Trajectory Planning and Decision-Making for Multi-Robot Systems with Robust and Resilient Connectivity Maintenance and Human-Robot Collaboration

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Abstract. *This work addresses the problems of motion planning and decision-making for multi-robot systems with emphasis on the maintenance of communication network properties such as resiliency and connectivity. Planners based on mixed-integer programming and model predictive control (MPC) are proposed, enabling the group of robots to perform tasks while maintaining network connectivity considering potential bounded disturbances and robot failures. The requirement of both omnidirectional and directional line of sight between agents for communication links to be formed is studied. A novel algorithm for human-robot collaborative teams, leveraging a combination of deep inverse reinforcement learning and MPC, is also proposed.*

Keywords: Multi-Robot Systems, Model Predictive Control, Mobile Networks, Human-Robot Collaboration, Inverse Reinforcement Learning

Student level: PhD. Date of conclusion: 18/03/2024. To be considered in CTDR.

1. Introduction

Recent decades have shown remarkable technological progress in the design of autonomous machines that are fundamental in sustaining the amenities of modern society. In spite of these advancements, there is a physical bound to what a single machine can do, and this limitation narrows down the scope of problems that can be solved by it. This motivates the study of *groups* comprised of autonomous systems that cooperate to solve complex problems. This paper addresses groups of mobile robots commonly referred to as Multi-Robot Systems (MRS) which are an important research subject in the fields of artificial intelligence, control theory, and robotics [Hadaegh et al. 2016]. Applications of MRS are widely discussed in the literature, e.g., agriculture [Adamides and Edan 2023] and firefighting [Harikumar et al. 2019].

One of the main challenges in the development of MRS is to plan their trajectories and decisions such that they harmoniously collaborate towards the same objective [Garcia et al. 2013]. A powerful technique used to design these planners is Model Predictive Control with Mixed-Integer Programming encoding (MPC-MIP), which can be employed to compute collision-free trajectories, as well as decisions that leverage the unique characteristics of an MRS, yielding a robust and efficient robot team. Issues that are unique to MRS, such as the maintenance of their communication network connectivity, can also be addressed by MPC-MIP planners, as shown in [Afonso et al. 2020]. Extensions of this problem are addressed in [Caregnato-Neto et al. 2020], where robust connectivity is discussed. In [Caregnato-Neto et al. 2022b] and [Caregnato-Neto et al. 2023c] where algorithms for resilient connectivity are proposed and in [Caregnato-Neto et al. 2023b, Caregnato-Neto et al. 2022a, Caregnato-Neto et al. 2023a] Line-Of-Sight (LOS) connections are studied.

The concept of MRS can also be extended to mixed groups comprised of humans and autonomous systems. The so-called Cyber-Physical-Human Systems (CPHS) are considered a major topic for future research in control [Annaswamy et al. 2023]. In particular, Human-Robot Collaboration (HRC) stands out as a key application of CPHS, being fundamental in the design of collaborative MRS that can support humans. The development of models for the prediction of human behavior that enable the design control strategies for the robots is outlined as a key element in the development of CPHS [Annaswamy et al. 2023]. Traditionally, fields such as Psychology rely on descriptive models of human behavior which are based on first principles [Annaswamy et al. 2023]. However, recent advances in machine learning (ML) techniques have enabled an increasing number of sophisticated data-driven models for human motion and decisions [Liu et al. 2023]. As a quantitative methodology, ML offers the benefit of providing models in the form of mathematical expressions or algorithms that are naturally encoded into machines [Fuchs et al. 2023].

In light of these remarks, this paper proposes several solutions based on MIP, MPC-MIP, and ML, to solve multiple MRS coordination problems under network connectivity constraints and the CPHS problem, i.e., the collaboration of a human-robot team in similar contexts. The effectiveness of the algorithms is demonstrated with extensive statistical analysis, realistic simulations in the Gazebo environment, and experimental demonstrations with real robots.

1.1. Contributions

- The planner proposed in [Afonso et al. 2020] was expanded to address the issue of robust connectivity. [Caregnato-Neto et al. 2020].
- The concept of resilient robust connectivity was devised. The trajectory planning and decision-making system was expanded with a recovery mode that allows the MRS to reorganize itself to recuperate the robust connectivity property in the event of malfunctioning agents [Caregnato-Neto et al. 2022b].
- The viability of a centralized MPC-MIP approach for real-time trajectory planning and task allocation under robust connectivity constraints was demonstrated experimentally using a group of differential drive robots. [Caregnato-Neto et al. 2023c].
- The issue of LOS-dependent connections between agents was studied. A novel LOS constraint based on virtual halfspaces was proposed and encoded in a MIP framework [Caregnato-Neto et al. 2022b].
- A novel concept to enforce LOS connections based on intermediary points was idealized. The approach was compared to the virtual halfspaces method in terms of conservatism using Monte Carlo simulations [Caregnato-Neto et al. 2022a]

- An alternative encoding of the intermediary points approach was proposed. The novel method requires fewer constraints and optimization variables to encode LOS conditions on MIP models. Monte Carlo simulations were employed to demonstrate that this improvement provides better performance in terms of computational time [Caregnato-Neto et al. 2023b].
- These results were expanded to account for directed LOS, where connections are under the additional requirement of proper alignment (relative orientation) between agents. Conditions for connectivity of the ensuing directed network, represented by a digraph, considering a Robot Chain Control System (RCCS) under a Visible Light Communication (VLC) network, were proposed and encoded as constraints of a MIP model [Caregnato-Neto et al. 2023a].
- The proposal of novel control architecture entitled Adaptive Robot Motion for Collaboration with Humans using Adversarial Inverse Reinforcement learning (ARMCHAIR), which leverages the integration between AIRL and MPC-MIP for motion planning and task allocation of a human-robot team [Caregnato-Neto et al. 2024].

2. Preliminaries

2.1. Scenario

Consider a MAS constituted of $n_a \in \mathbb{N}$ agents. Let their dynamics and kinematics be approximated by the following discrete-time state-space equations

$$\mathbf{x}_i(k+1) = \mathbf{A}_i\mathbf{x}_i(k) + \mathbf{B}_i\mathbf{u}_i(k),\ \mathbf{y}_i(k) = \mathbf{C}\mathbf{x}_i(k),\ i \in \{1, 2, \ldots, n_a\}, \tag{1}$$

where $\mathbf{x}_i \in \mathbb{R}^{n_{x,i}}$, is the state vector; $\mathbf{u}_i \in \mathbb{R}^{n_{u,i}}$ is the input vector; $\mathbf{y}_i \in \mathbb{R}^{n_y}$ is the position vector. The pair of state space matrices $\mathbf{A}_i \in \mathbb{R}^{n_{x,i} \times n_{x,i}}$ and $\mathbf{B}_i \in \mathbb{R}^{n_{u,i} \times n_{u,i}}$ is controllable; $\mathbf{C}_i \in \mathbb{R}^{n_y \times n_{x,i}}$ is a matrix that extracts the variables representing the position of an agent from its state vector. The states and inputs are bounded by the polytopes $\mathcal{X}_i \subset \mathbb{R}^{n_{x,i}}$ and $\mathcal{U}_i \subset \mathbb{R}^{n_{u,i}}$, respectively.

The MAS operates within a region represented by the polytope $\mathcal{A} \subset \mathbb{R}^{n_y}$. See Figure 1 for an example. This space is filled with $n_o \in \mathbb{N}$ obstacles, represented by the

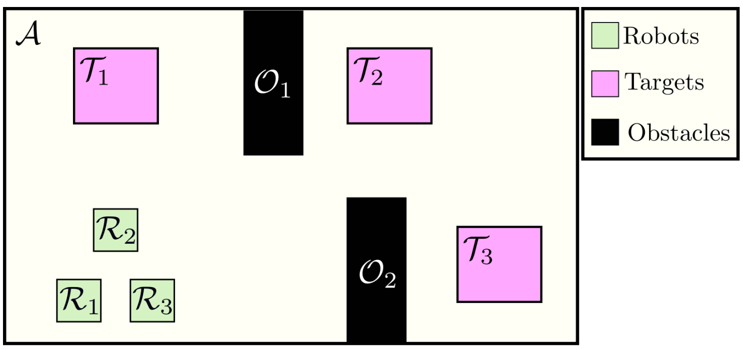

Figure 1. Example of planar scenario with three agents. The last target $\mathcal{T}_3$ is mandatory, while $\mathcal{T}_1$ and $\mathcal{T}_2$ are visited only if advantageous.

polytopes $\mathcal{O}_g \subset \mathbb{R}^{n_y}$. Additionally, let the polytope $\mathcal{R}_j \subset \mathbb{R}^{n_y},\ j \in \mathcal{I}_{n_a}$, represent the body of j-th agent, with the space occupied by this agent at time step k is written as

$\mathcal{R}_j(k) = \mathbf{y}_k(k) \oplus \mathcal{R}_j$. Within the region $\mathcal{A}$, there are also $n_t \in \mathbb{N}$ targets represented by the polytopes $\mathcal{T}_e \in \mathbb{R}^2$. The mission of the MAS is completed if the last target $\mathcal{T}_{n_t}$ is visited by any agent; the remaining targets are optional and must be visited only if advantageous to the overall mission. The objective of the MAS is to complete this mission while minimizing a compromise between the rewards collected by visiting optional targets, the duration of the mission, and the control effort of the robots.

2.2. Connectivity

The communication network of the group is represented by a graph $\mathcal{G}(k) = \{\mathcal{V}, \mathcal{E}(k)\}$, where $\mathcal{V} = \{v_1, v_2, \ldots, v_{n_a}\}$ is the set of vertices representing agents. The set of edges is denoted by $\mathcal{E}(k)$ with them corresponding to the time-varying connections between robots. Fig. 2 summarizes the connectivity properties addressed in this work. In Fig. 2a, one observes a robust network, where even if a vertex is removed (as depicted in Fig. 2b), the resulting graph remains connected. Resiliency is illustrated by Fig. 2c; the network updates its configuration to recover the robustness property lost after ν_1 is removed, characterizing a resilient and robust system.

Fig. 3 presents the types of connections that can be formed between the robots. In 3a, connections (represented by the edges of $\mathcal{G}$) are formed based on *proximity* dictated by the connectivity regions of each robot. Fig 3b illustrates the *omnidirectional* Line-Of-Sight (LOS) requirement, where a connecting between a par of robots is created if the line segment connecting two robots is not obstructed by any obstacles. Finally, 3c shows the *directional* LOS condition, where the robots cast a connectivity region depending on their orientation, also yielding graphs with directed edges (digraphs).

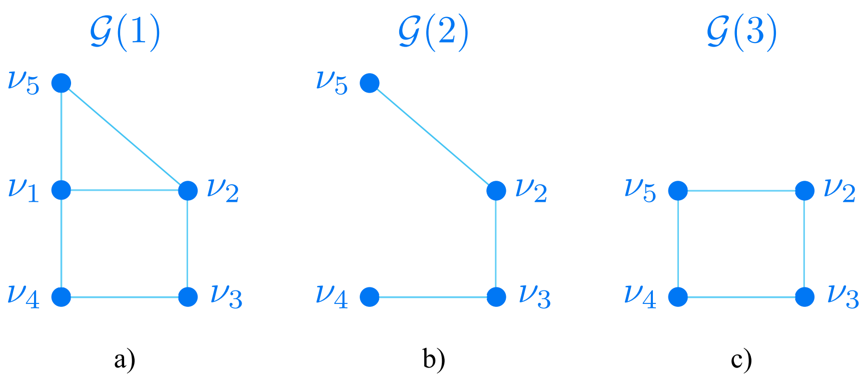

Figure 2. a) Robust network. b) $\mathcal{G}$ remains connected when a vertex is removed. c) Recovery of the robustness property (resiliency).

2.3. Mixed-integer Model Predictive Control

In a conventional Model Predictive Control (MPC) scheme, sequences of inputs for a system are computed periodically as the solution of a finite horizon optimization problem. The first element of this sequence is applied to the plant and its response is measured after a period corresponding to one time step. The optimization is then repeated taking into account the new state of the system. As time progresses, the prediction horizon recedes towards the subsequent time steps; this particular behavior characterizes the so-called *receding horizon* strategies.

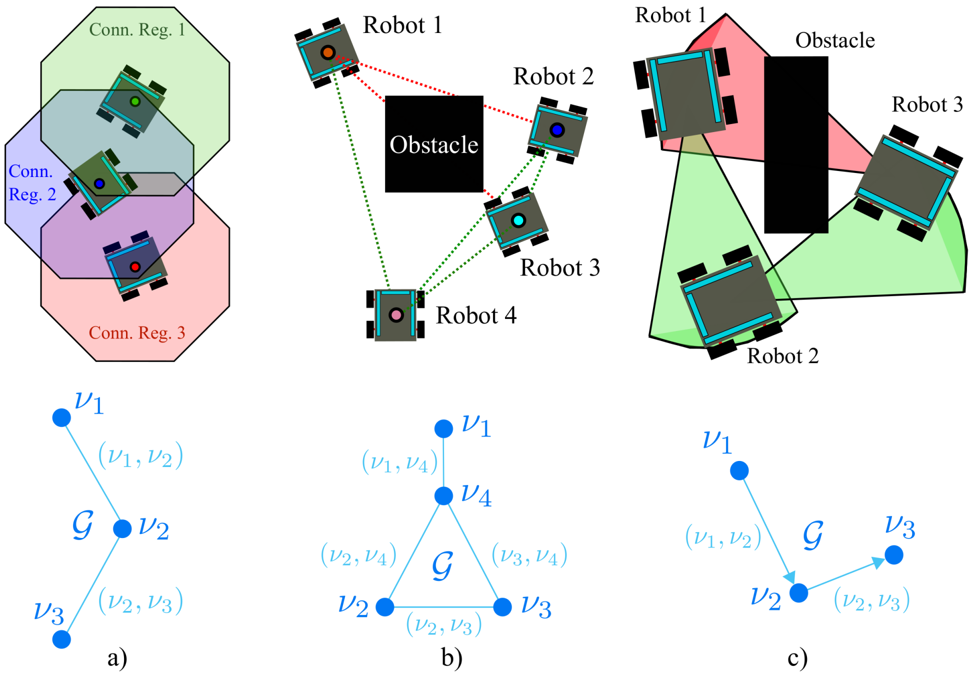

Figure 3. Examples of a) proximity, b) omnidirectional LOS, and c) directional LOS connectivity.

In discrete time, a typical MPC formulation can be written as the following optimization problem

$$\min_{\mathbf{x},\mathbf{u}} J = \sum_{\ell=0}^{N} f(\mathbf{x}(\ell+1|k), \mathbf{u}(\ell|k)), \text{ s.t.}, \forall \ell \in \{0, 1, \ldots, N\}, \tag{2}$$
$$\mathbf{x}(0|k) = \mathbf{x}(k), \ \mathbf{x}(\ell+1|k) = \mathbf{g}(\mathbf{x}(\ell|k), \mathbf{u}(\ell|k)),$$
$$\mathbf{x}(\ell+1|k) \in \mathcal{X}, \ \mathbf{u}(\ell|k) \in \mathcal{U},$$

where $\mathbf{x} \in \mathbb{R}^{n_x}$ and $\mathbf{u} \in \mathbb{R}^{n_u}$ are the states and inputs of the system, respectively. Indices such as $(\ell|k)$ represent the prediction of a variable at the ℓ-th time step carried out at time step k. The number of predictions is determined by the prediction horizon $N \in \mathbb{N}$.

While the presented MPC scheme can be used to solve a multitude of conventional control problems, the issue of trajectory planning presents additional challenges. Planning trajectories that prevent collisions between a robot and obstacles is notoriously difficult due to the ensuing nonconvexity of the optimization's search space. Moreover, when an MRS is considered, avoiding collisions between robots is also a concern.

One solution to address this problem is the use of MPC with Mixed-Integer Programming encoding (MPC-MIP), in which binary decision variables are introduced in the receding horizon optimization problem. These variables allow the implementation of many useful schemes; for example, a constraint can be relaxed after a few time steps using the "Big-M" technique, $\forall \ell \in \{0, 1, \ldots, N\}$,

$$\mathbf{P}_x \mathbf{x}(\ell+1|k) \leq \mathbf{q}_x + b(\ell+1|k) \mathbf{1}_{n_x} M,$$

where $b \in \{0, 1\}$ is a binary variable, $\mathbf{1}_{n_x} \in \mathbb{R}^{n_x}$ is a column vector comprised of ones and $M \in \mathbb{R}$ a constant large enough to relax the constraint if $b(\ell+1|k) = 1$. See

[Caregnato-Neto et al. 2022b] for details on the selection of M. The use of the "Big-M" approach and the optimization variables enable the implementation of constraints that guarantee collision avoidance and connectivity maintenance, as well as allow the integration of decision-making problems into the optimization model [Afonso et al. 2020].

3. Resilient Robust Connectivity

The following constraint was proposed to impose robust connectivity to the robot's network as an additional constraint on optimization model (2), $\forall i \in \{1, 2, \ldots, n_a\}$, $\forall \ell \in \{0, \ldots, N\}$,

$$\deg_i(\ell+1|k) + \deg_j(\ell+1|k) \geq n_a - n_a b^{con}_{i,j}(\ell+1|k),\ i < j \leq n_a, \tag{3}$$

where $\deg_i$ is the degree of vertex representing the ith robot, $b^{con}_{i,j}$ can take the value of one if robots i and j are close enough to each other.Resiliency is guaranteed with a novel routine denominated SELECTMODE which is invoked at each time step, with the updated graph object, that represents the current communication network, as an input. If a vulnerable network is detected, SELECTMODE switches to the *recovery mode*, where the robots reorganize themselves to recover the robustness of their communication network. Otherwise, a nominal mode, where the robots try to accomplish the mission as described in Section 2, is activated.

An example of the proposed motion planning algorithm with resilient robust connectivity guarantee is presented in Fig. 4a. Five robots are deployed in an obstacle-filled environment with 5 targets, with $\mathcal{T}_5$ being mandatory and the remaining ones optional (to be visited only if worth considering fuel and time expenditure). The robots must maintain a robustly connected network at all times, as depicted in Fig. 4b. At time step $k = 4$, robot 5 fails, stopping and becoming an obstacle ($\mathcal{O}_6$). As a result, vertex 5 is removed from the network (Fig. 4c), yielding a vulnerable network (removal of vertex 2 disconnects the graph). The vulnerability triggers the *recovery mode* for one time step, when the robots ignore the targets and try to recover the robustness property of the network, which is accomplished after one time step $k = 5$, as illustrated by Fig. 4d. Then, the *nominal mode* is activated again and the robots finish the mission, visiting all targets.

4. Demonstrations with multi-robot platform

The demonstrations were performed in the Autonomous Computational Systems Laboratory (*Laboratório de Sistemas Computacionais Autonômos* – LAB-SCA) at ITA. The experimental setup is presented in Fig. 5, where the main components can be observed: a) the camera, b) the computer, and c) the operation field.

A group of five differential robots from the Very Small Size (VSS) category, presented in Fig. 5d, were employed in the experiment. They were designed and built by students at ITA during the course *CMC10 - Design and Manufacture of Mobile Robots* in 2019. The architecture employed to control the multi-robot system is presented in Fig. 6, where an MPC-based motion planner takes measurements of the group's states, given by a computer vision algorithm and a Kalman filter, and replans the decisions and trajectories of the robots in real-time. The tracking controllers leveraged the Dynamic Feedback Linearization (DFL) method. The wheel velocity controllers were designed with

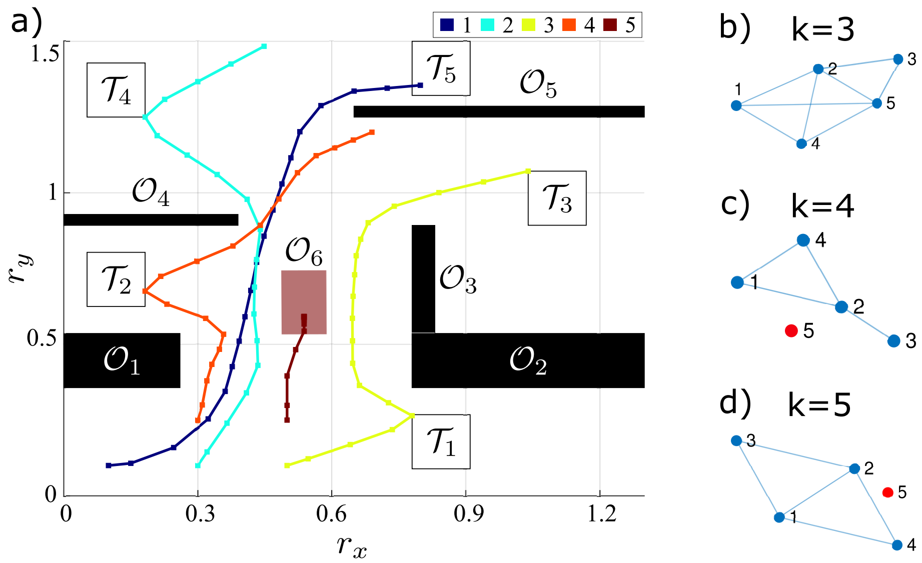

Figure 4. a) Trajectories of five robots collaborating to reach targets; robot 5 fails at time step $k = 4$, becoming an obstacle ($\mathcal{O}_6$). Communication network at time steps: b) $k = 3$, c) $k = 4$, and c) d) $k = 5$.

proportional-integral (PI) control. We also improved the robustness using the constraint tightening approach with real tracking data collected from each robot.

Fig. 7 and 8 depicts the results of the experiment with the group. As shown in the snapshots, the communication network remained robustly connected, considering proximity connections, at all times while the robots collected the targets.

5. Line of Sight

This section addresses the issue of LOS connectivity, where connections are dependent on a clear LOS between agents. We start with the omnidirectional (Figure 3b) and then the results are extended to the directed LOS (Figure 3c).

Two approaches to encode the omnidirectional LOS requirement for connections

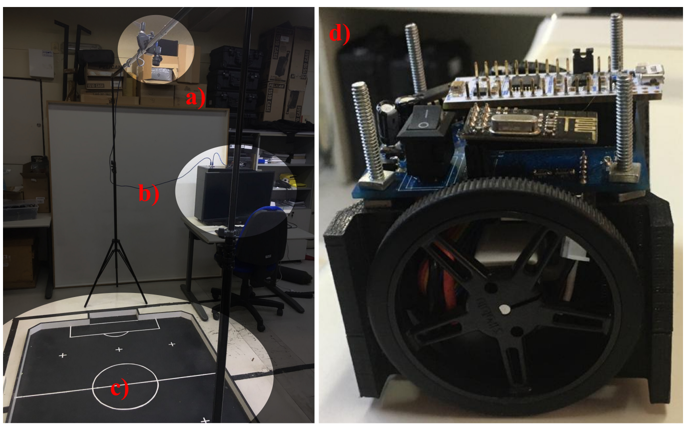

Figure 5. a) Camera used for the position measurement. b) Machine employed for computation of the algorithms. c) Soccer field where the agents operate. d) Very Small Size (VSS) robot.

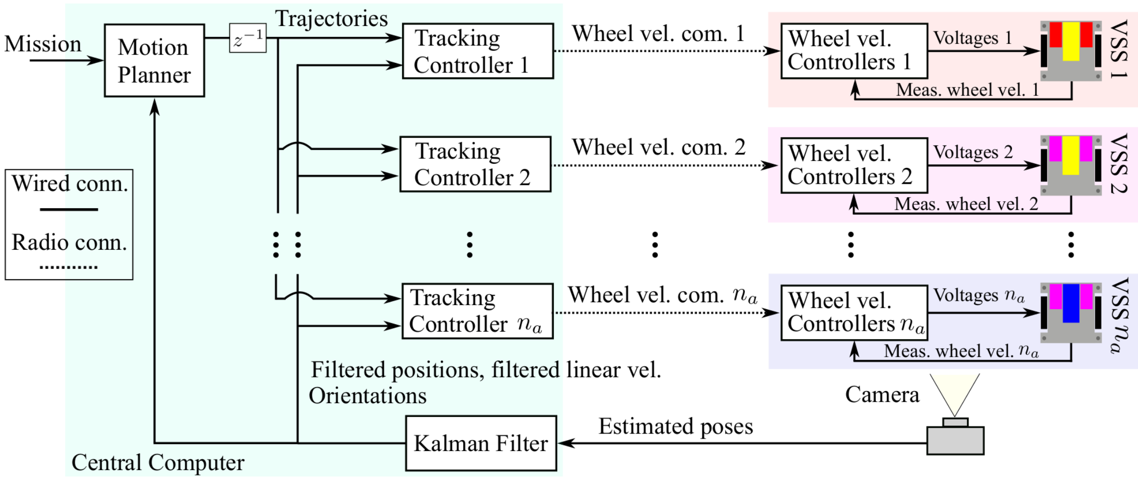

Figure 6. Overview of the proposed control architecture and experiment setup.

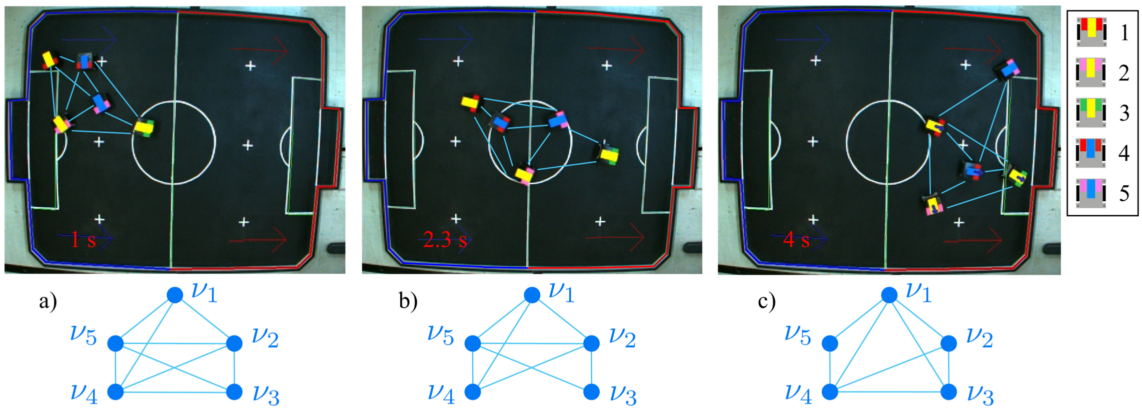

Figure 7. Snapshots of the experiment taken at distinct time steps.

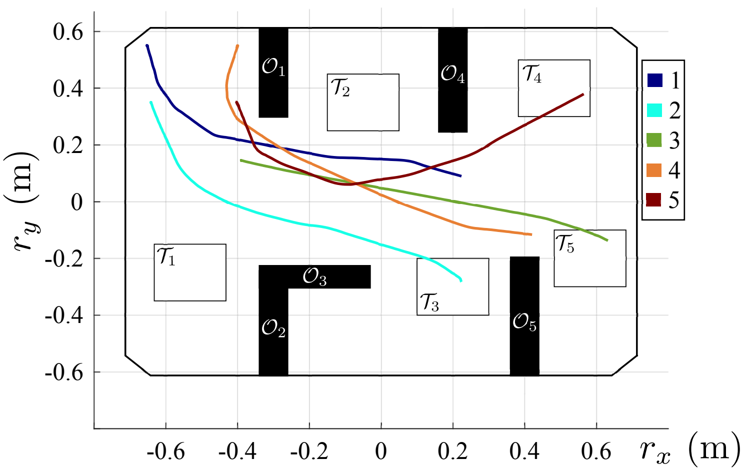

Figure 8. Trajectories of the robots during the experiment. A video of the experiment is available at `https://youtu.be/fyb47v_3n_s`.

between agents were presented: virtual halfspaces [Caregnato-Neto et al. 2022b] and intermediary points [Caregnato-Neto et al. 2022a, Caregnato-Neto et al. 2023b]. Evaluations demonstrated that the latter strategy yields less conservative results than the former. The new encoding based on the intermediary point concept presented in [Caregnato-Neto et al. 2023b], was compared to the earlier approach in [Caregnato-Neto et al. 2022a], demonstrating that the novel method yields simpler models resulting in shorter optimization times.

Finally, the issue of directed LOS, where connections require the robots to be properly aligned with each other, was investigated in the context of coordinating a Robot Chain Control System (RCCS) using Visible Light Communication (VLC) to exchange information in an exploration task. VLC is a wireless transmission technology in which information is exchanged through the modulation of visible light beams, where flashlights can be used as emitters and solar panels as receivers.

The RCCS is a type of MRS with a leader, a base, and transmission relays. It has been theorized to be used with VLC to perform inspection and maintenance of pipelines and underground facilities [Zhao et al. 2019, Zhao et al. 2022]. In these cases, the base provides commands, whereas the relays position themselves to connect the leader, who performs the task, with the base. The LOS requirement of VLC has been addressed in scenarios with obstacles and corners with point-to-point communication nodes generated by the relays robots [Zhao et al. 2022].

The results of the MILP implementation of directed LOS connectivity constraints for the RCCS-VLC problem considering an MRS comprised of three Turtlebots3 in a realistic Gazebo simulation are presented in Figs. 9 and 10. The leader (robot 3) performs the inspection by visiting all two targets while robots 1 and 2 serve as relays, connecting the base with the leader.

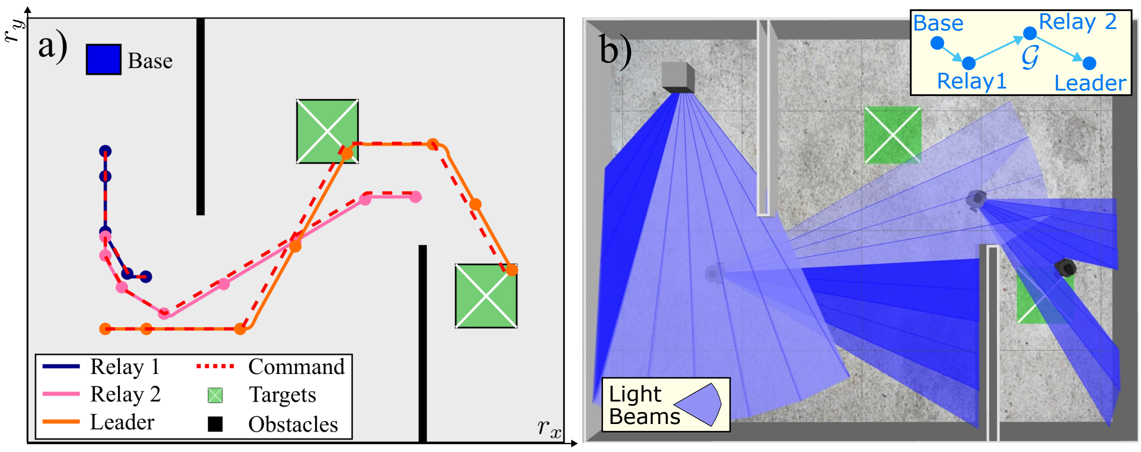

Figure 9. a) Trajectory tracking performance of the Turtlebots3 during the Gazebo simulation. b) Final pose of the robots in the simulator. Simulation video available at: `https://www.youtube.com/watch?v=xDju9YRVrtg`

6. Human-Robot Collaboration

This section presents a novel architecture for Human-Robot Collaboration (HRC) entitled Adaptive Robot Motion for Collaboration with Humans using Adversarial Inverse Reinforcement learning (ARMCHAIR), which leverages the integration between Adversarial Inverse Reinforcement Learning (AIRL) and Model Predictive Control with Mixed-integer Programming encoding (MPC-MIP) for HRC [Caregnato-Neto et al. 2024].

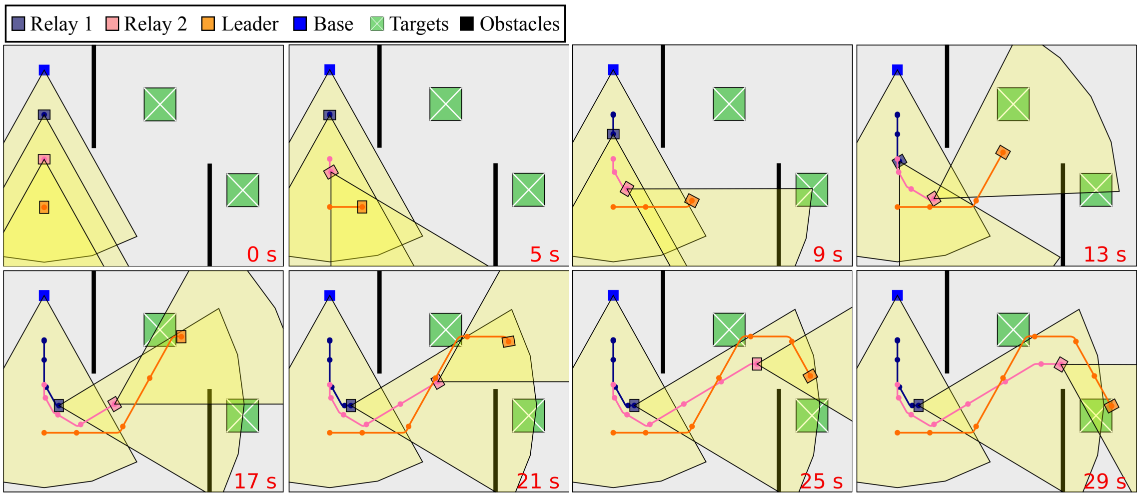

Figure 10. Snapshots of the Turtlebots' position during the Gazebo simulation at critical time steps.

ARMCHAIR differentiates itself from other techniques by providing: a) the proper movement coordination with collision avoidance and connectivity maintenance that are necessary for the coexistence of humans and robots enrolled in the same task; and b) collaborative harmonious task allocation, where the robot's tasks are periodically updated to synergize with human decisions, effectively avoiding conflicts and enabling the *collaboration* between the MRS and human towards the same goal despite the uncertainty in the human decision-making process.

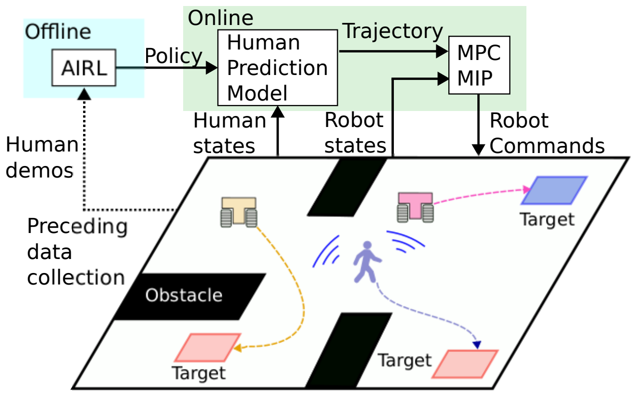

Figure 11. ARMCHAIR control architecture. The AIRL offline layer provides a human prediction model that is used by the MPC-MIP algorithm to compute proper trajectories and decisions for the MRS in a closed loop.

Fig. 11 illustrates the ARMCHAIR's architecture. A deep neural network is trained on human (or synthetic) demonstrations using the AIRL algorithm. This data describes how a human would perform the task of exploring an environment, such as the one presented in Fig. 1. The training is performed *a priori* in an offline stage. As an output, AIRL provides a policy that describes the most likely actions of the human given a state describing its current position and the environment. The policy is then used to compute the most likely course of action of the human, which is then integrated into the MPC-MIP optimization that provides trajectories and decisions for the robot group, allowing them to complement the efforts of the human in the task.

An example is provided in Fig. 12, considering an environment where the cells in blue and yellow are targets with the latter being more attractive to the human. The cell in magenta is the terminal state, whereas the black ones are obstacles. Solid lines represent factual movement and dashed lines predictions at particular time steps. Fig. 12a shows that the human is expected to visit all targets in the initial prediction. However, he deviates from the most likely trajectory and ignores target 4 (Fig. 12c). The closed-loop operation of MPC-MIP allows the robot team to recover from the unexpected human behavior and robot 2 is dispatched to reach target 4, resulting in the mission being completed with all targets being visited (Fig. 12d). These results demonstrated that ARMCHAIR enables not only proper coordination, i.e., collision avoidance between the human and the robots, but also allows the group to collaborate, supporting the human in spite of the inherent uncertainty of his behavior.

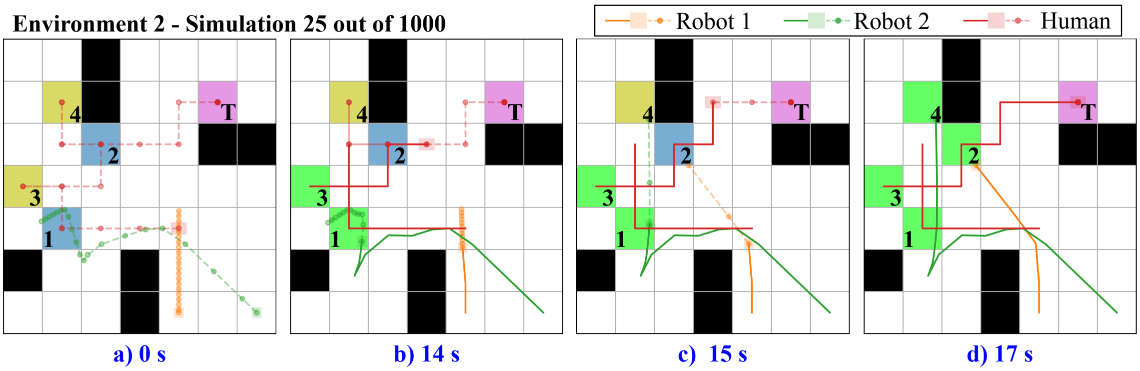

Figure 12. Key time steps of ARMCHAIR's Monte Carlo simulation 25 out of 1000.

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