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A novel preference articulation operator for the Evolutionary Multi-Objective Optimisation of classifiers in concealed weapons detection

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ABSTRACT

The incorporation of decision maker preferences is often neglected in the Evolutionary Multi-Objective Optimisation (EMO) literature. The majority of the research in the field and the development of EMO algorithms is primarily focussed on converging to a Pareto optimal approximation close to or along the true Pareto front of synthetic test problems. However, when EMO is applied to real-world optimisation problems there is often a decision maker who is only interested in a portion of the Pareto front (the Region of Interest) which is defined by their expressed preferences for the problem objectives. In this paper a novel preference articulation operator for EMO algorithms is introduced (named the Weighted *Z*-score Preference Articulation Operator) with the flexibility of being incorporated *a priori*, *a posteriori* or *progressively*, and as either a primary or auxiliary fitness operator. The Weighted *Z*-score Preference Articulation Operator is incorporated into an implementation of the Multi-Objective Evolutionary Algorithm Based on Decomposition (named WZ-MOEA/D) and benchmarked against MOEA/D-DRA on a number of bi-objective and five-objective test problems with test cases containing preference information. After promising results are obtained when comparing WZ-MOEA/D to MOEA/D-DRA in the presence of decision maker preferences, WZ-MOEA/D is successfully applied to a real-world optimisation problem to optimise a classifier for concealed weapon detection, producing better results than previously published classifier implementations.

1. Introduction

The optimisation of the accuracy and efficiency of classifiers in pattern recognition is a complex problem that is often poorly understood. For example, whilst numerous techniques exist for the optimisation of weights in Artificial Neural Networks (ANNs) (such as the Widroff–Hoff least mean squares algorithm and back propagation), there do not exist any hard and fast rules for choosing the structure of an ANN – in particular for choosing both the size (in term of number of neurons) and number of hidden layers used in the network. However, this internal structure is one of the key factors in determining the efficiency of the network and the accuracy of the classification. In recent years there has been some interest in using soft computing techniques such as Evolutionary Algorithms (EAs) to provide a solution to this problem [22], focussing on

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evolving the structure of an ANN to solve function approximation problems. However, complex classification problems often involve trade-offs between classification objectives that are not well suited to this kind of single objective approach.

One approach to solving complex engineering problems is to use Evolutionary Multi-Objective Optimisation (EMO) algorithms to address each of the conflicting objectives simultaneously. Typically, these EMO algorithms are run non-interactively with a decision maker setting the initial parameters of the algorithm and then analysing the results and the end of the execution process (which can often take hours or days to complete). This approach has been common since the late 1990s [2,34,36] and will lead to a set of potential solutions distributed across the whole trade-off surface. Whilst this is often appropriate for problems with a small number of objectives, in real world problems that involve the consideration of many objectives this trade-off surface can be very large. In these cases, the decision maker is usually more interested in a subregion of this solution space that satisfies some domain specific criteria. However, this can be complicated further by a lack of *a priori* knowledge about what trade-offs are achievable. To overcome these problems, progressive preference articulation methods have been proposed that take into account decision maker preferences (such as [4]) but these are frequently difficult to integrate with current state-of-the-art EMO algorithms, and the incorporation of user preferences is frequently disregarded in the EMO literature [6].

In this research the authors present the optimisation of the ANN architecture for a two objective problem and a five objective problem. The two objective optimisation is performed on an ANN that is classifying the radar signals into two groups which are *threat* and *non-threat*. The five objective optimisation is ambitious in the sense that it attempts to optimise the architecture of a number of ANNs each of which are trained to detect a specific threat item. This multi-objective optimisation is the more difficult of the two problems but will give a greater level of information to the user of the detection system. This will allow the security forces to react to specific threats in a more controlled manner as they will know the type of threat presented.

This paper introduces a novel method of progressive preference articulation in EMO algorithms which can provide improved performance in both the execution speed of the algorithm and in the quality of the solutions the algorithm produces. This method is then integrated into a state-of-the-art EMO algorithm and applied both to current benchmark optimisation problems from the literature and to a real-world classification problem in the field of concealed weapon detection. Section 1.1 introduces EAs and discusses their suitability to multi-objective optimisation. Section 2 describes the implementation of the progressive preference articulation method and discusses its effectiveness when applied to some deceptive test functions from the literature. Section 3 provides a full statistical analysis of the results of the integration of the proposed novel progressive preference articulation operator with a state-of-the-art EMO algorithm for two suites of benchmark test functions from the literature. Section 4 shows the effectiveness of the proposed framework in the optimisation of ANN structures when applied to a complex real-world classification problem in concealed weapon detection, the results of which are compared against existing published work. The main results from Sections 3 and 4 are then summarised in Section 5 and some conclusions about the use of and the effectiveness of the proposed framework and its suitability to the optimisation of ANN structures for classification are drawn.

1.1. Evolutionary algorithms

EAs are a powerful class of stochastic optimisation techniques that incorporate some of the principles of natural selection and population genetics to converge towards global optima [19]. They provide an iterative and population-based approach to optimisation that is capable of both exploring the search space of a problem and exploiting promising solutions found in previous generations. Typically the exploration of the search space is performed by using variation operators (such as mutation) that introduce an element of stochasticity into the optimisation process and aim to prevent premature convergence to local optima. In contrast, exploitation of promising solutions from previous generations is performed using a selection operator (and in part, recombination operators) that ensures preference is given to solutions that are considered fittest from the previous generation.

The robustness of EAs to multi-modal search landscapes containing many local optima (any other difficulties present in multi-objective search spaces) and the direct use of objective function information (rather than auxiliary knowledge such as derivative information) ensures that EAs are effective when applied to many problem types in which conventional optimisation methods may have difficulty. In addition, their population-based nature helps ensure that EAs are resilient when faced with noisy search spaces, as each generation contains more information about the shape of the fitness landscape than would be available to conventional, non-population based methods such as hill-climbing [26].

1.2. Multi-objective optimisation and EAs

The general form of a multi-objective optimisation problem can be described by an objective vector *f* and a corresponding set of design variables v; as can be seen in Eq. (1). Note that here minimisation can be assumed with no loss of generality.

$$\min_f(v) = (f_1(v), f_2(v), f_3(v), \ldots, f_n(v)) \tag{1}$$

Multi-objective optimisation problems often involve conflicts between multiple objectives, and as a result it is unlikely that there exists a single optimal solution. Instead, the solution of a multi-objective optimisation problem often consists