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Coordinated Target Assignment and Route Planning for Air Team Mission Planning

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Abstract

Planning air missions for a team flying in hostile environments is a complex task, since multiple interrelated goals need to be considered, e.g., performing the mission tasks and avoiding enemy fire. The target assignment and route planning for the team should therefore be performed in a coordinated way. The mission planner suggested in this work combines genetic algorithms and particle swarm optimization in order to solve these two problems in an interconnected manner. Simulations are used for testing and analyzing the approach. It is concluded that the mission planner is able to suggest suitable plans in complex scenarios with three interrelated objectives: low risk exposure, high mission effectiveness and short route length.

Keywords: Team mission planning, target assignment, route planning, path planning, particle swarm optimization, genetic algorithms.

Introduction

When planning an air mission, performed by a team of manned or unmanned aircraft, multiple interrelated goals need to be considered, such as accomplishing the mission task(s) and avoiding the enemy's air defense systems. It is often necessary to accept some risk exposure in order to complete the mission goals. On the other hand, it might be best to exclude some targets that are well protected by the enemy to ensure that the aircraft will be able to visit the others.

Team mission planning consists of two problems: target assignment and route planning. Target assignment determines which aircraft should visit which targets and route planning decides how an aircraft should fly in order to pass its assigned targets. These problems are highly correlated. The route planner needs to know which targets that the aircraft should visit. On the other hand, in order to evaluate a possible target assignment regarding risk exposure and route length, the routes must be known. The target allocation and route planning should therefore be solved in an interconnected manner.

Related Work

Route planning for a single aircraft within hostile environments has been studied extensively in the literature, see for example the review by Erlandsson (2015a). A team of aircraft can perform more complex mission tasks than a single aircraft and the literature provides examples of work regarding collaborative area coverage (Acevedo et al. 2013), coordinated attack missions (Quttineh 2012) and distribution of medical supplies (Kvarnström and Doherty 2010). However, these works assume that the missions are performed in areas without any risk exposure for the aircraft in the team. Beard et al. (2002) suggested a mission planner for coordinated target assignment that first calculated the k best routes for each aircraft to each target and could thereafter calculate an optimal target assignment. However, such an approach can be very computational demanding in scenarios with many targets or complex cost functions.

Another approach is to run separate route planners for each aircraft in the team, but let the route planners interact and exchange information. In this way, the coordinated route planner suggested by Besada-Portas et al. (2010) could minimize risk and route length for each individual aircraft but also include constraints to avoid collisions within the team. Zheng et al. (2005) described a mission planner for a team that should simultaneously reach a single target, where information regarding possible minimum and maximum times of arrivals was passed between the route planners and included as constraints to ensure that all the aircraft should arrive at the same time. A game theoretic approach was used byYan, Ding, and Zhou (2004), where the routes for one aircraft were evaluated against the current best routes for the other aircraft to ensure that the all aircraft could simultaneously arrive at their goal locations without collisions. None of these works handled the target assignment problem.

Lamont, Slear, and Melendez (2007) developed a mission planner for a swarm of aircraft where a genetic vehicle router (GVR) determined which aircraft should fly to which targets. The GVR interacted with route planners focusing on route length, climb and risk, in order to evaluate the target assignment. However, their mission planner did not capture the interrelations between low risk exposure and high mission effectiveness and would not exclude targets in case they were too dangerous to visit.

Contribution of the Work

The mission planner suggested in this work solves the target assignment and route planning problems in a coordinated way. Three highly interrelated objectives are modeled: high mission effectiveness, high survivability and short route length. Contrary to previous work, the mission planner can handle the dependencies between these objectives.

Mission goals and Objectives

The mission considered in this work, states that a team of aircraft should gather information about a number of interesting objects (targets) located within an area protected by enemy ground-based air defense systems. Three objectives are considered: route length (R), survivability (S) and mission effectiveness (M). The total fitness for a route for aircraft n will be calculated as the weighted sum:

$$f^n = w_R \cdot f_R^n + w_S \cdot f_S^n + w_M \cdot f_M^n, \tag{1}$$

where w_R, w_S and w_M are weight parameters that should capture the pilots' preferences regarding the objectives. Likewise, the fitness for the entire team plan is:

$$f^T = w_R \cdot f_R^T + w_S \cdot f_S^T + w_M \cdot f_M^T. \tag{2}$$

Route Length

The route length, R^n, for aircraft n is calculated as the sum of the Euclidian distance between the waypoints of the route. The route length fitness is:

$$f_R^n = 1 - \frac{\min(R^n, N_{tar}^n \cdot R_{nom})}{N_{tar}^n \cdot R_{nom}}, \tag{3}$$

where N_{tar}^n is the number of targets assigned to aircraft n and R_{nom} is the length of the shortest path between the start point and the destination. When evaluating a plan consisting of routes for all aircraft, the team route fitness is:

$$f_R^T = \frac{\sum_{n=1}^{N_{mem}} f_R^n}{N_{mem}}, \tag{4}$$

where N_{mem} is the number of members in the team.

Survivability

Survivability, S^n, denotes the probability that aircraft n can fly its route without getting hit by enemy fire and is calculated with the model proposed in (Erlandsson and Niklasson 2014). The model is based on a continuous-time Markov model with the states: Undetected, Detected, Tracked, Engaged and Hit. The probability for a transition between states is described with transition intensities λ_{ij} and depends on whether the aircraft is within any of the enemy's sensor or weapon areas, see Figure 1.

Let $\mathbf{p}(t)$ be the vector describing the state probabilities at time t and let $\Lambda(t)$ denote the rate matrix with the elements:

$$\Lambda_{ij}(t) = \begin{cases} \lambda_{ij}(t), & i \neq j \\ -\nu_i(t) = \sum_{j \neq i} \lambda_{ij}(t), & i = j. \end{cases} \tag{5}$$

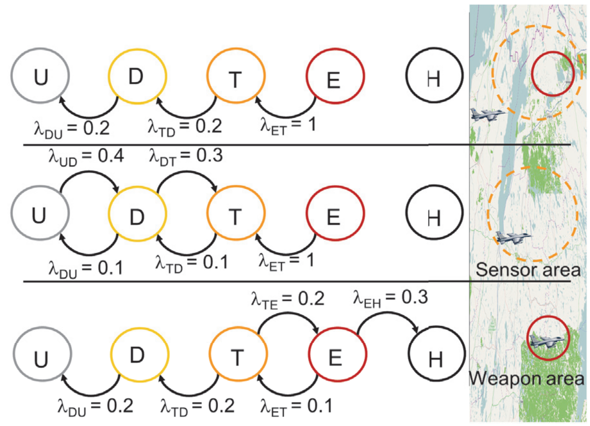

Figure 1: The survivability model has the states Undetected, Detected, Tracked, Engaged and Hit (denoted by their initial letter). The arrows show the possible state transitions when the aircraft is within a weapon area (*bottom*), a sensor area (*middle*) or outside all areas (*top*). Forbidden transitions are illustrated with the lack of arrows and have $\lambda_{ij} = 0$.

Λ is piece-wise constant and changes at the time points $t_0, t_1, t_2 \ldots$ when the aircraft enters or leaves an area. $\mathbf{p}(t_k)$ is calculated recursively as:

$$\mathbf{p}(t_k) = e^{\Lambda_{k-1}^T \cdot (t_k - t_{k-1})} \mathbf{p}(t_{k-1}), \tag{6}$$

where Λ_{k-1} is the constant rate matrix between t_{k-1} and t_k. The survivability for aircraft n at time t_s^n, is the probability that the process is not in the state Hit, i.e.,

$$S^n(t_s) = 1 - p_{Hit}(t_s^n). \tag{7}$$

The survivability fitness for a route flown by aircraft n is:

$$f_S^n = S^n(t_D^n), \tag{8}$$

where t_D^n is the time point when aircraft n reaches its destination. The team survivability fitness is calculated as:

$$f_S^T = \frac{\sum_{n=1}^{N_{mem}} f_S^n}{N_{mem}}. \tag{9}$$

Mission Effectiveness

Mission effectiveness is the probability that an aircraft could fly unharmed to its assigned targets. The individual mission fitness for an aircraft is calculated as:

$$f_M^n = \frac{1}{\tau_{nom}} \sum_{m \in M_T^n} \tau_m \cdot S^n(t_m^n), \tag{10}$$

where t_m^n is the time point when aircraft n visit target m and M_T^n is the set of targets assigned to the aircraft. τ_m is the score for visiting target m and $\tau_{nom} = \sum_{m \in M_T^n} \tau_m$ is a normalization factor. f_M^n is only affected by the targets assigned to the aircraft, even though a route might intersect additional target areas as well. When the team plan is evaluated, all aircraft that visit a target are included. The probability that target m is visited by at least one aircraft is:

$$P(m \text{ visited}) = 1 - \prod_{n=1}^{N_{mem}} (1 - S^n(t_m)). \tag{11}$$

The team mission fitness with N_{tar} targets is:

$$f_M^T = \frac{1}{\sum_m \tau_m} \cdot \sum_{m=1}^{N_{tar}} \tau_m \cdot \left(1 - \prod_{n=1}^{N_{mem}} (1 - S^n(t_m))\right). \tag{12}$$

Mission Planner

The mission planner is based on a genetic algorithm (GA), which is an optimization technique inspired by evolution (Whitley 1994). A population of individuals, representing possible target allocations, iteratively evolve towards better solutions. In order to evaluate an individual, a route planner calculates routes for all aircraft within the team given the target allocation. Algorithm 1 describes the mission planner with pseudocode.

Algorithm 1 Mission Planning

Create initial population randomly
for N_{GA} iterations **do**
    for all individuals **do**
        for all aircraft in team **do**
            Plan route to the assigned targets
            Calculate route fitness
        end for
        Calculate team fitness
    end for
    Insert best individual in new population
    while New population NOT full **do**
        Draw two parents from old population
        Create two children with cross over and mutation
        Insert children in new population if valid
    end while
end for

Initial Population

Each individual in the population has a chromosome representing a possible target allocation. A plan for N_{mem} team members and N_{tar} targets can be represented with a vector:

$$x_{TA} = [\underbrace{n_1, n_2, \ldots, n_m}_{member^1}, \underbrace{n_{m+1}, \ldots, n_{2m}}_{member^2}, \cdots \underbrace{\ldots, n_{Ntar}}_{member^{N_{mem}}}], \tag{13}$$

$$m = \frac{N_{tar}}{N_{mem}}, n_k \in 1 \ldots N_{tar} \text{ and } n_j \neq n_k \forall j \neq k.$$

This indicates that member 1 should first visit n_1, thereafter n_2 and so on. The condition $n_j \neq n_k \forall j \neq k$ implies that all targets will be visited and that no target will be allocated to more than one aircraft. In a scenario with N_{tar} targets, there are $N_{tar}!$ possible target allocations. A chromosome is represented with a number $x_{chrom} \in \{1 \ldots N_{tar}!\}$. The mapping between x_{chrom} and x_{TA} is illustrated in Figure 2. The chromosomes in the initial population is drawn randomly from a uniform distribution.

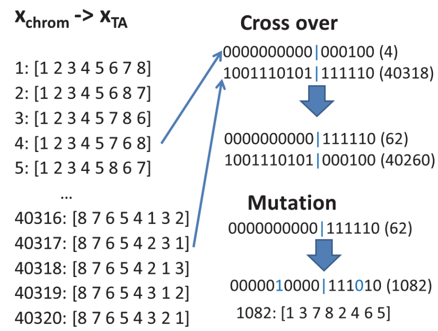

Figure 2: The left part shows a cutout of the mapping from x_{chrom} to x_{TA} for $N_{tar} = 8$. The right part illustrates the cross over and mutation operators.

Creating a New Population

The best gene in the old population is selected as the first individual in the new population. Thereafter two individuals, called parents, are drawn randomly from the old population, such that the probability that an individual is drawn is proportional to its fitness value, f^T in equation (2). The parents' chromosomes are expressed as binary numbers. The cross over operator selects a splitting point at random and creates two children by combining the parents' binary chromosomes, see Figure 2. The mutation operator thereafter changes the bits in the children's chromosomes with the probability p_{mut}. If a child is valid, i.e., $1 \leq x_{chrom} \leq N_{tar}!$, it is inserted in the new population. This procedure is repeated until the new population is full.

Route Planner

The fitness of an individual is calculated by planning routes for all team members for the individual's target assignment. The route planner is based on particle swarm optimization (PSO), which is a population-based algorithm inspired by the movements in flocks of birds (Kennedy and Eberhart 1995). PSO is suitable together with the survivability fitness function, since it handles fitness functions expressed for entire routes and does not require derivative information.

Let $\vec{x}_i$ be a vector with the position of particle i, which has the velocity $\vec{v}_i$ and the previous best position $\vec{p}_i$. The global best position of the entire swarm is denoted $\vec{p}_g$. In the route planner, a particle's position represents the route for one of the members. They are initialized with routes that enables the member to fly from the start position to the destination through its assigned targets. In each iteration, all particles' positions are updated according to:

$$\vec{v}_i \leftarrow \omega \vec{v}_i + \phi_1 \vec{U}_1^{rand} \otimes (\vec{p}_i - \vec{x}_i) + \phi_2 \vec{U}_2^{rand} \otimes (\vec{p}_g - \vec{x}_i). \tag{14}$$

$$\vec{x}_i \leftarrow \vec{x}_i + \vec{v}_i. \tag{15}$$

$\vec{U}_1^{rand}$ and $\vec{U}_2^{rand}$ denote two vectors with uniformly distributed numbers in the interval $[0, 1]$ with the same dimension as $\vec{x}_i$. $\otimes$ denotes component-wise multiplication. In this work, $\omega = 0.7298$ and $\phi_1 = \phi_2 = 1.49618$, which corresponds to the canonical version of PSO, see (Poli, Kennedy, and Blackwell 2007). If the new position has a higher fitness, f^n in equation (1), than the particle's previous position, $\vec{p}_i$ is updated with the new position. The global best position is updated in the same way, when applicable.

Simulations

The mission planner has been implemented and tested on four scenarios, where a team of two aircraft should visit eight targets. The PSO route planner was run during 80 iterations with 11 particles and the GA target allocation was run for 20 iterations with 50 individuals and $p_{mut} = 0.05$. The selection of parameters for the route planner was based on previous experience with PSO route planning, see (Erlandsson 2015b). The λ_{ij}s in Figure 1 were used for calculating the survivability, $\tau_m = 1$ for all targets and the weight parameters were $w_R = w_S = w_M = 1/3$.

Scenario 1

The first scenario is constructed so that it is possible to visit all targets without entering any enemy weapon area. Figure 3 shows the target allocation and routes for the team suggested by the mission planner. The routes enable the members to visit all targets and avoid all weapon areas resulting in 100% survivability for both aircraft. The routes include no obvious detours. Both team members visit the target in the middle (target 2), even though the target is only assigned to aircraft 1. However, aircraft 2 naturally passes through the target area between its assigned targets.

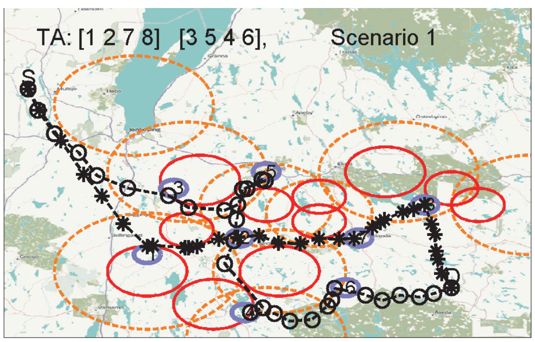

Figure 3: Scenario 1 includes 8 targets (circles with numbers) and are protected by the enemy's sensors (dashed circles) and weapons (solid circles). The team should fly from the start position (S) to the destination (D). The mission planner suggests that aircraft 1 should visit the targets [1-2-7-8] and follow the route with asterisk waypoints and aircraft 2 should visit the other targets and follow the route with circular waypoints.

Scenario 2

In the second scenario, two of the targets far from the destination are located inside weapon areas, see Figure 4. Aircraft 2 will be able to visit all its targets without entering any weapon areas and its survivability is 100%. The route planner finds a narrow passage between the many weapon areas in the middle of the scenario. This might be considered a risky behavior, but is a consequence of the survivability model, which considers all positions outside the weapon area as safe. In case there is uncertainty regarding the locations of the weapon areas, safety margins should be added.

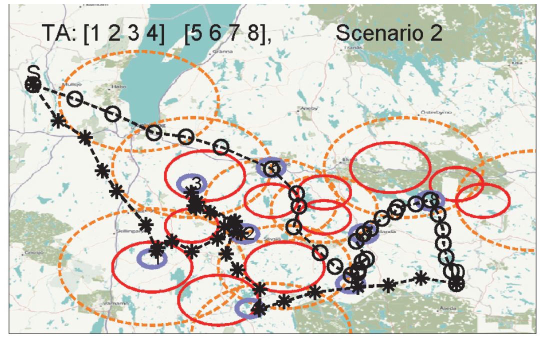

Figure 4: Target allocation and routes suggested by the mission planner for scenario 2.

Both of the targets within weapon areas are assigned to aircraft 1. The route starts with visiting target 1 and thereafter passes through target 2 before target 3. Even though, visiting target 2 before target 3 results in a longer route, this allocation is better, since the survivability at target 2 is higher.

The survivability fitness function at team level, f_S^T, is a sum. As shown in this scenario, this fitness function favors plans were all the risk is taken by a single member, since this will ensure that the other members can visit their targets. In case this is not a desirable behavior, one should consider other ways of constructing f_S^T.

Scenario 3

Figure 5 shows that aircraft 1 is able to visit all its targets without entering any weapon area in scenario 3. One could argue that it would be better to visit the targets in the order 1-2-5-8 and take a more northern route between 5 and 8. However, due to the location of target 8, it is difficult for the route planner to find such a passage.

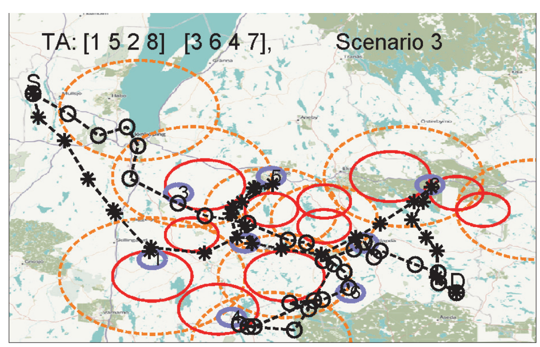

Figure 5: Target allocation and routes suggested by the mission planner for scenario 3.

Target 4 is located inside a weapon area that is quite close to the destination and it would be reasonable to visit this target last in the route. Aircraft 2 instead visits it as its third target and thereafter visits target 7 before flying to the destination. However, since the target is also visited by aircraft 1 with 100% survivability it is unnecessary that aircraft 2 visits this target. It is a limitation of the mission planner that it requires that all members visit equally many targets. As this example shows, it is sometimes better to let one aircraft focus on the difficult targets and let the other handle more targets.

Scenario 4

Scenario 4 is the most dangerous scenario with several targets within the enemy's weapon areas. Figure 6 shows that

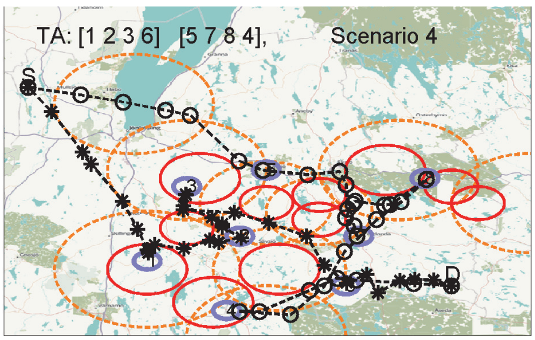

Figure 6: Target allocation and routes suggested by the mission planner for scenario 4.

aircraft 1 starts with visiting target 1, which is located within a weapon area. The beginning of the route goes outside of the sensor areas, and the probability that the aircraft will be detected when entering the weapon area is therefore fairly low. The route enters weapon areas twice, for target 1 and target 3, but these passages are short and the aircraft can reach the destination with 88% survivability. Aircraft 2 is able to visit its first three targets without entering any weapon area. The aircraft thereafter visits target 4 and reaches the destination with 94% survivability.

Target 6 is visited by both aircraft and the probability that the target will be visited is 99%, which is higher than the probabilities for each aircraft (88% and 94%). However, the route planner for member 2 is not aware that it should plan a route to visit the target, since the target is not allocated to the member. In the current formulation of the chromosomes, this is not possible since it is assumed that no target should be allocated to more than one aircraft. Relaxing this constraint would give the mission planner a larger search space. This could result in better plans, but might also require more computational time to find suitable plans.

Simulations with Different Weights

The four scenarios were also simulated with four different sets of weight parameters. Table 1 presents the resulting target allocation and fitness values for each simulation. Target allocations marked with a Δ are dominated by other solutions in the same scenario. A solution x_1 is said to be dominated by a solution x_2 if $f_k(x_1) \leq f_k(x_2)$, for all objectives k and at least one $f_k(x_1) < f_k(x_2)$ (Marler and Arora 2004). In the first scenario, the solution with equal weights dominates the other solutions. However, the differences between the solutions are small and all of them can be considered as suitable plans.

The highest survivability fitness, f_S^T, corresponds to the cases where the mission planner focuses on survivability ($w_S = 0.7$). Except in the first scenario, the mission planner excludes one or two of the targets. This is a reasonable behavior when the scenario is dangerous and the route planner is not able to find routes with high survivability. However, the team do visit some of the targets within the weapon areas, since the mission objective still applies, even though it has a lower weight ($w_M = 0.3$).

In scenario 2, the mission planner gets the highest f_M^T when it focuses on the mission, $w_M = 0.7$, but in scenario 4, the solution with equal weights has the highest f_M^T. This scenario illustrates the complexity of the planning problem and that the objectives are strongly interrelated. High mission effectiveness requires high survivability, at least in the beginning of the routes. On the other hand, in order to achieve a high survivability, it might be worth to exclude some targets as shown in the cases with $w_S = 0.7$. The objective of short route length implies that the routes should not be unnecessarily long within weapon areas, but might also enforce the team to take shortcuts across dangerous areas. This complexity motivates the need of an automated mission planner to aid the pilots to plan their missions, but also illustrates that it is not an easy task to select the weights.

The PSO route planner runs for a limited number of iterations and the routes are not always optimal, see e.g., Figure 5. The route planner is primarily used for evaluating the target allocations by calculating fitness values. It can therefore be argued that it is not important to find the optimal routes, but to find routes that are representative for the target allocation. When a target allocation has been selected, it is wise to run the route planner for more iterations in order to find the best routes.

Conclusions and Suggestions for Future Work

Planning a mission for a team flying inside hostile territory is a difficult task, since the plan should enable the team members to perform their tasks without exposing them to the enemy's weapons more than necessary. This work has proposed a mission planner that combines genetic algorithms for target allocation with particle swarm optimization for route planning. The mission planner handles three interrelated objectives: high probability for mission success, high survivability and short route length.

Simulations demonstrated that the mission planner is able to generate suitable plans in complex scenarios. The plans enabled the team to visit all targets with a high probability of reaching the destination unharmed. The route lengths were reasonable, even though some post processing to remove unnecessary waypoints and to smooth the curves would improve the routes in some scenarios. By changing the weight

Table 1: Target allocation and fitness values for the plans suggested by the mission planner with different set of weight parameters. Target allocations marked with a Δ are dominated by at least one other solution in the same scenario. A target marked with † indicates that the team will not visit the target.

	$w_R = w_S = w_M = 1/3$	$w_R = 0.70$, $w_S = w_M = 0.15$	$w_S = 0.70$, $w_R = w_M = 0.15$	$w_M = 0.70$, $w_R = w_S = 0.15$
S1	[1 2 7 8 3 5 4 6] f_R^T: 0.63, f_S^T: 1.0, f_M^T: 1.0	[1 2 3 4 5 8 7 6]$^{\Delta}$ f_R^T: 0.63, f_S^T: 0.99, f_M^T: 1.0	[1 3 6 4 5 2 7 8]$^{\Delta}$ f_R^T: 0.60, f_S^T: 1.0, f_M^T: 1.0	[1 2 5 8 3 7 6 4]$^{\Delta}$ f_R^T: 0.61, f_S^T: 1.0, f_M^T: 1.0
S2	[1 2 3 4 5 6 7 8] f_R^T: 0.60, f_S^T: 0.93, f_M^T: 0.96	[1 2 3 4 5 8 7 6] f_R^T: 0.62, f_S^T: 0.90, f_M^T: 0.96	[1 2 3† 6 5 8 4 7] f_R^T: 0.57, f_S^T: 0.97 f_M^T: 0.87	[1 2 3 7 5 6 4 8] f_R^T: 0.54, f_S^T: 0.93, f_M^T: 0.98
S3	[1 5 2 8 3 6 4 7] f_R^T: 0.51, f_S^T: 0.98, f_M^T: 1.0	[5 6 8 7 3 1 2 4] f_R^T: 0.61, f_S^T: 0.93, f_M^T: 0.99	[1 3 5 7 4† 2 6 8] f_R^T: 0.51, f_S^T: 1.0, f_M^T: 0.87	[1 2 5 4 3 6 7 8] f_R^T: 0.53, f_S^T: 0.94, f_M^T: 1.0
S4	[1 2 3 6 5 7 8 4] f_R^T: 0.52, f_S^T: 0.91, f_M^T: 0.98	[1 3 6 4 5 2 8 7] f_R^T: 0.57, f_S^T: 0.89, f_M^T: 0.95	[3† 6 8 4† 1 5 2 7] f_R^T: 0.50, f_S^T: 0.96, f_M^T: 0.7	[1 2 3 7 5 6 8 4]$^{\Delta}$ f_R^T: 0.48, f_S^T: 0.83, f_M^T: 0.98

parameters for the objectives, the mission planner can be instructed to focus on a certain objective. For instance, when the weight for survivability was high, a few of the targets inside the enemy's weapon range were excluded, since they were considered too dangerous to visit. However, setting the weights is not an easy task, since the objectives are highly interrelated. In two scenarios, the case with equal weights dominated the solutions with a high weight for mission success. Even though more simulations are needed to fully understand the connection between the weights and the resulting plans, these examples well illustrate the complexity of the planning problem.

For future work, it is interesting to perform a study with the potential end users of the system and investigate whether the plans suggested by the mission planner correspond to their expectations and needs. It is also important to study how to aid the users to transform their preferences regarding the objectives into weight parameters.

Acknowledgments

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