Impact of Communication Frequency on Remote Control of Automated Vehicles

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Impact of Communication Frequency on Remote Control of Automated Vehicles

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Abstract—**This paper investigates the impact of the communication frequency on the remote control of automated vehicles. In particular, we consider a remote controller, which receives vehicles' state information and issues control commands based on a model predictive control (MPC) framework, to steer the vehicles to reach their respective target position intervals at given specific times. We present a framework where both state information (from the vehicles to the controller) and control actions (from the controller to the vehicles) are communicated through a wireless network. Due to limited communication resources and possible channel impairments, information is not necessarily always provided to the destination (either the controller or the vehicles). Herein, we particularly focus on the communications to the controller and investigate the effect of frequency and last instant of communication. Our results quantify the impact of these factors on the system performance, and subsequently, underline the need for an efficient resource allocation scheme.**

I. INTRODUCTION

Intelligent transportation systems (ITS) and automated driving are increasingly receiving attention from both academia and industry, as they form a means by which car accidents, currently being mostly caused due to human error, can be reduced or completely eliminated. An important enabler of ITS is vehicular communication [1], which can provide improved situational awareness, enable efficient transport flows, and give advance accident warnings [2], [3]. Communication is also needed to support remote driving, e.g., in emergency situations [4] or remote coordination at intersections [5], [6]. In contrast to conventional communication [7], where rate and fairness are of primary importance, network control applications rely on different performance metrics.

Broadly speaking, network control systems comprise (possibly interacting) agents, steered by either a central or distributed controller, which share information via (wireless) links. Such information may be sensing data or control data [8]. Problems in network control involve mainly control and estimation over lossy or constrained networks [9]. Different approaches have been taken to address these problems, including letting sensors decide when it is useful to transmit information [10], and letting

the controller to request data from the most useful sensor [11]. The impact of packet losses on control cost and safety was evaluated in [12], while [13] developed a dedicated controller to mitigate the effect of packet losses.

In this paper, we consider the problem of remote control of multiple vehicles that must reach target position intervals at specific given times. For obtaining control signals, the vehicles need to send their state information to the remote controller, which computes a sequence of control actions for each vehicle to end up in its respective target position interval. The control problem is modeled so as to penalize control effort as well as violation of the target position intervals, and is solved every time a state information packet is provided at the controller. Our main objective is to evaluate the impact of the frequency and the last instant of communication on the vehicles' behavior, both in terms of the control cost as well as the constraint violation (i.e., not meeting the target). In the following sections, we provide an approach to evaluate both these metrics as well as their compound effect.

II. PROBLEM STATEMENT

A. Vehicles' Dynamics

We consider a set of M vehicles, remotely controlled by a central controller to reach their target states at the specific given times. The vehicles are considered as point masses, moving in straight lanes, with dynamics described by the following decoupled discrete-time linear equations

$$\mathbf{x}_{i,t+1} = \mathbf{A}_i\mathbf{x}_{i,t} + \mathbf{B}_i u_{i,t} + \mathbf{w}_{i,t}, \quad (1)$$

where $\mathbf{x}_{i,t} = [x_{i,t} \ v_{i,t}]^{\mathrm{T}} \in \mathbb{R}^2$ is the state of vehicle $i \in \mathcal{M} = \{1, 2, \cdots, M\}$ at time t, consisting of the position $x_{i,t}$ and speed $v_{i,t}$. Moreover, $u_{i,t} \in \mathbb{R}$ is the scalar control action, i.e., acceleration or deceleration, applied to the vehicle i in time interval $(t, t+1)$, and $\mathbf{A}_i$ and $\mathbf{B}_i$ are deterministic matrices, given by

$$\mathbf{A}_i = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}, \ \mathbf{B}_i = \begin{bmatrix} \frac{1}{2}\Delta t^2 \\ \Delta t \end{bmatrix},$$

where Δt is the duration of each time slot between every two consecutive discrete time instants t and $t+1$. $\mathbf{w}_{i,t} \in \mathbb{R}^2$ is also a zero-mean normally distributed disturbance with covariance matrix $\mathbf{Q}_i \in \mathbb{R}^{2\times 2}$.

Each vehicle i is assumed to know a noisy version $\mathbf{z}_{i,t}$ of its real state $\mathbf{x}_{i,t}$ at every time t:

$$\mathbf{z}_{i,t} = \mathbf{x}_{i,t} + \mathbf{v}_{i,t}, \tag{2}$$

with the observation noise $\mathbf{v}_{i,t}$ which is Gaussian with mean $\mathbf{0}_{2\times 1}$ and covariance matrix $\mathbf{R}_i \in \mathbb{R}^{2\times 2}$.

The vehicles are given the opportunity to send their state information $\mathbf{z}_{i,t}$ to the controller over a wireless uplink channel, for the purpose of remote control.

B. Controller Description

The remote central controller, upon receiving $\mathbf{z}_{i,t}$ from each vehicle i, solves an optimal control problem. This problem finds the required sequence of control actions, to be successively applied to the vehicle i in time slots before a given time T_i, so that it ends up in a target position interval satisfying

$$|x_{i,T_i} - \tilde{x}_i| \leq \xi_i, \tag{3}$$

where $|.|$ is the absolute value, and ξ_i is the allowed deviation from the target position $\tilde{x}_i$. We assume that the values T_i, $\tilde{x}_i$, and ξ_i are fixed; the choice of these parameters depends on the application, e.g., crossing an intersection in given times, or remote steering of automated vehicles (see Fig. 1). By neglecting processing and transmission delays, we assume both reception of state information and issuing control commands happen at an infinitesimal time epoch, which we label by t.

The obtained control actions are sent to the vehicles through a wireless downlink channel. Note that the revision of control actions based on the observation of states is of great importance. Otherwise, if the control plan is made once and not updated later on, the disturbances, as well as the uncertainties in observation and communication, would cause the real state trajectory to deviate from the estimated one, potentially violating (3). Therefore, feeding the controller with new information for updating control commands is significant, which highlights the role of communication.

C. Communication Framework

We consider a scenario in which there is only one communication resource block available, and hence, only one vehicle can communicate with the controller at each time t. Moreover, there is a centralized scheduler to assign the uplink resource block. No scheduling is required for the downlink, since at each time t, the controller communicates with the only vehicle which has sent information at the same time t. Let us introduce $\eta_{i,t}$, taking 1 if the resource is allocated to the vehicle i at time t, and 0, otherwise. We have $\sum_{i \in \mathcal{M}} \eta_{i,t} = 1, \forall t$.
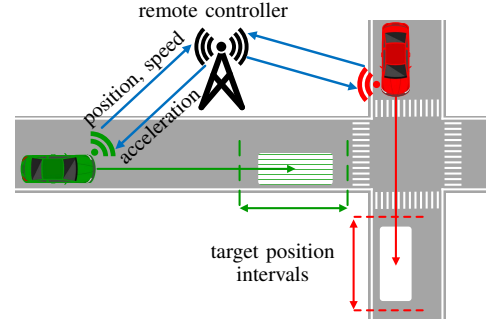

Fig. 1: Remote control of vehicles to reach their respective target position intervals at specific times.

We do not focus on any specific communication technology, and consider communication framework from a control application point of view. This allows us to focus on fundamental trade-offs between communication and system performance. However, to account for unreliability of communication channels which can causes packet loss, we define $\delta_{i,t}$ and $\gamma_{i,t}$, respectively for uplink and downlink communications, indicating if the communication between vehicle i and controller is successful at time t. Each of these variables is 0 for failed communication, and 1, otherwise.

III. METHODOLOGY

The problem of remote control of M vehicles with decoupled dynamics can be decomposed into M separate problems, each for the remote control of only one vehicle. Hence, without loss of generality, we focus our attention to one vehicle, and formulate a model predictive control (MPC) problem to remotely control it to end up in the target interval $[\tilde{x} - \xi, \tilde{x} + \xi]$ at a given time T. For simplicity, we discard the vehicle index i hereafter.

A. MPC Formulation

We consider the following MPC problem with the prediction horizon $N = T - t$, to be solved at time $t \in \{0, 1, \cdots, T-1\}$, if the state observation $\mathbf{z}_t$ is successfully transmitted from the vehicle to the controller:

$$\underset{\mathbf{u}_t}{\text{minimize}} \quad \|\mathbf{u}_t\|^2 \tag{4a}$$

$$\text{subject to} \quad u_{\min}\mathbf{1} \leq \mathbf{u}_t \leq u_{\max}\mathbf{1} \tag{4b}$$

$$\hat{\mathbf{x}}_{t+k+1|t} = \mathbf{A}\hat{\mathbf{x}}_{t+k|t} + \mathbf{B}u_{t+k|t}, \tag{4c}$$

$$\hat{\mathbf{x}}_{t|t} = \check{\mathbf{x}}_t, \tag{4d}$$

$$|\hat{x}_{T|t} - \tilde{x}| \leq \xi, \tag{4e}$$

where $\|.\|$ is the Euclidean norm on $\mathbb{R}^N$, and $\mathbf{u}_t := \left[u_{t|t}, u_{t+1|t}, \cdots, u_{t+N-1|t}\right]^{\mathrm{T}}$ is a sequence of N control actions found at time t, to be applied successively to the vehicle. The constraint (4b) bounds the control actions between $u_{\min}$ and $u_{\max}$. The predicted state trajectory at time t for $k = 0, 1, \cdots, N-1$, follows the dynamics

(4c) ignoring the random disturbances, where $\hat{\mathbf{x}}_{t+k|t}$ is the state prediction for k steps later, made at time t, with the control sequence to be obtained. Constraint (4d) initializes the recursion (4c) by $\check{\mathbf{x}}_t$ which is the estimated state at time t (see Section III-C), and finally, (4e) is to satisfy (3).

B. Control Sequence Update

The MPC is solved at time t, if $\eta_t = 1$ and $\delta_t = 1$, and the control sequence $\mathbf{u}_t$ is sent to the vehicle. If $\gamma_t = 1$, $\mathbf{u}_t$ is received by the vehicle and the control actions are applied sequentially. With every successful reception of uplink packet (i.e., state information), the control sequence is updated at the controller. If the downlink transmission is successful, the control sequence is overwritten at the vehicle as well. Otherwise, no new command is given to the vehicle and the current available control sequence is applied. The initial control sequence assumed by the vehicle is $\mathbf{u}_0 = \mathbf{0}$.

C. Filtering

The controller runs an estimator to feed the MPC with $\check{\mathbf{x}}_t$. We consider linear minimum mean square error (LMMSE) estimation, leading to the Kalman filtering approach, in which the state trajectory is predicted first, and predictions are updated based on available observations.

Let us denote by $\hat{\mathbf{x}}_{t|t-1}$ and $\hat{\mathbf{x}}_{t|t}$, the *a priori* and *a posteriori* state estimates at time t, respectively. Then, we have

$$\check{\mathbf{x}}_t \triangleq \hat{\mathbf{x}}_{t|t} = \hat{\mathbf{x}}_{t|t-1} + \eta_t \delta_t \mathbf{K}_t (\mathbf{z}_t - \hat{\mathbf{x}}_{t|t-1}), \quad (5)$$

where $\hat{\mathbf{x}}_{t|t-1} = \mathbf{A}\hat{\mathbf{x}}_{t-1|t-1} + \mathbf{B}u_{t-1|\bar{t}}$, in which $\bar{t} \leq t-1$ is the most recent time the controller has solved the MPC, in which $\eta_{\bar{t}} = \delta_{\bar{t}} = 1$. We note that it is not important what $\gamma_{\bar{t}}$ is, since the filtering is done at the controller side. The matrix $\mathbf{K}_t$ is also the Kalman gain at time t.

D. Feasibility

The MPC problem (4) can be infeasible, if $\check{\mathbf{x}}_t \notin \mathcal{X}_t$, where $\mathcal{X}_t$ is the set of all states at time t leading to a feasible solution. Infeasibility means that there are not sufficient control actions between $u_{\min}$ and $u_{\max}$, to satisfy constraint (4e). In order to solve this issue, we incorporate slack variables $s_t^{(1)}$ and $s_t^{(2)}$ to relax constraint (4e), and therefore, we obtain the following MPC problem:

$$\underset{\mathbf{u}_t, s_t^{(1)}, s_t^{(2)}}{\text{minimize}} \quad \|\mathbf{u}_t\|^2 + \rho(s_t^{(1)} + s_t^{(2)}) \quad (6)$$

$$\text{subject to} \quad (4b), (4c), (4d),$$
$$\hat{x}_{T|t} \leq \tilde{x} + \xi + s_t^{(1)},$$
$$\hat{x}_{T|t} \geq \tilde{x} - \xi - s_t^{(2)},$$
$$s_t^{(1)}, s_t^{(2)} \geq 0,$$

with a large enough value of ρ, which increases the cost, if constraint (4e) is violated, in case of insufficient control capabilities. The greater the slack variables are, the larger the feasible initial states set $\mathcal{X}_t$ would be. Since the cost increases with increasing slack variables, large slack variables are discouraged; hence, the constraint (4e) is satisfied as much as possible.

E. Cost Evaluation

The total cost J can be written as

$$J = J^{(\text{ctrl})} + J^{(\text{viol})}, \quad (7)$$

where

$$J^{(\text{ctrl})} \triangleq \sum_{t=0}^{T-1} u_t^2 \quad (8)$$

is the control cost, and

$$J^{(\text{viol})} \triangleq \rho \times \zeta \quad (9)$$

is the violation cost, i.e., the cost of violating (3). Here, u_t is the actual control action applied to the vehicle at time interval $(t, t+1)$, as explained in Section III-B, and ζ is the amount of violation of (3), given by

$$\zeta = [x_T - (\tilde{x} + \xi)]^+ + [(\tilde{x} - \xi) - x_T]^+, \quad (10)$$

in which $[\alpha]^+ = \max(0, \alpha)$.

IV. Numerical Results and Discussions

Assume there are M identical vehicles, sharing the communication channel based on Round-Robin scheduling (in uplink), in which each vehicle is given the transmission opportunity every M time slots. From each vehicle's point of view, communication period is equal to M. Evaluation of the effect of number of vehicles on each vehicle's cost, is the same as evaluation of the impact of communication frequency, when Round-Robin scheduling is used. In this section, we use numerical results to study the influence of two factors of communication, namely the frequency of communication, and the last communication instant, denoted by t_l, on the performance of system. To make the comparisons fair, the phase of communication is set so that in all cases there is communication at one step to the target time T, i.e., $t_l = T - 1$, when we evaluate the impact of communication frequency. In that way, there is minimum uncertainty at the target time T.

For simplicity, we assume that the observation noise is zero, and the state information provided for the controller is exact. Moreover, we assume $\delta_t = \gamma_t = 1, \forall t$, i.e., we do not consider the effect of channel impairments in the simulations. This, although not practical, facilitates understanding the impact of frequency and last instant of communication. However, our formulation is general and can account for packet losses.

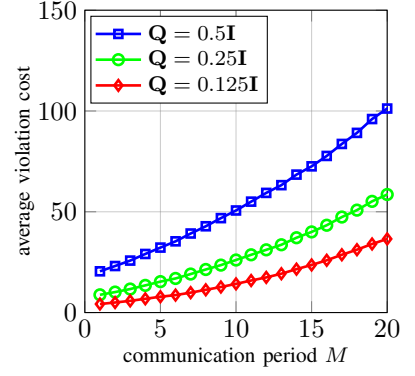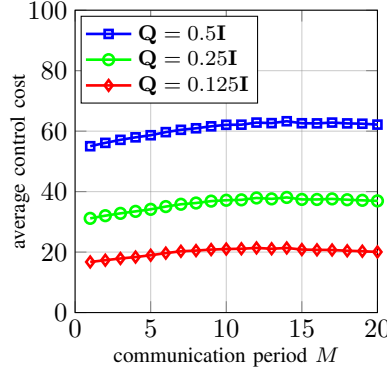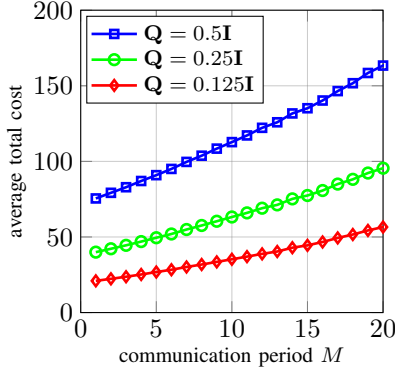In the simulations, which are done in MATLAB, we assume $T = 100$ (in discrete time), $\Delta t = 0.25 \, \text{sec}$,

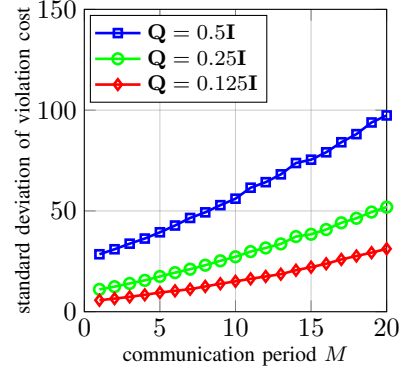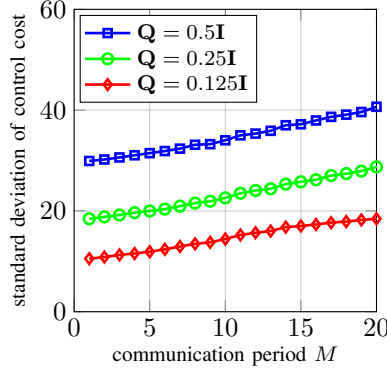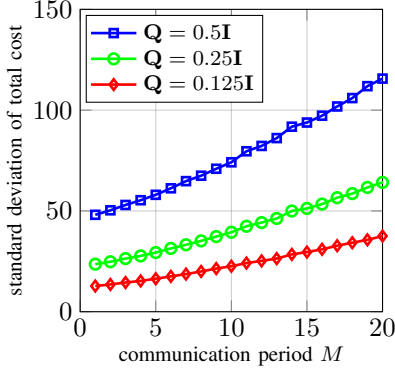Fig. 2: Average cost vs. communication period M for different covariance matrices of disturbance.

Fig. 3: Standard deviation of cost vs. communication period M for different covariance matrices of disturbance.

$\tilde{x} = 300$m, $\xi = 0.5$m, and $\rho = 10$. The initial state $\mathbf{x}_0 = [0 \text{ m } 12 \text{ m/ sec}]^{\mathrm{T}}$, and control limitations $[u_{\min}, u_{\max}] = [-2 \text{ m/ sec}^2, 2 \text{ m/ sec}^2]$ are considered in the simulations. For fair comparison, we use the same random number generator seeds, when the disturbance samples are generated. The curves have been obtained by the simulation results of 1000 realizations.

A. Impact of Communication Frequency

Fig. 2 shows the average cost vs. communication period M, for different values of disturbance covariance matrix $\mathbf{Q}$, with $t_l = T - 1$. One can observe that it is mainly the violation cost which has an increasing trend, leading the total cost to increase as well, when the communication period M increases. The reason for the increase in violations for larger communication period M is that although in all cases there is communication at time $T - 1$, with only one step to go and limited control, inevitable violations may occur, due to realizations which needed a lot of adjustment. This also explains why the control cost increase with M, for low values of communication period. At low values of M, it is possible to give more control in order to not violate the constraint as much as possible. However, at some value of M, the control limitation ($u_{\min}$ or $u_{\max}$) is reached for more realizations, and the control cost stops increasing with M. Thereafter, the less frequent communication, may even decrease the control cost, at the expense of

more violations, since fewer maximum/minimum control actions are applied.

Fig. 3 also illustrates the standard deviation of cost vs. M. As it is seen, the curves have increasing trends. The reason is that the less frequent observations lead to accumulation of uncertainty, which in turn may force more often aggressive control, when the control plan is revised. Also, due to accumulation of more disturbance samples, violation amounts would be more spread, which increase the standard deviation of violation cost.

B. Impact of Last Communication Instant

To evaluate the impact of this factor, in Fig. 4, we plot the average cost vs. the last communication instant t_l, for different values of M, with the disturbance covariance matrix $\mathbf{Q} = 0.25\mathbf{I}$. The less value of t_l, the larger corresponding non-communicating period between t_l and T, whose effect on the cost can be explained by the limitations on the control actions. As it is observed, for low values of M, (e.g., $M = 5$ and $M = 10$ in Fig. 4), the communication is frequent enough so that the control signal does not hit the saturation and one sees the expected result that the violation cost is smaller, if the last communication is closer to the end. The reason for this is that there is less uncertainty with a late communication. For larger M (e.g., $M = 20$ and $M = 50$ in Fig. 4), however, the control signal may hit the limits. Then, with the late adjustments, there might
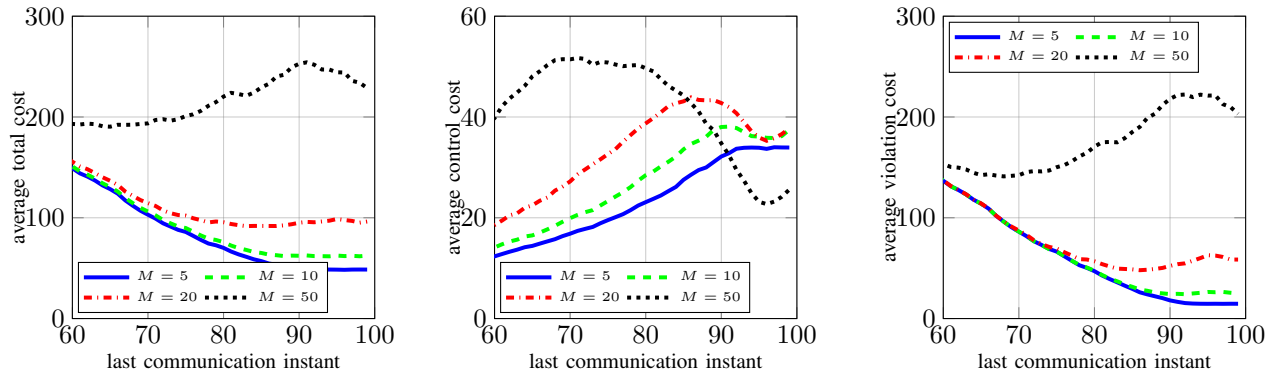
Fig. 4: Average cost vs. last communication instant for different communication periods with $\mathbf{Q} = 0.25\mathbf{I}$.

not be enough control action available to decrease the violation cost, while late adjustment may be preferred because of the less resulted uncertainty at time T. In fact, with larger M, there is a trade off between accumulated uncertainty and enough time to apply the control, which causes the non-monotonic behavior in the curves. This also explains why the control cost can be either lower or higher for larger M, when the communication is late.

V. CONCLUSIONS

We considered the problem of remote control of automated vehicles, and formulated an MPC problem to steer the vehicles to reach specific position intervals at given specific time instants. We studied two important communication factors; the frequency and the last instant of communication, in a multi-vehicle scenario when Round-Robin scheduling is used. Our results quantify the increase in the mean and the standard deviation of cost when vehicles communicate less frequently, where the performance degradation is mainly due to constraint violations. In addition, the effect of last communication instant is observed to depend on the system parameters and initial states of the vehicles. If the frequency of communication is high enough, it is better to have communications as close as possible to the target time. However, when communication frequency is low, the trade off between uncertainty and control capability affects the performance.

Our study highlights the need for smart communication resource allocation schemes from a joint control and communications perspective. Effect of more practical channel models, such as fading channels and packet losses in non-orthogonal multiple-access schemes is considered as an important future research direction.

ACKNOWLEDGMENT

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