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Human–robot communication for collaborative decision making — A probabilistic approach

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ABSTRACT

Humans and robots need to exchange information if the objective is to achieve a task collaboratively. Two questions are considered in this paper: what and when to communicate. To answer these questions, we developed a human–robot communication framework which makes use of common probabilistic robotics representations. The data stored in the representation determines what to communicate, and probabilistic inference mechanisms determine when to communicate. One application domain of the framework is collaborative human–robot decision making: robots use decision theory to select actions based on perceptual information gathered from their sensors and human operators. In this paper, operators are regarded as remotely located, valuable information sources which need to be managed carefully. Robots decide when to query operators using Value-Of-Information theory, i.e. humans are only queried if the expected benefit of their observation exceeds the cost of obtaining it. This can be seen as a mechanism for adjustable autonomy whereby adjustments are triggered at run-time based on the uncertainty in the robots' beliefs related to their task. This semi-autonomous system is demonstrated using a navigation task and evaluated by a user study. Participants navigated a robot in simulation using the proposed system and via classical teleoperation. Results show that our system has a number of advantages over teleoperation with respect to performance, operator workload, usability, and the users' perception of the robot. We also show that despite these advantages, teleoperation may still be a preferable driving mode depending on the mission priorities.

1. Introduction

1.1. Problem description and motivation

This work is concerned with combining the *perceptual* abilities of mobile robots and human operators to execute tasks collaboratively. It is generally agreed that a synergy of human and robotic skills offers an opportunity to enhance the capabilities of today's robotic systems, while also increasing their robustness and reliability [1–3]. Despite the fact that perception of the environment is a critical element in performing any task, *collaborative* human–robot perception has not been studied extensively. Systems which incorporate both human and robotic information sources have the potential to build complex world models, essential for both automated and human decision making.

Human and robotic perception is often complementary in terms of modality, uncertainty, and types of failures. Humans have rich perceptual abilities, especially at higher abstraction levels, *e.g.* human innate pattern recognition skills. Yet, people's performance is known to suffer from great variability between individuals and over time. On the other hand, robotic perception is highly consistent and accurate in measuring lower level descriptions such as geometric properties. At the same time, robotic perception has limited ability to generalise from preprogrammed concepts, *e.g.* in visual object recognition.

Human–robot collaboration typically involves communication. Important research questions for human–robot communication are [4]:

1. What type of information should be communicated?
2. When should communication occur?
3. Who should communicate with whom?
4. What medium should be used for communication?

This paper addresses the first two questions: *what* and *when* to communicate.

1.2. Approach

This work adopts a *peer-to-peer* interaction style to facilitate bidirectional communication between humans and robots. The Human–Robot Interaction (HRI) community generally agrees that humans and robots need to interact as peers to leverage each other's strengths effectively [2,1,5].

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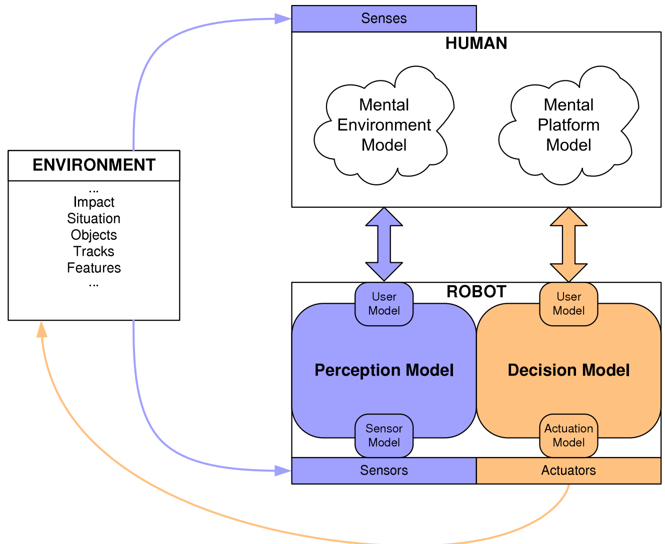


Fig. 1. Internal structure of humans and robots interacting with each other and the environment. Clouds represent mental models (not discussed here) while rounded rectangles represent computational models. Information exchange between humans and robots is based on *probabilistic* implementations of the perception and decision models.

The novel contribution presented here is to make use of probabilistic robotics representations for bidirectional human–robot communication. We classify this approach as *robot-centric* [6] because it takes existing probabilistic robotics algorithms as a basis for communication.

Fig. 1 shows the structured human–robot system comprising humans, robots, and the environment. Robots maintain two computational models: a perception and a decision model. In the field of mobile robotics, it has become common to implement both of these models probabilistically [7]. In our approach, all information exchange between humans and robots is derived from these models: *what* to communicate is determined by the probabilistic data stored in the models, *when* to communicate is determined by the internal inference mechanisms.

Probabilistic "data types" suitable for human–robot communication include actions, utility functions, observations, likelihoods, beliefs, and model parameters [4]. Mechanisms for information exchange are defined by the direction and initiation of the information flow which results in four simple *communication patterns*: robot-push, human-pull, human-push, and robot-pull. Table 1 lists a number of robotics applications using these communication patterns and data types.

This work focuses on human–robot information fusion as emphasised in the table. Human operators are regarded as information sources capable of contributing perceptual input at higher abstraction levels. Operators either submit information passively (human-push) [8], or receive requests from the robot as presented in this paper (robot-pull). Human input is subsequently fused probabilistically with robotic sensor observations.

1.3. Collaborative human–robot decision making

Human–robot fusion has previously been demonstrated for "pure" perception tasks such as information gathering [8]. The focus of this paper is on making better informed decisions using a decision-theoretic framework. Since decisions are based on information gathered by humans and robots, we refer to this application of human–robot fusion as *collaborative human–robot decision making*. To simplify the problem, this paper only considers "one-shot" decisions rather than the more general sequential decision problem [9].

In addition to the differences between human and robotic sensors mentioned in Section 1.1, robotic sensors typically yield observations at high rate and low cost whereas humans are often a valuable and limited resource [10]. In this paper, we introduce a mechanism to deal with this problem explicitly using the robot-pull communication pattern. Robots treat operators as a resource which can be queried for observations. Querying operators comes at a cost which has to be traded off against its expected benefit. *Value-Of-Information* (VOI) theory is used to compute how much value a human observation may add. Robots deciding when to query operators can be seen as a mechanism for *Adjustable Autonomy* (AA). Adjustments are triggered at run-time based on the amount of uncertainty in the robots' beliefs related to the task.

Collaborative human–robot decision making is experimentally demonstrated using a simulated mobile robot navigation task. Operators are remotely located and observe the world through the robot's sensors. We conducted a user study to compare our system to classical teleoperation. Initial results showed that our system has a number of advantages over teleoperation with respect to performance, workload, and usability [11].

This paper extends our previous work in multiple respects: firstly, the theory behind decision-theoretic human–robot collaboration is expanded and contrasted to related approaches to collaboration. Secondly, an analysis of the navigation task with respect to the VOI measure is presented. Thirdly, additional user study results are presented and evaluated. Finally, the user study results are facilitated to select appropriate driving modes for four mission scenarios.

The remainder of this paper is organised as follows. Section 2 reviews related work. Section 3 presents the decision-theoretic framework for collaborative decision making. The details and benefits of robot-pull are described in Section 4. Section 5 applies the framework to a navigation task while Section 6 presents results from the user study. Finally, Section 7 summarises the paper and discusses future work.

2. Related work

Related work comprises a number of areas: control fusion, humans as information sources, collaborative control, adjustable autonomy, dialog management, and VOI applications.

2.1. Control fusion

The approach presented in this paper can be seen as a particular solution to the general *control fusion* problem [12]: how to combine input from multiple sources to control a common resource. For the case where the common resource is a mobile robot, several *behaviour-based* architectures have been proposed, such as Subsumption [13] and Motor Schemas [14]. The integration of human input into these systems can be achieved by letting operators add or alter behaviours, for instance [14].

If there are multiple operators, *Collaborative Teleoperation* was proposed to come to a consensus over the shared resource, which can be a remotely located robot [12], or a "tele-actor" [15]. In that work, consensus is achieved by combining input from multiple operators into a single output stream using motion vector averaging [12] and dynamic voting [15].

In contrast to the behaviour-based methods, this work employs a purely deliberative control architecture. Rather than arbitrating multiple commands, perceptual input from humans and robots is fused using a probabilistic model, and decisions are made according to the model's beliefs and utility functions.

2.2. Humans as information sources

Different system functions can be automated when humans interact with automation [16]. Parasuraman et al. propose four func-

Table 1
Examples for human–robot communication using probabilistic data types. The focus of this work is emphasised.

Application	Comms. pattern	Prob. data type
Teleoperation	human-push	action
Adjustable autonomy	human-push, robot-pull	action, utility function
Task monitoring	robot-push, human-pull	belief, parameters
Human–robot fusion	**human-push**, **robot-pull**	**observation**, **likelihood**

tion classes: (1) information acquisition, (2) information analysis, (3) decision and action selection, and (4) action implementation. Letting human operators contribute perceptual information can be seen as choosing a low automation level for class (1) while classes (2)–(4) are fully automated.

The advantages of fusing information from humans and sensors have recently been recognised in the context of crisis management [17–19]. Pavlin et al. describe work on integrating human information originating from databases, webpages, mobile phones or interactive querying into their Distributed Perception Network (DPN) [17]. DPNs use a distributed Bayesian network and a representation which can be exploited to generate useful queries addressed at humans in the field. The example provided is a gas detection system where humans contribute information by reporting smell and health symptoms information queried via SMS or the web. The problem of modelling human operators has also been highlighted but no results are reported.

Project Rescue is another crisis management system explicitly acknowledging human operators as sensors [19]. First responders' observations and eyewitness accounts may be leveraged to gain a better assessment of the situation using human cognitive abilities. They emphasise the necessity of modelling the reliability of human reports with respect to perceptual and cognitive biases as well as to social background. Probabilistic modelling techniques are proposed as a potential solution. Implementation of the user modelling ideas to date are limited. The focus is on mapping humans' free text reports containing location information to probability distributions over "domains" which are 2D spatial grids [20]. The system does not perform fusion of human reports with sensor information.

2.3. Collaborative control

Work presented in this paper is most closely related to Fong's *Collaborative Control* which, like our approach, treats humans as a resource to robots [6,21,10]. Bidirectional communication in the form of human–robot dialog is used to exchange information of different types, such as commands, queries and responses. Fong classifies his system as a form of teleoperation which compensates for the limitations of the conventional approaches by integrating human expertise, typically into the control loop. However, it is also anticipated that operators can close perception loops, cognition loops or combinations of the above.

There are many parallels to our view of collaboration: robots are treated as peers, and perception loops are closed by posing queries. The main difference is the chosen approach: while Fong chooses no specific underlying mathematical method, we cast the problem of collaborative control in a probabilistic, decision-theoretic formulation whose benefits are presented in Section 4.3.

2.4. Adjustable autonomy

The fields of Adjustable Autonomy (AA) and Mixed Initiative Control aim at bridging the gap between full human control and autonomy [22,1,5,23,3]. The fundamental questions in these fields are how to decide whether and when to switch the level of autonomy and on what criteria to base that decision. In many AA systems, the human operators are in charge of switching between a set of predefined discrete modes, leaving a major responsibility with the operator, as pointed out in [24]. In contrast, our approach lets the robot decide when to query operators for additional input, based on the uncertainty in the robot's beliefs. This can be seen as a robot-initiated shift to lower autonomy at run-time.

Similar to us, Gunderson et al. believe that the level of autonomy should be based on the amount of *uncertainty*, which includes sensor inaccuracies, action failures and exogenous events [25]. They show in simulation that these three types of uncertainties have functional correlations to plan success. If a plan cannot be completed successfully, the agent needs to use external resources (*e.g.* humans) which can be accessed by adjusting its autonomy. They do not, however, address the question of how to model uncertainty or how a request for more information would be triggered.

Another approach addressing the problem of when to request help from human operators is presented by Sellner et al. [3]. As in our system, requesting help is one of several possible communication modes and is motivated by both the scarceness of the human resource and the requirement to integrate multiple robots. The decision of when to request help is computed using a decision tree, taking expected time delays and the likelihood of success into account. The latter requires a model of the user, which is another parallel to our work [26].

In Sellner's system, operators actively participate in the task, which is the large-scale assembly of structures in a simulated space environment. In contrast, we regard robots as the sole decision-makers and treat humans as their perceptual resource. The type of human input distinguishes our work from classical AA. Whereas AA systems typically transfer *decision-making* control to humans [23], our system queries humans for *observations*, and the decision making remains with the agent/robot. This exhibits true peer-to-peer interaction since humans are not able to override the robots' decisions.

2.5. Dialog management

Whether or not to ask an operator for input can be regarded as an *action* a robot may select to take. Probabilistic frameworks for action selection, such as POMDPs, have been used for human–robot dialog management [27,28]. In these approaches, the hidden state to be inferred is the user's intention, *e.g.* for an intelligent wheelchair application [27]. The POMDP action set includes clarification questions, and the reward function encodes how much the user is willing to accept those before getting annoyed.

The problem is different from ours: we focus on the representing the robots' tasks probabilistically and aim at incorporating human perceptual skills to help fulfil the tasks. Queries are triggered based on the uncertainty in the robots' beliefs related to the task, which does not require a model of the user's intentions. Instead, a simple model of the user's perceptual ability is proposed in Section 5.3.

2.6. Applications using VOI

Using VOI theory to decide what information source to query has been applied to a wide range of sensing applications, *e.g.* distributed sensor management [29], human activity recognition [30], and sensor networks [31]. To the best of our knowledge, this work is the first to apply VOI theory to human–robot communication.

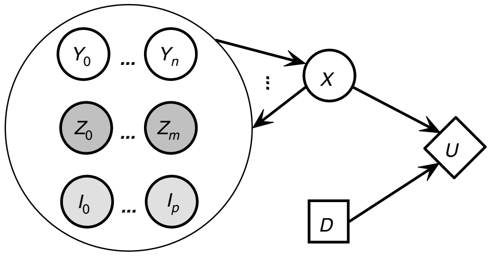


Fig. 2. Influence diagram with a single non-intervening decision node D and single utility node U. The world is represented by X and $Y = \{Y_0, \ldots, Y_n\}$ while information sources are represented by $Z = \{Z_0, \ldots, Z_m\}$ (dark grey, always observed) and $I = \{I_0, \ldots, I_p\}$ (light grey, occasionally observed). A "supernode" contains all Y, Z, and I nodes with an arbitrary network topology.

3. Decision-theoretic formulation

This section presents the mathematical framework for collaborative human–robot decision making. Two problems are addressed: how to act rationally, and how to decide when to query human operators.

3.1. Representation

A probabilistic representation should encode relationships between random variables qualitatively (model structure) and quantitatively (model parameters), and allow efficient inference. A class of graphical models fulfilling these requirements are *Bayesian Networks* (BNs). BNs encode beliefs about the world states represented as *chance nodes* using a Directed Acyclic Graph (DAG) [9].

Chance nodes are denoted by capital letters here, *e.g.* X. The realisation of a random variable is denoted by a small letter, *e.g.* x. If the variable is a vector as opposed to a scalar, it is printed in bold, *e.g.* $\mathbf{x}$. Chance nodes are either observed (*evidence* nodes) or unobserved (*hidden* or *latent* nodes). Nodes that can be observed are referred to as *information sources* in this paper. If a node Z is observed, it is instantiated with a value which is denoted as $\bar{\mathbf{z}}$.

BNs can be extended to *Influence Diagrams* (IDs) to model decision making under uncertainty [32]. IDs are generally able to represent information about the current state, possible actions, the state resulting from the action, and the utility of that state [9]. IDs extend BNs by adding *decision* and *utility* nodes. Decision nodes D represent choices available to the decision-maker (a set of possible actions). Utility nodes U encode a scalar utility function which values the consequences of decisions.

In addition to the DAG property inherited from BNs, two more structural properties are part of an ID: (1) there is a directed path comprising all decision nodes, and (2) utility nodes do not have children. The directed path property is required to ensure a temporal sequence of decisions [33].

For visualisation, standard conventions are adopted here: chance nodes are drawn as circles, decision nodes as squares, and utility nodes as diamonds.

An example of an ID is shown in Fig. 2. X and $Y = \{Y_0, \ldots, Y_n\}$ denote hidden world states, $Z = \{Z_0, \ldots, Z_m\}$ and $I = \{I_0, \ldots, I_p\}$ denote information sources. Z nodes are always observed and shown in dark grey while I nodes represent information sources which may or may not be observed (shown in light grey).

The ID contains a single decision node D with no chance nodes as children, implying that the decision has no effect on the world states. In this case, the decision is also referred to as a *non-intervening* decision. The utility node U depends on its parents – decision node D and chance node X. The network topology within the "supernode" containing Y, Z, and I is arbitrary.

3.2. Making decisions

For the case shown in Fig. 2, the best action can be found as follows. First, compute the *expected utility* (EU) of *action* vector $\mathbf{d}$ given observations $\bar{\mathbf{z}}$:

$$EU(\mathbf{d}|\bar{\mathbf{z}}) = E^{p(\mathbf{x}|\bar{\mathbf{z}})}\{U(\mathbf{x}, \mathbf{d})\} = \sum_{\mathbf{x}} U(\mathbf{x}, \mathbf{d}) p(\mathbf{x}|\bar{\mathbf{z}}) \tag{1}$$

where the computation of $p(\mathbf{x}|\bar{\mathbf{z}})$ marginalises out Y and I. Second, choose the action d^* which maximises the EU:

$$d^* = \operatorname*{argmax}_{\mathbf{d}} EU(\mathbf{d}|\bar{\mathbf{z}}). \tag{2}$$

The general decision problem with multiple decision nodes is to find the best sequence of decisions. The solution to the problem is a sequence that maximises the expected utility. One possibility is to convert the ID to a decision-tree [32]. In general, however, the tree is of exponential size. IDs can be solved more efficiently using, for example, strong junction trees [33].

3.3. Value-Of-Information

Rather than taking the action d^* in Eq. (2), a decision-maker might have the choice of consulting one of its information sources $\{I_0, \ldots, I_p\}$ in order to generate a more informed decision. Consulting an information source I_i is equivalent to obtaining the state of that chance node. For this paper, it is assumed that only a single information source can be consulted at any given time, which is referred to as *myopic* information gathering [9].

It is possible to calculate what we can *expect* to gain from consulting the information source *before* observing that node, by using its belief given all current evidence $p(\mathbf{i}_i|\bar{\mathbf{z}})$ [34]. The expected utility of the optimal action (*EUO*) *after* having observed I_i is

$$EUO(\mathbf{i}_i, \mathbf{d}|\bar{\mathbf{z}}) = \sum_{\mathbf{i}_i} p(\mathbf{i}_i|\bar{\mathbf{z}}) \max_{\mathbf{d}} EU(\mathbf{d}|\bar{\mathbf{z}}, \mathbf{i}_i). \tag{3}$$

The value of observing I_i is called the *Value-Of-Information* (VOI). It is calculated as the difference between the expected utility after having observed I_i and the currently available maximum expected utility:

$$VOI(\mathbf{i}_i, \mathbf{d}|\bar{\mathbf{z}}) = EUO(\mathbf{i}_i, \mathbf{d}|\bar{\mathbf{z}}) - \max_{\mathbf{d}} EU(\mathbf{d}|\bar{\mathbf{z}}). \tag{4}$$

Eq. (4) is valid for all network topologies. If there are several decision nodes, the directed path property determines the temporal order as described above. Before each decision is made, Eq. (4) can first be used to decide whether to obtain more information.

For the non-intervening case shown in Fig. 2, Eq. (4) can be computed as:

$$VOI(\mathbf{i}_i, \mathbf{d}|\bar{\mathbf{z}}) = \sum_{\mathbf{i}_i} p(\mathbf{i}_i|\bar{\mathbf{z}}) \max_{\mathbf{d}} \left(\sum_{\mathbf{x}} p(\mathbf{x}|\mathbf{i}_i, \bar{\mathbf{z}}) U(\mathbf{d}, \mathbf{x}) \right) - \max_{\mathbf{d}} \left(\sum_{\mathbf{x}} p(\mathbf{x}|\bar{\mathbf{z}}) U(\mathbf{d}, \mathbf{x}) \right). \tag{5}$$

Computing the VOI is relevant for intelligent information gathering systems where the goal is to maximise the amount of information collected [35]. Consulting an information source comes at a cost, so a sensible strategy is to consult that source only if the expected benefit is higher than the cost $C(\mathbf{i}_i)$:

$$VOI(\mathbf{i}_i, \mathbf{d}|\bar{\mathbf{z}}) - C(\mathbf{i}_i) > 0. \tag{6}$$

In this work, Eq. (6) is used as follows: if the cost for obtaining information from a human operator is smaller than the expected benefit, then ask the operator for an observation.

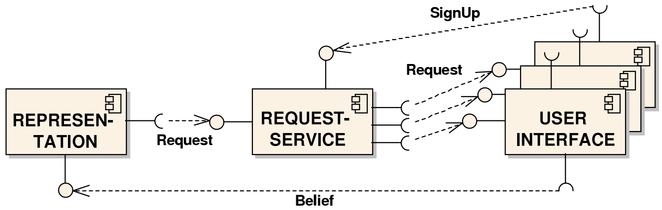


Fig. 3. Generic architecture for the robot-pull pattern. Rectangles are components with provided and required interfaces, shown as circles and semi-circles, respectively. Arrows indicate information flow.

4. Robots query humans

This section gives reasons why the proposed decision-theoretic framework is suitable for collaborative human–robot decision making with humans acting as a resource to robots.

4.1. Query types and triggers

The *types* of queries robots should pose are well defined if humans are regarded as information sources using a probabilistic representation: human operators are queried for *observations* which are subsequently incorporated into the representation as evidence. How to *trigger* a query is answered by VOI theory while satisfying the following requirements: only query for relevant information, pose queries in a reasonable order, and most importantly, take the cost of obtaining evidence into account.

For this paper, the cost of obtaining evidence is represented by a threshold which is fixed prior to a mission. A methodology to determine an appropriate threshold offline is described in [36]. More sophisticated approaches are possible and will be addressed in the future as discussed in Section 7.2.

4.2. Robot-pull architecture

Fig. 3 shows a generic[1] human–robot architecture for the robot-pull pattern. The Representation component generates requests, based on Eq. (6), which are sent to the RequestService. The RequestService acts as a query arbiter by relaying requests to suitable human operators, who are represented by user interfaces. Operators would have signed up previously by specifying the Quality of Service (QoS) they can provide, such as their *expertise* and the sensor *information type* they have access to (*e.g.* laser scan, camera image). When operators receive requests, they can submit observations via the `Belief` interface, shown in Fig. 3.[2]

The architecture is able to handle many-to-many interactions. Multiple user interfaces can be serviced by the RequestService. While Representation is shown as a single component, it can represent a multi-robot system, as discussed in the following section.

4.3. Difficulties with robot-pull

Special considerations arise when robots request information from human operators [21]: (a) what if operators are not available or do not answer queries, (b) how are individual differences amongst operators handled, and (c) how suitable is robot-pull for many-to-many interactions? A decision-theoretic framework can provide the following answers:

(a) *Autonomy:* a decision-theoretic framework can yield a decision at any time, *i.e.* the system is always capable of operating fully autonomously. Questions are only triggered if it is worthwhile obtaining additional observations due to high uncertainty about a relevant internal state. If no answers are received, the system remains capable of acting rationally by selecting the best decision using Eq. (2).

(b) *Uncertainty about operators:* varying levels of user expertise are taken into account because the robot needs to handle answers from experts and novices differently [21]. The level of user expertise is encoded as a probabilistic *Human Sensor Model* (HSM) in our approach [8]. Mathematically, there is no difference between a robotic and a human sensor model, reinforcing the notion of humans and robots acting as peers.

(c) *Scalability:* one concern with using a robot-pull pattern is its perceived inability to scale to multi-robot systems [38]. We argue that truly scalable systems can only be achieved if the representation is concerned solely with the *environment*, not the robotic platforms themselves. An example of such a representation is a map of the environment which is built using input from sensors and human operators [8]. Robots in the team make decisions based on the map only. In principle, this approach allows an unlimited number of robots to join the team [38]. This paper does not demonstrate scalability because the representation of choice is related to the robotic platform, as described next.

5. Navigation application

This section introduces a navigation application used to demonstrate collaborative human–robot decision making. The task is to navigate a robot through a 2-dimensional extruded maze in a simulated environment , as shown in Fig. 4. The maze contains four waypoints and two types of obstacles: solid columns, and spheres which the robot can safely push out of its way.

The robot is perfectly localised at all times. It is equipped with two on-board sensors: a laser scanner (180° field of view, 3 m range) and a camera. Information provided by the camera is not processed: reliable interpretation of images is still a largely unsolved research problem [39]. Humans, however, are excellent at this task and we exploit this capability by presenting images to operators to let them identify whether an obstacle is pushable or not.

5.1. Representation for navigation

The navigation algorithm makes use of the influence diagram (ID) shown in Fig. 5. The ID's structure resembles the one shown in Fig. 2 except for one difference: the navigation model contains *two* non-intervening decisions. All nodes in the navigation model have corresponding nodes in Fig. 2, as indicated by the variable names next to each node in Fig. 5 (X, Y, Z, I, D, U).

Many well-researched methods in machine learning and knowledge engineering address the problem of how to find such a model [9]. It is not the focus of this work, and therefore both the structure and the parameters were handcrafted here. Since all the nodes are discrete, the probability distributions and utility functions are represented as tables.[3]

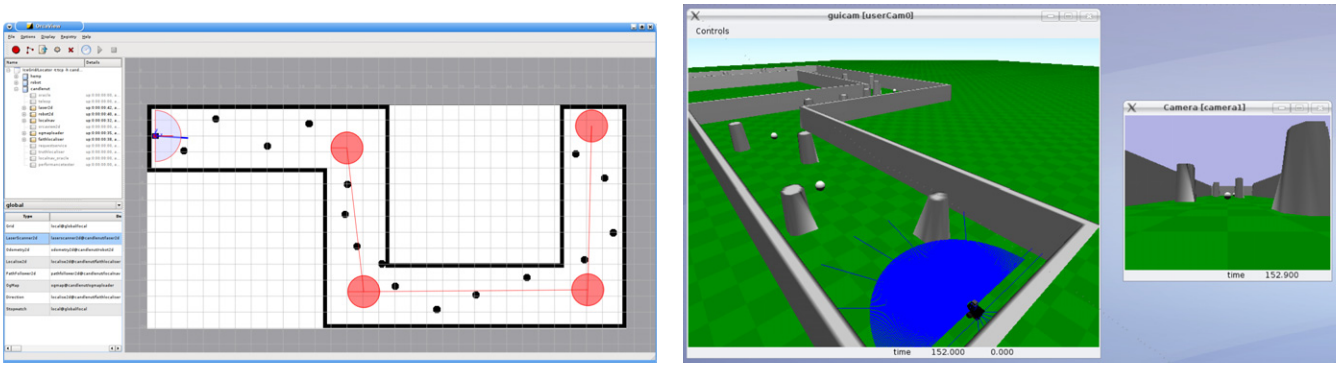
We do not propose this model as a well-suited solution to the navigation problem, especially because it is purely reactive, *i.e.* not capable of planning ahead. The model's purpose is to illustrate the human–robot information fusion mechanism for collaborative decision making.

At robot run-time, the model is instantiated at each time instance without taking priors into account, *i.e.* no filtering is

[1] *I.e.* not tied to a particular application/representation.

[2] An example of a similar system is the Amazon Mechanical Turk [37] — an online marketplace to distribute tasks humans perform better than computers.

[3] The reader is referred to [4] for discretisation levels and other details of the model.



(a) Occupancy grid map and the robot with its laser scan. The circles represent the waypoints to be reached.

(b) Three-dimensional view of the maze (left) and the camera image (right).

Fig. 4. Simulated extruded world for the navigation task: the maze contains walls, solid columns, and pushable spheres. The robot is equipped with a laser scanner and a camera.

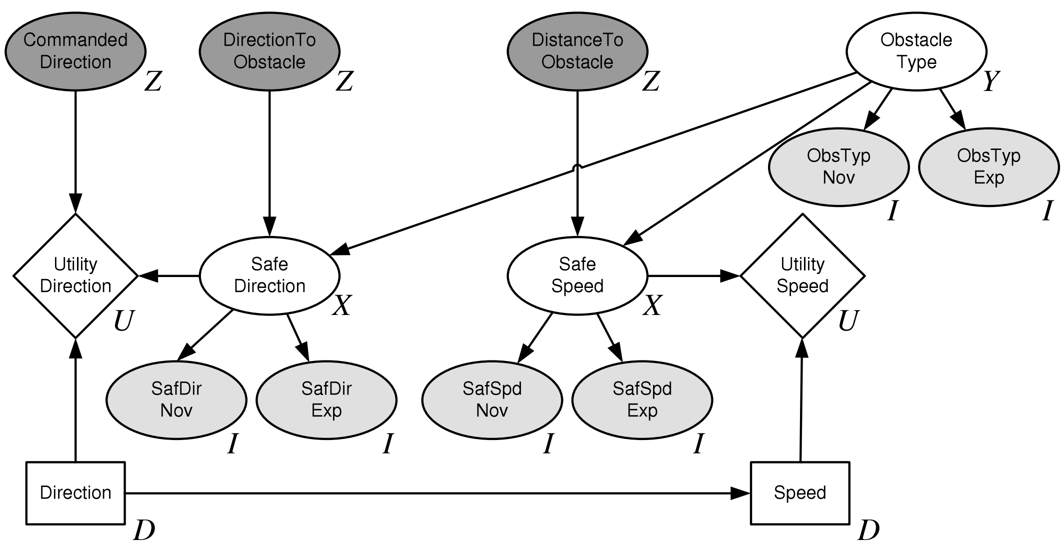


Fig. 5. Influence diagram representation for a navigation task. Ovals are chance nodes, squares are decision nodes, and diamonds are utility nodes. Dark grey nodes are observed by the robot, light grey nodes are human-observable. The variable names next to each node refer back to Fig. 2.

performed and inference is static. Two decisions need to be made at each time instance in the following order[4]: in which direction to move (decision node *Direction*), and with what speed (decision node *Speed*). The following section discusses how these decisions are made.

5.2. Making decisions

Robot-observable nodes are shown in dark grey in Fig. 5. First, the robot determines the direction to the next waypoint, which serves as evidence for the *CommandedDirection* node. Then, obstacle states are extracted from the current laser scan, which serve as evidence for *DirectionToObstacle* and *DistanceToObstacle* representing the direction and distance to the closest obstacle (if any).

After having incorporated all evidence from robotic sensors, the first decision the robot has to make is which direction to move. Alternatively, the robot can first query a human operator for more information. Human-observable nodes are shown in light grey in Fig. 5 and represent potential candidates for obtaining more information. The robot computes the VOI for all human-observable nodes using Eq. (5). When a human observation is received, it is incorporated into the representation as additional evidence. Finally, a direction is selected using Eq. (2). The procedure is then repeated for the *Speed* decision.

5.3. Human sensor models

Human-observable nodes are children of the latent variables *ObstacleType*, *SafeDirection*, and *SafeSpeed*. These nodes are considered higher-level in terms of abstraction and are easily understood by humans. *ObstacleType* encodes whether an obstacle is pushable or not. *SafeDirection* and *SafeSpeed* encode the direction and the speed which are currently safest.

Two types of human-observable nodes (novice/expert) are used to represent the different levels of uncertainty in the operators' answers: in plain terms, how much the answers can be trusted. Mathematically, the nodes encode Conditional Probability Distributions (CPDs), which we call Human Sensor Models (HSMs). HSMs are important for the VOI analysis: the more an answer can be trusted, the more valuable it is. An example is visualised in Fig. 6, which shows the VOI for all six human-observable nodes when the robot is in the following "critical" situation: an obstacle is very close to its right, which is also the direction it is commanded to go. The figure shows that information from an expert is more valuable than from a novice.

The horizontal line in Fig. 6 represents the (arbitrarily set) information cost threshold. In this scenario, three bars exceed

4 The order is set arbitrarily here and could be reversed.

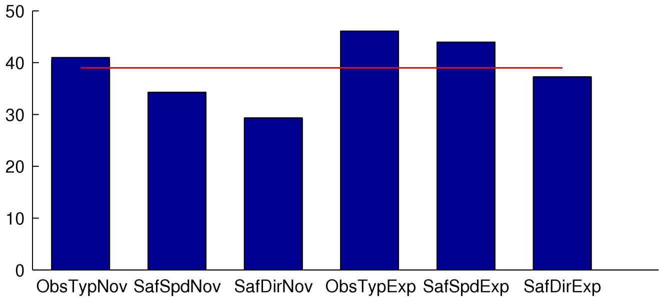


Fig. 6. VOI when the robot is in a "critical" state. The horizontal line represents the cost of consulting a human operator.

the threshold: *ObsTypExp*, *SafSpdExp*, and *ObsTypNov*, *i.e.* Eq. (6) is fulfilled for these three information sources. Thus, the RequestService would first try to consult an expert about the type of obstacle which is the most valuable observation which can possibly be obtained in this situation. If no experts are available, a novice would be queried for an opinion on the obstacle type.

5.4. Sensor information type

Besides expertise, a second QoS property is the type of sensor information operators have access to at run-time. In our experiments, operators may receive laser scans and/or the camera images. If only a laser scan is available (*e.g.* due to bandwidth constraints), the obstacle type (pushable or not) cannot be observed. For the scenario visualised in Fig. 6, a question about the safe speed (*SafSpdExp* — second highest bar) would be relayed to an expert.

5.5. VOI analysis

As mentioned above, the VOI varies depending on the situation the robot encounters when traversing the maze. Table 2 shows how the robot's states change when approaching an obstacle. Fig. 7 shows the VOI with respect to the three expert variables (the VOI plots for the novice variables follow the same shape but the values are lower). The three situations from Table 2 are marked in the VOI plots.

In situation (1), the robot has not encountered any obstacles and there is no information to be gained from asking for *ObsTypExp* ($VOI \approx 0$). There is a low expected gain from querying for *SafSpdExp* and *SafDirExp*.

In situation (2), the robot has detected an obstacle and knowing *ObsTypExp* has now become valuable. However, there is no change for *SafSpdExp* because the obstacle is still far away. The small reduction in VOI for *SafDirExp* compared to situation 1 can be explained as follows: in situation 1, the *DirectionToObstacle* was unspecified (*none*) while in situation 2 it is *left* which does not conflict with *CommandedDirection* (*straight*).

In situation (3), the robot has moved close to the obstacle. The VOI for all three variables is highest for this situation, *i.e.* an expert opinion on any of the variables is most valuable when the robot is closest to an obstacle. *CommandedDirection* (*left*) now conflicts with the *DirectionToObstacle* (also *left*), which increases the VOI for *SafDirExp*.

After passing the obstacle, the VOI drops to low values for all three variables.

6. User study

A user study was conducted to compare the robot-pull system to manual teleoperation (simple human-push). Initial results were published in [11]. In this paper, we present additional results with respect to performance and the participants' perception of the robot. Furthermore, the user study results are facilitated to predict the most appropriate driving mode for a number of common mission scenarios.

6.1. Objectives

Teleoperation is a well-understood research area and especially useful in unstructured environments, *e.g.* in search and rescue scenarios [40]. Well-known limitations of teleoperation are high operator workload and scalability [41]. Other problems of teleoperation are the dependence on the user's skills and the sensor information available to the user. Typically, users need to be trained experts to be capable of teleoperating a robot. In contrast, the robot-pull system poses simple questions that can be answered using common sense.

Based on this discussion, three objectives were identified for this user study: (a) to compare the proposed system to conventional teleoperation with respect to performance, operator workload, usability, and users' perception of the robot, (b) to investigate the influence of expertise and available sensor information on performance, and (c) to demonstrate performance variability for teleoperation.

For the user study, the cost threshold was fixed *a priori* based on the results reported in [36]. Wall and obstacle tracking was implemented to avoid repeated queries related to the same obstacle. To simplify technical terms for participants, the robot-pull system was referred to as "dialog" here.

6.2. Experimental design

6.2.1. Participants

Two groups of participants, experts and novices, were employed for the experiment: 22 participants (13 male, 9 female) with an average age of 30.7 (oldest 48, youngest 23) were recruited. The expert group consisted of 10 post-graduate or post-doc researchers from our robotics lab. None of them was familiar with the dialog system or had any prior information concerning the purpose of the study.

The novice group consisted of 12 participants who had no prior experience with mobile robots. All but one of the participants in the novice group held a university degree while none had an engineering background. Privacy was maintained by using anonymous user names for each participant.

6.2.2. Task

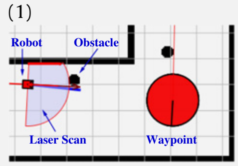
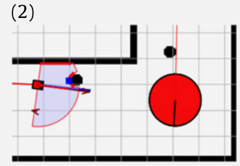
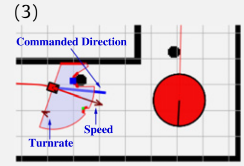
The objective was to navigate a remotely located robot through the maze shown in Fig. 4. The same maze was used for all experimental conditions. Participants received written instructions "to get the robot to its goal as quickly as possible while making sure it is safe".

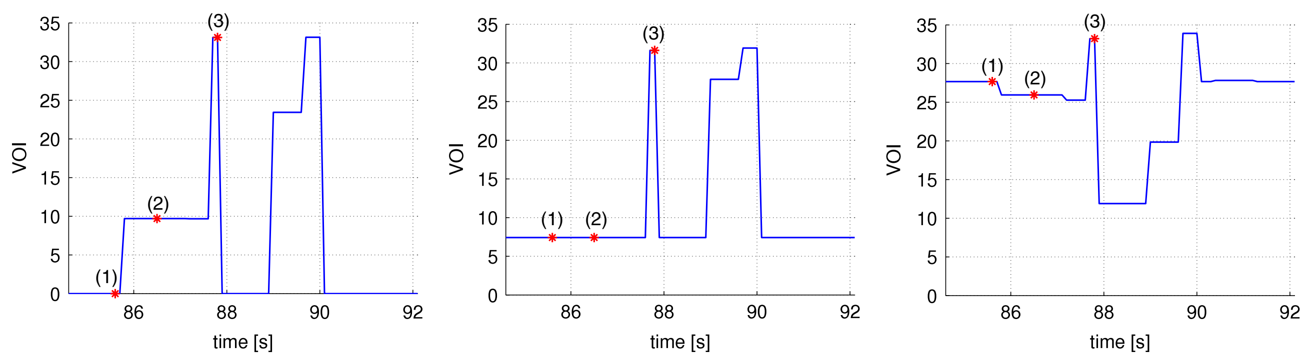
The experiment followed a within-subject design: all participants operated the robot using four different modes which represent the experimental conditions. The modes were generated by varying *driving style* and *information type* which are explained next.

Available driving styles were teleoperation and dialog. In teleoperation, participants operated the robot manually using a joystick, while the robot acted semi-autonomously in the dialog modes, as described in Section 5. The maximum speed was set to the same value for both teleoperation and dialog. In the dialog modes, the interactions between operator and robot were limited to an occasional query posed by the robot. If no answer had been received within 30 s, the robot made a decision without human input, as described in Section 4.3.

Information type relates to the sensor information relayed to the remotely located operator: either the laser scan only, or the laser scan and a camera image (participants did not have access to

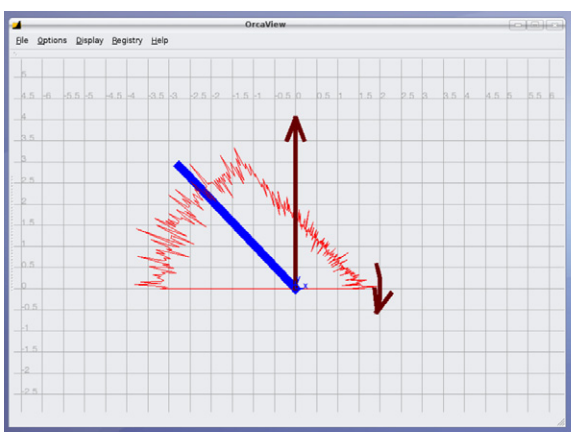
Table 2
Three consecutive situations and their corresponding states when encountering an obstacle.

	(1)	(2)	(3)
Situation			
CommandedDirection	*straight*	*straight*	*left*
DirectionToObstacle	*none*	*left*	*left*
DistanceToObstacle	*far*	*far*	*close*

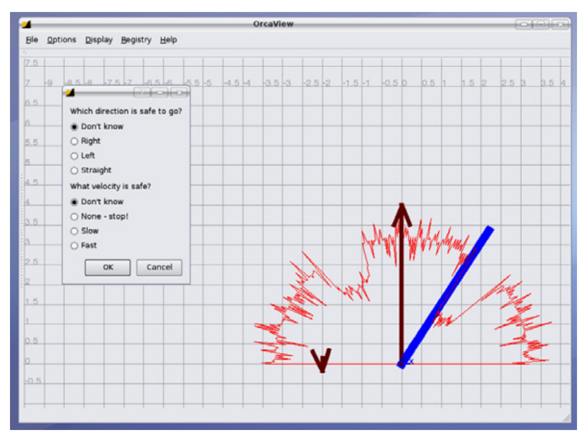


(a) *ObsTypExp*. (b) *SafSpdExp*. (c) *SafDirExp*.

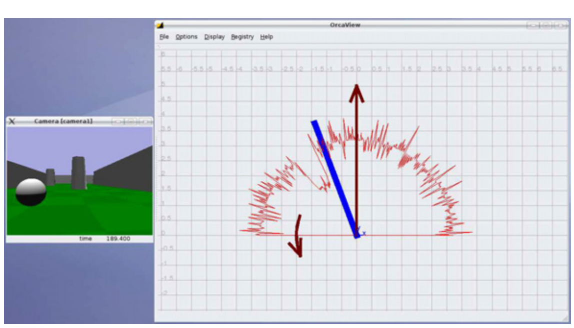
Fig. 7. VOI analysis for the robot approaching an obstacle in one of the experiments. The VOI values corresponding to the three situations shown in Table 2 are marked in the graphs.



(a) Teleop/laser.



(b) Dialog/laser.



(c) Teleop/camera.

(d) Dialog/camera.

Fig. 8. User interfaces for the four experimental modes: the zig-zag line is the robot's noisy laser scan, the solid bar indicates the direction to the next waypoint in the robot's coordinate frame, and the arrows give feedback about the current speed and turnrate, respectively. In the dialog modes (second column), the robot poses questions which show up as multiple-choice dialog boxes.

the global view). The four modes are shown in Fig. 8 and described in the figure's caption.

In order to measure workload, a secondary task was introduced. Participants were asked to add 2-digit numbers if and only if they had spare capacity to do so. A Graphical User Interface (GUI) was designed displaying four multiple choice answers. Answers could be entered using the buttons on the joystick (teleoperation modes) or by using the mouse (dialog modes).

6.2.3. Procedure

The experiment was conducted as follows. First, participants completed a pre-experiment questionnaire designed to gather demographic data and assess the participants' driving skills. After reading a set of instructions, teleoperation of the robot in the maze was practised for about 1 min. After that, the experiment started with one of the four modes. To account for learning effects, the order of testing was counterbalanced.

The experimenter, who had access to the global view on a separate computer screen (Fig. 4), monitored the progress of the experiment and noted the number of collisions.

After each task was completed, participants were asked to fill in a post-task questionnaire consisting of 7-point Likert scale test items (13 for teleoperation, 17 for dialog). After all four tasks were completed, a comprehensive post-experiment questionnaire was filled in, containing six multiple choice questions and three free text sections. The overall procedure took the average participant about 45 min.

All questionnaires and the full set of instructions participants received can be found in [4].

6.3. Measures

Measures used in this study were performance, workload, usability, and the users' perception of the robot.

Performance was measured using two variables: number of collisions and time to complete the task. For teleoperation, a collision was registered whenever the robot ran into an object. For the dialog modes, collisions were situations in which the robot could not keep driving by itself and needed to be freed by the experimenter. These situations sometimes occurred if participants answered inappropriately, *e.g.* after misinterpreting the laser scan shown in Fig. 8(b). Completion time was the total time it took to reach the last waypoint.

Workload was measured by two means: (1) the number of maths problems correctly solved, and (2) through introspection using the post-task questionnaire. Four statements were used for the latter derived from the NASA Task Load IndeX (TLX) method [42]. Usability was measured using five statements in the post-task questionnaire which were adapted to a navigation task from [43].

Remaining measures were related to the users' perception of their relationship to the robot in the different modes, namely safety, trust, intelligence, and partnership. They were assessed using the questionnaires.

6.4. Hypotheses

Based on the objectives listed in Section 6.1, the following experimental hypotheses were tested:

1. Performance-related hypotheses:
   (a) Dialog modes will be superior to teleoperation for both performance measures (number of collision, completion time).
   (b) Having access to camera images will result in better performance than having access to a laser scan only.
   (c) Experts will perform better than novices.
   (d) Performance will be more variable in teleoperation than in dialog and will depend on the available information type (laser/camera) and expertise (novice/expert).
   (e) There is a positive correlation between teleoperation performance and users' self-reported driving skills.
2. Workload will be higher in teleoperation than in dialog.
3. Dialog modes will be more usable than teleoperation.
4. The robot will be perceived as safer, more trusted, more intelligent, and more peer-like using dialog modes.

Table 3
Results from the three-way repeated-measures ANOVA using $F[1, 20]$. Three conventional significance levels are applied: $p < \{0.05, 0.01, 0.001\}$ represented by $\{*, **, ***\}$ (*n.s.* means not significant). Independent variables were ds: driving style, it: information type, ex: expertise.

Measure	Main effects					
	ds		it		ex	
	F	p	F	p	F	p
Collisions	11.7	**	6.9	*	1.1	*n.s.*
Completion time	0.3	*n.s.*	11.3	**	13.1	**
Workload (sec. task)	63.8	***				
Workload (introspection)	8.2	**				
Usability	5.5	*				
Perception of robot	20.3	***				
Measure	**Interactions**					
	ds × it		ds × ex			
	F	p	F	p		
Collisions	2.8	*n.s.*	3.0	*n.s.*		
Completion time	18.1	***	7.3	*		

6.5. Results

The experiment used a $2 \times 2 \times 2$ factorial design with two within-subjects variables (driving style, information type) and one between-subjects variable (expertise) [44]. The data was analysed by applying a three-way repeated-measures ANOVA (analysis of variance) which enables testing for the overall main effects of the three variables and their interactions. The level of statistical significance was set at $p = 0.05$. Three conventional levels are used to report results: {0.05, 0.01, 0.001}. If measures had no physical unit, they were scaled to a range of 0.0 to 1.0.

Results of the statistical analysis relevant to the hypotheses listed above are summarised in Table 3. A discussion of the results is presented below.

6.5.1. Performance

Most collisions occurred in teleoperation, particularly in teleop/laser, which accumulated twice as many as teleop/camera. As shown in Table 3, dialog was a significantly safer mode than teleoperation, supporting Hypothesis 1(a). Having a camera available also resulted in significantly less collisions when compared to having access to a laser scan only, supporting Hypothesis 1(b). No significant overall difference in the number of collisions between experts and novice could be found. The performance difference between laser & camera and novice & expert was greater in teleoperation than in dialog. However, these interaction effects were not statistically significant.

Completion times for teleoperation and dialog were nearly identical, contradicting Hypothesis 1(a). Having access to a camera yielded significantly faster completion times than having access to a laser scan only, supporting Hypothesis 1(b). Experts completed the task significantly faster than novices. Completion time differed more in teleoperation than in dialog modes. Significant interactions were found for both expertise and information type, *i.e.* completion time is dependent on both variables. This finding supports Hypothesis 1(d).

Hypothesis 1(e) is investigated next. As presented above, experts were significantly faster than novices in completing the task, but no significant difference between experts and novices was found for the number of collisions. For teleoperation, performance may depend on factors such as hand-eye coordination and driving experience, as predicted by Hypothesis 1(e). To investigate the relationship between users' driving skills and their teleoperation performance, a correlational analysis was conducted. Driving skills were assessed using data from the pre-experiment questionnaire: experience in car driving, computer use, video games, and remote driving, as well as hand-eye coordination and navigation skills. The data was scaled and a weighted sum was computed with a weight ratio of 1:1:2:2:10:10 with respect to the driving skill factors, yielding a single score. A similar method was used to obtain a single score for teleoperation performance: the number of collisions and completion times were scaled and summed. A Spearman correlation was computed yielding a statistically significant positive correlation between driving skills and teleoperation performance, confirming Hypothesis 1(e) ($r = +0.58$; $n = 22$; $p < 0.01$). As a comparison, the correlation between expertise and teleoperation was also significant but slightly smaller ($r = +0.53$; $n = 22$; $p < 0.01$).

6.5.2. Workload and usability

Workload as measured by the secondary task was significantly higher for teleoperation modes than for dialog modes, as shown in Table 3. The difference between teleop/laser and teleop/camera was small for the novice group. This seems surprising given that the camera view provides a larger sensor range than the laser. However, as indicated by seven participants in the free text section of the post-experiment questionnaire, having the camera and the laser led to information overload. For teleoperation, experts seemed to cope better with the overload than novices.

An alternative workload measure was obtained through introspection using four Likert-scale statements which were summarised into a single score. The results agreed with above: workload was perceived higher for teleoperation than for dialog, as shown in Table 3. Based on these results, Hypothesis 2 was validated.

Similar to workload, usability was measured by averaging results of five Likert-scale statements. Dialog modes were perceived as more usable than teleoperation modes, as shown in Table 3. Hypothesis 3 was therefore also validated.

6.5.3. Users' perception of the robot

The users' perception of the robot with respect to safety, trust, intelligence, and partnership were measured using single Likert statements in the post-task questionnaire. As before, the four measures were summarised into a single score for the statistical analysis. The robot was perceived significantly safer, more intelligent, more trustworthy and peer-like in the dialog modes compared to the teleoperation modes.

6.6. Discussion

6.6.1. Performance

The experimental results show that performance using classical teleoperation is highly dependent on the operators' expertise, their driving skills, and the available information type.[5] In contrast, performance results are more consistent when using the dialog system to operate the robot.

More collisions occurred in teleoperation than in dialog modes. However, the experiment also showed that completion time varies with expertise and the information type available to the operator. For example, the average expert completed the course 35 s faster using teleoperation than using dialog. Thus, a tradeoff exists between safety and timeliness when an appropriate driving mode needs to be selected. This is further explored in Section 6.7.

[5] Similar results are reported in [5].

6.6.2. Workload and usability

Operator workload was significantly lower for dialog modes than for teleoperation. This result has consequences for the scalability of a system: one human can operate multiple robots simultaneously. The allocation between robots and a human does not have to be fixed using dialog. It is possible to shift responsibilities dynamically in teams involving multiple robots and multiple humans. In terms of usability, dialog was perceived to be a better interaction mode than teleoperation.

6.6.3. Users' perception of the robot

Users attributed properties such as safety, trust, and intelligence to the robot while also acknowledging the robot as a peer. These factors are considered to play an important role for more effective collaboration in human–robot team settings [21].

6.7. Driving mode selection

This section facilitates the user study results to select an appropriate driving mode given a mission scenario. Four scenarios are introduced to illustrate the selection procedure:

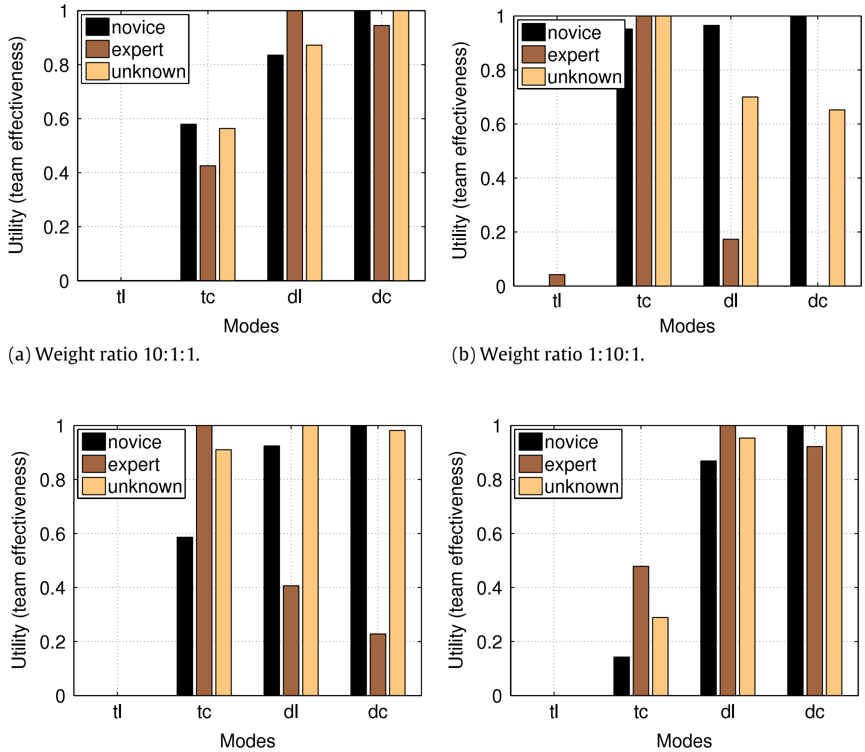
(a) *Planetary exploration*: a remote operation of an expensive robot. Humans cannot physically intervene in case of failures. We assume that multiple human operators are available.
(b) *Search and rescue (S&R)*: assumes a single robot and multiple operators engaged in an S&R task. The most important objective is to locate the victims as fast as possible.
(c) *S&R, limited bandwidth*: the same as the previous scenario with the additional assumption of a limited communication bandwidth.
(d) *Multi-robot system*: assumes a single operator who is in charge of multiple robots simultaneously, attending to one robot at a time.

To choose an appropriate driving mode, the priorities for each of the scenarios is taken into account. Three metrics are used to describe the scenarios: safety, timeliness, and workload. Numbers for the metrics are obtained from the results presented in Section 6.5: safety is measured by the number of collisions, timeliness by the completion times, and workload by the number of math questions correctly answered. The three metrics are combined into a single scalar utility by a weighted sum which is subsequently scaled to a [0; 1] interval. The most appropriate driving mode can be found by selecting the mode where the utility is 1. The utility can be interpreted as a measure for the *effectiveness* of the human–robot team [36].

The weights mentioned above represent the relative importance of each metric and are set as follows. For the planetary exploration scenario, the completion time is of secondary importance but the robot could be lost if it hits an obstacle. A weight ratio of 10:1:1 is manually chosen, emphasising the importance of safety over timeliness and workload. Fig. 9 shows that the dialog modes are preferable in this case: dialog/laser for experts and dialog/camera for novices.

For the S&R scenario, the weight ratio is chosen to be 1:10:1, reflecting the importance of completing the task in a timely manner. Under these conditions, the highest team effectiveness can be achieved by choosing dialog/camera for novices and teleop/camera for experts.

A weight ratio of 1:10:5 is chosen to represent the S&R scenario with limited communication bandwidth. Compared to the previous scenario, more emphasis is given to the human workload, thus avoiding excessive communication. The results for novices and experts are the same as above. For the case when the operators' expertise is unknown, the mode changed from teleop/camera to dialog/laser.



(a) Weight ratio 10:1:1.

(b) Weight ratio 1:10:1.

(c) Weight ratio 1:10:5.

(d) Weight ratio 1:1:10.

Fig. 9. Utility bars for choosing an appropriate driving mode for novices, experts, and operators with unknown expertise. The human–robot team effectiveness is highest when the utility is 1. Weights reflect the relative importance of safety, timeliness, and workload for four mission scenarios: (a) planetary exploration; (b) search and rescue (S&R); (c) S&R with limited communication bandwidth; (d) multi-robot system. The driving modes are tl: teleop/laser, tc: teleop/camera, dl: dialog/laser, dc: dialog/camera.

For the multi-robot scenario, the weight ratio is chosen to be 1:1:10, reflecting the importance of minimising the interactions with the robots and thus reducing the operator workload per robot. Under these conditions, the highest team effectiveness can be achieved by using the dialog modes: dialog/laser for an expert and dialog/camera for a novice.

6.8. *Dialog system evaluation*

This section presents results from the user study which are not directly related to the hypotheses listed in Section 6.4. Results are concerned with the dialog system only and serve as feedback to improve the system design.

The following measures were used to evaluate the dialog system: (1) the number of operator queries, (2) answer time,[6] (3) appropriateness of the queries, and (4) ease of answering different types of queries. The last two were evaluated using the questionnaires.

On average, the number of queries posed by the robot was 8.7 per episode, which corresponds to one query every 23 s. More queries were posed in dialog/camera than in dialog/laser due to the higher value in receiving information about the obstacle type. Experts sometimes indicated that they got bored with answering the same questions at regular intervals.

The average answer times per query were 8.1 and 7.5 s for the two modes. For experts, answer time was larger when a camera was available. This can be explained by the information overload mentioned in Section 6.5: experts tended to interpret the scene more thoroughly whereas novices answered quickly. This was observed subjectively by the experimenter and indicated by four participants of the experts group in the free text section of the post-experiment questionnaire.

Appropriateness of the queries regarding their frequency and content was ranked high with no statistically significant differences between the two driving modes and the novice/expert groups. Neither was there a statistically significant difference between the ease of answering the 3 different query types (*ObstacleType*, *SafeDirection*, *SafeSpeed*).

In summary, these results suggest that the dialog system posed an appropriate number of queries which can be answered in a reasonable time by both novice and expert users. However, we expect that user frustration may become a more important factor in real-world scenarios where interactions would be of longer duration.

7. Conclusions

7.1. *Summary*

We presented a human–robot communication framework designed for task-oriented information exchange between humans and robots. Bidirectional communication schemes are derived from probabilistic robotics representations which we classify as a robot-centric approach. The focus of this work is on human-to-robot information flow: humans contribute high-level perceptual information which robots fuse with lower level sensor information. This paper presented a particular application domain for human–robot fusion, namely collaborative human–robot decision making.

Two questions were addressed specifically: what and when to communicate. A decision-theoretic framework was proposed to give answers: all relevant information is contained in the representation, and Value-Of-Information theory determines when to query operators.

6 Answer time is also referred to as *Interaction Time* (IT) in the literature [45,46].

Collaborative human–robot decision making was implemented using a navigation task. The proposed system was compared to conventional teleoperation in a user study. Results indicated three main advantages:

1. Task performance does not depend as much on the operator's background, driving skills, and available sensor information.
2. Low workload leads to the potential of scaling up to large human–robot teams.
3. Higher usability and potential to achieve peer-to-peer human–robot interaction.

Despite these advantages, teleoperation may still be a preferable driving mode for a given mission. Four example scenarios served to illustrate the selection of an appropriate driving mode. Three metrics were used: safety, timeliness, and human workload. They were combined into an overall utility reflecting the human–robot team effectiveness. Values for the metrics were obtained from the user study results.

Finally, system properties regarding the number, content, and appropriateness of the robot-posed queries were evaluated. Users' feedback serves to improve the design for future experiments and a real-world deployment of the system.

7.2. Future work

While this paper presented results in simulation only, we plan to repeat the user study with a real robot and multiple operators. The software architecture presented in Section 4.2 was implemented using the Orca software framework [47] and can easily be ported to hardware. Subsequently, the system will be tested for specific applications (*e.g.* search and rescue) in order to validate our predictions for appropriate driving modes.

We also plan to apply the robot-pull pattern to tasks such as exploration and path planning, where the representation is concerned with the environment rather than the robotic platforms. These representations can be used to demonstrate the scalability of the approach in multi-robot, multi-user experiments. These types of applications will also require the formulation of the more general *sequential* decision problem, *e.g.* using POMDPs.

In this paper, the cost for obtaining information from an operator was represented by a fixed threshold. Future work will investigate the online adaptation of the threshold, employing user modelling techniques. For instance, if a model of the user's current workload exists, the cost can be adapted accordingly, as shown in [48]. The workload state could also be used to predict the operators' response time delays. Time delays are straightforward to integrate into the cost as part of VOI theory as shown, for example, in [35]. In summary, adapting the cost threshold online would result in a more intelligent system adapting its autonomy based on both the environment's and the human operators' current states.

Another benefit of a user model is its application to enhance the operators' *situational awareness*: by knowing the operators' state, robots can judge what information operators may currently require, resembling a smart robot-push communication pattern.

A further research area is to use the human–robot communication framework to enhance humans' trust in automated systems: using a human-pull pattern, operators may ask robots to *explain* their reasoning and decision making. The research question is how to translate probabilistic beliefs and inference mechanisms into human-understandable language, at appropriate abstraction levels and in a timely manner.

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