Design and Analysis of an Automated Heavy Vehicle Platoon

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Abstract: From the model set identification through the control design and robust performance analysis to the implementation and experimental verification, the whole design process for an automated vehicle platoon is presented. The goal is to demonstrate that safe platooning with acceptable performance can be achieved by utilizing the services already available on every commercial heavy trucks with automated gearbox. Using the services, the control design reduces to the selection of four design parameters, the static gain coefficients of the output-feedback-input-feed-forward controller common for every vehicle. It is experimentally demonstrated, that in normal driving maneuvers, the spacing errors are less than three meters.

1 INTRODUCTION

Safe control of vehicle platoons requires strict guaranteed bounds on inter-vehicle spacing errors. In order to avoid collision the sampled errors are best measured by its ℓ_∞ norm, so the bounds represent the worst-case peaks of the spacing errors. Consistent identification tools are the set membership methods in the ℓ_1 setting, see e.g. (Gustafsson and Mäkilä, 1996; Milanese and Belforte, 1982; Milanese, 1995). The identified model sets are employed for on-line model validation and a priori analysis of the control performance measured by the worst-case spacing errors.

Controllers for autonomous vehicle platoons usually consists of two levels of feedback controllers. At the lower level a local, vehicle specific controller is responsible for performing acceleration demands. The higher level control law is common for all vehicle, it is designed for satisfying string stability requirements of the whole platoon. Very short safety gaps can be guaranteed, under certain constraints on lead vehicle maneuvers, when detailed engine, gearbox and brake system models are available, see, e.g., in references (Nouveliere and Mammar, 2007; Gerdes and Hedrick, 1997; Liang et al., 2003). There is, however, some difficulties in the widespread applicability of these control methods. The required engine/gearbox/brake system models are usually not available and not reliable for every commercial heavy trucks. Beyond that, these controllers try to directly excite the brake cylinder pressures and throttle valve of the engine, which could also conflict with the existing control units, such as Electronic Brake System (EBS) and Engine Control Unit (ECU).

In this paper the goal is to explore the performance of an automated vehicle string where, in contrast to the former solutions, only the standardized and general services of the EBS and ECU are used. This work is an extension of the work that have been presented in reference (Rödönyi et al., 2012), where the focus was placed on the analysis of the spacing error bounds subject to heterogeneity in vehicle dynamics and inter-vehicle communication failures. Here we present two model set identification problems, one of which is an extension of the method introduced in (Nagamune et al., 1997; Nagamune and Yamamoto, 1998).

In Section 2 the mathematical model of the platoon is presented. The vehicle model set identification method is presented in Sections 3 and 4. The performance of a heterogeneous platoon is analyzed in Section 5. The experimental results are presented in Section 6.

Basic notations. The peak norm of a sequence $u(k)$ is denoted by $\|u\|_\infty = \sup_k |u(k)|$, ℓ_∞ denotes the space of sequences of finite peak norm. The peak-to-peak norm of a system H is defined by $\|H\|_1 = \sup_{u \neq 0} \frac{\|Hu\|_\infty}{\|u\|_\infty}$.

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2 STATE-SPACE MODEL OF VEHICLE PLATOONS

In this section the discrete-time version of platoon model and controller are briefly summarized.

The longitudinal dynamics of a single vehicle is approximated by the following first order nominal model with sampling time T_s

$$a_i(k+1) = \theta^*_{i1} a_i(k) + \theta^*_{i2} u_i(k), \;\; i = 0, 1, ..., n$$

where a_i and u_i denote the acceleration and acceleration demand of vehicle i, θ^*_{i1} and θ^*_{i2} denote constant parameters.

The spacing error of the ith follower vehicle is defined by $e_i(k) = x_i(k) + L_i - x_{i-1}(k)$ where L_i denotes the desired intervehicular space. Without loss in generality it can be assumed to be zero in the analysis. The position of the ith vehicle is denoted by x_i. For each vehicle, the spacing error dynamics can be written as follows

$$\begin{bmatrix} e_i(k+1) \\ \delta_i(k+1) \\ a_i(k+1) \end{bmatrix} = \left[\begin{array}{ccc|cc} 1 & T_s & 0 & 0 & 0 \\ 0 & 1 & T_s & -T_s & 0 \\ 0 & 0 & \theta^*_{i1} & 0 & \theta^*_{i2} \end{array}\right] \left[\begin{array}{c} e_i(k) \\ \delta_i(k) \\ a_i(k) \\ \hline a_{i-1}(k) \\ u_i(k) \end{array}\right]$$

where δ_i denote the relative speed of vehicle i and $i-1$. The open-loop model of the whole platoon

$$x(k+1) \;\; = \;\; A_d x(k) + B_d u(k) + E_d r(k)$$

is constructed by introducing the state vector $x^T = [a_0 \; e_1 \; \delta_1 \; a_1 \cdots e_n \; \delta_n \; a_n]$, control input vector $u^T = [u_1 \cdots u_n]$ and reference signal $r = u_0$.

The platoon controller is a modified version of the constant spacing strategy presented in (Swaroop, 1994, Section 3.3.4). The modification resides in that, instead of measured acceleration, control input is transmitted through the network. Consequently, the gear change has lower impact in the control signal than in the acceleration, so each vehicle can change gear without deceiving the followers; the vehicles react quicker to maneuver changes; and no need for filtering the rather noisy acceleration measurements. The control strategy is defined by the following equations

$$\begin{aligned} u(k) &:= u_L(k) + \hat{u}_N(k) \\ u_L(k) &= K_L x(k) \\ u_N(k) &= K_N x(k) + G_N r(k) + S u(k) \end{aligned}$$

where u_L contains the locally available radar information. Gain matrix K_L can be constructed based on the following definition

$$\begin{aligned} u_{L,1}(k) &= -k_1 \delta_1(k) - k_2 e_1(k) \\ u_{L,i}(k) &= -k_{1\beta} \delta_i(k) - k_{2\beta} e_i(k), \;\; i > 1 \end{aligned}$$

where i stands for the vehicle index and $k_1 := \frac{q_1+q_4+\lambda+\lambda q_3}{1+q_3}$, $k_2 := \frac{\lambda(q_1+q_4)}{1+q_3}$, $k_{1\alpha} := \frac{q_4+\lambda q_3}{1+q_3}$, $k_{2\alpha} := \frac{\lambda q_4}{1+q_3}$, $k_{1\beta} := \frac{q_1+\lambda}{1+q_3}$ and $k_{2\beta} := \frac{\lambda q_1}{1+q_3}$, where q_1, q_3, q_4 and λ are design parameters. Control signal u_N is constructed from the information received from the communication network

$$\begin{aligned} u_{N,1}(k) &= u_0(k) \\ u_{N,i}(k) &= \frac{1}{1+q_3} u_{i-1}(k) + \frac{q_3}{1+q_3} u_0(k) \\ & \quad -k_{1\alpha} \sum_{j=0}^{i} \delta_j(k) - k_{2\alpha} \sum_{j=0}^{i} e_j(k), \;\; i > 1 \end{aligned}$$

from which K_N, G_N and S matrices can be constructed.

The communication network has a sampling time of $T = NT_s$ and the packet is transmitted after $h < T$ constant delay. If $y(k)$ denotes the variable to be transmitted at the network input, then

$$\hat{y}(k) = \begin{cases} y(k-h) & \text{if } \frac{k-h}{N} \text{ is an integer} \\ \hat{y}(k-1) & \text{otherwise} \end{cases}$$

denotes the network output at the receiver.

The closed-loop system with the delayed communication is derived in (Rödönyi et al., 2012). The local part u_L of the controllers run with the faster sampling rate T_s. By closing the loop with u_L, re-sampling with NT_s, then closing the loop with $\hat{u}_N$ and assuming $r(k) = r(k+1) = ... = r(k+N-1)$ we arrive at the following system

$$\begin{aligned} z(k+N) &= A_z(h) z(k) + E_z(h) r(k) \\ A_z(h) &= \begin{bmatrix} A_L^N + B_0(K_N + SK_L) & B_1 + B_0 S \\ K_N + SK_L & S \end{bmatrix} \\ E_z(h) &= \begin{bmatrix} E_N + B_0 G_N \\ G_N \end{bmatrix} \end{aligned}$$

where the state-space is augmented to

$$z(k) = \begin{bmatrix} x(k) \\ u_N(k-N) \end{bmatrix}$$

and

$$\begin{aligned} B_1 &:= \sum_{j=0}^{h-1} A_L^{N-1-j} B_L, \; B_0 := \sum_{j=h}^{N-1} A_L^{N-1-j} B_L \\ E_N &:= \sum_{j=0}^{N-1} A_L^{N-1-j} E_L \end{aligned}$$

where $A_L = A_d + B_d K_L$, $B_L = B_d$, $E_L = E_d$. The spacing errors can be observed through matrixes C_i as $e_i(k) = C_i z(k)$, $i = 1, 2, ...n$.

3 IDENTIFICATION OF MODEL SETS

Nominal vehicle models and uncertainty sets are identified in the worst-case ℓ_1 setting. Two circumstances motivate the application of this identification approach. Both the brake system and the drive-line are functioning as an unknown nonlinear, hybrid systems with many thousands of program rows organizing finite state machines. A good description of noise statistics is not available and only reduced order models can be considered. It seems to be reasonable to consider only strict bounds on the disturbances and unmodelled dynamics. Strict bounds are also useful in the worst case analysis of spacing error bounds. On the other hand, these model sets may result in overly conservative (loose) description of the system. Sophisticated uncertainty model structures are required for control performance analysis problems, the elaboration of which is yet left to future work.

In order to obtain a preliminary view of the uncertainty in the vehicle dynamics and actuators including EBS and ECU softwares, two identification methods are presented in the section. The first one is an ARX-type model structure with time-varying parameters. The basic concept originates in the papers (Nagamune et al., 1997; Nagamune and Yamamoto, 1998), briefly presented in the following subsection. Then, these results are extended in several ways in Section 3.2. In the second method an OE model structure is identified in Section 3.4. Both methods are applied for experimental data of a heavy truck in Section 4.

3.1 Identification of Smallest Unfalsified Sets

Consider the following discrete-time linear single input single output model structure

$$G(z) = \frac{\sum_{i=1}^{m} b_i z^{-i}}{1+\sum_{i=1}^{m} a_i z^{-i}}, \ \ \theta \in P_\theta(\theta^*, \varepsilon)$$

with time-varying parameter vector $\theta = [a_1, \dots, a_m, b_1, \dots, b_m]^T$ defined in the cube $P_\theta(\theta^*, \varepsilon_\theta) := \{\theta :\ \|W(\theta^* - \theta)\|_\infty \leq \varepsilon\}$, where the a priori given diagonal matrix $W = \mathrm{diag}\{\frac{1}{\varepsilon_{\theta,1}}, \dots, \frac{1}{\varepsilon_{\theta,2m}}\}$ defines the shape of the cube with edges of length $2\varepsilon_{\theta,i}$. Given input output data set $\{u(k), y(k)\}_{k=1}^{l}$, the problem is to find the central parameter θ^* and the minimal size ε of the cube such that for every $k = m, \dots, l$ there exists a parameter $\theta \in P_\theta(\theta^*, \varepsilon)$ not invalidated by the measurements, i.e.

$$P_\theta(\theta^*, \varepsilon) \cap D_k \neq \emptyset \qquad \forall k = m, \dots, l$$

where $D_k := \{\theta :\ y(k) = \varphi^T(k)\theta(k)\}$ and $\varphi^T(k) = [-y(k-1), \dots, -y(k-m), u(k-1), \dots, u(k-m)]$. This problem can be solved by minimizing a convex function as follows

$$\varepsilon = \min_{\theta^*} \max_{m \leq k \leq l} \frac{|y(k) - \varphi^T(k)\theta^*|}{\|W^{-1}\varphi(k)\|_1}$$

In the following subsection the model structure is augmented by an additive disturbance term, and the worst case prediction error is minimized while an optimal shape of the parameter cube and a bound for the disturbance are determined.

3.2 Unfalsified ARX Model Set of Minimal Prediction Error in ℓ_∞

With the notation of the previous section we can define the following ARX type model structure, denoted by $\mathcal{M}$

$$\begin{aligned} \mathcal{M} = \{\, & y(k) = \varphi^T(k)\theta(k) + e(k), \\ & \theta(k) \in P_\theta(\theta^*, \varepsilon_\theta), \\ & e(k) \in P_e(\varepsilon_a),\ k = 1, \dots, l \,\} \end{aligned}$$

where

$$\begin{aligned} P_\theta(\theta^*, \varepsilon_\theta) &= \{\theta :\ \|W(\theta^* - \theta)\|_\infty \leq 1\}, \\ P_e(\varepsilon_a) &= \{e :\ |e| \leq \varepsilon_a\}, \\ \varepsilon_\theta &= [\varepsilon_{\theta 1}, \dots, \varepsilon_{\theta 2m}]^T, \\ W &= \mathrm{diag}\left(\frac{1}{\varepsilon_{\theta,1}}, \dots, \frac{1}{\varepsilon_{\theta,2m}}\right) \end{aligned}$$

The shape and size of the uncertainty set characterized by ε_θ and ε_a are unknown parameters. The only information given a priori is the data set $\{u(k), y(k)\}_{k=1}^{l}$.

In order to characterize consistency of the model set with the data, define hyperplane D_k in the $n+1$ dimensional extended parameter space of $p := [\theta^T\ \ e]^T$

$$D_k := \{p :\ y(k) = [\varphi^T(k)\ \ e(k)]p\}$$

Let $P(\theta^*, \varepsilon_\theta, \varepsilon_a) := \{p = [\theta^T\ e]^T :\ \theta \in P_\theta(\theta^*, \varepsilon_\theta),\ e \in P_e(\varepsilon_a)\}$ denote the parameter set defining model set $\mathcal{M}$ in the extended parameter space.

Definition 1 (Consistency). *The parameter set $p \in P(\theta^*, \varepsilon_\theta, \varepsilon_a)$ can reproduce the data if*

$$P(\theta^*, \varepsilon_\theta, \varepsilon_a) \cap D_k \neq \emptyset \qquad \forall k = m, \dots, l \tag{1}$$

For given data $\varphi(k)$ and model set parameters θ^*, ε_θ and ε_a the output $y(k)$ that the model set can generate lies between the bounds

$$\begin{aligned} \overline{y}(k) &= \max_{\theta \in P_\theta(\theta^*, \varepsilon_\theta)} \varphi^T(k)\theta + \varepsilon_a \\ \underline{y}(k) &= \min_{\theta \in P_\theta(\theta^*, \varepsilon_\theta)} \varphi^T(k)\theta - \varepsilon_a \end{aligned}$$

With these bounds, the parameter set identification problem can be formulated as follows.

Problem 1. *Assume that we are given a data set* $\{u(k), y(k)\}_{k=1}^{l}$. *Find a model set characterized by* θ^*, ε_θ *and* ε_a *such that* (1) *is satisfied and that minimizes* $\gamma := \frac{1}{2}\|\overline{y}(k) - \underline{y}(k)\|_\infty$.

3.3 Solution Via Linear Programming

It will be shown that Problem 1 leads to the solution of a linear programming (LP) problem. In contrast to the solution of (Nagamune et al., 1997), where for each D_k a minimum necessary size parameter $\varepsilon = \varepsilon(D_k, \theta^*)$ is determined for a given θ^*, we characterize consistency with the help of the output bounds

Lemma 3.1. *Consistency condition* (1) *is satisfied if and only if there exist* θ^*, ε_θ *and* ε_a *such that*

$$y(k) \leq \varphi^T(k)\theta^* + |\varphi^T(k)|\varepsilon_\theta + \varepsilon_a, \; k = m, \ldots, l \quad (2)$$
$$y(k) \geq \varphi^T(k)\theta^* - |\varphi^T(k)|\varepsilon_\theta - \varepsilon_a, \; k = m, \ldots, l \quad (3)$$

where $|.|$ *element-wise takes the absolute value of the argument.*

Proof. We only need to show that $\max_{\theta \in P_\theta(\theta^*, \varepsilon_\theta)} \varphi^T(k)\theta = \varphi^T(k)\theta^* + |\varphi^T(k)|\varepsilon_\theta$ and $\min_{\theta \in P_\theta(\theta^*, \varepsilon_\theta)} \varphi^T(k)\theta = \varphi^T(k)\theta^* - |\varphi^T(k)|\varepsilon_\theta$, then the statement follows from the definitions. The linear function $\varphi^T(k)\theta$ over a convex polytope takes up its extreme values at the vertices of the polytope. Let the vertex set of $P_\theta(\theta^*, \varepsilon_\theta)$ be denoted by $\mathcal{V}$,

$$\mathcal{V} = \left\{ \theta : \; \theta = \theta^* + \begin{bmatrix} \pm\varepsilon_{\theta,1} \\ \vdots \\ \pm\varepsilon_{\theta,2m} \end{bmatrix} \right\}$$

where $\pm$ means all combinations. From this the claims follow. $\square$

The following theorem summarizes our results.

Theorem 3.2. *The model set* $\mathcal{M}$ *which is consistent with the data set* $\{u(k), y(k)\}_{k=1}^{l}$ *and minimizes* $\gamma = \frac{1}{2}\|\overline{y}(k) - \underline{y}(k)\|_\infty$ *is the solution of the following LP problem.*

$$\min_{\theta^*, \varepsilon_\theta, \varepsilon_a} \gamma$$

subject to (2), (3) *and*

$$\gamma \;\; \geq \;\; |\varphi^T(k)|\varepsilon_\theta + \varepsilon_a, \;\; k = m, \ldots, l$$

The problem involves $4m+2$ variables and $3(l-m+1)$ inequality constraints, and can be efficiently solved by rutin CLP in the MPT toolbox for Matlab, (Kvasnica et al., 2004).

3.4 Identification of OE Models of Minimal Error in ℓ_∞

In this section an output error model structure is identified with the smallest error in ℓ_∞. Suppose, we are given a data set $\{u(k), y(k)\}_{k=1}^{l}$ and the model structure of LTI SISO systems in the form

$$G(z) = \frac{\sum_{i=1}^{m} b_i z^{-i}}{1 + \sum_{i=1}^{m} a_i z^{-i}}$$

The set of parameters is divided as $\theta_a = [a_1, \ldots, a_m]$ and $\theta_b = [b_1, \ldots, b_m]$. We are looking for θ_a and θ_b that minimize $\gamma := \|y(k) - \hat{y}(k)\|_\infty$, where $\hat{y}(z) = G(z)u(z)$. This optimization problem is nonlinear in parameter θ_a, therefore an nonlinear programming method can be applied. In case of small noises, good initialization for θ_a and determination of the model order can be attained by using the recent result (Soumelidis et al., 2011). Once θ_a is fixed, θ_b can be computed by linear programming as follows.

1. Formulate A, B, C, the controllability canonical state-space representation of $G(z)$. Then $C = \theta_b^T$. From this, $\hat{y}(k) = \theta_b^T \sum_{j=0}^{k-1} A^{k-j-1} B u(j)$
2. Solve the LP problem

$$\min_{\theta_b} \gamma$$

subject to

$$y(k) - \theta_b^T \sum_{j=0}^{k-1} A^{k-j-1} B u(j) \leq \gamma, \;\; k = m, \ldots, l$$

$$-y(k) + \theta_b^T \sum_{j=0}^{k-1} A^{k-j-1} B u(j) \leq \gamma, \;\; k = m, \ldots, l$$

4 MODELLING LONGITUDINAL VEHICLE DYNAMICS

Several braking experiments have been carried out with a Volvo FH, 24 tonne three-axle truck. ARX and OE models of order $m = 1$ are identified by using the methods described in the previous section.

4.1 ARX Model Structure

The LP method of Theorem 3.2 was applied to the model structure

$$a(k) = a(k-1)\theta_1(k) + u(k-1)\theta_2(k) + e(k)$$
$$\theta(k) := [\theta_1(k) \; \theta_2(k)]^T \in P_\theta(\theta^*, \varepsilon_\theta)$$
$$\|e(k) - e^*\|_\infty \leq \varepsilon_a$$

where $a(k)$ is the longitudinal acceleration computed by the available onboard computers based on wheel speed measurements, and $u(k)$ is the acceleration demand defined in an AutoBox connected to the vehicle's CAN network. An offset error of the measurements can be taken into consideration with parameter e^*. The unknown parameters of the model are the central parameters θ^* and e^*, and the bounds of the parameter and noise variation, ε_θ and ε_a, respectively.

The one-step ahead prediction of the optimal model is plotted in Figure 1. The central parameters θ_1^* and θ_2^* correspond to a time constant of 1.13s and a gain of 9.5 when the model is transformed to continuous time by zero order hold ($T_s = 0.01$). For the parameter variation we get $\varepsilon_\theta^T = [0.180.20]1e-12$.

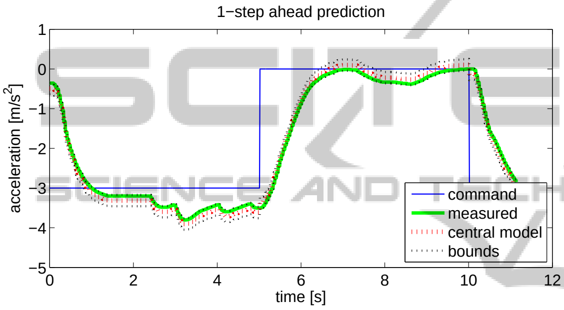

Figure 1: One step ahead prediction with the central model with parameter θ^* in a braking experiment. Bounds for the prediction, $\bar{y}$ and $\underline{y}$, are also plotted (thin dotted black lines).

Fixing the maximum allowed noise level ε_a, the optimization can be performed in the remaining variables. Figures 2 and respectively 3 show the dependence of the prediction error bound and the optimal parameters on the chosen noise levels. It can be seen that forcing the model set to represent uncertainty by the time-variation of parameters will result in overly conservative models. At the optimum, the uncertainty is described by almost entirely the noise term. We must conclude that a more sophisticated uncertainty description is necessary.

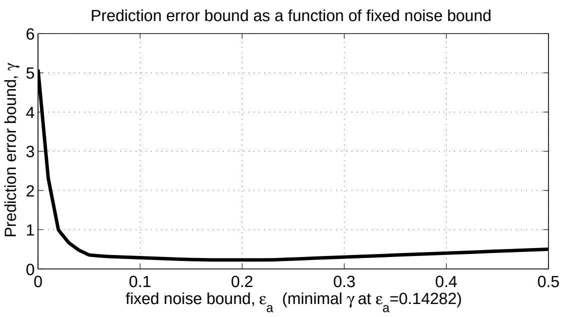

Figure 2: Worst case prediction error as a function of fixed noise bound ε_a in the ARX model structure.

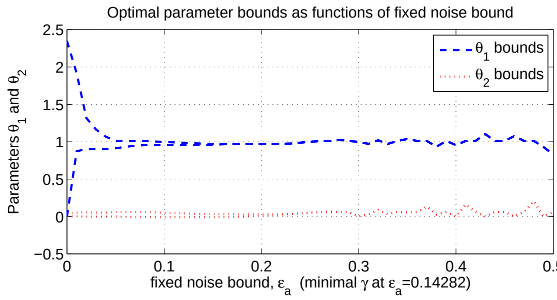

Figure 3: Parameter bounds as functions of fixed noise bound ε_a in the ARX model structure.

4.2 OE Model Structure

The output-error model structure

$$a(k) = a(k-1)\theta_1 + u(k-1)\theta_2 + e(k) - e(k-1)\theta_1$$
$$\|e(k) - e^*\|_\infty \leq \varepsilon_a$$

is identified by applying the LP method presented in Section 3.4 for identifying θ_2 while θ_1 is determined by simple line search. The optimal parameters correspond to a time constant of 0.9s and a gain of 1.25 when the model is transformed to continuous time by zero order hold ($T_s = 0.01$). The fit of the model and the error bounds are plotted in Figure 4. This model can serve as nominal models in the performance analysis of the platoon.

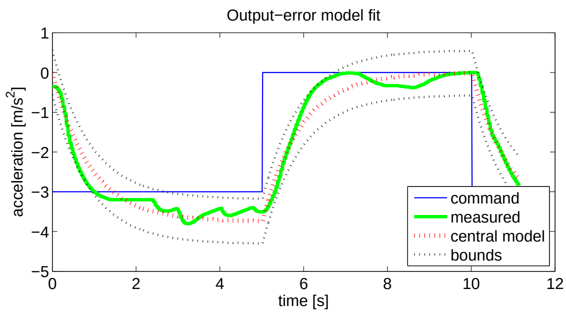

Figure 4: Fit of the OE model with parameter to the measurements in a braking experiment. Bounds for the error are also plotted (thin dotted black lines).

5 PERFORMANCE ANALYSIS OF HETEROGENEOUS PLATOONS

For the case of heterogeneous platoons with nominal LTI models, spacing error bounds in ℓ_∞ are analyzed.Assume that the allowable reference input $r = u_0$ satisfies $\|u_0\|_\infty \leq u_{max}$, where u_{max} is a given bound. Then, the worst-case peaks of the spacing errors, as functions of communication delays, can be computed as follows

$$\varepsilon_i(h) \quad := \quad \|e_i(h,t)\|_\infty = \sum_{j=0}^{\infty} |C_i e^{A_z(h)t} E_z(h)| u_{max}$$

In the following numerical analysis $\varepsilon_i(h)$, $i = 1,\dots,n$, are computed when the platoon is not homogeneous in nominal vehicle parameters θ_i^*. It is assumed that both $\theta_{i,1}^*$ and $\theta_{i,2}^*$ may differ from vehicle to vehicle

$$\Theta \quad = \quad [\theta_{1,1}^*\ \theta_{1,2}^*\ \theta_{2,1}^*\ \theta_{2,2}^*\ \dots\ \theta_{n,1}^*\ \theta_{n,2}^*],$$

$$\theta_{i,1}^* = 1 - \frac{T_s}{\tau_i} \quad \theta_{i,2}^* = \frac{T_s g_i}{\tau_i} \quad \begin{array}{l} \tau_i \in \{0.6, 0.8\} \\ g_i \in \{0.9, 1.1\} \end{array}$$

where time constant τ_i and gain g_i are parameters of the continuous-time vehicle models and may take up their extremal values. It can be shown that the worst-case platoon configuration is the case when the vehicle model parameters are extremal and alternating in order. This means that if the platoon is of length $n+1$, it is enough to compute $\varepsilon_i(h)$, $i = 1,\dots,n$ for $(n+1)^4$ systems. Taking the maximum and minimum for the $(n+1)^4$ systems, Figure 5 show the worst case and best case bounds as functions of the vehicle index i. The lower bounds are achieved in case of homogeneous platoons. For a given set of allowable maneuvers, this analysis directly provides hints on choosing safety gaps between the vehicles in the different control modes, such as $L_i > \varepsilon_i$, assuming zero initial conditions. The analysis is carried out for a range of network delays from $h = 0$ to $h = 8T_s$, but network delay of this range has negligible impact on the bounds.

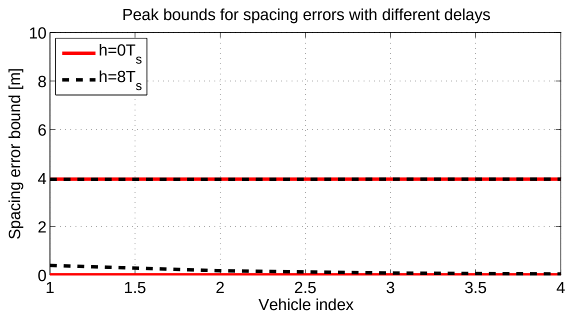

Figure 5: Lower and upper bounds on spacing errors, ε_i for different network delays. Uncertainty is present in both θ_{i1} and θ_{i2}. Lower bounds (around zero) correspond to homogeneous platoons. Upper bounds at $\varepsilon_i = 4$ correspond to platoons of alternating vehicle dynamics.

In the case when gain coefficients are estimated on-line, for example with the help of parameter adaptation methods described in (Swaroop, 1994), acceleration demand can always be scaled so that θ_{i2} parameters can be set to $\theta_{i2} = 1$. Then, spacing errors are bounded as shown in Figure 6. The bounds reduced to about one meter.

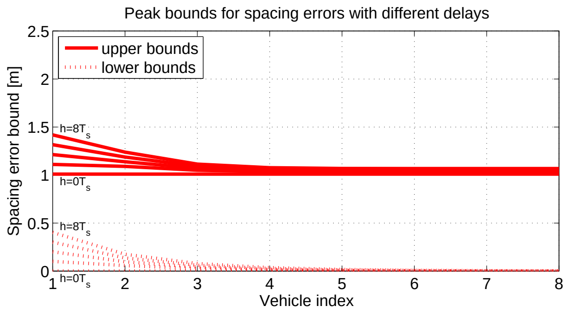

Figure 6: Lower and upper bounds on spacing errors, ε_i for different network delays. Uncertainty is present only in θ_{i1}.

6 EXPERIMENTAL RESULTS

The control strategy presented in Section 2 is implemented on a platoon of three heavy trucks and tested on a 3km long flight-strip. The leader vehicle, driven by a driver, is a MAN TGA two-axle tractor of 18 tonne with load cage. The second vehicle is a Volvo FH 24 tonne three-axle truck. The third one is a Renault Magnum two-axle tractor of 18 tonne with a semitrailer, See Fig. 7. It is important to remark that all vehicles are equipped with automatic gear change, thus acceleration can be attained purely by software.

The communication network consists of radio transceivers operating on the open 868MHz ISM narrow-band.

Figure 7: Experimental vehicles in project TruckDAS.

The experimental scenario is started with a 'joining in' maneuver in which the leader vehicle passes the others which are travelling at constant speed. When the last vehicle in the platoon is caught by the radar of the joining vehicle and its driver enables the joining maneuver by pressing a deadman-button, the joining vehicle is accelerated and braked by given constant values and for sufficient time so that the vehicle arrives approximately at the prescribed distance with speed near that of the platoon. After the braking period the spacing controller is switched on. When both joining maneuvers are finished, the leader vehicle can accelerate and decelerate and finally stop.

Nine experiments of similar maneuvers were carried out on a 3km long pathway. The maximum spacing error was not greater than 3m during braking, i.e. in the direction of collision danger. During driving maneuvers, the maximum leg was not greater than 8m.

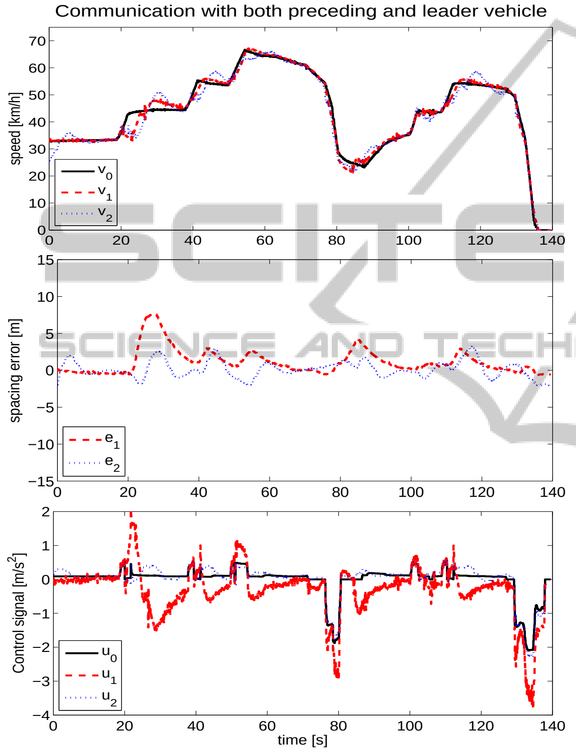

Figure 8: Platoon control experiment.

7 CONCLUSIONS

According to our experiences in a platoon of three vehicles with different types and properties, a safety gap of 3m can be safe if the following conditions hold: deceleration of the leader vehicle is not greater than $2m/s^2$ and there is some dwell time between intensive acceleration and abrupt braking maneuvers so that transients can cease.

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