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Probabilistic Task Assignment for Specialized Multi-Agent Robotic Systems

Omar AL-Buraiki, Pierre Payeur
School of Electrical Engineering and Computer Science
University of Ottawa
Ottawa, Canada
[oalbu060, ppayeur] @uottawa.ca

***Abstract*—— This paper introduces a probabilistic approach for assigning specialized individual agents among a robotic swarm to corresponding constrained tasks. Based on the assumption that each individual agent possesses specialized capabilities, the proposed approach evaluates probabilistic fitting of the available robot individuals based on the requirements imposed by the current task, which takes the form of a recognized target object in a specific environment. A formal matching scheme is developed to evaluate a task-agent fitting score among all available agents. It assigns the most qualified and available specialized robotic agent as the best responder to perform the recognized task. A simulation study is presented to validate the efficiency and robustness of the proposed approach.**

Keywords— task-agent assignment, specialized task allocation, probabilistic representation, swarm robotics.

I. INTRODUCTION

A multi-agent robotic system is composed of multiple interacting agents within a bounded space, while collective behavior emerges from the interaction between the agents and with the environment. In this paper the concept of specializing the individual agents to respond to constrained tasks is explored. A formalism is introduced for task allocation in the context of a collaborative swarm of mobile robots. Unlike previous work that considers heterogeneity among the robotic agents mainly from their physical construction, here a specific definition of specialization is introduced. It leverages the embedded hardware and software characteristics of each agent. As a result, an advanced form of specialized labor division emerges in the swarm, which divides the labor among the individual members based on best matching the specific requirements of the task to each robot's capabilities. This form of task allocation can reduce equipment cost and increase the net efficiency of the swarm. The proposed probabilistic scheme computes a specialty fitting score, which supports optimal task allocation. As qualified agents are assigned to corresponding tasks with different scores, a form of prioritization among robotic agents also emerges. The following section reviews state-of-the-art approaches for automated task-agent allocation. Section III details the proposed framework, while section IV links the approach with target object recognition that defines the tasks considered. The formal task-agent matching process is defined in section V, and experimental results are reported in section VI.

II. STATE-OF-THE-ART

Previous research works introduced many task-agent assignment solutions such as maximum matching algorithms [1] that match equal number of vehicles and tasks. A perfect matching problem [2] involves having a convention to map a set of n robots to another set of m tasks. In these approaches, task-agent assignment is addressed without considering agent's specialization.

Stochastic or probabilistic task-agent assignment techniques have also been proposed. Jones and Mataric [3] built a state transition probabilistic model to respond to changing tasks. Two agents perform a foraging task with equal probabilities. They keep their current foraging state and observe the environment in their vicinity. The current foraging state is re-evaluated based on new observations, and the probability of the robot's state priority changes with respect to the observed foraging task. Then, based on the current probability, the robot can change its foraging state. Smith and Bullo [4] proposed a task-agent assignment probabilistic algorithm called "grid assignment algorithm" to partition the targets environment to a grid of cells. Then the available robots in each cell are assigned to the targets that occupy the same cell. Claes et al. [5] addressed spatial task assignment as a multi-agent planning problem using a Markov decision process. The proposed model aggregates the effect of the other team members into a probabilistic model to control the individual agents that are trying to perform spatially distributed tasks. Lang and Toussaint [6] introduced a probabilistic model to define object-action relevance. The proposed model involves a subset of objects that are relevant for specific planning purposes. The model is used in [7] to compute a sequence of actions and apply approximate inference to control the robot planning, grasping and reasoning for the arrangement of table-top objects. Yasuda et al. [8] proposed a response threshold probabilistic model to control the individuals that perform a food foraging process. As a result, robots with a probability that exceeds a specific threshold can leave the nest. Then they search for food. Recently, Wu et al. [9] introduced a task assignment probabilistic model based on environmental stimulus and the agent's response threshold. The environmental stimulus is modeled based on a specific time increment, and decrement with every active agent. This threshold level is increased when the total number of similar agents is decreased. The system is modeled for battlefield attacks and the transition probability can only transfer the individual agents among the swarm between two task states for the entire targets. It neither matches nor takes the decision to make specialized agents interact with the current tasks.

III. Proposed Approach

The proposed approach forms a probability-based allocation mechanism for mobile robots equipped with specialized capabilities to best match with constrained tasks detected in their environment. Fig. 1 illustrates the overall objective of the task-agent allocation process. When a group of specialized robotic agents navigate in a given workspace, observer agents search for target objects from a list of predefined objects of interest. Once a target is detected through visual pattern recognition [10], automated allocation of a robotic agent is initiated for the task to be completed (e.g. reach to the object for closer observation, track or pick the object, etc). The goal is to assign the most capable specialized agent to respond to a detected task. The proposed solution considers the swarm members to be intrinsically identical in their lower genetic level (e.g. similar mobile platforms) and extrinsically different in their higher functionality level (e.g. on-board sensors or actuators, communication and reasoning capabilities). This results in specialized capabilities for each individual agent forming an overall multi-agent system with non-homogeneous functionalities.

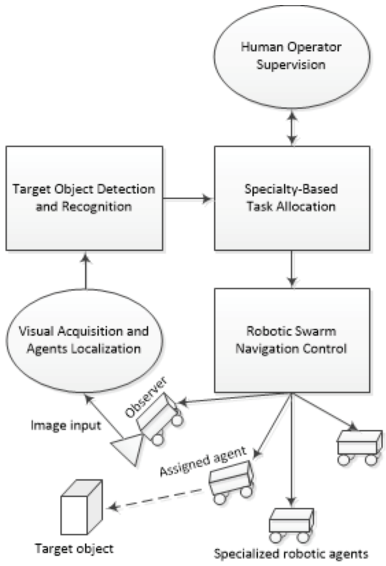


Figure 1: General framework for specialized task-agent allocation.

To achieve this goal, two coupled spaces are defined for coordinating the specialized robotic individuals in the swarm. A schematic diagram of the coupled coordination spaces is shown in Fig. 2. The control space tackles control considerations related to robots' dynamics, swarm's navigation, group formation and transition [11]. The specialization space optimizes the match between the task requirements and the individual robots' specialization, which is the core contribution of this paper. The objective of the specialization space is to divide the labor amongst the swarm from the perspective of the individuals' specialty in the presence of cooperation between the agents.

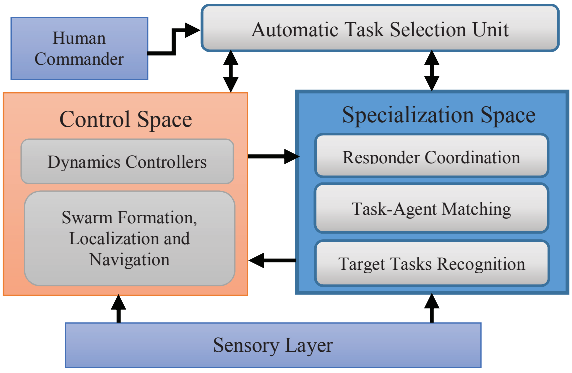


Figure 2: Coupled spaces architecture for specialized agents' coordination.

In the specialization space, a task-agent probabilistic approach is defined for matching characteristic features perceived on detected tasks with robot embedded specialties. It relies on an uncertain representation of the observed features, which provides a task specific signature that can be matched with predefined corresponding specialized functionalities of the swarm's individuals. As such, this work focuses on characterizing the specialization of the agents as heterogeneous individuals with respect to their functionalities and on the evaluation of a task-agent fitting score that is required for assigning robots to specific tasks. The coordination of individual agents to the corresponding tasks addresses three main problems: 1) target task recognition, 2) task-agent specialty matching, and 3) coordination of the optimal specialized responder. An automatic task selection unit (ATSU) is introduced in [12] which is responsible for decision making on assigning the best specialized robot to a corresponding target object. In addition, a human supervisor is preserved in the control loop for strategic guidance, as depicted in Fig. 1 and 2.

IV. Recognition of Task Characteristics

In practice, target object detection and recognition in the robot environment is performed via modern deep learning pattern recognition methods, which rely on a set of visual features observed via color cameras mounted on some of the robotic agents that are part of the swarm [10].

From a more general perspective, the proposed solution considers predefined Gaussian distributed spatial features, $\boldsymbol{X}_k$, to recognize target objects in a 2-dimensional environment. In a typical scenario, while the agents navigate the workspace, an embedded perception system collects information from the surrounding environment and extracts data from the dominant features, $\boldsymbol{X}_k$, on the observed targets. Then, the detected features are categorized through a classification mechanism. This provides information to the task-agent matching stage that is discussed in section V. The latter determines a confidence level in the fit between the detected target and any specialized agent.

A. Target Object Recognition and Features Extraction

To map the appropriate agents to the corresponding tasks independently, the dominant features on the target objects are separated into classes. The observed data for each feature, $\boldsymbol{X}_k$, are encoded as a vector of z observed samples, that is $\boldsymbol{X}_k = \{x_j : j = 1, \cdots, \mathrm{z}\}$, where $x_j \in \mathcal{R}^2$ is a Gaussian distributed random sample of a 2-dimensional spatial feature, visually observed, with mean μ and variance σ^2. Also, $k = 1,2, \ldots, F$, where F is the maximum number of features that are expected to be observed on a target object. The total number of distinctive features to be estimated creates a set of vectors, here called the features vector, $\boldsymbol{X} = [\,\boldsymbol{X_k}: k = 1,2,\dots,F]$. It is also assumed that each feature, $\boldsymbol{X}_k$, is associated with one specific class, C_i, of target objects. These classes are also the ones considered available for training the target recognition stage on a number of predefined target objects [10]. Moreover, each class is associated with an action of a specific nature to be performed by one of the capabilities of the robotic agents. The feature space is therefore comprised of F predefined features that characterize the target objects, and are associated with the available specialized capabilities of the robots in the swarm. The confidence level in the recognition of these features, estimated as a probability, is leveraged in a matching scheme that computes the specialty fitting score of the agents to interact with each type of target.

A pre-trained neural network with a set of F classes, C, where $C \in \{C_i: i = 1,2,\dots.,F\}$, is used to retrieve observed features, $\boldsymbol{X}_k$, from the visual perception of a given target. This leads to the posterior probability, $P(C_i|\boldsymbol{X}_k)$, that represents the probability that the observed feature, $\boldsymbol{X}_k$, belongs to each class C_i, estimated by the Bayesian rule.

$$P(C_i|\boldsymbol{X}_k) = \frac{p(\boldsymbol{X_k}|C_i)P(C_i)}{p(\boldsymbol{X_k})} \tag{1}$$

with $i = 1,2,\ \dots,F$, and where $p(\boldsymbol{X}_k|C_i)$ is the class-conditioned probability density function [13] that describes the Gaussian distribution of the feature, $\boldsymbol{X}_k$, in each predefined class C_i; $P(C_i)$ is a prior probability of the class C_i, which is evaluated from the given training data set. If M_{tr} is the total number of patterns that are available for training and M_{tr_i} of them belong to C_i, then a prior probability of this class can be computed as:

$$P(C_i) = \frac{M_{tr_i}}{M_{tr}} \tag{2}$$

$p(\boldsymbol{X}_k)$ is the probability density function of the feature $\boldsymbol{X}_k$ over all classes, which is given by:

$$p(\boldsymbol{X}_k) = \sum_{i=1}^{F} p(\boldsymbol{X}_k|C_i)P(C_i) \tag{3}$$

This probability density function of the feature $p(\boldsymbol{X}_k)$ is evaluated for all classes and does not affect the evaluation of the posterior probability, $P(C_i|\boldsymbol{X}_k)$, in Eq. (1) since all quantities are a function of C_i [13]. As such, the denominator in Eq. (1) can be considered as a normalization constant, substituted by $\frac{1}{\xi}$, to ensure that the posterior distribution on the left-hand side integrates to one. Thus, the posterior probability is evaluated as:

$$P(C_i|\boldsymbol{X_k}) = \xi\, p(\boldsymbol{X}_k|C_i)P(C_i) \tag{4}$$

As a result, the estimated features, $\boldsymbol{X}_k$, recognized on the target objects are associated to the classes that have the maximum estimated posterior probability, Eq. (4). The overall probability is computed collectively to evaluate the specialty-fitting score of the proper agent, as will be detailed in section V.

B. Probability Density Estimation

Based on the assumption that a features vector, $\boldsymbol{X}$, is distributed according to the class-conditioned probability density function, $p(\boldsymbol{X}_k|C_i)$, for $i = 1, 2, ,\dots, F,$ classes, $p(\boldsymbol{X}_k|C_i)$ forms a likelihood function parameterized as $\boldsymbol{\alpha} = [\mu,\ \sigma^2]^{\boldsymbol{T}}$, for the distribution of features across the classes. This likelihood function is used to estimate the features distribution parameters by exploiting the available set of training data in each class. In theory, it is assumed that the classes are mutually independent and the parameter estimation problem can be solved for each class independently [13].

V. TASK-AGENT MATCHING APPROACH

In the present work, the task-agent specialty matching problem consists of matching the best suited specialized agents with their corresponding target objects, or tasks, with a maximum level of confidence. In practice, for a given matching assignment, an agent responds to a specific task when the agent's specialty offers a sufficient fitting score with the task requirements. However, a given agent can also qualify for different tasks but with different specialty fitting levels. The proposed task-agent matching approach leverages the probabilistic formulation introduced in section IV. It comprehends two sub-systems, that 1) evaluate the specialty fitting score between the detected task and a specialized agent; and 2) coordinate the most specialized and available agent to the current task.

A. Specialization Definition and Coding

The swarm of robots $\{R_i, i = 1,2,\dots,a\}$ consists of a specialized individual agents, R_i, and provides F different specialized roles or capabilities that are encoded in each agent's binary specialty vector, $\boldsymbol{S}_i$: $\{\mathrm{s}_k, k = 1,2,\dots,F\}$. Each entry defined as $\mathrm{s}_k = 1$ means that the robot possesses the corresponding necessary capability; and $\mathrm{s}_k = 0$ indicates that the robot is not equipped with the necessary capability to tackle a feature X_k that is meant to correspond to a given class C_k, among F of them. Let us assume an outdoor scenario in which the individual agents of a robotic swarm are specialized to perform specific tasks such as picking up a box, or rescuing a person, and these tasks are to be performed on land or on water covered areas. The dominant features of the task will be land, water, box, and person. In this case, the specialty vector of each agent R_i will be defined as $\boldsymbol{S}_i \in \mathcal{R}^{1\times F}$, with $F = 4$ considered features.

The goal of the matching scheme is to maximize the task-agent fitting score. The fitting scores of the swarm's individuals that would be subject to the current task, are defined as:

$$\varphi(i) = \boldsymbol{S}_i \boldsymbol{P}_T \tag{5}$$

where $\varphi(i) \in \mathcal{R}^{1\times 1}$ represents the specialty fitting score achieved by an individual agent of identity, i, based on the constraints raised by the detected features on the target. $\boldsymbol{P}_T \in \mathcal{R}^{FX1}$ represents the probability transition vector of the specialized features, which is a function of the estimated posterior probabilities, Eq. (4), of the recognized features on the target, which is given by:

$$\boldsymbol{P}_T = \left[\sum_{k=1}^{F} P(C_1|\boldsymbol{X}_k) \quad \sum_{k=1}^{F} P(C_2|\boldsymbol{X}_k) \quad \cdots \quad \sum_{k=1}^{F} P(C_F|\boldsymbol{X}_k)\right]^T \tag{6}$$

As defined above, $\boldsymbol{S}_i \in \mathcal{R}^{1\times F}$ is a predefined robotic agent's specialty vector that consists of binary variables. When a given agent does not have the capabilities required to match with the features recognized on a target, the corresponding probabilities of these features are excluded from the fitting score of the given agent. As a result, the proposed specialty fitting score, $\varphi(i)$, emphasizes that each agent offers a specific level of competencies as a collective sum of the probabilities of the recognized features on a given task. Each $\varphi(i)$ contributes as a diagonal element (i,j) of the swarms' cumulative specialty fitting score matrix, $\boldsymbol{Q} \in \mathcal{R}^{a\times a}$, that is:

$$\boldsymbol{Q} = \begin{bmatrix} \varphi(1) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \varphi(a) \end{bmatrix} \quad (7)$$

B. Best Responder Coordination

To support realistic scenarios, the proposed framework addresses the agents availability beyond their specialty, because a robot may not always be available when called in service. Therefore, a scheme for the best responder assignment coordination that considers the current agents availability status is also proposed. It assigns the most specialized agent to the recognized task in the presence of two coordinating constraints: the cumulative specialty fitting score, $\boldsymbol{Q}$, Eq. (7), and the agents' availability status, denoted as $\boldsymbol{\vartheta}_S$. The objective of the coordination scheme is to return the specialty fitting scores of only the available agents, so that the most qualified agent among them can be assigned the task, even though it may not be the very best one (i.e. a less competent but available agent at time of target object discovery).

A binary availability vector, $\boldsymbol{\vartheta}_S \in \mathcal{R}^{a\times 1}$, is defined based on the current internal status of each robot. At the time of swarm deployment, the internal flag of the deployed agents raises to "available" while the internal flag of agents that are not available is set to "withdrawn". Then, whenever the system finds an "available" agent that qualifies for the detected task, the availability flag keeps its fitting score active, and the detected task is assigned to this agent if the score is maximum. In contrast, agents with an internal flag "withdrawn" are deactivated, and the system may need to find another "available" agent. The proposed availability status vector of the robots, $\boldsymbol{\vartheta}_S \in \mathcal{R}^{a\times 1}$, is defined as:

$$\vartheta_S(i) = \begin{cases} 1, & if \quad R_i \;\; is \text{ "}available\text{"} \\ 0, & if \quad R_i \;\; is \text{ "}withdrawn\text{"} \end{cases} \quad (8)$$

Consequently, the task-agent coordination scheme can be synthesized as a specialty fitting scores vector, defined as:

$$\boldsymbol{\Psi_S} = \boldsymbol{Q\vartheta_S} \quad (9)$$

where $\boldsymbol{\Psi_S} \in \mathcal{R}^{a\times 1}$ returns the specialty fitting scores for available agents, or 0 for withdrawn units, with respect to the current task.

C. Human in the Loop

For a more responsive dynamic operation of the proposed approach, a *minimum fitting threshold* (MFT), η, is also implemented as a safety measure that guarantees a minimum fitting score below which no agent will be selected. To control this parameter, a human operator who supervises the swarm sets the MFT value for the task allocation system, either before the deployment of the swarm or during the operation. The MFT can vary to different levels based on the requirements of the task or in association with operational conditions. This way human skills and understanding of the situation can be shared with the robots by changing this parameter to influence the minimum required level of trust in the recognized target objects. The value of η for the team is given by:

$$\eta = \lambda\varphi_{max} \quad (10)$$

where, $\varphi_{max} \in \mathcal{R}^{1\times 1}$, is the agent's maximum expected collective score that results when all of the agent's capabilities are matched with the detected target's features. To define, φ_{max}, let us consider that the maximum number of constraints, that are expected to be raised by each single target, equals to l_{max}. Then the maximum expected collective score, φ_{max}, of the agent to fit with l_{max} task requirements can be defined as:

$$\varphi_{max} = \sum_{l=1}^{l_{max}} p(\boldsymbol{X}_l|C_l) \quad (11)$$

where $p(\boldsymbol{X}_l|C_l)$ is the class-conditional probability of the target's feature, $\boldsymbol{X}_l$, in its predefined class, C_l, amongst l_{max} constraints.

The human operator can select the desired MFT required by changing, λ, in Eq. (10) in between two ranges, respectively a low specialty level (LSL) and a high specialty level (HSL). The minimum limit of LSL, $\lambda > A$, has to drive the task-agent allocation scheme to match the minimum specialized capabilities of the available agents to the estimated task. However, in many applications it is desired to ensure a higher level of safety with higher requirements on the matching level between the available agents' capabilities and the recognized tasks. In such cases, the human operator enforces the system to work in the HSL range by setting λ above a specific level B to ensure that only robots with a higher level of competence can intervene, where:

$$\begin{cases} LSL: & \mathrm{A} < \lambda \le \mathrm{B}, \\ HSL: & \mathrm{B} < \lambda \le \mathrm{C}, \end{cases} \quad (12)$$

Therefore, the vector of specialty fitting scores, $\boldsymbol{\Psi_S}$ defined in Eq. (9), is further refined to accommodate only the scores of the available agents that achieve the MFT. As a result, the refined specialty fitting scores vector, $\boldsymbol{\Psi}_{MFT} \in \mathcal{R}^{a\times 1}$, becomes:

$$\boldsymbol{\Psi}_{MFT}(i) = \begin{cases} \boldsymbol{\Psi_S}(i), & \mid \boldsymbol{\Psi_S}(i) \ge \eta \\ 0, & \mid \boldsymbol{\Psi_S}(i) < \eta \end{cases} \quad (13)$$

with, $\boldsymbol{\Psi_S}$, defined in Eq. (9). Accordingly, the most qualified and available responder agent to the detected task is selected automatically considering the human operator's strategic guidance. The identification index of the best-suited and available responder above the minimum fitting threshold is given by:

$$\emptyset_{BEST\ RESPONDER\ INDEX} = i \mid i \in max\{\boldsymbol{\Psi}_{MFT}\} \quad (14)$$

VI. Simulation Experiments

To validate the proposed task-agent matching approach, experiments are conducted in simulation. Three different target objects are assumed to be distributed over two different environments, with each one having special terrains that are water-covered (cyan) or land (brown) areas, as shown in Fig. 3a, 4a, and 5a. A swarm of six individual robots is deployed in 2-dimensional workspace. Two robots are specialized to perform on each type of target (T_1, T_2, T_3), and each robot has an individual preference for a specific environment, (water workspace (W_{WS}) or land workspace (L_{WS})) associated with its physical construction. The features, X_k, can be related to the nature of the target objects or to specific environment constraints. Therefore, $X_k \in \{T_1, T_2, T_3, W_{WS}, L_{WS}\}$. The targets and the environmental constraints are color-coded in the figures below. Table 1 defines the specialized agents matching with corresponding targets and environment characteristics, whereas Table 2 defines the categorization of the given targets and their specific surrounding environment constraints in five different classes. In practice, these classes are pre-trained in a deep learning network from sample image datasets representing them in order to perform target object recognition [10]. This component remains beyond the scope of this paper, and features belonging to each class are considered available in the simulation.

TABLE 1: SPECIALIZED CAPABILITIES OF EACH INDIVIDUAL ROBOT.

Robot #ID	Target Type	Workspace	
		Water-Covered (W_{WS})	Land (L_{WS})
R_1	T_1 (red)		√
R_2	T_1 (red)	√	
R_3	T_2 (blue)		√
R_4	T_2 (blue)	√	
R_5	T_3 (green)		√
R_6	T_3(green)	√	

TABLE 2: CATEGORIZATION OF TARGETS AND ENVIRONMENT CONSTRAINTS

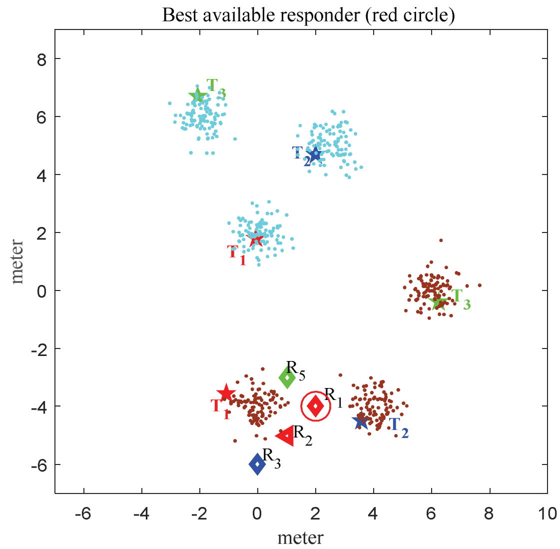
Target or environment constraint	Class
T_1 (red)	C_1
T_2 (blue)	C_2
T_3 (green)	C_3
L_{WS} (brown)	C_4
W_{WS} (cyan)	C_5

The proposed mechanism is simulated in two scenarios. The first scenario considers a LSL for the task-agent matching fitting process with an imposed MFT value, η. The latter is set by Eq. (10), with $\lambda = 0.4$. The second scenario tests the proposed approach with a different level of MFT. For the first scenario, Fig. 3a shows the assignment of agent R_1, with Eq. (14), to a target of type T_1 (red star) that is located on land. As shown in Fig. 3b, the overall specialty fitting score of the most specialized and available agent is 1.909, computed by Eq. (13), which exceeds the minimum confidence threshold set to 0.8, eq. (10). Table 3 presents comprehensive results of the individuals' specialty fitting scores with respect to the recognized task, T_1, the agents' availability status, the overall task-agent fitting score, the MFT, as well as the specialty threshold control variable λ, used in this case. It is also shown that agents R_4 and R_6 are withdrawn.

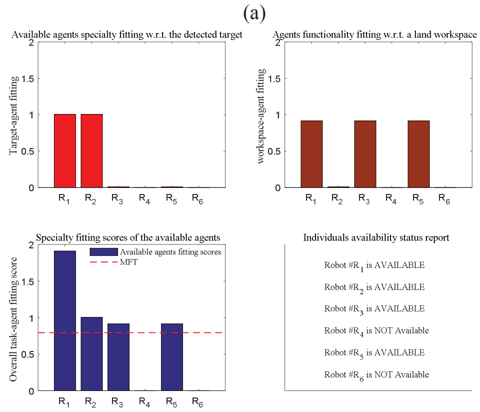
In Fig. 4, a different simulation demonstrates a situation where the most component agent, here R_4, that is not currently available, can be dynamically substituted by an alternative but less qualified agent. In this scenario, agent R_4 achieves a specialty fitting score of 1.909 to respond to a target of type T_2 (blue star) that is located on water, but is not available. However, agent R_3, is available and comes out as the next best qualified agent with a specialty fitting score of 0.999, as shown in Table 4, even though agent R_3, is best suited to operate on land. In such a case, the system can still assign R_3 to respond to target of type T_2 on water-covered area, with Eq. (14), since it is available and its fitting score is above the MFT of 0.8. This case illustrates the inherent flexibility of the proposed framework.

TABLE 3: SPECIALIZED CAPABILITIES ASSOCIATED WITH INDIVIDUAL ROBOTS WITH RESPECT TO TASK TYPE 1 ON LAND WORKSPACE.

Agent ID#	*Individual agents fitting scores*	*Available agents*	*Available agents fitting scores*	*Min. fitting threshold with $\lambda = 0.4$*
R_1	1.909	1	1.909	
R_2	0.999	1	0.999	
R_3	0.910	1	0.910	0.8
R_4	0.000	0	-	
R_5	0.909	1	0.909	
R_6	0.000	0	-	



(a)

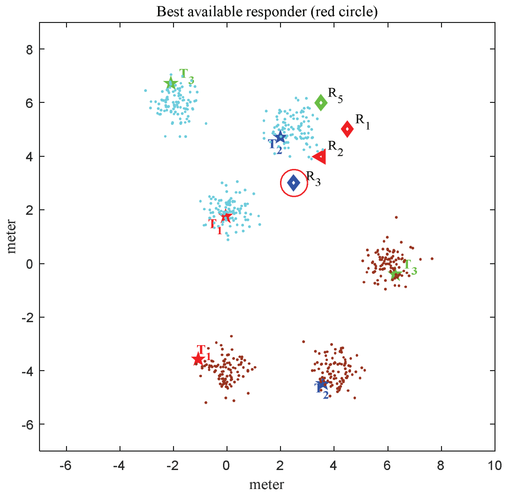


(b)

Figure 3: a) Assigning agent R_1 to a task of type 1 on land area, and b) specialty fitting scores of the available robots and minimum fitting threshold w.r.t. the current task.

TABLE 4: SPECIALIZED CAPABILITIES ASSOCIATED WITH INDIVIDUAL ROBOTS WITH RESPECT TO TASK TYPE 2 ON WATER-COVERED WORKSPACE.

Agent ID#	*Individual agents fitting scores*	*Available agents*	*Available agents fitting scores*	*Min. fitting threshold with $\lambda = 0.4$*
R_1	0.000	1	0	
R_2	0.910	1	0.910	
R_3	0.999	1	0.999	0.8
R_4	1.909	0	-	
R_5	0.000	1	0	
R_6	0.910	0	-	



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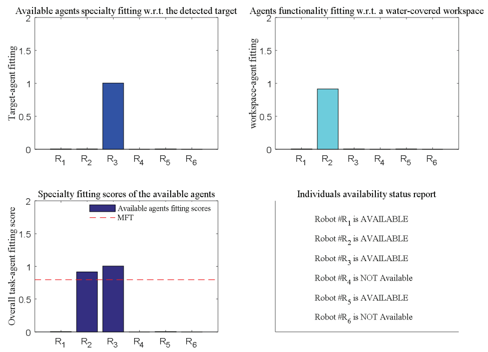


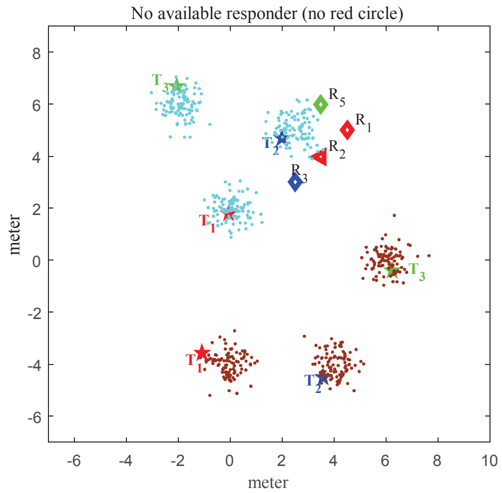
(b)

Figure 4: a) Assigning agent R_3 to a task of type 2 on water-covered area, and b) specialty fitting scores of the available robots and minimum fitting threshold w.r.t. the current task.

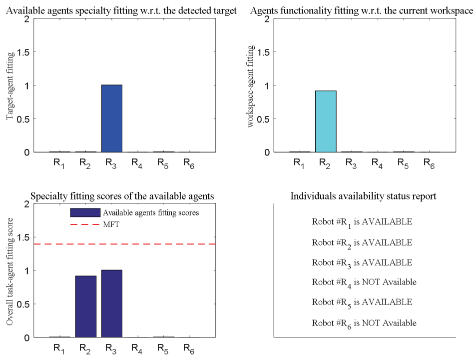
In the second scenario considered, the human operator raises up the MFT to increase the minimum level of competence required for a successful task assignment by selecting, λ, in the HSL range. The responses of the proposed approach when the confidence threshold is increased are presented in Fig. 5, with $\lambda = 0.7$, corresponding to a higher MFT of 1.4, as shown in Table 5, which is above all achieved specialty fitting scores, using Eq. (13). Even though agent R_3 is available and somewhat competent, its specialty fitting score does not exceed the minimum fitting threshold in this case. As a consequence, no agent is assigned to the detected task. This experiment exemplifies that higher safety levels (i.e. higher MFT) can be set on demand to ensure that only robots equipped with all required functionalities to perform a specific task are assigned at any given point in time. As a result, while guaranteeing a minimum safety level, execution is performed on recognized targets, whenever possible, with the most competent and available agent that is selected as the best responder.

TABLE 5: SPECIALIZED CAPABILITIES ASSOCIATED WITH INDIVIDUAL ROBOTS WITH RESPECT TO TASK TYPE 2 ON WATER-COVERED WORKSPACE, WHEN HIGHER COMPETENCE LEVEL IS IMPOSED.

Agent ID#	*Individual agents fitting scores*	*Available agents*	*Available agents fitting scores*	*Min. fitting threshold with $\lambda = 0.7$*
R_1	0.000	1	0	
R_2	0.910	1	0.910	
R_3	0.999	1	0.999	1.4
R_4	1.909	0	-	
R_5	0.000	1	0	
R_6	0.910	0	-	



(a)



(b)

Figure 5: a) No assignment to a task of type 2 on water-covered zone due to higher required MFT = 1.4, with $\lambda = 0.7$, and b) fitting scores of the available robots w.r.t. the current task.

VII. CONCLUSION

A representation for specializing individual members of a robotic swarm was introduced. The specialized capabilities of individual agents are modeled and matched to corresponding features recognized on target objects with a quantified uncertainty level. The estimated probabilities of detected features on a target, corresponding to a specific task, are collectively summed up to tune the task-agent matching scheme. The latter is also extended to coordinate the specialized individuals with the corresponding tasks by considering agents availability state. Input from a human operator can be involved in the task assignment process to control and change the system's operational conditions, which results in a safer and more selective task allocation operation. Simulation results demonstrate that the proposed approach is successful at properly assigning specialized agents to corresponding constrained tasks while guaranteeing a minimum safety level driven by user input.

Future developments will involve the refinement of robust target objects detection, and performing the evaluation of the proposed framework with more advanced integration and experimental validation on real systems.

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