LLM-Based Task Planning for Navigating Companion Robot from Emotion Signals

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***Abstract*— The emergence of companion robots is promising to alleviate loneliness and improve mental health. It is critical to develop accurate task plans attuned to the various emotional states of a human partner. Given the complexity and variability inherent in human mental states, manually creating plans for companion robots is not feasible. Recent framework that integrates Large Language Models (LLMs) with Planning Domain Definition Language (PDDL) for automated task planning produces precise and flexible task plans. However, this framework has not been applied to companion robots, especially those responding to emotional states. This work introduces a new task planning strategy utilizing LLM and PDDL for companion robots. Simulation results demonstrate that the proposed method enables the robot to successfully navigate and offer support in response to detected states of sadness emotion. The method can convert unstructured natural language descriptions into structured task planning information. This strategy may enhance the interaction quality of companion robots and make them more empathetic and contextually aware in their social support roles.**

Keywords—Companion Robot, Electroencephalogram, Large Language Model, Emotion Signals, Navigation, Task Planning.

I. Introduction

The advent of companion robots, as one type of medical robotics [18-21], offers a promising solution to combat social isolation and loneliness [1,2], particularly in individuals with depression. These companion robots [3], similar to therapy robots [4], provide on-demand emotional support and adapt their interactions based on real-time detection and interpretation of human emotional states. While they show potential in delivering constant companionship, ethical concerns regarding personal privacy and freedom due to continuous monitoring arise. Therefore, it is crucial to maintain a balance between offering companionship and preserving human privacy and ensure that the robot's presence is supportive rather than intrusive. The effectiveness of companion robots depends on their ability to act as socially aware entities and provide companionship appropriately and as needed.

Recent advancements in technology have enabled the use of electroencephalogram (EEG) signals for accurately identifying human emotional states [5]. EEG signals can assist robots to complete the companion tasks. By integrating EEG-based emotional state detection, companion robots can be more effectively simulated to support a human partner [6], and tailor their interactions based on these detected emotional cues. Furthermore, the incorporation of Large Language Models (LLMs) has marked a new frontier in identifying human emotions [7-8]. LLMs analyze complex patterns in language use and offer an additional layer of emotional understanding. Emotion signals acquired from EEG sensing [9] or LLM technologies can enhance the empathy and responsiveness of companion robots and make them more attuned to the emotional needs of their human partners.

The effective navigation of companion robots depends on the creation of accurate task plans for ensuring their presence is supportive and non-intrusive. Given the dynamic and varied nature of a human partner's emotional states and physical activities in daily life, manual planning of a companion robot is impractical. Recent studies [10-11] have explored the integration of LLMs with Planning Domain Definition Language (PDDL) for automated task planning. This integration facilitates the generation of precise and adaptable plans for robotic actions. However, this strategy has not been applied in the field of companion robots, particularly those guided by emotion signals. Such an approach could improve the way companion robots interact and respond to human needs, and make them more empathetic and contextually aware in their social support.

To better combat depression and support mental health, a novel task planning strategy is proposed for companion robots using LLM and PDDL. Emotion signals detected from EEG or chatting procedure can be used to generate the task plans for navigating a companion robot. In this paper, the introduction and related works are presented in the first and the second parts. The third section presents the proposed method. The experimental results and conclusion are given in the fourth and the fifth components.

II. Related Works

A. Navigating Robot via Emotion Detection

Companion robot simulation was explored using EEG signals for dynamic adaptation to human emotions, enhancing robot's ability to provide emotional support [6]. Incorporating EEG-based emotional recognition into navigation planning, these robots adjust their behavior according to users' emotional states and improves social interaction and responsiveness. Jiang et al proposed an emotion-based interactive navigation approach for robots, using a variable artificial potential field and virtual emotional barriers to tailor obstacle avoidance behaviors, verified through MATLAB simulations and ROS-based TurtleBot 2 experiments [12]. A method for mobile robot control in dynamic environments was introduced and focused on human impressions of robot movements [13]. It emphasizes the importance of natural, comfortable, and sociable navigation, and presents a fuzzy controller developed to balance navigation objectives with human emotional responses, evaluated through questionnaires and simulated environments.

B. LLM for Robot Planning

LLM+P as a framework combining LLMs with classical planners for robot planning was proposed [10, 21-25]. It translates natural language descriptions into PDDL, uses classical planners for solutions, and reconverts these into natural language. LLM+P outperforms LLMs in generating optimal plans for robot planning scenarios, as demonstrated in comprehensive experiments. LLM-Planner was introduced [11] as a method utilizing large language models for few-shot planning in embodied agents. It enhances LLMs with physical grounding for task completion in visual environments. Using minimal training data, LLM-Planner shows competitive performance on the public dataset and demonstrates potential for versatile and sample-efficient embodied agents.

III. Proposed Method

In the proposed method, the integration of high-level planning logic and low-level execution and control logic will be explored for a companion robot navigation that responds to human emotion signals. This bifurcation of logic not only streamlines the method but also clarifies the implementation process. It allows for a more nuanced and effective interaction between the robot and its human partner. The core of this interaction hinges on the utilization of EEG-based emotion signals, which are incorporated into both the high-level planning and the low-level execution phases. This dual-level integration of EEG signals facilitates a more empathetic and responsive robotic companion.

A. Framework of the Proposed Method

A novel framework is introduced for companion robotic navigation and control based on human emotion signals, as demonstrated in Fig.1. This framework begins with the detailed description of the problem and its domain, which are then input into a LLM. The LLM generates specific plans formulated in PDDL. A key aspect of this process is the incorporation of context into the LLM's planning stage including the interpretation of human partner emotion signals captured through portable EEG device. These contextual details ensure that the generated plans are not only efficient and practical but also sensitively attuned to the emotional state of the human user. Once these plans are created by LLM, they are transmitted to the companion robot for executing its navigation and control in a manner that is both responsive and empathetic to the human.

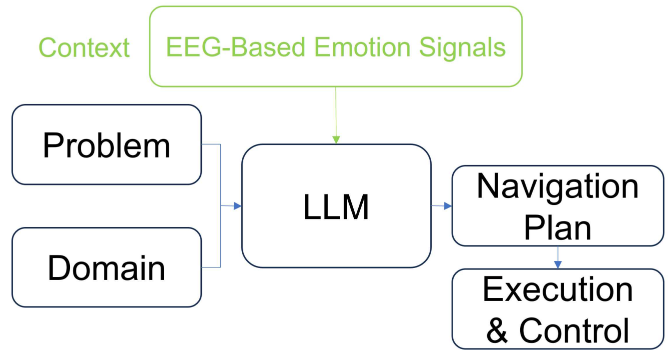

Fig. 1. The framework of the proposed navigation via LLM-based planning and emotion signals.

B. PDDL Generation from LLM

For the high-level planning logic in the proposed method, the effectiveness of the LLM+P framework [10] is demonstrated for leveraging the advanced capabilities of GPT-4 [17] as a LLM for the generation of structured PDDL files.

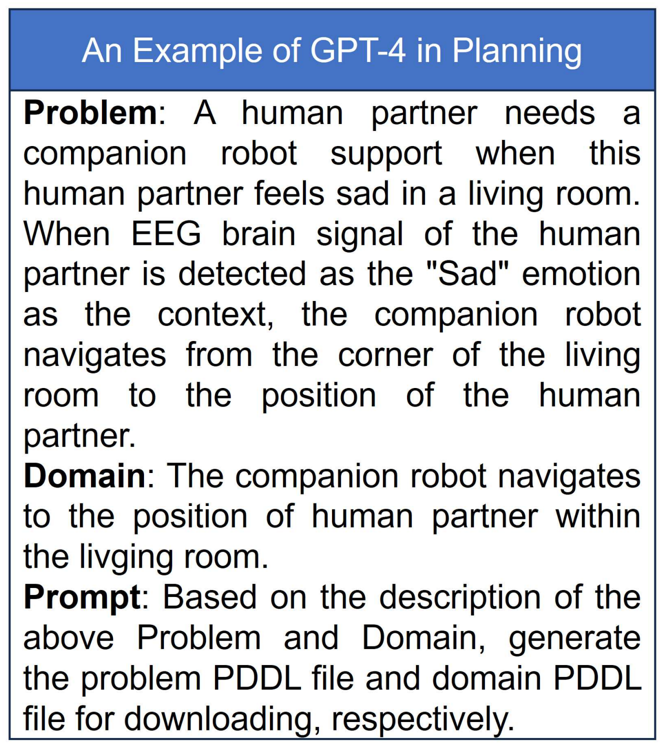

Fig. 2. One example of GPT-4 as a LLM in planning the companion robot. Both problem PDDL and domain PDDL files are output from GPT-4.

Initially, GPT-4 is provided with detailed descriptions of the problem and domain in a natural language format as shown in Fig.2. This process includes the integration of context-specific information such as emotion detection through EEG signals to tailor the solution to scenarios where emotional sense is critical. Upon receiving this information, GPT-4 proficiently translates the unstructured description into structured PDDL files including both problem and domain files. These structured PDDL files are key in enabling a companion robot to navigate and provide emotional support and companionship to human partners. This approach not only streamlines the process of programming complex robotic behaviors but also opens new avenues for creating more empathetic and responsive robotic companions in various care settings.

The generated domain PDDL file outlines a domain for robotic navigation with the primary goal of responding to human emotions in a living space. As shown in Fig.3, the domain is structured with basic Stanford Research Institute Problem Solver (STRIPS) [14] requirements and defines several key predicates to describe the state of the robot and the human. These predicates include whether the robot is in the room, at the corner of the room, near a human, if the human feels sad, and if the robot is ready for interaction.

An Example of PDDL Domain File Generated by GPT-4 with Context

```
(define (domain CompanionRobotNavigation)
  (:requirements :strips)
  (:predicates
    (is-in-room ?robot)
    (is-at-corner ?robot)
    (is-near-human ?robot)
    (human-feels-sad)
    (robot-ready ?robot)
  )

  (:action navigate-to-human
    :parameters (?robot)
    :precondition (and (is-in-room ?robot) (is-at-corner
?robot) (human-feels-sad))
    :effect (and (not (is-at-corner ?robot)) (is-near-
human ?robot))
  )

  (:action react-to-emotion
    :parameters (?robot)
    :precondition (and (is-near-human ?robot) (human-
feels-sad))
    :effect (robot-ready ?robot)
  )
)
```

Fig. 3. One example of the domain PDDL file written by GPT-4.

Besides predicates, two main actions are defined within this domain. The first action of "navigate-to-human" is triggered under specific conditions: the robot must be in the room and at the corner, and the human must be feeling sad. When these preconditions are met, the action results in the robot no longer being at the corner and instead being near the human. The second action of "react-to-emotion" is designed for the robot to become ready to support or assist once it is navigated to a human who is feeling sad. This structured approach allows for the development of a companion robot that can not only detect human emotions through EEG signals like sadness but also respond by navigating to and preparing to assist the human in need. It emphasizes the robot's role in providing emotional support and companionship.

An Example of PDDL Problem File Generated by GPT-4 with Context

```
(define (problem SadHumanSupport)
  (:domain CompanionRobotNavigation)
  (:objects
    robot1 - robot
  )
  (:init
    (is-in-room robot1)
    (is-at-corner robot1)
    (human-feels-sad)
    (not (is-near-human robot1))
    (not (robot-ready robot1))
  )
  (:goal
    (and (is-near-human robot1) (robot-ready robot1))
  )
)
```

Fig. 4. An example of the problem PDDL file written by GPT-4.

The problem PDDL file as shown in Fig.4 focuses on a single companion robot - robot1, which represents a robot tasked with providing support to a human. The initial state of this scenario outlines that robot1 is located within a room, specifically at a corner. A human partner within the same environment is feeling sad. Additionally, the robot is not near the human and is not in a ready state to interact or assist. The goal of this problem is twofold: firstly, to bring the robot into proximity with the human (is-near-human robot1), and secondly, to transition the robot into a ready state (robot-ready robot1). This setup encapsulates a situation where a robot is programmed to recognize and respond to human's emotional distress like sadness, by navigating towards them and preparing itself for offering emotional support and companionship in a human-centric environment.

C. Robot Navigation Using Emotion-Based Plans

To simulate a living room, map as shown in Fig.5, a visual representation of layout on a 100x100 occupancy grid is created. This map is characterized by clear boundaries representing the walls of the room with an exception for a door opening. Within this defined space, various pieces of furniture are strategically placed. A sofa is positioned against one wall. While directly opposite it, a TV is set up by creating a typical living area arrangement. Central to the room is a table. Surrounding this table are four chairs. The map provides a clear overview of a living room's layout via highlighting the spatial relationships between different furniture items and the overall structure of the living space. This setup not only helps in visualizing the living room's arrangement but also serves as a useful tool for planning navigation paths a simulated or real-world environment.

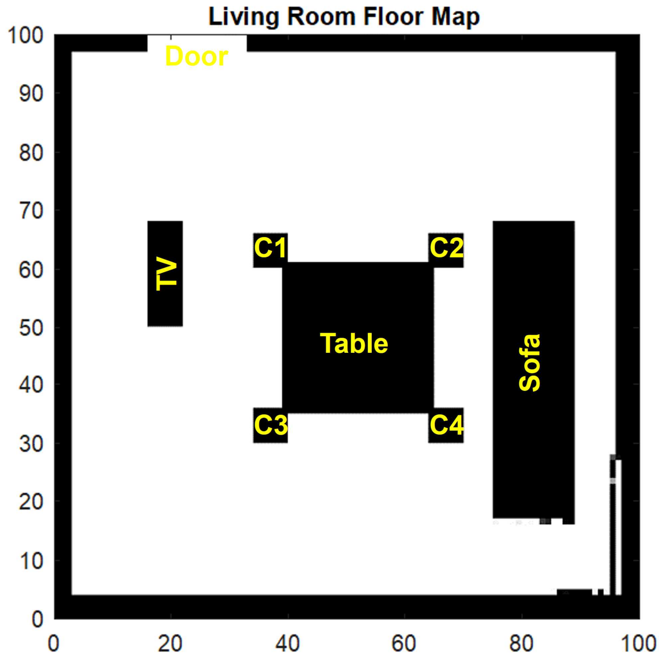

Fig. 5. A floor map of a living room scenario. A companion robot navigate

For the low-level execution and control logic, a companion robot formulates its route considering the barriers present in the living room environment. For robot path planning, an effective global planner is the A* algorithm [15, 27], which is deterministic in nature by computing the distance from the start to the end points by optimizing the cost function:

$$f(n) = g(n) + h(n), \quad (1)$$

where *g(n)* represents the expense of traveling from the starting point to a given node, and *h(n)* denotes the estimated least expensive path from the current node to the destination. A* path planning is implemented on MATLAB for navigating the companion robot in a simulation environment of Fig.5.

D. Emotion Detection via EEG Signal Representations

In companion robot simulation, we explore the integration of EEG signal-based emotion detection utilizing traditional Common Spatial Pattern (CSP) representations [16]. A significant aspect of our simulation includes the emulation of emotional states derived from CSP representations. The detection of a "Sad" emotion via CSP representation initiates the robot's navigation by employing the A* algorithm within MATLAB for completing the emotional support task. Different regions on CSP represent deviated electrical potentials on the human brain's scalp. These CSP representations are monitored sequentially in real-time to accurately track the emotional states. Once a CSP represents the “Sad” emotional state, the companion robot is triggered for performing tasks as created in both high-level planning logic of PDDL files and low-level execution and control logic with A* algorithm.

IV. Experimental Results

In our study, the performance of companion robot navigation was meticulously evaluated using the simulated map depicted in Fig.5. The initial path plotted for the robot to reach the human partner is illustrated in the left sub-figure of Fig.6. This sub-figure showcases the initial trajectory planned for the robot, highlighting its journey towards the human in need of companionship. The right sub-figure provides a detailed view of the robot's complete route, encompassing both its movement towards the human partner and its subsequent return to the corner of the room. This comprehensive depiction provides insights into the robot's navigation capabilities within a simulated environment.

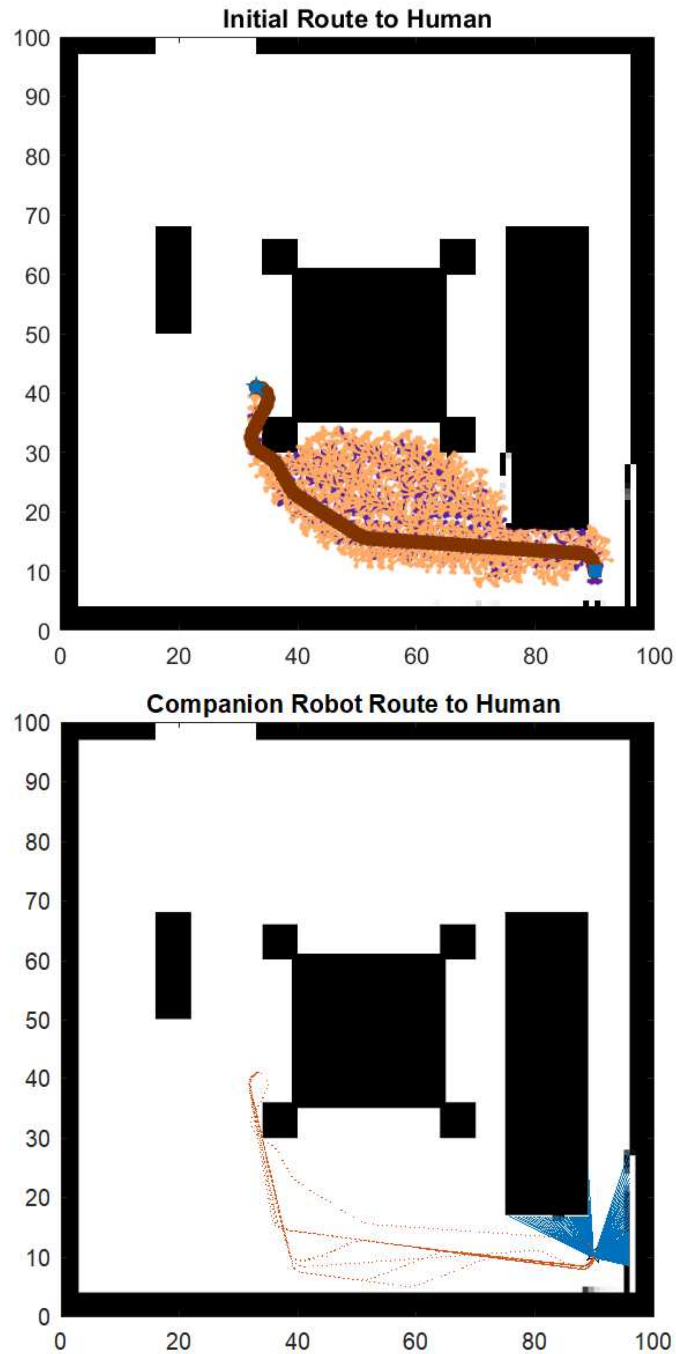

Fig. 6. Initial route to human is presented in the left figure, and companion robot route to human and back at the corner of the living room is illustrated in the right figure.

The domain PDDL file's two primary actions, "react-to-emotion" and "navigate-to-human," are effectively mirrored in the low-level execution logic of the companion robot. This integration shows an advancement over traditional manual planning methods because the high-level planning achieved through GPT-4 offers enhanced flexibility with its ability to process natural language inputs. However, the current system requires a manual process to bridge high-level planning with low-level execution, with a gap in creating an automatic pipeline for this connection. To address this, our future work aims to develop a seamless integration between these two components and enable a more efficient and autonomous operation of companion robots.

CONCLUSION

In conclusion, the work introduces a novel task planning strategy for a companion robot by utilizing the synergy of LLM and PDDL under the LLM+P framework. The experimental results show that structured PDDL files can be efficiently and flexibly generated from unstructured natural language descriptions, in compared to inflexible manual planning. The simulated companion robot is enabled to navigate towards and support a human partner in need of emotional support. Future work will focus on the development of a physical companion robot in a real-world environment by leveraging this LLM-based planning approach integrated with EEG signals.

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