Towards Cooperative Guidance in Air-Defense: Extending Weapon-Target Assignment into the Mid-Course Phase

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Keywords: Weapon-Target Assignment (WTA), Cooperative Guidance, Multi-Agent Systems, Online Task Assignment, Combinatorial Optimization, Missiles, Air-defense

Abstract. As modern threats evolve through coordinated swarm attacks, static or pre-launch assignments for air-defense systems become outdated mid-engagement, necessitating in-flight reassignment. Therefore, cooperative guidance is introduced, extending dynamic Weapon-Target Assignment (WTA) from launch-time coordination into the mid-course flight phase. A decentralized architecture is proposed that couples WTA with trajectory guidance via informed cost functions. The information consensus-based WTA optimization procedure enables real-time adaptability under communication constraints. The Hungarian algorithm is chosen for its deterministic, low-complexity performance for the repeated optimizations. A simulation example illustrates mid-course reassignment triggered by target maneuvering, demonstrating the feasibility of collaborative flight-path adaptation.

Introduction

This work discusses cooperative guidance for air-defense systems, extending state-of-the-art launch coordination with dynamic Weapon-Target Assignment (WTA) in the mid-course phase. As modern threats evolve through coordinated swarm attacks [1, 2], we assume that static launch-time coordination becomes insufficient. While dynamic WTA improves responsiveness through sequenced launches [3, 4], a continuous in-flight cooperation is the next step. Enabled by network-centric warfare [5, 6], cooperative guidance allows effectors to jointly reassign targets in-flight, adapting to dynamic threats in real time. We propose a cooperative guidance concept for an onboard module, that integrates WTA and trajectory guidance via cost-informed assignments. It enables real-time adaptability with limited computational resources. The decentralized approach avoids single points of failure [7].

A dynamic optimization of assignments and collaborative adaption of intercept flight paths in real-time throughout the unpropelled mid-course of the missiles after their boost-phase, shall maximize intercept success probabilities. This cooperation allows to dynamically react to erratically evolving environments. The approach is expected to increase effectiveness for the air-defense while additionally saving on costly resources.

Background on Weapon-Target Assignment

The WTA problem can be approximated as a linear assignment problem. The best combination of all possible effector/target assignments is evaluated by a combinatorial optimization. To solve the linear assignment problem mathematically, scalar cost values c_{ij} for the assignment of each effector $i \in [\![1, N]\!]$ to each target $j \in [\![1, M]\!]$ are to be defined. This relationship is schematically shown in Fig. 1.

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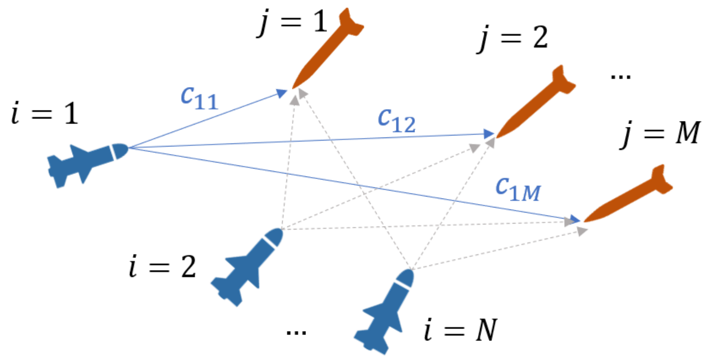

Fig. 1: Assignment Costs Illustration

The sum of these costs ought to be minimized by selecting an optimal assignment which is described by

$$\min_{x}\left(\sum_{i=1}^{N}\sum_{j=1}^{M} c_{ij}\ x_{ij,\tau}\right), \tag{1}$$

where the binary variables x_{ij} represent the assignments of effectors to targets either at time τ or the previous timestep $\tau - 1$ (as in Eq. 3). This optimization shall be subject to the following constraints:

$$\begin{aligned}
&\text{C1 (binary assignment variables):} \quad \forall i \in [\![1, N]\!], \forall j \in [\![1, M]\!], \quad x_{ij} \in \{0,1\} \\
&\text{C2 (exactly one target assigned per effector):} \quad \forall i \in [\![1, N]\!], \quad \sum_{j=1}^{M} x_{ij} = 1 \\
&\text{C3 (bounds on effectors per target):} \quad \forall j \in [\![1, M]\!], \quad \left\lfloor \frac{N}{M} \right\rfloor \leq \sum_{i=1}^{N} x_{ij} \leq \left\lceil \frac{N}{M} \right\rceil
\end{aligned} \tag{2}$$

The first constraint (C1) enforces that the assignment variables x_{ij} are binary, indicating whether worker i is assigned to task j. The second constraint (C2) ensures that each worker is assigned to exactly one task. The third constraint (C3) limits the number of effectors assigned to any target between the floor and ceiling of the ratio $\frac{N}{M}$ for an even distribution of effectors across targets.

Cooperative Guidance Architecture

Cooperative guidance integrates WTA and trajectory guidance. While simultaneous optimization of assignment and trajectory is theoretically optimal, it is computationally prohibitive [8, 9] for onboard use. We instead adopt a separated approach: the trajectory guidance law is recognized in the cost function c_{ij} (e.g., via time-to-go estimates), enabling good performance with low complexity. A closed loop is created: the assignment defines the target for the mid-course guidance and in turn, guidance-relevant metrics feed into the cost function. A fully connected mesh enables decentralized cooperation (Fig. 2). Each effector exchanges state or cost estimates with peers (depending on the WTA algorithm selection in the next section), while receiving target data from a central node.

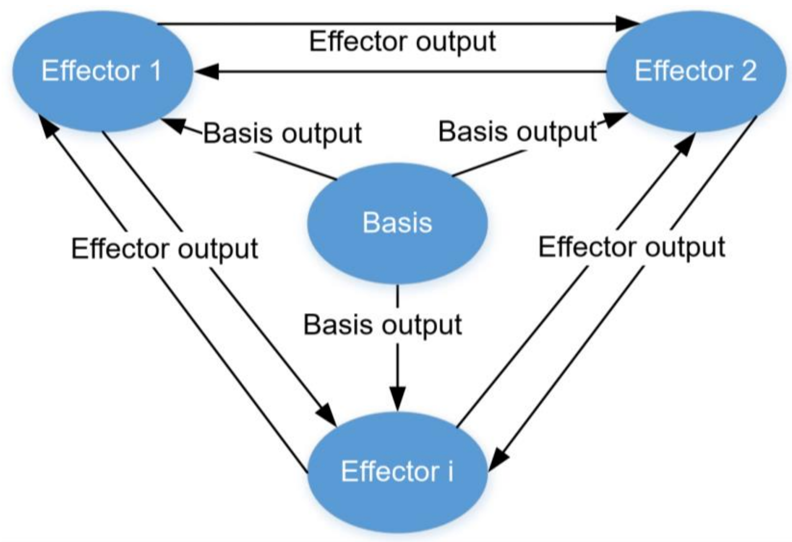

Fig. 2: Ideal Communication Scheme

Since cost function design bounds the decision quality for any optimization algorithm, the assignment optimization is assumed to be predominantly driven by a sound exploitation of flight mechanical and operational knowledge (e.g. regarding target/asset classification). As [10] outlines, WTA optimization objective is usually either based on minimization of target survivability or maximization of asset survivability. We suggest a multi-objective, cost-driven WTA optimization approach that achieves the following set of high-level objectives:

1) maximization of asset-survivability (e.g. by distance to predicted intercept area),
2) minimization of general threat level imposed by targets (e.g. via time-to-go) and
3) maximization of energy reserves (e.g. through predicted speed at intercept).

These objectives ought to be cast into combined cost parameters for any assignment of effectors to targets via a weighted sum, such that the WTA problem can be optimized by selecting a combination of assignments which minimize the overall costs. The systematic exploitation of domain-knowledge for the cost factors in order to achieve and balance these high-level objectives is not yet clear and should be investigated in future work. A manually tuned additional cost (i.e. switching cost) s can be added to the cost function (cf. Eq. 1) for previously not-assigned combinations as

$$\hat{c}_{ij} = c_{ij} + s\,(1 - x_{ij,\tau-1}) \tag{3}$$

to penalize undesired high-frequency reassignments.

Weapon-Target Assignment Algorithm Selection

For the development from coordination to cooperation, some high-level requirements are derived for the WTA definition and its optimization algorithm. Due to the continuous evaluation, consistent solutions must be ensured in order to avoid wasteful perpetual swapping of assignments. Particularly for development, reproducibility is beneficial. This requires deterministic optimization algorithms. The optimization, including the calculation of a cost function as well as the solution, is time-critical. According to Eq. 2, the optimization algorithm must be able to ensure that every effector has exactly one target assigned to it (if targets are available) and every target can have different numbers of effectors assigned to it, depending on the symmetry of the number of participants.

In conjunction with the type of future connections and expected failures/limitations, a design decision needs to be made between information or assignment consensus. Fig. 3 illustrates a qualitative comparison of both approaches.

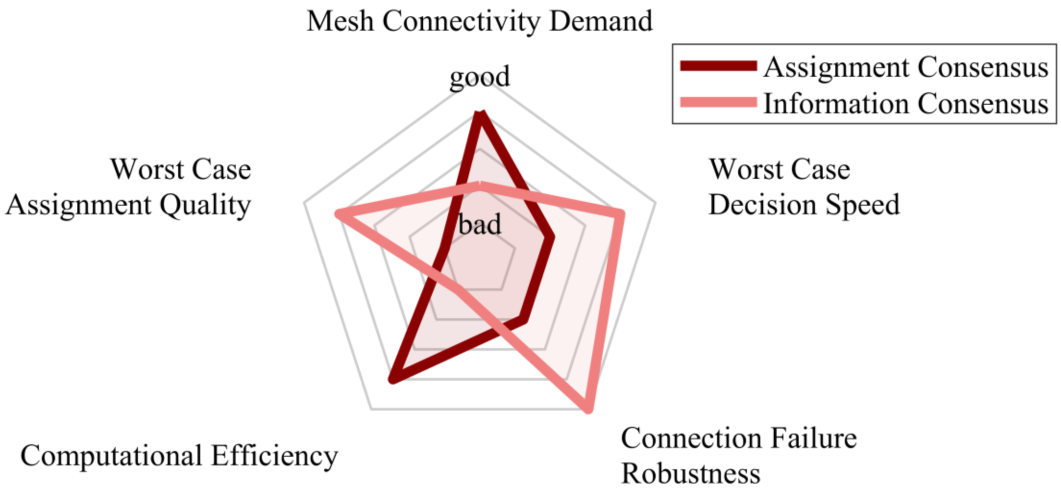

Fig. 3: Assignment vs. Information Consensus Trade-off

In scenarios with stable, short-range connections, assignment consensus methods operating on nearest-neighbor communication schemes can be effective [11]. Contrarily, information consensus tends to demand increased mesh connectivity. The required communication bandwidth varies between the two approaches. For information consensus, it depends on the cost function and its required information, whereas for assignment consensus, it depends on the specific framework used (e.g., transmitting entire bundles of bids simultaneously or one bid at a time, in turn requiring more communication iterations) [11].

However, when frequent connection failures are expected, information consensus enables compensation techniques like dead-reckoning (state estimation) on each effector, allowing to maintain a consistent assignment optimization plan [11]. Given the limited maneuverability of missiles, dead-reckoning techniques should work well for short durations. Particularly if flight dynamics and guidance are known for all effectors, well-informed predictions can then be made with continuous uplinks for target and asset information, reducing the requirements on effector-to-effector communication frequency. Reaching assignment consensus may be delayed due to communication latencies, potentially leading to decisions being made beyond a critical "point-of-no-return" in dynamic environments (worst case decision speed in Fig. 3). Information consensus combined with state estimation can make more up-to-date decisions. Nevertheless, solving the global assignment problem onboard every effector significantly increases computational demands. A simulation study comparing information vs. assignment consensus approaches with missiles under uncertainties and unstable connections should be pursued in future work.

Consulting survey papers on multi-robot task assignment such as [7] suggests that as long as communication network topology is not assumed as too restricted and computational demands are feasible, the simple Hungarian algorithm [12] (extended for rectangular cost matrices) for information consensus is the preferred choice. For cases of numerical superiority, the cost matrix has to be replicated to the right, such that the number of "virtual" (copied) targets is higher than the number of effectors to address C3 in Eq. 2. Computational demands remain feasible as long as no too complex simulations or trajectory optimizations for the WTA cost function are used and computational requirements are dominated by other subsystems (e.g. image processing in infrared seekers). Benefits of the Hungarian algorithm were previously demonstrated in similar multi-agent problems [13].

Simulation Test

The concept is exemplarily tested with a 3 effector vs. 3 targets simulation from launch until target interception (based on a simple proximity collision logic) in Fig. 4. Forward simulations with the model and guidance algorithms are performed in each iteration, to estimate the time-to-go for each effector/target combination as the only WTA cost parameter considered in this example. A simple Proportional Navigation Guidance (PNG) algorithm is used for trajectory guidance. The WTA is performed online with 1 Hz. Effector trajectories (in the back of the figure) are color-coded by assigned target. The effectors launch successively and allocate themselves such that each target is assigned to one effector. Mid-flight, the right-most (purple) target turns to the left. It is consecutively reassigned to effectors from right to left during the maneuver, such that the summed-up time-to-go for all effectors remains lowest. All computations are performed in each effector model. The entire simulation takes only a few seconds on a consumer laptop, demonstrating feasibility on embedded systems under real-time constraints.

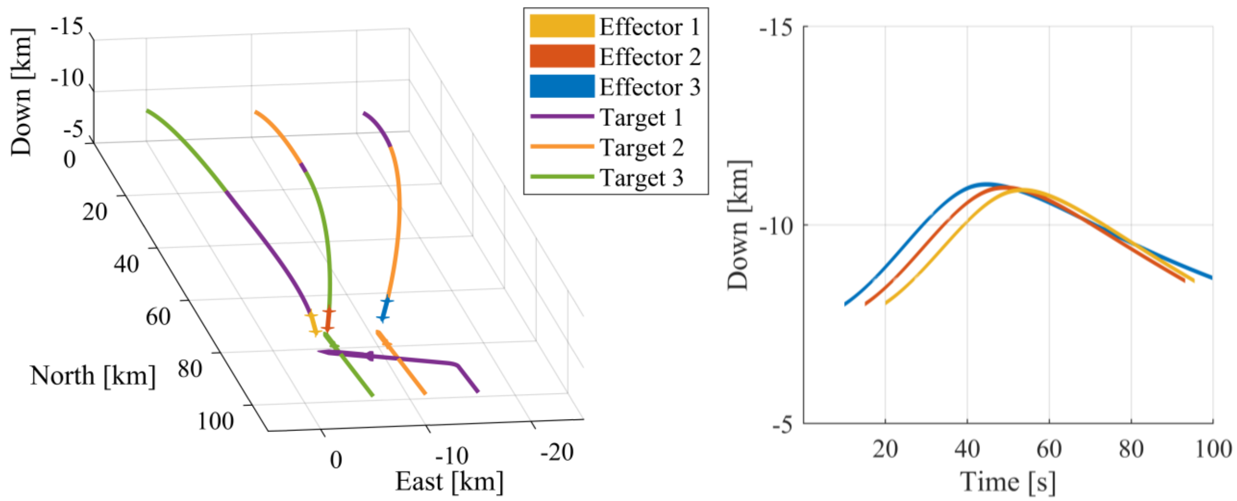

Fig. 4: Illustrative Scenario: Mid-Course Reassignment Triggered by Target Maneuver

Conclusion

This paper introduces the concept of cooperative guidance for air-defense systems, extending WTA into the mid-course flight phase. We propose a decentralized, onboard architecture that tightly couples WTA with trajectory guidance through cost-informed feedback, enabling real-time adaptation to evolving threats. The integration of well-established components (e.g. Hungarian algorithm) into a lightweight, cooperative missile guidance loop represents a novel approach to adaptive air-defense. This work lays the conceptual foundation for future implementation and evaluation. Quantitative evaluation and cost function design will be presented in follow-up work. The framework paves the way for adaptive, resilient air-defense systems capable of countering next-generation swarm threats.

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