

On the effects of latency in teleoperated driving: stability and performance analysis

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ABSTRACT

One of the biggest challenges in teleoperation is the latency in communication and actuation, which usually degrades the control performance and sometimes even makes the remote control impossible. In this paper, the effects of latency on the lateral and yaw dynamics of vehicles are investigated during teleoperated driving (ToD). A kinematic bicycle model is equipped with a generic curvature-based controller to represent the teleoperated vehicle. The stability of motion, the convergence rate to a desired trajectory, and the robustness against changes in longitudinal velocity and latency are quantified. It is also shown that the curvature has non-negligible impact on stability, convergence and robustness. Packet losses in the wireless communication and sampled-data control result in a periodic latency. We compare the stability and performance of ToD maneuvers under constant latency and periodic latency. Our results show that the stability of a ToD maneuver under periodic latency is similar to that under constant latency, unless the latency variations in the periodic latency are large. We use numerical simulations of different maneuvers to verify our analytical results for different latency profiles.

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1. Introduction

As the deployment of artificial intelligence in autonomous driving has been accelerated in the past decades [1–3], the risk and safety concerns of driverless vehicles also grew, especially when these vehicles experience onboard system failures. Teleoperated driving (ToD) may be utilised to help automated vehicles in such emergency situations. In addition, ToD may be used in other applications such as fleet delivery and valet parking [4].

As it takes time for the information to go through the communication network, latency plays a pivotal role in teleoperated tasks [5–7]. In case of ToD, latency originates from multiple sources, and it often becomes large enough to cause significant challenges in the operation of the vehicle [8,9]. Testing platforms for ToD have been developed with the consideration of latency to test and improve the performance of ToD via experiments [10,11].

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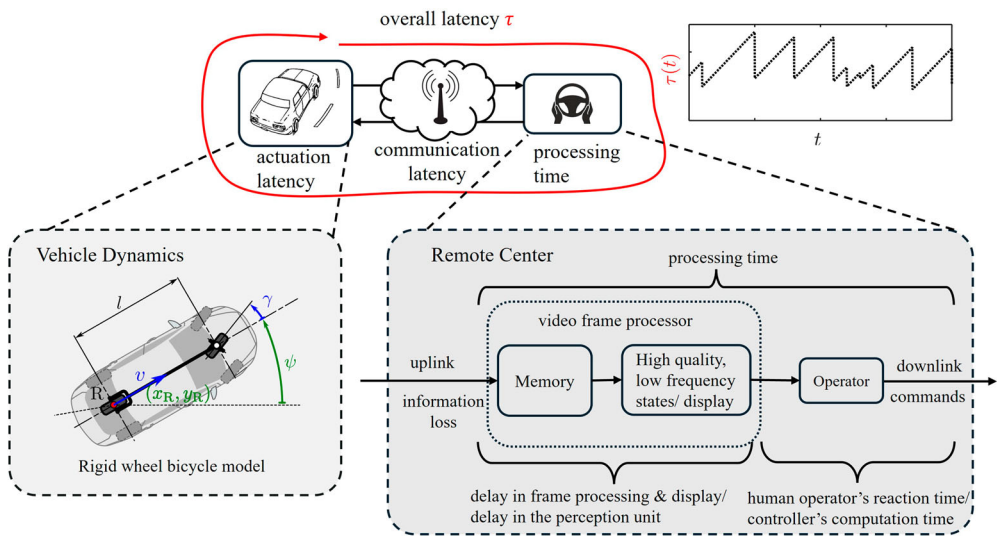


Figure 1. Components in a ToD control loop.

In this work, we aim to quantify the effects of latency in a mathematically rigorous fashion. As illustrated on the top of Figure 1, the overall latency in ToD is composed of the communication latency, the actuation latency, and the processing time of the remote operator. Communication latency refers to the time required to transmit the information through the mobile networks, including the time needed for encoding/decoding as well as the travel time of packets [12–15]. The actuation latency [16] arises from the time required for the actuator to execute the control command. For example, delays may arise in steering controllers and in mechanical actuators [17–21]. The processing time is the time required by the remote operator to generate control commands based on the input information. This includes the image processing time [22], operator sampling time [23] and/or human reaction time [24,25]. In this paper, we consider the overall latency in the ToD system as the sum of the communication latency, actuation latency and processing time, and this overall latency may vary in time as explained below.

For instance, packet loss may occur in the communication network when the transmission data demand is high and the bandwidth is limited. The effect of packet loss can be modelled by increasing the overall delay in the ToD control loop. Assuming that the vehicle actuators continue to execute the same command until a new one is received, the latency increases linearly in time between command updates [26–28]. Once a new command is put in place, the latency drops to its base value, creating a sawtooth-shape profile as illustrated in the top right of Figure 1. The effects of such sawtooth-shape latency on the longitudinal vehicle dynamics has been studied in the context of controlling connected automated vehicles [29,30]. In contrast, this paper focuses on the analysis of the lateral and yaw dynamics in the context of ToD.

Research efforts have been made on reducing communication latency and on mitigating the effects of latency in ToD [31–33]. In general, latency causes troubles in vehicle control [34–37] and researchers have been working around it for decades [38–40]. Predictors [41–45] have been used to compensate for actuation delay and communication delay

in connected automated vehicles. In addition, state-augmenting strategy [46], can also be applied to ToD. The main contribution of this paper is to theoretically quantify ToD performance under latency. In particular, we examine the stability, the convergence rate and the robustness of the ToD system against changes in the overall latency, the longitudinal velocity and the path curvature. Our results provide guidelines for designing and planning ToD tests and maneuvers in real-world scenarios.

The paper is organised as follows. In Section 2, we establish the ToD control loop by introducing the vehicle model, the controller form, and the latency models. In Section 3, we derive the stability condition and the performance boundaries analytically under the assumption of constant latency and we also extend such analysis for time-varying, periodic latency. We provide numerical simulations for a remote parking scenario in Section 4 and conclude the main results with insights on future directions in Section 5.

2. Teleoperated driving system model

In this section, we model the principal components of the ToD system. The vehicle dynamics are represented using a bicycle model that captures the lateral dynamics of the vehicle. Because we want to keep the model as simple as possible, we neglect the effects of the tires, powertrain, and other subsystems. This results in a so-called kinematic bicycle model. The remote operator is represented using a simple, yet general path-following controller. Lastly, we introduce time-varying latency into the closed-loop ToD system.

2.1. Vehicle dynamics and control

Consider a kinematic bicycle model of a vehicle [47,48], where v is the longitudinal velocity and l is the wheelbase. As shown in the left of Figure 1, the centre of the rear axle R has the coordinates (x_R, y_R) , while the orientation of the vehicle is given by the yaw angle ψ , and γ denotes the steering angle. Assuming no side slips at the wheels, the dynamics of the vehicle are given by the differential equations

$$\begin{aligned}\dot{x}_R &= v \cos \psi, \\ \dot{y}_R &= v \sin \psi, \\ \dot{\psi} &= \frac{v}{l} \tan \gamma,\end{aligned}\tag{1}$$

where the dot represents the derivative with respect to time t .

For the general task of following a given path, we rewrite the Equation (1) with respect to the path. This is done by projecting the point R onto the path, see Figure 2. The closest point to R along the path is point C, which is located at (x_C, y_C) and has the tangential angle ψ_C and the curvature κ . Therefore, the lateral deviation from the path is defined as

$$\varepsilon = -(x_R - x_C) \sin \psi_C + (y_R - y_C) \cos \psi_C,\tag{2}$$

and the relative yaw angle is defined as

$$\theta = \psi - \psi_C.\tag{3}$$

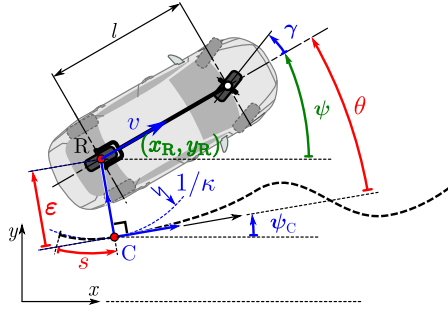


Figure 2. Kinematic bicycle model with respect to path coordinates.

Using these coordinates (1) can be re-formulated as

$$\begin{aligned}\dot{s} &= \frac{v \cos \theta}{1 - \kappa \varepsilon}, \\ \dot{\varepsilon} &= v \sin \theta, \\ \dot{\theta} &= \frac{v}{l} \tan \gamma - \frac{v \kappa \cos \theta}{1 - \kappa \varepsilon},\end{aligned}\quad (4)$$

where s is the arclength at point C. Inspired by previous works [48,49], we consider path-following controllers of the general form

$$\gamma_d = \arctan \left(l \kappa - k_1 (\theta + \arctan(k_2 \varepsilon)) \right), \quad (5)$$

to assign the desired steering angle. Here the term $l \kappa$ is the feed-forward signal based on the curvature of point C and k_1, k_2 are the feedback control gains.

2.2. Latency in teleoperated driving

In real-world implementations, the steering angle commands cannot be achieved immediately due to latency. In this work we assume that the vehicle can realise the desired steering command γ_d with some delay, that is, $\gamma(t) = \gamma_d(t - \tau)$ in (4) and (5). The feedback law (5) represents a generic controller, and it provides a good approximation of human steering [50]. When incorporating the latency in (5), the closed-loop system can be described by the delay differential equations

$$\begin{aligned}\dot{s}(t) &= \frac{v(t) \cos \theta(t)}{1 - \kappa(t) \varepsilon(t)}, \\ \dot{\varepsilon}(t) &= v(t) \sin \theta(t), \\ \dot{\theta}(t) &= -\frac{v(t) \kappa(t) \cos \theta(t)}{1 - \kappa(t) \varepsilon(t)} + \frac{v(t)}{l} \left(l \kappa(t - \tau) - k_1 \left(\theta(t - \tau) + \arctan(k_2 \varepsilon(t - \tau)) \right) \right).\end{aligned}\quad (6)$$

The delay τ represents the overall latency including the communication latency, the processing time of the remote operator and the actuation time of the vehicle. This sum is

usually time-varying since the communication latency changes with varying network traffic [49,51]. Observe that both the longitudinal velocity v and the curvature κ depend on time.

Figure 3 is to demonstrate that the latency in ToD can be time-varying with an irregular sawtooth shape, and it may be approximated by periodic sawtooth latencies. The dashed curves in Figure 3 depict time-varying latency profiles obtained from simulating communication networks under two different communication conditions. The sawtooth shape comes from the fact that the control commands are generated at a slower frequency compared to sampling frequency of the sensor. Moreover, packet loss happens randomly, and the travel time of each packet also follows a random distribution. These effects result in stochastic time-varying latency profiles. Data 1 in Figure 3(a) and Data 2 in panels (b) and (c) represent two edge scenarios. In case of Data 1, all transmitted packets are received while in case of Data 2 only 10 percent of all packets are received. Details behind these two edge cases and the underlying probabilistic models are presented in [49,52]. Previous research [49] indicates that the latency variation and the deviations in ToD behaviours are not significant when the packet loss rate is low. However, as demonstrated below, having high packet loss rate significantly affects the latency variations which may also impact the ToD performance.

The sawtooth shape of Data 1 aligns well with a periodic sawtooth latency profile. For the data, the minimum in each tooth is slightly different due to the difference between the network transmission frequency and the remote controller processing rate, but this difference is negligible. The sawtooth shape of Data 2 may also be approximated with a periodic latency profile, but the differences are now larger due to the stochastic nature of the packet drops in the data. We provide two example periodic signals to approximate the Data 2: a one-tooth periodic latency in panel (b) and a two-tooth periodic latency in panel (c). All periodic approximations are constructed such that the minimum delay $\tau_{\min}$ and the average delay τ_{ave} are the same for the data and for the approximating periodic signal. For the one-tooth periodic signal, the maximum delay becomes $\tau_{\max} = \tau_{\text{ave}} + (\tau_{\text{ave}} - \tau_{\min})$ and this is typically not the same as the maximum delay for the data. The length of each period is $T = \tau_{\max} - \tau_{\min} = 2(\tau_{\text{ave}} - \tau_{\min})$, and the shape is determined as well. For the two-tooth periodic signal, two maximum delays $\tau_{\max,1}$, $\tau_{\max,2}$ are required. In this case, the shape of the two-tooth latency profile is also determined if the period T is given. More details about the two-tooth periodic latency will be discussed in Section 3.2.

Note that there exist many different stochastic data profiles which share the same $\tau_{\min}$ and the same τ_{ave} . We restrict the shape to the one-tooth and two-tooth profiles here for simplicity, but one may create periodic delay profiles with more ‘teeth’ to better capture different peaks in the stochastic latency profile. Analysing the dynamics under stochastic delay variations is challenging [53], but it was demonstrated in [54] that using the periodic approximations may allow one to capture the key phenomena in terms of stability and input-output behaviour. In fact, the difference in the sampling frequency of multi-level control indeed leads to multiple-tooth periodic delay [55], which may also happen in teleoperated driving even with perfect communication. Our method is able to generalise the stability analysis for those problems and study the difference between the constant and periodic delays. As in some scenarios using constant average delay may be adequate [56,57], in the next section we analyse the stability and performance under constant delay first, before presenting the results for periodic delays.

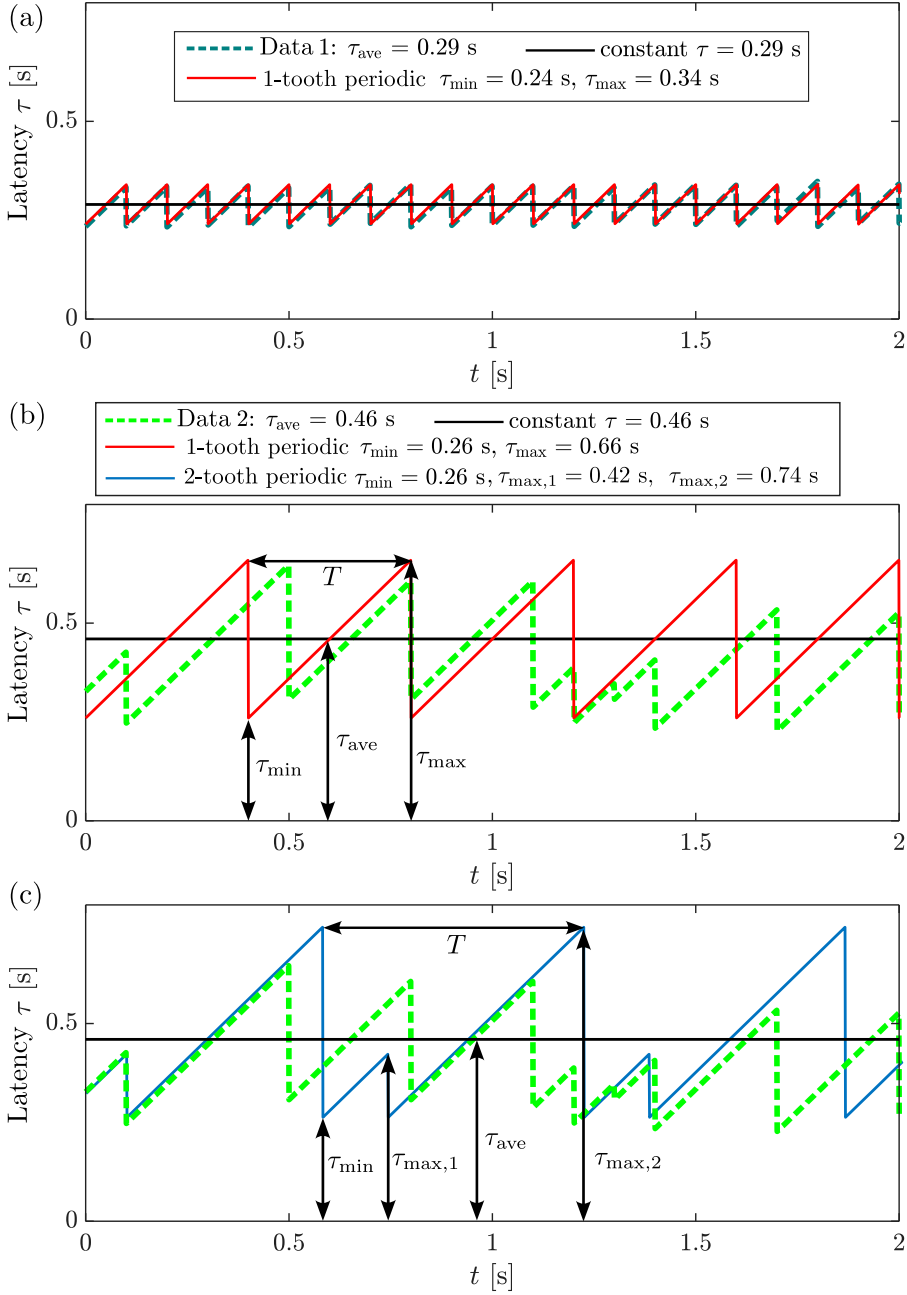


Figure 3. Two examples of stochastic time-varying latency under different communication network conditions (Data 1 and Data 2). These are compared to their constant latency approximations (black lines) and periodic latency approximations (red and blue curves).

3. Linear stability and performance analysis

In this section, we study the stability and control performance of the closed-loop dynamics (6) under both constant and periodic latency profiles.

For stability analysis we assume that the vehicle is running with a constant longitudinal velocity $v(t) \equiv v_*$ while trying to approach a circular reference path of constant curvature $\kappa(t) \equiv \kappa_*$. Accordingly, the desired steady-state solution is

$$s_*(t) = v_* t, \quad \varepsilon_*(t) \equiv 0, \quad \theta_*(t) \equiv 0. \quad (7)$$

By defining the perturbations $\tilde{s} = s - s_*$, $\tilde{\varepsilon} = \varepsilon - \varepsilon_*$, $\tilde{\theta} = \theta - \theta_*$, we can obtain the linearised system

$$\begin{aligned} \dot{\tilde{s}}(t) &= v_* \kappa_* \tilde{\varepsilon}(t), \\ \dot{\tilde{\varepsilon}}(t) &= v_* \tilde{\theta}(t), \\ \dot{\tilde{\theta}}(t) &= -v_* \kappa_*^2 \tilde{\varepsilon}(t) - \frac{v_* k_1 k_2}{l} \tilde{\varepsilon}(t - \tau) - \frac{v_* k_1}{l} \tilde{\theta}(t - \tau). \end{aligned} \quad (8)$$

This can be nondimensionalized by using the scaled quantities $\hat{t} = t v_*/l$, $\hat{\tau} = \tau v_*/l$, $\hat{s} = \tilde{s}/l$, $\hat{\varepsilon} = \tilde{\varepsilon}/l$, $\hat{\theta} = \tilde{\theta}$ to obtain

$$\begin{aligned} \hat{s}'(\hat{t}) &= l \kappa_* \hat{\varepsilon}(\hat{t}), \\ \hat{\varepsilon}'(\hat{t}) &= \hat{\theta}(\hat{t}), \\ \hat{\theta}'(\hat{t}) &= -l^2 \kappa_*^2 \hat{\varepsilon}(\hat{t}) - k_1 k_2 l \hat{\varepsilon}(\hat{t} - \hat{\tau}) - k_1 \hat{\theta}(\hat{t} - \hat{\tau}), \end{aligned} \quad (9)$$

where the prime represents the derivative with respect to the dimensionless time $\hat{t}$ and the latency in the new system is now the dimensionless delay $\hat{\tau}$. The nondimensionalisation does not alter the stability properties of the original system (8), but demonstrates that the velocity and the latency have the same effect on stability. In fact, varying v^* and τ such that $\hat{\tau} = \tau v_*/l$ is kept the same means that the vehicle is running along the same trajectory in space, see the example in [58].

To simplify the notation, we utilise the dimensionless gains

$$\begin{aligned} k_\theta &= k_1, \\ k_\varepsilon &= k_1 k_2 l, \end{aligned} \quad (10)$$

corresponding to the yaw angle error and lateral error, respectively. As the stability is determined by the second and third rows of (9), we arrive at the system

$$\begin{aligned} \mathbf{x}'(\hat{t}) &= \mathbf{a}\mathbf{x}(\hat{t}) + \mathbf{b}\mathbf{x}(\hat{t} - \hat{\tau}), \\ \mathbf{x} &= \begin{bmatrix} \hat{\varepsilon} \\ \hat{\theta} \end{bmatrix}, \quad \mathbf{a} = \begin{bmatrix} 0 & 1 \\ -l^2 \kappa_*^2 & 0 \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} 0 & 0 \\ -k_\varepsilon & -k_\theta \end{bmatrix}. \end{aligned} \quad (11)$$

3.1. Constant latency

First, we consider a constant overall latency, which also results in a constant dimensionless delay $\hat{\tau} = \tau v_*/l$. The characteristic equation of (11) is given by

$$\lambda^2 + k_\theta \lambda e^{-\lambda \hat{\tau}} + k_\varepsilon e^{-\lambda \hat{\tau}} + l^2 \kappa_*^2 = 0, \quad (12)$$

which has infinitely many characteristic roots λ in the complex plane due to the delay. The rightmost roots give the dominant behaviour of the system. When all characteristic roots

are on the left half complex plane, the steady state solution is stable, and the real parts of the rightmost roots indicate how fast the state of the dynamical system converges to the steady state (7). Thus, we quantify the control performance using the real part of the rightmost roots. When the leading roots are on the negative real axis, the system converges to the steady state without oscillations. When the imaginary parts of the rightmost roots are nonzero, oscillatory behaviour is observed (see Figure 6(b,c) for demonstration).

By substituting $\lambda = \rho + j\omega$, $\omega \geq 0$ into the characteristic Equation (12), one can solve for the gains k_θ and k_ε as a function of ρ and ω . We compute performance boundaries on the plane of the gain parameters as curves that belong to a given convergence rate ρ . For $\omega = 0$, we have the performance boundaries

$$\begin{aligned} k_\theta &= -e^{\rho\hat{\tau}}((\rho^2 + l^2\kappa_*^2)\hat{\tau} + 2\rho), \\ k_\varepsilon &= -e^{\rho\hat{\tau}}(\rho^2 + l^2\kappa_*^2) - \rho k_\theta, \end{aligned} \quad (13)$$

that are straight lines in the $(k_\theta, k_\varepsilon)$ plane. For $\omega > 0$, we obtain

$$\begin{aligned} k_\theta &= e^{\rho\hat{\tau}} \frac{(\omega^2 - l^2\kappa_*^2 - \rho^2) \sin(\omega\hat{\tau}) - 2\rho\omega \cos(\omega\hat{\tau})}{\omega}, \\ k_\varepsilon &= e^{\rho\hat{\tau}} \left((\omega^2 - l^2\kappa_*^2 - \rho^2) \cos(\omega\hat{\tau}) + 2\rho\omega \sin(\omega\hat{\tau}) \right) - \rho k_\theta. \end{aligned} \quad (14)$$

which are curves parameterised by the angular frequency ω such that the angular frequency increases from $\omega = 0$ as moving along the performance boundary.

Substituting $\rho = 0$ yields the stability boundaries

$$k_\varepsilon = -l^2\kappa_*^2, \quad (15)$$

and

$$\begin{aligned} k_\theta &= (\omega^2 - l^2\kappa_*^2) \frac{\sin(\omega\hat{\tau})}{\omega}, \\ k_\varepsilon &= (\omega^2 - l^2\kappa_*^2) \cos(\omega\hat{\tau}). \end{aligned} \quad (16)$$

The performance boundaries of different convergence rates (including the stability boundaries) are shown in Figure 4(a–c) for curvatures $\kappa_* = 0 \text{ m}^{-1}$, $\kappa_* = 0.125 \text{ m}^{-1}$ and $\kappa_* = 0.2 \text{ m}^{-1}$, respectively. The other parameter are chosen as $l = 2.73 \text{ m}$, $v_* = 3 \text{ m/s}$ and $\tau = 0.46 \text{ s}$, yielding $\hat{\tau} = 0.5$. The maximum steering angle of a passenger car is usually 30–45 degrees [59]. For a steering angle $\gamma_{\max} = 30^\circ = 0.5236 \text{ rad}$, the circular path has the radius of $R = l / \tan(\gamma_{\max}) = 4.73 \text{ m}$, which corresponds to the curvature $\kappa_* = \tan(\gamma_{\max}) / l = 0.21 \text{ m}^{-1}$. The outmost boundaries belong to $\rho = 0$. These stability boundaries enclose the stable (lightly shaded) area, for which $\rho < 0$. As ρ decreases, the region enclosed by performance curves shrinks as illustrated by darker shadings.

Eventually the area disappears at $\rho = \rho_{\text{fast}}$, which gives the fastest convergence rate in space. This happens when the slope of (13) and the slope of (14) for $\omega \rightarrow 0$ become equal. This yields

$$\rho_{\text{fast}} = -\frac{2}{\hat{\tau}} + \sqrt{\frac{2}{\hat{\tau}^2} - l^2\kappa_*^2}, \quad (17)$$

when $\hat{\tau} \leq \sqrt{2}/(l\kappa_*)$. For $\hat{\tau} > \sqrt{2}/(l\kappa_*)$ the fastest convergence rate can be determined numerically but in this case the longitudinal velocity is so large that the kinematic bicycle

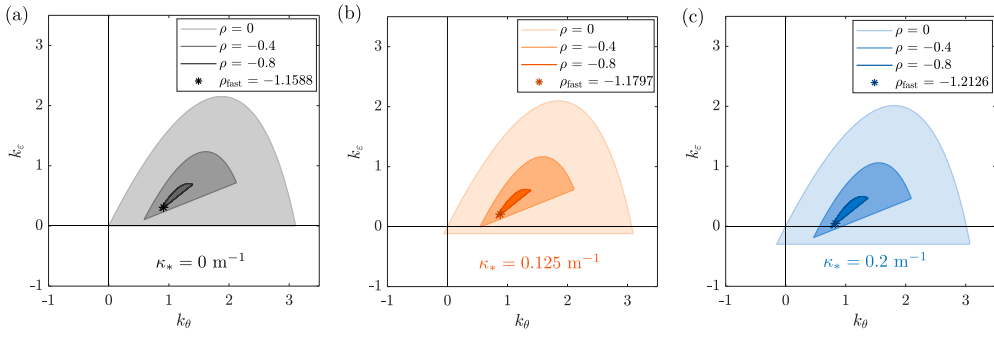


Figure 4. Performance boundaries and stability boundaries for $\hat{\tau} = 0.5$ ($l = 2.73$ m, $v_* = 3$ m/s and $\tau = 0.46$ s). The stars indicate gains of fastest convergence. Different panels correspond to different curvatures: (a) $\kappa_* = 0$, (b) $\kappa_* = 0.125$ m $^{-1}$, and (c) $\kappa_* = 0.2$ m $^{-1}$.

model loses its validity. According to (13) the control gains corresponding to the fastest convergence are

$$\begin{aligned} k_{\theta}^{\text{fast}} &= -e^{\rho_{\text{fast}} \hat{\tau}} \left((\rho_{\text{fast}}^2 + l^2 \kappa_*^2) \hat{\tau} + 2\rho_{\text{fast}} \right), \\ k_{\varepsilon}^{\text{fast}} &= -e^{\rho_{\text{fast}} \hat{\tau}} (\rho_{\text{fast}}^2 + l^2 \kappa_*^2) - \rho_{\text{fast}} k_{\theta}^{\text{fast}}. \end{aligned} \quad (18)$$

When following a straight path ($\kappa_* = 0$), the fastest convergence rate (17) and gains (18) simplify to

$$\rho_{\text{fast}} = \frac{\sqrt{2} - 2}{\hat{\tau}}, \quad (19)$$

and

$$\begin{aligned} k_{\theta}^{\text{fast}} &= e^{\sqrt{2}-2} \frac{2\sqrt{2} - 2}{\hat{\tau}}, \\ k_{\varepsilon}^{\text{fast}} &= e^{\sqrt{2}-2} \frac{10\sqrt{2} - 14}{\hat{\tau}^2}, \end{aligned} \quad (20)$$

respectively, see [33].

The fastest convergence rate (17) is plotted as a function of $\hat{\tau}$ in Figure 5(a) for different curvature values. For small dimensionless delay values $\hat{\tau} < 0.5$, the fastest convergence rate changes rapidly and the influence of the curvature is negligible. Note that for $\kappa_* = 0$, ρ_{fast} increases monotonically with $\hat{\tau}$, while for $\kappa_* > 0$, the curve has a maximum. The location of fastest convergence gains (18) are shown in Figure 5(b) for different curvature values. Along each curve, the dimensionless delay increases from right to left and stars mark the fastest convergence gains when $\hat{\tau} = 0.5$ (also shown in Figures 4 and 6).

Since these curves intersect the stability boundary (16) for other delay values, the fastest convergence gains for a certain $\hat{\tau}$ may still lead to unstable behaviour if the dimensionless delay is increased to $\hat{\tau}_{\text{cr}}$. For example, in Figure 6(a), the blue star marks the fastest convergence gains for $\hat{\tau} = 0.5$, and this is located on the stability boundary of the larger delay $\hat{\tau}_{\text{cr}} = 1.38$. The same control gains correspond to different leading characteristic roots in

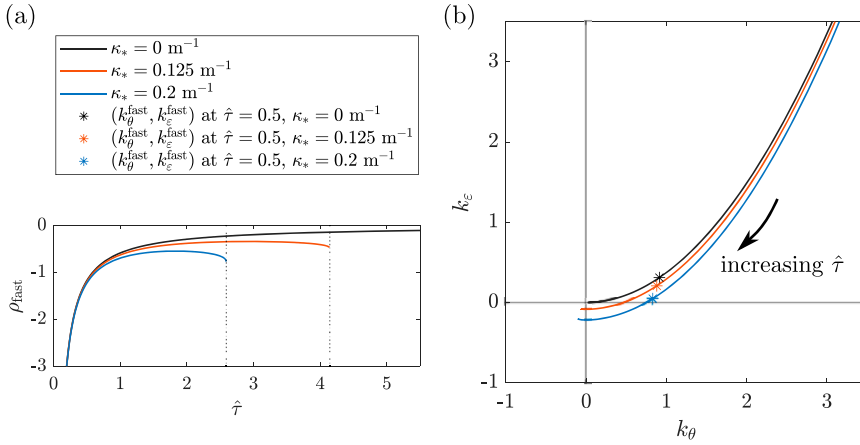


Figure 5. (a) Fastest convergence rates for different curvatures as a function of the dimensionless delay. (b) Fastest convergence gains for different curvatures.

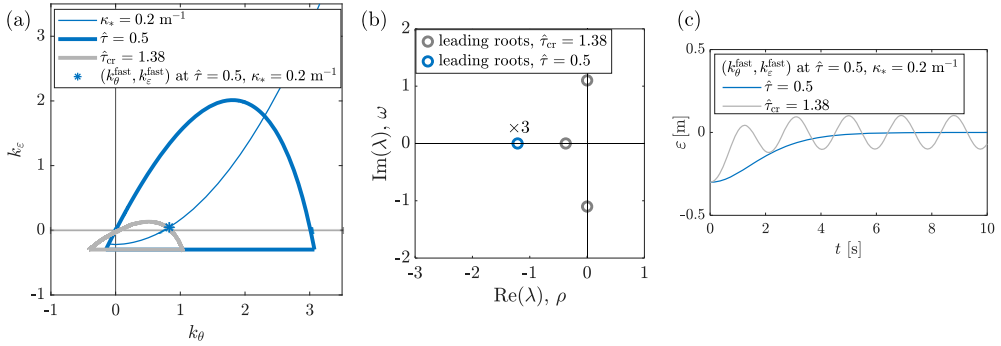


Figure 6. Stability chart, characteristic roots and simulations of following a circular path (radius 5 m) under $\hat{\tau}$ and $\hat{\tau}_{\text{cr}}$ while using the same control gains. (a) The fastest-convergence gains obtained for $\hat{\tau}$ are located on the stability boundary for $\hat{\tau}_{\text{cr}}$. (b) The leading characteristic roots for the same gains under different dimensionless delays. (c) Simulation of lateral error while using the two different delays.

panel (b), due to the change in the dimensionless delays. For $\hat{\tau} = 0.5$ the leading roots are given by a triple root with negative real part, while for $\hat{\tau}_{\text{cr}} = 1.38$ two of these roots form a purely imaginary complex conjugate pair. Simulations of the lateral error under different dimensionless delays are shown in panel (c). For $\hat{\tau} = 0.5$ the error decays, while for $\hat{\tau}_{\text{cr}} = 1.38$ periodic oscillations develop, whose angular frequency is close to that of the leading roots.

One can derive the critical dimensionless delay $\hat{\tau}_{\text{cr}}$ for which the stability is lost when the fastest convergence control gains are chosen for a certain dimensionless delay $\hat{\tau}$. By setting the Equation (16) equal to (18) yields

$$\begin{aligned} k_\theta^{\text{fast}}(\hat{\tau}) &= k_\theta(\hat{\tau}_{\text{cr}}, \omega_{\text{cr}}), \\ k_\varepsilon^{\text{fast}}(\hat{\tau}) &= k_\varepsilon(\hat{\tau}_{\text{cr}}, \omega_{\text{cr}}), \end{aligned} \quad (21)$$

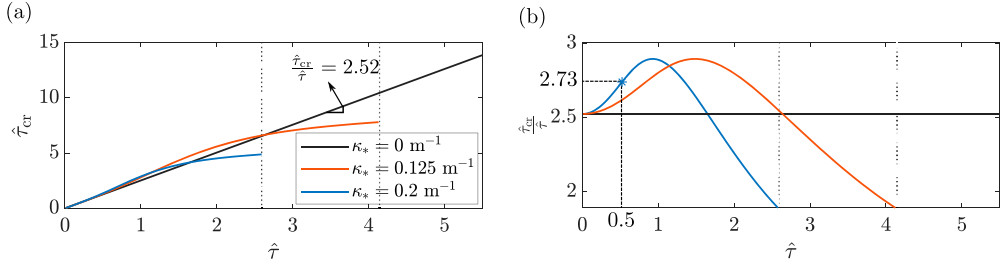


Figure 7. (a) Critical dimensionless delay as a function of the dimensionless delay. For the straight path ($\kappa_* = 0 \text{ m}^{-1}$), the slope is constant. (b) Robustness coefficients as a function of the dimensionless delay.

which can be solved for $\hat{\tau}_{cr}$, ω_{cr} given $\hat{\tau}$, as shown in Figure 7(a) for different curvatures κ_* . We define a robustness coefficient $\hat{\tau}_{cr}/\hat{\tau}$ to represent how much increase in the dimensionless delay the system can withstand before it loses stability. The robustness coefficients shown in panel (b) correspond to the slope of the curves in panel (a).

For circular paths ($\kappa_* > 0$), the coefficient first increases and then decreases with $\hat{\tau}$. These changes occur faster for larger values of curvature. For $\kappa_* = 0.2 \text{ m}^{-1}$ and $\hat{\tau} = 0.5$, the coefficient is around 2.73, yielding $\hat{\tau}_{cr} = 1.38$.

For straight paths ($\kappa_* = 0$), Equation (21) can be solved analytically, giving the universal constant

$$\frac{\hat{\tau}_{cr}}{\hat{\tau}} = \sqrt{\frac{2}{p^2 + \sqrt{p^4 + 4q^2}}} \sin^{-1} \left(\sqrt{\frac{2p^2}{p^2 + \sqrt{p^4 + 4q^2}}} \right) \approx 2.52, \quad (22)$$

where $p = e^{\sqrt{2}-2}(2\sqrt{2} - 2)$ and $q = e^{\sqrt{2}-2}(10\sqrt{2} - 14)$, cf. (20). This is reflected as the straight black lines in Figure 7.

3.2. Periodic latency

In this section, we study the stability and convergence of system (11) under periodic saw-tooth latency profiles. By discretizing time, a corresponding discrete-time system is derived and the stability is studied via the state transition matrix of the augmented state over one period.

First, we consider the latency profile where the delay increases from $\tau_{\min}$ to $\tau_{\max}$ with gradient 1 before dropping back to $\tau_{\min}$, see Figure 8(a,d). The period of these oscillations is $T = \tau_{\max} - \tau_{\min}$ while the average delay is $\tau_{\text{ave}} = (\tau_{\max} + \tau_{\min})/2$. Rescaling the time by v/l , the dimensionless delay increases with slope 1 from $\hat{\tau}_{\min}$ to $\hat{\tau}_{\max}$ within each period of $\hat{T} = \hat{\tau}_{\max} - \hat{\tau}_{\min}$. This variation is a result of the zero-order hold applied on the input, which is equivalent of making $\mathbf{x}(\hat{t} - \hat{\tau})$ constant over $\hat{\tau} \in [\hat{\tau}_{\min}, \hat{\tau}_{\max}]$.

We discretise time while choosing the time step $\Delta\hat{t}$ such that $\hat{\tau}_{\min} = n\Delta\hat{t}$, $\hat{\tau}_{\max} = m\Delta\hat{t}$ where $n, m \in \mathbb{Z}^+$. Due to the zero-order hold, for $\hat{t} \in [k\Delta\hat{t}, (k+1)\Delta\hat{t}]$, we have $\mathbf{x}(\hat{t} - \hat{\tau}) \equiv \mathbf{x}((k-i)\Delta\hat{t}) = \mathbf{x}_{k-i}$, where $\hat{\tau}(\hat{t}) = \hat{t} + (i-k)\Delta\hat{t}$ and $i = n + (k \bmod (m-n))$. Using semi-discretization [56], we can obtain the discrete-time system

$$\mathbf{x}_{k+1} = \mathbf{P}\mathbf{x}_k + \mathbf{R}\mathbf{x}_{k-i}, \quad (23)$$

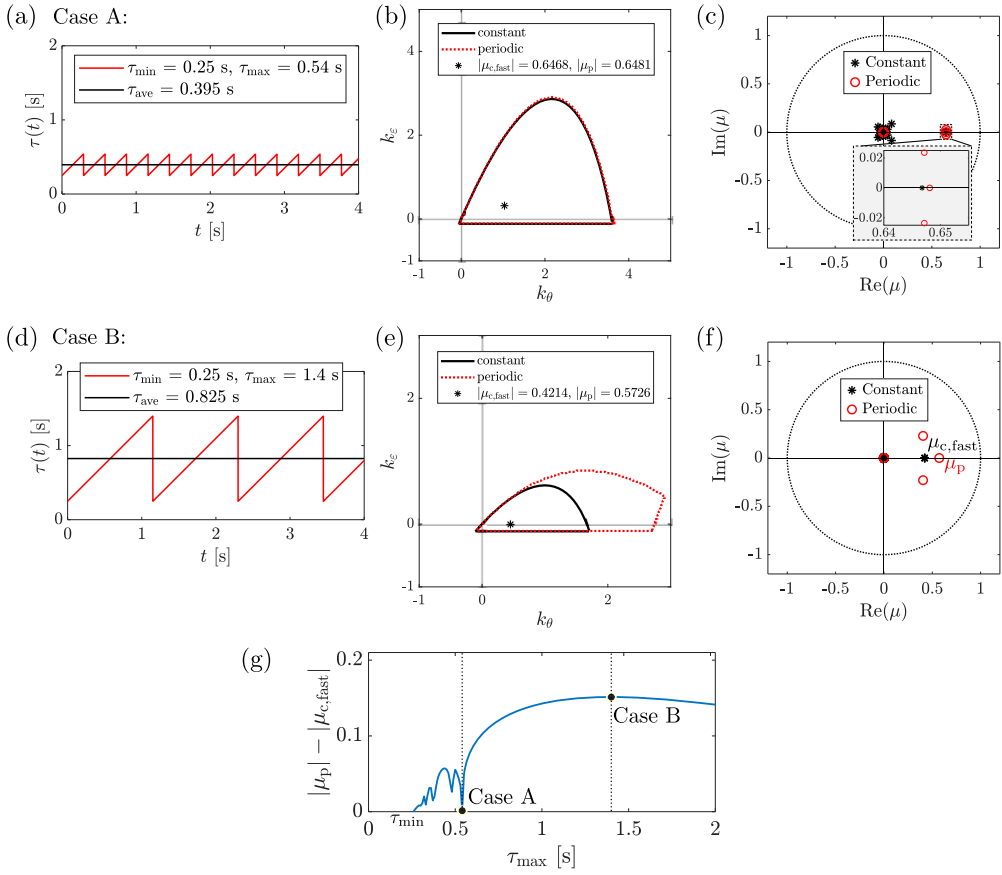


Figure 8. Comparing the stability boundaries and the characteristic multipliers under constant and periodic sawtooth latency profiles, when the gains are chosen based on the fastest convergence under the constant average of the periodic sawtooth latency for $v = 3$ m/s, $\kappa_* = 0.125$ m⁻¹. Case A (panels (a)–(c)) and Case B (panels (d)–(f)) differ in the value $\tau_{\max}$. (g) Difference in the magnitude of the largest characteristic multiplier when considering constant vs. periodic latency.

where

$$\mathbf{P} = \mathbf{e}^{\mathbf{a}\Delta\hat{t}}, \quad \mathbf{R} = \int_0^{\Delta\hat{t}} \mathbf{e}^{\mathbf{a}(\Delta\hat{t}-s)} \mathbf{d}s \mathbf{b} = (\mathbf{P} - \mathbf{I})\mathbf{a}^{-1}\mathbf{b}, \quad (24)$$

and the last equality only holds when $\mathbf{a}$ is invertible, which is the case when $\kappa_* > 0$. For $\kappa_* = 0$ (straight path) $\mathbf{a}$ is not invertible and we have

$$\mathbf{P} = \begin{bmatrix} 1 & \Delta\hat{t} \\ 0 & 1 \end{bmatrix}, \quad \mathbf{R} = \begin{bmatrix} -k_\theta \Delta\hat{t}/2 & -k_\varepsilon \Delta\hat{t}/2 \\ -k_\theta & -k_\varepsilon \end{bmatrix} \Delta\hat{t}. \quad (25)$$

From the system (23), we construct an augmented system

$$\mathbf{X}_{k+1} = \mathbf{A}_i \mathbf{X}_k, \quad (26)$$

where

$$\mathbf{X}_k = \begin{bmatrix} \mathbf{x}_k \\ \mathbf{x}_{k-1} \\ \vdots \\ \mathbf{x}_{k-i} \\ \vdots \\ \mathbf{x}_{k-m+1} \end{bmatrix} \in \mathbb{R}^{2m}, \quad \mathbf{A}_i = \begin{bmatrix} \mathbf{P} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{R} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{I} & \mathbf{0} & & & \cdots & & & \mathbf{0} \\ \mathbf{0} & \mathbf{I} & & & \cdots & & & \mathbf{0} \\ \vdots & \vdots & & & \ddots & & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & & & \ddots & & \mathbf{I} & \mathbf{0} \end{bmatrix}, \quad (27)$$

and the matrix $\mathbf{R}$ is located in the $(i+1)$ -st block column of $\mathbf{A}_i$. This system describes the discrete time dynamics between $\hat{t} = k\Delta\hat{t}$ and $\hat{t} = (k+1)\Delta\hat{t}$, while the index i changes periodically with k . The computation cost increases with the decrease of discretization time step $\Delta\hat{t}$. We choose $\Delta\hat{t}$ such that the greatest common divisor of m and n is 1 to achieve the minimum computation cost while maintaining the accuracy of the stability boundary calculation.

For stability we look at the discrete-time system over one period $\hat{T} = (m-n)\Delta\hat{t}$:

$$\mathbf{X}_{k+m-n} = \mathbf{A}\mathbf{X}_k, \quad \mathbf{A} = \prod_{i=n}^{m-1} \mathbf{A}_i, \quad (28)$$

where k is the starting index of each period. This system is stable if and only if all the characteristic multipliers (i.e. the solutions of $\det(\mu\mathbf{I} - \mathbf{A}) = 0$) are within the unit circle, that is, $|\mu| < 1$. To determine the fastest convergence with periodic sawtooth latency profile, we minimise the absolute value of the outermost multiplier.

The same methodology can be applied for other periodic sawtooth type delay profiles. For instance, we consider the case where two teeth of different sizes are contained with a period, as shown in Figures 3(c) and 10(a). Assume that the delay first increases from a minimum value $\tau_{\min}$ to $\tau_{\max,1}$ and then again increases from $\tau_{\min}$ to another value $\tau_{\max,2}$. The period of this profile is $T = \tau_{\max,1} + \tau_{\max,2} - 2\tau_{\min}$. When $\tau_{\max,1} = \tau_{\max,2} = \tau_{\max}$ one obtains two periods of the one-tooth periodic delay profile. The average delay can be calculated as

$$\tau_{\text{ave}} = \frac{(\tau_{\max,1} + \tau_{\min})(\tau_{\max,1} - \tau_{\min}) + (\tau_{\max,2} + \tau_{\min})(\tau_{\max,2} - \tau_{\min})}{2T}. \quad (29)$$

After rescaling time with v/l , we discretise it with time step $\Delta\hat{t}$ such that $\hat{t}_{\min} = n\Delta\hat{t}$, $\hat{t}_{\max,1} = m_1\Delta\hat{t}$ and $\hat{t}_{\max,2} = m_2\Delta\hat{t}$ where $n, m_1, m_2 \in \mathbb{Z}^+$. Then we have $\hat{T} = (m_1 + m_2 - 2n)\Delta\hat{t}$. Again, we can construct an augmented system similar to (26), (27), where $m = \max\{m_1, m_2\}$. Then the discrete-time system over one period $\hat{T}$ gives

$$\mathbf{X}_{k+m_1+m_2-2n} = \mathbf{A}\mathbf{X}_k, \quad \mathbf{A} = \prod_{i=n}^{m_1-1} \mathbf{A}_i \prod_{j=n}^{m_2-1} \mathbf{A}_j. \quad (30)$$

Stability again can be determined by examining whether the outermost characteristic multipliers (i.e. the largest solutions of $\det(\mu\mathbf{I} - \mathbf{A}) = 0$) are within the unit circle.

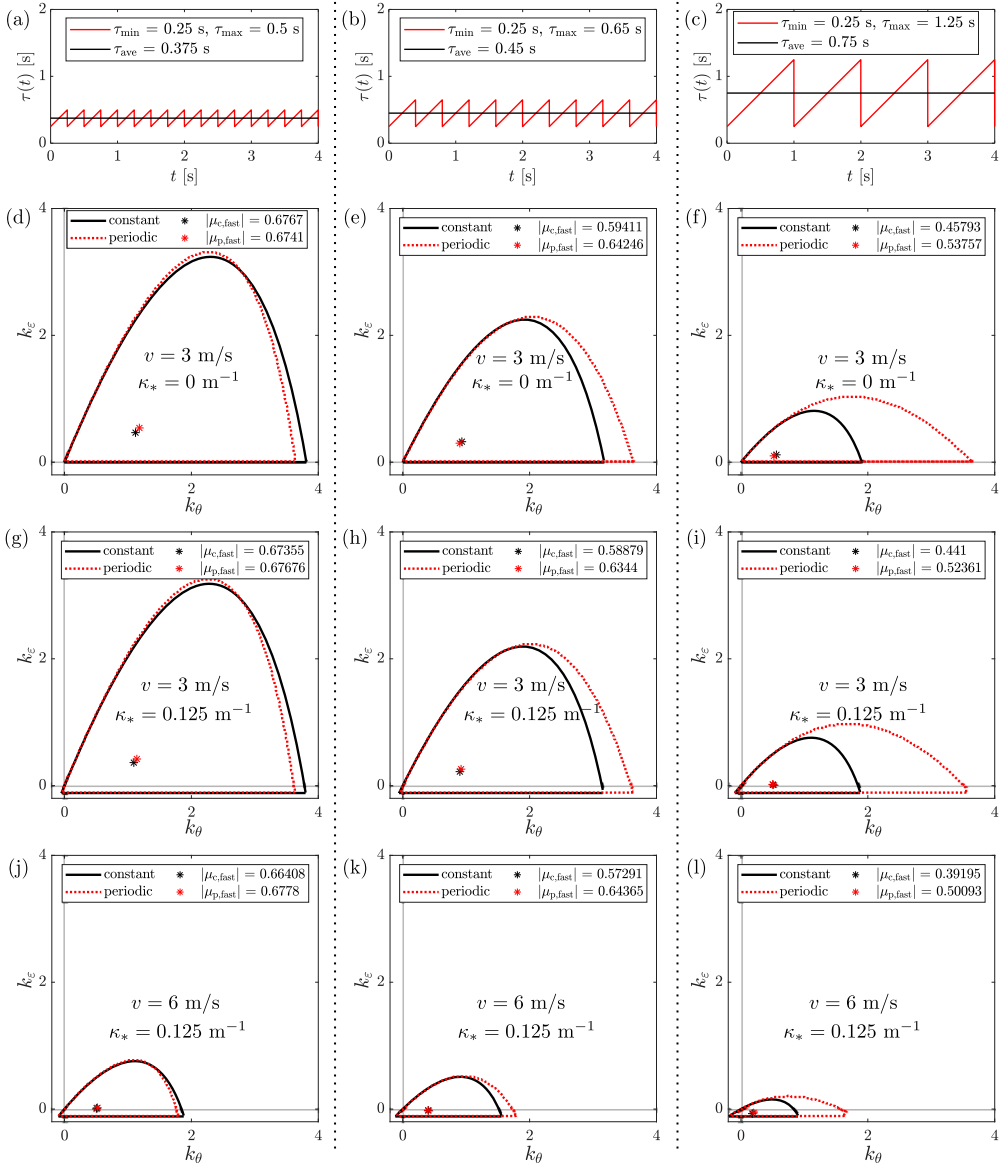


Figure 9. (a)–(c) Three different sawtooth latency profiles with same τ_{min} but different τ_{max} . (d)–(l) Comparing stability charts for periodic sawtooth latency profiles and the corresponding average constant latency for different curvatures and longitudinal velocities when $l = 2.73$ m.

3.3. Comparison of performance under constant and periodic latencies

In this section, we compare the stability and convergence properties of ToD systems with different latency approximations: constant latency versus periodic sawtooth latency.

To compare the stability under constant latency (which was analysed in continuous time) to the stability under periodic latency (which was analysed in discrete time), we need to convert the characteristic roots of the continuous-time system into the characteristic

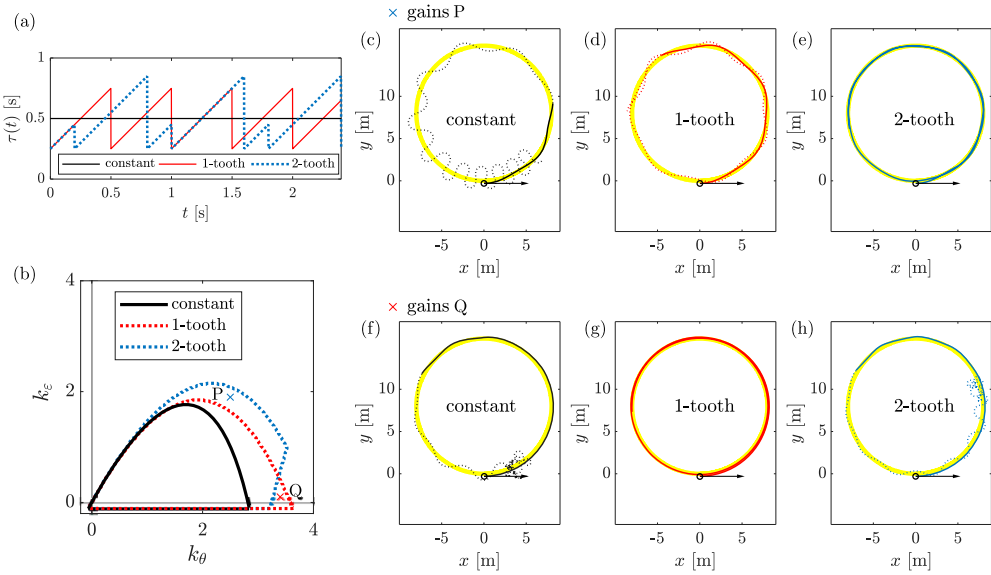


Figure 10. Stability and simulations under latency profiles for $v = 3 \text{ m/s}$, $\kappa_* = 0.125 \text{ m}^{-1}$. (a) Three delay profiles share the same average latency $\tau_{\text{ave}} = 0.5 \text{ s}$. (b) Stability charts for three latency profiles. Two gain combinations marked as P and Q are selected for simulations. (c)–(e) Simulations with gains P under different latency profiles. (f)–(h) Simulations with gains Q under different latency profiles. Dotted sections of the trajectories indicate that the steering angle exceeds 45 degrees.

multipliers used in the discrete-time system. Namely, $\mu = e^{\lambda \hat{T}}$ which yields $|\mu| = e^{\rho \hat{T}}$ where $\hat{T}$ is the period. That is, the fastest-convergence rate ρ_{fast} in the continuous time corresponds to

$$|\mu_{\text{c,fast}}| = \left| e^{\rho_{\text{fast}} \hat{T}} \right|. \quad (31)$$

If the fastest convergence control gains are chosen based on the constant latency analysis, the performance drops under the periodic latency.

The sawtooth latency profile in Figure 8(a) has a minimum value $\tau_{\min} = 0.25 \text{ s}$ and the maximum value $\tau_{\max} = 0.54 \text{ s}$. The corresponding stability boundaries are shown in panel (b) together with the stability boundaries (15), (16) of the continuous-time system with constant average latency $\tau_{\text{ave}} = 0.395 \text{ s}$. The fastest convergence gains k_θ^{fast} , $k_\varepsilon^{\text{fast}}$ under the constant latency are marked by the black star. The characteristic multipliers of these gains are plotted in panel (c) under constant latency (black) and periodic latency (red). The periodic latency results in $(2m - 3)$ characteristic multipliers which are either zero or very close to zero where $2m$ is the dimension of the augmented state in (27). These $(2m - 3)$ multipliers correspond to characteristic roots with large negative real parts, which are indicated as black stars around the origin. One of the three leading multipliers is located at the real axis and the other two form a complex conjugate pair. The real multiplier has the largest magnitude and this is denoted by μ_p . There are also three leading multipliers for the constant latency in the discrete-time representation corresponding to the three leading characteristic roots in Figure 6(b). These coincide at the real axis and are denoted by $\mu_{\text{c,fast}}$. As shown by the zoom in panel (c), $\mu_{\text{c,fast}}$ is slightly closer to the origin than μ_p .

The sawtooth latency profile in Figure 8(d) also has minimum value $\tau_{\min} = 0.25$ s but now the maximum value is $\tau_{\max} = 1.4$ s, yielding the average latency $\tau_{\text{ave}} = 0.825$ s. The corresponding stability boundaries are shown in panel (e) and these indeed show significant deviations between the constant delay and the periodic delay cases. The multipliers corresponding to the fastest convergence gains (calculated for constant delay) are plotted in panel (f), where the difference between the leading multipliers becomes $|\mu_p| - |\mu_{c,\text{fast}}| = 0.1512$. The positive value indicates that the periodic latency model converges to the steady state slower than the constant latency model. To further illustrate this performance degradation, in Figure 8(g) we plot the difference $|\mu_p| - |\mu_{c,\text{fast}}|$ as a function of the maximum latency $\tau_{\max}$ between 0.26 to 2 s, while keeping the minimum latency at $\tau_{\min} = 0.25$ s. This becomes more pronounced when the difference between $\tau_{\min}$ and $\tau_{\max}$ is large. The periodic latency profiles of Case A and Case B are marked on the curve.

To further illustrate the behavioural differences between the constant and periodic latencies, we plot the stability boundaries for different values of $\tau_{\max}$ in Figure 9. As $\tau_{\min}$ is kept the same, τ_{ave} increases with $\tau_{\max}$. The charts in each column correspond to the latency profiles in the first row. As the average latency increases (from left to right), the stable regions shrink. The stability boundaries of the constant latency and the periodic latency remain close unless $\tau_{\max}$ is significantly larger than $\tau_{\min}$. Moreover, we demonstrate the impacts of curvature and longitudinal velocity while increasing the curvature from 0 to 0.125 m^{-1} (from the second to the third row), and increasing the velocity from 3 m/s to 6 m/s (from the third to the fourth row). The increase of curvature shifts the stable region down while the increase of velocity reduces the size of the stable region. We can observe that the black stability boundaries in the panels (i) and (j) are identical as these correspond to the same dimensionless delay $\hat{\tau}_{\text{ave}}$.

For the case of periodic latency in discrete time, its fastest convergence gains correspond to the smallest leading multipliers denoted by $|\mu_{p,\text{fast}}|$. These can be obtained numerically and are marked by red stars in Figure 9(d–l). These are close to the fastest convergence gains obtained under the constant delay approximation, marked by the black stars. Still, the convergence at the black star (under constant latency) is always faster than at the red star (under periodic latency). That is, although having periodic latency instead of constant latency may increase the size of stable region and enable the use of larger control gains, the best performance becomes worse since the maximum latency increases.

Different sawtooth latency profiles have different stability boundaries, even when their average latency is the same. The three profiles in Figure 10(a) have the same average $\tau_{\text{ave}} = 0.5$ s, and the two periodic profiles share the same minimum latency $\tau_{\min} = 0.25$ s. The one-tooth latency profile has the maximum $\tau_{\max} = 0.75$ s (yielding the period 0.5 s), while the two-tooth latency has the maxima $\tau_{\max,1} = 0.45$ s and $\tau_{\max,2} = 0.85$ s (yielding the period 0.8 s). The corresponding stability boundaries are depicted in panel (b). As in the two-tooth latency profile, the maximum latency is greater than in the one-tooth latency profile, the stability boundaries deviate more from those obtained for constant delays.

To further interpret the stability chart, we select two sets of control gains from different regions of the chart and perform numerical simulations for the nonlinear system (6). The vehicle starts from a position of (0, -0.3) m (i.e. small lateral deviation) and having 0 yaw angle (i.e. aligning with the path). The trajectories of the simulations are shown in panels (c)–(e) for gain combination $k_\theta = 2.5$, $k_\epsilon = 1.9$ (marked by P in panel (b)) and in

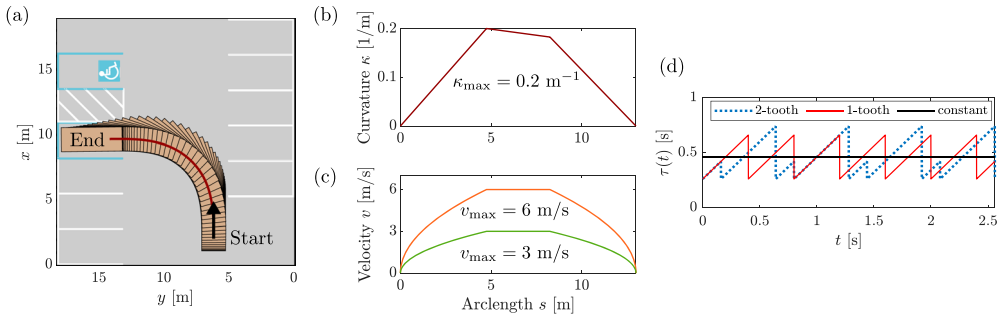


Figure 11. Path reference used for simulations. (a) Reference path (brown curve) of the rear axle centre point with the vehicle depicted as moving along the path (b) Curvature plan for a left turn path. (c) Two velocity plans defined along the path. (d) Three types of latency profiles with $\tau_{ave} = 0.46$ s.

panels (f)–(h) for gain combination $k_\theta = 3.4, k_\varepsilon = 0.1$ (marked by Q in panel (b)). Note that in the system (6), there is no additional saturation on the steering angle (except the arctan which saturates at ± 90 degrees). For this reason, the unstable trajectories may reach unrealistically large steering angles. We use dotted line for the part of the trajectory after the steering angle exceeds the limit of 45 degree. Since point P is within the stable region of two-tooth latency profile but outside the other two stable regions, the trajectory only converges to the path in the former case. For point Q, which is located within the stable region of one-tooth latency profile but outside the other two stable regions, the trajectory only converges under the one-tooth scenario. This demonstrates that with periodic latency, a larger stability region can be possibly achieved, and that the shape of the periodic latency plays an important role when $\tau_{min} \ll \tau_{max}$.

4. Simulation of teleoperated driving

In this section, we perform numerical simulations of ToD maneuvers in a parking lot to demonstrate how the latency and speed of the ToD maneuver impact the performance. We relate these simulations to the stability analysis presented in the previous sections.

We consider the task of maneuvering a vehicle in a parking lot, following a desired path indicated by the brown curve in Figure 11(a). The curvature along the path is shown in panel (b) with maximum value $\kappa_{max} = 0.2 \text{ m}^{-1}$ which corresponds to a typical minimum turning radius for a conventional automobile. Velocity plans along the path are shown in panel (c) for two different maximum velocities $v_{max} = 3 \text{ m/s}$ and $v_{max} = 6 \text{ m/s}$. The simulations are conducted under three different latency profiles as shown in panel (d). These all possess the same average $\tau_{ave} = 0.46$ s. For both periodic latency profiles we set $\tau_{min} = 0.26$ s. For the one-tooth profile we have $\tau_{max} = 0.66$ s (yielding the period 0.4 s) while for the two-tooth profile we have $\tau_{max,1} = 0.42$ s and $\tau_{max,2} = 0.74$ s (yielding the period 0.64 s). They are also shown in Figure 3(b,c) as examples to approximate the stochastic delay Data 2.

The control gains are selected as $k_\varepsilon = 0.5, k_\theta = 1.5$ and these are marked in the stability charts in Figure 12(a,d,g) as a blue diamonds. When simulating the system (6) we also consider delay in realising the desired velocity. That is, we use $v(t) = v_d(t - \tau)$, where

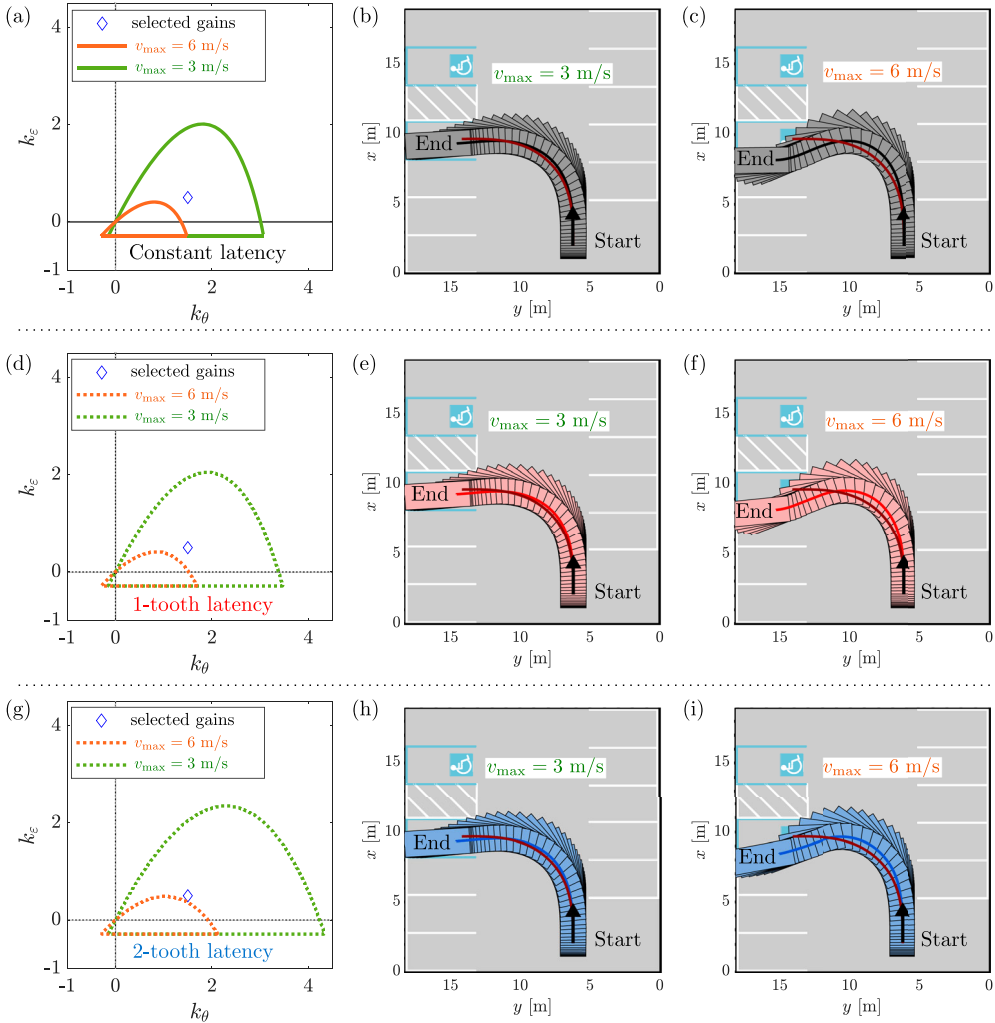


Figure 12. Stability charts and simulations under different latency profiles and velocity profiles. The stability charts correspond to constant curvature $\kappa_* = \kappa_{\max} = 0.2 \text{ m}^{-1}$ and a constant velocity $v_* = v_{\max} = 3 \text{ m/s}$ or $v_* = v_{\max} = 6 \text{ m/s}$ as indicated. (a)–(c) Stability charts and simulations under constant latency $\tau_{\text{ave}} = 0.46 \text{ s}$. (d)–(f) Stability charts and simulations under one-tooth latency profile. (g)–(i) Stability charts and simulations under two-tooth latency.

$v_d(t) = v(s(t))$ is given by the velocity plan along the path. Without any latency the vehicle can follow the path and the velocity plans perfectly.

Considering a constant non-zero latency, the vehicle starts to deviate from the path, as shown in Figure 12(b,c). Since having larger velocity corresponds to a larger dimensionless delay and a smaller stable region in panel (a), the control gains, which are inside the stable region for smaller maximum velocity, are located outside the stable region for larger maximum velocity. Correspondingly, the vehicle is not able to follow the desired path in panel (c) even though the latency is the same as in panel (b). When ToD is performed under one-tooth periodic latency and two-tooth periodic latency, the corresponding stability charts

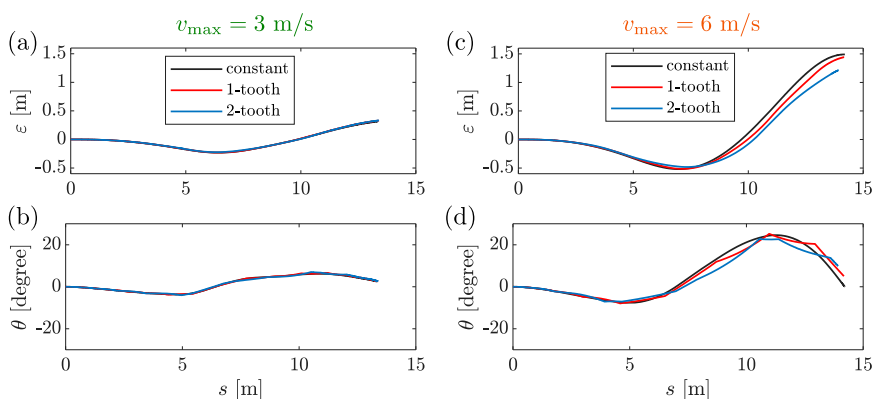


Figure 13. The lateral and yaw errors along the path under different latency profiles.

and simulations are depicted in panels (d)–(f) and panels (g)–(i), respectively. The vehicle exhibits similar behaviours under the three different latency profiles when trying to follow the same path and the same velocity plan.

We show the lateral error and the yaw error between the realised trajectory and the closest point on the desired path under different delay profiles in Figure 13. The lateral and yaw errors along the path for the sawtooth latency simulations are close to those under constant latency. Panels (a) and (b) indicate that the effect of sawtooth variation in latency on the trajectory is negligible for smaller maximum velocity. For larger maximum velocity, the deviations between the trajectories obtained for different latency profiles become more significant as demonstrated in panels (c) and (d). As the constant latency results in the smallest stability region, see Figure 12(a,d,g), it also has the largest lateral error along the path among three cases, see Figure 13(c). This shows that using the constant average latency approximation for the actual time-varying latency may expect a worse performance, depending on the choice of the control gains. Lastly, observe that the yaw error is not smooth along the path in panels (b) and (d). This is due to the discontinuities in the sawtooth latency which directly affects the yaw angle.

5. Conclusion

In this paper, we presented how the overall latency, longitudinal velocity and the path curvature affect the performance of teleoperated driving (ToD) through analytical and numerical studies. We derived the equations of motion and performed a re-scaling of space and time. The resulting simplified equations depended on the dimensionless delay, that captured the effects of velocity and latency, and on the curvature of the path. We quantified the performance of ToD by analysing the stability and the convergence rate. For a given constant velocity, overall latency and path curvature, the gains corresponding to the fastest convergence were derived in closed form as a function of dimensionless delay and the path curvature. We quantified the robustness of ToD against changes in the delay and velocity. When following a straight path, the aforementioned best performance gains allow the ToD system to remain stable even when the latency or maneuver speed increases up to 2.52 times.

We also considered periodic latency for ToD and analysed the corresponding system. Due to the nature of command generation and information sharing in ToD, the latency profile for ToD has a sawtooth shape. We captured these latency variations in our model; and determined their effects on stability and performance. Our results show that the fastest convergence gains for ToD under sawtooth-type periodic latency are close to those under constant latency. In some cases, having a periodic sawtooth latency increased the stable domain for ToD, but it did not improve the rate of fastest convergence.

The presented comprehensive stability and performance analysis can be used to select appropriate control gains, maneuvers, and wireless network resources for different ToD scenarios. Our work can be further extended by considering stochastic variations in the latency of ToD. In addition, different latency components may affect ToD in different ways. For instance, the degradation of the state estimation caused by the packet loss may further deteriorate ToD performance on top of the delay effect. More complicated vehicle models can also be studied including models with tire dynamics and steering dynamics, even when the parameters are learned from data. The stability analysis presented in this paper can be applied to such models while considering controllers in different forms. We plan to use our insights for studying the closed-loop dynamics of the ToD system under latency in different driving scenarios.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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