TAMER: Task Allocation in Multi-robot Systems Through an Entity-Relationship Model

Branko Miloradović, Mirgita Frasheri, Baran Cürüklü, Mikael Ekström, and Alessandro Vittorio Papadopoulos(✉)

Mälardalen University, Västerås, Sweden
{branko.miloradovic,mirgita.frasheri,baran.curuklu,mikael.ekstrom, alessandro.papadopoulos}@mdh.se

Abstract. Multi-robot task allocation (MRTA) problems have been studied extensively in the past decades. As a result, several classifications have been proposed in the literature targeting different aspects of MRTA, with often a few commonalities between them. The goal of this paper is twofold. First, a comprehensive overview of early work on existing MRTA taxonomies is provided, focusing on their differences and similarities. Second, the MRTA problem is modelled using an Entity-Relationship (ER) conceptual formalism to provide a structured representation of the most relevant aspects, including the ones proposed within previous taxonomies. Such representation has the advantage of (i) representing MRTA problems in a systematic way, (ii) providing a formalism that can be easily transformed into a software infrastructure, and (iii) setting the baseline for the definition of knowledge bases, that can be used for automated reasoning in MRTA problems.

1 Introduction

In the past decades, the interest in Multi-Agent Systems (MASs) has grown due to their suitability in representing applications where actors have different interests, and to their distributed nature that increases performance, scalability, and robustness [12]. Earlier papers from the 1980s and 1990s mostly focused on the properties and collaborative behaviour of MASs putting the emphasis on the specific aspects of the problem to be solved, e.g., communication, topology, robot group composition, and collaborative behaviour. Proposed solutions were usually verified in simulation environments.

As the complexity of the MAS missions started to increase, e.g., in terms of number of required agents, number of tasks to be completed, heterogeneity of capabilities required to complete some tasks, etc., more attention has been

This work was supported by the Aggregate Farming in the Cloud (**AFarCloud**) European project, with project number 783221 (Call: H2020-ECSEL-2017-2), DPAC research profile funded by KKS (20150022), the FIESTA project funded by KKS, and the UNICORN project. Projects are supported by ECSEL JU and the VINNOVA.

M. Baldoni et al. (Eds.): PRIMA 2019, LNAI 11873, pp. 478–486, 2019.
https://doi.org/10.1007/978-3-030-33792-6_32

devoted to the multi-robot task allocation (MRTA) problem, which has become an established research direction [2]. In order to tame such an emerging complexity, several taxonomies have been proposed in the literature. Gerkey and Matarić [5] introduced the first taxonomy for MRTA problems, proposing three main dimensions that specified the type of tasks, type of robots, and type of assignment. Other taxonomies have been proposed in the following years, further highlighting the complexity of the MRTA problem. However, most of them are do not build on previous ones, leading to a fragmented and possibly overlapping set of taxonomies.

This paper surveys the existing taxonomies, in order to capture the important dimensions of MRTA problem configurations and to understand differences and similarities. In addition, this paper presents the Task Allocation in Multi-Robot System Entity-Relationship (TAMER) model, an Entity-Relationship (ER) model that captures the most relevant aspects of the surveyed MRTA taxonomies. The goal of TAMER is to provide a unified view of the existing taxonomies, and a tool to classify and relate the different dimensions in a more structured and systematic way. Adding new dimensions on top of existing taxonomies requires a clear understanding of how they could fit in the big picture. In fact, newly proposed aspects may overlap with, may be coupled with, or may contain certain properties already captured by other dimensions. TAMER simplifies such process providing a more formal approach to tame the complexity of the MRTA taxonomy problem. TAMER offers a general model that includes the different dimensions proposed by the surveyed taxonomies (Sect. 2), and it can be thought of as a unifying approach to the MRTA taxonomy problem, allowing for extending the classification with new dimensions in a non-redundant way, in the attempt of providing a unique framework for the definition of the relevant dimensions in MRTA problems.

The contribution of this paper is twofold: (i) To provide an overview of MRTA taxonomies, analysing how the research axes evolved over the past few decades, and identifying differences and similarities among them (Sect. 2); (ii) To formalize the MRTA problem through TAMER, an ER conceptual model that includes the most relevant aspects of the identified MRTA research axes (Sect. 3).

2 Overview of the MRTA Taxonomies

The categorization of the MRTA problems across various dimensions has been extensively investigated by several researchers in the past three decades. Earlier taxonomies [1,3,12], from the 1990s and the beginning of 2000s, focus more on the communication, the cooperation, and the robot capabilities dimensions. Table 1 summarizes the main surveyed taxonomies, and the respective proposed dimensions. In these taxonomies, the task allocation dimension plays a minor role. The work presented by Gerkey and Matarić [5] is the first one to shift the focus from former dimensions, into the direction of task allocation. This trend has been followed in the past decade and a half, expanding the original MRTA dimensions [6,7,10].

Table 1. Summary of the proposed dimensions classification in MRTA taxonomies.

Dimension	Reference							
	Dudek *et al.* [3]	Cao *et al.* [1]	Stone *et al.* [12]	Lau & Zhang [8]	Gerkey & Matarić [5]	Landén *et al.* [7]	Korsah *et al.* [6]	Nunes *et al.* [10]
Group composition	✓	✓						
Robot capabilities	✓	✓	✓		✓			
Communication	✓	✓	✓					
Topology	✓	✓	✓					
Cooperation		✓	✓		✓		✓	
Resources	✓		✓	✓				
Environment		✓				✓		
Allocation				✓	✓	✓		✓
Task interrelatedness			✓			✓	✓	✓

The group composition represents a crucial aspect of a MAS, and has been addressed explicitly as the group architecture and size [1], collective composition [3], and degree of heterogeneity [12]. The robot group composition has been addressed in the original MRTA taxonomy with the introduction of Single-Robot (SR) and Multi-Robot (MR) tasks, and Single-Task (ST) and Multi-Task (MT) robots dimensions. In order to have heterogeneity in the robot group composition, individual robots must have different capabilities. The range of robot capabilities is very broad going from the ability to model other agents and learning [1], processing ability [3], to the ability to perform tasks concurrently [5].

The communication and topology dimensions were an important part of early taxonomies, however, with the shift of focus towards task allocation and task interrelatedness, the communication was usually assumed to be failure-free and it did not have an effect on the problem configuration or solution design. Nevertheless, these dimensions are of major importance in MASs and they have been divided into several sub-dimensions. They include the way of interaction [1], the communication range, bandwidth, and topology [3], and the communication language and protocols [12].

Another fundamental aspect in MASs is the interaction among agents, which can be intentional or emergent [1]. Furthermore, agents can have competitive or benevolent behaviour, negotiate and make commitments in order to reach their goals [12]. In later papers, the cooperation is usually assumed to be intentional and benevolent [5,6] or it is not been taken into account at all [7,10]. When resources are finite [8], resource conflict may arise [1], thus a resource manager is needed [12]. Conflicts can be related to sharing space, objects, equipment, or communication. If agents are physical units acting within an environment, geometric problems may occur [1]. The environment is classically classified as static or dynamic [7]. Sudden and unplanned changes in the environment may have different consequences on the problem configuration, ultimately leading to a task re-allocation.

Another major part of the MRTA taxonomy is the task allocation dimension. This dimension can be further divided into Instantaneous Assignment (IA) and

Time-Extended Assignment (TA) [5]. If the allocation is done by an agent, then the allocation is internal and is considered as a task in MAS, otherwise, it is assumed that the allocation process is external [7].

In order to cover the gaps that were left by the taxonomy proposed by Gerkey and Matarić [5], by not addressing interrelated utilities and task constraints, several different taxonomy additions were proposed [6,7,10]. Landén *et al.* [7] defined unrelated utilities and interrelated utilities as well as independent tasks and constrained tasks. On the other hand, Korsah *et al.* [6] covered both of these dimensions with a single dimension: the degree of interrelatedness. Although not identical, these concepts are related, so both utilities and constraints have an impact on the degree of interrelatedness between both agents and tasks. Instead of utility, Lau and Zhang [8] express the degree of objective fulfilment in profit. Although Gerkey and Matarić [5] state that their work does not include interrelatedness between tasks explicitly, it can be noted that MR tasks do require some sort of synchronization between robots, while MT robots must have intra-related schedules in the case of TA. In addition, Nunes *et al.* [10] distinguish between temporal and ordering constraints, by adding Time Windows (TW) and Synchronization Precedence (SP) under TA. Furthermore, MRTA problem can be deterministic if the output of the model is completely determined by the initial conditions or stochastic if a model of the uncertainty is available. Despite the importance of uncertainty in robotics, most MRTA models are deterministic and deal with uncertainty only at execution time. Finally, all constraints can be divided into hard and soft constraints.

3 The TAMER Model

The TAMER model (shown in Fig. 1) aims at covering the relevant aspects of the MRTA problem, by adopting a systematic approach to unify the different dimensions presented in the former taxonomies. TAMER is an Entity-Relationship

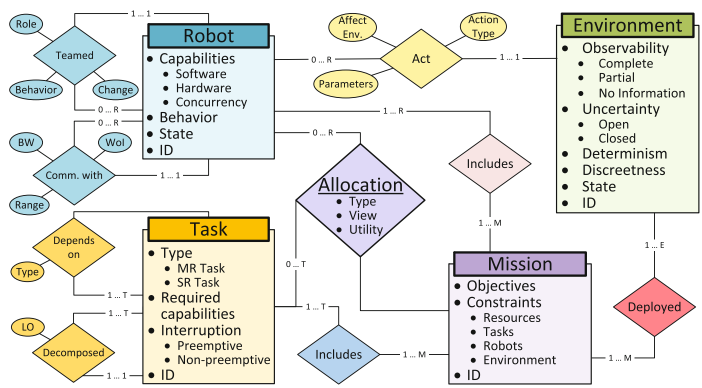

Fig. 1. The TAMER model.

(ER) model that defines the relevant entities of MRTA, and how they relate among them. TAMER unifies the previously proposed taxonomies, in a unique taxonomy that makes sure that the different dimensions are all necessary and sufficient to describe the fundamental problem configuration. TAMER also includes for all the entities and relationships a minimal set of attributes that captures the most relevant aspects presented in former taxonomies. Note that the proposed set of attributes does not aim for completeness, but it represents a core set that can be easily extended thanks to the TAMER approach.

3.1 Entities

TAMER consists of four entities: (i) *Robot*, (ii) *Environment*, (iii) *Task*, and (iv) *Mission*.

Robot. The *Robot* entity consists of the state, behaviour and capability attributes[1]. The state attribute covers those variables that are considered of interest in a particular context, e.g., velocity, position, orientation, and battery level. Different contexts might require different sets of variables, thus the state attribute is not specified in detail. The behaviour refers to the level of autonomy displayed by a robot. A robot might be able to display a particular level of autonomy that is fixed over time, or the level of its autonomy can be adaptive. Due to changing circumstances, the dependencies among robots can change, and, as a result, the autonomy levels change as well [4]. Both adaptive and fixed autonomy have an impact on the cooperation among the agents. Whereas the former allows for dynamic patterns and different levels of cooperation, the latter implies fixed patterns and a predefined level of cooperation.

The capability attribute covers the abilities of a robot, both at the hardware and software levels. These abilities can correspond to different levels of abstraction. For instance, at a low-level an ability might refer to processing power, concurrency, and/or computational resources, whereas at a high-level an ability might relate to being able of doing some action, e.g., grasping a mug.

Environment. The *Environment* entity is characterized by the following attributes: state, observability, uncertainty, determinism, discreetness, and additional constraints. As for the state attribute, different variables that describe the environment could be relevant in different contexts, e.g., the location of dynamic obstacles at a specific timestamp. The observability attribute takes values such as complete, partial, or no information. The uncertainty, on the other hand, refers to the dynamics in the environment, i.e., whether the environment does not change (closed) or changes overtime (open). Determinism, discreetness are characteristics described by Russell and Norvig [11, Chapter 2]. The additional constraints attribute serve the purposes of describing the environment in terms of rules and laws that are applicable and shape how the problem is formulated.

Task. The task entity consists of type required capabilities, and interruption attribute. The task type attribute is identical to the Gerkey and Matarić [5]

[1] All entities have an ID attribute, that uniquely distinguishes between instances of the same entity. The ID is not further discussed in this paper.

definition of SR and MR tasks. Required capabilities attribute describes the capability a robot needs to possess in order to execute a certain task. If a task can be temporarily interrupted without requiring its cooperation, in order to do some other task, then the task being interrupted is said to be preemptive. Preemptive tasks are of very common occurrence in real-time systems.

Mission. Mission entity encapsulates mission objectives, available resources, and constraints that are part of the problem domain. This is where the problem configuration as well as the objectives are defined. Mission constraints are constraints, which are imposed by some external actor, which is configuring the mission problem, e.g., human operator. These constraints can relate to resources, robots, tasks, and environment. For example, a constraint, which says that robot i can use at most 50% of its battery is considered to be resource constraint. Similarly, a set of n tasks to be completed is a task constraint. TW are another example of task constraints. A robot constraint may restrict, e.g., the number of robots that can be used in a specific mission. Specific constraints can be imposed regarding environment, e.g., in the form of forbidden areas, which must not be visited, or crossed.

3.2 Relationships

TAMER also includes nine relationships: (i) *Teamed*, (ii) *Communicate with*, (iii) *Act*, (iv) *Depends on*, (v) *Decomposed*, (vi) *Allocation*, (vii) *Includes Robot*, (viii) *Includes Task*, and (ix) *Deployed*.

Teamed. Robots can be part of teams within a MAS, and as such be in a *Teamed* relationship with one another. Attributes that characterize such relationship are state, behaviour, role, and dynamics. The state of a team could be specified by the size of the team, its composition in terms of robot capabilities, and the behaviour of the team. This attribute is similar to the behaviour attribute of the robot entity, however in this case it refers to the overall behaviour of the team that emerges from the local robot behaviours. The role attribute describes what hierarchical position a robot has in a particular team, e.g., leader or peer. The dynamics attribute refers to whether the team can change in time in terms of composition or hierarchy, among other variables.

Communicate with. *Communicate with* is also a relationship between robots, and has four attributes: type, range, bandwidth, and way of interaction. Communication type includes broadcast and one-to-one communication. Range and bandwidth describe physical properties of the communication channel. Way of interaction expresses whether a robot communicates directly with another robot, or indirectly, e.g., stigmergy where communication happens via the environment. The problem can depend on the upper bound of the bandwidth and range, which is a characteristic of a specific environment. Notice that the specification of this relationship defines the network topology, i.e., which robot communicates with whom.

Act. The *Act* relationship connects the robot and the environment entities to each other. A robot can act in an environment, and as a result have an impact on the state of the environment. Similarly, the environment can act on the robot and affect its state. This relationship is characterized by the type of action, parameters of the action, and affect on environment. A specific action can be described by a set of parameters, e.g., the action name could be one such parameter which defines what the action is. More parameters could be specified depending on the need. The *affect on the environment* attribute distinguishes between active and passive actions on the environment. The former covers actions that change the environment, whereas the latter covers actions that do not change the environment, e.g., a robot's movement.

Depends on. *Depends on* is a relationship between task entities describing their dependencies. This relationship has a *type* attribute. The type attribute, specifies what is the type of task dependency, i.e., *inter-dependent* (there are dependencies within robot's schedule), and *cross-schedule dependent* (there are dependencies within different robots' schedules). These dependencies can be utility related, synchronous, or time windows. Ordering constraints are treated as a special case of synchronization constraints.

Decomposed. Tasks can be atomic or divisible. The representation of the tasks is a design choice, and it may depend on the final purpose of the modeling. Tasks that are considered atomic from a high-level planning perspective, can be seen as divisible at the low level perspective, e.g., when agents need to coordinate to complete a more complex task. For example, Miloradović *et al.* [9] considered MR tasks as atomic in a high-level mission planning approach, while Zlot [13] deal with the task decomposition and allocation with Logical Operators (LO).

Allocation. The main relationship in the taxonomy that binds together mission, task, and robot entity is the allocation. The allocation can assign $0 \dots T$ tasks to $0 \dots R$ robots. If 0 tasks are assigned to 0 robots it means there is no allocation, hence no mission. However, it is still possible to have 0 tasks allocated to m robots, meaning that these m robots will not be used in a mission. The allocation consists of allocation type (IA or TA), allocation view (internal, external [7], or hybrid) and utility function.

Includes. The *includes* relationship connects the mission with the robot and task entities. This defines which tasks and robots are included in the mission. To have a mission, there must be at least 1 task allocated to at least 1 robot.

Deployed. After the allocation is done for a defined mission, through the *deployed* relationship the mission is deployed in the environment for execution. This means that missions are further constrained and shaped by the specific environment they should be executed in.

3.3 Discussion

The MRTA problem needs to consider all the presented aspects in order to represent a specific deployment. MRTA algorithms are in charge of populating the allocation relationship, based on the set of available robots, on the mission composed of the different tasks, and on the description of the environment.

The need for the TAMER model is motivated by the emerging complexity, both of the MRTA taxonomies and MAS missions. Most of the proposed taxonomies analyze the MRTA problem from different angles, and possibly introducing additional dimensions that are indirectly covered by other ones. TAMER model has several advantages. First, it allows for a systematic and structured representation of MRTA taxonomies. In fact, the taxonomies presented in Sect. 2 are included or can be reduced to specific instances of the TAMER model, avoiding redundancies and overlaps. For example, different topologies of communication are not directly represented in the TAMER model, but are a result of the relation *Communicate with*, that specifies the adjacency matrix of the communication topology, including additional attributes, such as the Range, the Bandwidth, and the Way of Interaction. Also, in TAMER all the attributes are assumed to be able to vary over time, while keeping a consistent knowledge base of the problem configuration.

The second important advantage of TAMER is that it adopts a classical approach for data/knowledge representation. As a result, TAMER defines a complex data structure that can be used for the definition of software infrastructures in MRTA problems, and for MRTA algorithms. Moreover, the TAMER model can be extended to include additional semantics to enable automated reasoning in MRTA problems.

Finally, TAMER adds two additional research axes: Multi-Mission problems and Multi-Environment problems. It allows multiple missions to be defined and deployed in the multiple or shared environment with the possibility of sharing robots and resources among the missions. The multi-mission and multi-environments aspects have not been extensively explored.

4 Conclusion

This work provides an overview of the main taxonomies for MRTA problems, analyzing and relating the different components (in this paper referred to as axes, or dimensions) proposed in the literature. Such dimensions may overlap or represent different aspects of the MRTA problem, but they seldom provide a general view on it. In order to tame the emerging complexity coming from the different taxonomies, we proposed TAMER, an ER model that provides a unified view on the MRTA problem, with the aim of remove potential redundancies in the classification, as well as a structured way to add or remove additional dimensions. As future work, TAMER can be extended to define a knowledge base for enabling automated reasoning in MRTA problems.

References

1. Cao, Y.U., Fukunaga, A.S., Kahng, A.B.: Cooperative mobile robotics: antecedents and directions. Auton. Robots **4**(1), 7–27 (1997). https://doi.org/10.1023/A:1008855018923
2. Dasgupta, P.: Multi-robot task allocation for performing cooperative foraging tasks in an initially unknown environment. In: Jain, L.C., Aidman, E.V., Abeynayake, C. (eds.) Innovations in Defence Support Systems -2. SCI, vol. 338, pp. 5–20. Springer, Heidelberg (2011). https://doi.org/10.1007/978-3-642-17764-4_2

3. Dudek, G., Jenkin, M., Milios, E.: A taxonomy of multirobot systems. In: Robot Teams: From diversity to Polymorphism, pp. 3–22 (2002)
4. Frasheri, M., Curuklu, B., Ekström, M., Papadopoulos, A.V.: Adaptive autonomy in a search and rescue scenario. In: 12th IEEE SASO (2018)
5. Gerkey, B.P., Matarić, M.J.: A formal analysis and taxonomy of task allocation in multi-robot systems. Int. J. Robot. Res. **23**(9), 939–954 (2004)
6. Korsah, G.A., Stentz, A., Dias, M.B.: A comprehensive taxonomy for multi-robot task allocation. Int. J. Robot. Res. **32**(12), 1495–1512 (2013)
7. Landén, D., Heintz, F., Doherty, P.: Complex task allocation in mixed-initiative delegation: a UAV case study. In: Desai, N., Liu, A., Winikoff, M. (eds.) PRIMA 2010. LNCS (LNAI), vol. 7057, pp. 288–303. Springer, Heidelberg (2012). https://doi.org/10.1007/978-3-642-25920-3_20
8. Lau, H.C., Zhang, L.: Task allocation via multi-agent coalition formation: taxonomy, algorithms and complexity. In: ICTAI, pp. 346–350 (2003)
9. Miloradović, B., Çürüklü, B., Ekström, M.: A genetic mission planner for solving temporal multi-agent problems with concurrent tasks. In: Tan, Y., Takagi, H., Shi, Y., Niu, B. (eds.) ICSI 2017. LNCS, vol. 10386, pp. 481–493. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-61833-3_51
10. Nunes, E., Manner, M., Mitiche, H., Gini, M.: A taxonomy for task allocation problems with temporal and ordering constraints. Robot. Auton. Syst. **90**, 55–70 (2017)
11. Russell, S.J., Norvig, P.: Artificial Intelligence: A Modern Approach. Pearson Education Limited, Malaysia (2016)
12. Stone, P., Veloso, M.: Multiagent systems: a survey from a machine learning perspective. Auton. Robots **8**(3), 345–383 (2000). https://doi.org/10.1023/A:1008942012299
13. Zlot, R.M.: An auction-based approach to complex task allocation for multirobot teams. Ph.D. thesis, Carnegie Mellon University, Pittsburgh, PA (2006)