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1st Aniketh Ramesh
Extreme Robotics Lab
University of Birmingham
Birmingham, United Kingdom
axr1050@student.bham.ac.uk

2nd Christian Alexander Braun
Institute of Control Systems
Karlsruhe Institute of Technology
Karlsruhe, Germany
christian.braun@kit.edu

3rd Tianshu Ruan
Extreme Robotics Lab
University of Birmingham
Birmingham, United Kingdom
txr094@student.bham.ac.uk

4th Simon Rothfuß
Institute of Control Systems
Karlsruhe Institute of Technology
Karlsruhe, Germany
simon.rothfuss@kit.edu

5th Sören Hohmann
Institute of Control Systems
Karlsruhe Institute of Technology
Karlsruhe, Germany
soeren.hohmann@kit.edu

6th Rustam Stolkin
Extreme Robotics Lab
University of Birmingham
Birmingham, United Kingdom
r.stolkin@cs.bham.ac.uk

7th Manolis Chiou
Extreme Robotics Lab
University of Birmingham
Birmingham, United Kingdom
m.chiou@bham.ac.uk

***Abstract*—Adjusting the level of autonomy in human-machine systems (e.g., human-robot systems) holds great potential for achieving high system performance while maintaining operator involvement. To support operators with the task of setting the proper level of autonomy, we present a novel approach to realise a Model Predictive Controller that determines the optimal LoA for each tessellation in the robot's path plan based on the estimated performance degradation due environmental adversities. We also report on an experimental evaluation of a mixed-initiative system where both the operator and the Model Predictive Controller are in charge of dynamically adjusting the level of autonomy cooperatively while performing a challenging navigational task with a mobile ground robot in a high-fidelity simulation. To this end, we conducted a user study with 15 participants comparing the performance and user experience of the model predictive system with a state-of-the-art system. The results show significant benefits of the model predictive system in terms of a reduction of conflicts for control and an improved user experience. Additionally, there are indications of benefits in terms of robot health and, consequently, performance for the model predictive system.**

***Index Terms*—Mixed initiative control, Adaptive automation, Variable autonomy, Levels of autonomy, Levels of automation**

I. Introduction

Future human machine systems will not operate on a fixed level of autonomy (LOA) [1]. Instead, such systems will be able to adjust the amount of autonomous functionalities and operator support on-the-fly to match the requirements of the respective situation [2]. Such systems, which can leverage the complementing competencies of Robot AI and humans [3] are called Variable Autonomy (VA) systems [4]–[6]. Their potential to be highly flexible and resilient to adversities makes them useful in fields like space exploration [2], search and rescue robotics [3], [4], military systems [7] and automated driving [8].

While most early variable autonomy systems solely relied on adaptive automation systems that automatically adjust their LOA (e.g. [9], [10]), Mixed-Initiative (MI) systems provide the operator with assistance in setting the LOA through an adaptive automation while still allowing for the flexibility to deviate from the chosen LOA if desired [11]. Multiple studies found benefits in terms of user preference and performance when using MI systems as opposed to pure adaptive automations [4], [12]–[14]. Nevertheless, the cooperation of the adaptive automation and the operator in setting the appropriate LOA leads to new challenges like the *conflict for control* [4] which occurs if the operator and the adaptive automation disagree on which LOA to choose. Additionally, it is still an open research question if the performance of current adaptive automations and MI systems can be improved further.

Our previous work [15], [16] introduced Model Predictive Systems capable of automatically adjusting the LOA in human-robot teams. These systems optimise *robot health* [17] to reduce the probability of robot failure during task execution. The robot health metric combines information available in the form of models of the environment, robot, or human into a

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scalar metric that estimates the runtime performance degradation faced by a robot during task execution [17]. Although our proof-of-concept simulation studies show the effectiveness of Model Predictive systems [15], [16], their realisation on a human-robot system has not yet been examined.

In this paper we present a novel approach to realise a Model Predictive Controller (MPC) for LoA switching, which predicts the optimal LoA for each tessellation in the robot's path plan. We describe our implementation of a Mixed Initiative Variable Autonomy (MI VA) system that uses this MPC AI to initiate LOA switches. A rigorous experimental evaluation of task performance, cognitive availability, and overall user experience of our MI VA system is outlined by comparing it to a state-of-the-art MI system, and its results are presented.

To this end, Section II elaborates on the results of related studies and systems available in literature to choose a suitable one for comparison. The implementation of the MPC for the given use case is described in Section III, subsequently Section IV elaborates on the used experimental methodology. The results are presented in Section V and discussed in Section VI with a brief conclusion in VII.

II. State of the Art

Several studies have investigated the effects of VA systems e.g., on performance and workload. Parasuraman et al. [9] examine the effects of adaptive task allocation in a flight simulation scenario. They consider an adaptive automation system to allocate tasks either to the operator or the automation based on the operator's performance. The results show that the adaptive system leads to improved performance compared to a fixed task allocation.

Prinzel et al. [18] developed a system using electroencephalogram (EEG) measures for adaptive task allocation. The EEG signals are used to measure operator workload and adjust the level of automation accordingly. The study found that their system reduces both the task load perceived by the participants and the task error score compared to a control group. Aricò et al. [19] present a more recent study supporting these results.

Kaber and Endsley [10] investigate the effects of LOA and adaptive automation on performance, situation awareness, and workload in a Multitask simulation. LOA shifts were performed according to predefined schedules. The use of adaptive automation led to improved secondary task performance and workload while maintaining situation awareness and primary task performance. These findings are supported by [7] analyzing an adaptive automation adjusting LOA based on task load during a reconnaissance mission with an unmanned ground vehicle.

While the previously mentioned works investigated systems that adjust their LOA automatically, more recent research considers systems that allow for a cooperative LOA adjustment of operator and automation: Li et al. [12] investigate the use of such a mixed-initiative system to support human-automation collaboration during a space teleoperation task. The study found that the mixed-initiative system led to better performance compared to adaptive automation systems. The studies in [4], [13] confirm the benefits of mixed-initiative systems over pure adaptive automations.

The Expert Guided Mixed Initiative Control Switcher (EMICS) system of [4] compares current task performance to the task performance expected from a *task expert*. If the current performance is worse than the expected performance, an LOA switch is initiated. EMICS is of special interest for our work as it is both a recent contribution in the research field of mixed-initiative LOA adjustment and features a comparable robotic application like our simulation studies in [16]. Hence, EMICS is used as the state-of-the-art system for the comparative study presented in this paper.

III. Model Predictive Controller for LOA switching

This section outlines our formulation of the problem, describes the required assumptions, and motivates them with relevant literature. Our main contribution here, is that we describe a data-driven method to estimate the expected performance degradation due to adversities in the environment, by combining techniques from automated path planning and computer vision. We then use the robot vitals and robot health framework [17] as a performance criterion, to map the state of the environment to the optimal LoA during runtime. We also describe how the system was implemented for our study and comment on how our approach can be generalised.

A. Problem Formulation

Consider a variable autonomy robot with LoAs $\{\alpha_1, \alpha_2, \ldots, \alpha_m\}$, carrying out a navigation task in an extreme environment. Here each value α is one possible LoA realisation from $\mathcal{A}$, the continuum between Manual Control and Full Autonomy. This environment is filled with adversities or performance degrading factors that may degrade the robot's performance during its runtime. We scope our work on field repairable and non-terminal [20] performance degradation that the robot faces during runtime, i.e, any performance degradation faced by the robot can be fixed by switching the robot to Manual control by a remote operator, or by triggering pre-programmed recovery behaviours.

Once the robot is given a navigation goal, the robot's automated planner creates a feasible path plan P. This path plan can be decomposed into a series of n tessellations $P = \{s_0, s_1, \ldots, s_n\}$, where each tessellation s_i is an area in the map through which the robot has to locomote to reach the goal. The set of all possible tessellations is denoted by S. We assume the tessellations sizes are chosen such that the effect of performance degradation that the robot experiences in each tessellation is independent of the other. Implementing tessellation decomposition online will be the focus of our future work, however readers are referred to existing literature [21], [22] on the topic for a thorough review of path plan decomposition techniques.

During task execution, a robot can encounter a variety of performance degrading factors. Each factor denoted by

f is an element belonging to the set of all possible performance degrading factors $\mathcal{F}$. In each tessellation, a robot can encounter a set of m performance degrading factors $F = \{f_1, f_2, \ldots, f_m\},\ m \geq 0$. Alternatively, $F = \emptyset$ indicates that there is no performance degradation present in the given tessellation. Let $I : S \mapsto \mathcal{P}(\mathcal{F})$ represent a function that can scan tessellation i and return a set of all performance degrading factors present in it, such that $I(s_i) = F_i,\ F_i \subseteq \mathcal{F}$. Techniques to detect information about the environment are being researched extensively in the existing literature. One approach is to use image semantics and computer vision techniques [23], [24] to detect performance degrading factors. Alternatively, air-ground collaborative teams can be used where a drone looks ahead on the map, detects performance degrading factors, and communicates it to the ground robot [25]. Therefore, we assume that in any tessellation s_i, the robot is able to look ahead and calculate $I(s_{i+1}) = F_{i+1}$ using the onboard camera and other sensors.

Let function $H_{exp} : \mathcal{F} \times \mathcal{A} \mapsto R$ denote a function that calculates the expected robot health [17] for a given tessellation given the performance degrading factors and the robot's level of autonomy. This gives $H_{exp}(F_i, \alpha_i) = H_i$. Therefore, the level of autonomy most appropriate for a tessellation is one that maximises the robot's health:

$$\alpha_i^* = \underset{\alpha \in A}{\operatorname{argmax}}\, H_{exp}(F_i, \alpha_i) \tag{1}$$

The MI VA system designed using the proposed MPC is represented in figure 1. Every time a robot enters a new tessellation, the state information $I(s_{i+1}) = F_{i+1}$ is calculated and provided to MPC system. The MPC AI then chooses the appropriate LoA for the system and sends that command to the Control Mixer. The Control mixer then sends velocity commands to the robot accordingly from either the human (through joystick input), or from the robot controller responsible for autonomous navigation. Additionally, the operator at any given time has the capability to trigger switches, and changing the LoA set by the MPC system.

B. Implementation

For clear demonstration, we introduce an example of an indoor scenario to adapt the model. Based on the environment, we segment the tessellations as shown in Figure 2. Using the shortest feasible path P from the start to the goal (shown as a dotted white line) the arena was split up into tessellations (marked A, B, C, D). The shape of each tessellation was decided based on the kind of performance degrading factor present in that area. The letter A denotes areas where no performance degradation is present (i.e., $F = \emptyset$). Laser noise was present in B, and uneven terrain was present in C. In D, both laser noise and uneven terrain affected task performance.

We use data from our previous work [17] to calculate the expected robot health for each type of performance degrading factor. That is, robot health from previous simulations of a mobile robot navigation through an area with high laser scanner noise, is used to estimate the H_{exp} in the tessellation marked B. Similarly, H_{exp} for tessellations C and D were calculated based on the robot health values for uneven terrain with and without laser noise (respectively). These values were calculated for each level of autonomy and stored in a lookup table.

Therefore, H_{exp} for each ordered set (F, α) was substituted as the average health of the robot when navigating through the performance degrading factor F using LoA α. The algorithm then uses (1) in real time to decide the optimal LoA for the tessellation. Similarity measurement [26], i.e., matching each new tessellation with the appropriate value of H_{exp}, is hard coded for this implementation. However, we aim to address this in our future work. More generalisable approaches in the future could adapt scene recognition and traversability estimation techniques [27]–[29] to calculate the expected health for any tessellation.

IV. Experimental Methodology

The experiment investigates the effect of two MI VA system designs on task performance, overall user experience, and cognitive workload. Inspired by previous experiments by Chiou et al. [6], each participant in this study used both EMICS and MPC to carry out a mobile robot navigation task in a simulated arena filled with performance degrading factors. Simultaneously, they carried out a secondary mental rotation task during the experiment. The secondary task was used to induce additional cognitive workload on the operator, and simulate the high stress nature of robotic missions in extreme environments.

The robot used an MI VA system with 2 LoAs - 1) Waypoint-based autonomous navigation and 2) Manual Control by an operator using a joystick. For waypoint navigation, the Husky robot used the standard ROS Navigation stack. The operator could dynamically switch between the LoAs using buttons on their joystick. Two experimental conditions were tested - EMICS and MPC MI VA System. We hypothesised that in comparison with EMICS, the MPC MI VA system will yield a better user experience, better performance in the navigation task, more cognitive availability for a secondary task and lower operator cognitive workload.

A. Experiment Design

The primary task was a mobile robot navigation task based on an arena used in our previous experiments [17]. The design of this arena was based on environment typically encountered in Urban Search and Rescue tasks. A 2D scan of the arena was first created for robot navigation planning. After the scan was created, performance degrading factors like unforeseen obstacles, uneven terrain, and laser noise were added to the arena to degrade autonomous navigation performance (see Fig. 3). To simulate the uncertainty and dynamic situations encountered during navigation tasks in extreme environments, the presence and location of these performance degrading factors were neither incorporated into the robot's planner, nor were they communicated to the operator before the task.

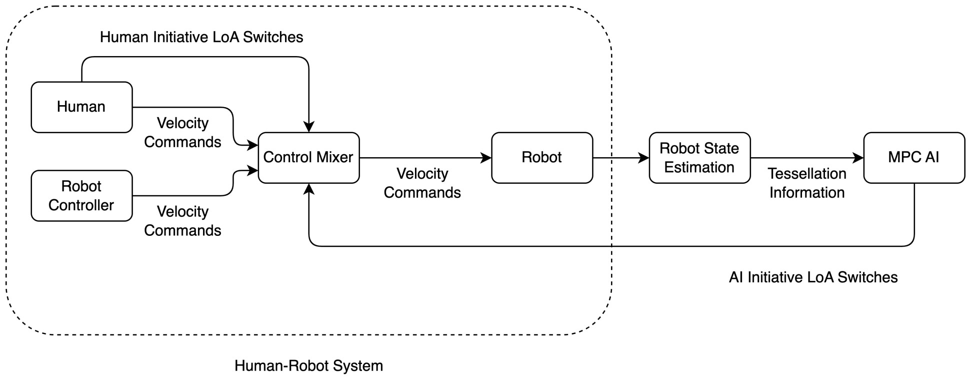

Fig. 1. Block Diagram of the Mixed Initiative Variable Autonomy System that uses the Model Predictive Controller AI

Fig. 2. The tessellations (A to D) and the feasible robot path plan P (dotted line) for the navigation task

A 3D object mental rotation task was used for the secondary task [30]. This is a visuospatial task added to increase the overall cognitive demand of the task and recreate high workload environments for robot operators (e.g., the need to multitask in the remote inspection or robot-assisted disaster response). Here participants were successively presented with two 3D objects and asked if they are the same or different. An example of two sets of 3D objects are shown in Fig. 4 Objects that were the same but rotated were classified as the same, but mirrored objects were classified as different. Like the experiments carried out in [31], the secondary task was carried out by the operator simultaneously alongside the primary task. While carrying out the primary task, the participant simultaneously looks at the secondary task and says yes or no (i.e. yes-same, no-different) and the experimenter presses the corresponding keys to log the data. The control unit used by each participant is shown in Fig. 5.

B. *Experimental Procedure*

A total of 15 test subjects participated in the experiments, with usable data from 14 subjects. Data from one participant had to be discarded because of a technical error during the experiment. The experiment had a within-subjects study, where all participants carried out both conditions. To minimise the learning and fatigue effects, the order of the conditions was counterbalanced for half the participants. On arrival, participants first filled out a background information questionnaire to indicate if they had prior experience playing games, operating heavy machinery, or using AI tools for work. Then, participants were introduced to basic robot navigation and LoA switching on a specialised training arena [31], [32]. They used this arena to practice manually controlling the robot and were asked to demonstrate minimum proficiency before moving on to the task. This was done to ensure confounding factors due to varying skill levels were minimised. Next, a different training arena was loaded with additional obstacles and sensor noise. Here participants were introduced to a couple of scenarios autonomous navigation is degraded (e.g., due to unforeseen obstacles and laser noise), how they impact the navigation, and how LoA may improve navigation in such situations. It was explained to the participants that the scenarios demonstrated were not exhaustive and that there may be other factors in the experiment which can degrade robot performance. To prevent priming participants with knowledge of how either of the MI VA systems worked, they were not provided training to use the EMICS and MPC systems.

Participants were then introduced to the secondary task. After explaining the task to them, they were given time to practice the task, following which their baseline performance on the secondary task was recorded. Before starting the first experimental condition, the 2D map of the arena was shown to the participants. The start and end points of the primary

Fig. 3. Navigation Task Arena (L to R): 1) Empty, 2) With obstacles and uneven terrain, 3) 2D map with start and finish points marked, and locations where performance degradation is introduced.

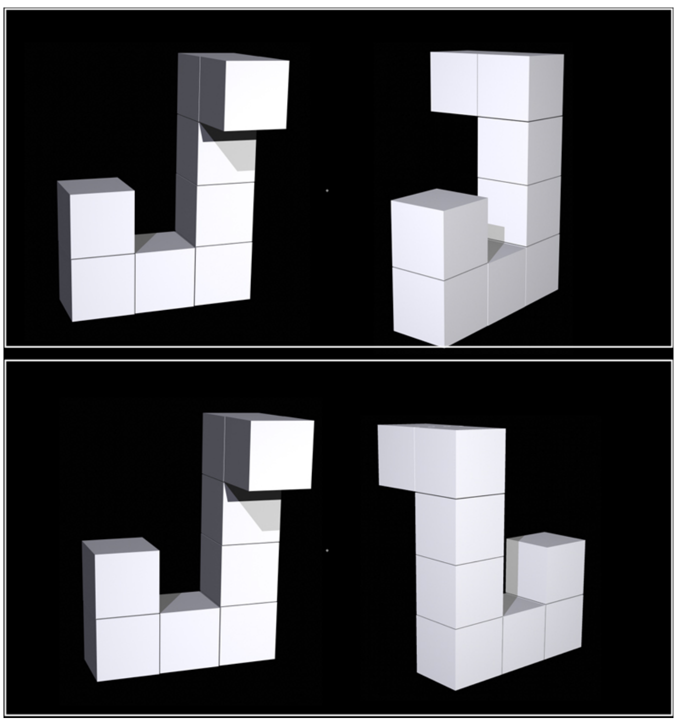

Fig. 4. Examples of two sets of 3D Objects presented to participants in the secondary task. The objects on the top are different from each other and the bottom are the same.

(navigation) task were shown to the participants. They were informed that the waypoints for navigation were predetermined and set by the experimenter automatically for both experimental conditions. Each participant was told explicitly to focus on the primary task, prioritise robot safety and minimise the risk of robot failure. They were then asked to focus on the secondary task only when they had the time.

Lastly, before starting the first experimental conditions, each

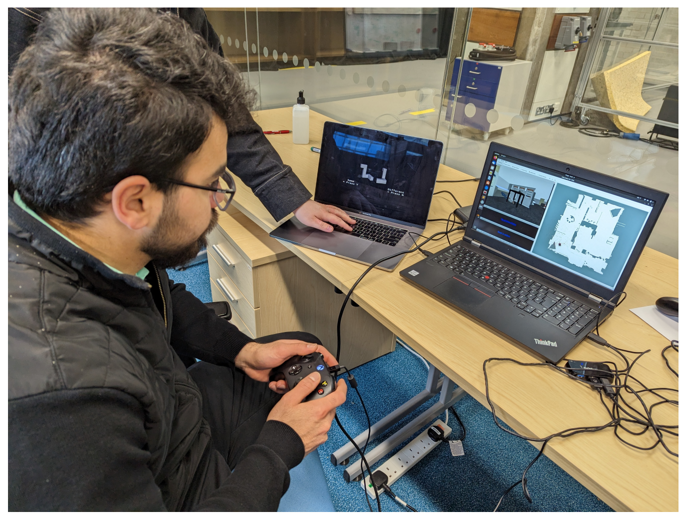

Fig. 5. The control unit used for the experiment. The participant controls the robot using a joystick and views it on the screen. The secondary task is shown on another laptop, and is monitored by the experimenter

participant was told that an AI would be assisting them with LoA switching. It was made clear that both the participant and the AI had equal authority and the option of switching LoAs, i.e., that none of the agents was the ultimate authority or ultimately in charge of LoA switching. Participants were also told that the AI might sometimes trigger LoA switches the operator disagreed with, i.e., the operator may have to override the AI's decision. In such situations, participants were asked to verbally state 'Conflict' so that the experimenter can note it down. Independently, the experimenter also observed and counted the number of conflicts, i.e., instance of operators overriding AI initiated LoA changes with 2 seconds. This was done to compensate for situations where the operator may forget to verbally acknowledge conflicts. After finishing each experimental condition, the participants filled out a raw NASA-TLX rating questionnaire to indicate the overall cognitive workload experienced during each experimental condition. Lastly, before ending the experiment, each participant was asked, "If you were to carry out this navigation task in a new environment using the same robot, which AI would you prefer for assistance with LoA switching?".

V. Results

Results from experiments conducted on 14 participants were computed and summarised in Table I. The participants were within the age group of 23-35, with the approximately 65% male and 35% female participants. Around 50% of the participants reported no prior experience with operating remote heavy machinery, or with using AI and robots for work on a regular basis. 46% of the participants indicated they frequently play video games involving driving, flight simulation and third person shooters, RPGs (roleplaying games), and sports. The paired Wilcoxon's Test was used to check for statistical differences between both conditions in each metric, as they were non-parametric matched pairs of data and had a sample size of N=14. The null Hypothesis H_o was that no statistical difference exists between the two experimental conditions.

In the primary task (i.e., robot navigation), no statistically significant differences were observed in the total runtime. The EMICS system and MPC system varied significantly ($p < 0.05$) in how they utilized the LoAs. While 64% of the task was spent in autonomy using the EMICS system, the MPC used autonomy for only 55% of the total runtime. Consequently, the mean robot health for the MPC system during runtime was 3.591, and during the use of autonomy was 3.791; which was higher than the EMICS system which had an average health of 3.506 and 3.329 during autonomy. Conversely, the average response time in the secondary task was significantly ($p < 0.05$) better when EMICS was used (7.923 Seconds, MPC = 10.443 Seconds). While the mean number of objects detected in EMICS (30.067) was higher than MPC (27.2), the overall accuracy in both experimental conditions was relatively the same (88.158% for EMICS and 89.169 for MPC). Conflicts for control reported by participants were 55% less when they used the MPC system than the EMICS system. This was confirmed by the experimenter's observations, where in comparison to EMICS, 65% fewer conflicts were observed for the MPC system.

Although the perceived cognitive workload of the MPC system was lower on average, no significant differences were observed in the NASA-TLX scores of both conditions. Out of 14 participants, 9 said they would prefer using the MPC system if they were to carry out a navigation task in a new environment. Among the others, 4 felt no difference, and 1 participant preferred EMICS over MPC.

Most participants reported a better overall user experience while using the MPC system and felt the conflicts of control were the main reason for the difference between the systems. Upon further enquiry, participants reported that they trusted the LoA switches of the MPC system more, contributing to its overall ease-of-use. For example, one of the participants said - "It felt the MPC system made LoA switches that I would have". Another participant said they "found MPC more reliable, as it intimated me about the problems before I even saw them, whereas EMICS was useless to the point that I'd rather switch manually".

VI. Discussion

This study demonstrates that information about a robot's runtime performance degradation in the form of Robot Vitals and Robot Health [17] can be used to realise a predictive LoA switching AI agent for Mixed-Initiative Variable Autonomy systems. State-of-the-art approaches [4] to designing such systems highlight they are prone to conflicts for control between the AI and Operator. While negotiation [33] and operator state estimation [34] provide generalisable methods to counter conflicts for control, we propose a predictive approach that tackles some of the fundamental reasons conflicts happen. Our predictive approach improves upon the performance criteria used by the EMICS system, by using robot health as a performance criterion. The robot health uses a set of multiple vitals, which combine different aspects of robot performance degradation to give more depth to the metric. Hence, the MPC system is able to understand the environment better and suggest LoA switches that the operator is more inclined to agree with.

Experimental evidence suggests that our predictive approach to switching is comparable to state-of-the-art in total runtime, causes fewer conflicts for control, and improves the overall user experience. The experiment also shows that the MPC system uses autonomy more prudently. The MPC system uses teleoperation in situations where the aggregate risk of robot failure is higher and uses autonomy in situations where the effect of performance degradation on the robot is low. Additionally users reported fewer conflicts for control and made fewer switches during the runtime. This suggests that participants accepted AI initiated LoA switches more while using the MPC system. This indicates that the MPC system enables effective servicing of robots and improves overall robot safety during its runtime.

Operators took longer to respond to their secondary tasks when using the MPC system. This is likely due to the additional time spent in manual control for the MPC system. Since operators were explicitly told to prioritise robot safety, extended periods of manual control added more cognitive demand to the operator thereby impacting the time taken to respond to the mental rotation task. Subsequent studies can help alleviate this demand by allowing operators to trigger pre-programmed recovery behaviours [35] when they want to focus on a secondary task.

The MPC system is a predictive system and can minimise the conflicts for control and risk of robot failure by pre-emptively making LoA switches. On the contrary, reactive systems like EMICS, which monitor robot performance online, help mitigate unforeseen problems. Reactive approaches to LoA switching can also easily encode expert knowledge and

TABLE I
SUMMARY OF STATISTICAL ANALYSIS

Primary Task	**EMICS**	**MPC**	**Paired Wilcoxon Test, Two Tailed**
Total Runtime (Seconds)	Mean = 170.907, SD = 19.590	Mean = 177.788, SD = 18.759	Z- Value = -1.1614, W Value = 34, p = 0.246
Average Health	Mean = 3.506, SD = 0.492	Mean = 3.591, SD = 0.416	Z- Value = -0.596, W Value = 43, p = 0.549
Number of LOA Switches	Mean = 13.714, SD = 3.604	Mean = 11.786, SD = 4.979	Z- Value = -0.816, W Value = 39.5, p = 0.410
Average Health during Manual Control	Mean = 3.329, SD = 0.516	Mean = 3.283, SD = 0.455	Z- Value = -0.534, W Value = 44, p = 0.596
Average Health during Autonomy	Mean = 3.579, SD = 0.562	Mean = 3.791, SD = 0.398	Z- Value = -1.099, W Value = 35, p = 0.271
Percentage of Runtime the Robot was Manually Controlled	Mean = 36.307, SD = 12.868	Mean = 44.572, SD = 8.361	Z- Value = -2.417, W Value = 14, p = 0.016*
Percentage of Runtime the Robot was Autonomous	Mean = 63.693, SD = 12.874	Mean = 55.430, SD = 8.416	Z- Value = -2.47, W Value = 14, p = 0.015*
Conflicts for Control Reported by Experimenter	Mean = 6.429, SD = 1.910	Mean = 2.214, SD = 1.424	Z- Value = -3.296, W Value = 0, p = 0.001*
Conflicts for Control Reported by Operator	Mean = 3.857, SD = 2.381	Mean = 1.714, SD = 1.489	Z- Value = -2.620, W Value = 8, p = 0.009*
Secondary Task	**EMICS**	**MPC**	**Paired Wilcoxon Test, Two Tailed**
Average Response Time (Seconds)	Mean = 7.923, SD = 3.348218	Mean = 10.443, SD = 6.099	Z- Value = -2.215, W Value = 21, p = 0.026*
Total Answered	Mean = 30.067, SD = 14.405	Mean = 27.2, SD = 14.189	Z- Value = -1.3497, W Value = 31, p = 0.177
Accuracy %	Mean = 88.158, SD = 10.088	Mean = 89.169, SD = 7.121	Z- Value = -0.313, W Value = 35, p = 0.756
NASA-TLX	**EMICS**	**MPC**	**Paired Wilcoxon Test, Two Tailed**
Total Workload	Mean = 50, SD = 14.821	Mean = 46.667, SD = 12.605	Z- Value = -1.224, W Value = 33, p = 0.222

*p<0.05

ground truth information during missions. Therefore, in the future we aim to create AI agents that combine the strengths of both predictive and reactive LoA switching capabilities for Mixed-Initiative variable autonomy systems. One possible limitation of our approach is that smaller tessellation sizes may result in multiple LoA changes in quick succession. This may cause more conflicts for control and higher workloads. We aim to address this in our future work through Degree of Autonomy adjusting systems [15], [16]. In contrast to LoAs, DoAs enable input blending and smoother transitions between different levels of operator control over the robot's actions.

Anecdotally, one of the participants who preferred EMICS over MPC stated - 'While MPC is Objectively better at LoA switching, EMICS makes silly mistakes which are easier to identify and correct. However, MPC may make smarter mistakes that are harder to detect. Hence, I would rather use EMICS'. As the MPC MI VA was more complex (i.e., predictive using an aggregate metric) than the EMICS (straight forward goal-directed error metric and reactive approach), actions of MPC MI VA were harder to anticipated. This remark indicates that transparency and explainability should be key design concerns for MI robotic systems.

VII. CONCLUSION AND OUTLOOK

This paper presented a novel approach to realize a Model Predictive Controller AI for Level of Autonomy switching and implemented a Mixed Initiative Variable Autonomy system using this controller. For each tessellation on the robot's path plan the AI determined the optimal Level of Autonomy based on the expected robot health [17], a metric to estimate performance degradation due environmental adversities. On a mobile robot navigation task, the proposed approach yielded performance comparable to state-of-the-art Mixed Initiative Variable Autonomy Systems, with fewer conflicts for control between the AI and the operator, and better user experience. Experiments on this system also showed that the AI switched to autonomous navigation for situations where there was low risk of robot failure. When there was a high probability of robot failure, i.e., its autonomous capabilities being compromised due to performance-degrading factors, the AI switched to manual control by a human operator. Therefore, the proposed approach enables autonomous robots to seek assistance from human operators to prevent or mitigate failure, thereby improving robot safety during task execution.

In the future, we plan carry out experiments with real robots. We aim to incorporate computer vision and machine learning techniques to estimate the expected robot health in real time. Lastly, we also aim to realize a Degree of Autonomy switching system to enable smooth transitions between different levels of operator input.

REFERENCES

[1] T. B. Sheridan and W. L. Verplank, "Human and computer control of undersea teleoperators," Massachusetts Inst of Tech Cambridge Man-Machine Systems Lab, Tech. Rep., 1978.

[2] N. Y.-S. Lii, P. Schmaus, D. Leidner, T. Krueger, J. Grenouilleau, A. Pereira, A. Giuliano, A. S. Bauer, A. Köpken, F. S. Lay *et al.*, "Introduction to surface avatar: the first heterogeneous robotic team to be commanded with scalable autonomy from the iss," in *Proceedings of the International Astronautical Congress, IAC*. International Astronautical Federation, IAF, 2022.

[3] M. Chiou, G.-T. Epsimos, G. Nikolaou, P. Pappas, G. Petousakis, S. Mühl, and R. Stolkin, "Robot-assisted nuclear disaster response: Report and insights from a field exercise," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2022, pp. 4545–4552.

[4] M. Chiou, N. Hawes, and R. Stolkin, "Mixed-initiative variable autonomy for remotely operated mobile robots," *ACM Transactions on Human-Robot Interaction (THRI)*, vol. 10, no. 4, pp. 1–34, 2021.

[5] M. Chiou, S. Booth, B. Lacerda, A. Theodorou, and S. Rothfuß, "Variable autonomy for human-robot teaming (vat)," in *Companion of the 2023 ACM/IEEE International Conference on Human-Robot Interaction*, 2023, pp. 932–934.

[6] M. Chiou, R. Stolkin, G. Bieksaite, N. Hawes, K. L. Shapiro, and T. S. Harrison, "Experimental analysis of a variable autonomy framework for controlling a remotely operating mobile robot," in *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2016, pp. 3581–3588.

[7] K. Cosenzo, J. Chen, L. Reinerman-Jones, M. Barnes, and D. Nicholson, "Adaptive automation effects on operator performance during a reconnaissance mission with an unmanned ground vehicle," in *Proceedings of the human factors and ergonomics society annual meeting*, vol. 54, no. 25. SAGE Publications Sage CA: Los Angeles, CA, 2010, pp. 2135–2139.

[8] M. Flad, P. Karg, A. Roitberg, M. Martin, M. Mazewitsch, C. Lange, E. Kenar, L. Ahrens, B. Flecken, L. Kalb *et al.*, "Personalisation and control transition between automation and driver in highly automated cars," *Smart Automotive Mobility: Reliable Technology for the Mobile Human*, pp. 1–70, 2020.

[9] R. Parasuraman, I. Mououa, and R. Molloy, "Effects of adaptive task allocation on monitoring of automated systems," *Human Factors*, vol. 38, no. 4, pp. 665–679, 1996.

[10] D. B. Kaber and M. R. Endsley, "The effects of level of automation and adaptive automation on human performance, situation awareness and workload in a dynamic control task," *Theoretical Issues in Ergonomics Science*, vol. 5, no. 2, pp. 113–153, 2004.

[11] S. Jiang and R. C. Arkin, "Mixed-initiative human-robot interaction: definition, taxonomy, and survey," in *2015 IEEE International conference on systems, man, and cybernetics*. IEEE, 2015, pp. 954–961.

[12] H. Li, N. Sarter, C. Wickens, and A. Sebok, "Supporting human-automation collaboration through dynamic function allocation: The case of space teleoperation," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 57, no. 1. SAGE Publications Sage CA: Los Angeles, CA, 2013, pp. 359–363.

[13] H. Ruff, G. Calhoun, E. Frost, K. Behymer, and J. Bartik, "Comparison of adaptive, adaptable, and hybrid automation for surveillance task completion in a multi-task environment," *Proceedings of the Human Factors and Ergonomics Society*, vol. 1, pp. 155–159, 2018.

[14] G. Calhoun, "Adaptable (Not Adaptive) Automation: The Forefront of Human–Automation Teaming," *Human Factors*, 2021.

[15] C. A. Braun, A. Ramesh, S. Rothfuß, M. Chiou, R. Stolkin, and S. Hohmann, "Model predictive degree of automation regulation for mobile robots using robot vitals and robot health," in *22nd IFAC World Congress, in press*. IFAC, 2023.

[16] ——, "Model predictive control of the degree of automation optimizing robot health," in *2023 IEEE 17th International Symposium on Applied Computational Intelligence and Informatics (SACI), in press*. IEEE, 2023.

[17] A. Ramesh, R. Stolkin, and M. Chiou, "Robot vitals and robot health: Towards systematically quantifying runtime performance degradation in robots under adverse conditions," *IEEE Robotics and Automation Letters*, vol. 7, no. 4, pp. 10 729–10 736, 2022.

[18] L. J. Prinzel, F. G. Freeman, M. W. Scerbo, P. J. Mikulka, and A. T. Pope, "A closed-loop system for examining psychophysiological measures for adaptive task allocation," *International Journal of Human-Computer Interaction*, vol. 13, no. 2, pp. 213–237, 2001.

[19] P. Aricò, G. Borghini, G. Di Flumeri, A. Colosimo, S. Bonelli, A. Golfetti, S. Pozzi, J.-P. Imbert, G. Granger, R. Benhacene, and F. Babiloni, "Adaptive automation triggered by eeg-based mental workload index: A passive brain-computer interface application in realistic air traffic control environment," *Frontiers in human neuroscience*, vol. 10, 2016.

[20] J. Carlson and R. R. Murphy, "How ugvs physically fail in the field," *IEEE Transactions on robotics*, vol. 21, no. 3, pp. 423–437, 2005.

[21] B. Patle, A. Pandey, D. Parhi, A. Jagadeesh *et al.*, "A review: On path planning strategies for navigation of mobile robot," *Defence Technology*, vol. 15, no. 4, pp. 582–606, 2019.

[22] J. R. Sánchez-Ibáñez, C. J. Pérez-del Pulgar, and A. García-Cerezo, "Path planning for autonomous mobile robots: A review," *Sensors*, vol. 21, no. 23, p. 7898, 2021.

[23] T. Ruan, H. Wang, R. Stolkin, and M. Chiou, "A taxonomy of semantic information in robot-assisted disaster response," *arXiv preprint arXiv:2210.00125*, 2022.

[24] Y. Zhu, D. Gordon, E. Kolve, D. Fox, L. Fei-Fei, A. Gupta, R. Mottaghi, and A. Farhadi, "Visual semantic planning using deep successor representations," in *2017 IEEE International Conference on Computer Vision (ICCV)*, 2017, pp. 483–492.

[25] I. D. Miller, F. Cladera, T. Smith, C. J. Taylor, and V. Kumar, "Stronger together: Air-ground robotic collaboration using semantics," *IEEE Robotics and Automation Letters*, vol. 7, no. 4, pp. 9643–9650, 2022.

[26] J. Qi, D. Song, H. Shang, N. Wang, C. Hua, C. Wu, X. Qi, and J. Han, "Search and rescue rotary-wing uav and its application to the lushan ms 7.0 earthquake," *Journal of Field Robotics*, vol. 33, no. 3, pp. 290–321, 2016.

[27] R. O. Chavez-Garcia, J. Guzzi, L. M. Gambardella, and A. Giusti, "Learning ground traversability from simulations," *IEEE Robotics and Automation letters*, vol. 3, no. 3, pp. 1695–1702, 2018.

[28] C. Sevastopoulos, K. M. Oikonomou, and S. Konstantopoulos, "Improving traversability estimation through autonomous robot experimentation," in *Computer Vision Systems: 12th International Conference, ICVS 2019, Thessaloniki, Greece, September 23–25, 2019, Proceedings 12*. Springer, 2019, pp. 175–184.

[29] S. Matsuzaki, H. Masuzawa, and J. Miura, "Image-based scene recognition for robot navigation considering traversable plants and its manual annotation-free training," *IEEE Access*, vol. 10, pp. 5115–5128, 2022.

[30] G. Ganis and R. Kievit, "A new set of three-dimensional shapes for investigating mental rotation processes: validation data and stimulus set." 2 2016. [Online]. Available: https://figshare.com/articles/dataset/A_new_set_of_three_dimensional_stimuli_for_investigating_mental_rotation_processes/1045385

[31] A. Ramesh, M. Englund, A. Theodorou, R. Stolkin, and M. Chiou, "Robot health indicator: A visual cue to improve level of autonomy switching systems," *arXiv preprint arXiv:2303.06776*, 2023.

[32] M. Chiou, M. Talha, and R. Stolkinl, "Learning effects in variable autonomy human-robot systems: how much training is enough?" in *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)*. IEEE, 2019, pp. 720–727.

[33] S. Rothfuß, M. Chiou, J. Inga, S. Hohmann, and R. Stolkin, "A negotiation-theoretic framework for control authority transfer in mixed-initiative robotic systems," in *2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. IEEE, 2022, pp. 921–928.

[34] D. Panagopoulos, G. Petousakis, A. Ramesh, T. Ruan, G. Nikolaou, R. Stolkin, and M. Chiou, "A hierarchical variable autonomy mixed-initiative framework for human-robot teaming in mobile robotics," in *2022 IEEE 3rd International Conference on Human-Machine Systems (ICHMS)*. IEEE, 2022, pp. 1–6.

[35] M. Rigter, B. Lacerda, and N. Hawes, "A framework for learning from demonstration with minimal human effort," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 2023–2030, 2020.