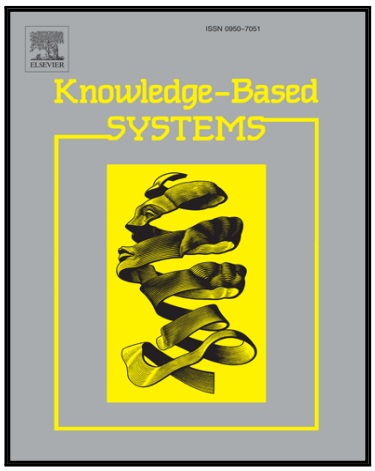

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Shahrzad Saremi, Seyedali Mirjalili*, Andrew Lewis, Alan Wee-Chung Liew, Jin Song Dong

Institute for Integrated and Intelligent Systems, Griffith University, Brisbane, 4111 QLD, Australia
**seyedali.mirjalili@griffithuni.edu.au*

Abstract

Multi-objective problems with conflicting objectives cannot be effectively solved by aggregation-based methods. The answer to such problems is a Pareto optimal solution set. Due to the difficulty of solving multi-objective problems using multi-objective algorithms and the lack of enough expertise, researchers in different fields tend to aggregative objectives and use single-objective algorithms. This work is a seminal attempt to propose the use of multi-objective algorithms in the field of hand posture estimation. Hand posture estimation is a key step in hand gesture recognition, which is a part of an overall attempt to make human-computer interaction more like human face-to-face communication. Hand posture estimation is first formulated as a bi-objective problem. A modified version of Multi-Objective Particle Swarm Optimisation (MOPSO) is then proposed to approximate the Pareto optimal font of 50 different postures. The main motivation of integrating a new operator (called Evolutionary Population Dynamics — EPD) in MOPSO is due to the nature of hand posture estimation problems in which parameters should not be tuned in a same manner since they show varied impacts on the objectives. EPD allows randomising different parameters in a solution and provides different exploratory behaviours for the parameters of an optimisation algorithm rather than each individual solution. The MOPSO algorithm is equipped with a mechanism to randomly re-initialise poor particles around the optimal solutions in the archive. The improved MOPSO is tested on ZDT and CEC2009 test functions and compared with the standard MOPSO, NSGA-II, and MOEA/D. The results show that the proposed MOPSO (MOPSO+EPD) significantly outperforms MOPSO on the majority of test functions in terms of both convergence and coverage. MOPSO+EPD also approximates well-distributed Pareto optimal fronts for most of the postures considered in this work. The post analysis of the results is conducted to understand the relationship between the parameters and objectives of this problem (design principals) for the first time in the literature as well.

Keywords: Multi-objective problems, Multi-objective optimisation, Multi-Objective Particle Swarm Optimisation, MOPSO, Hand Posture Estimation

1. Introduction

Evolutionary Algorithms (EA) [1] have been popular technique to find optimal solutions for optimisation problems. Such algorithms are reliable alternatives compared to conventional gradient-based algorithm mostly due to a better global search. This originates from population-based nature of EAs. In population-based algorithms, a population of candidate solutions is improved by the algorithm. This results in a better exploratory behaviour of an algorithm compared to algorithms with one candidate solution. The consideration of a problem as a black box is another advantage of EAs. The internal equations used in the problem is not essential for EAs to operator, making them suitable for real-world problems with unknown search landscape. By contrast, conventional gradient-based algorithms require calculating the derivation of search landscape.

Despite the advantages of EAs, optimisation of real-world problems using them involves several difficulties: multi-modality [2], local optima [3], constraints [4], varying parameters type [5], multiple objectives [5], and uncertainties [6]. Local optima are sub-optimal and should be avoided by an algorithm. Note that all global solutions are locally optimum in their neighbourhoods, but sub-optimal solutions compared to the global optimum is not desirable when solving a problem. Real problems have a large number of local optima which