CENTRIPETAL ACCELERATED PARTICLE SWARM OPTIMIZATION AND ITS APPLICATIONS IN MACHINE LEARNING

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This Thesis is dedicated to my beloved family for their endless support and encouragement.

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ABSTRACT

Nowadays, meta-heuristic optimization algorithms have been extensively applied to a variety of Machine Learning (ML) applications such as classification, recognition, prediction, data mining and web mining, combinatorial optimization and so on. The majority of them imitate the behavior of natural phenomena to find the best solution. The algorithms find promising regions in an affordable time due to exploration and exploitation ability. Although the mentioned algorithms have satisfactory results in various fields, none of them is able to present a higher performance for all applications. Therefore, searching for a new meta-heuristic algorithm is an open problem. In this study, an improved scheme of Particle Swarm Optimization (PSO) based on Newtonian's motion laws called Centripetal Accelerated Particle Swarm Optimization (CAPSO) has been proposed to accelerate learning process and to increase accuracy in solving ML problems. A binary mode of the proposed algorithm called Binary Centripetal Accelerated Particle Swarm Optimization (BCAPSO) has been developed for discrete (binary) search space. These algorithms have been employed for problems such as non-linear benchmark functions, Multi-Layer Perceptron (MLP) learning and the 0-1 Multidimensional Knapsack Problem (MKP). The results have been compared with several well-known meta-heuristic population-based algorithms in both continuous (real) and binary search spaces. From the experiments, it could be concluded that the proposed methods show significant results in function optimization for real and binary search spaces, MLP learning for classification problems and solving MKP for binary search space.

ABSTRAK

Kini pengoptimum algoritma meta-huristik sudah digunakan dengan meluasnya dalam pelbagai aplikasi mesin pembelajaran (ML) seperti pengklasifikasian, pengecaman, ramalan, pencarian data dan pencarian jaringan, pengoptimum kombinasi dan sebagainya. Kebanyakan aplikasi ini meniru keadaan fenomena semulajadi bagi mendapatkan penyelesaian terbaik. Algoritma akan mendapatkan ruang yang sangat sesuai dalam jangkamasa tertentu mengikut keupayaan eksplorasi dan eksploitasi. Walaupun algoritma tersebut memberi keputusan yang memuaskan di dalam banyak bidang, namun tidak satu pun diantaranya dapat mneghasilkan prestasi yang lebih tinggi untuk semua aplikasi. Maka, untuk mencari algoritma meta-huristik yang baru merupakan suatu cabaran yang nyata. Di dalam kajian ini, skim *Particle Swarm Optimization* (PSO) yang diperbaharui berdasarkan hukum gerakan Newtonian yang dipanggil *Centripetal Accelerated Particle Swarm Optimization* (CAPSO) telah dicadangkan bagi mempercepat proses pembelajaran dan meningkatkan ketepatan untuk menyelesaikan masalah-masalah ML. Mod binari algoritma yang dicadangkan yang dinamakan *Binary Centripetal Accelerated Particle Swarm Optimization* (BCAPSO) dibangunkan untuk pencarian ruang diskret (binari). Kesemua algoritma tersebut telah digunakan bagi mengatasi beberapa kesulitan seperti fungsi penanda aras bukan linear, pembelajaran *Multi-Layer Perceptron* (MLP) dan 0-1 *Multidimensional Knapsack Problem* (MKP). Keputusan telah dibandingkan dengan beberapa algoritma meta-huristik berdasarkan populasi yang terkenal carian ruang nyata dan binari. Daripada eksperimen, boleh disimpulkan bahawa kaedah yang dicadangkan menunjukkan hasil yang signifikan bagi fungsi pengoptimum untuk nyata dan pencarian ruang binari, pembelajaran MLP bagi masalah-masalah klasifikasi dan penyelesaian MKP untuk pencarian ruang binari.

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LIST OF ABBREVIATIONS

ABC	-	Artificial Bee Colony
ACC	-	Accuracy
ACO	-	Ant Colony Optimization
AE	-	Average Error
AI	-	Artificial Intelligence
AIS	-	Artificial Immune System
ANNs	-	Artificial Neural Networks
APSO	-	Adaptive Particle Swarm Optimization
AUC	-	Area Under Curve
BA	-	Bootstrap Algorithm
BCAPSO	-	Binary Centripetal Accelerated Particle Swarm Optimization
BGSA	-	Binary Gravitational Search Algorithm
BO	-	Bees Optimization
BP	-	Back-Propagation algorithm
BPSO	-	Binary Particle Swarm Optimization
CAPSO	-	Centripetal Accelerated Particle Swarm Optimization
CAPSO-MLP	-	Particle Swarm Optimization Multi-Layer Perceptron
CD	-	Check-and-Dropt
CEM	-	Cross Entropy Method
CLPSO	-	Comprehensive Learning Particle Swarm Optimization
COPs	-	Combinatorial Optimization Problems

CP	-	Charged Particle
CS	-	Cuckoo Search
CSS	-	Charged System Search
DSA	-	Differential Search Algorithm
DE	-	Differential Evolution
DMS-PSO	-	Dynamic Multi-Swarm Particle Swarm Optimization
FA	-	Firefly Algorithm
FFNN	-	Feed–Forward Neural Network
FN	-	False Negative
FP	-	False Positive
GA	-	Genetic Algorithm
GbSA	-	Galaxy-based Search Algorithm
GLS	-	Guided Local Search
GPSO	-	Global-topology Particle Swarm Optimization
GSA	-	Gravitational Search Algorithm
GSA-MLP	-	Gravitational Search Algorithm Multi-Layer Perceptron
GSO	-	Glowworm Swarm Optimization
HMM	-	Hidden Markov Model
HMO	-	Honey-bee Mating Optimization
HPSO-TVAC	-	Hierarchical Particle Swarm Optimizer with Time-Varying Acceleration Coefficients
HS	-	Harmony Search
ICA	-	Imperialist Competition Algorithm
ICA-MLP	-	Imperialist Competition Algorithm Multi-Layer Perceptron
ICRO	-	Improved Check-and-Repair Operator
ILS	-	Iterated Local Search
IWD	-	Intelligent Water Drops
KH	-	Krill Herd

LBCAPSO	-	Local-topology Binary Centripetal Accelerated Particle Swarm Optimization
LCAPSO	-	Local-topology Centripetal Accelerated Particle Swarm Optimization
LPSO	-	Local topology Particle Swarm Optimization
MAE	-	Mean Absolute Error
MKP	-	Multidimensional Knapsack Problem
ML	-	Machine Learning
MLP	-	Multi-Layer Perceptron
MOGA	-	Multi-Objective Genetic Algorithm
MS	-	Monkey Search
MSE	-	Mean Square Error
PF	-	Penalty Function
PSO	-	Particle Swarm Optimization
PSO-MLP	-	Particle Swarm Optimization Multi-Layer Perceptron
RBF	-	Radial Basis Function
RFD	-	River Formation Dynamics
ROC	-	Receiver Operating Characteristics
RSO	-	Reactive Search Optimization
SA	-	Simulated Annealing
SD	-	Standard Deviation
SO	-	Spiral Optimization
SS	-	Scatter Search
TLBO	-	Teaching-Learning-Based Optimization
TN	-	True Negative
TP	-	True Positive
TS	-	Tabu Search
UCI	-	University of California at Irvine
VNS	-	Variable Neighborhood Search

VPSO	-	Von –Neumann topology Particle Swarm Optimization
WNN	-	Wavelet Neural Network

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CHAPTER 1

INTRODUCTION

1.1 Overview

Machine Learning (ML) (Shavlik and Dietterich, 1990; Michie *et al.*, 1994; Mitchell, 1997, Bishop, 2007; Marsland, 2009) is a branch of Artificial Intelligence (AI) concerned with many learning algorithms and problems. Different ML algorithms have been successfully employed to solve real-life problems. The goal of ML research is computer learning based on training data to recognize complex patterns of datasets, or to make intelligent decisions based on data. In ML, optimization provides a valuable framework for thinking about, formulating and solving many problems.

Optimization problems have located at the heart of most ML approaches. Many algorithms from the class of exact and approximate optimization algorithms have been presented to deal with ML applications. However, exact optimization algorithms such as dynamic programming, branch-and-bound and backtracking (Neapolitan and Naimipour, 2004; Tanaka *et al.* 2009; Ferrer *et al.*, 2009; Manerba and Mansini, 2012; Smet *et al.*, 2012) have shown good performance in addressing ML applications, they are not efficient in a high-dimensional search space. In the applications, the search space increases exponentially with the problem size, hence solving these problems using the algorithms (such as exhaustive search) is not practical. Therefore, many researchers are interested in utilizing approximate algorithms like meta-heuristic algorithms in this regard.

Artificial Immune System (AIS) (Farmer *et al.*, 1986), Genetic Algorithm (GA) (Holland, 1975; Tang, 1996), Ant Colony Optimization (ACO) (Dorigo *et al.*, 1996), Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995; Shi and Eberhart, 1998), Artificial Bee Colony (ABC) (Karaboga, 2005), Imperialistic Competitive Algorithm (ICA) (Atashpaz-Gargari and Lucas, 2007), Gravitational Search Algorithm (GSA) (Rashedi *et al.*, 2009) and Charged System Search (CSS) (Kaveh and Talatahari; 2010) are samples of meta-heuristic algorithms.

The meta-heuristic algorithms have applied as learning algorithm in for tackling complex problem such as neural network learning (Dehuri *et al.*, 2011; Qasem and Shamsuddin, 2011), image processing (Lu and Chen, 2008; Yang, 2011), function optimization (Kaveh and Talatahari, 2010; Rashedi *et al.*, 2010), data mining (Sousa *et al.*, 2004; Freita and Timmis, 2007), pattern recognition (Senaratne *et al.*, 2009; Zhao and Davis, 2011), control objectives (Baojiang and Shiyong, 2007; Karakuzu, 2009; Xie *et al.*, 2009) and combinatorial optimization problems (Al-Dulaimi and Ali, 2008; Defersha and Chen, 2010; Angelelli *et al.*, 2010).

Even though, they have been illustrated good performance, there is no a specific algorithm to find the best solution for all problems in continuous (real) and discrete (binary) search spaces. In other words, some algorithms have a better solution for a number of particular problems. Therefore, searching for a new meta-heuristic algorithm which can operate on two-valued functions, real and binary search spaces, would be beneficial.

In this thesis, the proposed methods of Centripetal Accelerated Particle Swarm Optimization (CAPSO), Local topology of Centripetal Accelerated Particle Swarm Optimization (LCAPSO), Binary Centripetal Accelerated Particle Swarm Optimization (BCAPSO) and Local topology of Binary Centripetal Accelerated Particle Swarm Optimization (LBCAPSO) are proposed for real and binary search spaces. The methods are evaluated by some ML applications in continuous and discrete search spaces such as function optimizations, Multi-Layer Perceptron (MLP) learning for classification problems and Multi-dimensional Knapsack Problem (MKP). The rationale of proposing this study is given in the problem background followed by the thesis statement with research questions, goal of the study, objectives, scope and importance of the research.

1.2 Problem Background

Traditional algorithms such as branch-and-bound, dynamic programming, backtracking which are in the class of exact algorithms are inefficient in solving many high-dimensional optimization problems of ML. In these problems, the search space grows exponentially with the problem size hence; the exhaustive search is not practical using the algorithms. Also, the algorithms are inflexible to adapt a solution with a problem (Chan and Tiwari, 2007). In these algorithms, a problem is modeled in such a way that can be solved by these algorithms. This generally requires making several assumptions which might not be easy to validate in many situations. Therefore, a set of more adaptable and flexible algorithms are required to overcome these limitations.

Based on this motivation, a numerous algorithms inspired by nature have been proposed in the literature. Among them, meta-heuristic algorithms have shown satisfactory abilities to handle such problems. In these algorithms, the goal is to explore efficiently the search space in order to find (near-) optimal solutions. These algorithms have various advantages (Jin and Branke, 2005; Du and Li, 2008, Zhan *et al.*, 2009, Sarıçiçek and Çelik, 2011; Valdez *et al.*, 2011, Mezmaz *et al.*, 2011; Kim *et al.*, 2012) to name a few:

1. They are robust and can adapt solutions with changing conditions and environment.
2. They can be applied in solving complex multimodal problems.
3. They may incorporate mechanisms to avoid getting trapped in local optima.
4. They are not problem-specific algorithm.
5. These algorithms are able to find promising regions in a reasonable time due to exploration and exploitation ability.

6. They can be easily employed in parallel processing.

To achieve the above advantages and to have better solution in different applications, many meta-heuristic population-based algorithms have been proposed so far and employed in many ML problems.

GA is one the oldest meta-heuristic algorithms. It has been widely used in ML (Goldberg, 1989; Shapiro, 2001). A combined ML with GA was proposed for controller design by Filipic (1999). Also, a general method was presented for identification of an optimal non-linear mixed effects model (Bies *et al.*, 2006). This included structural, inter-individual random effects and residual error models using ML and GA. In other research, Sarkar *et al.* (2012) offered an accuracy-based learning system called DTGA (Decision Tree and GA) to enhance the prediction accuracy of classification problems. Moreover, a Two-stage Genetic Clustering Algorithm (TGCA) was suggested by He and Tan (2012) to determine the appropriate number of clusters and partition of dataset.

D'Souza *et al.* (2012) used several meta-heuristic algorithms such as Simulated Annealing (SA), PSO, GA and AIS to optimize Dial-A-Ride Problem (DARP). From the results, it could be concluded that AIS method provided more efficient optimal solutions. Al-Obeidat *et al.* (2010) developed PSO for PROAFTN which is a classification method and belongs to the class of supervised learning algorithms. The method applied PSO to elicit the PROAFTN parameters during the learning process. To evaluate the quality of approach, it was tested on some datasets and compared with several ML techniques. The method had considerably performance better than other ML techniques used. Furthermore, a hybrid of improved PSO algorithm with Wavelet Neural Network (WNN) was introduced (Yue-bo *et al.*, 2012) to simulate the aerodynamic model for flight vehicles. The proposed method was compared with some well-known method such as the hybrid of GA with WNN and SVM. The simulated results indicated that the presented method has more efficiency than the others for aerodynamic modeling.

Another meta-heuristic algorithm applied in ML is ACO. Azar and Vybihal (2011) proposed a method using ACO to optimize the accuracy of software quality predictive models for classification new data. In other study, Loyola *et al.* (2012) presented an approach to predict web user behavior using learning-based ACO.

Xu and Duan (2010) provided a shape-matching approach to visual target recognition for aircraft at low altitude using ABC algorithm. Also, Sulaiman *et al.* (2012) employed a hybrid of ABC and Least Square Support Vector Machine (LS-SVM) for solving real and reactive power tracing problem. The compared results with LS-SVM, the hybrid of GA and SVM demonstrated that the proposed method was more efficient than others in terms of determining the optimal values of hyper-parameters of LS-SVM.

Tayefeh-Mahmoudi *et al.* (2009) employed ICA to optimize the weights of MLP network for classification problems and compared the results with PSO, GA, Resilient Back-Propagation (RPROP) and Min Finder. The results illustrated that ICA performed better results.

Also, GSA was applied for function optimizations by Rashedi *et al.* (2009). The algorithm offered a better performance than PSO and GA in many cases. In another study, Bahrololoum *et al.* (2012) used GSA for a prototype classifier in multiclass datasets. The results of proposed method were compared with PSO, ABC and nine other classifiers on some well-known datasets. The results indicated that GSA was more efficient than the others.

Although the mentioned algorithms have obtained satisfactory results in various fields of ML, there are some unavoidable disadvantages. For instance, GA has the inherent drawbacks of prematurity convergence (Leung *et al.*, 1997; Hrstka and Kučerová, 2004; Hong *et al.*, 2011; Pavez-Lazo and Soto-Cartes, 2011) and unpredictable results. Also; it uses complex functions in selection and crossover operators and sometimes, the encoding scheme is difficult (Moslemipour *et al.*, 2012). PSO suffers from trapping into local optima and slow convergence speed (Deep, M. Thakur, 2007 (a), 2007 (b); Tsoulos, 2008; Zhan *et al.*, 2009; Zhan *et al.*, 2011; Gao, 2012), whereas GSA and ICA take long computational time to achieve the results. Furthermore, some of these algorithms have several parameters to tune and often parameters setting is a challenge for various optimization problems (Tashkova, 2011). Meanwhile, none of meta-heuristic algorithms are able to present a higher performance than others in solving all problems. Another noteworthy point is that many problems are expressed in a binary representation. In other words, some solutions are encoded binary form or some problems are binary in nature. Nevertheless, some meta-heuristic algorithms are designed for only continuous (real) or discrete (binary) search space and sometimes, they have good performance just on one of the search spaces. For example, ICA and the original of ACO have been designed for continuous and discrete search space respectively. Also, binary PSO (Kennedy and Eberhart, 1997) has some inherent disadvantages such as poor convergence rate and failure to achieve desired results (Nezamabadi-pour *et al.*, 2008) which bring about a decrease in performance of algorithm in the binary search space. Therefore, the enhancement of performance of previous meta-heuristics or even introduction of new ones in minimizing the disadvantages seems to be necessary. Hence, a new optimization meta-heuristic algorithm has been proposed based on Newtonian's motion laws and PSO algorithm to improve convergence speed and to avoid trapping into local optimum and setting many parameters. The algorithm is named Centripetal Accelerated Particle Swarm Optimization (CAPSO) and can be applied for both continuous and discrete high-dimensional search spaces.

1.3 Research Statement with Research Questions

Traditional optimization algorithms cannot provide proper results for ML problems with high-dimensional search space since the search space exponentially increases with the size of problem and exhaustive search is impractical. Also, existing meta-heuristic algorithms suffer from different drawbacks such as lack of providing optimum solution for all problems, getting stuck in local optima, tuning many parameters, slow convergence rate and high run-time. Also, some meta-heuristic algorithms are designed for only continuous (real) or discrete (binary) search space and sometimes, they have good performance only in one of the search spaces. However, the algorithms are robust and have the ability of adapting with changing environment.

Therefore, more works are still required to develop the performance of meta-heuristic algorithms in ML. Hence, new meta-heuristic algorithms are introduced in the study for both continuous and discrete search spaces to cope with the shortcomings.

Consequently, based on the above issues, the main research question is:

Are the proposed meta-heuristic algorithms beneficial for learning process enhancement in ML?

Thus, the following issues need to be addressed:

1. Could the proposed methods improve the learning process and accelerate the convergence rate in ML?
2. Is it possible that the algorithms need no parameters setting?
3. Could the proposed algorithms have good performance in both real and binary search spaces?

1.4 Goal of the Research

The aim of this research is to propose an improved scheme of Particle Swarm Algorithm (PSO) based on the Newtonian's motion laws, which is called Centripetal Accelerated Particle Swarm Optimization (CAPSO) to accelerate the learning and convergence procedure of classifiers in real and binary search spaces.

1.5 Objectives of the Research

In order to answer the above questions, the objectives of this thesis have been identified as:

1. To propose efficient meta-heuristic algorithms for both real and binary search spaces.
2. To improve the performance of meta-heuristic algorithms for optimizing non-linear functions in both real and binary search spaces.
3. To enhance ANN learning using the proposed method.
4. To evaluate the performance of combinatorial optimization problems in binary search space.

1.6 Scope of the Study

To achieve the mentioned objectives, the scope of this study is bounded as follows:

1. Twenty three unimodal and multimodal high-dimensional non-linear benchmark functions have been chosen to validate and to compare the performance of proposed algorithms with some meta-heuristic algorithms in real search space (Yao *et al.*, 1999; Rashedi *et al.*, 2009).
2. Twenty four unimodal and multimodal high-dimensional non-linear benchmark functions have been selected to assess the efficiency of proposed algorithms in binary search space (Yao *et al.*, 1999; Rashedi *et al.*, 2010).
3. Six datasets on binary class classification problems (http://www.ics.uci.edu/~mlearn/MLRepository.html) have been used to validate the hybrid learning of proposed algorithm with MLP. The datasets are: Hepatitis, Heart Disease, Pima Indian Diabetes, Wisconsin Prognostic Breast Cancer, Parkinson's disease and Echocardiogram (Heart attack). The performance of the proposed method is measured

based on convergence towards error, Sensitivity, Specificity, and classification accuracy.

4. Twenty five datasets for MKP (OR-Library: http://people.brunel.ac.uk/~mastjjb/jeb/orlib/mknapinfo.html) are applied to test the performance of proposed methods for combinatorial optimization problems in binary search space.
5. All meta-heuristics used in the study are in the class of population-based global search meta-heuristic algorithms.
6. The programs have been customized, developed and applied to the problems using MATLAB R2011a software.

1.7 Importance of the Study

The study investigates the capabilities of meta-heuristic algorithms in Machine Learning (ML). The performance of the proposed methods is evaluated using some applications in ML such as function optimization, Multi-Layer Perceptron (MLP) learning for pattern classification tasks and solving the 0-1 Multidimensional Knapsack Problem (MKP). The approaches are tested to detect whether the methods are efficient in the applications.

1.8 Thesis Organization

This thesis consists of eight chapters. The first is the introductory chapter. The second and third chapters describe the background as well as the previously published work in the field of meta-heuristic algorithms and Machine Learning (ML). The fourth chapter describes the research methodology of this study. Chapter 5, 6 and 7 provide the proposed methods and their analysis of results on some ML applications. Finally, the summary of this study is presented in Chapter 8. The details of each chapter are as follows:

Chapter 2, *Meta-heuristic Algorithms*, provides a review on concept and techniques applied in meta-heuristic algorithms. Also, related works are elucidated in real and binary search spaces. Finally, the discussion and summary of this chapter are given.

Chapter 3, *Machine Learning and Its applications*, presents ML algorithms and the related problems. Some ML applications are reviewed in this chapter such as ANN learning, combinatorial optimization problems in binary search space and the optimization of unimodal and multimodal high-dimensional function. Moreover, a broad overview about the basic concepts and traditional techniques of ANN learning are described especially, the hybrid learning of MLP network with meta-heuristics is elucidated in details. Furthermore, the hybrid of the 0-1 MKP and meta-heuristics is discussed in this chapter. Lastly, the chapter will be finished by a summary.

Chapter 4, *Research Methodology*, comprises of research methodology, a general framework for each phase of the study and descriptions about the overall solving-tools and standard techniques adopted.

Chapter 5, *Centripetal Accelerated Particle Swarm Optimization (CAPSO) in Real and Binary Search Spaces*, presents the encoding of the proposed algorithms and evaluates their performance using some non-linear benchmark functions in the search spaces.

Chapter 6, *Enhancement of Multi-Layer Perceptron (MLP) Learning Using Centripetal Accelerated Particle Swarm Optimization (CAPSO),* uses the hybrid learning of proposed algorithm and MLP network to improve the ability of the network in term of accuracy for classification problems. Finally, the results and discussion of the proposed method on several medical datasets are compared with some previous methods in the literature.

Chapter 7, *Binary Centripetal Accelerated Particle Swarm Optimization (BCAPSO) For Solving 0-1 Multidimensional Knapsack Problem (MKP),* presents the methods of solving the 0-1 MKP using meta-heuristic algorithms. Three methods of Penalty Function (PF) technique, Check-and-Dropt (CD) and Improved Check-and-Repair Operator (ICRO) algorithms are proposed to improve the 0-1 MKP solutions. Also, the performance of each method is compared, analyzed and benchmarked with previous methods.

Chapter 8, *Conclusion and Future Works*, discusses and highlights the contributions and findings of the research work and provides suggestions and recommendations for future studies.

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