A New Swarm Collection Tasking Approach for Persistent Situational Awareness

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ABSTRACT

Swarm technology applications involving mobile ad hoc sensor agents is growing increasingly and expandable to multiple military problem domains such as tactical intelligence, surveillance, target acquisition, and reconnaissance *(ISTAR). In ISTAR, a team of semi-autonomous sensors cooperatively achieve collection tasking and execution to bridge the gap between information need and information gathering in order to maintain persistent situational awareness. State-of-the-art contributions largely expose multi-dimensional problem complexity. Highlighting limited on-board sensor platform resource capacity and energy budget, they often adopt ad hoc prescribed sensor behaviors, leading to over conservative connectivity constraints, biased decision-making and/or fusion solution structures. These may arbitrarily convey a significant opportunity cost and detrimentally impact overall performance. An innovative approach is proposed to handle the mobile ad hoc sensor network/swarm collection tasking problem, subject to on-board limited processing power and bounded energy budget for data dissemination/communication routing. Driven by limited on-board power considerations, collection planning is centralized and episodically mediated by a swarm leader, while plan execution is decentralized. Collection planning relies on a new open-loop with feedback decision model formulation. It consists to repeatedly solve a static decision problem maximizing collection value over a receding time horizon. Episodic decision-making is conditioned by incoming requests, cumulative collection value, ongoing resource commitments, remaining resource capacity and feedback from the previous stage. The approach combines a new compact graph representation and a sound approximate decision model to perform sensor agent path planning optimization, subject to periodic connectivity in order to achieve information-sharing, fusion, situational awareness and dynamic retasking/planning. The proposed minimum spanning tree communication scheme conferring swarm topology-awareness, in conjunction with the advocated connectivity constraint handling approach offer the desired flexibility to significantly expand overall observable domain; explore a larger solution space; reduce energy consumption; maximize network extent; and provide expected collection gains ultimately enhancing situational awareness.*

1.0 INTRODUCTION

Sharing commonality with fixed and mobile ad hoc sensor/agent network (MANET), emerging swarm technology applicable to multiple military problem domains is growing increasingly. It ranges from Force protection, offensive and defensive coalition operations (e.g. coalition urban environment), combat support, intelligence, surveillance and reconnaissance missions, mission planning, command and control, logistics and emergency management, to name a few [1]. A typical problem domain of interest includes tactical ISTAR, in which a swarm of semi-autonomous sensors jointly perform collection tasking to enable and maintain situational awareness at the tactical edge. Constrained collection tasking optimization and base-level observation/communication actions coordination govern adaptive swarm behavior. Both play a key role in maintaining persistent situational awareness reducing uncertainty (maximize information gain) on state estimation while timely informing decision-makers. Key comprehensive references on mobile sensor networks may be found in [2] and [3]. Selected surveys on specific unmanned aerial vehicle (UAV) network dimensions such as swarming, coverage task planning and communication have alternatively been reported in [4]-[6]. Relevant to swarm coordination, reference [7] alternatively proposed a general survey on multi-agent systems. Those surveys highlight the various conditions and stringent constraints driving the choice of a particular swarm or ad hoc sensor network solution to properly operate at the tactical edge.

This work focuses on a mobile ad hoc sensor network/swarm collection tasking problem, subject to on-board limited processing power and bounded energy budget for data dissemination/communication routing. Typical assets include heterogeneous unmanned fully/semi- autonomous systems/platforms dedicated to collection and/or communication. An innovative swarm collection tasking approach is proposed to maintain persistent situational awareness in a tactical context. The open-loop with feedback approach aims at maximizing collection value to carry out a diversity of collection tasks over a receding time horizon while periodically ensuring maximum collection dissemination (to a sink node) subject to energy budget constraints, as well as supporting fusion, situational awareness and dynamic retasking/planning. The reported novelties are multifold: A novel graph representation to capture combinatorial complexity, and a new mathematical formulation derived from a sound approximate decision model exploiting prior knowledge (bounding the number of task visits). Then, communication planning/routing aimed at disseminating collection is based either on a minimum spanning tree problem solution to minimize energy consumption. Consequently, the approach, allows to significantly expand observable areas, and relax myopic planning, improving collection tasking, while providing an upper bound on solution optimality when using exact methods. It also reduces costly energy consumption to ultimately mediate fusion and situation awareness, as well as to support next tasking coordination episode through periodic team connectivity reinforcement.

The remainder of the paper is broken down as follows. Section 2 introduces the swarm collection tasking problem. A new swarm collection tasking approach is then highlighted in section 3. A general overview is presented and its main features underlined. An innovative collection graph representation and a mathematical formulation are then further described respectively. Details on the communication planning /routing scheme are then presented. Then, problem complexity reduction is briefly discussed in section 4. Finally, the main reported contributions and anticipated future work are summarized in section 5.

2.0 PROBLEM DESCRIPTION

Given a set of weighted collection requirements/task requests, the basic collection tasking problem consists to allocate collection assets or agents $a \in Ag$ (e.g. unmanned autonomous systems, unmanned aerial/ground vehicles, aircraft/helicopters) to tasks in order to optimize single or multiple objectives (typically to maximize collection value) over a predetermined time horizon. It focuses on a mobile ad hoc sensor network/swarm collection tasking problem, subject to on-board limited processing power and a bounded energy budget for data dissemination/communication routing.

A typical collection tasking context for ISR mission tasks such as target (e.g. vehicles, weapons) search, detection, tracking and identification behavior is pictured in Figure 1. It defines a grid cognitive map representation reflecting situational awareness over a specific region of interest, capturing prior knowledge, belief and/or known probability distribution on cell occupancy and target behavior. Accordingly, collection coordination amongst connected cooperative swarm members (sensor agents) shown in red is mediated by the swarm leader (displayed in blue) through centralized planning, to maximize collection value and maintain persistent situational awareness. Collection plan execution is decentralized. The swarm leader interchangeably acts as a local sink node consuming sensor readings /observation outcomes from source nodes before achieving data fusion, followed by team's collection task and communication planning. Episodic sink election may be determined either randomly based on residual energy level in order to share a fair cost across the swarm, or reuse state-of-the art election schemes [8].

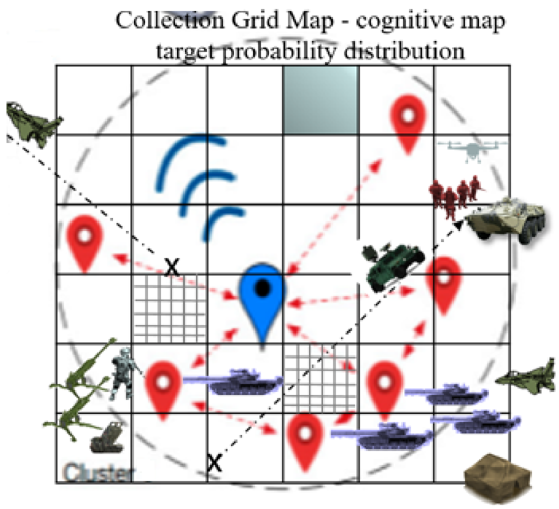

Figure 1 - Swarm Collection Tasking Context. Collection assets (red) include heterogeneous unmanned fully/semi- autonomous systems/platforms dedicated to collection and/or communication. Coordination is mediated by the swarm leader (blue).

Maintaining persistent situational awareness aims at maximizing swarm collection value defined as the cumulative products of respective task value (weight) and related task plan quality of collection (QoC), summed over all visited tasks. It consists to maximize relative coverage on search tasks; maximize probability of success over detection/localization/tracking tasks; and maximize information gain (minimize entropy) over target/behavior identification tasks.

3.0 APPROACH OVERVIEW

3.1 Main Features

An innovative swarm collection tasking approach aimed at maintaining persistent situational awareness in a tactical context is proposed. Using a network flow optimization framework exploiting the new graph representation, the approach sequentially maximize overall collection value and periodically maximize disseminated collection over receding horizons for a mobile ad hoc swarm, subject to on-board limited processing power and bounded energy budget for data dissemination/communication routing. Collection tasking is based upon a novel open-loop with feedback (OLF) formulation as shown in Figure 2. Episodic decision-making is conditioned by incoming requests, cumulative collection value, ongoing resource commitments, remaining resource capacity and feedback from the previous stage. Communication is achieved via periodic team connectivity reinforcement (topology control). Accordingly, topology control over agent swarm is ensured by either building a minimum spanning tree or solving a separate optimization problem minimizing communication cost. The open-loop with feedback approach aims at maximizing collection value to carry out a diversity of collection tasks over a receding time horizon T while periodically performing maximum collection dissemination (to a sink node) at time ΔT_d , subject to energy budget constraints, as well as supporting fusion, situational awareness and dynamic retasking/planning during time interval ΔT_{pl}.

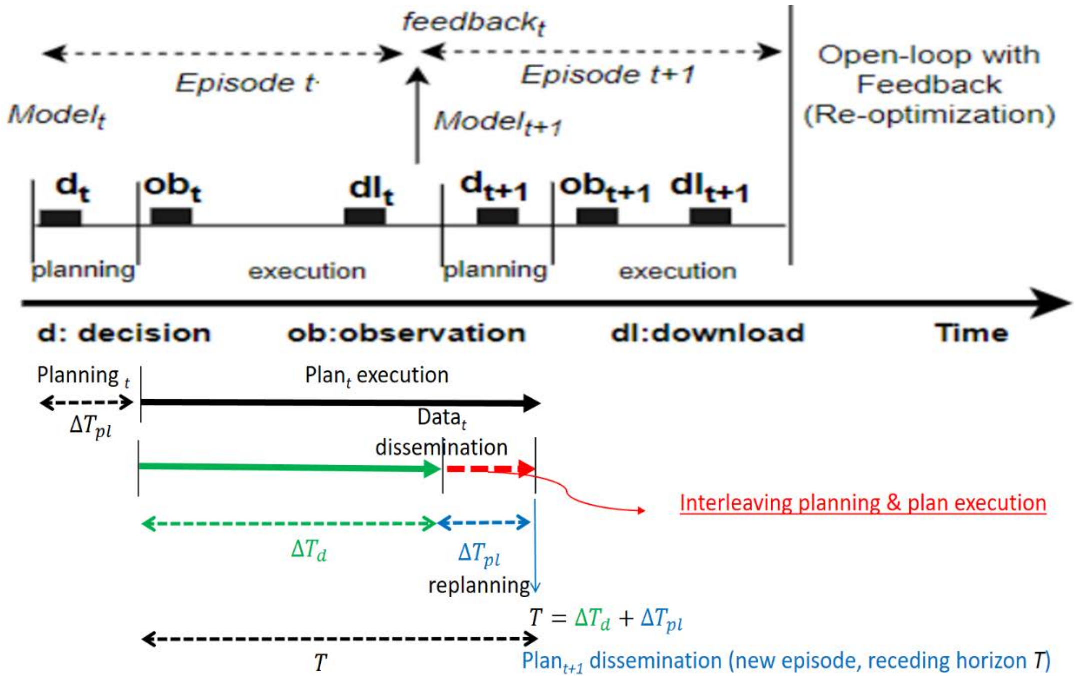

Figure 2 - Open-loop with feedback collection tasking optimization over receding time horizon *T*. An episode involves decision (d), collection/observation (ob) and data dissemination (dl) actions.

3.2 Collection Tasking

A new network flow optimization –based approach is envisioned to handle the mobile ad hoc sensor network/swarm collection tasking problem. It couples adaptive collection tasking and communication planning subject to resource capacity constraints (power/fuel, memory storage, duty cycle) over a rolling planning time horizon.

3.2.1 Collection Graph Representation

A new directed acyclic graph representation for each agent $a \in Ag$ is introduced to capture collection asset observation moves (opportunities) over a limited time horizon. The network structure is exploited for an episodic collection tasking problem with duration ΔT, including a set of tasks $r \in M = \{1,2,\ldots,m\}$ to be serviced by a swarm of sensor agents a in Ag over a receding time horizon $T > \Delta T$, subject to a variety of resource capacity, itinerary and time constraints. Collection tasking occur episodically every period ΔT. An agent a collection network interleaves two graphs connected via a set of predetermined nodes reflecting candidate communication positions for that agent as shown in Figure 3. Each graph is bi-partite including collection site nodes and intermediate communication nodes. A first cyclic graph $G_1(V_1,A_1)$ captures legal observation moves or collections that can be carried out by the agent a over a period ΔT starting from an origin position node O. The set of vertices V_1 represents feasible task visits /collection opportunities by the sensor agent. A task can be

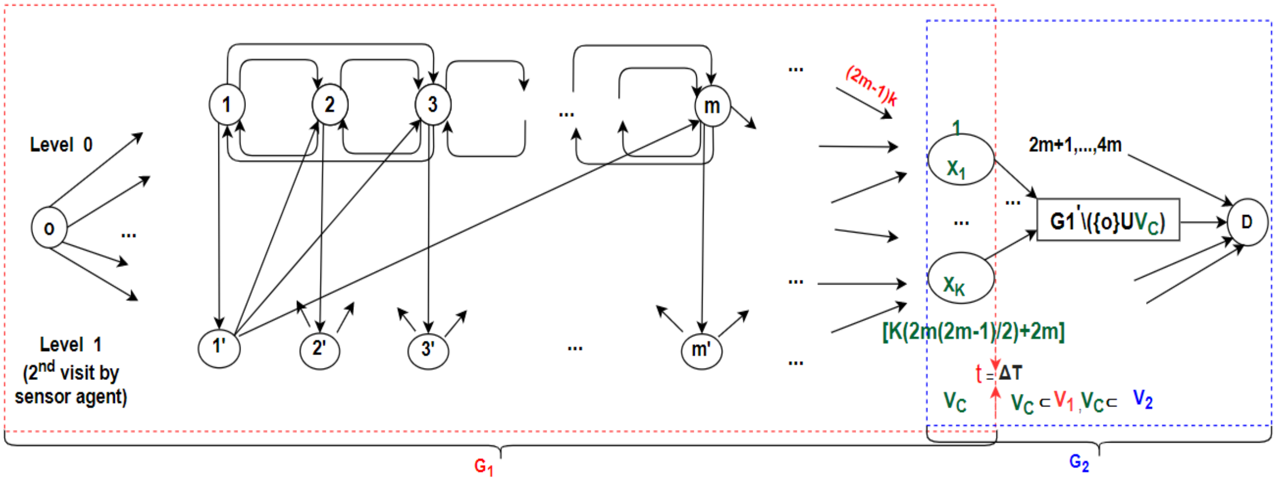

Figure 3 - Agent Collection Graph with communication at ΔT, over planning horizon T (exceeding period ΔT).

associated with multiple vertices. Terminal nodes forming a set of vertices $V_c \subset V_1$ define a communication layer. These correspond to predetermined candidate positions that can ensure periodic communication at time ΔT. Typically, an agent may be located on a specific task site or at one out of K different discrete positions determined along a path connecting two task sites, forming the set of communication vertices $V_c \subset V_1$ ($|V_c| = K(2m(2m\text{-}1)/2) + 2m$). The set of arcs A_1 refers to possible legal node transitions connecting two vertices. A second cyclic graph $G_2(V_2,A_2)$ partly overlapping $G_1(V_1,A_1)$ then depicts longer term path collection planning beyond agent communication at ΔT up to the end of time horizon T. Accordingly, the set of vertices G_2 first shares terminal candidate communication position nodes V_c from G_1, before duplicating remaining G_1 core topology structure including related task/observation nodes. Duplicated task nodes capturing possible moves over remaining time horizon T are then connected to a fictitious terminal destination node D. G_1 shows a two-layer structure referring respectively to a first and a possible/optional second visit (collection/observation) to be conducted over a given task by the asset if desired. Any path connecting origin O and destination D nodes from the graph $G_1 \cup G_2$ constitutes a collection path solution for agent a.

An integer binary decision variable x_{ia} related to node visit $i \in V$ defines a basic agent a path's construct. Accordingly, a path solution for sensor agent a includes vertex i if $x_{ia} = 1$. A service time svc_{ia} is associated with each task collection site i accounting for observation duration by agent a. The decision variables x_{ia} are coupled to binary flow decision variables u_{ija} characterizing node transition from i to j ($u_{ija} = 1$). A travel time $travel_{ija}$ is associated with each node transition to cover the distance separating i and j. Agent a communication occurring at time ΔT is mediated through x_{ka} binary decision variables reflecting candidate position nodes $k \in V_c$ to ensure periodic information exchange. Therefore, assuming to visit a node at most once, a feasible sensor agent path solution may be built by moving along arcs across the directed acyclic network $G(V,A) = G_1(V_1,A_1) \cup G_2(V_2,A_2)$ connecting O to D nodes, while instantiating a sequence of flow decision variables along the way. It should be noticed that the selected acyclic agent graph representation keeps polynomial the number of vertices and arcs in the problem size, with set cardinality $|V|$ and $|A| \in O(m^2K)$.

3.2.2 Connectivity

Periodic swarm connectivity is imposed to support observation outcomes dissemination, data/information fusion, situation assessment and replanning at the sink node. It is ensured through a novel constraint formulation iteratively connecting respective agent position node at ΔT to one another. Based on an iterative neighborhood construction S_l set procedure establishing for a sensor agent a degree of linkage l reflecting the number of hops necessary to reach a predetermined sink position node, overall connectivity is originally achieved using a simple linear formulation to reinforce a natural flow between consecutive S_l sets. Figure 4 pictures a specific swarm/team configuration dividing the swarm in two sets to ensure agent node connectivity.

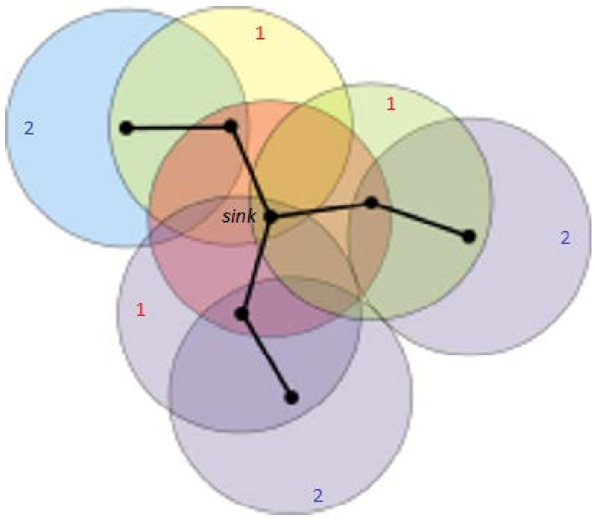

Figure 4 – Sensor agents divided in 2 sets S_1 and S_2, respectively based on hop distance to the centrally located sink node.

Iterative neighborhood construction set procedure - Disjoint sets S_l of possible periodic agent position nodes (k,a) $V_c \times Ag$ are first iteratively pre-generated for $l = 0,1,2,\ldots,$ based on single hop distance with neighbor agent positions, to feasibly and ultimately disseminate information (e.g. cumulative observation outcomes) to a sink (leader) located l-hop away to a predetermined rendezvous position k^{RDV}.

$N_0 = V_c \times Ag|sink$: set of possible agent position nodes (k,a) at ΔT
$S_0 = \{(\text{initial position, sink})\}$
$l=1$
while ($S_{l-1} \neq \emptyset$) *do*
S_l: {agent position nodes (k,a) in $N_l = N_0 | \bigcup_{j=0}^{l-1}\{Sj\} \subseteq V_c \times Ag$, having 1-hop distance from S_{l-1} and then, l-hop distance with sink node}
Agent position node (k,a) is within 1-hop distance (or adjacent) from (k',a') if both agents a,a' can mutually exchange/ communicate (k',a') is within (k,a)'s communication range. Such condition can be verified through a pre-computed binary adjacency matrix $Adj_{kk'}^{aa'}$
$l=l+1$
end while
$L=l-1$
Return S_l and L for $l = 0,1,2,\ldots,L$

Computational complexity of the neighborhood generation procedure $\in O((|V_c|\,|Ag|)^2)$ and can be computed offline. Exploiting the sets S_l an innovative linear inequality constraint set can be specified to iteratively reinforce swarm connectivity. Inspired from a formulation for a flow conservation constraint in directed acyclic graphs, the proposed inequality expression ensures an agent currently located to a position in S_l to be successfully connected to at least 1-hop neighbor agent whose current location is in S_{l-1}, one hop closer to the sink. The detailed mathematical connectivity constraint formulation is given in the next section.

3.2.3 Mathematical Decision Model

The approach relies on a mathematical quadratic programming formulation exploiting problem structure (collection graph or network) and prior domain knowledge to compute an efficient solution. Departing from a general complex non-linear objective function supporting multiple collector assignments on every task, it relies on an approximate objective function enabling utilization of well-known commercially available exact problem-solving techniques such as CPLEX [9]. It is founded on a limited Taylor series expansion of the original objective function, coupled with a maximum number of visits (2 or 3) constraint to pay on a task, a typical feature observed on high-quality computed path solutions.

The parameters and variables used to specify the basic problem model formulation are described as follows:

H: mission time horizon

T: receding planning time horizon

ΔT: communication period

SEQ: integer parameter exceeding maximum number of nodes any agent path solution can include over horizon *T*.

<u>Task requests:</u>

M: set of task requests $r \in \{1,2,\ldots,m\}$

v_r : value of task *r*

A_r : area of interest (AOI) of task request *r*

T_r^l: task *r* time window visit lower bound

T_r^u: task *r* time window visit upper bound

Collection assets/agents: Ag: set of heterogeneous assets/agents $a \in \{1,2,\ldots,n\}$ $dist\_max_a$: maximum cumulative distance (duty cycle) characterizing an agent $a \in Ag$ path solution (equivalent to a traveling energy budget). E_a^{coll}: asset a collection energy capacity/budget eo_a: energy consumption rate for a collection opportunity/observation by asset a es_a: energy consumption rate for collection opportunity transition by asset a $setup_a$: set-up time of collection asset a E_a^{comm}: asset a communication energy capacity/budget Transition: $travel_{ija}$: agent a transition/travel time associated with vertex transition from i to j. It corresponds to the distance $dist_{ij}$ over agent a velocity ratio. $dist_{ij}$: distance separating vertices i and j.	Collection/observation opportunities: t_{ia}: agent a collection opportunity i visit time, $i \in V_a/\{O,D,V_c\}$. svc_{ia}: agent a service and set-up time associated with collection opportunity $i \in V_a/\{O,D,V_c\}$. p_{ia}: probability of successful agent a observation associated with collection opportunity i q_{ia}: normalized aggregated quality of collection associated with agent a assignment to collection opportunity i. $0 \leq q_{ia} \leq 1$. It reflects a task-dependent measure of performance that can be derived from a mixture of prior knowledge, prediction models, simulation and/or subproblem optimization using a fast task-dependent planning heuristic. $q_{iai'a'}$: normalized compound/fused/ aggregated quality of collection associated with agent a and a' assignments to collection opportunity i and i' respectively, related to a given task. $0 \leq q_{iai'a'} \leq 1$ $cost_{ia}$: agent a observation cost associated with collection opportunity i $cost_{max}$: maximum financial budget associated with team collection observation
Connectivity: k^{RDV}: predetermined sink (leader) rendezvous position at ΔT. $k^{RDV} \in V_c$. S_l: set of agent position nodes $(k, a) \in V_c \times Ag \mid sink$ within l-hop distance from the rendezvous sink position node at ΔT. L: Maximum length/extent of the agent swarm/network ensuring connectivity at ΔT.	$Adj_{kk'}^{aa'}$: binary adjacency matrix reflecting that agent a' located in position $k' \in V_c$ and agent a located in position $k \in V_c$ are within respective communication range and can mutually exchange (or not). $\|V_c\| = mK$ Communication: svc_{ia}: agent a service time associated with vertex $i \in V_c$, accounting for agent a communication duration (assumed to be zero by default to maximize planned collection value).

Decision variables

x_{ia}: agent a collection network binary decision variable indicating whether node i is scheduled. The assignment $x_{ia} = 1$ indicates that vertex i visit is scheduled. Note that for $k \in V_c$ reflecting candidate position nodes ensuring periodic information exchange at time ΔT, the instantiation $x_{ka} = 1$ refers to an agent disseminating observation outcomes/ receiving revised collection plan from/in position k.

u_{ija}: agent a collection network binary flow decision variables characterizing node transition from i to j. The assignment $u_{ija} = 1$ indicates a transition from node i to j.

seq_{ia}: integer or real decision variable, serializing visits in the agent a collection network to avoid undesirable disjoint directed cycles as subpath solutions. $0 \leq seq_{ia} \leq SEQ$.

The decision model consists in maximizing collection value CV as follows:

$$\max\ CV = \sum_{r \in M} v_r \left(\sum_{a \in Ag} \sum_{i \in V_{G_{1a} \cup G_{2a}}(r)} q_{ia} x_{ia} - \sum_{a \in Ag} \sum_{i \in V_{G_{1a} \cup G_{2a}}(r)} \sum_{a' \in Ag} \sum_{\substack{i' \in V_{G_{1a'} \cup G_{2a'}}(r) \\ (i,a) < (i',a')}} (q_{ia} + q_{i'a'} - q_{iai'a'})\, x_{ia} x_{i'a'} \right)$$

Subject to:

$x_{ia} = \sum_{k:(k,i) \in A(G_{1a} \cup G_{2a})} u_{kia} \quad i \in V_a/\{o, D\}, a \in Ag$ (2)	Bound on node visits: $\sum_{i:(i,j) \in A(G_{1a} \cup G_{2a})} u_{ija} \leq 1 \quad j \in V_a, a \in Ag$ (3)
Periodic communication: $\sum_{(i,j) \in A(G_{1a})} (svc_{ia} + travel_{ija})\, u_{ija} \leq \Delta T \quad a \in Ag$ (4)	Planning time horizon: $\sum_{(i,j) \in A(G_{1a} \cup G_{2a})} (svc_{ia} + travel_{ija})\, u_{ija} \leq T \quad a \in Ag$ (5)
Itinerary/Duty cycle: $\sum_{(i,j) \in A(G_{1a} \cup G_{2a})} dist_{ij} u_{ija} \leq dist\_max_a \quad a \in Ag$ (6)	Energy collection budget: $\sum_{i \in V_a} eo_a svc_{ia} x_{ia} + \sum_{(i,j) \in A(G_{1a} \cup G_{2a})} es_a (setup_a + travel_{ija})\, u_{ija} \leq E_a^{coll} \quad a \in Ag$ (7)
Collection cost: $\sum_{a \in Ag} \sum_{i \in V_a} cost_{ia} x_{ia} \leq cost_{max}$ (8)	
Connectivity: $x_{ka} \leq \sum_{a' \neq a,\, (k'a') \in S_{l-1}} Adj_{kk'}^{aa'}\, x_{k'a'} \quad a \in Ag,\, k \in V_c, (k,a) \in S_l,\, l \in \{1..L\}$ (9) $\sum_{(k\,a) \in V_c \times Ag/sink \mid \cup_l S_l} x_{ka} = 0$ (10)	
Known sink node position for communication rendezvous *RDV*: $x_{k^{RDV}sink} = 1$ (11)	

Flow Conservation: $\sum_{i:(i,j)\in A(G_{1a}\cup G_{2a})} u_{ija} - \sum_{k:(j,k)\in A(G_{1a}\cup G_{2a})} u_{jka} = 0 \quad j \in V_a/\{o,D\},\ a \in Ag$ (12)	
Origin and destination path nodes: $\sum_{i\in V_{1a}} u_{oia} = 1,\ \sum_{i\in V_{2a}} u_{iDa} = 1 \quad a \in Ag$ (13)	Disjoint subpath solutions free (prohibited isolated cycles): $seq_{ja} + SEQ(1 - u_{ija}) \geq seq_{ia} + 1 \quad (i,j) \in A(G_{1a}\cup G_{2a}),\ a \in Ag$ (14) $seq_{ia} \leq SEQ\ x_{ia} \quad i \in V_a,\ a \in Ag$ (15)
$x_{ia}, u_{jka} \in \{0,1\} \quad i \in V_a, (j,k) \in A(G_{1a}\cup G_{2a}), a \in Ag$ (16) $seq_{ia} \geq 0 \quad i \in V_a, a \in Ag$	

The episodic mixed-integer quadratic program consists in maximizing swarm collection value as governed by Eq. (1), subject to constraints (2)-(16). It is defined as the cumulative products of respective task value (weight) and related task plan quality of collection, summed over all visited tasks. In Eq. (1), V(*r*) ⊂V refers to vertices relevant to task *r*. Swarm collection value maximization correlates with persistent situational awareness maintenance and may be expressed through relative coverage over search tasks, probability of success over detection/localization/tracking tasks and information gain (minimize entropy) over target/behavior identification tasks. Explicit quality of collection functions involving various sensor mix utilization for such tasks may be found in [10]. Constraint sets (2)-(3) capture node visit and flow variables relationship and, a single node visit at most. Expressions (4)-(5) reflect gent path solution temporal constraints. Inequalities (6)-(8) refer respectively to episodic maximum traveling distance defining a duty cycle, an energy budget devoted to collection activities and a financial budget associated to each visit. Periodic swarm/network connectivity is translated by the constraint formulation (9)-(11), based on iterative neighborhood sets construction. Combined with flow conservation, inequality (9) iteratively ensures swarm connectivity, connecting agents positioned in consecutive neighborhood sets S_l and S_{l-1} distanced by one hop, back-propagating up to the sink position. The latter naturally imposes all current agent positions at time ΔT to be part of neighborhood sets, a condition reinforced by inequality (10) to exclude disconnected/prohibited communication zones, and subject to a known predetermined sink location at ΔT expressed by Eq. (11) to ensure a link to a remote base/command station. Graph flow conservation is ensured through constraints sets (12)-(13). Inequalities (14)-(15) prohibit unsuitable disjoint cyclic subpath components, imposing an implicit order by sequencing node visits. Should task time windows be considered, inequalities (14)-(15) would be modified to introduce a continuous node time variables $t_{ia} \in [0,1]$ defining effective node *i* visit time in order to meet visit ordering/precedence and time window ($t_{ia} \in \left[\frac{T_i^l}{T}, \frac{T_i^u}{T}\right] x_{ia}$) constraints respectively:

$$t_{ja} + (1 - u_{ija}) \geq t_{ia} + \frac{(svc_{ia} + travel_{ija})}{T} \quad (i,j) \in A(G_{1a}\cup G_{2a}),\ a \in Ag \tag{14'}$$

$$\frac{T_i^l}{T} x_{ia} \leq t_{ia} \leq \frac{T_i^u}{T} x_{ia} \quad i \in V_a,\ a \in Ag \tag{15'}$$

Binary integer and continuous decision variable domains are specified in expressions (16).

3.3 Communication Planning/Routing

Cumulative sensor observations and task plan dissemination between sensor agents is assumed to be driven by limited on-board sensor power budget making casual information-sharing via intermittent contacts very costly. This energy-constrained communication condition rather imposes the swarm to adopt a suitable topological configuration to ensure periodic connectivity. Information-sharing is devoted to disseminate observation outcomes and to enable centralized sensor fusion and episodic dynamic replanning at the sink site.

Periodic data dissemination enabling feasible sensor data routing is facilitated through an innovative linear constraint formulation based on recurrent node neighborhood construction, reinforcing sensor network connectivity or topology control at the end of each period. Relieved from maintaining persistent connectivity, collector network nodes can then cost-effectively reach attractive distant sites, improving overall situational awareness. Observations locally collected by sensor agents are then disseminated toward the sink node at the end of each episode. Dissemination is based on a minimum spanning tree agent network (swarm) solution over an undirected graph, minimizing overall communication cost. A minimum spanning arborescence extracted from a directed graph would alternatively be derived should asymmetric communication be considered. A minimum spanning tree is a subset of weighted edges extracted from a connected graph relating all vertices together, without any cycles and with the minimum possible total edge weight (e.g. communication cost) as shown in Figure 5. Such a tree is generated at the sink site in polynomial time using Kruskal’s method [11] for an undirected graph or Edmond’s algorithm [12] for a directed graph. It can be exploited to both ensure collected data dissemination and, local sensor agent retasking over the next episode. Consequently, the resulting tree structure may be shared across the team, making members topology-aware ahead of time. Accordingly, topology-awareness at communication time enables swarm nodes (sorted in decreasing hop-distance order to the sink) to easily and quickly derive low cost message routing tables. It minimizes overall message-passing, further down toward the sink, therefore reducing energy consumption to a bare minimum.

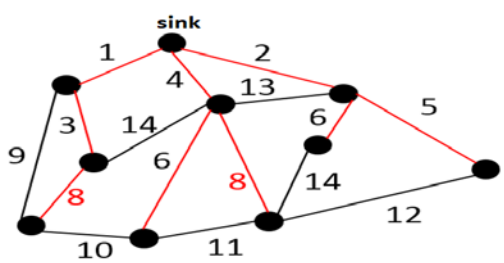

Figure 5 – Swarm minimum spanning tree structure shown in red, connecting the root (sink) to other sensor agents. Weights on edges refer to communication cost.

4.0 DISCUSSION - COMPLEXITY REDUCTION

Problem complexity can be further reduced considering a combination of factors such as temporal discretization, shorter planning time horizon, and restricted search space exploration limiting graph node transitions to nearest neighbor tasks to overlook unnecessary high cost transitions. Connectivity constrainedness drives also complexity as it strongly depends on candidate position set cardinality over possible agent positions to achieve periodic communication and information-sharing. Some strategies may nonetheless be envisioned to reduce computational complexity and simplify problem-solving. They provide faster computation and easier constraint handling at the cost of additional traveling time, energy consumption and opportunity losses resulting in information gain or collection value degradation. A first scheme might consist to bound the number of candidate positions sparsely distributed between close/neighbor task sites while ignoring unlikely intermediate positions between distant task locations. This comes at the expense of additional waiting time and possibly slight collection value degradation. Distance separating neighbor candidate positions should be larger than minimum agent communication range. An alternate strategy is to impose symmetric communication to facilitate information-sharing between the sink and agent nodes in both directions. Partitioning sensor agents in subteams or confining their movement to a closed neighborhood to ensure periodic local connectivity with the base station is another option, but may significantly impact solution quality. At the other end of the spectrum, imposing a team rendezvous position among predetermined candidate locations, or simply relying on a subset of dedicated agents defining communication hub nodes in a fixed subnetwork guaranteeing periodic swarm connectivity, remain of course optional well-known fallback strategies. However, it is unclear that benefits expected from those naive and convenient communication schemes will outweigh the multiple collection opportunity losses and the additional energy consumption and travel costs incurred by all sensor agents to share information.

5.0 CONCLUSION

An innovative swarm collection tasking approach has been proposed to maintain persistent situational awareness in a tactical setting. It defines a new open-loop with feedback decision model problem formulation for a mobile ad hoc sensor network/swarm aimed at maximizing collection value in servicing a diversity of tasks subject to a variety of resource capacity and side constraints. The selection of a centralized decision-making configuration mediated through a sink node is mainly driven by energy constraint considerations. Exploiting a new compact graph representation to capture combinatorial complexity, and using a sound approximate decision model, asset tasking relies on path planning optimization over a receding time horizon while periodically imposing sensor connectivity in order to efficiently support data and plan dissemination enabling fusion, situational awareness and dynamic retasking/planning. Accordingly, adaptable to easily reflect or mimic known information-sharing schemes, a novel connectivity constraint is introduced to take on the mobile ad hoc sensor swarm collection tasking decision model, extending swarm's ability to better meet task demand. The latter condition plays a key role in relaxing artificially imposed connectivity constraints, further expanding observable domain, and reducing energy consumption expectedly resulting in additional information gain. The new problem formulation also paves the way toward a computable upper bound on solution optimality, if exact problem-solving methods are used.

Future work aims at implementing problem-solving algorithms to carry out comparative performance study as well as investigating the relative impact of various swarm communication schemes on collection gains. Other research directions include learning collection tasking coordination, collective belief-sharing management, and fusion in distributed settings involving multiple co-evolving clusters. Alternative work consists to explore adaptive planning and communication coordination under harsh operational conditions, data source heterogeneity, and net latency due to unreliable communication channels or node failures.

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