# Supporting task-oriented collaboration in human-robot teams using semantic-based path planning

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## ABSTRACT

Improvements in robot autonomy are changing the human-robot interaction from low-level manipulation to high-level task-based collaboration. For a task-oriented collaboration, a human assigns sub-tasks to robot team members. In this paper, we consider task-oriented collaboration of humans and robots in a cordon and search problem. We focus on a path-planning framework with natural language input. By the semantic elements in a shared mental model, a natural language command can be converted into optimization objectives. We import multi-objective optimization to facilitate modeling the "adverb" elements in natural language commands. Finally, human interactions are involved in the optimization search process in order to guarantee that the found solution correctly reflects the human's intent.

**Keywords:** Path planning, Multi-objective optimization, Semantic-based HRI

## 1. INTRODUCTION

As robot sensing, perception and decision-making improves, the human's role in human-robot interaction progressively shifts from teleoperator to supervisor to teammate.[1] This shift toward human-robot teaming means that the relationships between the human and the robot in a team to execute tasks together appear more and more to be collaboration. Although there exists asymmetries between the capabilities and properties of a human and a robot, concepts from human-human teaming can be useful and important. Specifically, the concept of a shared mental model, which originates from the theories of human collaboration, has been applied to analyze the collaborative process between humans and robots as well.[2]

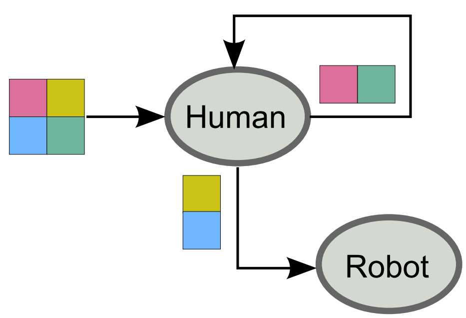


Figure 1. An example of task-oriented human-robot collaboration.

Consider a problem where team-wide collaboration is driven by a task shared by the team members. The collaboration can be viewed as a parallel performance of the sub-tasks by different agents. This type of collaboration can be modeled as a task decomposition. In models created from a task decomposition, the team supervisor takes the responsibility of task decompositions and distributes the sub-tasks to different team members. In a human-robot team, the team supervisor is usually a human. Figure 1 illustrates an example of task decomposition and allocation. A human supervisor decomposes the task into sub-tasks and then assign some to human team members and some to robot team members.

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This type of relationship indicates the importance of the communication between a human and a robot. Effective communication determines the execution efficiency and the correctness of the outcome. One of the functions of the shared mental model is to facilitate the mutual understanding and ground communication among the team members. Of particular importance is how shared mental models enable a more collaborative approach to problem solving, facilitated by communications that operate at a higher, more tactical or strategic level of abstraction. A complex process of parameter setup for a human to define a sub-task will reduce the team performance in a cordon and search task.[3]

In a cordon and search problem, a robot could be assigned to "screen" a sub-region that is not easily accessible to a human. Instead of relying on teleoperation, the robot now can be autonomous enough to execute the sub-task alone. In the collaborative perspective, the human only needs to express the requirements of the sub-task and provide information that the robot needs in sub-task execution. In this paper, we assume that the team supervisor assigns the sub-tasks using a verbal command. More specifically, we assume that the human supervisor issues directives to a robot. Furthermore, we assume that from a small set of possible commands, the directives are grounded using spatial references that specify key locations for performing specific sub-tasks. Finally, we assume that the directives are associated with a small number of adverbial modifiers that provide qualitative information about intent.

This does not require the robot to understand perfectly what the human said, but rather to model the verbal command. The semantic elements in natural languages are often extracted and formed into a graphical model. Bayesian inference can be applied to infer the meaning of a sentence.[4] A learning process can also be imported to tune the likelihood of the primitives by using an HMM.[5] For tasks like cordon and search, plenty of the elements in a sentence depend on the spatial information in the workspace. Thus, spatial labeling is imported to help convert a human's command into robot's navigation primitives.[6] This enables robot motion planning to be generated by a semantic interpreter.[7] In this paper, we are interested in modeling and solving a robot path-planning problem from a human's verbal command in a framework of task-oriented human-robot collaboration.

Current technologies can already support the language parsing process. A semantic structure is usually composed of the key elements of a sentence, like a noun, verb and etc. Ignoring some other elements leads to information loss. When researchers consider adverbial cues in human languages, an adverbial modifier may be modeled as belief revision.[8] We notice that a verbal command contains information not only what to do but also how to do. It means that we should extract the search objectives and constraints from a verbal command to obtain the criteria. The criteria evaluates the performance of a sub-task execution.

In this paper, we propose a framework to support the path-planning problem from a verbal command. Using the idea of a shared mental model, we import a semantic labeling process to generate a semantic model of the workspace in Section 2. The labeled elements can be used to help the teammate interaction and task execution. Specifically, we show how an optimization problem can be created by translating a verbal command. We are interested in extracting information, like adverb elements, to create the multi-objective optimization in Section 3. We propose an interactive method to find the optimal solution of a path-planning problem. In Section 4, we propose the system framework and the solutions on the robot path-planning.

## 2. SEMANTIC LABELING AND COMMAND

A shared mental model provides a common ground among the teammates of the collaborative process. When the interaction between a human and a robot is based on natural language, the semantic objects must be shared by the team members so that the teammates can understand each other. In a cordon and search task, the information depends greatly on the semantic labels of spatial objects. It is natural to introduce a labeling process to generate the semantic objects on the map of the workspace. These *semantic labels* will be used in sub-task definitions and teammate interactions in the shared mental model. We also need a *task grammar* to define the sub-tasks and organize the semantic elements. Because terms and sentences usually imply different meanings in different types of sub-tasks, a task grammar could help the teammates understand the purposes of each other correctly. In this way, a verbal command can be viewed as an action with logical constraints on a set of semantic elements. The form is determined by the task grammar.

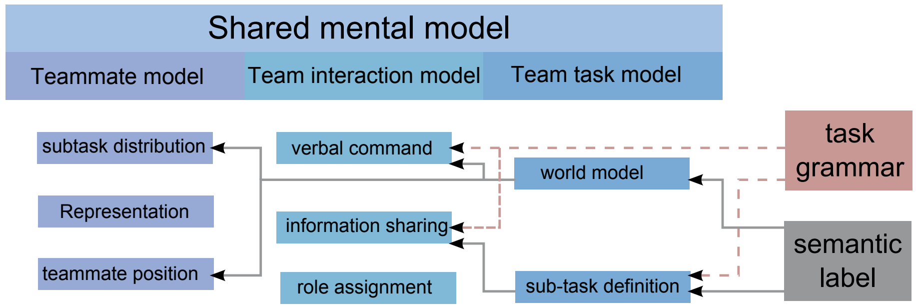


Figure 2. How task grammar and semantic labels support a shared mental model.

A shared mental model of a cordon and search team can be decomposed[3] into three sub-models. We list only some elements that are relevant with a cordon and search task as following.

- **A teammate model** provides the knowledge of teammates skills, abilities and tendencies.
  - A *sub-task distribution* indicates how the sub-tasks are assigned to team members.
  - The *teammate positions* indicate the positions of the teammate, localized relative to the spatial semantic objects.
  - The *representation* indicates how the teammate encodes information and problems.
- **A team interaction model** provides the knowledge of roles, responsibilities, information sources, communication channels and role interdependencies.
  - A *role assignment* defines the roles of the members in a team.
  - A *verbal command* describes the format of a command.
  - An *information sharing* represents the information exchange format between team members.

  **A team task model** provides the knowledge of procedures, equipment, situations, constraints.
  - A *semantic world model* is a representation of the workspace with semantic labels.
  - A *sub-task definition* defines the sub-tasks and its objectives.

Figure 2 illustrates how these elements in a shared mental model depend on the task grammar and the semantic labels. The task grammar and semantic labels support the world model and the sub-task definitions. The world model and the sub-task definitions can then be used to generate verbal commands and help information sharing.

Consider the cordon and search for a human-robot team in an urban area. The labeling process is run before the cordon and search starts. Semantic labels are assigned to the sub-regions and the objects in the map. Supplementary information can be attached to expand the support to different tasks. We also expect that semantic labels are used to support a more flexible grammar. We categorize the labels into three types.

- **Indoor** The “indoor” label defines the region of an indoor environment in the search space.
- **Outdoor** The “outdoor” label defines the region of an outdoor environment in the search space. There are several sub-types on an outdoor label. For the purpose of this paper, we consider only three.
  - *market*: The “market” label usually defines sources of information, where there is high probability of interested events occurring.
  - *risky*: The “risky” label indicates these regions have potential risks, which will be considered when safety is an objective in path planning.

  - *unknown*: We usually consider unlabeled regions as "unknown" by default, which indicates the lack of prior information.

- **Feature** The "feature" label defines the objects in the search space. They can be used for objects of interest, location indicators and etc. There are two types of feature labels, which are
  - *2D*: "2D" label defines the objects on the ground.
  - *2.5D*: "2.5D" label defines the objects on the walls of the architectures.

Figure 3 illustrates possible semantic labels for a notional world.

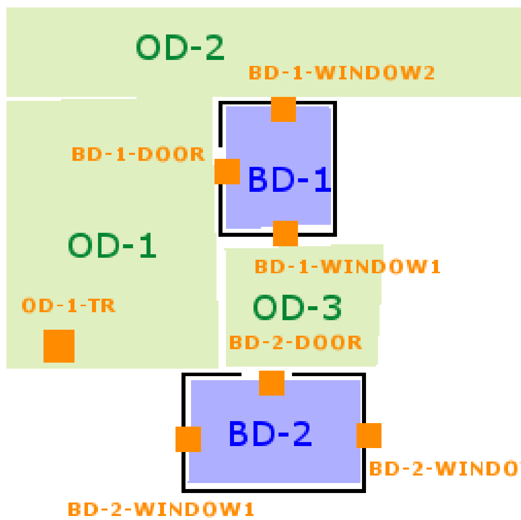



Figure 3. A labeled map of an urban environment.

Given the semantic labels of a spatial world model, we can define a task grammar by the characteristics of the sub-tasks. We assume a task grammar that specifies a task, one or more constraints, and one or more adverbs that specify how the task should be performed or how the constraints should be managed. Equation 1 is an example of a task grammar that is used in a cordon and search task.

$$
\begin{aligned}
< Start > &\rightarrow < CommandPhrase > \\
< CommandPhrase > &\rightarrow < ScreenCommand > | < ProceedCommand > \\
< ScreenCommand > &\rightarrow < Adverb > \text{ Screen the } < FeatureQuantifier > < Feature > \text{ of the } \\
&\quad\; < BlockId > \\
< ProceedCommand > &\rightarrow \text{Proceed } < Adverb > < PrepPhrase > \text{ to the } < FeatureQuantifier > \\
&\quad\; < Feature > \text{ of the } < BlockId > \\
< Adverb > &\rightarrow \text{covertly } | \text{ safely } | \text{ quickly } | \text{carefully} \\
< FeatureQuantifier > &\rightarrow \text{back } | \text{ front } | \text{ side} \\
< Feature > &\rightarrow \text{door } | \text{ window } | \text{ exits} \\
< BlockType > &\rightarrow \text{BD- } | \text{ OB-} \\
< PrepPhrase > &\rightarrow < PrepSegment > \text{ the } < BlockId > | \text{ between the } < BlockId > \\
&\quad\; \text{and the } < BlockId > \\
< BlockId > &\rightarrow < BlockType > < Id > \\
< PrepSegment > &\rightarrow \text{around } | \text{ left-of } | \text{ right-of}
\end{aligned}
\tag{1}
$$

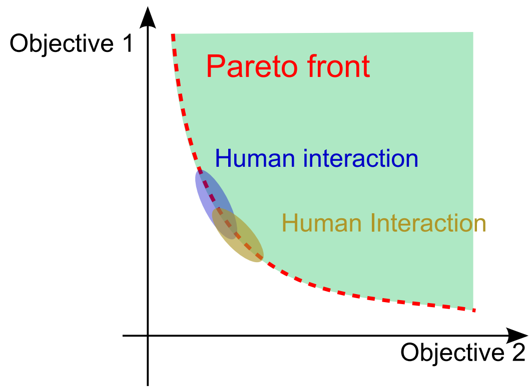



Figure 4. Interactive multi-objective optimization.

For example, if a human tells a robot to "carefully screen the OB-2", this command defines a sub-task as a "screen" action. "OB-2" is a semantic label, which constrains the task to specific work region. Besides what to do in a sub-task, this verbal command also implies how to evaluate the performance of this sub-task. Some of the objectives inherit from the properties of a screen action, the other objectives are from the adverb, e.g. "carefully". This turns the path-planning problem in the sub-task into a multi-objective optimization problem as described in the next section.

## 3. INTERACTIVE MULTI-OBJECTIVE OPTIMIZATION

The adverb in a sentence can be very important and informative. In a cordon and search task, using "carefully", "quickly" or "covertly" imply very different ways of performing the task. More generally, a verbal command from a human contains multiple objectives and constraints, which means that the robot's path-planning problem is a multi-objective optimization problem. Table 1 gives an example on different objectives implied by different adverbs in cordon and search. Four adverbs indicate different objectives that the robot's path planner may need to respect.

Table 1. Different objectives implied by different adverbs.

| Adverb | Covertly | Safely | Quickly | Carefully |
|---|---|---|---|---|
| Objectives | min visibility<br>max smoothness | min exposure<br>min danger | min path length | max smoothness<br>min collision risk |

Notice, as illustrated in Table 1, that the robot requires a precise definition so that the problem is mathematically solvable. By contrast, a human may convey and process the information in fuzzier terms. In terms of the representation element of the teammate model, this means that there is a mismatch between the human and the robot. More specifically, there is a mismatch between the precise mathematical objectives required by the robot and the possibly ambiguous adverbial modifier specified by the human. To solve such a problem, we propose a posterior method that allows the robot to specify a range of possible solutions, and allows the human to select from this range.

Specifically, we use the notion of *Pareto optimality* to evaluate the solutions in a multi-objective optimization problem. A solution is called "Pareto optimal" if no other solution has better fitness values in all the objectives. This means that a Pareto optimal solution cannot be improved on one objective without downgrading other objectives. A set that consists of all the Pareto optimal solutions is a *Pareto front*. Figure 4 illustrates a Pareto front for a minimization problem.

The task grammar from Section 2 allows two different types of information to be shared among the human supervisor and the robot: the specific task to be performed (encoded as the verb and noun) and an adverbial qualifier on how the task should be performed. The verb and noun specify hard constraints that must be satisfied by the solution generated by the robot's path planner. By contrast, the adverbial modifier represents a soft constraint that the path should satisfy.

We assume that the soft constraint is fuzzy, meaning that there are several possible paths that would satisfy the soft constraint, and selecting from among these possible paths. requires an ability to balance various tradeoffs. The Pareto front represents all possible tradeoffs, so a specific adverbial modifier does not specify a single point in the Pareto front, but rather a region of the Pareto front; any solution within this region might match the human's intent. This is illustrated on Figure 4 as the shaded ovals. We are developing a tool that allows a human to interactively explore this region to select a path that balances tradeoffs which satisfy human intent. This tool bridges the difference between the way a human and a robot represent a task, and thus facilitates more effective shared mental models.

In terms of the robot's path planner, since the solutions generated from the multi-objective planner are Pareto optimal, information communicated from the planners to the human allow the human to refine their intent by selecting among these tradeoffs. We introduce this interactive multi-objective optimization to solve the path planning problem modeled from a human verbal command.

Unfortunately, the solution space of a path planning problem has been greatly expanded. This increases the difficulty of solving the multi-objective optimization problem. Following related work on blending metric-based and topological approaches to path planning, we are developing a robot path representation using waypoints and trajectories that connect two neighboring waypoints. This enables a two layer planning in order to enhance the planning efficiency:

- A coarse layer generates the waypoints.
- A fine layer generates the trajectories between the waypoints.

The planning in both layers follow the same objectives and constraints.

When we have a shared mental model with semantic labels and a path planner that solves the multi-objective optimization problem, we can provide an efficient framework of optimized path-planners that can be flexible and adaptive to new forms of objective definitions from new scenarios and new information sources.

## 4. SYSTEM FRAMEWORK

We propose the system flow shown in in Figure 5. Either the human supervisor or an automated object recognizer labels the search space to initialize a shared mental model. With the shared mental model, a parse converts a verbal command from the human into a sub-task abstraction for the robot. In the path planning problem, this abstraction is encoded as a mathematical model of the optimization problem. Each adverb in the task grammar is associated with a different planning objective. The path planner generates the set of Pareto optimal solutions and the human selects one that matches his/her intent. After a solution is found, it is sent to a robot to execute.

We are currently developing tools to test our approach. The map of a workspace is firstly labeled by a supervisor. A labeled map is shown in Figure 3. We assign semantic IDs to different sub-regions by using "indoor" and "outdoor" labels. We label the doors and windows of several regions, which are frequently used in the verbal commands of a cordon and search task. Moreover, we label some significant objects on the ground to facilitate localizing the positions of task execution. Within the labeled map, a verbal command, "go quickly to location BD-2", is read and parsed into multi-objectives and constraints by the task grammar. A path planner finds an "optimal" solution through interactive multi-objective optimization. The planning is currently on a discretized map, which is a hexagonal description of the test environment, which is shown in Figure 6(a). Thus, the format of a planned path is a sequence of hexagonal cells. This path is then converted into a sequence of waypoints, which is shown in Figure 6(b). We test the task execution in the Gazebo simulator by using a virtual turtlebot, which is illustrated in Figure 6(c). The implementation can be easily migrated to a real turtlebot.

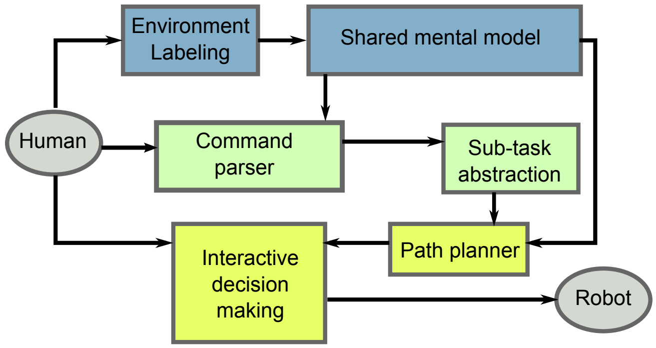
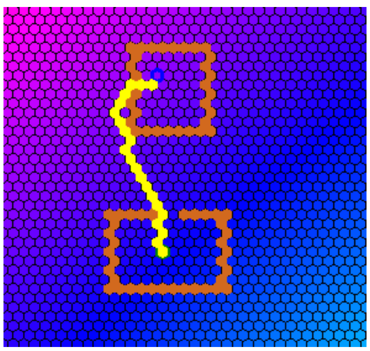
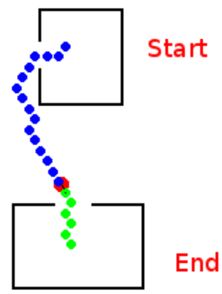


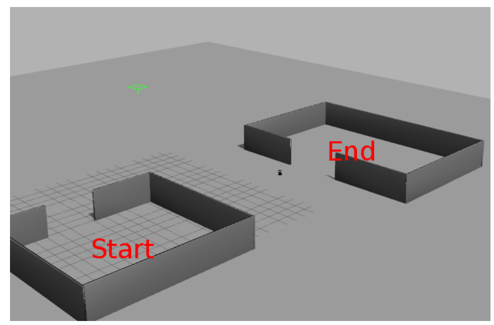

Figure 5. The process of a semantic-based path planning.



(a) Planned path from hexagonal map.




(b) Task execution monitor.




(c) Task execution in Gazebo simulator.

Figure 6. Simulation with the Gazebo simulator.

Figure 6(b) shows a task execution monitor, which provides the progress of task execution. An execution monitor GUI, shown in Figure 6(b), displays the sequence of waypoints of a planned path and continuously receives the position updates from the virtual robot, which is used to check how the task is executed. The blue points are reached waypoints and the green points are the waypoints to be reached. The process is shown in Figure 6.

## 5. SUMMARY

In order to support the task-oriented collaboration in a human-robot team, natural language can be used for the interaction between the human and the robot. A shared mental model is needed for the collaboration to help the team members understand each other correctly. The shared mental model is initialized through a semantic labeling process. With a labeled world model and a task grammar, a robot can translate a verbal command from the supervisor into a multi-objective path planning problem. A human interactive decision making process is introduced to find the preferred solution and correct the potential bias from the problem modeling. The planned path can be interactively obtained from the Pareto solution set.

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