Agent-Task Assignation Based on Target Characteristics for a Swarm of Specialized Agents

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***Abstract*— A systemic agent-task specialized assignation approach for collaborative unmanned systems is introduced in this paper. It is formulated by matching specialized robotic agents with the recognition of specific characteristics on targets in an environment. The recognition stage leverages visual features detection on objects present in the surrounding of the robotic agents via embedded sensors. A given target's zone of influence is generally defined as a circular area surrounding any detected target object, with the latter corresponding to a specific task to be dealt with by a specialized robot. Within the zone of influence around a target a switching process for the leadership of the swarm is initiated. Appropriateness of assignation, smoothness and safety of the transition form the major factors of performance considered. The framework is formulated to deal with static and moving targets and their corresponding zone of influence, which leads to the consideration of overlapping task zones. The proposed system involves robots control, leader switching and agent-task assignation processes in relation with the detected target characteristics. Simulation experiments are conducted to validate the proposed system, and demonstrate that an effective coordination of the specialized agents around the corresponding targets is achieved.**

Keywords*— *Specialized agents; heterogeneous robots; tasks assignation; formation control; robots coordination; swarm robotics.

I. Introduction

Motivated by the latest developments in the field of unmanned autonomous systems and cooperative control, this research aims to contribute to the evolution of the future generation of collaborative robots, for them to be smarter, more accurate and specific. For that matter, the individual robots, or agents, of collaborative robotic systems will need to be specialized, while ensuring accuracy and ability to perform diverse tasks.

General coordination of the formation is a critical asset in swarm robotics. In this paper, specialized agents are considered. Individual robot members of the swarm are assigned to specific tasks to be performed in the environment, based on sensors or actuators embedded on each robot. Tasks are associated respectively with specific types of object. A central assumption is also that the selected specialized agent will take the leading role of the swarm once associated with a specific task, until the latter is completed. As a result, swarm's reformation and efficient transition in the robot's leading role must be achieved. Therefore, the goal of this research is to evolve a swarm of robots to be well functioning as collaborative agents, under considerations of specialization of the agents.

Turgut et al. [1] report a flocking behavior method for a swarm of robots. Motion coordination for a group of heterogeneous mobile robots is also introduced by Stranieri et al. [2]. These methods provide solutions to multi-robot systems from a flocking coordination point of view, while the coordination of the individual agents is controlled with equal properties. A collective transportation method is proposed by Ferrante et al. [3] for a group of three robots to collect an object to be transported between two locations. However, the main task of the swarm is to transport the target object by combining equal capabilities from the whole group of robots. Wessnitzer and Melhuish [4] propose a multi-robot behavior mechanism to enable a swarm of robots, and to decide which one of two targets to be captured first. At the end, the distributed robots converge into one large group to hunt one target at a time, while the distributed individuals are initialized with equal coordination probabilities.

A resource selection mechanism is proposed in [5] to choose the best resources available, which can fit the group's needs. The collective group's behavior leads the available agents to enter and stay at the same resource. Discrimination is applied to select the best resources, but the proposed mechanism also considers robots as similar functioning agents. Recently, Scheidler et al. [6] proposed a collective behavior decision-making method for multi-robot systems or swarms. The method enables the robots among the swarm to select action priority. However, the authors mention that the collective behavior leads all robots to execute the same action.

Ma and Koenig [7] introduce an optimal target assignment and path finding (TAPF) approach for swarms of robots to partition the swarms into groups, and to assign each agent among each group to a target. The proposed TAPF approach minimizes the targets' make span. However, it addresses the problem from the perspective of assigning equal agents to equal targets. A software application for tasks assignment purposes in a heterogeneous swarm is designed in [8]. The proposed

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algorithm divides the tasks into smaller sub-tasks which are then assigned to an optimal number of agents. Zavlanos et al. [9] propose an auction algorithm that allows every agent to independently determine a task to be assigned to. The agents can bid for the tasks to which they wish to be assigned to. However, the proposed actuation algorithm treats the agents equally and assigns the individuals based on local information without considering any specialized constraints. An auction method for agent-task allocation in multi-agent systems is also proposed in [10] based on the Contract Net Protocol. This approach assigns the applicable robots to perform the current task but the cooperation is at the level of the agent-task assignment only. This approach enables the cooperation between the auctioneer agent and the capable agent to respond to the current task, but then the system agent undertakes the execution process as a single agent system.

This paper studies the problem of robotic swarm coordination from a different perspective to most of the current literature. More specifically, it examines the design of a multi-agent collaborative team involving specialized agents. The latter are defined as a number of robotic agents with different and specific capabilities. The proposed approach solves the problem of specialized agent-task assignation using a formulation of collaborative formation. The specialization of each agent can be related to the type of unmanned system considered (UGV, UAV, UUV), or take the form of particular robot embedded sensors, actuators, computational power, or communication links. The main concept is to make each robot best prepared or equipped to respond to a certain range of tasks, such as exploring, collecting, holding, tracking, etc. For example, in a search and rescue scenario for a person lost in forest, consideration must be given to the presence of lakes and different land characteristics, as well as to the nature of the task, rescuing a person. In this case, an ideal swarm would be composed of agents that have different capabilities, such as agents designed to operate on irregular grounds, and others on water-covered areas. The agents' embedded functionalities should also be specialized toward robots with capabilities to detect humans via vision or infrared sensors, others to provide first aid, and some equipped to grasp, lift up and carry a body.

The proposed framework formulates a rigorous process to improve adaptivity and responsiveness of the swarm, by taking into account such specialized agents. It also defines how the swarm formation is managed in the robots workspace. Finally, it establishes how the formation transition happens from each specific task to the other. As a result, a generic framework for coordinating a swarm of heterogeneous robots, driven by agent-task specialty matching, is formulated. This paper represents a significant expansion on previous work [11] to tackle more advanced and realistic scenarios in the context of unmanned systems.

II. PROPOSED APPROACH

The proposed framework is composed of a two-stage cascaded control structure, shown in Fig. 1. The system relies on: 1) an original Automatic Task Selection Unit (ATSU), which is responsible for the decision making process and tasks selection, and represents the core component of this paper; and 2) a dynamics and swarms formation control stage that ensures smooth navigation of the swarm, which is detailed in [11]. In the proposed strategy, the task selection system operates in two main modes, a manual mode and an automatic mode. The system's operator is given an access at a supervisory level to switch in between these modes at the beginning of the operation. That is, choosing whether the robots should search for a specific pre-identified task to be performed, in manual mode; or to run in automatic mode where the swarm of robots will rely on an embedded sensory stage to explore their surrounding environment and identify various objects uniquely associated with tasks to which they will respond. Accordingly, for each detected task, the system will evolve through three corresponding states that are a *Search state*, a *Task state*, and an *Execution state*. Fig. 2 presents a schematic diagram of these three states and the related search, task and execution zones.

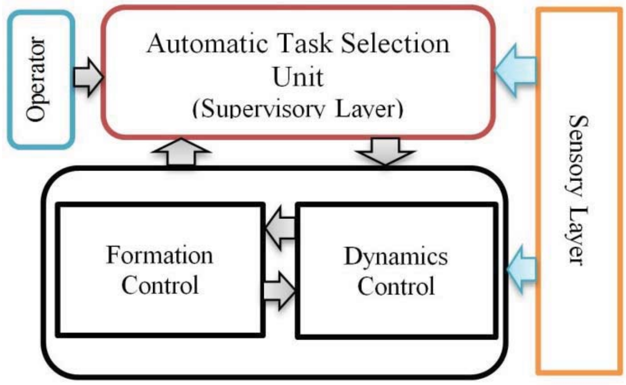

Figure 1. Proposed control structure.

A cooperative leader-follower formation is adopted in the search state to scan the environment (gray area in Fig. 2) until sensors mounted on-board the robots recognize a given task to be performed, implemented as a specific target object in the environment, and within reach of the formation. Next, the system executes the process of agent-task assignation that selects the most qualified robot to intervene on the specific task detected, as will be detailed in Section III.

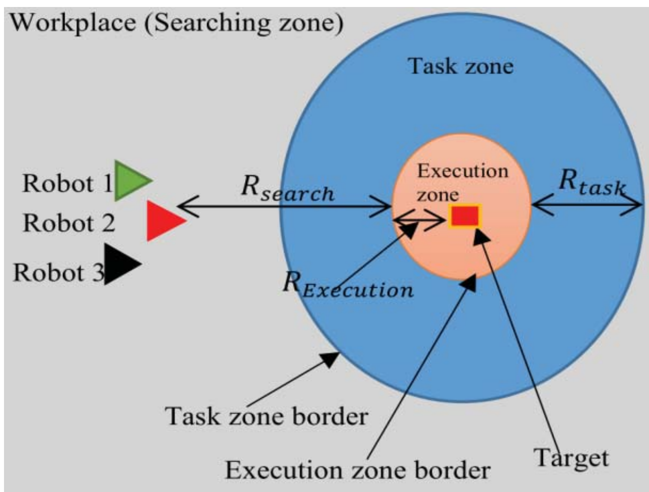

Figure 2. Three states of operation (Search, Task, and Execution).

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III. Operation Modes and States

As mentioned above, the task assignation problem is modelled under two different modes: manual or automatic. Under manual operation, an external operator preselects the target location, while under automatic operation the system uses embedded sensors to search for a desired target while patrolling the workspace. Once the group of robots is located within a given subspace, their initial priority is to navigate over that subspace and search for recognizable targets upon which they can perform a specific task. During this searching process, the robots navigate and keep a cooperative formation where a by default swarm's leader generates the path and the other group members follow.

A. Manual Mode

In the manual mode of operation, the system is driven under close supervision with a human-in-the-loop approach. The human operator can intervene to send a specific robot to a known location, while that robot will still perform the task autonomously once assigned to it. This mode is suitable when there is a known number of tasks to be achieved at known locations. The human operator commands the system to reach a specific target, one at a time. This can improve efficiency when relying on on-board task detection is not necessary, or even possible. Then, the cooperative swarm proceeds iteratively through the three states defined in Section II for each target. After the task is completed, the ATSU takes control and robots stand and wait for the operator to command them to change the mode of operation to automatic, or keep to the manual mode while aiming at a new manually identified target.

B. Automatic Mode

When the specificity, locations and number of tasks to be executed are not known in advance, the automatic task selection mode is preferable. It supports automation of the task detection and recognition, the assignation of the proper specialized agent, and the task execution processes. In automatic mode, robots aim to collaboratively complete the entire series of tasks which can be detected in the workspace, while leveraging the specializations available among the group of agents. This process capitalizes on the visual characteristics of target objects that make them recognizable without consulting a supervisor.

C. Search State

To make the proposed framework generic, specialized robotic agents are identified as $A \in \{1, \ldots, a\}$, where a is the number of agents available. Different tasks are assumed to be available in the environment, each identified as $T \in \{1, \ldots, t\}$, where t is the number of different target objects that the system can recognize, each being associated with a specific task. Under specialization considerations that are emphasized in this work, a specific agent is chosen to perform each of these specific tasks, as defined through a lookup table.

Let us assume that the agents start their navigation while searching for the tasks existing in the workspace. One of the specialized robots is assigned as the default group leader during the search phase. The path of the swarm is then planned to begin from the current initial positions of each of the agents. The trajectory is designed to make the swarm survey the entire workspace in order to successively perform all tasks that can be detected. For the sake of system's validation and simulation, the coordinates of robots are defined in a global reference frame XY, as shown in Fig. 3. The position of each robot is defined as its center point, (x_A, y_A).

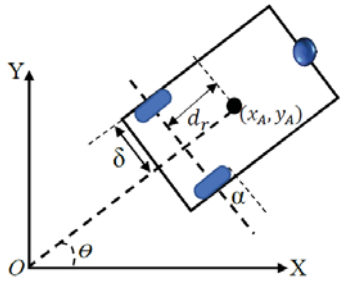

Figure 3. Coordinates of mobile robot in global frame {X,Y}.

D. Task State

When the sensing system mounted on robots recognizes a given target and localizes it, at position (x_T, y_T) in the global reference frame, and also identifies its type T_{type}, corresponding to a specific task. The system measures the Euclidean distance between the target and the center point coordinates, (x_{center}, y_{center}), for all robots in the swarm, estimated by eq. (1), as the group of robots continues to approach the given target position.

$$[x_{center} \quad y_{center}]^T = \frac{1}{a}\sum_{i=1}^{a}[x_i \quad y_i]^T \qquad (1)$$

This process continues until the group of robots enters the area that surrounds the selected target. A variable radius, R_{task}, characterizes the task's zone of influence that surrounds any target, represented as the task zone border in Fig. 2. The radius is predefined based on the depth of field of sensors embedded on the robots and operates as a switching edge to trigger the transition of the swarm to the task state in preparation to execute an operation on the recognized target object. As soon as the center point of the swarm formed by all robots involved enters the task zone, the ATSU identifies which agent is competent to perform this specific task based on Algorithm 1, then it switches the swarm's state to the task state and assigns the selected agent to become the leader of the swarm.

Algorithm 1: Leader selection from specialization

Step1: RGB-D sensing detects task and estimates the
$Task\ parameters = (x_T, y_T, T_{type})$
Step2a: Estimate Euclidean distance (ED) between (x_T, y_T) and current center point position of the swarm,
$[x_{center} \quad y_{center}]^T$; then compare ($ED$) with ($R_{task}$).
ATSU: if $ED \leq R_{task}$ then switch to Task state.
else remain in Search state;
Step 2b: ATSU checks Task Type (T_{type});
Select suitable specialized robot to perform the recognized task, via lookup table as new swarm's leader
L = specialized A; where $A \in \{1, 2, \ldots, a\}$
Return leader agent identity, L.
Step 3: Assign new leader coordinates:
ATSU: with $i = L$, where $L \in \{1, 2, \ldots, a\}$
new leader position $(x_l, y_l) \leftarrow (x_i, y_i)$;
Return the new leader coordinates (x_l, y_l).

Within the task zone, the new leader coordinates (x_l, y_l) are computed from the current position of the assigned agent, (x_L, y_L). While the system operates in the task state, the swarm smoothly transitions its formation to a new distribution adequate to perform the given task, with the most competent agent now leading the formation. Then, the robots continue approaching the target until they reach close to it.

When the switching to a new leader takes place, its current state, which was reached during the search state, is considered as the start point to reach further toward the target, that is:

$$State(L) = [x_l, y_l, \theta_l, V_l, \omega_l]^T \quad (2)$$

where θ_l represents the current heading angle of the leader robot, and V_l, ω_l correspond to its current linear and angular velocities. Then an iterative local path planning process is defined where the next desired position for the leader within the task zone is computed at each time step as the middle point between the task position and the current position of the assigned leader. Collision avoidance is dealt with at a lower control level using repulsive potential fields, as discussed in [11]. Assuming that the current position of the leader is (x_l, y_l) and the task position is (x_T, y_T), then the next desired state for the leader in the task zone is:

$$\mathrm{State}'(\mathrm{L}) = [x_l', y_l', \theta_l', V_l', \omega_l']^T \quad (3)$$

where the new leader position is defined in eq. (4) and (5), and the heading angle of the robot, θ_l', is set to aim toward the target's position, as defined in eq. (6).

$$x_l' = x_l + \frac{x_T - x_l}{2} \quad (4)$$

$$y_l' = y_l + \frac{y_T - y_l}{2} \quad (5)$$

$$\theta_l' = \mathrm{atan2}\left(\frac{y_l' - y_l}{x_l' - x_l}\right) \quad (6)$$

The updated linear and angular velocities (V_l', ω_l') of the leader are calculated as follows:

$$\begin{bmatrix} V_l' \\ \omega_l' \end{bmatrix}^{\mathrm{T}} = \dot{q}^T S^{-1} \quad (7)$$

where:

$$\dot{q} = [(x_l' - x_l), (y_l' - y_l)]^T \quad (8)$$

$$S = \begin{bmatrix} \cos(\theta_l') & -d_r \sin(\theta_l') \\ \sin(\theta_l') & d_r \cos(\theta_l') \end{bmatrix} \quad (9)$$

where d_r is the distance between the center of the robot and its rear axle, as shown in Fig. 3.

While the leader traverses the task zone, the followers continue their progression up to the execution zone border and then hold their positions until the assigned specialized agent completes the task.

E. Execution State

During the progression, robot embedded sensors continue to monitor the distance separating the task position, (x_T, y_T), from the assigned leader coordinates, (x_l, y_l). Simultaneously, the leader continues to approach the target. From the moment the leader hits the execution zone, of radius $R_{execution}$, the ATSU switches the swarms' formation to the final state of the process. The execution state ensures that the selected specialized robot performs the task. The follower robots then reconfigure themselves to reach a distribution around the leader, and they stop at the execution zone border. During the execution state, the followers are meant to provide a cooperative coordination and are exploited as stationary sensors to support accurate localization of the leader robot while it performs the task.

IV. Special Cases

A. Dual Task Zones

The proposed framework is designed to consider realistic scenarios encountered with collaborative robots in normal operation. A first case is that of dual task zones, which correspond to areas in the workspace that are within the zone of influence of more than one target, as a result of targets that exhibit a large area of influence, or moving targets which make their respective area of influence to overlap with others for certain periods of time. This scenario is illustrated in Fig. 4, where two targets (blue and red) share a mutual portion of the workspace. The proposed ATSU is designed to tackle such situations. Whenever dual task areas of influence are detected close to the location of one of more targets, the system switches temporarily to manual mode and the operator is consulted to choose which target is given the execution priority. Then, the ATSU drives the system to perform the preferred target first. Once that target is resolved, robots move directly toward the second target that is located in the dual task area. When all of the dual zone's targets are executed, the ATSU switches formation control back to the search state in automatic mode, which resumes the regular operation to look for a new task in the workspace. This introduces an interesting level of prioritization into the framework which can serve several purposes, including strategic guidance for human-in-the-loop systems. For the purpose of validation in simulation, the operator is considered as a human being. However, this layer in the controller could be replaced by an automated supervisory layer.

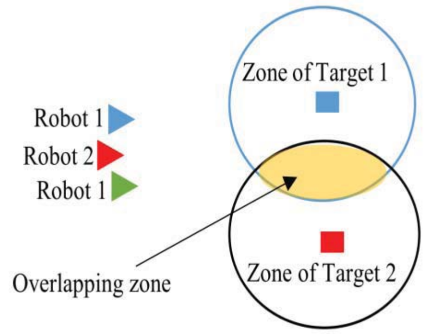

Figure 4. Overlapping zones of influence.

B. Moving Targets

Another important case to be considered is when targets are changing their position over the workspace, such as in scenarios where people, animals or motorized devices are associated with tasks to be performed (e.g. assistive robotics or moving threats). Such scenarios are also supported in the proposed automatic mode of operation. When robot embedded sensors report different positions for successive measurements on a given target, the formation control scheme exploits an additional and specially designed “target following” intermediate state. This state temporarily replaces the task state, and the swarm keeps following the mobile target until it is reached. This assumption is supported by the fact that whenever a target would be continuously moving faster than the maximum speed the group of robots can reach, the completion of the task would be compromised anyhow. Once the target can be reached, the usual execution state is triggered and the task completion proceeds normally. An overview of all operational modes and full mission operation is presented in the flowchart of Fig. 5.

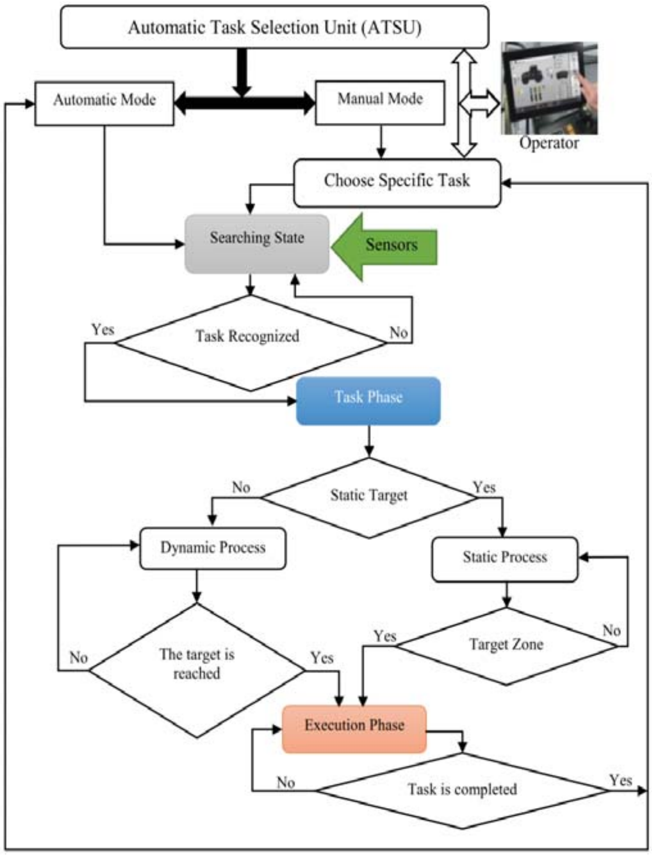

Figure 5. Schematic structure and sequencing for all operational modes.

V. Experimental Results

Simulation experiments are conducted to validate the conceptual framework using Simulink. For system’s validation purposes the case with three robots, $a = 3$, to serve as specialized agents associated to three different types of targets, $t = 3$, is considered. Here, it is assumed that every agent is specialized to only perform one type of task. For clarity and generality, the specialized agents and the corresponding tasks to be matched are marked with corresponding colors. Colored lines in Fig. 6 to 9 depict robots’ paths, and tasks are represented by colored square dots circled by dotted lines. The latter indicate their respective zone of influence. In the automatic mode of operation, during the search state, the agents navigate over the workspace and keep their cooperative group formation as they follow the swarm’s default leader (e.g. “red triangle” agent in Fig. 6a) until the on-board sensing system recognizes a first target (blue square). Thereafter the system switches first to the task state where the blue agent becomes the leader, and subsequently to the execution state, as shown in Fig. 6b-d to perform that task. The system returns back to search for a new target and automatically transitions the formation to re-assign the default leader (red triangle) ahead of the swarm (Fig. 6e-f) with the other agents performing as followers again. Subsequently, the ATSU assigns the proper specialized agents to perform other available tasks (blue agent in Fig. 6g; green agent in Fig. 6i), therefore alternating in between search, task and execution states (Fig. 6e-j), as expected. In Fig. 6k-l, when a red target (red square) is detected, the system assigns the red agent (red triangle), which is also the default swarm’s leader, to execute the detected task. The red agent therefore continues to lead the swarm through the task and execution states. For simulation purposes, a task is considered fulfilled when the proper specialized robot hits the position of the matching target. Then the target symbol changes to black, which indicates that the given task has been executed, as shown in Fig. 6d, h, i and l.

When the manual mode of operation is selected, this means that one target, manually selected by the operator, is the first one to be performed. In this case, the ATSU immediately selects the robot that is the one specialized to execute this specific task and this robot immediately becomes the leader. Fig. 7 provides an illustration of such a situation as the group of robots skips over the blue task because the red task was manually selected by the operator and therefore has priority. As such, the red robot becomes the leader and drives the group toward the red target while the blue robot remains a follower even though the group passes close by the blue target. This scenario demonstrates the flexibility of the proposed framework to reliably implement prioritization functions in the control of the swarm. Following priority task completion, the swarm can either resume to search state in automatic mode, or be provided a second priority target to execute in manual mode.

Fig. 8 represents the condition of overlapping zones of influence, that is when more than one target’s zone of influence share common sections of the workspace. In such a scenario, the ATSU consults the system’s operator to select the target that should be executed first. In the simulation illustrated in Fig. 8a, the operator selects the red task to be performed in priority. Once the selected task is completed (Fig. 8c), then the robots switch the leading role automatically to execute the blue task as it shares the same area of influence. The new leader (blue) is smoothly transferred into the leading role for the group of agents while the other agents become followers, as shown in Fig. 8d-f. Once the conflicting tasks are resolved, the swarm switches back to the regular process outside the dual-task zone, as shown in Fig. 8g-h. The default red leader agent drives the swarm in exploration to eventually perform the left-hand side green task and the other red tasks successively.

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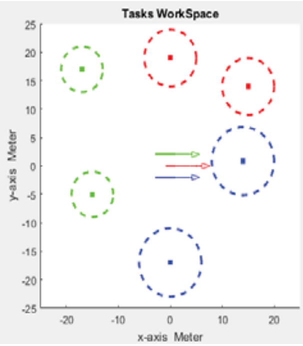
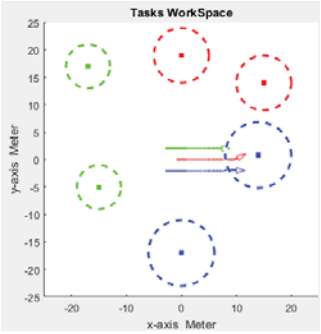
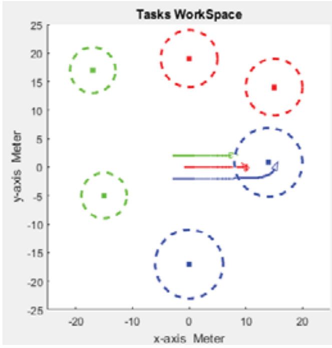


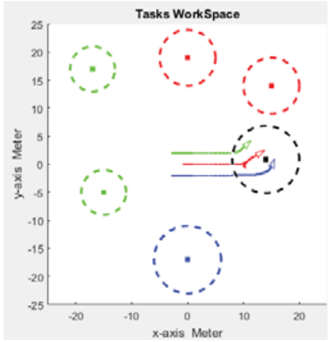
(a): Robots in Search state with red leader.



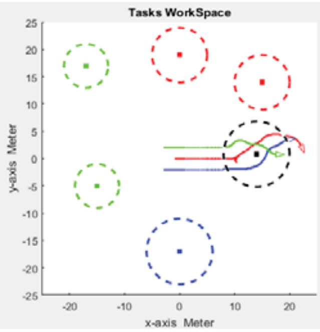
(b): Robots switched to Task state.



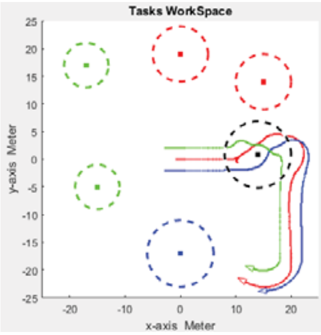
(c): Execution state with blue leader.



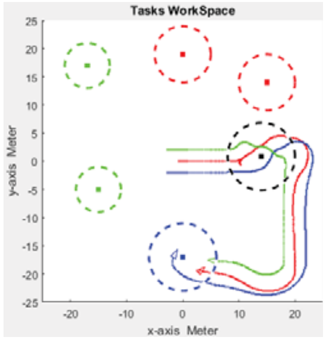
(d): Blue task completed.



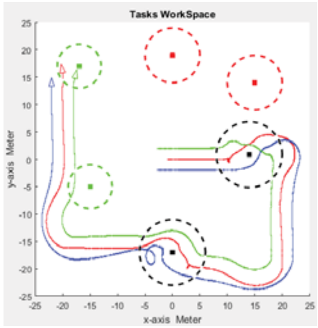
(e): Back to Search state with red leader.



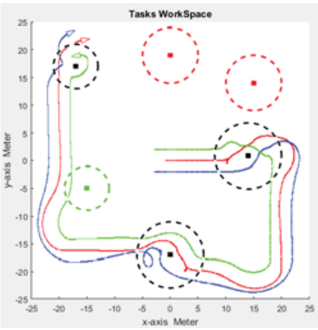
(f): Robots in Search state.



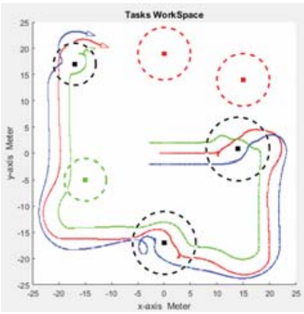
(g): Switched to execute the second blue task.



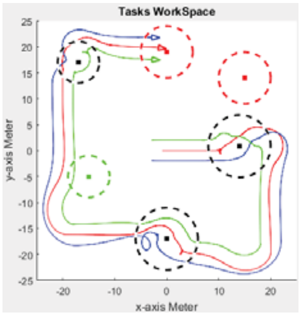
(h): Green task out of sensing range (skipped).



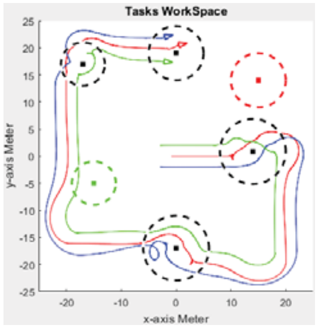
(i): Third detected task (green) executed.



(j): Swarm switched back to Search state.

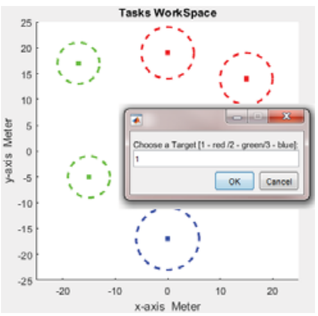


(k): Swarm switched to execute red task with default leader (red robot).

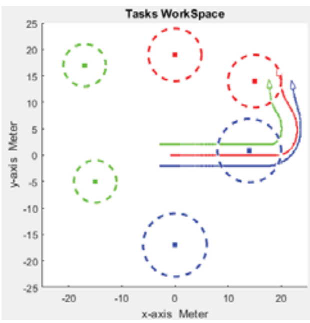


(l): Forth detected task (red) executed.

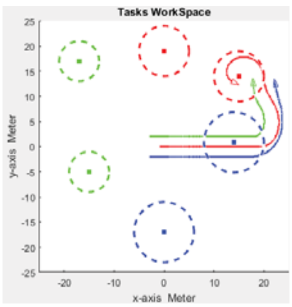
Figure 6. Successive tasks completion in automatic mode of operation.



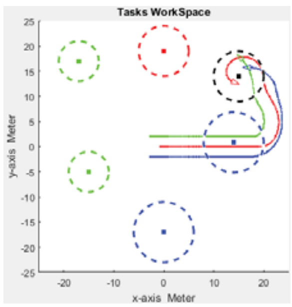
(a): Task type1 (red) selected by supervisory layer.



(b): Heading towards the first red target.

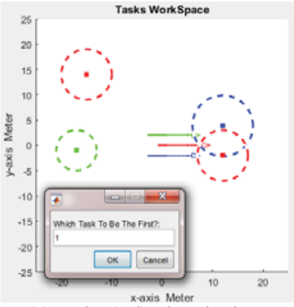


(c): Priority task under execution.

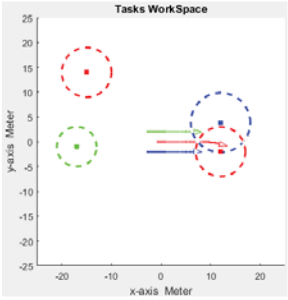


(d): Priority task completed.

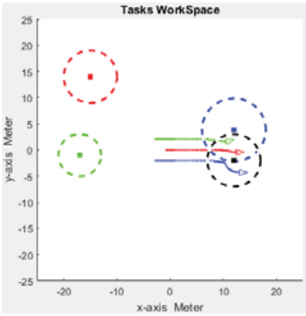
Figure 7. Specific task completion in manual mode of operation.



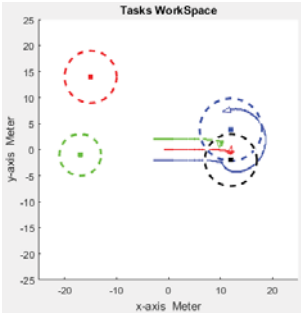
(a): Task 1 (red) selected to have priority.



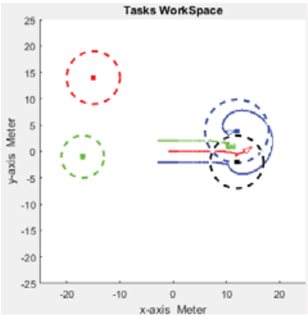
(b): Red robot remains leading to complete red task.



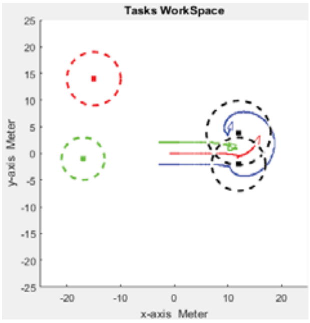
(c): Red task completed.



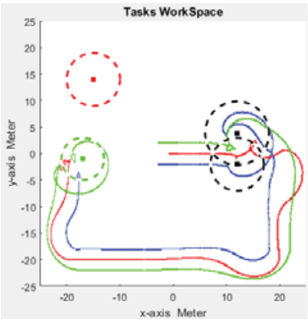
(d): Blue robot becomes leader until 2nd task completion.



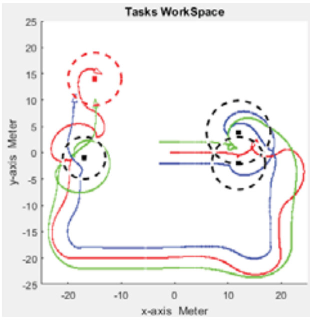
(e): Blue leader executing the blue task.



(f): Blue task completed.

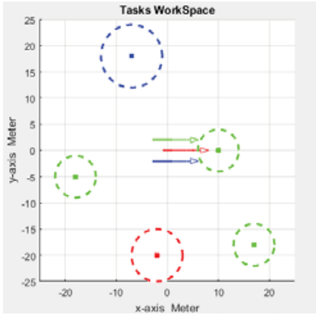


(g): Green task performed (regular process).

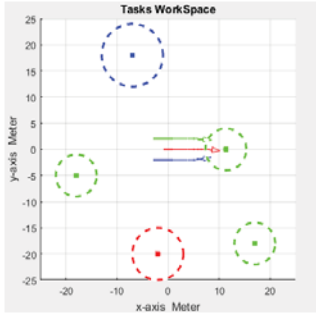


(h): Red task performed (regular process).

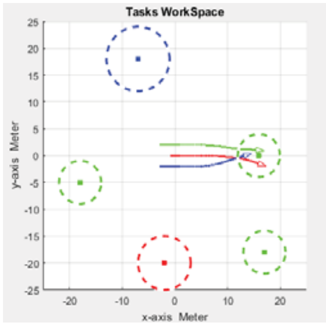
Figure 8. Successive tasks execution with (a-c) overlapping zones of influence with task 1 (red) selected by operator as having priority, which drives the red robot to remain the leader until the red task is completed; (d-f) second priority task (blue) being performed with blue robot transitioned to leader position; and (g-h) swarm resumes to the search state outside the overlapping zones of influence, then searches for other tasks (green, then red) to be executed with corresponding leader robots.



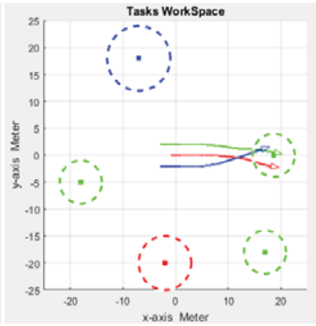
(a): Green moving target detected (Target Following state).



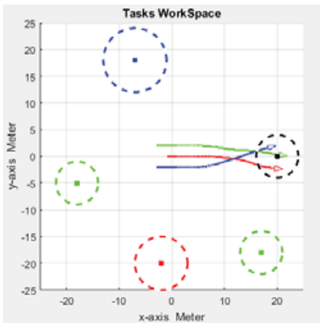
(b): Target reached while being pursued by the swarm.



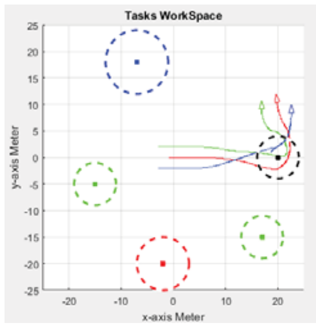
(c): Green agent transitioning toward leader position.



(d): Execution state with green leader.



(e): Green task completed.



(f): Swarm switches back to Search state with default red leader.

Figure 9. Scenario with a dynamic target: (a) green moving target detected; (b-c) green target being pursued by group of robots with green agent transitioning toward leader position; (d-e) green target reached and task executed by matching green leader robot; and (f) swarm pursuing search for other targets with default red leader agent returning to leader position.

Finally, Fig. 9 shows a scenario where a moving target is involved. The swarm of robots initially follows a moving green target while it attempts to evade from the swarm. The temporary "target following" state is triggered until the target can be reached by the swarm (Fig. 9a-c). At that point, the corresponding specialized green agent is assigned as the leader agent and executes the task (Fig. 9d-e). Once completed, the system returns in the standard search state, which reinstates the default red agent in the leader position until other targets are detected (Fig. 9f).

The experimental results demonstrate the conceptual validity of the proposed agent-task assignation framework. Efficient cooperative navigation and swarm's formation control as well as smooth switching and transition of the leadership in between the specialized individuals is achieved. The ATSU is robust enough to deal with any number of targets, including several targets that are sharing the same specialized zones. It also supports prioritization to take place in between targets, via an embedded supervisory layer that can be manually driven or fully automated. The three states of the proposed operation, from broad search to execution, provide the necessary support for the ATSU to respond to the exploratory, tracking, and task execution components typically found in swarm robotic scenarios. Considering situations of overlapping areas or shared zones of influence, as well as moving targets, brings the proposed protocol closer to realistic operational contexts.

VI. Conclusion

A systemic framework for the coordination and formation control of specialized robotic agents working in collaboration is presented in this paper. Specialized individuals are defined as robotic agents equipped to fulfill particular tasks that require specific physical, mechanical or sensing capabilities. The response of specialized agents to their corresponding tasks is formulated to ensure that an optimal match is achieved between the specialized agents capabilities and the detected targets' characteristics.

A multipurpose Automatic Task Selection Unit (ATSU) is designed that operates in two modes, either under close supervision by a human operator or in a fully automated mode. In the latter mode, a succession of states are used to drive the process, respectively: searching for targets; detecting and recognizing targets via embedded sensors, which also involves a transition phase that brings the most competent agent to become the leader of the swarm; and finally executing the related task with the most compatible agent.

Experimental results demonstrate that a group of robots operating under the proposed coordination framework can effectively assign the suitable specialized robots to perform specific tasks, even under more challenging scenarios with targets in proximity of each other, where prioritization becomes essential, or when targets are moving.

In future work, this framework will be refined with the development of a probabilistic agent-task matching process that will further leverage the intrinsic uncertainty associated with the recognition of a target object's characteristics from embedded sensors. The recognized characteristics of the targets will be classified, identified and best matched to the corresponding specialized robots' capabilities. In addition, validation on physical systems is to be conducted.

Acknowledgments

The authors wish to acknowledge the contribution of H. M. Busiquia to the development of the graphical simulator for this research. The authors also wish to acknowledge Hadhramout Establishment for Human Development (HEHD), Mukalla, Yemen, for funding the first author's Ph.D. studies, as well as Natural Sciences and Engineering Research Council of Canada.

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