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Published in:
Nonlinear and Hybrid Systems in Automotive Control

DOI:
10.1109/AIM.2001.936845

2001

2001 IEEE/ASME International Conference on
Advanced Intelligent Mechatronics Proceedings
8—12 July 2001 • Como, Italy

Modeling of Drivers' Longitudinal Behavior

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Abstract— **In the last years, many vehicle manufacturers have introduced advance driver support in some of their automobiles. One of those new features is Adaptive Cruise Control (ACC), which extends the conventional cruise control system to control of relative speed and distance to other vehicles. In order to design an ACC controller it is suitable to have a model on drivers' behavior. Our approach to find dynamical models of the drivers' behavior was to use system identification. Basic data analysis was made by means of system identification methodology, and several models of drivers' longitudinal behavior are proposed, including both linear regression models and subspace based models. Detection when a driver is changing his behavior in various situations to a deviant behavior is useful. To that purpose a GARCH model was used to model the driver in arousal situations, where the driver changes behavior, is proposed.**

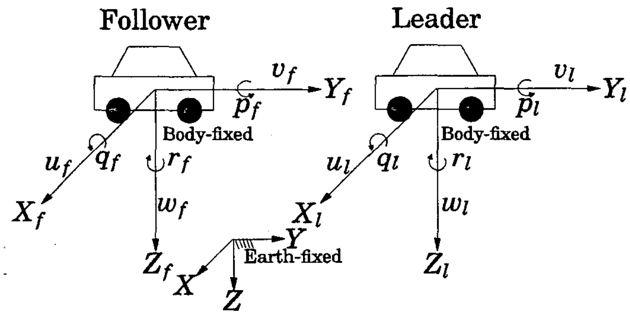

Fig. 1. Body-fixed and earth-fixed reference frames.

I. Introduction

Systems that support a driver in traffic situations and reduce the total driver workload, have been studied since the 1950s. Several of these support systems aim towards fully or partially automatic driver assistance system, such as those for longitudinal control often called ACC system [10], [11], [12], [17]. Much attention to ACC devices has also appeared in the PATH project [9]. The motivation for these systems is that they are aiming to increase the driving comfort, reduce the traffic accidents and increase the flow throughput. These ACC systems autonomously adjust the vehicle's speed according to current driving conditions. In order to accomplish driver comfort the system must resemble driver behavior in traffic and the system must avoid irritation of the driver and the surrounding traffic. Therefore, to design a system that resembles the natural longitudinal behavior a good model of a driver is needed. There exist several models of the drivers' longitudinal behavior, which all aim to describe various parts of the drivers' behavior. The model structures are different, some are based on cognitive models [6], [7], [15], [18] or are general longitudinal models [2], [16], [22] or only car-following models [4], [1], [3]. Most of them have one thing in common in that they are using static models.

II. Material and Methods

A. Equipment and experimental setup

Fig. 1 shows a car following situation. The speed of the preceding and following vehicle is denoted v_l and v_f, and the distance between the vehicles is denoted ΔY, headway $\Delta Y = y_l - y_f$. The relative speed is defined as:

$$\Delta v = v_l - v_f = \frac{d}{dt}\Delta Y \qquad (1)$$

There are four types of situations, where data have been collected: following, cutting-in, braking, and mode changing. Cutting-in situations describe a scenario wherein a vehicle cuts in front of the driver's vehicle from an another lane. In the braking situations the headway distance decreased under the individual minimal headway distance, and the driver braked to reestablish the headway distance. In mode-changing situations the driver shifted from uninfluenced driving to car following. Data collection of various situations have been done on public roads as well as on test tracks. Seven different drivers of various sex and age (23-35) participated in the data collection. The data acquisition was performed in the summer of 2000 during good weather conditions. The equipment consisted of two cars, Volvo S70, one car was equipped with a radar from CelciusTech, that was used to measure the distance to the front vehicle ΔY and it's relative speed Δv. A practical difficulty was that the radar must have good resolution, also at small distances and that the relative speed measured with high resolution. In some of the situations, a laser from IBEO was also used, to measure ΔY and Δv. The other car used as front vehicle had the property that it was possible to program the car to drive along a trajectory. By using that feature, it was possible to reproduce the situation and to let all the different drivers drive the

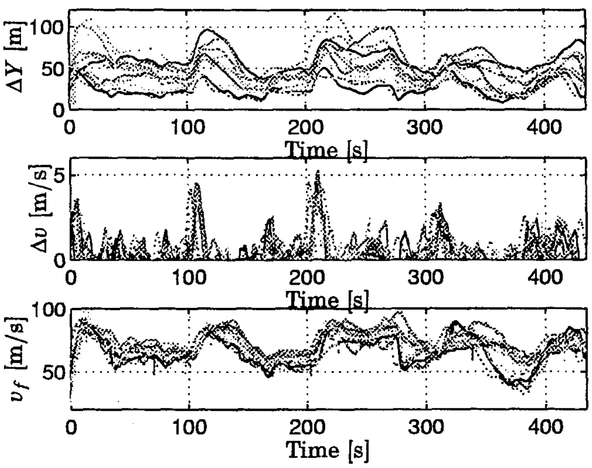

Fig. 2. Data collection from of the inputs in one following situation. Data are from 7 different drivers.

same situation.

B. Data Analysis

The collected data variables are space headway (ΔY), differential velocity (Δv), velocity (v_f), throttle angle (α_t), brake pressure (p_b). A natural choice of inputs to the driver model are ΔY, Δv, and v_f. The outputs are then α_t, p_b.

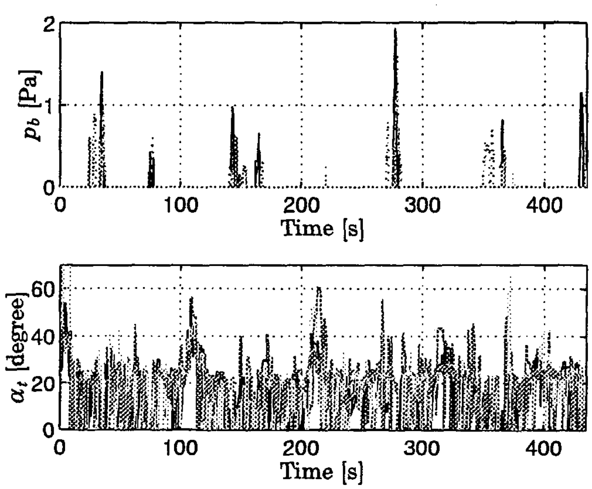

Fig. 3. Data collection from of the outputs in one following situation. Data are from 7 different drivers.

Fig. 2 and 3 shows data from a following situation in which seven different drivers participated. There are individual differences between the drivers, but also large similarities among their behaviors. The major differences between the drivers consist in the choice of space headway and safety distance.

Basic data analysis was made by means of system identification methodology [13]. Autospectra, cross-spectra and coherence spectra of the inputs (ΔY, Δv, and v_f) and outputs (α_t and p_b), were made for assessment of the various signals levels and relationship.

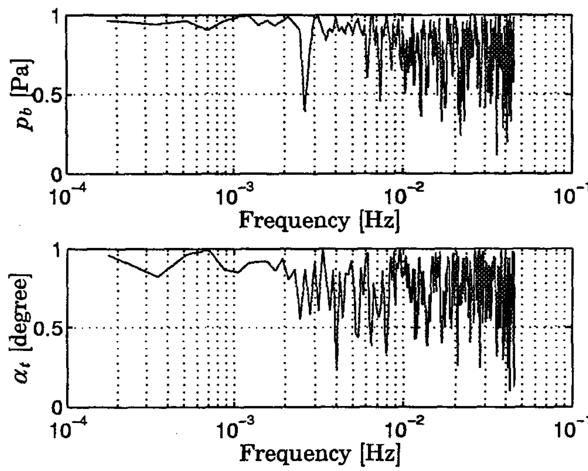

Fig. 4. Coherence spectra between the inputs and the outputs. The upper figure: coherence between inputs $[\Delta Y \quad \Delta v \quad v_f]$ and the output p_b. The lower figure: coherence between inputs $[\Delta Y \quad \Delta v \quad v_f]$ and the output α_t.

In Fig. 4 the coherence among inputs and outputs are shown. The coherence is high, which can be interpreted as an indication that there exists a linear relationship between the inputs and the outputs. Note that the coherence spectra for p_b is higher, than for α_t.

C. Modeling

The human driver is a closed-loop system, as in Fig. 5, where the feedback is the front vehicles velocity v_l. All the experiments were performed in closed-loop feedback operation and there may be systematic problems how to obtain relevant information from this type of experiments [13, Ch. 8]. If there is feedback during the experiment the data may not be informative enough to design a valid model of the driver. The system is of multi-input multi-output structure.

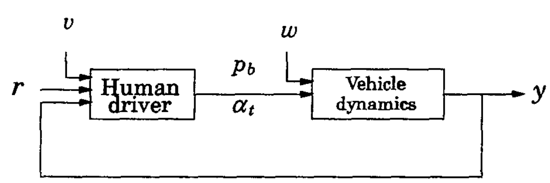

Fig. 5. Structure of a human driver in car-following. r is the inputs to the driver from the lead vehicle. v is the observation noise, w is the motor noise, and y is the car position and velocity.

We use the inputs and outputs chosen to make a direct identification of the human driver. Different models have been used, which in short described below.

C.1 Linear regression models

To find if there is some relationship between the input data and the output, a linear regression model is estimated, with the regressors. The linear regression model takes on the format

$$y_k = [\Delta Y_k ... \Delta Y_{k-n} \Delta v_k ... \Delta v_k ... v_{f_k} ... v_{f_{k-n}}]\,\theta + e_k \qquad (2)$$

where n is the estimated order and e_k is additive errors. A linear regression model of high order was estimated. Since the model order is high, it may be assumed that the computed residual ε_k is a good approximation of the noise e_k. The residual sequence is used in pseudolinear regression to estimate a model of lower order.

C.2 State-space models using subspace-based identification

A discrete-time time-invariant system in state-space realization:

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k + w_k \\ y_k &= Cx_k + Du_k + v_k \end{aligned}$$

where w_k and v_k are noise.
The problem is to estimate the order n of the system and the system matrices A, B, C, D. In Fig. 6 is a schematic representation of the identification problem. The subspace method is well suited for modeling of multivariable systems [13]. The subspace method base the criteria of determinate the order of the model on singular-values. To determinate the order a Hankel matrix is constructed [20], [19]. The choice of order is based on the singular values of the Hankel matrix. However, if there is a strong noise influence then this criterion degrades and becomes non-conclusive.

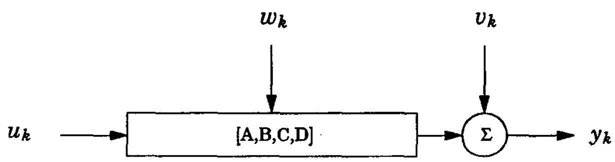

Fig. 6.

C.3 Behavioral model

Behavioral model identification may be suggested in cases without clear-cut distinction of signals as inputs or outputs [21], [14]. This may be preferable since there is interaction between the driver and the car. There are also interactions between the driver and other vehicle, for example in cutting-in situations. The behavioral method has great similarities with the subspace method, but differs in its absence of explicit separation among inputs and outputs. Thus, the estimated state-space model represents all the dynamics, both for the inputs and for the outputs. Then by matrix fraction description an input-output model is obtained.

III. Results and validation

In all cases, identification accuracy was measured using Variance-Accounted-For (VAF).

$$VAF = 1 - \frac{var(y - \hat{y})}{var(y)} \times 100\% \qquad (3)$$

In the model estimation the normalized ΔY, Δv, v_f, α_t and p_t was used.

A. Linear regression

A linear regression model of order n=30 was estimated and is shown in Fig 7. The model captures some of the driver behavior. One reason why not even this high-order model succeeds in modeling the driver may be that the experiment setup is a closed-loop system. The model is better in predicting the driver's throttle angle α_t behavior, than the brake pressure p_b behavior. A possible background would be that the acceleration and deceleration have different explanations, for example that deceleration could be explained by air resistance or topography. The residual analysis of the model is shown in Fig 8 and it is found that the residual from output α_t and the output p_b have different distributions. The residuals of this high order model were further used to estimate a pseudolinear regression model. The result is shown in Fig. 9, and the model capture most of the driver's behavior, even the braking behavior.
VAF scores for the linear regression model are 41.1% (p_b) and 46.2% (α_t) whereas the VAF scores for the pseudolinear regression model: 89.9% (p_b) and 73.2% (α_t) respectively.

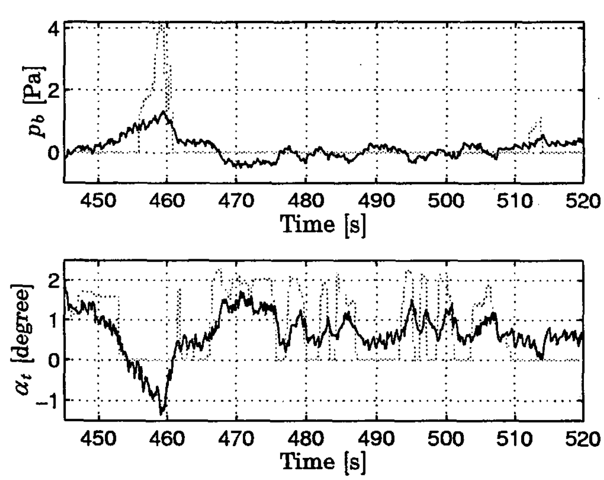

Fig. 7. Data (*grey*) and simulated output data from a linear regression model of order n=30 (*black*).

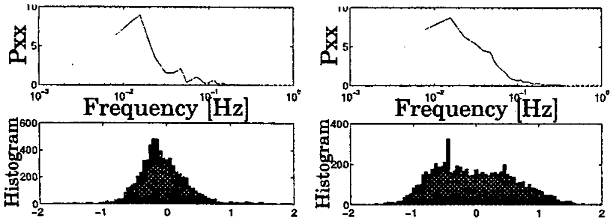

Fig. 8. Histogram and auto-correlation of the residuals from a thirtieth order linear regression model. To the left is the residuals of output p_b. To the right is the residuals of output α_t.

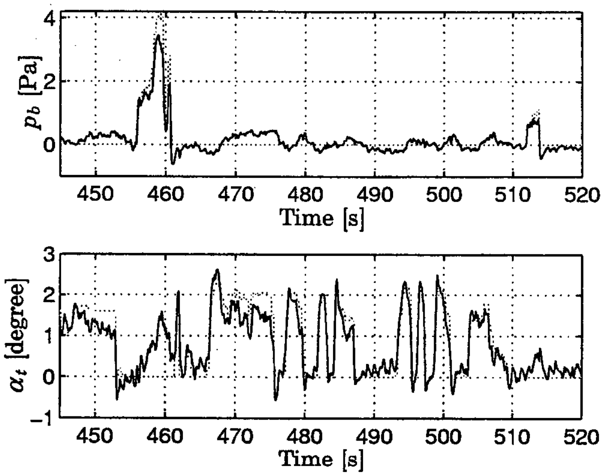

Fig. 9. Data (*grey*) and simulated output data from a pseudolinear regression model of first order (*black*).

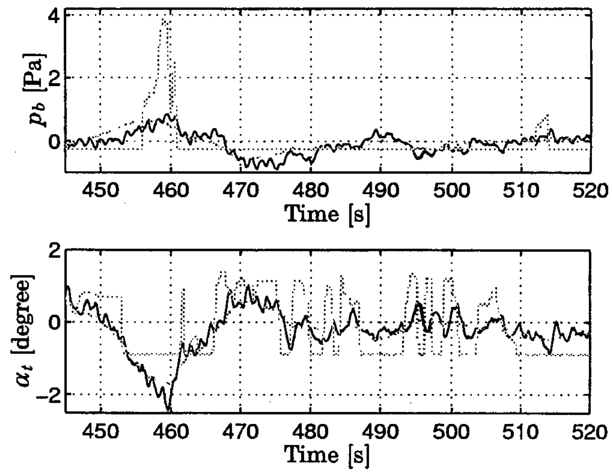

Fig. 10. Data (*grey*) and simulated output data from state-space models using subspace methods, n=5 (*dashdot*), and n=15(*solid*).

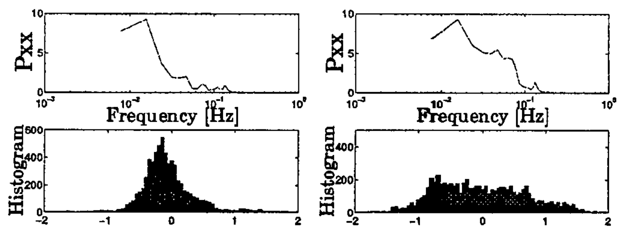

Fig. 11. Histogram and auto-correlation of the residuals from a fifteen order sub-spaced model. To the left is the residuals of output p_b. To the right is the residuals of output α_t.

B. Subspace-based identification

The state-space models using subspace methods have been designed by using the SMI Toolbox[1] in Matlab. n Fig. 10 the data and simulated output data have been compared and it is found that lower order models of state-space models have problems to capture the behavior of the driver. The state-space models capture some of the driver's behavior (Fig. 10). Best result was obtained for the model order n=15, but there are some possible time delays. The estimated model n=15 is better to capture the driver's throttle behavior than the brake behavior with VAF scores: 44.3% (p_b) and 48.7% (α_t). The residual analysis of the model is shown in Fig. 11 and like in for the linear regression model the residual for α_t have different different distributions.

C. Behavioral model

A behavioral model of order n=7 was estimated and is shown in Fig 12. The model captures the driver behavior very good, it captures both the braking behavior and the throttle behavior. The residual analysis of the model is shown in Fig. 13 and they both seem to have normal distributions. VAF scores for the behavioral model are 81.9% (p_b) and 92.2% (α_t).

[1]http://control-lab.et.tudelft.nl/ haver/smi/smi.html

D. The 'arousal behavior'

We notice that the residual ε from the seventh order behavior model for p_b becomes large when the braking starts. We may call this phenomenon 'arousal behavior' and estimate a Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) model [5], [8]. A GARCH(r,m) model is:

$$u_t = v_t\sqrt{h_t} \tag{4}$$

where v_t is an independently distributed Gaussian sequence with zero mean and unit variance and h_t is:

$$\begin{aligned} h_t &= \kappa + \delta_1 h_t + \delta_2 h_{t-2} + \cdots + \delta_t h_{t-r} \\ &\quad + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \cdots + \alpha_m u_{t-m}^2 \end{aligned} \tag{5}$$

where $\kappa \equiv [1 - \delta_1 - \delta_2 - \cdots - \delta_r]\zeta$. In Fig. 14 the squared residual sequence is shown, and the residual of p_b seems to increase linearly during the brake part. The estimated third order linear regression models for the different drivers capture the behavior of the residual well, Fig. 14, 15, and 16. In Fig. 17 the impulse

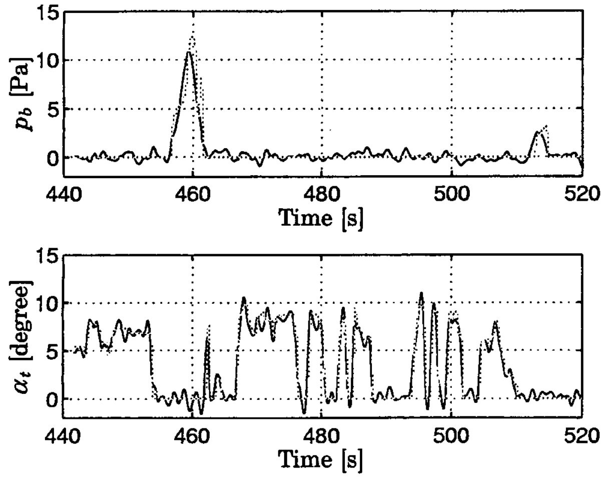

Fig. 12. Data (*grey*) and simulated output data from a behavioral model(*black*).

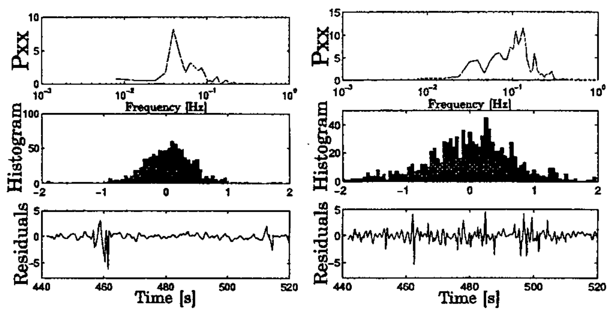

Fig. 13. Residuals of output p_b from a behavior model n=7 (*left*). Residuals of output α_t from a behavior model n=7 (*right*). Notice that the residual of the output p_b becomes large when the time is around 460s.

response from the linear regression of the second driver. Notice that there is an association between the arousal behavior in the brake situation and the throttle behavior, respectively.

IV. Conclusion

We have studied the dynamical longitudinal behavior of drivers' and models designed with various model structure. The design approach to use system identification, such as linear regression, state-space models using subspace methods, and behavioral models was found to work fairly well, especially with the behavioral models. The accuracy differs between the various model structures, and the best VAF scores are achieved by the behavioral model. Progress of the VAF scores for increasing model orders and for various model structures is shown in Fig. 18. The modeling of the arousal behavior was found to work well. The proposed model captures the deviant behavior in arousal situations.

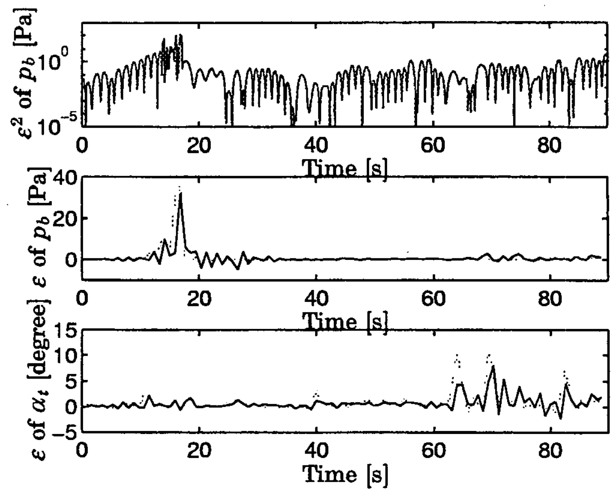

Fig. 14. Upper figure shows squared residuals ε from the behavioral model n=7, illustrating the heteroscedasticity variance properties. Center and lower figures show residuals ε from driver 1 (*dashed*) and simulated residuals ε from a linear regression model (*solid*).

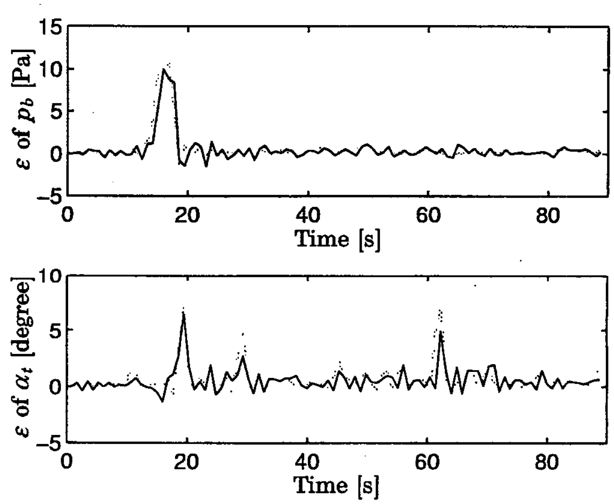

Fig. 15. Residuals ε from driver 2 (*dashed*) and simulated residuals ε from a linear regression model (*solid*).

Acknowledgments

This work was a joint project with partners of Volvo Technological Development Corporation and the Department of Automatic Control, Lund University. The authors thank NUTEK for financial support.

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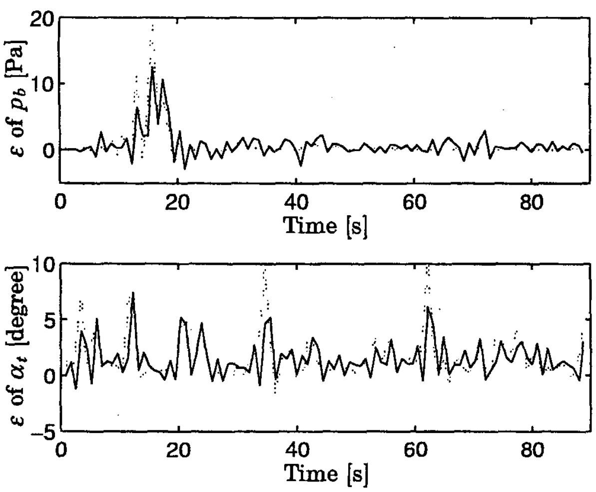

Fig. 16. Residuals ε from driver 3 (*dashed*) and simulated residuals ε from a linear regression model (*solid*).

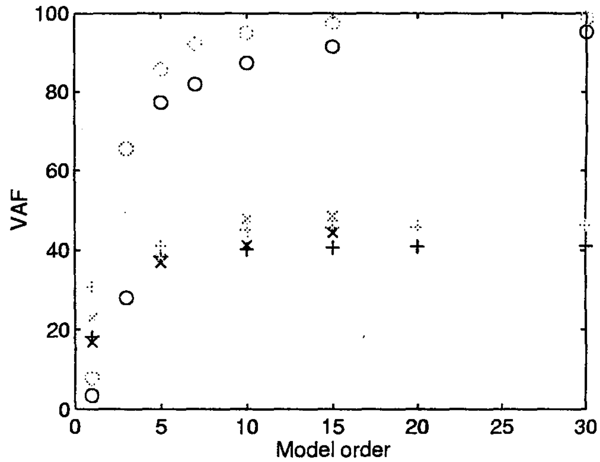

Fig. 18. VAF scores (p_b (*grey*) and α_t (*black*)) for various model structures and model order (*linear regression model +, state-space model using subspace methods x, and behavioral model o).*

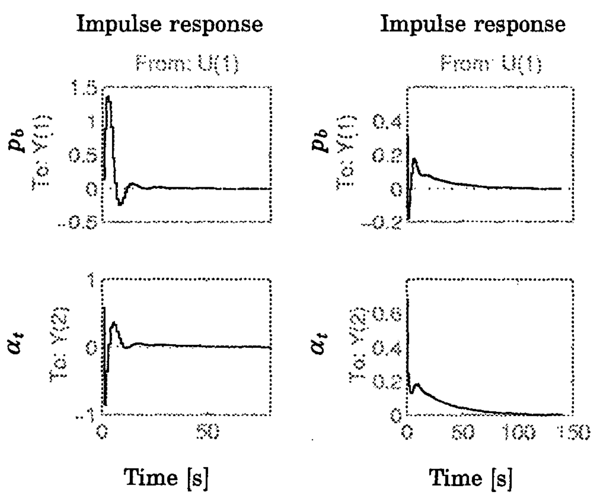

Fig. 17. Impulse response where input is residual from p_b (*left*) and impulse response where input is residual from α_t (*right*)

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