

A Multi-Objective A* Search Based on Non-dominated Sorting

Mohammad Haqqani, Xiaodong Li, and Xinghuo Yu

School of Computer Science and Information Technology, RMIT University
{mohammad.haqqani,xiaodong.li,x.yu}@rmit.edu.au

Abstract. This paper present a *Non-dominated Sorting based Multi Objective A* Search (NSMOA*)* algorithm for multi-objective search problem. It is an extension of the *New Approach for Multi Objective A* Search (NAMOA*)*. This study aims to improve the selection phase of the *NAMOA** algorithm which can affect the performance of the algorithm considerably, especially when the number of non-dominated solutions increases to a large number during the search. This research proposes a new sorting method that allows selection and expansion of the partial solutions be carried out more efficiently. The results demonstrate that our algorithm expands fewer nodes and explores a smaller region of solution space using the same heuristic.

Keywords: A* Search, Multi-Objective Optimization, Non-dominated Sorting.

1 Introduction

Finding the shortest path in a graph is a classical optimization problem with a large number of applications. For instance, shortest path algorithms are applied to automatically find the shortest route between two different locations. In this scenario, travel time is usually considered as the main objective. However, it is sometimes necessary to have more than just one objective. For example, you may be interested in routes that are not only faster but also cheaper. People who want to use public transportation have several criteria for their journey as well (i.e. number of transfers, monetary cost, comfort of the journey etc.). The multi-objective shortest path problem considers more than one objective that need to be optimized simultaneously, and these objectives may be in conflict with each other. In multi-objective search the aim is to find the Pareto optimal solutions, i.e., paths that are not dominated by any other solutions in the search space with respect to all objective functions. Real-world multi-objective optimization problems are often NP-hard even for bi-criteria problems [10].

Selection and expansion of open nodes are the basic operations in A*. In the original A*, each open node is a partial solution which can be expanded. However, this cannot be directly applied to multi-objective problems; where paths may reach the same node at the different times. Moreover, solution costs in

multi-objective search is not a scalar value and cannot be fully ordered. Therefore, selecting one of the partial solutions (which may or may not be on the same node) is one of the most important tasks in multi-objective path finding. Selecting a solution from non-dominated set is an important issue in MOA^* . If the selection is done in an efficient way the number of nodes that we have to expand decreases (due to the elimination based on solutions that we have already found) and the overall complexity of the algorithm can be reduced as well. In selection phase of the $NAMOA^*$ algorithm [9], a partial solution is selected randomly from all the non-dominated solutions to expand.

Multi-objective path finding problems have received tremendous attention in the past few decades. An extension of Dijkstras algorithm [3] to the multi-objective case is presented by Hansen[4]. In [6] Loui demonstrated that some of the stochastic search problems could be mapped to multi-objective ones. Stewart and White [2], described MOA^* , a multi-objective augmentation of A^* [5], and also provided proofs on admissibility, node expansion, as well as comparison of various heuristics' efficiencies. In [1] Dasgupta extended the MOA^* and presented versions for non-consistent heuristic A^* (MOA^{**}) with limited memory A^* ($MOMA^*$). In [10, 11] Perny and Spanjaard presented a generalization of MOA^* focusing on a specific application for a Web access problem. Mandow and Perez de la Cruz considered the extension of A^* to the multi-objective case, outlined a new algorithm ($NAMOA^*$ -New Approach to Multi-objective A^*), and briefly discussed its admissibility in [8]. More recently, Mandow presented a revision on $NAMOA^*$ and presented new proofs on its admissibility, node expansion. [9].

This paper presents an extension to the algorithm which was presented by Mandow [9]. The algorithm is fully described, and an example is presented to explain the algorithm. For proofs of admissibility and optimality of $NAMOA^*$, we highly recommend the readers to take a look at $NAMOA^*$ presented by Mandow [9].

This paper is organized as follows: Section 2 reviews previous relevant studies in scalar search and points out analogies and differences with the multi-objective search problem. Section 3 presents $NSMOA^*$ algorithm and illustrates its behaviour with an example to demonstrate its differences from $NAMOA^*$. Section 4 provides an experimental comparison of results between $NSMOA^*$ and $NAMOA^*$. Finally, conclusions are summarized in section 5.

2 Preliminaries

This section presents an overview of A^* search as well as non-dominated sorting algorithms. At first, we describe the scalar A^* search and discuss its properties. The extension to multi-Objective A^* is discussed, and then the differences are identified. We will also describe the crowding distance which is the parameter that we used for non-dominated sorting phase of our algorithm.