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# Improved assignment with ant colony optimization for multi-target tracking

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ABSTRACT

Detecting and tracking ground targets is crucial in military intelligence in battlefield surveillance. Once targets have been detected, the system used can proceed to track them where tracking can be done using Ground Moving Target Indicator (GMTI) type indicators that can observe objects moving in the area of interest. However, when targets move close to each other in formation as a convoy, then the problem of assigning measurements to targets has to be addressed first, as it is an important step in target tracking. With the increasing computational power, it became possible to use more complex association logic in tracking algorithms. Although its optimal solution can be proved to be an NP hard problem, the multidimensional assignment enjoyed a renewed interest mostly due to Lagrangian relaxation approaches to its solution. Recently, it has been reported that randomized heuristic approaches surpassed the performance of Lagrangian relaxation algorithm especially in dense problems. In this paper, impelled from the success of randomized heuristic methods, we investigate a different stochastic approach, namely, the biologically inspired ant colony optimization to solve the NP hard multidimensional assignment problem for tracking multiple ground targets.



## 1. Introduction

Typically, target tracking starts with track initiation where successive measurements are analyzed to determine whether they constitute a trajectory, so that presence of a target could be declared. Then the generated track is maintained by updating the target kinematics with the measurements obtained. If there are not (frequent) enough measurement collected from the target then the track is dropped. There are several reasons why a track does not receive a valid measurement for updating. The main reason is that the probability of detection ($P_D$) of the sensors used is always less than perfect. Target being obstructed by an object and not being able to assign the correct measurement due to the presence of other targets are amongst other reasons. When there is more than one target present in the surveillance region it is referred to as multiple target tracking and data association problem, i.e., assigning the right measurement to the right track, has to be addressed efficiently.

Although multi-target tracking has been widely studied (Bar-Shalom & Blair, 2000; Deb, Yeddanapudi, Pattipati, & Bar-Shalom, 1999; Popp, Pattipati, & Bar-Shalom, 2001; Wang, Kirubarajan, & Bar-Shalom, 1999), most of the algorithms have weaknesses when targets move close to one another, as they are in a convoy. Efficient and fast measurement to target assignment with reduced computational load has an increased importance in such applications. Since the problem to be dealt with is a NP hard problem, there is no complete solution available, thus, near optimal solutions with reduced computation becomes more important in terms of resource management as the computation time saved could be used to perform other tasks within the surveillance system.

Thus, the data association problem, where the measurements are assigned to the established tracks, is a crucial step in multi-target tracking applications. From the simple nearest neighbor method to a complex multiple hypothesis tracking, tracking literature is filled with a plethora of solutions in finding which measurement came from which target in a complex multi-target environment. These methods show progressive advancement in performance by exploiting the escalating computational capacities available. Recently, research on assignment methods has shown great success for solving the data association problem (Bar-Shalom & Blair, 2000; Deb et al., 1999; Popp et al., 2001; Sinha & Kirubarajan, 2004; Wang et al., 1999). In the assignment method, the data association problem is converted to a 0–1 optimization problem where the total distance/benefit of assigning targets to measurements is minimized/maximized (Wang et al., 1999).

The early assignment algorithms use only a list of measurements from a single time scan, which will be correlated with the targets being tracked. This way, the resulting data association problem can be formulated as a 2D asymmetric assignment problem, which can be solved efficiently by polynomial time algorithms such as Munkres, auction and JVC (Bar-Shalom & Blair, 2000). With cheap computational power available however, a desire arose to

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exploit further lists of measurements in making data association decisions. Unfortunately, additional lists render the assignment a multidimensional problem, which is well known to be NP hard (Deb et al., 1999). Thus, a variety of approximations were proposed to find solutions to the multidimensional assignment problem. In the state of the art method, Lagrangian relaxation is used to find a solution in polynomial time (Sinha & Kirubarajan, 2004). This method also provides a measure of accuracy for the solution found (Bar-Shalom & Blair, 2000; Deb et al., 1999; Popp et al., 2001; Sinha & Kirubarajan, 2004). However, in Sinha and Kirubarajan (2004) it is stated that with this method, a complete assignment hypothesis tree is needed and over 90% of the computing power is spent on the creation of this assignment hypothesis tree rather than solving the assignment problem. To reduce the computational effort, a randomized method was proposed in Sinha and Kirubarajan (2004) to build the assignment hypothesis tree randomly and to solve the assignment problem on this reduced tree. This method has demonstrated superior performance both in computational time and accuracy. Furthermore, the randomized method was able to create multiple assignment hypotheses without any additional computation; i.e., it can produce "*m*" good solutions, which can also be exploited by multiple-target tracking algorithms.

Inspired by this success, we turn to investigate a different randomized method for solving the assignment problem encountered in multi-target tracking applications. Our interest lies in a biologically inspired algorithm, the ant colony optimization (ACO). The ACO is colony based algorithm designed to solve a wide range of discrete combinatorial problems such as traveling salesman and quadratic assignment problems (Demirel & Toksari, 2006; Gambardella, Taillard, & Dorigo, 1999; Schaub & Mermoud, 2009; Tsutsui, 2008; Wong & See, 2009). Also, in Randall (2004) ACO was utilized to address the generalized assignment problem. Moreover, there are various examples that ACO has been employed to solve real life problems such as the weapon-target assignment problem for resource management (Shang, 2008) or the cell assignment problem in PCS networks (Shyua, Linb, & Hsiaoa, 2006). Although there have been successful applications of ACO for finding approximate solutions to NP hard problems of multidimensional assignment, the application of the method to the assignment problem in multi-target tracking has been rather limited. The only direct application, to the authors' best knowledge, is presented in Xu and Wang (2006) where ACO was used to solve the association problem both between measurements and measurements and tracks in a bi-static sonar system. There are several variants of ACO algorithm for different applications and in this study, we will be using the MAX–MIN ant system (MMAS) variant of the ACO for the solution of multidimensional assignment problem in GMTI tracking.

This paper is organized as follows; in Section 2 mathematical definition of the multidimensional assignment problem is presented where the ACO approach is outlined Section 3. Section 4 describes the simulation environment and simulation results are presented in Section 5. Last section gives some concluding remarks.

## 2. Multi-frame measurement to track assignment problem

In hard-decision based multi-target tracking algorithms, at each scan time a set of measurements is populated in order to be assigned to the existing tracks so that each track can be updated. Thus, the non-trivial problem of finding which observed measurement is originated from which target, has to be solved. If this measurement set consists only of a single list of measurements, the problem is referred to as the "2D assignment problem". If any further lists of measurements are to be used, the problem becomes "*multidimensional assignment problem*".

Given a finite set of tracks $T = \{0, 1, 2, \ldots, n\}$, a set of measurement lists $S = \{M_1, M_2, \ldots, M_{S-1}\}$ where each list consists of $k$ measurements belonging to frame $s$, $M_S = \{0,1, \ldots, m_k\}$, and a matrix of association costs $C(t, i_1, i_2, \ldots, i_{s-1})$, where each element represents the cost of associating a track $t$ to a single measurement from each one of the $s-1$ measurement frames; the objective of the multidimensional assignment problem is to find the track to measurement associations with the minimum cost satisfying the following constraints (Bar-Shalom & Blair, 2000):

At each scan,

1. Each track (except for track zero) is to be associated with at most one measurement.
2. Each measurement (except for measurement zero) is to be associated with at most one track.

Track zero and measurement zero are dummy variables. Track zero represents the case where no track can be found to be associated with a measurement. This may possibly be caused by a spurious measurement (false alarm) or a valid measurement from a new track initiator, i.e., a new target. Likewise, measurement zero represents the case where no measurement can be found to be associated with a given track, therefore it is a misdetection. Mathematically these criteria can be formulated as (Wang et al., 1999):

$$\min_{\rho} \sum_{t=1}^{n} \sum_{i_1=0}^{m_1} \cdots \sum_{i_{s-1}=0}^{m_{S-1}} C(t, i_1, i_2, \ldots, i_{s-1}) \rho(t, i_1, i_2, \ldots, i_{s-1}) \tag{1}$$

subject to:

$$\begin{aligned} &\sum_{i_1=0}^{m_1} \sum_{i_2=0}^{m_2} \cdots \sum_{i_{s-1}=0}^{m_{s-1}} \rho(t, i_1, i_2, \ldots, i_{s-1}) = 1 \quad \text{for} \ \ t = 1, 2, \ldots, n \\ &\sum_{t=1}^{n} \sum_{i_2=0}^{m_2} \cdots \sum_{i_{s-1}=0}^{m_{s-1}} \rho(t, i_1, i_2, \ldots, i_{s-1}) = 1 \quad \text{for} \ \ i_1 = 1, 2, \ldots, m_1 \\ &\sum_{t=1}^{n} \\ &\sum_{i_1=0}^{m_2} \cdots \sum_{i_{s-2}=0}^{m_{s-2}} \rho(t, i_1, i_2, \ldots, i_{s-2}) = 1 \quad \text{for} \ \ i_{s-1} = 1, 2, \ldots, m_{s-1} \end{aligned} \tag{2}$$

where $\rho$ is the binary assignment variable taking value of 1 only when track $t$ is assigned to the associated $(S-1)$-tuple measurements.

### 2.1. Assignment cost

In this work, we assume no unresolved targets. Therefore, each measurement can only emanate from a target or be a false detection. False detections are assumed to be distributed uniformly in the field view of the sensor having a volume $\Psi$. The sensor is assumed to have misdetections, thus a detection probability, denoted as $P_D$ is given to the sensor. Conditioned on the target states, measurements are assumed to be independent from each other. In what follows, $m_s^i$ denotes the measurement $i$ at scan $s$, $t$ denotes track $t$ and $u(i)$ is a binary indicator function taking the value of 1 only if measurement $i$ is associated with track $t$.

With such assumptions, likelihood of measurement $i$ from scan $s$, being associated to track $t$ is given by Sinha and Kirubarajan (2004),

$$\Lambda(m_s^i|t) = (1 - P_D)^{1-u(i)} (P_D p(m_s^i|t))^{u(i)} \tag{3}$$

Since false detections are uniformly distributed in the field of view of the sensor, the likelihood of a false alarm (target zero) is calculated as:

$$\Lambda(m_s^i|t_0) = 1/\Psi^{u(i)} \tag{4}$$