An Analysis of Degraded Communication Channels in Human-Robot Teaming and Implications for Dynamic Autonomy Allocation

Michael Young, Mahdieh Nejati, Ahmetcan Erdogan and Brenna Argall

Abstract The quality of the communication channel between human-robot teammates critically influences the team's ability to perform a task safely and effectively. In this paper, we present a nine person pilot study that investigates the effects of different degradations of that communication channel, and within three shared-autonomy paradigms that differ according to how and at what level control is partitioned between the human and the autonomy. Accordingly, the rate and granularity of the human input differs for each shared-autonomy paradigm. We refer to each paradigm according to the input expected from the user, namely high-level, mid-level and low-level control paradigms. We find three primary insights. First, interruptions in the signal transmission (dropped signals) decrease safety and performance in modes where continuous and high-bandwidth inputs from the human are expected. Second, decreased transmission frequency offers a trade-off between safety and performance for low-level and mid-level control paradigms. Lastly, noise alters the safety of high-level input since the user is not continually correcting the signal. These insights inform us when to shift autonomy levels depending on the quality of the communication channel, which can vary with time. Knowing the ground truth of how the signal was degraded, we evaluate a recurrent neural network's ability to classify whether the communication channel is experiencing lowered transmission frequency, dropped signals or noise, and we find an accuracy of 90% when operating with low-level commands. Combined with the key insights, our results indicate that a framework to dynamically allocate autonomy between the user and robot could improve overall performance.

All authors are with:
Rehabilitation Institute of Chicago, Chicago, IL
Northwestern University, Evanston, IL

Michael Young, e-mail: mikesyoung@u.northwestern.edu
Mahdieh Nejati, e-mail: m.nejati@u.northwestern.edu
Ahmetcan Erdogan Ph.D., e-mail: ahmetcan.erdogan@northwestern.edu
Brenna Argall, Ph.D., e-mail: brenna.argall@northwestern.edu

1 Introduction

In recent years, the world increasingly relies on human-robot teams to perform various functions in defense, human assistance and field operations. In these teams, the human operator interacts differently with the robotic system depending on the task. In some cases, the user issues low-level commands where they are in charge of the majority of control. In others, the user provides high-level commands, such as goals, which the robot works towards achieving. Indeed, there are a multitude of control levels in between and the level is typically set before the team sets out to accomplish a given task. However, there are many scenarios in which performance might improve if the control allocation shifted online between the two entities.

One reason that autonomy levels might benefit from shifts is signal degradation. In the domain of user-operated assistive robots, such as a robotic wheelchair, the commands issued by the user may degrade due to human motor impairment, fatigue or pain. There is a parallel to field robotics where the user operates a robot at a distance. In this case, the signal may degrade due to barriers between the robot and operator or environment changes such as severe weather. In both scenarios, operators are susceptible to distraction or work overload that may affect performance and transmit through the control signal. Other reasons to shift autonomy may include hardware issues or changes in the environment that prevent either the robot or the user from providing reliable control signals. For example, a person using a powered wheelchair may move from indoors to a busy sidewalk where more moving obstacles are present and the subject can no longer avoid collisions independently.

In the domain of assistive robots, the signals provided by motor-impaired users in many ways mirror those of compromised communication channels: the user signals are often noisy due to artifacts left by their impairment (noise), limb weakness may result in undetectable commands by the interface (dropped signal) and the rate at which the user provides commands may also vary due to factors like fatigue and pain (transmission frequency).

To study how shared-autonomy performance changes with signal degradation on the communication channel between the human and the autonomy, we conduct a nine person pilot study to inform future decisions on how autonomy should be allocated. In the study, subjects use three levels of control to perform daily-life tasks with a robotic wheelchair while we modulate the signal to simulate real-world challenges. Furthermore, we assess the feasibility of detection of a degraded communication channel so that we can switch autonomy automatically when necessary. The end goal is to provide a dynamic autonomy allocation framework that will improve the safety and performance of human-robot teams in both field and service robot applications.

2 Related Work

Here we review related literature on autonomy allocation. Much of the literature develops paradigms for determining beforehand which autonomy level to use [2] [11]. These take into account factors such as task criticality, task accountability and environment complexity. However, these static, *a priori* methods are often not robust to the varying mental load of the user and changing environment.

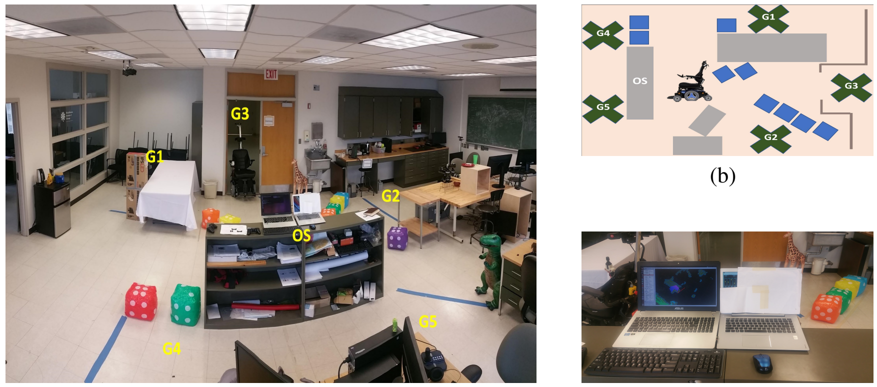
Fig. 1 Robotic wheelchair.

Other works [15] [16] [17] investigate physiological parameters, using sensors such as EEG and ECG, as an indication of a user's cognitive load. (Cognitive load can play a critical role in successful teleoperation and control of robots [9].) The physiological parameters are used to indicate when the autonomy should change control levels. For the domain of these works (pilots and military), to expect the physiological signals is reasonable, as soldiers and military pilots already wear highly instrumented and sensorized gear. For assistive robotics however, it is unlikely that we would have access to such signals due to both fiscal constraints and user preference.

Trust between the user and robot has drawn interest from researchers as a metric to allocate autonomy. In the field of human-robot interaction, several studies [4] [7] [8] outline key factors, such as feedback, environment and age, that influence a human's trust in automation, which ultimately affects the team's performance. In other work, researchers calculate trust in both the robot and the human through performance-based metrics [13] and by comparing the autonomy signal and the user input [3]. Trust shows promise as a factor to influence autonomy allocation, and we expect other metrics may also play a role, such as communication channel quality.

Most similar to our work, Choiu *et. al.* [5] perform a virtual experiment where subjects navigate a mobile robot through an obstacle course while noise is added at a specific section of the map. The users operate in three modes (1) full teleoperation (2) goal selection and (3) manual switching between goal selection and full teleoperation. They demonstrate that a dynamic allocation of autonomy controlled by the user (mode 3) outperforms the other two modes when faced with a distraction task.

Our work differs from the state of the art in several ways. We conduct an experiment using a physical system and modulate the signal with three degradation schemes: dropped signals, transmission frequency and noise. This helps us to identify when performance or safety has declined, and we furthermore do so for multiple levels of (static) autonomy allocation. From these results, we gather insights for a dynamic autonomy allocation framework and demonstrate a signal degradation detection technique to be used within said framework.



(a) (b) (c)

Fig. 2 Experimental Setup. (a) Task layout: (G1) Docking station. (G2) Turn in place for orientation, (G3) Doorway traversal, (G4) Left turn (wide), (G5) Right turn (tight), (OS) Operator Station. (b) Layout diagram showing five goals. (c) Operator station.

3 Methods and Design

The focus of this study is human-robot teams in which the robot is jointly controlled by robotics autonomy and a human operator. In these scenarios, the *robot* relies on the control commands from the human operator and its own sensor readings. The quality of the *communication channel* which relays this information between the operator and the robot impacts the team's interaction. If degraded, it can obstruct the transmission of information needed for successful task completion.

The human operator can control the robot with different levels of command granularity: from low-level commands using teleoperation, through increasingly higher levels of commands until (nearly) full autonomy. While low-level commands give the human operator more control over the minutia of task execution, higher-level commands may be all that are practical when the communication channel is degraded—for example, due to increased distance of communication, human fatigue or other external factors.

The purpose of this study is to investigate the effect of various degradations of the signal coming from the human and how this changes with various control levels (autonomy allocations)—that is, which control levels are invariant or particularly susceptible to a given signal degradation. We design an experiment to investigate this scenario in a controlled laboratory environment. Towards this aim, nine subjects control the navigation of a mobile robot to multiple goal locations. The robot is commanded with three different levels of control granularity, while the signal is artificially modulated to capture different features of communication channel quality. The task performance, safety, control signals and human attention are monitored during task execution. The following subsections elaborate on details of the design and protocol.

3.1 Control Level

Humans command mobile robots using different control levels with varying degrees of command granularity, typically dictated by the task, environment and/or the user's cognitive load. The user signal might encode *low-level* control commands—for example, the speed and direction at every instance in the trajectory. Commonly, for low-level control the user operates the mobile robot using an interface like a joystick with some visual information provided by their own eyes, on-board cameras or a sensorized environment. In other formulations, the operator may provide *mid-level* control commands—for example, discrete longer-duration actions such as turn right or go forward. Such commands might be provided via switches, button presses or voice, to name a few. In *high-level* control, the operator provides even higher level information—for example, the human might indicate a task or goal, through selections on a screen or natural language, for example.

In this study, we consider three levels of shared control:

1. **Low-level Control** (C_L): Using a PS3 controller *joystick*, the user provides a continuous stream of linear and angular velocities to control the robot. The autonomy steps in only to prevent collisions [1], and the execution trajectory otherwise is determined by the human operator.
2. **Mid-level Control** (C_M): Using the PS3 controller *buttons*, the user provides discrete directional commands: such as "turn left" and "forward". The autonomy executes these commands, taking care also to avoid obstacles.[1]
3. **High-level Control** (C_H): The user provides end goals or waypoints for the robot to navigate towards via a point-and-click visual interface using RVIZ.[2] An autonomous path planner calculates a safe trajectory from the current robot pose to the human-provided target pose, while avoiding obstacles.

3.2 Signal Modulation

The quality of signals received from the human by the robotic system depends on the quality of the communication channel between them, which can be influenced by human and environmental factors. In various scenarios involving a mobile robot, the signals may be sent over wireless networks. The wireless signals can be affected by many external factors such as weather, electrical interference, radio frequency interference and distance, to name a few.

Signal quality can be quantified according to different properties such as the signal frequency, transmission frequency and noise. In this study, we replicate these factors in a controlled setting, where three signal properties are *individually* modulated. For each of the following signal properties, we test three different *levels*

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[1] Note the primary differences between C_L and C_M are the discrete input and the rate of input.

[2] RVIZ is a 3D visualization tool distributed with the Robot Operating System (ROS).

of signal modulation by changing the threshold values: low modulation, moderate modulation and a high level of modulation. The thresholds which determine the modulation settings were chosen empirically during the experiment design phase.

1. **Dropped signals**: Every input signal is assigned a random number η sampled from a Gaussian distribution $\eta \sim \mathcal{N}(0, 1/3)$. If η is greater than a preset threshold, the corresponding input signal is dropped. (In our implementation, the three thresholds were $[0.6, 0.5, 0.4]$.) The result is *lost* information.
2. **Transmission Frequency**: The rate ρ at which the robot receives the user's command over the communication channel is varied, within a preset range. (In our implementation, the three values of ρ were $[5, 10, 15]$ Hz.) The result is a *delay* in the receipt of information.
3. **Noise**: A random value ε is sampled from a zero-mean Gaussian distribution, with a different variance σ^2 for each combination of control level and modulation level. The noise is implemented differently depending on the control level:

    a. Low-level control (C_L): ε is continuously added to the control signal at low, moderate and high levels of variance. (In our implementation, $\sigma^2 = [0.6, 0.8, 1.0]$.)
    b. Mid-level control (C_M): If ε is greater than the preset noise threshold, one of the commands is chosen randomly. (In our implementation, the thresholds were $[1.0, 0.92, 0.85]$ and $\sigma^2 = 1/3$.)
    c. High-level control (C_H): ε is multiplied by a distance value d dictated by the task, and $d \cdot \varepsilon$ is added to the goal position provided by the user. (In our implementation, d is set at $[6, 8, 10]$ cm and $\sigma^2 = 1$.)

Participants perform each task under 10 experimental conditions: three modulation levels for each of three signal properties (dropped signals, transmission frequency, noise), plus an unmodulated (clean) signal.

3.3 Experimental Setup and Tasks

We use a robotic powered wheelchair in this experiment. This wheelchair, shown in Figure 1, is a commercially available Permobile wheelchair that we retrofit with a laser scanner, RGB-depth sensor and on-board computer. These components plus our software suite provide additional autonomous capabilities such as doorway detection, obstacle avoidance and path-planning, to name a few.

The test environment is located in the Assistive and Rehabilitation Robotics Laboratory at the Rehabilitation Institute of Chicago. The setup consists of an obstacle course as shown in Figure 2. The operator is positioned at the operator station[3] (Fig. 2(c)) and can clearly observe the robotic wheelchair for each task.

Wheelchair tasks are chosen for measuring task performance, safety and control signals. A distraction task is also included for measuring human attention.

Wheelchair Tasks. The tasks are selected to cover a range of commands and non-trivial control strategies. In the domain of assistive powered wheelchairs, some of the challenging daily tasks include obstacle avoidance, navigating through tight spaces and correcting orientation for a desired pose. The following five tasks are selected from the Wheelchair Skills Test (WST) [14] and illustrated in Figure 2(b): (G1) Dock at a table (G2) Turn in place for orientation correction (G3) Doorway traversal (G4) Wide left turn and (G5) Tight right turn.

The goals are located such that the distance traversed from the center of the room to each of the five goal positions is equal. Achieving the above goals requires careful maneuvering around obstacles and controlling the linear and angular velocity of the robot's trajectory.

As seen in Figure 2(a), blue tape lines on the floor mark the goals. In order for the goal to be considered as successful, the wheelchair frame needs to fully cross the blue line. The operator is located at the operator station and has full visibility of the wheelchair for all five goals.

Distraction Task. To measure and evaluate the operator's cognitive workload and strategic behavior, we include a distraction task in the experiments. Distraction tasks such as this are commonly employed in psychophysiological studies.

We use the U.S. Air Force Multi-Attribute Task Battery (US AF_MATB) software developed and distributed publicly by the U.S. Air Force Research Laboratory [12] and well-studied throughout the human factors literature. For this study, the "Gauges" subtask from System Monitoring is selected (Fig 3). In normal operating behavior, the yellow gauge indicator fluctuates within one tick of the center gauge. A malfunctioning gauge goes beyond this normal operating range. The user's task is to monitor the gauges and send a correcting signal when a gauge has malfunctioned by pressing the corresponding key (i.e. F1, F2, F3 or F4). The speed of the gauges and the rate of malfunction are tunable.[4] All other adjustable parameters were kept at default settings.

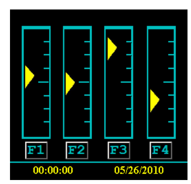


Fig. 3 Distraction Task.

[3] We have the subjects stand at a static operator station, instead of riding the wheelchair, in order to allow for the assessment of subject attention using an established distraction task [12] that is well-studied within the human factors literature. This task requires the subject to monitor a screen and interact with a keyboard, which was an overly cumbersome setup to have onboard the wheelchair.

[4] For this study, we use the following System Monitoring Subtask Basic Parameters: (a) Gauge Speed Lower Limit = 2, (b) Gauge Speed Upper Limit = 4, (c) Correct Fault Identification Pause = 10 and (d) Gauge Malfunction Timeout = 10. We use the keyboard as the only input option.

3.4 Procedure

The experimental protocol and consent form was approved by Northwestern's Institutional Review Board (IRB). The full session lasted for approximately two hours.

Participants. Nine consenting able-bodied adults (age range: 21-28) participated in the experiments. The subjects included those with varying levels of skill and experience with robotic devices: from no experience to regular usage.

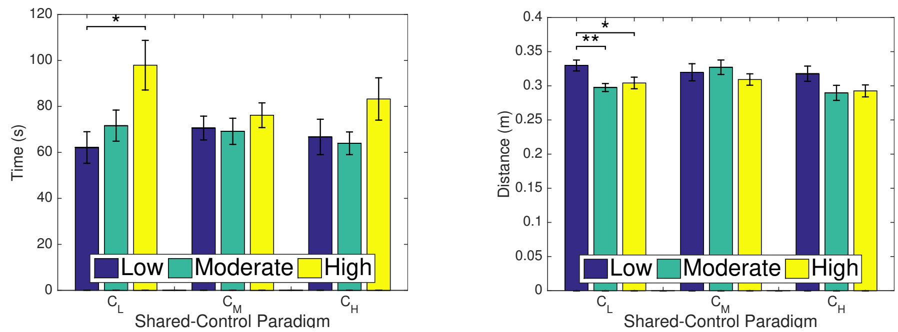
Protocol. The participants were introduced to the mobile robot and given an overview of the experiment and the wheelchair tasks. They were shown each task and given complete instructions on what constituted a completed goal. Then they were introduced to the distraction task. They were instructed on the normal operating behavior of the gauge and what was considered a malfunction. They were shown how to respond appropriately and given time to practice monitoring and operating the distraction task. It was stressed to the users that they should treat both wheelchair and distraction tasks with equal importance. The session began after the participant became familiar with each task and the nature of the experiment. They were informed that their control input may be randomly varied, but they were not given the details about what features of the signal would be varied or how.

Each session consisted of *three sections* corresponding to the three control levels: C_L, C_M, and C_H. For each of three control levels, 30 trials were performed, covering all 10 combinations of modulation type-level (3 modulation types $\times$ 3 modulation levels + 1 clean run) with 3 tasks executed per combination. (Which 3 tasks were randomly assigned and balanced, such that across subjects each combination was performed the same number of times for each task, and within a given subject across all combinations each task was performed the same number of times.) The order of the control levels, modulations and modulation levels was randomized and balanced across participants in order to minimize bias due to fatigue.

Each *section* of the experiment consisted of *two phases*: (1) an instruction phase and (2) a test phase. In the instruction phase, the participant was shown how to use the control level for the current section of the experiment and allowed time to become familiar with its operation. This time varied for each participant. After the participant was comfortable, the 30 trials of the test phase began. For each trial, the subjects were given their next goal after the completion of the current one. Subjects were not aware of which modulation setting was applied to their control signals. For safety, collision avoidance remained on at all times.

Metrics. In accordance with the literature on assistive and mobile robotics, we chose two metrics:

1. **Performance**: Calculated as the time from task initiation until the goal was reached. This metric is important for scenarios where the objective is to optimize time, for example crossing a busy road in a timely manner.
2. **Safety**: Calculated as the average distance from the closest obstacle to the robot at each time-step of the task execution. This metric is useful when physical safety is a priority; for example, operation in a crowd where the user and those around them are safer the farther the wheelchair is from any person or object.



(a) Average task time.

(b) Average distance to obstacles.

Fig. 4 Effect of modulating the dropped signal. Data from three modulation levels (Low (blue), Moderate (green), High (yellow), Sec. 3.2) for each of three shared-control paradigms (C_L, C_M, C_H). Plots show (a) task time and (b) distance to obstacles, averaged over all tasks and subjects.

4 Experiment Results

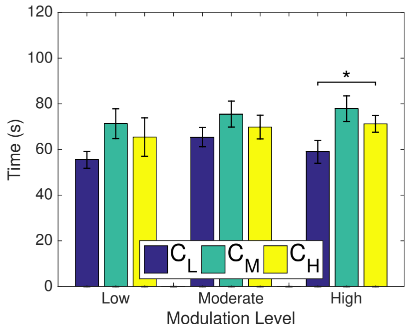
This section highlights key results from our pilot experiment for each metric. Statistical analysis is performed using analysis of variance (ANOVA) where group labels are either modulation level or shared-control paradigm. If statistical significance is found ($p < 0.05$), a pairwise t-test is performed and results are indicated in Figures 4, 5 and 6. For all plots, * denotes $p < 0.05$, ** $p < 0.01$ and *** $p < 0.001$.

Dropped Signals. Looking at performance for control level C_L, we notice that dropping the signal significantly alters a user's ability to complete a task within a reasonable time frame, shown in Figure 4(a). Namely, a statistically significant difference in task time is found between the low and high modulation levels ($p < 0.05$). Figure 4(b) shows that safety is also significantly compromised with a dropped signal ($p < 0.05$).

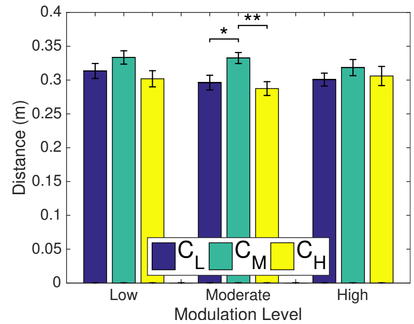
Conversely, dropped signals do not appear to significantly affect control levels C_M and C_H. This suggests that when the signal is degraded by drop, the autonomy should switch away from C_L since both safety and performance are compromised. The results further suggest that an appropriate threshold, above which the amount of dropped signal is considered too damaging for C_L, should be set between the low and moderate modulation levels.

Channel Frequency. The results of lowered channel frequency suggest some trade-offs between safety and performance. Figure 5(a) indicates C_L provides the best task time performance across all modulation levels, and significantly so for highly delayed signals ($p < 0.05$). However, Figure 5(b) shows that C_M is safer as users tend to operate farther from obstacles, significantly so at moderate modulation levels ($p < 0.01$).

Signal Noise. Signals degraded by noise can play a role in the safe operation of the robot. Safety is more compromised across all noise levels in C_H compared to both C_L and C_M. While this difference is not statistically significant, it likely



(a) Average task time



(b) Average distance to obstacles.

Fig. 5 Effect of modulating channel frequency. Data from three shared-control paradigms (C_L (blue), C_M (green), C_H (yellow)) for each of three frequency modulation levels (Low, Moderate, High, Sec. 3.2). Plots show (a) task time and (b) distance to obstacles, averaged across all tasks and subjects.

would have practical implications. On average, the robot moves 3.6 cm closer to obstacles when operating under C_H with noise at all levels, as shown in Figure 6(b). For context, the ADA requires doorways to be only 11 cm wider than our Permobil wheelchair, so 3.6 cm can be significant. Somewhat surprisingly, noise otherwise appears to have little effect on performance or safety for control levels C_L and C_M.

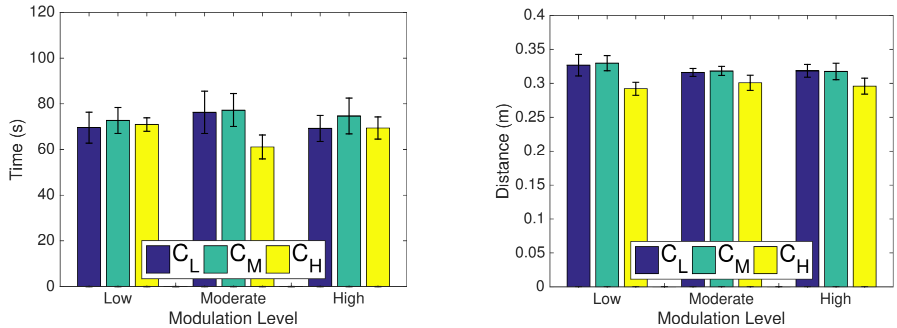
Distraction Task. The results of ANOVA on the distraction task performance do not indicate any statistical significance across control levels or modulation levels. Across all paradigms, the percent correct gauge responses of triggered faults is 62.0% ± 26.4%.

5 Signal Degradation Detection

The results of the experiment suggest that the signal quality influences both the performance and safety of the user differently in each control level. In real-world scenarios, operating in a degraded state could lead to a mission-critical failure or compromise the safety of a patient. Thus, it is important to allocate control and autonomy appropriately in real-time. The first step is to detect the quality of the signal. This section outlines the use of specific machine learning techniques to classify the state of the signal's degradation.

When in C_L or C_M the robot receives from the user only motion commands. In C_H, the robot receives only a goal. If the communication channel has degraded at all, the robot would need to detect the channel quality using only this information.

We choose a recursive neural network (RNN) structure using long short-term memory cells (LSTM) that classifies the user's commands over a set time period as either clean, noisy, dropped or lowered transmission frequency. The RNN LSTM is



(a) Average task time (b) Average distance to obstacles.

Fig. 6 Effect of modulating signal noise. Data from three shared-control paradigms (C_L (blue), C_M (green), C_H (yellow)) for each of three noise modulation levels (Low, Moderate, High, Sec. 3.2). Plots show (a) task time and (b) distance to obstacles, averaged across all tasks and subjects.

chosen because of its ability to retain information about the previous state or input. Moreover, results in speech processing show that a bidirectional LSTM (BLSTM) structure, which shares information about future states, improves the classification rate [6]. We test both in our analysis (since there is additional computational complexity associated with the BLSTM). In our implementation, a snapshot of the signal from the human— continuous velocity commands, discrete motion commands or goal positions, depending on the control level—for a designated number of samples is the input to the RNN, which outputs a classification of the signal's state.

To obtain unbiased results, we use three-fold cross validation where, in each fold, 6 subjects (randomly balanced) are used to train and the 3 remaining subjects to test. The reported accuracy in Table 1 is the average of the three models from the cross validation. The data is split into samples of 30 consecutive points in time and then randomized for both training and testing. We also ensure the data is split using approximately equal amounts of all classes. The algorithm used for training is Adam [10] with a maximum of 200 epochs. This process is repeated for each control level. Since the signal type is different for each control level and robot will always know its current control level, it is necessary and reasonable to train separate networks.

When operating under C_L, it is critical to determine when the signal is dropping because of the significant decrease in safety and increase in average task time. In Table 1, both the unidirectional and bidirectional LSTM achieve a classification accuracy between 70-80% when classifying all 4 possible signal states.

The results, however, indicate that primary source of error is false positives between the clean and lowered transmission frequency samples—the network could not differentiate reliably between the two. Since for C_L lowered transmission frequency does not appear to affect performance or safety (Figure 5), both transmission frequency and clean modulations can be bundled into a single class, which increases the accuracy to $\sim$90% for both models. This 10% error might further be reduced by taking an ensemble approach or the mean over several time intervals rather than a single 30 sample segment, for example.

When predicting degradation in control levels C_M and C_H, the network could not accurately differentiate between the different signal degradation types. On average, it achieved a classification accuracy of around 25% (where random performance is also 25%). The user inputs are at a lower frequency in these two control levels, which causes the data to be sparse and have long periods of time without a command. This sparsity and time between commands is likely the primary issue with this approach. Thus, other methods will need to be explored in the future to determine when the signal has degraded when in control levels C_M and C_H.

In summary, we have developed a general model able to classify the signal of users whose data has not yet been observed, which performs well under low-level shared-control paradigms. Also, we see that the bidirectional model does not provide much improvement in the 3-class formulation. Therefore, if computational power is a limiting factor, the unidirectional model provides comparable results.

6 Insights for a Dynamic Autonomy Allocation Framework

In human-robot teams, mobile in particular, signal quality and human attention, awareness and workload changes constantly. Thus, it is vital that the robot can detect when the user is hindered or if the autonomy cannot succeed in performing the desired task. With this knowledge, control can be allocated in real-time to either the human or robot, or some mix of the two. Knowing that the prediction of signal degradation type is feasible for a low-level control command, we will use the results of the experiment to provide insight into when and how autonomy should be allocated for use in a dynamic autonomy allocation framework

When the communication channel is dropping signals, the human-robot team should shift away from a low-level shared-control paradigm. In the low-level paradigm, the operator can continuously correct their commands to adjust the robot's behavior. The more often the signal is dropped, the less often the user can correct the behavior of the robot, leading to both performance and safety decreases (Figure 4). Based on our results, the autonomy should shift when the dropped rate surpasses a threshold between the low and moderate modulation amounts.

Architecture	Classes	Accuracy (%)		
		C_L	C_M	C_H
LSTM	4	73.1	27.7	26.2
BLSTM	4	75.8	30.8	28.7
LSTM	3	89.8	46.8	47.7
BLSTM	3	89.8	46.7	52.5

Table 1 Prediction accuracy results for single-layer 128-cell LSTM and BLSTM architectures.

A reduction in transmission frequency requires the design to prioritize either safety or performance. Our results show that low-level control provides the best performance when the channel frequency drops a lot to the high modulation frequency level. Conversely, safety is significantly improved by operating at moderate levels in a mid-level shared-control paradigm. If a reduced channel frequency is detected and the level is known, the autonomy can shift between C_M and C_L. If the level is unknown, the designer will need to prioritize safety or performance to decide which paradigm to use.

The autonomy should shift from high-level control when the communication channel is noisy. Lack of continuous correction may also have impacted the safety in the high-level shared-control paradigms when afflicted by a noisy communication channel. Here, the user provides only a goal for the mobile robot, and noise may place that goal closer to an obstacle. Moreover, we found that noise did not affect performance or safety in C_L (despite many subjects expressing a less enjoyable experience). Thus, if avoiding hazards is a critical component of the function of the robot, detecting noise and moving to a paradigm that allows for more operator correction may prove helpful.

7 Conclusion

The experimental results demonstrate the need for a framework that can dynamically allocate autonomy between the user and robot to optimize both performance and safety. Based on an analysis of the data, some control levels are explicitly better than others under certain degraded states of the communication channel between the human and the robot. We hypothesize that the rate at which a user can send corrective signals —which is dictated by the specific shared-control paradigm— explains these findings. Additionally, the experimental results suggest that a designer may need to choose between safety and performance when the transmission frequency is lowered. The results provide insight that can inform the design of a framework to dynamically adjust the control level when the quality of the signal changes in real-time. The first step in the design of such framework is to identify the degradation state of the signal. When in lower-level control, RNN LSTMs can reliably predict the state of the communication channel. However, more work is needed for classifying the signal in the other shared-control paradigms. This work lays the foundation for a framework that will be able to optimize the safety and performance of patients using assistive devices as well as human mobile robot teams.

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