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Event-triggered Scheduling for Infrastructure-supported Collaborative Vehicle Control ⋆

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Abstract: This paper investigates the design of event-triggered scheduling and medium access control for the real-time coordination of multiple vehicles through an infrastructure node. The key motivation of our proposed event-triggered mechanism is to concurrently address safety aspects of the vehicle control and the efficient usage of network resources of the vehicle-to-infrastructure (V2I) protocol. While the real-time guarantees needed for safety are achieved by a novel coordination scheme in the medium access layer, the event-triggered mechanism improves the real-time performance of the control task. The coordination scheme enabled through the topology of the V2I network limits the number of successive data dropouts and we prove stability of the estimator at the infrastructure that monitors the state of the vehicle group. Numerical studies on a platooning case study validate our theoretical results.

Keywords: Networked Control, Event-triggered Scheduling, Vehicle-to-Infrastructure Communications, Medium Access Control, Platooning

1. INTRODUCTION

In this paper, we envision a scenario where multiple autonomous vehicles are controlled through the infrastructure that coordinates their collective behavior by fusing the available sensor information of each vehicle illustrated in Fig. 1 for 3 vehicles. Typical application areas include the coordination of traffic at intersections and autonomous parking lot management. Our study will mainly focus on aspects of vehicle-to-infrastructure communications (V2I) that enable real-time guarantees while providing an efficient usage of network resources for contention-based carrier sense multiple access (CSMA) over the wireless medium. Prioritizing data packets based on their content will help us to ensure delivery of important packets with shorter latencies while filtering out redundant messages from the network. The idea of content-based prioritization is realized by an event-triggered mechanism in the vehicle-to-infrastructure link, while the infrastructure sends messages periodically. Each vehicle determines the importance of providing its information to the infrastructure. If the obtained value exceeds a threshold, it will request to transmit the information to the infrastructure. In order to resolve contention among concurrent requests, the medium access is coordinated by the infrastructure that assigns priorities in a predefined periodic fashion. In this way, we are capable to retain real-time properties for our strategy similarly as for time-triggered contention-free schemes, while still having the benefits of event-triggered medium access in terms of efficiency and average latency.

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There exist several works that give suggestions on the implementation of state-based scheduling algorithms in wireless networks. The work in Christmann et al. (2014) develops an implementation of the Try-Once-Discard protocol (TOD) proposed by Walsh et al. (1999), for wireless networked control systems. The methodology is based on the arbitration phase in the CAN bus., while the work in Mamduhi et al. (2014) suggests a randomized version of TOD. By considering an event-triggered architecture similar to ours, Muehlebach and Trimpe (2015) propose an LMI-based synthesis approach.

The MAC layer of our V2I scheme is related the IEEE 802.11e Enhanced Distributed Channel Access (EDCA) Quality of Service (QoS) extension, also found in Vehicular Ad Hoc Networks, Bilstrup et al. (2008). As EDCA is not capable for providing real-time guarantees, we give a modified version that has some parallels to Barradi et al. (2010). Moreover, initial ideas on event-triggered beaconing for position tracking in vehicular environments are proposed in Rezaei et al. (2010).

While our work targets the interaction of control and communications at the level of the medium access control (MAC) layer, there also exist approaches, such as in Gatsis et al. (2014) and Gatsis et al. (2015), that focuses on the synthesis of networked controllers at the physical layer of the communication protocol. In this work, we however do not consider effects arising from imperfections at the physical layer.

The salient feature of our proposed MAC protocol is its bound on the number of successive data dropouts depending on the number of vehicles and contention-free slots available. This makes the method attractive also for other

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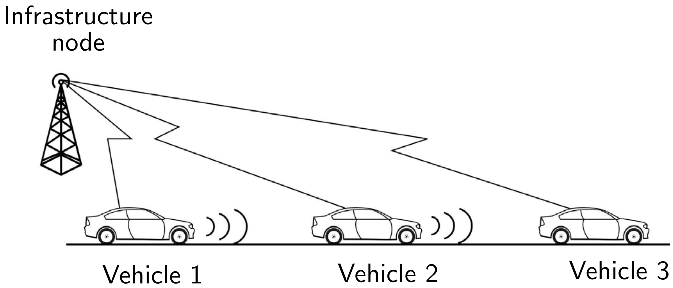

Fig. 1. Illustration of the evisioned infrastructure-supported collaborative vehicle coordination.

event-triggered controllers that impose a constraint on the maximum allowable number of successive dropouts, e.g. see Wang and Lemmon (2011) and Dolk and Heemels (2015).

The contributions of this paper can be summarized as follows. First, we propose a novel data scheduling scheme for distributed linear quadratic control systems based on event-triggered medium access with centrally coordinated prioritization. While the event-triggering mechanism considers the discrepancy between locally and remotely state estimations, the priority assignment scheme coordinated by the infrastructure node yields a time-varying periodic pattern. Second, we investigate the real-time guarantees of our approach. By relating our event-triggered scheme to a time-triggered scheduling strategy, we are able to give bounds on the worst-case transmission latency and show boundedness of the mean square error of the global state estimate at the infrastructure node. The latter makes use of results of our recent work in Molin et al. (2015b). Third, we give a design guideline that allows an implementation of our proposed scheme in the wireless MAC layer which only needs slight modification of existing protocols that are based on IEEE 802.11 with Quality-of-Service (QoS) capabilities. Finally, we demonstrate our method numerically on a infrastructure-supported vehicle platooning task.

The system model is introduced in Sec. 2, while its real-time properties are analyzed in Sec. 3. Sec. 4 gives a guideline for the implementation of the transmission scheme and Sec. 5 evaluates the obtained results on a numerical case study.

2. SYSTEM MODEL

2.1 Dynamical system

For the sake of generality, we introduce the system model in its most generic form while it will be specialized to the collaborative vehicle control setting in further sections. We consider a linear discrete-time system

$$x_{k+1} = Ax_k + Bu_k + w_k \tag{1}$$

with (A, B) being controllable and A invertible – the latter is satisfied for most sampled-data systems due to the properties of the matrix exponential,

$$x_k \in \mathbb{R}^n,\ u_k \in \mathbb{R}^p,\ A \in \mathbb{R}^{n\times n},\ B \in \mathbb{R}^{n\times p}$$
$$x_0 \sim \mathcal{N}(0, R_0), \quad R_0 \in \mathbb{R}^{n\times n}, R_0 > 0$$
$$w_k \sim \mathcal{N}(0, R_w), \quad R_w \in \mathbb{R}^{n\times n}, R_w > 0.$$

Assuming M agents, each agent $j \in \mathcal{M} = \{1, \ldots, M\}$ takes measurements y_k^j,

$$y_k^j = C^j x_k + v_k^j \tag{2}$$

with $(A, [C_k^{1\mathsf{T}}, \ldots, C_k^{M\mathsf{T}}]^\mathsf{T})$ being observable and

$$y_k^j \in \mathbb{R}^{m_j},\ C^j \in \mathbb{R}^{m_j\times n}$$
$$v_k^j \sim \mathcal{N}(0, R_v^j), \quad R_v^j \in \mathbb{R}^{m_j\times m_j}, R_v^j > 0.$$

The control input u_k is composed of $u_k = [u_k^{1\mathsf{T}}, \ldots, u_k^{M\mathsf{T}}]^\mathsf{T}$ with $u_k^j \in \mathbb{R}^{p_j}$ being the control input at agent j. The control law is given by

$$u_k = -L\hat{x}_{k|k-1} \tag{3}$$

with stabilizing gain L, i.e., $A - BL$ being Hurwitz, and $\hat{x}_{k|k-1}$ being the state estimate at the infrastructure node that is broadcasted to each agent at the beginning of each sampling period. Furthermore, we assume that there are $N_\mathrm{T} \leq M$ slots available within the sampling period, in which agents can transmit data to the infrastructure node.

2.2 Local filtering

In this section, we define the local filtering structure in each sensor node. It is not presumed that the state can be fully recovered at one sensor node by its local measurements, i.e., (A, C^j) is not observable in general. Similar as in Battistelli et al. (2012), we aim at a representation in which a sensor node focuses on the estimation of its observable subspace of the state x_k. For time-invariant linear systems, it is well known, e.g., Antsaklis and Michel (2006), that there exists a non-singular state transformation T^j that separates the state space into an observable and unobservable subspace, such that

$$(T^j)^{-1}AT^j = \begin{bmatrix} A_1^j & 0 \\ A_{21}^j & A_2^j \end{bmatrix}, \quad C^jT^j = \begin{bmatrix} C_1^j & 0 \end{bmatrix}$$
$$T^j = \begin{bmatrix} T_1^j & T_2^j \end{bmatrix}, \quad (T^j)^{-1} = \begin{bmatrix} D_1^j \\ D_2^j \end{bmatrix}$$

with (A_1^j, C_1^j) being observable. Let n_o^j be the dimension of the observable subspace of agent j. Then, the local filter at agent j estimates the state $x_k^j = D_1^j x_k \in \mathbb{R}^{n_o^j}$ of the subsystem evolving by

$$\begin{aligned} x_{k+1}^j &= A_1^j x_k^j + D_1^j w_k \\ y_k^j &= C_1^j x_{k+1}^j + v_k^j. \end{aligned} \tag{4}$$

The minimum mean square error (MMSE) estimator $\hat{x}_{k|k}^j$ of x_k^j is given by the Kalman filter

$$\hat{x}_{k|k}^j = \hat{x}_{k|k-1}^j + K_k^j(y_k^j - C_1^j\hat{x}_{k|k-1}^j) \tag{5a}$$
$$P_{k|k}^j = (I_{n_o^j} - K_k^jC_1^j)P_{k|k-1}^j \tag{5b}$$
$$\hat{x}_{k+1|k}^j = A_1^j\hat{x}_{k|k}^j + D_1^jBu_k \tag{5c}$$
$$P_{k+1|k}^j = A_1^jP_{k|k}^j(A_1^j)^\mathsf{T} + D_1^jR_w(D_1^j)^\mathsf{T} \tag{5d}$$

where $K_k^j = P_{k|k-1}^j(C_k^j)^\mathsf{T}(C_1^jP_{k|k-1}^j(C_1^j)^\mathsf{T} + R_v^j)^{-1}$ and $\hat{x}_{0|-1}^j = 0$, $P_{0|-1}^j = D_1^jR_0(D_1^j)^\mathsf{T}$. I_n denotes the identity matrix in $\mathbb{R}^n$. As the state estimate $\hat{x}_{k|k-1}$ is broadcasted to all agents, u_k is available at each agent.

At the infrastructure node, there runs an estimator that predicts $\hat{x}_{k|k}^j$, which is implemented by the recursion

$$\tilde{x}_{k|k}^j = \begin{cases} \hat{x}_{k|k}^j & \text{data sent from agent } j \\ \tilde{A}_1^j\tilde{x}_{k|k}^j + D_1^jBu_k & \text{otherwise} \end{cases} \tag{6}$$

This data will be needed for defining the triggering rule and when fusing information at the infrastructure.

2.3 Event-triggered scheduling

This section is devoted to the communication architecture that defines which agents are scheduled to transmit their information to the infrastructure. The communication logic is outlined in Fig. 2 for agent j. Based on the data available, each agent first computes the discrepancy Δ_k^j between the local state estimate $\hat{x}_{k|k}^j$ and the corresponding remote prediction $\tilde{x}_{k|k}^j$ that relates to the worthiness of the information content at agent j. Whenever the value exceeds a threshold β^j, we try to transmit information to the infrastructure. This corresponds to the first decision element in Fig 2. We denote δ_k^j as the triggering variable defined by

$$\delta_k^j = \begin{cases} 1 & \text{try to send } \hat{x}_{k|k}^j \\ 0 & \text{remain silent} \end{cases} \tag{7}$$

The triggering rule is defined as follows

$$\delta_k^j = \mathbb{1}_{\Delta_k^j > \beta^j}. \tag{8}$$

where $\mathbb{1}_{(\cdot)}$ is the indicator function, $\Delta_k^j = \|\hat{x}_{k|k}^j - \tilde{x}_{k|k}^j\|_{\Gamma^j}^2$, $\Gamma^j > 0$, $\beta^j > 0$ and $\|z\|_\Gamma^2 = z^\mathsf{T}\Gamma z$. As it can happen that the number of requesting agents exceeds N_T, a contention resolution mechanism needs to be present. We propose the following prioritizing scheme, in which each agent has a time-varying priority α_k^j defined as

$$\alpha_k^j = (kN_\mathrm{T} + j - 1) \mod M. \tag{9}$$

We will highlight how this scheme can be realized in a slightly modified MAC layer of IEEE 802.11e in Sec. 4. Synchronized knowledge of the time index k at each agent can be enforced by transmitting the global time during the broadcasting period of the infrastructure node. The arbitration mechanism picks the agents with the N_T largest priorities α_k^j with $j \in \{i \in \mathcal{M} | \Delta_k^i \geq \beta^i\}$. This refers to the second decision block in Fig. 2. Due to the fact that all priorities are distinct, this uniquely defines the set $\mathcal{M}_k^\mathrm{R} = \{i_1, \ldots, i_{r_k}\} \subset \mathcal{M}$ denoting the set of successfully transmitting agents at time k, where $r_k \in \{0, \ldots, N_\mathrm{T}\}$ is the number of received measurements at time k. Regarding the triggering logic, the infrastructure knows only $\mathcal{M}_k^\mathrm{R}$.

2.4 Fusion rule

The fusion rule at the infrastructure node consists of three parts: (i) estimation update using the transmitted data, (ii) the incorporation of event information, and (iii) prediction of the estimate. While step (i), (iii) are related to standard results in linear estimation, part (ii) uses a technique developed in Molin et al. (2015b) related to covariance intersection (CI) that has been proposed by Julier and Uhlmann (1997).

The estimation update is obtained by the BLUE (best linear unbiased estimator) criterion that is given by

$$\hat{x}_{k|k} = W_k^0 \hat{x}_{k|k-1} + \sum_{i \in \mathcal{M}_k^\mathrm{R}} W_k^i \hat{x}_{k|k}^i \tag{10}$$

where the gains W_k^0, W_k^i, $i \in \mathcal{M}_k^\mathrm{R}$ are obtained from Li et al. (2003) and their explicit expressions are omitted here

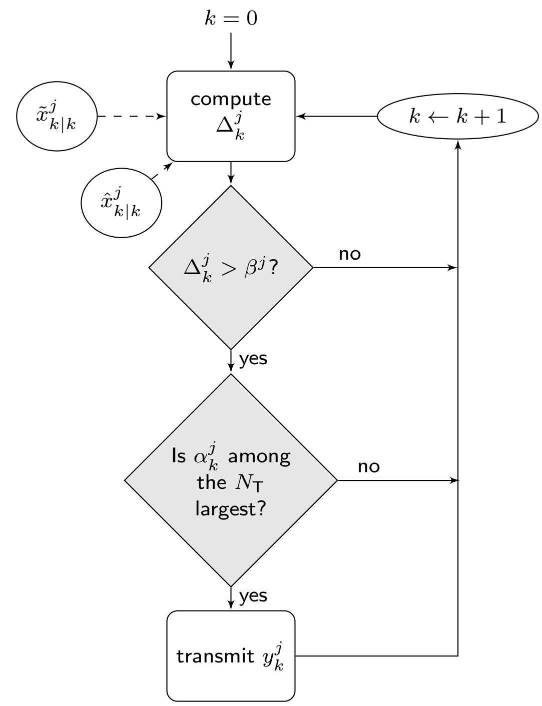

Fig. 2. Decision diagram for transmission logic at agent j.

as they are not essential for the analysis in the subsequent section. Let $P_{k|k}$ be the corresponding predicted error covariance matrix of $\hat{x}_{k|k}$. Note that this update step is omitted if $r_k = 0$.

The event information (EI) is data that emerges due to the absence of transmissions. There are two situations when this can be beneficial for improving our estimate. Either, there is a transmission slot remaining ($r_k < N_\mathrm{T}$). In this case, the infrastructure can conclude that the event condition is not met for all non-transmitting agents at time k, i.e., $\delta_k^j = 0$ implies that $\|\hat{x}_{k|k}^j - \tilde{x}_{k|k}^j\|_{\Gamma^j}^2 \leq \beta^j$ for all agent $j \neq \mathcal{M}_k^\mathrm{R}$. Or, if $r_k = N_\mathrm{T}$, then the infrastructure knows at time k that the event condition is not met for all non-transmitting agents having a higher priority than that of the least prioritized agents in $\mathcal{M}_k^\mathrm{R}$. Based on $\mathcal{M}_k^\mathrm{R}$, we define the set of these agents as

$$\mathcal{M}_k^\mathrm{EI} = \begin{cases} \{i \in \mathcal{M} \mid i \neq \mathcal{M}_k^\mathrm{R},\ \alpha_k^i > \min_{\ell \in \mathcal{M}_k^\mathrm{R}} \alpha_k^\ell\} & r_k = N_\mathrm{T} \\ \{i \in \mathcal{M} \mid i \neq \mathcal{M}_k^\mathrm{R}\} & r_k < N_\mathrm{T} \end{cases}$$

The task of incorporating event information into the state estimation procedure is performed by the modified CI approach developed in Molin et al. (2015b). The major advantage of CI is that it yields consistent estimates without relying on the knowledge of cross-correlations between estimates, see Julier and Uhlmann (1997). According to Theorem 2 of Molin et al. (2015b), the event information can be transformed into the virtual transmission of a consistent pair of estimates given by (6) with predicted error covariance matrix $\tilde{P}_{k|k}^j$ given by

$$\tilde{P}_{k|k}^j = P_{k|k}^j + \frac{n_o^j}{2 + n_o^j} (\beta^j)^2 (\Gamma^j)^{-1}.$$

The modified CI yields the fused estimate $\hat{x}_k$ and is then defined as

$$P'^{-1}_{k|k} = \omega^0 P^{-1}_{k|k} + \sum_{j\in\mathcal{M}_k^{\mathrm{EI}}} \omega^j T_1^j (\tilde{P}^j_{k|k})^{-1} (T_1^j)^\mathsf{T} \quad (11)$$

$$P'^{-1}_{k|k}\hat{x}'_{k|k} = \omega^0 P^{-1}_{k|k}\hat{x}_{k|k} + \sum_{j\in\mathcal{M}_k^{\mathrm{EI}}} \omega^j T_1^j (\tilde{P}^j_{k|k})^{-1} \tilde{x}^j_{k|k} \quad (12)$$

with weights $\omega^j > 0$, $\omega^0 + \omega^{i_1} \cdots + \omega^{i_{r_k}} = 1$. There exist different approaches for selecting appropriate weights ω^j, e.g., Niehsen (2002). The transformation matrix T_1^j ensures that the estimate and covariance of agent j are embedded appropriately in the original state space.

The prediction step at the infrastructure is given as

$$\hat{x}_{k+1|k} = A\hat{x}'_{k|k} - BL\hat{x}_{k|k-1} \quad (13)$$

$$P_{k+1|k} = AP'_{k|k}A^\mathsf{T} + R_w. \quad (14)$$

3. REAL-TIME AND PERFORMANCE GUARANTEES

In the following, we analyze the system presented in the previous section with respect to two complementary aspects: real-time properties of the communication network and bounds on the estimation performance. The proposed arbitration mechanism shows that there is a bound on the number of consecutive packet dropouts if the agent is trying to access the medium continuously. This is because of the definition of the priorities α_k^j in (9).

Proposition 1. If $\delta_\ell^j = 1$ for all $\ell \geq k_1$, then there exists an $k_2 \in \{k_1, \ldots, k_1 + \lfloor \frac{M}{N_\mathrm{T}} \rfloor\}$ such that $j \in \mathcal{M}^{\mathrm{R}}_{k_2}$.

Proof. Fix an arbitrary index j. Note that agents take priorities in the set $\{0, \ldots, M\}$. Within a time period of length $\lfloor \frac{M}{N_\mathrm{T}} \rfloor\} + 1$, there will be a priority α_k^j that is at least $M - N_{\mathrm{slot}} - 1$. This priority value guarantees the transmission in case $\delta_\ell^j = 1$ as there are at most $N_{\mathrm{slot}} - 1$ potential agents with a higher priority.

□

It should be noted that the above result makes the arbitration method appealing for event-triggering schemes beyond our proposed strategy that poses conditions on the maximal allowable number of successive data dropouts, e.g., Wang and Lemmon (2011) and Dolk and Heemels (2015).

The subsequent analysis will be closely related the notion of consistent estimates. Adopted from Jazwinski (2007); Julier and Uhlmann (1997), its definition is as follows.

Definition 1. (Consistency). Let $\hat{x}_{k|k}$ be an unbiased estimate of x_k and let $\hat{P}_{k|k}$ be the predicted error covariance matrix corresponding to the estimate $\hat{x}_{k|k}$. Then, the pair $(\hat{x}_{k|k}, \hat{P}_{k|k})$ is said to be *consistent* when

$$\mathbf{E}[(x_k - \hat{x}_{k|k})(x_k - \hat{x}_{k|k})^\mathsf{T}] \leq \hat{P}_{k|k}.$$

For the sake of brevity, we assume in the remainder of this section that $N_\mathrm{T} = 1$. The results can however be shown similarly for communication systems with $N_\mathrm{T} > 1$.

Theorem 1. Let $N_\mathrm{T} = 1$. Then, the error covariance matrix can be bounded uniformly by

$$\mathbf{E}[(x_k - \hat{x}_{k|k})(x_k - \hat{x}_{k|k})^\mathsf{T}] \leq \bar{P} \quad (15)$$

for a sufficiently large time step $k > k_1$.

Proof. Due to the consistency-preserving property of the BLUE estimator in (10), the CI in (11)–(12), and the prediction step in (13)–(14), see Jazwinski (2007), Molin et al. (2015b), and Battistelli and Chisci (2014), and the fact that $(\hat{x}^j_{k|k}, P^j_{k|k})$ and $(\tilde{x}^j_{k|k}, \tilde{P}^j_{k|k})$ are consistent estimates, we know that the pair $(\hat{x}'_{k|k}, P'_{k|k})$ is a consistent estimate at any time k. This implies that it suffices to analyze the predicted error covariance matrix $P'_{k|k}$ at the infrastructure node. As the data used in the BLUE fusion step do not increase the error covariance matrix, Julier and Uhlmann (1997), we can restrict ourselves to the situation in which no transmissions occur over the considered period. Therefore, the step in (10) is omitted implying that $P_{k|k} = P_{k|k-1}$. Subsequently, we study the interaction of the CI method with the prediction step.

Rather than considering the error covariance matrix $P'_{k|k}$, we focus on the corresponding information matrix $\Omega'_{k|k} = P'^{-1}_{k|k}$ and aim to find a lower bound on $\Omega'_{k|k}$ in the following. The covariance update in (14) yields for the information matrix

$$\Omega_{k+1|k} = h(\Omega'_{k|k}) \quad (16)$$

with $h(\Omega) = A^{-\mathsf{T}}\Omega A^{-1} - A^{-\mathsf{T}}\Omega(\Omega + A^\mathsf{T} R_w^{-1} A)^{-1}\Omega A^{-1}$. We will rely on Lemma 1 fact (ii) in Battistelli and Chisci (2014) that is restated here for completeness.

Lemma 1. (Battistelli and Chisci (2014)). Let A be invertible. For a given matrix $\bar{\Omega} \geq 0$, there exists a γ with $0 < \gamma \leq 1$ such that $h(\Omega) \geq \gamma A^{-\mathsf{T}}\Omega A^{-1}$ for any $\Omega \leq \bar{\Omega}$.

According to (11) , we have

$$\Omega'_{k|k} = \omega^0 h(\Omega'_{k|k}) + \sum_{j\in\mathcal{M}_k^{\mathrm{EI}}} \omega^j T_1^j \tilde{\Omega}^j_{k|k} (T_1^j)^\mathsf{T} \quad (17)$$

Due to consistency of the estimate $\hat{x}'_{k|k}$ and the optimality properties of the MSSE estimator, see Kay (1993), we have the following inequality

$$\Omega'_{k|k} \leq \Big(\mathbf{E}[(x_k - \hat{x}'_{k|k})(x_k - \hat{x}'_{k|k})^\mathsf{T}]\Big)^{-1} \leq \Omega^{\mathrm{CKF}}_{k|k}$$

where $\Omega^{\mathrm{CKF}}_{k|k}$ is the information matrix of the centralized Kalman filter which is the MMSE estimator in case of having access to all available measurements. As $R_w, R_v^j > 0$, there is a uniform bound on $\Omega^{\mathrm{CKF}}_{k|k}$ that can be denoted as $\bar{\Omega}$. Hence, we can apply Lemma 1 to (17) in order to obtain

$$\Omega'_{k|k} \geq \omega^0\gamma A^{-\mathsf{T}}\Omega'_{k-1|k-1}A^{-1} + \omega^j T_1^j \tilde{\Omega}^j_{k|k}(T_1^j)^\mathsf{T} \quad (18)$$

with $0 < \gamma \leq 1$ and where the index j is chosen with the maximal priority α_k^j, which corresponds to the worst-case event information with $\mathcal{M}_k^{\mathrm{EI}} \neq \varnothing$. From (9), we observe that the index sequence of agents having maximal priority over time corresponds to a round robin schedule with decreasing order of the agent indices, i.e. it yields the sequence $j_k = [\mathcal{M}_k^{\mathrm{EI}}]_k = [M, M-1, \ldots, 2, 1, M, M-1, \ldots]$. As we can assume that $|\mathcal{M}_k^{\mathrm{EI}}| = 1$ for any time k in our case, we have for the weight $\omega^{j_k} = 1 - \omega^0 = \bar{\omega}^0$. Thus, by repeating the steps (17) and (18) M times, we have

$$\Omega'_{k|k} \geq (\omega^0\gamma)^M (A^{-M})^\mathsf{T}\Omega'_{k-M|k-M}A^{-M} + \sum_{\ell=0}^{M-1} (\omega^0\gamma)^\ell \bar{\omega}^0 (A^{-\ell})^\mathsf{T} T_1^{j_{k-\ell}} \tilde{\Omega}^{j_{k-\ell}}_{k-\ell|k-\ell} (T_1^{j_{k-\ell}})^\mathsf{T} A^{-\ell}$$

Due to the fact that the subsystem x_k^j is observable by agent j, we can conclude that the corresponding error covariance matrix $\Omega_{k|k}^j$ can be bounded uniformly for sufficiently large $k > k^j$. This implies that there exists a $\bar{\Omega}^j > 0$ such that $\tilde{\Omega}_{k|k}^j \geq \bar{\Omega}^j$ for $k > k^j$. For notational convenience, we assume that the time step is a multiple of the number of agents, i.e. $k = \kappa M - 1$, $\kappa \in \mathbb{Z}^+$. The result will hold similarly for the other time steps k. Then, we obtain a lower bound for $\Omega'_{k|k}$ for sufficiently large $k > k_1$,

$$\bar{\Omega} = \sum_{\ell=0}^{M-1} (\omega^0 \gamma)^\ell \bar{\omega}^0 (A^{-\ell})^\mathsf{T} T_1^{\ell+1} \tilde{\Omega}^{\ell+1} (T_1^{\ell+1})^\mathsf{T} A^{-\ell}. \quad (19)$$

Based on the fact that $(A, [C_k^{1\mathsf{T}}, \ldots, C_k^{M\mathsf{T}}]^\mathsf{T})$ is observable, we can conclude by standard system-theoretic arguments, see Antsaklis and Michel (2006), that $\bar{\Omega} > 0$. By taking $\bar{P} = \bar{\Omega}^{-1}$, we can conclude the proof. □

A conclusion from the above theorem is that the estimator at the infrastructure is stable in the sense of bounded mean square error in the limit $k \to \infty$ as each error covariance matrix $P_{k|k}^j$ of the local MMSE estimators will converge to a bounded positive definite matrix. The inequality in (15) can be viewed as a worst-case bound on the covariance matrix at each time k, in which no transmissions occur at any time and the estimate is solely recovered through event information. In that way, the obtained bound in (15) is valid when conditioning on any scheduling pattern present until time k.

4. IMPLEMENTATION

The MAC layer of IEEE 802.11e with service differentiation EDCA divides data packets into access categories (AC). For each AC, different channel access parameters are assigned, the main being the time to sense the medium and decide if it is free (AIFS), and the minimum/maximum length of the random backoff intervals (CW). It has been pointed out in Barradi et al. (2010) that the standard settings of these parameters in the control channel (CCH) only increase the chances of transmission with lower latencies rather than giving hard real-time guarantees. This is because of the fact that lower prioritized packets may interfere with higher prioritized ones. In order to overcome this issue, we define M ACs with a fixed CW that decreases with increasing priority α_k^j defined in (9). These ACs are the highest priority tasks, while the remaining traffic will be assigned to ACs that have a minimum CW that is larger than the CW of priority $\alpha_k^j = 0$.

At the start of each super-frame, the infrastructure node sends a beacon containing generic information of the communication channel, the state estimate $\hat{x}_{k|k-1}$ of the system, the number of vehicles, and the current time step counter k. We presume that the data packets from the agents for state estimation have equal size that is known beforehand. This enables us to define a period of contention-free N_T transmission by also taking into account the AIFS and the contention window. After this contention-free period, there is a possibility of having contention-based data transfer. This is however not considered in this paper and we assume for simplicity that the super-frame ends after the contention-free period. At the end of each super-frame, all data packets that could not be transmitted to the infrastructure are discarded.

5. NUMERICAL STUDY

In this study, we will apply our proposed approach to a collaborative driving scenario that is controlled by the infrastructure. In particular, we focus on the platooning of a group of vehicles that can be viewed as an elementary control task needed in many situations in which vehicles are to be coordinated autonomously. The dynamic model for the longitudinal control of each vehicle is adopted from Molin et al. (2015a) with a sampling period of 100 ms which is assumed to be synchronized with the beaconing of the communication system. Suppose a chain of $M = 12$ vehicles ordered according to their indices such that vehicle 1 is the leading vehicle and 2 until M are the following vehicles. The system state of the model is given by the velocity of the leading vehicle, v_k^1 and the followers, v_k^j, $k \in \{2, \ldots, M\}$, and the distance between vehicles denoted as d_k^j, $k \in \{2, \ldots, M\}$. With $x'_k = [v_k^1, d_k^2, v_k^2, \ldots, v_k^M, d_k^M]^\mathsf{T}$. The system matrices are

$$A' = \begin{bmatrix} a_0 & & & & & \\ \lambda & 1 & -\lambda & & \mathbf{0} & \\ & & a_0 & & & \\ & & & \ddots & & \\ & \mathbf{0} & & & \lambda\ 1 & -\lambda \\ & & & & & a_0 \end{bmatrix}, \; B' = \begin{bmatrix} b_0 & & & & \\ b_1 & -b_1 & & \mathbf{0} & \\ & b_0 & & & \\ & & \ddots & & \\ & \mathbf{0} & & b_1 & -b_1 \\ & & & & b_0 \end{bmatrix}$$

with $a_0 = 0.98$ and $\lambda = 0.1$, $b_0 = 1.0 \times 10^{-3}$, $b_1 = 0.05 \times 10^{-3}$. The control objective for the group of vehicles is that the distance is kept constant at 3 m, while the lead vehicle tracks a random and time-varying reference velocity v_k^{ref}. The reference v_k^{ref} is incorporated as a system state. In order to achieve this control task, we use a centralized linear quadratic controller with integral input related to the velocity of the lead vehicle and the distance of the followers. By augmenting the integral state i_k^j , we have the state $x_k = [v_k^{\mathrm{ref}}, v_k^1, d_k^2, v_k^2, i_k^2, \ldots, v_k^M, d_k^M, i_k^M]^\mathsf{T}$ to be estimated at the infrastructure node. The process noise for v_k^j and v_k^{ref} has standard deviation 0.05, while d_k^j and i_k^j are modeled with small standard deviation of 0.001. Each vehicle j measures its velocity with standard deviation $\sigma_v = 0.01$ of the measurement error, while the follower $j > 1$ measures additionally distances to its preceding vehicle with the same standard deviation. For robustness purposes, we assume that the integral state is measured under noise with $\sigma = 0.001$. By fusing the broadcasted and the local estimate, the used state estimate for the control action is slightly modified in this numerical study. With regard to the communication network, we assume that there is dense traffic with a large number of participants. This is reflected in our communication model by a small number of transmission slots available per sampling period where we have $N_\mathrm{T} = 2$. The event-trigger is given with $\Gamma^j = I$ and $\beta^j = 0.1$ for any $j \in \{1, \ldots, M\}$.

Suppose that the reference velocity v_k^{ref} will drop from 14 to 5 m/s at a random point in time, which is geometrically distributed with mean M. Figure 3 illustrates the behavior of the platoon when the lead vehicle brakes at time 100 s $\pm$ 1s. When using our event-triggered approach for infrastructure-assisted vehicle control, the distances remain positive. In the time-triggered system, the behavior is similar to the event-triggered system in the best-case, while distances d_k^2 and d_k^3 can not be kept above 0 in the worst-case scenario. The differing behavior for the shown sample paths are due to the timely reaction of the event-triggered approach while the time-triggered schedule has a worst case delay of 5 time steps to update the reference change at the infrastructure node. By running Monte Carlo simulations with 10 000 trials, none of the sample paths led to a vehicle collision for the event-triggered approach, while collisions occurred in 19.7% of the cases when using time-triggered scheduling.

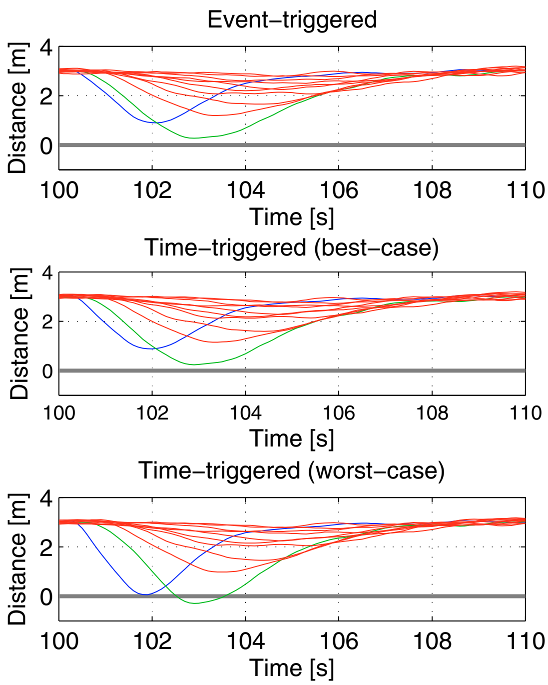

Fig. 3. Inter-vehicle distances, d_k^2 (blue), d_k^3 (green), $d_k^4, \dots, d_k^{12}$ (red), after braking of the leader at 100 s.

6. CONCLUSION

This paper demonstrated how to incorporate event-triggered data processing strategies for infrastructure-assisted collaborative vehicle control. We showed that our novel approach is capable of efficiently using communication resources while ensuring real-time properties. In particular, the numerical results on a platooning scenario outlined the potential of event-triggered strategies compared to conventional methods.

Future work will include the consideration of more complex collaborative vehicle tasks and a more detailed model of the communication system including unreliabilities.

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