Proceedings Paper:

Zhang, Qi, Stefanakos, Ioannis, Camara Moreno, Javier et al. (2023) Towards Lifelong Social Robot Navigation in Dynamic Environments. In: Towards Autonomous Robotic Systems:24th Annual Conference, TAROS 2023 Cambridge, UK, September 13–15, 2023 Proceedings: Extended Abstracts. 24th Towards Autonomous Robotic Systems Conference (TAROS), 13-15 Sep 2023 Springer, GBR, pp. 46-51.

Towards Lifelong Social Robot Navigation in Dynamic Environments*

Qi Zhang[1], Ioannis Stefanakos[1], Javier Cámara[2], and Radu Calinescu[1]

[1] Department of Computer Science, University of York, York, UK
[2] ITIS Software, Universidad de Málaga, Málaga, Spain

Abstract. We describe a work-in-progress approach to solving the problem of robot navigation in dynamically changing, social environments. Our approach employs reinforcement learning informed by a continually updated model that predicts the evolution of the environment, and handles two common scenarios: (1) a person moving within the environment, and (2) static obstacles with positions that change over time. We assess the effectiveness of the approach in a simulated assistive-care application in which a mobile robot supports a person with mild cognitive or physical impairments with simple everyday tasks.

Keywords: Reinforcement Learning · Navigation · Self-Adaptive Systems · Assistive-Care Robots.

1 Introduction

Autonomous robots have been increasingly deployed alongside humans, operating in complex environments and in various domains such as assistive-care [5], manufacturing [14], and nuclear fusion [3], among others. Assistive-care robots [4] are emerging as a vital tool for providing care and support to the elderly in their homes [6]. These robots are designed to perform tasks that include retrieving objects, aiding in mobility, monitoring health metrics, and offering medication reminders [15].

Machine learning (ML) algorithms have enabled a personalized assistance offered by these robots through their adaptation to the different challenges and preferences of users [10], fostering a higher level of independence for older adults. However, an important challenge still largely unaddressed is ensuring lifelong performance of ML (i.e., the ability to adapt to changes during long-term assistance) in assistive robotics for elderly care [9]. Navigating in complex and constantly changing environments presents potential hazards to human-robot interactions. For instance, an unexpected collision between the robot and a human could lead to the person falling. Thus, ensuring that assistive-care robots maintain a high-level of effectiveness and adaptability during long-term assistance is of utmost importance. This includes the ability to avoid collisions with humans moving within the environment and obstacles whose positions may change from

* Supported by Assuring Autonomy International Programme.

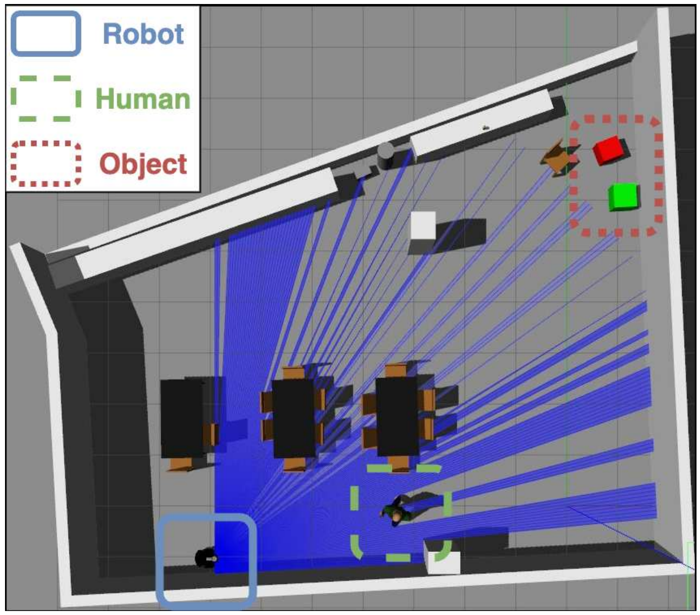

Fig. 1. View of a large open plan kitchen area in Gazebo[3] simulation environment.

time to time (e.g., furniture). Moreover, by achieving lifelong performance, the robots can provide consistent service to people with mild cognitive and/or motor impairments whose condition may evolve over time, resulting, for instance, in changes in movement patterns (erratic trajectories, speed variation, etc.).

In this work-in-progress study, we aim to enhance the navigation capabilities of a robot within a dynamic environment where human paths and object locations change over time. Solving this problem presents challenges, such as anticipating human trajectories, and proactively adapting to changing environmental conditions before undesirable situations are given (e.g., those that entail a high risk of collision with people and objects). To overcome these challenges, we propose an approach that employs reinforcement learning to endow a robot with the ability to reach a target location within the environment while avoiding collisions both with static and dynamic obstacles.

2 Navigation in Dynamic Environments

Figure 1 depicts the environment that we employed to evaluate our approach, which corresponds to a large open plan kitchen area with various static obstacles, such as chairs and tables. In a healthcare assistance scenario, the trajectories of human movement can often be unpredictable (e.g., erratic trajectories

[3] `https://gazebosim.org/home`

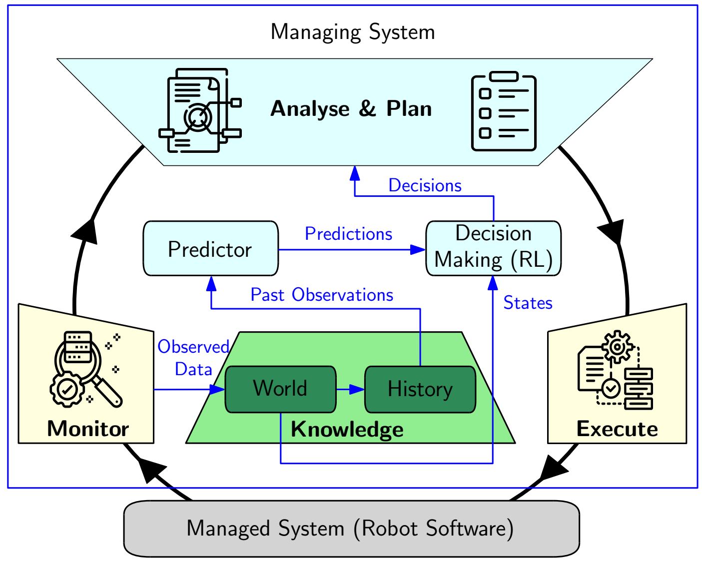

Fig. 2. MAPE-K Loop via Reinforcement Learning.

derived from cognitive and motor impairments) and static obstacles may frequently change location due to situations such as a patient forgetting to return items to their original locations. The co-existence of these two factors can pose challenges for existing navigation algorithms to handle effectively. A human participant serves as a moving obstacle, with changing motion patterns (walking speed, direction) to which the robot has to adapt at runtime in order to reach the goal position while avoiding collisions. To simulate cluttered environments commonly found in elderly care settings, the position of static obstacles, such as chairs, changes over time, mimicking real-world scenarios where a person may leave clothing on the ground or rearrange the furniture from time to time.

3 Overview of the Approach

Our approach employs MAPE-K [7], which is regarded as one of the most successful paradigms to build autonomic and self-adaptive systems. MAPE-K consists of four stages arranged in a feedback loop (Monitor, Analyse, Plan, Execute) and a Knowledge base. As illustrated in Figure 2, the MAPE-K loop in our approach is supported by a reinforcement learning framework, which is incorporated in the software running in the robot. The Monitor stage focuses on gathering world data, which includes the robot's distance to obstacles and the coordinates of the human in the environment, and incorporates it into the World model. Simultaneously, the world observations are incorporated into the History model, which is tasked with preserving past observations to be consumed by the Predictor component. The Predictor component is integrated into the loop to predict the human state within a short time horizon, including its trajectory. World data about current state obtained from the World model, along with predictions from the Predictor component, serve as inputs to the Decision Making reinforcement learning (RL) component. These inputs include the distance to obstacles, target location information, values from the action space, and predicted human coordinates. Subsequently, the set of actions generated as output by the RL component are set for execution. In our instantiation of MAPE-K, the Analyse and Plan stages are unified into a single stage supported by the tandem operation of the Decision Making and Predictor components.

4 Related Work

Significant research has been conducted on robot navigation and path prediction in various environments. The study in [8] examines a robot's ability to navigate among humans in a manner that adheres to social norms and ensures safety. However, it does not account for changes in the position of static obstacles over time, and the performance diminishes with increasing map size. A path planning approach, introduced in [11], identifies paths in either static or dynamic cluttered environments, but is primarily applied within a grid-based model framework without real-world scenarios. The use of occupancy values from presampled trajectories as part of the observation space is highlighted in [1] as an effective way to reduce training time for human path prediction. The authors plan to adjust their reward function for more complex obstacle scenarios. A hybrid online planning approach for navigation in hospital-like settings is presented in [13], with plans to further develop this approach by incorporating a learning-based strategy. While previous research on navigation in dynamic environments is often focused on adapting to dynamic obstacles such as humans, it frequently overlooks changes in static obstacle locations and the prediction of human paths, which are crucial for maintaining safety in scenarios with potential erratic human behaviour due to mild cognitive and motor impairments.

5 Conclusion

In this paper, we present a method for lifelong navigation based on a dynamic and cluttered environment. Within the framework of a self-adaptive system, the navigation task is formulated as a reinforcement learning process. In such a way, the robot acquires the ability to navigate towards a designated goal while avoiding both moving humans and obstacles that change position over long time.

In future work, we aim at enhancing the method's ability to predict human movement paths at runtime, provide safety guarantees (e.g., minimising probability of collisions against obstacles) by complementing RL with quantitative verification techniques [2,12], and explicitly considering trade-offs among multiple qualities (e.g., level of disruption to the human vs. usefulness in task assistance). We also plan to broaden the range of scenarios to assess the generality of our approach and evaluate how it performs under a diverse set of situations.

References

1. Akmandor, N.U., Li, H., Lvov, G., Dusel, E., Padir, T.: Deep reinforcement learning based robot navigation in dynamic environments using occupancy values of motion primitives. In: Intelligent Robots and Systems. pp. 11687–11694 (2022)
2. Casimiro, M., Garlan, D., Cámara, J., Rodrigues, L., Romano, P.: A probabilistic model checking approach to self-adapting machine learning systems. In: Software Engineering and Formal Methods. vol. 13230, pp. 317–332 (2021)
3. Devlin-Hill, B., Calinescu, R., Cámara, J., Caliskanelli, I.: Towards scalable multi-robot systems by partitioning the task domain. In: Towards Autonomous Robotic Systems. vol. 13546, pp. 282–292 (2022)
4. Feil-Seifer, D., Mataric, M.: Defining socially assistive robotics. In: Rehabilitation Robotics. pp. 465–468 (2005)
5. Hamilton, J., Stefanakos, I., Calinescu, R., Cámara, J.: Towards adaptive planning of assistive-care robot tasks. In: Formal Methods for Autonomous Systems. vol. 371, pp. 175–183 (2022)
6. Hebesberger, D., Körtner, T., Gisinger, C., Pripfl, J.: A long-term autonomous robot at a care hospital: A mixed methods study on social acceptance and experiences of staff and older adults. Int. J. Soc. Robotics **9**(3), 417–429 (2017)
7. Kephart, J.O., Chess, D.M.: The vision of autonomic computing. IEEE Computer **36**(1) (2003)
8. Lu, X., Woo, H., Faragasso, A., Yamashita, A., Asama, H.: Robot navigation in crowds via deep reinforcement learning with modeling of obstacle uni-action. Advanced Robotics **37**(4), 257–269 (2023)
9. Okamura, A.M., Matarić, M.J., Christensen, H.I.: Medical and health-care robotics. IEEE Robotics & Automation Magazine **17**(3), 26–37 (2010)
10. Qureshi, M.A., Qureshi, K.N., Jeon, G., Piccialli, F.: Deep learning-based ambient assisted living for self-management of cardiovascular conditions. Neural Computing and Applications **34**(13), 10449–10467 (2022)
11. Reguii, I., Hassani, I., Rekik, C.: Mobile robot navigation using planning algorithm and sliding mode control in a cluttered environment. Journal of Robotics and Control **3**(2) (2022)
12. Riley, J., Calinescu, R., Paterson, C., Kudenko, D., Banks, A.: Reinforcement learning with quantitative verification for assured multi-agent policies. In: Agents and Artificial Intelligence. pp. 237–245 (2021)
13. Silva Mendoza, S., Verdezoto, N., Paillacho, D., Millan Norman, S., Hernandez, J.D.: Online social robot navigation in indoor, large and crowded environments. In: Robotics and Automation (2023)
14. Stefanakos, I., Calinescu, R., Douthwaite, J.A., Aitken, J.M., Law, J.: Safety controller synthesis for a mobile manufacturing cobot. In: Software Engineering and Formal Methods. vol. 13550, pp. 271–287 (2022)
15. Vázquez, G., Calinescu, R., Cámara, J.: Scheduling of missions with constrained tasks for heterogeneous robot systems. In: Formal Methods for Autonomous Systems. vol. 371, pp. 156–174 (2022)