency. For instance, many real-life optimization problems in engineering and science are tough and complicated. They cannot be addressed in an exact approach within a reasonable time. Choosing approximate algorithms is the alternative way to solve these kinds of problems. Approximate algorithms can further be divided into two categories, which are heuristics and metaheuristics. Heuristics are problem dependent and suitable to a specific problem while metaheuristics are more general and applicable to a huge number of optimization problems. They can be adapted to handle any optimization problem. Metaheuristics solve problem by exploring a large solution search space of the problem. These algorithms accomplish this by decreasing the valuable size of the space and by exploiting that space effectively.

2. RESEARCH METHODOLOGY

The proposed algorithm is called as Opposition-based Simulated Kalman Filter (OBSKF). The original SKF is selected as a parent algorithm and the OBL is embedded in SKF. OBL is employed in SKF after the estimation process. This implementation generated opposite population which is potentially fitter compared to the current ones. Figure 1 shows the flowchart of the algorithm. Initially, OBSKF generates randomly initial population or candidate solutions. At initialization stage, the jumping rate value, *Jr*, the initial value of error covariance estimate, *P*(0), the process noise value, *Q*, and the measurement noise value, *R*, are determined. Then, the fitness of agents in the population is calculated based on objective function. After that, $\boldsymbol{X_{best}(t)}$ and $\boldsymbol{X_{true}}$ are updated based on SKF steps. The algorithm continues with prediction, measurement, and estimation equivalent to SKF.

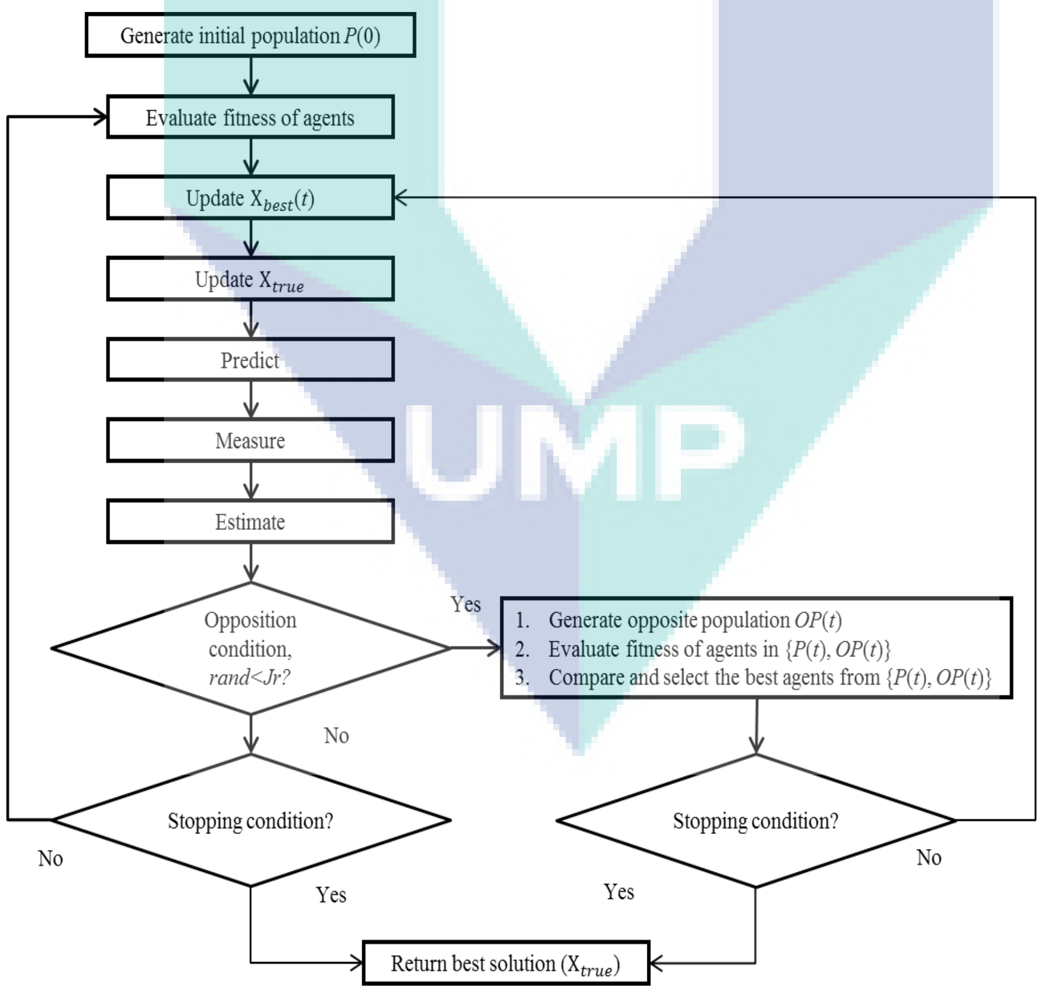

Figure 1. Flowchart of OBSKF algorithm

3. LITERATURE REVIEW

A number of significant optimization algorithms and application of OBL are reviewed in this chapter. Some researchers have employed the OBL concept in optimization algorithm and successfully enhance the performance of the algorithm. SKF is a new optimization algorithm and OBL has not been applied to improve its performance. Therefore, the motivation of this research is to improve the exploration capability of SKF by applying OBL.

4. FINDINGS

The performance of SKF algorithm was further improved through the application of OBL technique in SKF. Two variants of SKF has been introduced, which are OBSKF and COOBSKF. Therefore, these newly introduced algorithms can be categorized under opposition-based optimization algorithms

5. CONCLUSION

In literature, various optimization algorithms and opposition-based optimization algorithms have been reviewed. Some researchers have employed the OBL concept in optimization algorithm with the intention to enhance the performance of the algorithms. SKF is a new optimization algorithm and OBL has not been applied to improve its performance.

In this research, opposition-based simulated Kalman filter (OBSKF) and current optimum opposition-based simulated Kalman filter (COOBSKF) were introduced with the purpose to enhance the exploration capability of SKF. The performance of the proposed algorithms were evaluated and analyzed. Experiments were conducted on a comprehensive set of well-known complex benchmark functions to analyze and compare the algorithms. The results of experiments indicate that opposition-based simulated Kalman filter (OBSKF) has made some improvement towards exploration capability of SKF, while the current optimum opposition-based simulated Kalman filter (COOBSKF) improved the exploration capability of SKF significantly.

ACHIEVEMENT

i) Name of articles/ manuscripts/ books published

ii) Title of Paper presentations (international/ local)

a. An Opposition-based Simulated Kalman Filter algorithm for adaptive beamforming
b. Adaptive Beamforming Algorithm based on Simulated Kalman Filter
c. Feature Selection using Binary Simulated Kalman Filter for Peak Classification of EEG Signals
d. An Oppositional Learning Prediction Operator for Simulated Kalman Filter
e. An Analysis on the Number of Agents Towards the Performance of the Simulated Kalman Filter Optimizer

iii) Human Capital Development –

a. 1 Master Student, (MEL15005) Kelvin Lazarus

iv) Awards/ Others

v) Others

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APPENDIXES