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EVALUATING MOBILITY PERFORMANCE OF UNMANNED GROUND VEHICLES

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ABSTRACT

As the penetration levels of unmanned ground vehicles (UGV) in military applications increase, there is a growing need to evaluate their mobility across different latencies and various modes of operation ranging from pure teleoperation to full autonomy. State-of-the-art tools to evaluate mobility of ground vehicles do not address this need due to their not accounting for UGV technologies and the associated latencies. Although the trade-off between latency and performance has been thoroughly studied in the telerobotics literature and the results may qualitatively shed light onto the UGV domain, as well, a quantitative generalization is not possible due to the differences in context. Recognizing this gap, this paper presents a functional relationship between mobility and latency in high-speed, teleoperated UGVs under the context of path following. Specifically, data from human-in-the-loop simulations performed in this paper are combined with data from prior studies to span three vehicle types, three courses, and teleoperation latencies ranging from 0 s to 1 s. This combination yields for the first time a diverse data set for the context of path following in high speed, teleoperated UGVs. Based on this data set, empirical relationships are derived to quantify the trade-off between latency versus average speed and lane keeping error. This relationship can be used to establish a benchmark to evaluate the performance of autonomy-enabled UGV systems.

I. INTRODUCTION

MOBILITY of a vehicle refers to its capability to move quickly from point to point. Objective and quantitative assessment of vehicle mobility is an important need for the U.S. Army, as well as other practitioners when evaluating alternative ground vehicle technologies. On-road mobility refers to mobility of ground systems on hard, non-deformable surfaces such as concrete and pavement, and many dynamics codes are available for evaluating on-road mobility [1-3]. Off-road or cross-country mobility refers to ground vehicle mobility over soft and deformable terrains and is a much more challenging problem [4].

The standard approach used by the U.S. Army to evaluate the mobility of ground vehicles is the NATO Reference Mobility Model (NRMM) [4]. NRMM is a simulation tool developed and validated by the U.S. Army's Tank Automotive Research, Development, and Engineering Center (TARDEC) and Engineer Research and Development Center (ERDC) that aims to predict a vehicle's mobility capability in terms of effective maximum speed under both on-road and cross-country conditions.

One of the important limitations of the NRMM is that it does not offer a methodology and standard for evaluating the

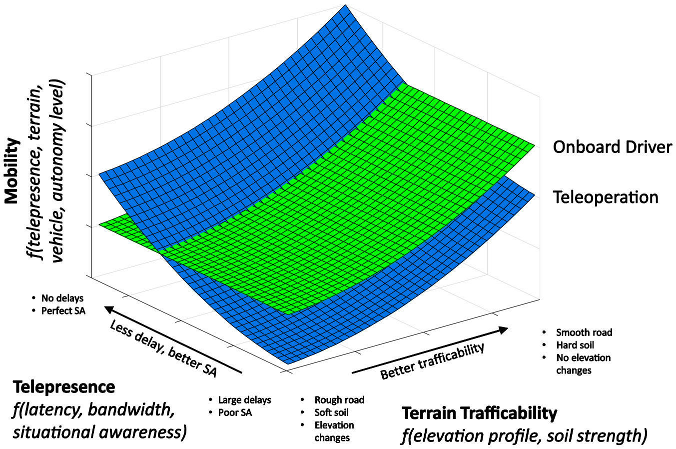

Fig. 1. Notional Relationship – Teleop vs. Human Onboard

mobility performance of unmanned ground vehicle (UGV) technologies. These technologies are also referred to as intelligent vehicle technologies, which involve the use of sensors and information to feed control algorithms to enhance the mobility of the system. These technologies include existing fielded systems such as anti-lock braking systems (ABS), traction control, active suspensions, and track tensioners. UGVs are critical assets for the Army to improve safety and effectiveness; therefore, having a standard means of evaluating their mobility performance is of critical importance. Addressing this need, however, is a challenging problem due to the wide range of operating modes UGVs may have and the large variations that exist in the particular technologies that can be employed to enable a desired mode of operation. Examples include operating under teleoperation, semi-autonomous, or fully autonomous modes. This paper focuses on teleoperation.

Teleoperation refers to the mode in which the operator sits in a remote location and sends commands to the vehicle over a wireless network, which the vehicle then executes while sending back sensor information, such as vehicle states or camera images of its surroundings. One challenge with this arrangement is that all networks have some amount of latency, meaning that both the execution of the operator's commands and the transmission of sensor information back to the operator are delayed. These latencies can significantly affect the mobility performance. Hence, it is important to quantify the relationship between latency and mobility performance.

TARDEC has developed notional relationships to illustrate how the mobility performance of ground vehicles may be affected by changes in telepresence and terrain trafficability (Fig. 1). The independent variables are telepresence, which considers latency, bandwidth, and situational awareness, and terrain trafficability, which considers elevation profile and soil strength. The dependent variable is mobility, which may be captured by speed, error, % go/no-go, or other metrics of mobility. The onboard driver surface plot assumes constant telepresence throughout, since the situational awareness of the driver does not change. Human factors such as distraction and fatigue are not considered in this notional relationship. In some scenarios, a vehicle driven by an onboard driver may outperform a remotely operated vehicle. Such situations occur when telepresence is sufficiently poor all on types of terrain, from rough, soft soils to smooth, hard roads. Since the driver is remotely located in teleoperated vehicles, human-related protections, such as armor, and human vibration limits, both of which restrict mobility performance, are no longer needed. Therefore, teleoperated performance may overtake conventional performance once this improvement outweighs any degradation from poor telepresence, such as large latency in the system.

Note that the relationship described above is only notional and data are needed to turn a qualitative analysis into a quantitative one.

Evaluating the mobility of an unmanned vehicle under different latency conditions has been subject to much research using a range of vehicle platforms, including undersea robots [5], ground robots [6-9], golf-cart type vehicles [10], and the High Mobility Multipurpose Wheeled Vehicle (HMMWV) [11, 12]. Beyond vehicles, the effect of latency on teleoperation performance has also been studied extensively for robot manipulators [13-16]. Methods have also been developed to improve teleoperation performance under latencies [9, 12, 17]. The general conclusion from these studies is that regardless of the application, communication delays typically negatively affect teleoperation speed (task completion time or vehicle speed) in teleoperated systems. Other performance metrics that aim to quantify how accurately users can control the teleoperated systems are typically also affected negatively by delays. Improvements in performance varied when assistive technologies such as predictive displays were used to mitigate time delays.

Notwithstanding these studies, an important gap exists in the literature. Namely, there is a lack of data for teleoperated vehicles when it comes to high speed (>25 mph) operations. Among the studies reported above, only [12], [18] and [11] consider high speed applications, but only two delay conditions are analyzed. Therefore, it is unknown how performance metrics would quantitatively change as a function of delay across a range of delay values. It is also unknown what the interaction between mobility, latency and task complexity is for teleoperated vehicles. Even though the dependence of the latency-versus-performance relationship on task complexity has been well-known in the domain of telemanipulators [17], it is not yet fully studied for high-speed teleoperated vehicles.

Recognizing this challenge, the goal of this paper is to present a functional relationship between mobility and latency in UGVs that is developed using data collected under the same context. Results are obtained with a simulation framework that is under development to provide an objective and quantitative assessment tool to evaluate mobility of teleoperated UGVs across various latencies under a common context to establish the relationship between mobility and latency. Specifically, a Polaris MRZR 4 is considered as the vehicle platform and its mobility in a path following scenario is evaluated across a wide range of latencies and two modes of operation. In particular, the direct teleoperation mode is considered as the benchmark and a delay compensation scheme is evaluated against this benchmark using average speed and lane keeping error as the mobility metrics. These data are then combined with prior data obtained under the same context of path following, but with another two vehicle platforms and courses. The combined data set yields a diverse data set to derive empirical relationships between latency versus average speed and lane keeping error for path following in high-speed, teleoperated UGVs. The results from this study will provide the foundation to the mobility-latency relationship, which seeks to describe how latency affects the mobility performance of teleoperated UGVs.

The rest of this paper is organized as follows. Sec. II first describes the simulation framework used in this study, including the details of the vehicle simulation environment and UGV operation modes. Then, the demographics of the human subjects and the test procedure are summarized. Background information is given about the data that was collected prior to this work and leveraged in this paper. Results and discussion of the experiments are given in Sec. III, and concluding remarks in Sec. IV.

II. EXPERIMENTAL METHODS

A. Vehicle Simulation Environment

This research utilizes the Rover Analysis, Modeling, and Simulation (ROAMS) environment [19] developed by NASA's Jet Propulsion Laboratory (JPL) and described in Fig. 2 for conducting simulated teleoperation tests using the architecture in Fig. 3, also developed by JPL. ROAMS is built on top of the Dynamics and Real-Time Simulation (DARTS) multibody dynamics engine, which employs Spatial Operator Algebra (SOA) algorithms to provide fast, accurate dynamics calculations.

Developed by JPL, the ROAMS model of the Polaris MRZR 4 uses the novel constraint embedding technique [20] to model the coupled dynamics and closed-loop dynamics of the vehicle's double wishbone and trailing arm suspensions to accurately capture the dynamics of the system. The full model contains 15 degrees of freedom.

ROAMS provides several ways of sending control commands to the vehicle. This research uses joystick input from a Logitech G27 Racing Wheel to allow the operator to control the throttle, brake, and steer angle directly. This allows simulation of pure teleoperation. ROAMS provides visual feedback to the user as shown in Fig. 4.

ROAMS also provides a straightforward way to extend and augment its capabilities, by creating Dshell models. In general, models receive some input, usually describing the state of the system or relaying commands from another model. The model then performs computations on the input and produces output that can be utilized by other models. Models can also affect the dynamics of the system directly by applying forces or torques to bodies.

In order to simulate teleoperation with a predictor, the predictor in [12] was implemented as a new Dshell model. The

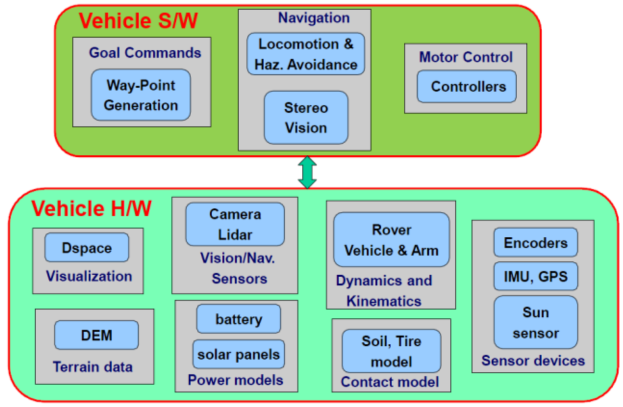

Fig. 2. ROAMS software framework

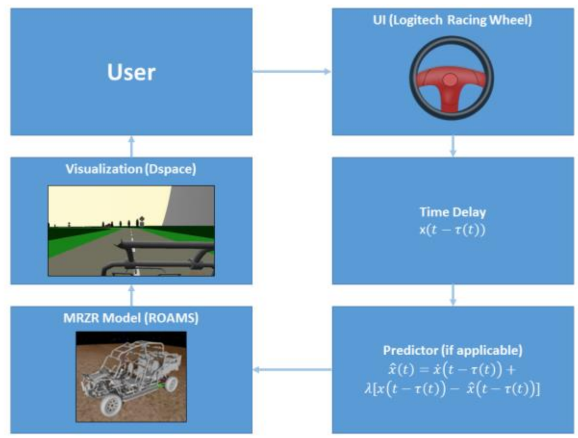

Fig. 3. ROAMS teleoperation schematic

Fig. 4. Visual feedback provided to the driver during simulated teleoperation

model receives a control command as input, computes the predicted control command, and makes the predicted command available to downstream models which apply torques to the wheels or modify the vehicle's steer angle. The predictor model also maintains the history of the control commands it has sent and received in order to perform future computations. The predictor is a first-order time delay system as shown in Fig. 3, where x represents the original signal and $\hat{x}(t)$ is its estimate at time t given $x(t-\tau)$ with τ representing the time delay. λ is the design parameter of the predictor and represents an

Fig. 5. Course for teleoperation trials (adopted from [12])

Table 1. Participant demographics

	Years of Having a Driver's License	Experience with Driving Simulators (0-3)	Experience with Driving with Delays (0-3)
Mean	18.5	0.42	0
Std. Dev.	11.3	0.53	0

integral gain that aims to attenuate the difference between χ and $\hat{x}$. For the details of the predictor, please refer to [12].

B. UGV Operation Modes

1) Pure teleoperation

The first operating mode considered in this study is pure teleoperation. In this case, the user sends steering, throttle, and brake commands to the vehicle using a Logitech steering wheel controller and pedals. The vehicle then executes these commands exactly.

In order to study the effects of latency, a one-way control delay is introduced between the operator and the vehicle. When the delay is nonzero, the vehicle receives the operator's commands *after* the operator sends them, but the operator receives undelayed sensor information from the vehicle.

2) Enhanced teleoperation

In order to compensate for the effect of latency, enhanced teleoperation trials introduce a predictor to aid the operator similar to the predictor in [12]. However, this study considers a wide range of latencies with one-way delay using a MRZR whereas the study reported in [12] looked at two levels of latency with two-way delays using a HMMWV. The predictor uses past values of a time-delayed signal to attempt to predict the current value of the signal. In this way, it aims to mitigate the effects of latency by feeding the vehicle the estimated current control commands, rather than the delayed commands.

C. Participants

This study consisted of 7 participants, with a wide range of on-road driving experience. Table 1 shows various demographic data for the participants. Each participant rated their experience with driving simulators and their experience driving with delays on a scale from 0-3, with 0 indicating no experience, and 3 indicating a high level of experience. It is worth noting that, although the participants varied widely in actual driving experience, they all reported very little experience with driving simulators, and no experience driving with delays.

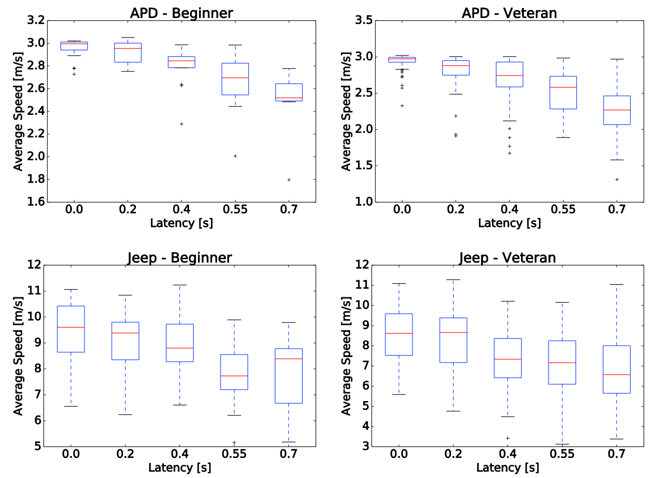

Fig. 6. Average speed vs. latency in the Kiosk experiment

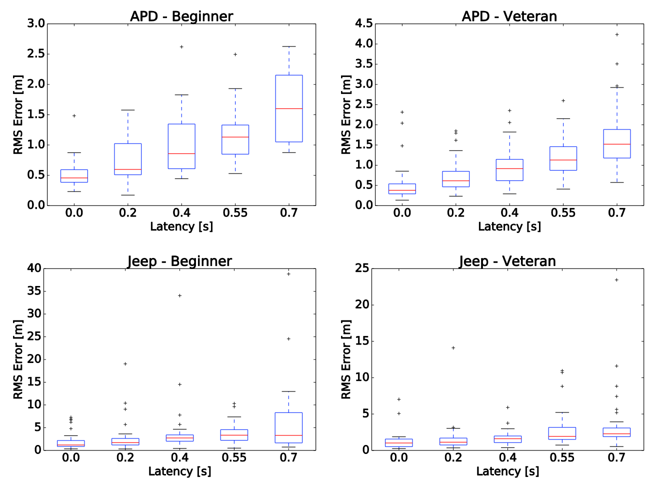

Fig. 7. Error area vs. latency in the Kiosk experiment

D. Teleoperation Test Procedure

In this research, 7 operators completed 3 successful direct teleoperation trials at each of 6 different latencies. The data generated was used to develop a preliminary relationship between driver performance and latency.

Users were instructed to drive along a curved track (Fig. 5), finishing the course as quickly as possible while remaining as close to the centerline as possible. The vehicle's speed and position were recorded at each time step, in order to determine the average speed and lane-keeping error. If the user strayed off of the track (delimited by the shaded region surrounding the road in Fig. 5) for more than 5 seconds continuously, or if the vehicle experienced 2-wheel lift-off at any time, the simulation was deemed a failure and repeated.

Prior to the testing phase, a training phase was conducted, in

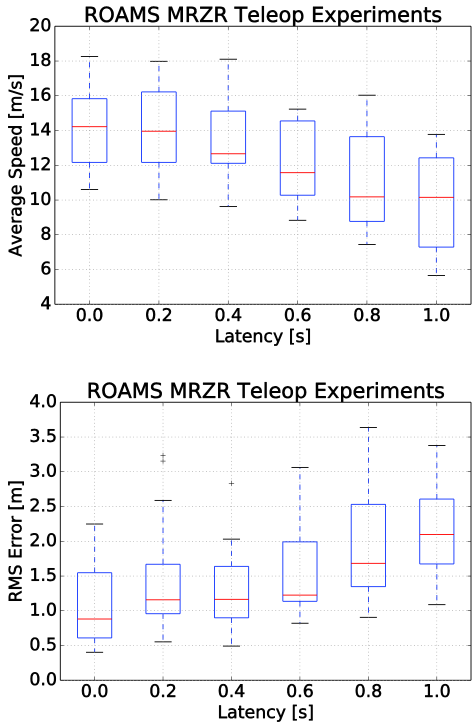

Fig. 8. Results from ROAMS pure teleoperation experiments: average speed (top) and root-mean-square of lane keeping error (bottom)

which each user had the opportunity to become familiar with the simulation environment and controls. Each user performed several practice runs at each latency, until the user's performance became consistent. For the recorded results, runs were performed in order of increasing latency, starting from no latency up to 1 second of latency.

After users completed the first round of testing, they performed an identical teleoperation task while employing the predictor shown previously in Fig. 3 to compensate for the control delay similar to the predictor used in [12].

E. Additional Data

TARDEC engineers performed a study similar to the one described above during the Kiosk project [21]. Participants were asked to drive a simulated teleoperated vehicle, either the Autonomous Platform Demonstrator (APD) [22] or the Jeep, along a predefined path under various network delays. A total of 1292 trials were performed. The metrics, average speed and error area, are depicted in Figs. 6 and 7. The conclusion from this study was that as latency increases, average speed decreases, and error increases. The data available from this Kiosk study is combined with the data obtained in this work to obtain a larger dataset to generate the latency versus mobility relationship derived in Sec. III.

III. Results and Discussion

The results from one of the 7 operators were determined to be an outlier with very low speeds, thus that data was not

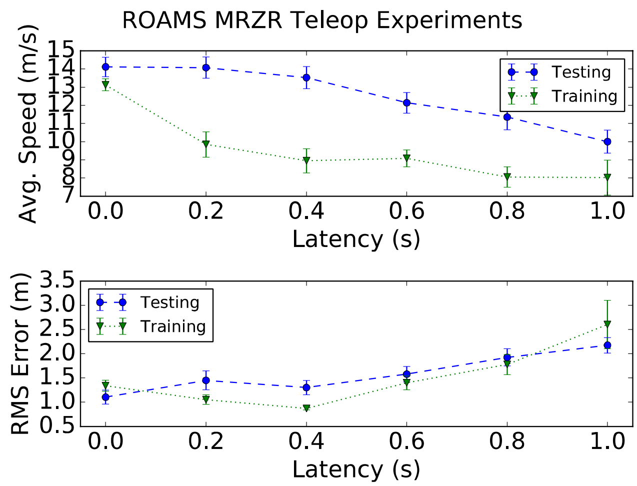

Fig. 9. Comparison between training and post-training teleoperation performance and latency. Error bars represent the standard error of the mean.

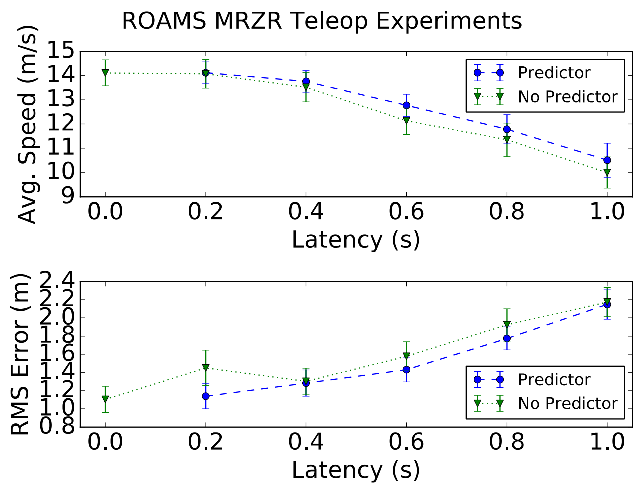

Fig. 10. Comparison between pure and enhanced teleoperation performance and latency. Error bars represent standard error of the mean.

included in the analyses. The results from all other operators are presented in Fig. 8. The general trend is clear: as the latency increases, the average speed decreases, and the lane-keeping error increases. It is also interesting to note the significant, sudden decrease in performance when the latency reaches 0.6 seconds. This was also the point at which most users stated that the latency became subjectively noticeable.

These results confirm the trends observed in the literature. Moreover, they provide a higher level of granularity, and show that the decrease in performance is not uniform as the latency increases. Finally, these results establish the baseline performance under pure teleoperation.

Fig. 9 shows the comparison between data collected during training and data collected after users were sufficiently trained. The trends indicate users drove more aggressively after training. That is, they achieved higher average speeds and experienced increased lane-keeping error in most latencies.

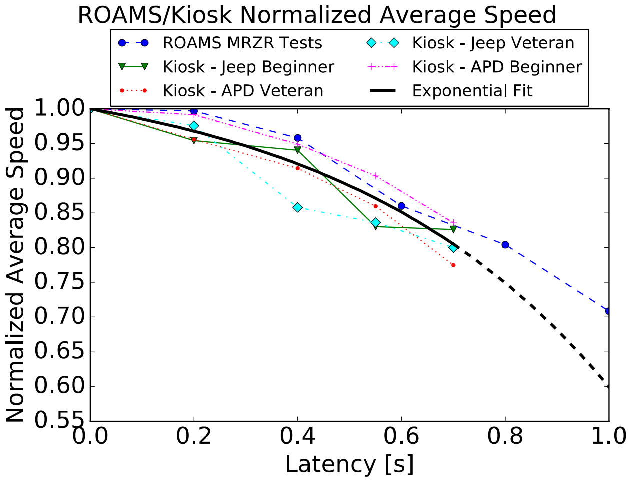

Fig. 11. Mobility – Latency relationship for average speed

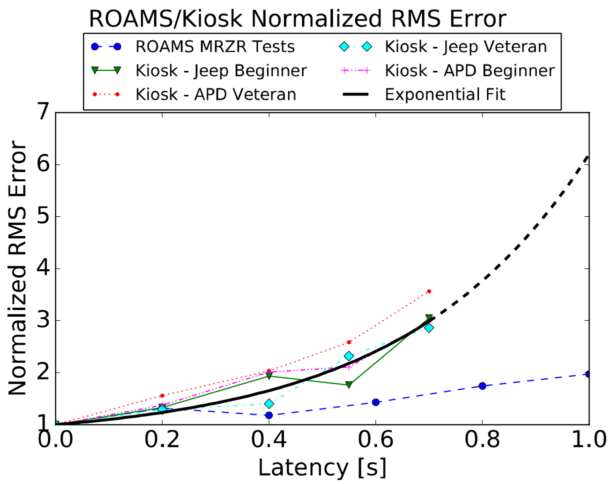

Fig. 12. Mobility – Latency relationship for root-mean-square (RMS) of the lane keeping error

Fig. 10 compares the results with and without the use of predictors. Repeated measures ANOVA analysis with a significance level of 0.05 shows that the differences in both average speed and average RMS error when the predictor is introduced are statistically significant ($F = 5.88$, $p = 0.016$ and $F = 4.14$, $p = 0.044$, respectively).

Runs that met the failure criteria described previously were not included in the results. However, it is worth noting that 29% and 36% of the runs attempted by drivers without and with the predictor enabled were deemed as failures, respectively.

With several sources of teleoperation data, a relationship between latency and performance can then be developed. Fig. 11 and 12 show the comparison of normalized average speed and error versus latency using both the TARDEC Kiosk data, described in the background section, and ROAMS simulation results presented in Fig. 14. The Kiosk data includes results for the beginner (easy) and veteran (difficult) courses when driving the APD and Jeep. The data were normalized by the performance at zero latency. It is clear that average speed decreases and lane keeping error increases as delay increases.

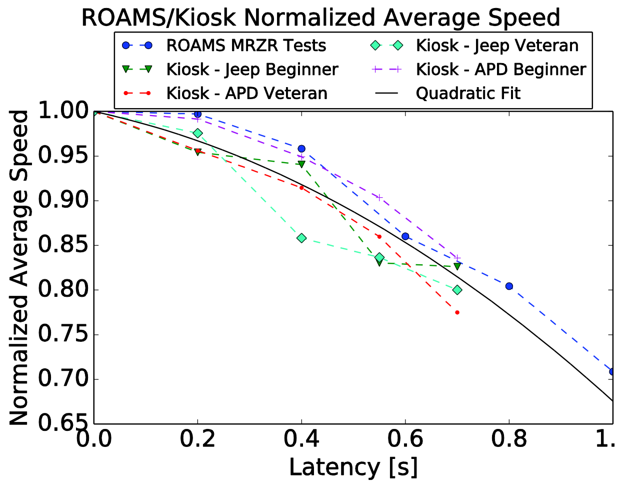

Fig. 13. Mobility – Latency relationship for average speed

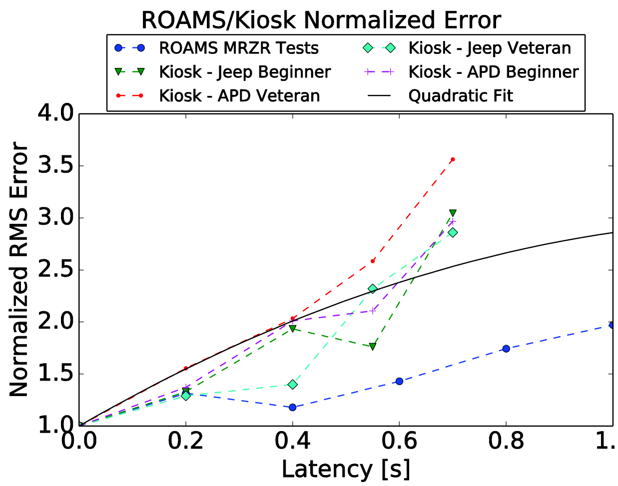

Fig. 14. Mobility – Latency relationship for root-mean-square (RMS) of the lane keeping error

More importantly, exponential and polynomial regression was used to generate the empirical equations shown in Eqs. (1) through (2) that hold true for the normalized teleoperation data in Figs. 11 through 15, respectively. Two methods of regression analysis were used to compare approaches, with the exponential fit providing a better trend. Given that the majority of the data lies at or below 0.7s latency, only data from 0-0.7s was used in determining the equations below, as the small number of data points from 0.7s-1.0s were found to unfairly bias the curve fit.

$$\text{Speed}(\tau) = -0.07e^{1.93\tau} + 1.07 \quad (1)$$

$$\text{Error}(\tau) = 0.29e^{2.93\tau} + 0.71 \quad (2)$$

$$\text{Speed}(\tau) = 1.00 - 0.12\tau - 0.20\tau^2 \quad (3)$$

$$\text{Error}(\tau) = 1.00 + 2.96\tau - 1.10\tau^2 \quad (4)$$

These relationships may serve as a preliminary benchmark for path following with high-speed teleoperated UGVs, against which other UGV technologies, such as different levels of autonomy, can be compared. Further investigation, including the collection of experimental data, should be conducted to validate this relationship developed through simulation.

Limitations of this work are summarized as follows. The experiments have been performed with a relatively low number of human subjects. Collecting data from more subjects would increase the statistical power of the analysis. The participants were given a training time to become familiar with the simulator under all latencies, but they were not trained to drive with the predictors. A training time with the predictors can improve the performance of the subjects. Furthermore, the tests were not conducted in a randomized order, hence learning effects may be present in the data. A randomized order is preferred for future human subject studies. Finally, the bilateral delays in the communication between the driver and vehicle were lumped into a single control delay. This lumping increases the amount of delay to be compensated by a single predictor and degrades its performance. Implementing the control and sensing delays bilaterally and using two separate predictors to compensate them, as is the case in a real application, is expected to yield better results.

IV. Conclusion

This paper considers teleoperated UGVs and establishes a benchmark for the trade-off between their mobility and teleoperation latencies in the context of path following. To this end, human-in-the-loop simulations are performed with a simulated Polaris MRZR 4 vehicle platform under latencies ranging from 0 s to 1 s. These data are then combined with prior data obtained with two other vehicle platforms and driving courses to create a diverse data set, based on which empirical relationships are derived to quantify the abovementioned trade-off. The results show that the trends in the latency versus normalized average speed are consistent across different platforms and driving courses. The variation in the normalized root-mean-square lane keeping error is found to be higher compared to that of the average speed; nevertheless, a common trend still exists. These results can be used as a preliminary benchmark to evaluate the performance of other UGV technologies.

V. FUTURE WORK

Future work aims to characterize the performance of autonomy-enabled systems. These systems provide the capability to improve mobility performance compared to the teleoperation of military vehicles at high speeds.

If the UGV possesses some level of autonomy, a semi-autonomous mode of operation can become feasible. This mode aims to take advantage of a human's ability to make complex decisions and to quickly process a large amount of sensory information, and a computer's ability to control some functions of the vehicle with high bandwidth, high accuracy, and minimal delays. Examples include studies on haptic shared control [23] and semi-autonomous obstacle avoidance [9]. In this mode of operation, the challenge is to identify how to manage the responsibility of driving between the human and the computer to best leverage their unique capabilities and maximize mobility.

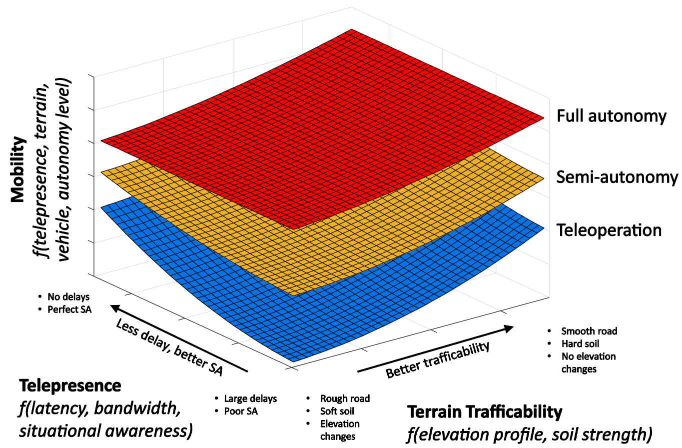

Fig. 16. Notional Relationship – Levels of Autonomy

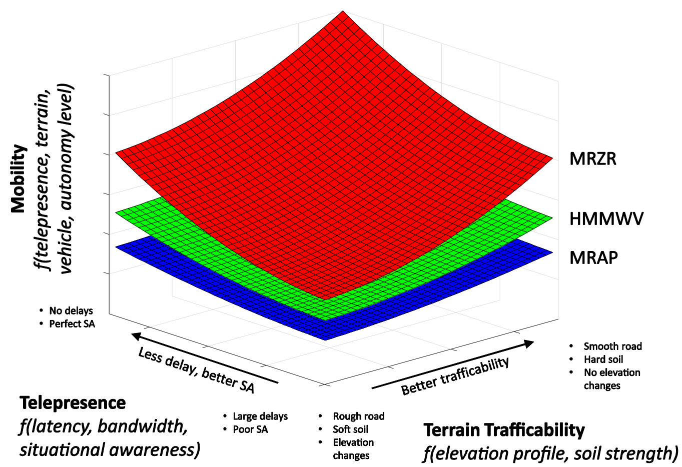

Fig. 17. Notional Relationship – Vehicle Comparison

The fully autonomous mode of operation is the Army's ultimate goal for UGVs. Although estimates of the time frame necessary to fully develop such technology range from five years to several decades, significant accomplishments have already been made in this domain. Examples include control algorithms based on model predictive control for path planning and obstacle avoidance [24].

The notional relationship in Fig. 16 shows how adding autonomy is expected to increase mobility performance of ground vehicles. The added assistance of semi-autonomy may improve performance over teleoperation, since less workload is expected to be imposed upon the remote driver. Likewise, full autonomy could improve upon semi-autonomy. Assuming all sensing and computations are performed onboard the vehicle, telepresence for full autonomy is considered constant throughout.

Fig. 17 describes a notional relationship comparing mobility performance of a light (MRZR), a medium (HMMWV), and a heavy (MRAP) military vehicle against one another with each system possibly using different levels of autonomy. This allows users to quickly compare the mobility performance between different platforms. Ongoing research aims to quantify the relationship between vehicles, autonomy, mobility, telepresence, and terrain characteristics with physical and/or simulation test data.

Ongoing research into semi-autonomous and fully autonomous control algorithms intends to demonstrate the benefits of autonomy on traditionally manned ground vehicles [9, 23, 24]. These autonomous systems can be classified by the Autonomy Levels for Unmanned Systems (ALFUS) framework which uses three categories for classification: human independence, mission complexity, and environmental complexity [25].

In addition, autonomous waypoint following and MPC-based path following simulations are ongoing to demonstrate how the addition of autonomy affects mobility performance when compared to the teleoperation baseline. Both algorithms consider obstacle avoidance while the MPC-based algorithm also considers vehicle dynamics during planning and motion execution. Once complete, semi-autonomous algorithms will be tested in simulation to further develop the autonomy-mobility-latency relationship. The same path following scenario and metrics as presented in this study are to be used to characterize performance of the Polaris MRZR 4 UGV in the autonomy-enabled simulations.

An experimental testing effort is currently ongoing using a Polaris MRZR 4 vehicle equipped with sensors, such as GPS, IMU, cameras, and LiDAR, to enable teleoperation through full autonomy. Tests are to be performed on fine grained and course grained soils with varying moisture content under several levels of autonomy. Metrics similar to those already described in previous sections will be recorded. Taking the mobility-latency relationship one step further, the data will be analyzed to determine how mobility is affected by latency and autonomy. The experimental results will also be used to perform verification and validation (V&V) of the simulation results presented in this study.

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