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Associating optical measurements of MEO and GEO objects using Population-Based Meta-Heuristic methods

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Abstract

Currently several thousands of objects are being tracked in the MEO and GEO regions through optical means. The problem faced in this framework is that of Multiple Target Tracking (MTT). The MTT problem quickly becomes an NP-hard combinatorial optimization problem. This means that the effort required to solve the MTT problem increases exponentially with the number of tracked objects. In an attempt to find an approximate solution of sufficient quality, several Population-Based Meta-Heuristic (PBMH) algorithms are implemented and tested on simulated optical measurements. These first results show that one of the tested algorithms, namely the Elitist Genetic Algorithm (EGA), consistently displays the desired behavior of finding good approximate solutions before reaching the optimum. The results further suggest that the algorithm possesses a polynomial time complexity, as the computation times are consistent with a polynomial model. With the advent of improved sensors and a heightened interest in the problem of space debris, it is expected that the number of tracked objects will grow by an order of magnitude in the near future. This research aims to provide a method that can treat the association and orbit determination problems simultaneously, and is able to efficiently process large data sets with minimal manual intervention.

Keywords: Multiple Target Tracking; Data association; Orbit determination; Combinatorial optimization

1. Introduction

Cataloging space debris can be put in the more general framework of Multiple Target Tracking. The MTT problem can be summarized as follows. A region contains any number of target objects of which the states are unknown. Starting from a set of S scans, collected by any number of sensors, both the total number of targets and their states have to be estimated. A scan is defined as a set of observations that all originate from different targets. For a mathematical formulation of the MTT problem, the reader is referred to (Deb et al., 1997). The fields where MTT problems are encountered are numerous, examples are the tracking of targets in a military context (Rakdham, 2009), and the tracking of particles resulting from high energy collisions in particle physics (Pusztaszeri et al., 1996).

The MTT problem also takes the occurrence of both false alarms (sporadic measurements) and missed detections into account. The problem consists of two interrelated parts, namely data association and state estimation. In the data association part the observations from the different scans have to be associated to the correct targets. The state estimation part then takes these associated groups of observations and estimates the target state. This

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leads to a search for the permutation that results in the target state estimates that best approximate the measurements, according to a certain metric (e.g. the Mean Squared Error). The number of scans S that are used in the problem correspond to its dimension. For a dimension of $S \geqslant 3$ the number of possible permutations greatly increases and the problem becomes NP-hard (Poore and Gadaleta, 2006). For instance, in the case where $S = 2$ with two observations per scan, there will be a total of seven possible permutations. However for the $S = 3$ case with two observations per scan, there will be 87 of these permutations (Aristoff et al., 2013). Any problem can be classified as being either a problem with P or NP complexity. The P stands for Polynomial, which means that it can be solved in a polynomial time. If we say that the problem size is denoted by n then the computation time will be e.g. n^2 (or any other order). The NP stands for Nondeterministic Polynomial time. This means that the computation time is not described by a polynomial but for instance could be 2^n. The computation time of an NP problem will quickly become unrealistically large. Despite its challenges, several attempts have been made to solve the $S \geqslant 3$ MTT problem in an efficient manner. The Multiple Hypothesis Tracking (MHT) algorithm (Blackman, 2004; Aristoff et al., 2013) seeks to find the optimum solution to the MTT problem by employing a branch and bound methodology. In order for this algorithm to have a realistic computation time the MTT problem has to be greatly simplified. Another approach to the problem is to seek an approximate solution that can be obtained in a realistic computation time. An algorithm has a realistic computation time when it has a Polynomial time complexity. Examples of algorithms that seek an approximate solution are the Lagrangian relaxation technique (Deb et al., 1997), and the GRASP algorithm (Robertson, 2001). The alternative to solving the $S \geqslant 3$ problem is to solve the $S = 2$ problem. This problem has the favorable computational complexity of $\mathcal{O}(n^2)$. Recent work in this area can be found in Siminski et al. (2014), Fujimoto et al. (2014) and Schumacher et al. (2013). These methods evaluate pairs of observations, and take a definitive decision on whether to associate the two observations or not. This can lead to wrong associations, since no information besides those two observations are taken into account (an $S \geqslant 3$ MTT approach would consider more observations, as well as the possibilities of false alarms and missed detections). The severity of this problem depends on the target density in the region of interest. So to solve the MTT problem applied to a densely populated area (e.g. satellite clusters, break-up events) an efficient way has to be found to search through the possible permutations. The MTT problem represents a so-called track based approach, where the state of each object is explicitly resolved. Another possible approach to cataloging space debris is by using a population based approach. Such an approach aims to statistically represent the debris population. An example of such a method is the AEGISS-FISST method (DeMars et al., 2015).

The goal of this paper is to identify an algorithm that can overcome the pitfalls of an $S = 2$ algorithm, without possessing an unfavorable computational complexity. To this end a series of Population-Based Meta-Heuristic (PBMH) algorithms are proposed. These algorithms are a popular choice when faced with a (combinatorial) NP-Hard optimization problem (Reeves, 1995; Beasley and Chu, 1995). The Genetic Algorithm (GA) is a popular PBMH algorithm which was conceived in the 1960s (Goldberg, 1999). Since then the GA has been successfully applied to many different (combinatorial) NP-hard problems spread out over many different domains. A part of the appeal of the GA is its versatility, i.e. its structure does not depend on the problem. Since the coming of the GA there have been other developments in the field of PBMH algorithms. Other algorithms with a high potential are the Population Based Incremental Learning (PBIL) (Baluja, 1994) and the Differential Evolution (DE) (Onwubolu, 2009) algorithms. Both of these algorithms have shown some promise when applied to combinatorial optimization problems.

Only optical sensors are considered in this work, these provide Right Ascension α and Declination δ values. A few important terms that are used throughout the paper are defined as follows:

- Observation: a Right Ascension and Declination pair at epoch $t : (\alpha, \delta)_t$.
- Tracklet: a series of seven observations at 30 s intervals, already determined to stem from the same object.
- Fence: a set of tracklets that all belong to different objects.

In this work also a method of tracklet association is used that is heavily based on the previous work done by Siminski et al. (2014). It should be seen as an extension to that method. The paper is organized as follows. In the next section the Optimized Boundary Value Initial Orbit Determination (OBVIOD) method is presented. In the third part the basic principles of each of the PBMH algorithms are discussed. The fourth part covers the application of the resulting algorithm to three test cases. In the fifth part attention is given to the computational complexity of the algorithms. Finally the paper is closed with the conclusions that can be drawn and the outlook for future research in this area.

2. The Optimized Boundary Value Initial Orbit Determination (OBVIOD) method

The Boundary Value method developed by Siminski et al. (2014) is used as a foundation for this algorithm. The method employs a loss function with a favorable topography. The association uses the Mahalanobis distance as a criterion, this is a χ^2 distributed statistically significant value. Besides this, it gives an initial orbit which can be