

PMT: OPPOSITION BASED LEARNING
TECHNIQUE FOR ENHANCING
METAHEURISTIC ALGORITHMS
PERFORMANCE

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I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

A handwritten signature in black ink, appearing to read 'Hammoudeh Shehadeh Ehmaid Alamri', is written above a horizontal line. The signature is stylized and includes the letters 'mri' written below the main signature.

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DEDICATION

Dedication to

Those Who Deserve a Better Education.

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ABSTRAK

Algoritma metetauristik telah menunjukkan prestasi yang memberangsangkan dalam menyelesaikan masalah pengoptimuman dunia yang canggih. Walau bagaimanapun, banyak algoritma metaheuristik masih mengalami kadar penumpuan yang rendah kerana kurang keseimbangan antara ekplorasi (iaitu carian pada ruang berpotensi baru) dan eksploitasi (iaitu manipulasi jiran terbaik yang sedia ada). Dalam masalah pengoptimuman kompleks tertentu, kadar penumpuan masih menjadi masalah kerana adanya potensi tinggi untuk terperangkap dalam optima lokal. Teknik pembelajaran umum berasaskan pembangkang (OBL) menghasilkan prestasi yang memberangsangkan untuk menangani isu ini. Walaubagaimanapun, Teknik pembelajaran umum berasaskan pembangkang OBL selalunya menumpukan pada penyelesaian hanya pada satu arah berlawanan. Menangani isu kelemahan OBL ini, penyelidikan ini mencadangkan teknik pembelajaran umum berasaskan pembangkang (OBL) baru yang diilhamkan oleh fenomena semulajadi sistem cermin selari yang dikenali sebagai Teknik Cermin Selari (PMT). Seperti pendekatan OBL sedia ada, PMT menghasilkan penyelesaian berpotensi baru berdasarkan calon yang dipilih pada masa ini. Tidak seperti teknik yang berasaskan OBL sedia ada, PMT menghasilkan lebih daripada satu calon dalam pelbagai arah. Bagi menilai prestasi dan kesesuaiannya, PMT telah diadaptasi untuk empat algoritma metaheuristik kontemporari: Evolusi Perbezaan (DE), Pengoptimuman Gerombolan Partikel (PSO), Simulasi Penyepuhlindapan (SA), dan Algoritma Pengoptimuman Ikan Paus (WOA), untuk menyelesaikannya 15 fungsi penanda aras beserta 2 masalah khusus melibatkan rekabentuk kimpalan beam dan rekabentuk tekanan kapal selam. Secara eksperimen, PMT menunjukkan hasil yang memberangsangkan dengan mempercepatkan kadar penumpuan terhadap algoritma asal dengan jumlah penilaian kecergasan yang sama.

ABSTRACT

Metaheuristic algorithms have shown promising performance in solving sophisticated real-world optimization problems. Nevertheless, many metaheuristic algorithms are still suffering from a low convergence rate because of the poor balance between exploration (i.e. roaming new potential search areas) and exploitation (i.e., exploiting the existing neighbors). In some complex problems, the convergence rate can still be poor owing to becoming trapped in local optima. Opposition-based learning (OBL) has shown promising results to address the aforementioned issue. Nonetheless, OBL-based solutions often consider one particular direction of the opposition. Considering only one direction can be problematic as the best solution may come in any of a multitude of directions. Addressing these OBL limitations, this research proposes a new general OBL technique inspired by a natural phenomenon of parallel mirrors systems called the Parallel Mirrors Technique (PMT). Like existing OBL-based approaches, the PMT generates new potential solutions based on the currently selected candidate. Unlike existing OBL-based techniques, the PMT generates more than one candidate in multiple solution-space directions. To evaluate the PMT's performance and adaptability, the PMT was applied to four contemporary metaheuristic algorithms, Differential Evolution, Particle Swarm Optimization, Simulated Annealing, and Whale Optimization Algorithm, to solve 15 well-known benchmark functions as well as 2 real world problems based on the welded beam design and pressure vessel design. Experimentally, the PMT shows promising results by accelerating the convergence rate against the original algorithms with the same number of fitness evaluations comparing to the original metaheuristic algorithms in benchmark functions and real-world optimization problems.

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LIST OF ABBREVIATIONS

AI	Artificial inelegant
OBL	Opposition-Based Learning
DE	Differential Evolution
PMT	Parallel Mirror Technique
PMS	Parallel Mirror System
WOA	Whale Optimization Algorithm
GWO	Grey Wolf Optimizer
HS	Harmony Search
SA	Simulated Annealing
PSO	Particle Swarm Optimization
QOBL	Quasi-Opposition Based Learning
RQOBL	Quasi-Reflection Opposition-Based Learning
COOBL	Current Optimum Opposition-Based Learning
GOBL	Generalized Opposition
CO-OBL	comprehensive opposition
SOBL	Super Opposition
COBL	Center-Based Sampling
FOBL	Fitness-based Opposition

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