Towards Personalized Explanation of Robotic Planning via User Feedback

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Abstract—Prior studies have found that providing explanations about robots’ decisions and actions help to improve system transparency, increase human users’ trust of robots, and enable effective human-robot collaboration. Different users have various preferences about what should be included in explanations. However, little research has been conducted for the generation of personalized explanations. In this paper, we present a system for generating personalized explanations of robotic planning via user feedback. We consider robotic planning using Markov decision processes (MDPs), and develop an algorithm to automatically generate a personalized explanation of an optimal robotic plan (i.e., an optimal MDP policy) based on the user preference regarding four elements (i.e., objective, locality, specificity, and abstraction). In addition, we design the system to interact with users via answering users’ further questions about the generated explanations. Users have the option to update their preferences to view different explanations. The system is capable of detecting and resolving any preference conflict via user interaction. Our user study results show that the generated personalized explanations improve user satisfaction, while the majority of users liked the system’s capabilities of question-answering, and conflict detection and resolution.

I. INTRODUCTION

Prior studies (e.g., [1]–[4]) have found that providing explanations about robots’ decisions and actions help to improve system transparency, increase human users’ trust of robots, and enable effective human-robot collaboration. Different users have various preferences about what should be included in explanations, depending on users’ goals, interests, and background knowledge. However, a recent survey [1] finds that little research has been conducted for the generation of personalized explanations. To fill in this gap, we present in this paper a system for generating personalized explanations of robotic planning via user feedback.

There are several challenges to address in developing this work. First, what user preference elements should we consider when customizing explanations for an individual user. Second, how does the system generate personalized explanations that fit within user preferences. Third, how can the system interact with users for feedback and what information to communicate. Last but not least, how should we evaluate the effectiveness of the generated explanations. We provide an overview of how does this work address these challenges as follows.

Inspired by the line of works [5], [6] in the verbalization of robot experiences using natural language, we define a user preference tuple with four elements: the objective of robotic planning, locality (i.e., which segment of the robotic plan should be explained), specificity (i.e., what level of details to include in the explanation), and abstraction (i.e., what vocabulary to use in the explanation). We consider robotic planning using Markov decision processes (MDPs), which is a popular modeling formalism for robotic planning under uncertainty [7]. We develop an algorithm to automatically generate a personalized explanation of an optimal robotic plan (i.e., an optimal MDP policy) based on a given user preference tuple. The algorithm outputs an ordered list of sentences instantiated using a structured language template.

Insights from social sciences [8] show that humans prefer interactive explanations (e.g., via user-system dialogues) and contrastive explanations (e.g., “Why A rather than B”). Therefore, we design the system to interact with users via question-answering. After being presented with an explanation, the user can ask further (structured) questions to clarify the robotic plan. For example, “Why does the robot move east rather than taking a different action in the landmark?” The system answers the user’s question with a contrastive explanation: “The robot moves east in the landmark because it is part of the optimal robotic plan to achieve the mission objective, while taking a different action in the landmark cannot guarantee the mission objective.”

During the interaction with the system, users have the option to update their preferences (e.g., for viewing different explanations of the same robotic plan, or for replanning with different objectives). The system checks if there is any conflict between the updated and the previous user preferences, and guides users step by step to resolve any preference conflict. Then, the system generates new explanations and/or plans based on the updated preferences. Finally, the system terminates once users stop choosing to update their preferences.
To evaluate the proposed system, we adopt the commonly used subjective evaluation method. We designed and conducted an online user study with 88 users via Amazon Mechanical Turk. We asked users about their understanding and satisfaction with different types of explanations. As a baseline for comparison with personalized explanations, we also presented users with basic explanations (i.e., a concatenation of sentences describing the robot’s action in every state of the robotic plan) that are not customized based on user preferences. In addition, we asked users if they liked the system’s capabilities of question-answering, and conflict detection and resolution. The study results show that personalized explanations generated using our system can lead to better user satisfaction than basic explanations; and users reported a similar level of understandings about both types of explanations. Furthermore, 82.95% and 93.18% of users indicated that they liked the system’s question-answering capability and conflict-resolving capability, respectively.

Contributions. We summarize the major contributions of this work as follows.

- We developed a system for generating personalized explanations of robotic planning based on user preferences.
- We equipped the system with capabilities to interact with users for feedback, answer users’ questions about the generated explanations, and detect and resolve user preference conflicts.
- We designed and conducted a user study to evaluate the proposed system with 88 users via Amazon Mechanical Turk, which showed encouraging results.

Paper Organization. The rest of the paper is organized as follows. We survey the related work in Section II present the system for generating personalized explanations of robotic planning in Section III describe the online user study design in Section IV discuss the study results in Section V and draw conclusions in Section VI.

II. RELATED WORK

Explainable AI (XAI) [9] has been drawing increasing interest in recent years. The goal of an XAI system is to provide explanations about its decisions and actions for better transparency. The notions of explainability are domain-dependent. Many XAI systems for data-driven applications relate explainability with interpretability, and build simplified models that approximate complex (black-box) machine learning mechanisms (e.g., deep neural networks) [10], [11]. By contrast, XAI systems for robots aim to explain robots’ behavior and inform about robots’ intents to human users. Existing works have presented explanations for robots in different formats: text-based language (e.g., [2], [4]), graphs and images (e.g., [12]), and expressive lights (e.g., [13]). We adopt the most commonly used text-based explanations.

Specifically, we use structured language templates to instantiate explanations, which has been explored in several prior works. A concept of verbalization was introduced in [5], which enables robots to describe their experiences (e.g., navigation, perception) through structured language. An autonomous policy explanation approach was presented in [4], which synthesizes descriptions of robots’ optimal policies and responds to users’ queries instantiated using language templates. In addition, an approach was proposed in [14] to describe counterexamples (e.g., illustrating why mission requirements are violated) of robotic planning using structured sentences. Our recent work [2] investigated the automated generation of contrastive explanations represented as structured language.

Nevertheless, as identified in a recent survey [1] on explainable robots, little research has been conducted for personalized explanations. A user-aware approach was presented in [15] to customize explanations of robot actions based on user age (children or adults). Context-aware explanations (i.e., selecting the best explanation to provide based on the context) have been explored for human-robot teaming [16] and robot navigation [17]. None of these works consider personalized explanations based on user preferences.

Personalized explanations based on user preferences have been investigated in other application domains, such as recommendation systems [18]. In addition, social media and recommendation systems have looked at the possibility of conflicts regarding user preferences. Social media preference conflicts occur when users disagree over preferences such as a post’s share settings and are easily resolved by following one user’s preference based on the situation [19]–[21]. Recommendation system conflicts arise when no product or action matches a user’s preferences and resolution occurs by explaining why a choice is shown or recommending a new preference to set [22], [23]. However, there has been little work to detect conflicts within the user preferences themselves, especially for robotic planning explanations, as these types of personalized explanation conflicts are often more complex, involving multiple preferences and possibly resolving in an unsatisfying way.

III. APPROACH

We develop a system for generating personalized explanations of robotic planning via user feedback, as illustrated in Figure 1. After obtaining the initial user preference $\rho$ (Section III-A), the system computes an optimal robotic plan $\pi^*$ based on the objective specified in the user preference (Section III-B), and generates an explanation $\varepsilon$ of the robotic plan based on the user

$\varepsilon$.
Next, the system interacts with the user for feedback, including answering the user’s questions about the robotic plan and, if the user desires, updating the user preference (Section III-D). The system detects and resolves any preference conflict (Section III-E). Based on the updated preference \( \rho' \), the system computes a new robotic plan and generates an explanation. This process iterates until the user stops choosing to update the user preference.

A. User Preference

We use a tuple \( \rho = (ob, lo, sp, ab) \) to represent the user preference, which includes the following four elements:

- **Objective** (denoted \( ob \)) of the robotic planning (e.g., finding the shortest/safest route).
- **Locality** (denoted \( lo \)) describes the segment(s) of the robotic plan that the user is interested in. The user may want to know the robotic plan in the global environment (e.g., the entire map), or only part of it (e.g., a region of the map).
- **Specificity** (denoted \( sp \)) indicates the level of detail to include in the explanation: a summary of the robotic behavior in a pre-defined set of critical states (e.g., states representing landmarks), or a detailed narrative about every state.
- **Abstraction** (denoted \( ab \)) determines the corpus of the explanation to describe the robot’s concrete state-based world representation (e.g., move west in grid 12) or high-level representation (e.g., move along the corridor in the landmark).

Note that the above definitions of locality, specificity and abstraction are inspired and adapted from [5].

B. Robotic Planning

We consider robotic planning based on MDPs, which can be denoted as a tuple \( (S, s_0, A, \delta, R) \), where \( S \) is a finite set of states, \( s_0 \in S \) is an initial state, \( A \) is a set of actions, \( \delta : S \times A \times S \to [0,1] \) is a probabilistic transition function, and \( R : S \times A \times S \to \mathbb{R} \) is a real-valued reward function. The goal of planning is to compute an optimal policy \( \pi^* : S \to A \) for a given objective specified in the user preference \( \rho \). There are various MDP planning methods. For example, reinforcement learning [24] can learn an optimal policy that maximizes the cumulative reward \( \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t, s_{t+1})] \), where \( \gamma \) is a discount factor. The proposed system is agnostic to the choice of planning methods and can be used to explain any MDP policy in general.

Consider the route planning for a robot navigating in the \( 5 \times 5 \) grid map shown in Figure 2. We build an MDP model with 25 states. Each state corresponds to a grid in the map. The starting state \( s_0 \) is grid 20 (labelled with S). The action space is given by the robot’s navigation directions (shown as arrows in Figure 2). We assume that the robot can move to the next grid in its intended direction with a probability of 0.8. Otherwise, the robot will stay put or move in other directions with a combined probability of 0.2. We design two reward functions: a distance reward \( R_1 \) that counts the negation of the number of navigated grids, and a safety reward \( R_2 \) that counts the negation of number of navigated red grids (representing crowded passage where the robot is more likely to collide with pedestrians). Suppose that the user gives an objective of finding the shortest route for the robot to navigate from the starting location (grid 20) to the destination (grid 4). The resulting optimal route is the red route in the map. Suppose that the user’s objective is to find the safest route for the robot. The resulting optimal route is the green route in the map, which does not pass through any crowded passage (no red grids) despite being longer in distance than the red route.

C. Generating Explanation

Algorithm 1 illustrates the procedure of generating a personalized explanation \( \varepsilon \) (i.e., an ordered list of sentences) of an optimal robotic plan \( \pi^* \) based on the user

1Note that negations are needed here because reinforcement learning maximizes the cumulative reward, and we want to minimize the total distance (resp. safety risk) for the shortest (resp. safest) route.
Algorithm 1: Generating explanation sentences

Input: A user preference $\rho = (ob, lo, sp, ab)$, an optimal robotic plan $\pi^*$, an MDP $(S, s_0, A, \delta, R)$, a structured language template $\tau$

Output: An ordered list of sentences $\varepsilon$

1. $\varepsilon \leftarrow \{\}$
2. $S' \leftarrow \text{findStates}(S, lo, sp)$
3. $V \leftarrow \text{findCorpus}(ab)$
4. $Q \leftarrow \{s_0\}$
5. while $Q$ is non-empty do
6. remove a state $s$ from the head of $Q$
7. find the action $a \leftarrow \pi^*(s)$
8. for all state $s'$ with $\delta(s, a, s') > 0$ do
9. insert $s'$ to the tail of $Q$
10. end for
11. if $s \in S'$ then
12. instantiate a sentence $e \leftarrow \tau(V, s, a)$
13. add $e$ to the tail of $\varepsilon$
14. end if
15. end while
16. return $\varepsilon$

preference $\rho$. The algorithm uses a $\text{findStates}(S, lo, sp)$ function (line 2) to identify the set of MDP states $S'$ that need to be explained, based on the user preference of locality $lo$, i.e., which segment(s) of the robotic plan that the user is interested in, and specificity $sp$, i.e., the level of details that the user wants to know (every state or predefined critical state). The algorithm also uses a $\text{findCorpus}(ab)$ function (line 3) to determine the vocabulary $V$ for the explanation, given the user preference of abstraction $ab$ (concrete or high-level world representation). The algorithm uses a queue $Q$ for the topological sorting of MDP states (line 4-10). For each state $s \in S'$, the algorithm instantiates a sentence $e$ using a structured language template $\tau(V, s, a)$ as follows:

The robot $\langle action a \rangle$ in $\langle state s \rangle$.

The template is instantiated with words in the vocabulary $V$ to describe the state $s$ and the action $a = \pi^*(s)$ given by the robotic plan. The instantiated sentence $e$ is then added to an ordered list $\varepsilon$. The algorithm terminates when $Q$ is empty, and returns the ordered list of sentences $\varepsilon$ as an explanation of the robotic plan.

Following the robot navigation example described in Section II-B, suppose that the user gives a preference $\rho = (ob, lo, sp, ab)$ with the objective $ob$ of finding the shortest route, the locality $lo$ of considering the route segment between the landmark and the destination, the specificity $sp$ of describing every state, and the abstraction $ab$ of using the vocabulary about the robot’s concrete world representation. Based on this user preference, Algorithm 1 generates the following ordered list of sentences as a personalized explanation of the optimal robotic plan (red route in Figure 2):

1) The robot moves east in grid 12.
2) The robot moves north in grid 13.
3) The robot moves east in grid 8.
4) The robot moves north in grid 9.
5) The robot stops in grid 4.

Suppose that the user gives a different preference $\rho' = (ob', lo', sp', ab')$ with the objective $ob'$ of finding the safest route, the locality $lo'$ of considering the entire route, the specificity $sp'$ of including only critical states (start, landmark, destination), and the abstraction $ab'$ of using the vocabulary about the high-level world representation. Based on the new user preference, Algorithm 1 generates the following ordered list of sentences as a personalized explanation of the optimal robotic plan (green route in Figure 2):

1) The robot moves along the corridor in the start.
2) The robot moves along the corridor in the landmark.
3) The robot stops in the destination.

D. User Feedback

According to insights from the social sciences [8], a good explanation shall be interactive (e.g., via a dialogue between the user and the system) and contrastive (e.g., explaining “Why A rather than B”). Therefore, we design the proposed system to be able to interact with the user for feedback and provide contrastive explanation as further clarification about the robotic plan.

Specifically, after showing the user an explanation generated by Algorithm 1, the system allows the user to ask questions about the explained robotic plan using the following structured language template:

Why does the robot $\langle action \rangle$ rather than take a different action in $\langle state \rangle$?

The user can instantiate the question template with words describing the robot’s action and state taken from the displayed explanation sentences. The system then answers the question using a contrastive explanation with the following structured language template:

The robot $\langle action \rangle$ rather than taking a different action in $\langle state \rangle$, because it is part of the optimal robotic plan to achieve the $\langle objective \rangle$, while taking a different action in $\langle state \rangle$ cannot guarantee the $\langle objective \rangle$.

For example, the user asks “Why does the robot move east rather than taking a different action in grid 12”? The system answers with a contrastive explanation: “The robot moves east in grid 12, because it is part of the optimal robotic plan to achieve the shortest route, while taking a different action in grid 12 cannot guarantee the shortest route.”

The interaction between the user and the system continues until the user has no further questions. At this
point, the system asks if the user would like to update the current preference. The system then checks if there is any preference conflict as follows.

E. Preference Conflict Detection and Resolution

The system detects and resolves any conflict between the updated user preference $\rho' = (ob', lo', sp', ab')$ and the previous user preference $\rho = (ob, lo, sp, ab)$ using various rules. The conflicts are as follows:

- **Soft conflict** if the objective remains the same ($ob' = ob$) but any other elements of the preference tuple change ($lo' \neq lo \lor sp' \neq sp \lor ob' \neq ab$). The system confirms if the user just wants to view a different explanation of the same robotic plan, assuming that the same objective of robotic planning results in the same plan. If the user replies “yes”, then the system uses Algorithm 1 to generate a new personalized explanation based on $\rho'$, and follows with the user feedback interaction as described in Section III-D. If the user replies “no”, the system asks the user to update $\rho'$ to reflect the intended changes.

- **Hard conflict** if the preference of the objective changes ($ob' \neq ob$). The system confirms if the user indeed wants to update the planning objective. If the user replies “yes”, then the system computes a new optimal robotic plan based on the updated objective $ob'$ and generates a new personalized explanation about the new plan based on $\rho'$. If the user replies “no”, the system asks the user to update $\rho'$.

- **No conflict** if $\rho' = \rho$. The system interacts with the user to confirm that the user has finished updating. If the user replies “no”, then the user needs to provide a new preference different from $\rho'$. If the user replies “yes”, the system terminates.

IV. User Study Design

**Experiment Domain.** We designed and conducted an online user study to evaluate the system proposed in the previous section. We recruited 88 individuals with a categorical age distribution of 0 (0-17); 2 (18-24); 49 (25-34); 26 (35-49); 9 (50-64); and 2 (65+) using Amazon Mechanical Turk. We showed these users the same categorical age distribution of 0 (0-17); 2 (18-24); 49 (25-34); 26 (35-49); 9 (50-64); and 2 (65+) using Amazon Mechanical Turk. Each map comes with a set of pre-computed optimal routes for robotic navigation, with respect to a set of predefined objectives that users can choose from. We also asked users to choose their preference about objective, locality, specificity and abstraction for generating personalized plans and explanations. After being presented with an explanation, users were allowed to ask further questions. We instantiated the question templates as described in Section III-D. In addition, users were allowed to update their preferences, in order to view new routes and/or explanations.

**Manipulated Factor.** We manipulated one factor: the explanation type. In addition to personalized explanations, we presented users with basic explanations as a baseline for comparison. These explanations were presented in a randomized order. A basic explanation is a concatenation of sentences describing the robot’s action in every state along the optimal route, using the vocabulary of the concrete state-based world representation.

**Dependent Measures.** For each explanation, we asked users to rate on a 5-point Likert scale the level that they understood the explanation, and the level that they were satisfied with the explanation. We also asked users to choose which of the two types of explanations they preferred overall. In addition, we asked users whether they liked the system’s capability of answering their further questions about an explanation. We asked users to rate on a 5-point Likert scale their understanding and satisfaction about the system’s answers to their questions. Lastly, we asked users whether they liked the system’s capability of detecting and resolving conflicts with user preferences, and asked about their satisfaction rate on a 5-point Likert scale.

**Hypotheses.** We have two hypotheses in this study:

- **H1:** Personalized explanations can lead to better user understanding than basic explanations.
- **H2:** Personalized explanations can lead to better user satisfaction than basic explanations.

V. Results

We observed that users in the online study selected preferences across all available options of objective, locality, specificity, and abstraction. This observation confirms our assumption that user preferences are diverse, and thus important to consider in explanations. In addition, we observed a total of 178 preference updates among 88 users. Figure 3 shows a breakdown of the numbers: 35 users chose not to update their preferences,
while 53 users (60.23% of the study group) updated their preferences at least once during the study.

Figure 4 shows the mean and standard deviation of users’ 5-point Likert ratings of their understanding about basic and personalized explanations, which indicate that users understood both types of explanations in a similar level. A possible reason for the similar level of understanding is the simplicity of maps and routes used in the study. We use one-way analysis of variance (ANOVA) to evaluate the hypothesis H1. The statistical results are: (\(\alpha = 0.1\)), \(F(1,1582) = 0.117, p \leq 0.733\), Not Significant. Thus, the hypothesis H1 is rejected.

Figure 5 shows the mean and standard deviation of users’ 5-point Likert ratings of their satisfaction about basic and personalized explanations, which indicate that users were slightly more satisfied with personalized explanations. In addition, when asked to choose which type of explanations they preferred, 92.04% of users preferred personalized explanations over basic explanations in general. This higher level of satisfaction may be caused by the perceived increase in user agency (i.e., the ability of users to make choices and act independently \([25]\)), since the users were able to choose the aspects of the explanations themselves. Additionally, by choosing the factors themselves, users were able to better guarantee that they would “like” the explanations more. The one-way ANOVA results of evaluating the hypothesis H2 are: (\(\alpha = 0.1\)), \(F(1,1582) = 3.446, p \leq 0.064\), Significant. Thus, the hypothesis H2 is accepted.

Finally, 93.18% of users indicated that they liked the system’s capability of detecting and resolving preference conflicts. The study results show that users were satisfied with the system’s conflict detection and resolution capability at a rate of 4.31 (SD: 0.82) out of 5. Such a high satisfaction rate is likely due to the system clearly presenting information about the conflict occurring and suggesting possible resolution steps when conflicting preferences are entered. Thus, reducing the user’s cognitive burden.

VI. Conclusion

In this paper, we present a system for generating personalized explanations of robotic planning based on user preferences. The system also has the capabilities to interact with users for feedback, answer users’ questions about the generated explanations, allow users to update their preferences, and detect and resolve any user preference conflict. The results of our user study show that customizing explanations based on user preferences increases user satisfaction, but does not improve user understanding of explanations. Furthermore, 82.95% and 93.18% of users in our study indicated that they liked the system’s question-answering capability and conflict detection/resolution capability, respectively. In the future, we plan to extend this approach to generate personalized explanations for multi-user, multi-agent applications.
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