Enhancing Human-Robot Connection in Space Teleoperation through Shared Mental Model Creation

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***Abstract*— Previous research in human-robot-interaction in teleoperation suggests that human-robot teams with a Shared Mental Model (SMM) are able to achieve better task performances and lower the mental workload of the user. To create a SMM, the robot must be able to estimate the task model of the user and incorporate knowledge about the user into its user model. Most existing concepts use probabilistic methods or symbolic reasoning frameworks, with predefined features for estimating the user's teleoperation goal. They are therefore highly dependent on a-priori knowledge about the task, thus limiting their flexibility. Only very few approaches mention or explicitly take into account knowledge about the individual user and lack adaptability to human behavior and user preferences. Machine Learning (ML) based concepts, on the other hand, are more flexible to adapt their SMM during the user interaction, but require a lot of data points for precise estimation. In this paper, we propose a new approach to address these limitations by combining the advantages of symbolic and subsymbolic methods, and dividing our estimation of the user's teleoperation goal into subgoals next to the overall task goal. Furthermore, by integrating the knowledge about the individual user and human decision-making into the prediction of the user's task goal, we can improve SMM creation of human-robot teams for teleoperation. Our approach is applied to an example space exploration task in a planetary surface habitat by a telerobotic team. The SMM implementation is described and analyzed, followed by an outlook on future development and validation.**

I. INTRODUCTION

While robots become more and more autonomous in the execution of well defined tasks, teleoperation still plays an important role in various domains, for example for the exploration of unknown environments in space or search and rescue operations. Many approaches in recent years aimed to enhance robot teleoperation from a user-centered perspective, but there are still open challenges which increase the complexity of teleoperation tasks, for example if the system does not provide suitable information about the remote environment to the user [1]. A concept to formalize the information shared between robot and operator in a teleoperation setting is the concept of SMM, which has been used a lot over the last years in various research works in the domain of Human-Robot-Interaction (HRI), e.g. [10] [2] [12]. It refers to the situation, in which members of a team hold compatible mental representations about their task as well as about intentions and preferences of team members. Based on a SMM, the robot can identify misconceptions of the user, e.g. about the remote environment, or help in achieving the known task goal. Our contribution in this paper is a concept for creating a SMM among robot and user, which means that we enable the robot to estimate the mental model of the user with a focus on the user's task goal. For that, we identify limitations of previous approaches based on literature research. Many approaches in the area of SMM estimation are based on a-priori defined features or rules which are combined with probabilistic ML methods or symbolic reasoning frameworks to estimate the task model of the user. They therefore require a lot of handcrafting and lack adaptability to other tasks. On the other hand, ML based approaches often require a lot of data which is hard to gather for example in the space context. Also, less research has been done into the direction of adapting the SMM creation to an individual user and not generalizing over all users of a system. The concept we propose in this paper combines methods able to incorporate hand-crafted, a-priori defined

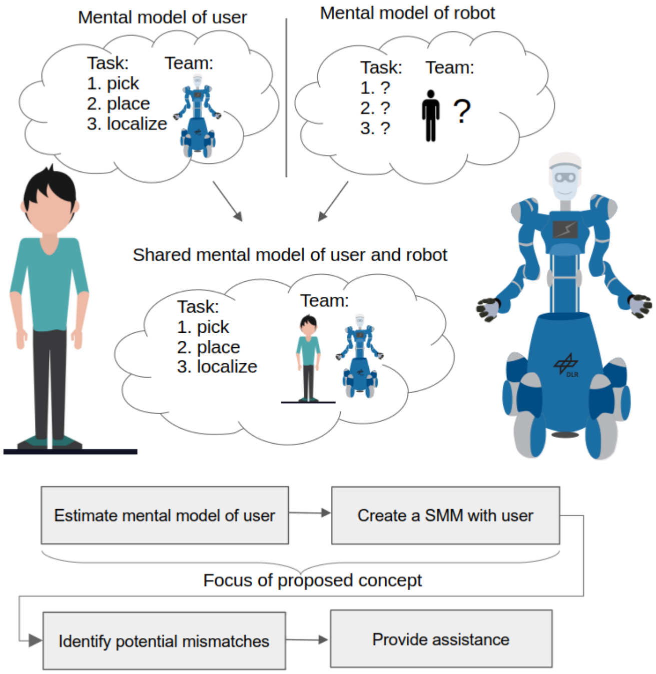

Fig. 1. User and robot holding a SMM in a teleoperation setting describes, that they hold compatible mental representations about the task to be achieved as well as about the respective teammate. If a SMM is established among user and robot, the robot can make use of the information to identify eventual misconceptions of the user, e.g. about the remote environment or the capabilities of the robot, or assist in achieving the task goal. Our focus in this paper is on enabling the robot to establish a SMM with the user.

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DOI: 10.1109/Telepresence66096.2025.11521393

features with ML based methods adaptable to individual users. We enable the robot to create a SMM with the user through estimating the task model of the user and taking into account available information about the user himself. We furthermore show the workflow of our proposed SMM estimation system on a space exploration task and present further developments.

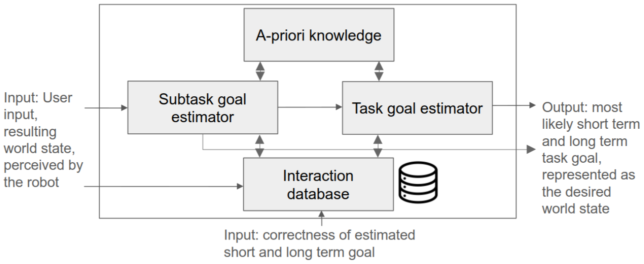

Fig. 2. Overview of the components for our concept on SMM estimation

II. RELATED WORK

A. Mental Model and Shared Mental Model Definition

The term *mental model* originally has been widely used in the human factors domain to describe and explain the mental representations humans form about their environment [1]. It has also been associated with the concept of Theory of Mind (ToM) in psychology, which describes the ability to attribute thoughts, intents and desires to others [22]. Recent surveys have shown that its definition in literature and research works is not homogeneous [2]. It has been adapted in the human-machine interaction domain to explain and structure human-machine interactions and explain eventual failures or errors based on mismatched mental models the user holds about the device or system. Based on that, different categories or types of mental models have been developed and used in literature, one of them being the SMM in the context of human-human teaming and adapted to human-autonomy/robot teaming [3]. A SMM describes the knowledge base team members (whether human or robot) share to achieve a common goal. If the SMM is accurate, it is seen to be strongly related to increased task performance and lower mental workload of the user [3]. Shared mental models are described in literature to be made up of multiple models: the *task model* and the *team model*, also called the *user model*. The task model hereby includes strategies to achieve the task, including the task goal, likely scenarios, environmental constraints etc. while the user model holds a representation of the team members, their interaction among each other as well as information about their knowledge and skills [3] [5].

B. Shared mental model estimation in robotic teleoperation

The concept of shared mental models has been applied in various research works in the context of HRI in teleoperation as well as collaboration of humans and robots in the same physical space. A focus of the majority of approaches in this area is to estimate the user's task goal to assist accordingly. Many approaches, like [5] [12] [3], use probabilistic methods like bayesian modeling to construct a SMM in a robot. To achieve this, the model requires a-priori knowledge about the mapping from user inputs to the desired task goal. Recent surveys like [8] or [10] point out that current approaches lack to account for individual differences among human users and not able to adapt during interaction time. Furthermore, only very few approaches take into account the user model as part of the SMM or even include models about human behavior. Examples for e.g. accounting for bounded rationality of human behavior are [4] or using a cognitive architecture like ACT-R to mimic human reasoning in [10]. There also exist approaches using similar techniques without explicitly mentioning the concept of SMM but instead use the term *intent estimation*. For example, in [4], the authors propose a bayesian method for operator intent estimation based on hand-crafted features like distance to a goal point to predict the most likely goal point. In [7] the operator has to define a set of contexts and action probabilities to allow the model to predict the action intent of the user. Methods able to adapt their estimation during the interaction of the user with the teleoperation system often build upon deep learning or reinforcement learning based approaches, like [17] or [18]. They require a lot of data points to be trained for precise estimation and lack explainability. We classify the mentioned approaches in the area of SMM estimation in tab. I using the following criteria:

- The approach is able to adapt to an individual user by explicitly incorporating knowledge about the user or a model about human behavior (User model).
- The approach is able to incorporate predefined facts or rules about the mapping of human behavior to a likely task goal (A-priori knowledge).
- The approach is able to adapt its estimation of the SMM over multiple interactions (Long term adaption).

To the best of our knowledge, no concept for SMM creation so far has taken all of the mentioned criteria into account. In the concept we propose in this paper, we include all of them to account for human behavior and differences among individual users, being able to adapt our estimation based on learning during interaction as well as to incorporate a-priori knowledge. Our concept enables the robot to create a precise SMM with the user in a teleoperation task. This allows the robot to identify eventual mismatches and is expected to improve the positive effects linked to holding a SMM, like better task performance or lower mental workload.

TABLE I
RECENT SMM ESTIMATION CONCEPTS FOR ROBOT TELEOPERATION

	User model	A-priori knowledge	Long term adaption
[3]	✓	✓	
[5]	✓	✓	
[13]		✓	
[10]	✓	✓	
[16]		✓	
[18]		✓	✓
[17]			✓

III. FRAMEWORK

A. *Formalization of the problem statement*

In a teleoperation scenario in which the robot initially does not know about the task goal which the operator wants to achieve, it is crucial for the robot to acquire this information as part of creating a SMM with the user. For defining the SMM structure, we use the definition of [15] according to which a SMM, M_{SMM}, consists of a task and a user model. The robot needs to estimate the task model M_T and combine it with available knowledge about the user, represented in the user model M_U to infer the user's intended task goal. According to the findings of [9], humans break down a task T into subtasks with subgoals. A subtask T_{Sub} is described to consist of a task goal G_{Sub} and a sequence of actions $A_{Sub} = (a_1, a_2, ..., a_n)$ of which the user expects they are suitable to achieve the goal, resulting in $T_{Sub} = \{G_{Sub}, A_{Sub}\}$. The (sub-)task goal represents the world state in the remote environment which the user wants to achieve. The overall task is made up of a sequence of subtasks: $T = (T_{Sub1}, T_{Sub2}, ..., T_{Subn})$ Based on that, the task model represents the mapping of the sequence of actions to the task goal, even if this strategy might not be complete, resulting in $M_T : A \rightarrow G$. The user model M_U incorporates knowledge related to the task execution specific to an individual user or about human behavior in general. This can for example include a mapping of a sequence of actions to a (sub-)task goal, which is specific to a user: $M_U : A_{User1} \rightarrow G$. Overall, the M_{SMM} can be described as $M_{SMM} : M_T \times M_U \rightarrow G$.

B. *Overview*

To account for the features we identified as relevant to improve SMM creation, we propose the framework structure as shown in fig. 2. The user inputs lead to the resulting world state of the remote environment. This sequence of user input and the resulting world state, as shown in fig. 3, is passed to the framework. We define the following modules:

- A-priori knowledge component: contains predefined knowledge about both the user and the task.
- Interaction database: records the input (user input and resulting worldstate), the estimated short and long term goal as well as (if available) a flag, if the estimation was correct.
- Subtask goal estimator: estimation of the next subtask goal, taking into account a-priori knowledge and recorded interactions.
- Task goal estimator: estimation of the overall task goal, taking into account also the estimated subtask goal.

In the following, we explain the modules in more detail.

C. *A-priori knowledge component*

The a-priori knowledge component holds rules and facts about how user actions can possibly be related to (sub-)task goals. They can be generalized over all users (task model) or specific to an individual user (user model). The facts and rules can for example be formulated by domain experts or extracted from earlier interactions. We divide the available knowledge into declarative, such as facts, and procedural knowledge, for example "if...then.." rules. One example for storing a fact in the declarative memory related to the user is an identifier of the individual user who is about to interact with the system. Procedural rules related to the task goal can be for example "if the user commands the robot close to an object, the intent might be to interact with it". The information stored within this component is especially important if no or only few interactions with the system have happened. The data structure can be seen similar to the procedural and declarative memory of cognitive architectures like ACT-R, but still allows to be integrated e.g. in a bayesian estimation function as likelihood indicator.

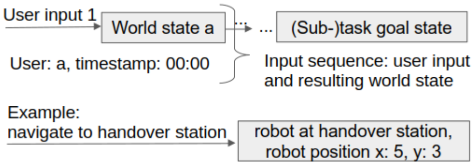

Fig. 3. The interaction database stores interactions with the system in form of the user input(s) and the resulting world state of the remote environment. It adds an identifier to the individual user as well as a timestamp to it. An example for it is the user inputs the task-level command "navigate to handover station". It leads to the resulting world state on a symbolic level of the robot being at the handover station as well as on a geometric level to a change of the robot's position.

D. *Interaction database*

To allow for adaptation of the SMM estimation during the interaction and learning to refine the SMM estimation over multiple interactions, we record interactions of the user with the system and store them in a database. To ensure scalability of the system, methods to store only relevant data and remove data if not used anymore from the database, e.g. through mechanisms similar to forgetting in human cognition, are important to investigate. The sequence of user inputs and resulting world states are stored and labeled with a timestamp and an identifier to the individual user, which helps to account for individual user preferences and behavior in the user model. With that, the estimation modules can for example retrieve all interactions specifically done by this user or only take interactions of the current session into account. The interaction database also stores, if the estimated task goal was correct, to refine later SMM predictions.

E. *Subtask goal estimator*

The component aims to estimate the next subtask goal of the user. It is especially important if there is not enough information available to precisely estimate the overall task goal at once. This is for example the case if the user interacts with the system for the first time at all or for the first time within a certain context. In these situations, no or only a few recorded interactions are available to form a prediction about the next desired world state of the user. Therefore, especially methods which can effectively incorporate a-priori knowledge are helpful. This can be for example probabilistic methods like bayesian estimation or symbolic reasoning frameworks. Especially cognitive architectures like ACT-R which aim to replicate human reasoning, are helpful to account for the user model by integrating knowledge about human decision making. As soon as there are more data points available, the subtask goal estimator can make use of recorded interactions. This means that the subtask goal estimator is able to incorporate learned mappings from user inputs to possible subtask goals. If provided by the robot, also information of the robot's task planner can be included, e.g. if preconditions of further robot actions are satisfied by the current world state. With combining methods like probabilistic approaches, symbolic and subsymbolic reasoning concepts, we follow the principle of *hybrid artificial intelligence systems* [21] to combine the strengths of different approaches. Adding to that, the integration of Large Language Model (LLM) based methods is interesting to investigate as they provide a natural user interface through speech or text. The predicted subtask goal is passed to the task goal predictor and to the output of the SMM estimation framework.

F. Task goal estimator

Similar to the subtask goal estimator, we combine different methods to estimate the overall task goal of the user. Even if it might not be feasible to predict the overall task goal, trying to estimate the subtask as far as possible in the future can still be helpful to provide assistance. Precisely estimating the overall task goal will most of the time only be successful if the robot has recorded enough interactions with the user and within the current context to be able to infer the overall task goal from it. For this, e.g. deep learning approaches like Long Short-Term Memory (LSTM) can be helpful. Also, reinforcement learning or transformer based methods can be suitable for this task. The selection of the most valuable method is dependent on context dependent requirements, like amount and structure of available data.

IV. USE CASE IMPLEMENTATION AND PRELIMINARY ANALYSIS

We analyze our approach based on a first use case example in a orbit-to-surface teleoperation setting to demonstrate the workflow of our proposed concept. It is inspired from observations of the previous Surface Avatar telerobotic experiments [19]. In these experiments, an astronaut on-board the International Space Station (ISS) commands a team of heterogeneous robots on ground to execute tasks from the domain of space exploration and infrastructure maintenance. The Robot Control Terminal (RCT) on-board the ISS, as shown on the left in figure 5, consists of two input devices to physically interact with the robots for teleoperation: a three degrees-of-freedom (DOF) joystick, and a sigma.7 device [24], which provides force reflection in up to 7-DOF. Furthermore, a laptop with a Graphical User Interface (GUI), also called Operator User Interface, provides video streams of the cameras of the robots as well as a virtual map of the environment in bird's-eye view, which is constructed based on the information the robot holds about the environment. It also allows for commanding the robotic assets in supervised autonomy through task-level commands as a part of the overall Scalable Autonomy teleoperation scheme, which allows the user to command a robotic team with different levels of immersion and task delegation [19], [26]. The task-level commands allow the robot to execute short task sequences autonomously under human operator supervision, e.g. "pick the rock sample". The robotic team on ground consisted of four systems: Rollin' Justin, a humanoid robot on wheels, Bert, a quadruped robot, a lander with a robotic arm, all three robots of the German Aerospace Center (DLR) as well as the Interact rover from European Space Agency (ESA) [25]. Fig. 4 shows the ISS crew in orbit commanding the robotic team using the RCT during the orbit-to-surface experiment session in July 2024. Rollin' Justin offers a huge variety of task-level commands due to its wide range of capabilities. Although they are prefiltered through a mission control component [23], observations during the experiment indicated that the large number of possible task-level commands offered by the robot makes it difficult to choose the most suitable one for the current task. One of the tasks executed by two ISS crew members during the Surface Avatar experiment in July 2024 was to command Rollin' Justin to pick up a sample from a handover station previously collected by the Interact rover of the surface robotic team. Justin is then commanded to navigate to an analyzer device for sample drop-off, and further processing. The layout of the experiment area can be seen in fig. 5 on the right. A possible sequence of task-level commands the astronaut could choose to achieve

Fig. 4. A SMM supports the astronaut during teleoperation of robotic assets. The top picture shows NASA astronaut Jeanette Epps on-board the ISS during a Surface Avatar orbit-to-surface telerobotic experiment session in July 2024 and the bottom right shows the robotic team which she commanded, consisting of Rollin' Justin, the Interact rover, the quadruped Bert and the lander arm. Creating an SMM between astronaut and robot includes estimating the task goal, as part of the task model, and including individual user preferences, as represented in the user model.

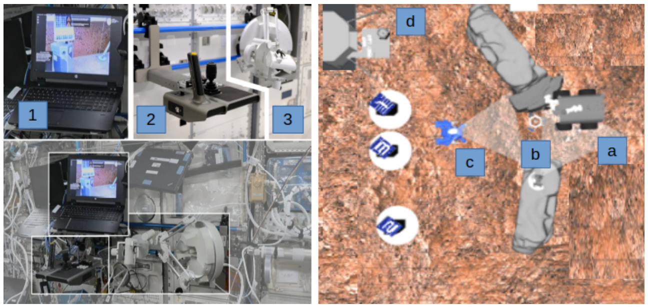

Fig. 5. Left: RCT, which consists of 1. the Operator User Interface software installed on a standard ISS issue laptop with a large variety of functions including camera video streams from the robotic team, and managing of task-levels commands, as well as 2. the joystick and 3. the sigma.7 [24] for different teleoperation modalities. Right: A layout of the experimental area with the different assets and the robotic team. In this scenario, the Interact rover (a) places a sample into the handover station (b) which is picked up by Rollin' Justin (c) to bring to an analyzer device installed on a robotic lander (d).

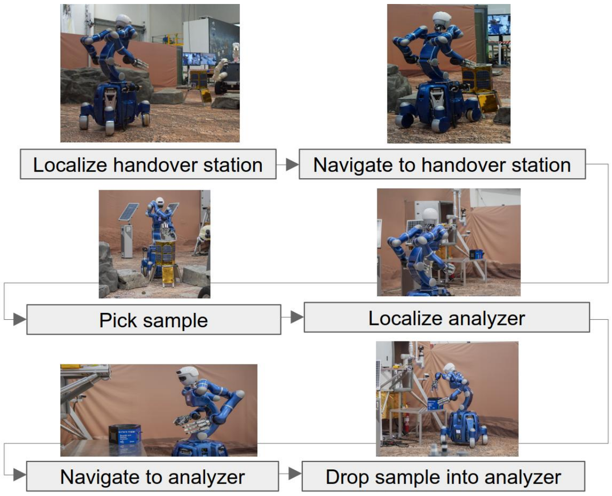

Fig. 6. Example sequence of user inputs as task-level commands to command the robot to pick a sample from a handover station, navigate to an analyzer and drop it into it. The user has to choose the commands from a huge variety of different task-level commands offered by the robot Rollin' Justin.

the task goal is shown in fig. 6. In the context of our concept, the resulting world state after executing a supervised autonomy command in the correct sequence represents a subtask goal. If Rollin' Justin is able to estimate the subtask or task goal of the astronaut, it can assist based on that, for example by recommending the task-level commands suitable to achieve the (sub-)task goal. In the following, we show the components of our proposed framework for SMM creation and explain its advantage for the described use case.

A. Subtask goal estimation using the a-priori knowledge component

When the astronaut executes the task for the first time, with no interactions being recorded in the database, the estimation is completely based on a-priori defined knowledge about the user and assumptions about the mapping from user inputs to subtask goals. Useful assumptions which can be formulated as "if...then..." rules for this use case are:

- If the astronaut commands the robot towards an object, then the probability that the (sub-)task goal can be achieved through an interaction with the object is higher.
- If the astronaut commands the robot to turn its camera towards an object, then the probability that the (sub-)task goal can be achieved through an interaction with this object is higher.
- If a resulting world state satisfies the preconditions for a supervised autonomy command, which were not satisfied before, this command is more likely to represent the path to the next desired world state.

Task-level commands satisfying one or more of these rules are more probable, which means that the world state resulting from the execution of the command is a probable subtask goal of the user. The set of likely subtask goals consists of the resulting world states of the available robot commands, which can be given equal probability in the beginning. When the astronauts starts to command Rollin' Justin towards the handover station, the resulting world state of the command "localize handover station", which is associated with the object handover station, gets a higher probability than other commands. This can be achieved using a probabilistic method, for example a bayesian model, similar to [4], by using the three above defined rules to calculate the likelihood of observing the sequence of user inputs and world states depending on the goal states.

B. Task goal estimation and interaction database

All interactions are recorded in the database, together with the task goal. This means that after the user executed the task at least once, the robot is able to match the current world state with the ones stored in the interaction database. If a sufficient similarity can be achieved, in our example e.g. on a symbolic level based on satisfied preconditions of robot actions or a learned representation, the task goal of the matched sequence can be a first prediction goal. The world state after the robot dropped the sample into the analyzer represents the overall task goal. If the interaction database contains a lot of different interaction sequences, the data can be used to train e.g. a LSTM based method to predict the most likely task goal. Then, if the user moves towards the handover station, the robot can predict that a likely overall task goal can be to pick up the sample and drop into the analyzer. It can then trigger measures to support the user in achieving this task goal, e.g. by recommending the entire sequence of task-level commands saved for this task goal.

Overall, our proposed concept supports the astronaut in achieving the task goal through establishing a SMM between astronaut and robot. It enables the robot to estimate the task model of the astronaut, even if no previous interactions with the system are recorded, through incorporating a-priori knowledge about the mapping from user inputs to (sub-)task goals. As soon as more interactions are recorded in the interaction database, our approach leverages this information to adapt the estimation and move towards predicting the overall task goal of the user if possible. By storing an identifier of the individual user, our approach can take user preferences into account. As shown in the use case example, the subtask or task goals are related to the resulting world states of task-level commands, which allows the robot to assist through recommending the best suited command for achieving the next (sub-)task goal to the user.

V. CONCLUSION AND FUTURE WORK

In this paper, we proposed a new approach for enhancing the creation of a SMM among user and robot. Our concept combines declarative and procedural knowledge about mapping of user actions to likely task goals with learned behavior about the user during the interaction. We furthermore focus on taking into account individual user preferences and assumptions about human behavior, for example by labeling stored interactions to the individual user. While we showed the workflow of our concept using a use case from the domain of space exploration, it can also be applied to terrestrial applications, for example in a household scenario, in which the user commands a robot to help with everyday tasks. The concept requires further evaluation and comparison of different ML learning based methods to account for the adaptability of the created SMM during one and over multiple interactions. Also, we will further investigate on a suitable data structure for storing the interaction sequences. Based on that, the conduction of user studies to compare the result of the SMM estimation with ground truth data, in the form of the user's task goals, is needed to refine the approach.

ACKNOWLEDGMENT

This work is supported by euROBIN, the European ROBotics and AI Network (Grant agreement 101070596), funded by the European Commission.

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