A review on task planning in Human-Robot Teams

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Abstract—With the development of safe collaborative robots, the introduction of these systems into human teams, as teammates, is starting to occur in sectors such as space, military and industry. Consequently, to accomplish a seamless integration, evaluating human factors which can prevent human-robot teams from functioning well, and developing reliable, efficient algorithms for task planning is essential. This paper overviews recent literature on these issues and outlines some gaps in the optimization of task planning in Human-Robot Teams (HRT).

I. INTRODUCTION

Although present in several industries, robots rarely work side by side with people. In the manufacturing sector, for instance, robots are often physically separated from human working areas and tasks are divided without work or space overlap. Advances in robotic systems technology are enabling the integration of robots in human teams, offering the possibility to upgrade human capacities with robotics strengths. The introduction of collaborative robotics in this sector denotes a substantial paradigm shift, increasing automation levels in high-variability tasks that were usually low-automated (e.g., engine assembly) or increasing flexibility in highly automated, strict tasks.

Not only in manufacturing are these changes experienced, but also in space and military applications, where teams subject to highly uncertain, risky and stressful environments, effectively perform complex tasks under tight ordering, timing or resource constraints.

The members of such Human-Robot Teams (HRT) must collaborate, sharing the same workspace and objects, in a safe and efficient scenario. Creating a symbiotic relationship between humans and robots can lead to faster, more precise and reliable performance, but also to the reduction of stress, fatigue and ergonomic problems.

These outcomes are only possible if tasks are properly allocated and scheduled in time and space, while respecting the required constraints. Therefore, this paper reviews recent literature on these subjects in HRT. Studies about human acceptance of robotic systems are also reviewed, as this topic is of utmost importance if robots should be viewed as teammates.

II. HUMAN ACCEPTANCE OF ROBOTIC SYSTEMS

Ensuring the well functioning of HRT cannot rely only in proper planning. Indeed, this depends on the human acceptance of the robot as a teammate, and on a properly designed robotic system. This section overviews recent studies on this matter, focusing on the human feelings concerning the robotic counterpart, the adequate robot autonomy level, the level of human control during task assignment and the prioritization of human preferences in the HRT schedule.

A. Human feelings concerning robotics

Today, products are only integrated into daily routines if they please the human or are enforced to it. The level of trust in the system and in the robot, the perceived workload, and how the robot work fits the goals of the team, can greatly influence its integration. Studies from Takayama and Pantofaru and Sarkar et al. suggest that human interaction with robots is influenced by gender, past experiences with pets and other robots, and personality.

If robot actions mismatch the actions it is expected to do, then the teammate can be perceived as an extra workload, both physical and mentally, being an extra burden for the human. Robots should be competent and proactive; they should take work politics seriously, adhere to social norms and protocols, and be considerate and non-intrusive.

Other studies focusing on engagement found that the use of dialogue, emotion, perception of actions or care to capture attention can influence robot acceptance.

B. Level of Robot Autonomy

The engaging abilities of the robot are directly affected by the level of autonomy of the system and its automation reliability level. In their studies, Munzer et al. detect that people preferred semi-autonomous robots that can learn with time over fully autonomous systems. In the experiments, as participants felt robots were learning, they demanded more autonomy from them, aiming to decrease the time spent with non necessary tasks. However, increasing autonomy often increases the amount of time humans spend in supervisory mode, monitoring robots and their actions. This can ease human attention and decrease system performance, since automation is inherently imperfect. With highly automated systems, humans can also ignore important data and events, decreasing situational awareness.

C. Level of Human Control

Baraglia et al. evaluate proactivity and reactivity in HRT. The authors found that people would willingly give away control if their robotic teammate is proactive, but they would rather have control if it is reactive. The authors infer that people have preference for robots that are consistent and reliable. They also found that increasing proactivity in robots that learn human preferences over time might improve collaboration.
Some studies with HRT have been recently conducted with the goal of understanding the right level of decision-making authority and if humans would be satisfied by having a robot performing task allocation over them. Trying to retrieve autonomy from humans and transferring it to robots might lead man not to value the robotic presence and discourage human attention to details. This is an important trade-off that is both difficult and fundamental to evaluate in mixed teams [13].

Gombolay et al. [13,11] have conducted a series of studies to evaluate the influence of human control and satisfaction in task planning. In [11], the researchers wanted to test if humans would accept automatic task scheduling in manufacturing systems. They stated that highest human satisfaction levels are found when people have freedom to choose and the performance of the system is high. They infer that people like to have freedom of choice, but high performance impacts more participants satisfaction levels. Because decision making is a time consuming process, automated systems usually perform faster [13].

In Gombolay et al. [13], a study was conducted to understand how much control a human in a HRT must have over the robot tasks and his own tasks, by measuring worker satisfaction and team efficiency. During the tests, the team was usually more efficient in both assembly and rescheduling time when the robot had more control authority over task allocation. Workers preferred partial authority over the task process rather than total control, and having no control was preferable to having complete control. Subjects agreed that they were more likely to work with the robot again if the robot performed task allocation autonomously than if the subject and the robot shared task allocation authority. Overall, autonomy can improve team efficiency, but giving too little or too much control to the worker can be alienating or overwhelming, respectively.

D. Prioritization of human preferences

Another important aspect in system design is the prioritization of human preferences in a schedule. This is studied in Gombolay et al. [14], where authors inferred that people would prefer working in teams where their preferences are considered. In the experiments, the robot was responsible for scheduling the tasks, with and without giving priority to the human preferences. Some participants of the first group stated that team efficiency decreased and that the robot did not understand teams objectives. This leads one to infer that human preferences should not be valued over efficiency.

As shown, the acceptance of a planning software or method for HRT goes beyond its technology efficiency. A number of other factors must be taken into account besides minimizing makespan or costs. The experiments here described try to give the first step towards a seamless integration of the members in HRT, but are performed mostly with college students or in small manufacturing groups, giving people chores they are not experts in and are not their daily todos. There is a need to evaluate the acceptance of systems that plan human and robot collaboration in real world scenarios during a more extended period in order to observe if people would effectively use the system in a daily basis (scheduling systems are quite often distrusted by workers) and what are the key strengths and weaknesses on their implementation in the field.

III. TASK PLANNING IN HUMAN-ROBOT TEAMS

Introducing robots into human teams, as teammates, affects the way tasks are planned. Not only it should be integrated with the equipment and humans that directly work with it, but its skills shall be taken into account in team formation and system planning. Daily, there are tasks that need to be performed in a given time and space, respecting a pool of constraints. Allocation and scheduling are complex, and influenced by factors such as the size of the team and their organization, and the tasks to be performed.

When analysing such problems, we distinguish between two abstraction levels: the system level, where teams that have to perform a sequence of tasks are formed and resources are distributed to them; and the team level, where robots and humans must coordinate to complete these tasks and decide on the spot how to solve problems that appear. These abstraction levels are depicted in Figure 1

A. System Level

Humans have long invested in optimizing work distribution and team formation. At the system level, the relation between the tasks and the agents from different teams can affect work division, as expressed in Korsah et al. [20] taxonomy, that focus on task allocation in multi-robot teams. The authors divided the problem in four categories: no dependencies between tasks (the work of an agent is completely independent from the rest), in-schedule dependencies (intra-task dependencies), cross-schedule dependencies (inter-task dependencies) and complex dependencies (inter-schedule dependencies). The scheduling of tasks in multi-robot or human-robot teams lie on the later two categories, having these problems not yet a general mathematical definition in the combinatorial optimization literature [15,20]. As such, researchers have handled
this planning problem with approaches such as auctions, market-based methods, Markov Decision Processes (MDP), decentralized scheduling algorithms or distributed constraint optimization [32, 24].

Optimizing planning is specially important when teams must perform under hard conditions. For instance, missions on the moon imply scarce resources, time constraints and life risks, and therefore have been one of the fields where multi-agent task allocation and scheduling has been researched. Human-Robot Task Network Optimization (HURON), from Elfes et al. [8], plans human-robot missions on the moon, considering time, operation, consumables and resource constraints. HURON uses the mission information to create a state-space search graph that is iteratively built, giving as output the assignment of tasks to the different agents and respective schedules. In space, resource utilization has strong influence in performance. Hence, Singer and Akin [40] stack astronaut chores together and minimize human workload in space missions. Their method can switch tasks in time, such that no precedences are corrupted, generating flexible schedules.

Military and search missions also suffer from resource and time constraints. In Freedy et al. [10], a multi-agent adjustable autonomy framework for military use is presented. This is a platform that combines goal-oriented, multi-agent planning and coordination technology. The role allocation problem is seen as a Distributed Constraints Optimization Problem and team tasks are described in the individual roles, using Team Oriented Plans (TOP). In Hollinger et al. [21] is described a plan generation algorithm for environment clearance from adversarial targets that performs role allocation and creates a search schedule. The algorithm assumes that a given number of searchers are present and a graph whose nodes represent possible locations in the environment exist. Locations and times of the searchers are monitored and the adversarial target is assumed to have a worst-case posture. To generate the schedules, finite-horizon planning with spanning tree traversal methods are used. The goal is to generate a guaranteed search schedule that optimizes clearing. Due to the environment stress and pressure, the algorithm was design to enable the user to halt it if needed, generating a time-efficient, non-optimal plan.

Another planning solution is presented in Talamadupula et al. [43]. This planner was created for urban search and rescue with HRT and can represent and handle conditional goals (for instance, when the target position is unknown). The search relies on a weighted A* [18] forward search, using net benefit as the optimization criterion.

In production facilities, performance criteria further include minimal production changes, reduction in cycle time or ergonomics [46]. The work of Chen et al. [4] in hybrid assembly cells starts by dividing complex tasks into simpler ones and allocating them to the team members, given their skills. The authors use a generalized stochastic Petri Net to model the possible situations during assembly, including mistakes. Monte Carlo method is used to generate the finishing times of tasks and costs. These are optimized using a multi-objective optimizer, that finds the best task allocation of both human and robot in the cell. Also within cells, Takata and Hirano [42] propose a method for human-robot task allocation in scenarios where production volumes and products are supposed to change during time. First, the algorithm computes all allocation patterns, that are expressed by the allocation matrix. Then, the capabilities of the team members are checked. The algorithm then generates all possible scenarios with changes in production, weighted by their probability of occurrence, and compute their production costs. The resulting allocation pattern will be the one with the minimum expected total production cost, i.e., the team composition that can go through changes in the product models and the volumes demanded in the future with minimal production costs.

Even in the health sector can such algorithms help. In Gombolay et al. [15], TERCIO [12] is used to distribute resources and patients to nurses and schedule their tasks. TERCIO was designed for scenarios with logistic operations that benefit from improvements on resource usage, optimizing task allocation and schedule. The researchers divide the allocation and scheduling problem to insure tractability in real-time. They formulate the multi-agent coordination problem as a mixed-integer linear programming (MILP). The speed of the algorithm is due to a fast task sequencer inspired by real-time processor scheduling methods. It formulates feasible schedules that satisfy temporal and spatial constraints. The decision variables on the MILP are the order, allocation and start and end time of each task. Its goal is to minimize the makespan, subject to having an agent for each task, lower and upper bound time constraints, wait/precedence and deadline constraints, agent capabilities on task completion time in and physical constraints. It was also tested in manufacturing plants [12, 14], and have proved to be fast, taking 20 seconds to generate a schedule for up to 10 agent, 500 tasks.

Scalability to large teams and speed is important, but research is still far from perfection. As noted in [24], robust solutions that handle complex tasks, dynamic task assignment or heavily constrained task allocation are still underdeveloped.

B. Team Level

After allocation and scheduling, work content must be distributed within the teams. For instance, the framework of Johannsmeier and Haddadin [22] model this human-robot collaboration in three levels. Firstly, it allocates tasks among team members based on an abstract world model. Then, the agent-level skill planner implements the model and the parametrizable skills. Finally, robot skills are executed in real time, planning and executing trajectories, and controlling the robot.

When robots act as team members, the skills they have, and specially, they lack, must be considered, specially when problems must be handled on-the-fly. Due to safety concerns, work overlap between the robot and the human is commonly not allowed. Some systems, like the one created by Tsarouchi et al. [47], allocate sequential tasks such that team members are in separate workspaces. In the latter, task allocation and
planning is done via a decision-making algorithm based on decision sets like resource suitability, availability and operation time. The algorithm decides the most suitable team-member to do the task and scheduling is performed using depth search based on multiple criteria evaluation. The planner starts by sending a task request to an agent. The latter returns a cost, with the possibility to return further interaction requests. All the answers from the agents are weighted and the optimal task allocation is defined. The assembly processes are modelled with And/Or graphs at the team level and task sequencing is done via A* graph search.

On the other side, collaboration explores the strengths of the team members and avoids unnecessary space and time restrictions. Having a human in the loop increases flexibility and can be explored in the update pre-computed plans. The Hierarchical Agent-based Task Planner (HATP) extended by Sebastiani et al. [38] makes use of this idea by allowing humans and robots to negotiate online. The system uses HATP to generate different plans, that are merged into a Petri Network Plan. Portions of the plan can be chosen at execution time, depending on the state of human-robot interaction.

This interaction can be improved if the robot considers a priori known human preferences. For instance, the human aware task planner developed by Cirillo et al. [5] supports different human plan hypothesis to schedule tasks in a house cleaning robot. Providing a set of human agendas, goals and robot and human possible actions, the planner uses probabilities to explore the possible set of actions of the robot and its outcomes, based on a breadth first search. The authors assume deterministic task duration when planning the cleaning activities for the robot, that must comply with the interaction constraints expressed by the human beforehand. Another method, the Adaptive Preferences Algorithm developed by Wilcox et al. [48], is a robotic scheduling and control capability that adapts to human preferences during task execution. It was designed for manufacturing and focus on two pillars of the sector: flexibility on task completion time and hard scheduling constraints. The input of the algorithm is a Simple Temporal Problem with Preferences (STPP), that encloses the variables, constraints, preferences and the optimization function. The outcome is a dispatchably optimal form of the STPP, where each executable event has assigned a time within the specified timebounds and the preference function is maximized. It was tested in an industrial HRT, where a robot and a mechanic should place and torque fasteners, and the robot should adapt to the mechanics actions. The robot proved to adjust on-the-fly to changes in human preferences and timings.

As techniques evolve, preferences might be learned instead of being defined beforehand, increasing flexibility. Some authors avoided the need to code human behaviours in the real world by learning from experience. In Agostini et al. [11], plans are constantly generated using STRIPS-like planning operators [9] and are constantly refined by a learner, that evaluates multiple cause-effects possibilities and chooses the ones with highest probability to occur. This reasoning allows the robot to use deliberation in new situations and still act. If the planning operator fails, tasks to be performed are selected using policies set beforehand or recurring to human knowledge. In Talamadupula et al. [45], human beliefs and intentions are modelled and inferred over, predicting the teammate plan. This online recognition of plans, based on incremental inputs or observations, improves coordination behaviour and team performance. Modelling humans and robots via MDP is used by Koppula et al. [25] to predict human behaviour and anticipate their actions. The authors model the human-robot cooperation as a two-agent Markov decision game, whose goal is to complete the task. The human is observed during task execution and the degree of adaptability that he experiences is evaluated. By explicitly modelling human actions, his policies can be learned and used to improve robot policies. The authors also noted that changes in human behaviour during task execution can greatly influence the activities the robot should perform. PIKE, an online executive extended by Karpas et al. [23], verifies intent recognition and plan adaptation for temporally flexible plans with choice. The extension is intended to make PIKE robust to temporal uncertainty in task duration. PIKE, as presented in Levine and Williams [28], uses historical information to decide on values for decision variables and temporal durations. It takes a Temporal Plan Network with Uncertainty (TPNU) to execute as an input. Negotiation with the human is also foreseen, asking their input to relax constraints. Bayesian inference is used in Liu and Fisac [29] to predict the next human goal (based on their motion) and re-plan accordingly, respecting human intention. The authors apply goal inference at motion level to compute a collaborative plan at the task level and infer whether the human is deviating from the robot plan. To do this, the robot uses a maximum a posteriori estimate. If a deviation is detected, a new allocation of tasks is performed based on current state and human intent. Task allocation is based on a MILP, aiming for an execution order that minimizes completion times. The authors tested the algorithm with a web-based experiment with over 200 participants, having most reported preference to work with a robot that adapted to their intentions. In Kwon and Suh [27], the robot is able to solve proactive planning problems using composite node temporal Bayesian network, a framework that both infers the nature and time of an event using probability. The method is shown to decrease total execution time of tasks by anticipating preparatory actions and reduce delays in human-robot interaction. This enables the proactive robot to seamlessly integrate with humans and act accordingly to his actions.

However, this proactivity can take the human by surprise. Indeed, robots still miss important features that humans use daily, like communication skills. When working with another human beings, people talk and interpret reactions.

Monitoring and manipulating human attention is avoided by Caccavale and Finzi [3] in their framework. Plans of actions are represented as hierarchical task networks, and these actions can be re-ordered through speech and gestures. These signals are fuses to recognize human intention, which is used to replan actions in the spot. The robot can also communicate with
the robot through interactive behaviours. Clair and Matarić use effective verbal feedback to communicate with the human. Using sensors, the robot observes the human and infers the action he is doing. Then, the robot communicates to the human in one of three modes: role allocative mode (tells the human what he should do), self-narrative or empathetic. To handle noise, robot tasks are modelled using MDP. With this approach, the authors can allocate roles and tasks on-the-fly. Roncone et al. tries to integrate the above by creating robots able to plan under uncertainty, without full world knowledge and able to decide what to communicate to the human and when. Robots distribute roles and allocate tasks, being able to choose the best execution plan and optimize over its parameters, reducing human cognitive load. The authors predict human actions using Hierarchical Task Models. These high-abstraction models are transformed into low-level task planners using Partially Observed Markov Decision Processes, that model the commitment of both human and robot. The system proved to overcome human task allocation in experiments and is easily integrated with inexperienced humans.

C. Integrating System and Team Level Planning

The integration of planning at system and team levels is not straightforward. In one side, teams are formed having as basis the work to be done and their capacities. In the other, subtasks are distributed among team members. However, this partition of optimizing over the system first and within teams later might not yield optimized overall results.

Zhang and Shah try to address this multi-level optimization problem with the development of a multi-abstraction search approach (MASA), that optimizes both over agent distribution in the system and over assignment and scheduling at workplaces. MASA starts with an abstract agent placement that does not consider task allocation or scheduling and uses a MILP to create an initial solution. Then, this solution is improved by a hill climbing algorithm that considers task assignment within workspaces. Lastly, the solution is fine-tuned by considering both assignment and scheduling. TER-CIO was used to solve the lower level task assignment and scheduling. The algorithm was tested with simulated data from a production assembly line, and was compared to a MILP-based approximate approach and a conventional hill climbing algorithm, significantly outperforming them regarding solution quality and makespan.

Despite the importance of the problem, this integration is rarely envisioned, due to the complexity of such implementation. Indeed, the optimization of each team’s schedule often do not imply that the system is efficient. Also, the permanent change and unpredictability in human scenarios is difficult to incorporate into algorithms. Answers to what to do when a machine is down, when a material is missing or something unexpected happen are not easy to model. And while humans can think in the spot, often even they do not act efficiently, using a local interpretation of the system, rather than a systemic one.

Dealing with this unpredictability and interchangeability between system and team perspectives is difficult. Tools for planning and decision support that reason in both levels are still underdeveloped. Also, as flexibility is more and more a request, systems might also have to consider team modification on-the-fly. This is currently asked for in the manufacturing industry, where often robots that are idle must perform in other teams that lack resources.

We expect that experience from integrating collaborative robots in different sectors will allow better insights on the path to go and the adequability of the systems developed to the real world.

IV. Conclusion

As industries and processes evolve, the needs in flexibility and better resource usage increase. The integration of robotic partners in HRT can provide a mean to that end, as long as robots can be seamlessly incorporated as team members, and allocation and scheduling of tasks ensures optimized operating plans.

Humans have an important role on robotic systems acceptance. Their trust, the perceived workload or the adequate automation level are factors proved to influence the integration of robots in teams. Also, the schedule should prioritize team’s efficiency, since people have shown to value it more than having control over task distribution or having their preferences added to the schedule.

This efficiency can only be insured by having a robust approach that combines planning at the system and team levels. In the former, the distribution of resources into teams and the allocation and scheduling of tasks is performed. In the latter, work division among team members and on-the-fly reaction to unexpected problems take place. Usually, literature focus on one or another, rather than providing a solution that optimizes in both levels. Indeed, during our literature search, this bridge was only perceived in Zhang and Shah.

Also, little work was found that considers HRT existence during system level planning in manufacturing, which can indicate a trend to use common production scheduling algorithms that do not consider collaborative robots.

The development of efficient methods that can jointly optimize at the different levels, while re-planning on-the-fly over unforeseen problems, can take a step beyond human reasoning and support their decisions. For that, planning must consider constraints such as time, resources and consumables, but also team well functioning and improvement of the team members strengths.

In the end, a solution that optimizes over all abstraction levels and provides the best plans for the whole organization is intended. The methods used should be understandable by everyone, translating outcomes into performance indicators that provide real management insights. Additionally to addressing these gaps, it is of utmost importance to make research go from the lab computer to the real world.
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REFERENCES


