Driver-Model-Based Assessment of Behavioral Adaptation *

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Drivers intermittently engage in many driving and non-driving subtasks. Decisions to redirect attention are based on proximity of vehicle-state to situation-adaptive safety-margins such as time-head-way and time-to-line-crossing. In response to the non-driving task demands, drivers adapt their safety margins to absorb the longer response times resulting from diverted or reduced attention to the driving task. These increased safety margins enable driver to adopt a less demanding control strategy which is reflected in lower gains, longer delays, and a more non-linear response to vehicle state changes (i.e. increased remnant). Classical performance metrics of means and standard deviations in vehicle-state do not capture how drivers adapt their control-behavior to accommodate changing task demands because they are not grounded in driver behavior but in a low-pass filtered vehicle state. It is important to capture the driver's goals (i.e. safety margins) and how they manage these goals (i.e. control strategy) to understand why and how drivers behave as they do. A car following model is presented to demonstrate through identification of the model coefficients how drivers adapt their behavior to accommodate the experimentally imposed need to perform a demanding in-vehicle task.

Key Words: Driving Performance, Driver Assessment, Car Following Model, Driver Distraction, Driver Adaptation (20)

1. INTRODUCTION

Driver models embody our understanding of how drivers interact with and adapt to self and externally imposed driving and in-vehicle task demands. The coefficients of these models together with the external input and disturbance signals characterize and predict how drivers behave. Comparing model coefficients and characteristics across conditions and individuals provides a means to gain a fundamental understanding of the reason for any differences in statistical properties of the observed output variables of the environment-driver-vehicle system. The model coefficients offer a sensitive means to quantify differences between drivers and driving conditions.

Accurate quantification of driver performance and adaptation are important in assessment of: i) driver skill, ii) support system benefit, iii) in-vehicle task interference, iv) driving simulator fidelity, v) driver adaptation and learning, etc.

Model based assessment requires the development of an identifiable driver model whose coefficients and characteristics not only predict a vast number of changes in directly measurable driving behavior (e.g. speed and distance to lead vehicle plus their standard deviations) but also shows how they are correlated or causally linked through the model structure. The goal is to understand the most fundamental adaptation, limitation, or capability in characterizing driver behavior. Once these are discovered through model based assessment (i.e. identification), many standard metrics can be predicted and better understood. Driver performance is more sensitively assessed based on the driver actions or controller settings they adopted than on the vehicle state partly because of the strong low pass filtering characteristics of the vehicle; the vehicle essentially filters away highly valuable information about driver behavior. A similar philosophy has been adopted in the development of steering and behavioral entropy measure of driver performance and workload (1,3).

In this paper, focus is directed to the model based assessment of driver's adaptation to the need to perform a demanding in-vehicle task while following another vehicle whose speed fluctuates.

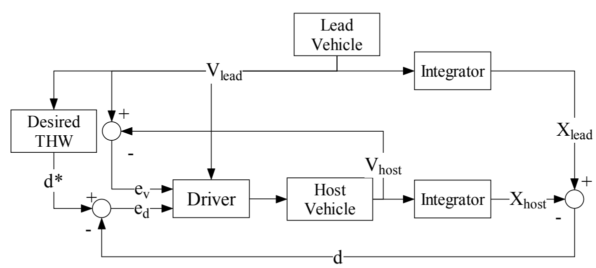

Fig. 1 Flow diagram of complete driver-vehicle interaction car following model. Input is the lead vehicle speed profile.

1.1 Coherence Technique

The coherence technique (5) is often used to quantify the effect of secondary task involvement on car following behavior. Its drawback is that the lead vehicle speed has to follow a sinusoidal profile whose frequency randomly changes slowly in the narrow frequency band around 0.028Hz (see Fig. 4 for an example speed profile). This signal is highly predictable in terms of extreme speeds as well as rough timing and magnitude range of acceleration and decelerations. The high sensitivity of the method contributes to its widespread use for assessing the relative effects of different tasks or support systems (4). Realizing that the coherence technique quantifies the modulus, delay, and coherence between the lead vehicle speed and the host vehicle speed, one can easily extend this to gain, phases, and

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coherences by adopting a car following model and a more naturalistic broader bandwidth lead vehicle speed profile. This is roughly the approach adopted in this paper, except a narrow band lead vehicle speed profile is used to first ground the proposed method in this well established coherence technique methodology before employing it on a natural broadband lead vehicle speed profile (future publication). However, an emergency lead vehicle braking event effectively excites the driver broad band and thus provides the excitation of the majority of poles and zeros that characterize the driver as a controller thus enabling and justifying identification of a full model. The model enables one to compute either analytically (left for future publication) or through simulation (used in this paper), the gains and phases to any sinusoidal input signal (i.e. the Bode plot of the transfer function between lead vehicle speed and host vehicle speed). Thus the proposed car following model based method is a generalization of the coherence technique to more realistic or a wider range of lead vehicle speed profiles and can thus be applied to real world naturalistic lead vehicle speed profiles.

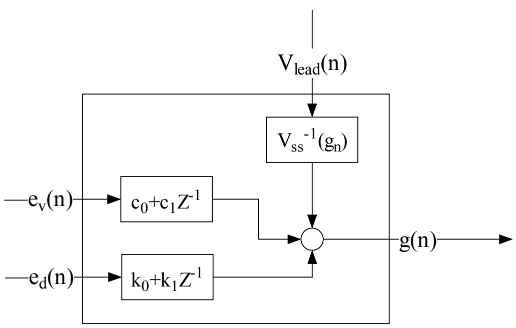

Fig. 2 Flow diagram of driver model. Eqns. in Sec. 5.#.

The coherence technique per se does not take into consideration whether the mean Time Head Way (THW) increases or decreases. As will be shown in detail below, this simple change in target THW is hypothesized to be the fundamental adaptation that drivers adopt to cope with the interfering driving and in-vehicle demands. When the coherence technique shows a decrease in gain, an increase in phase lag, and a decrease in coherence, more fundamentally, this means that subjects simply adopted a longer THW thereby enabling themselves to reduce their car following efforts to avail resources to the in vehicle tasks without necessarily degrading safety (i.e. the adopted THW and thus the safety is partly based on the expected lead vehicle decelerations and in vehicle task demands).

2. CAR FOLLOWING DRIVER MODEL

A car following driver model stands central to gaining insights into driver's adaptations to the need to perform in vehicle tasks. It is designed to aid in performance assessment and is therefore purposefully kept simple, interpretable and most importantly identifiable.

2.1. Driver Model

A flow diagram of the complete environment-driver-vehicle interaction is shown in Fig. 1. The target THW that drivers adopt (defined as median observed THW) is the result of the balance between a number of motivational, perceptual, and controllability factors. By changing the target THW and controller settings, drivers can safely and comfortably incorporate the need to perform in-vehicle tasks.

The driver as a controller (Fig. 2) is assumed to consists of three loops that contribute to the final pedal position: i) a PD controller on the distance error signal, ii) a PD controller on the speed error signals, and iii) a bias term that produces a pedal depression that would yield the current lead vehicle speed in steady state if maintained sufficiently long. The errors cause a change in pedal position away from steady state.

2.2. Predicted Adaptations to Secondary Task Needs

It is hypothesized that the primary adaptation to free up attentional and control resources to perform in-vehicle tasks is to adopt a longer target THW. This effectively increases the amount of time available to respond to lead vehicle decelerations. The causal mechanism to adopting a higher target THW can be characterized by a six step chain: i) drivers need periods of time during which they can not perceive any changes in lead vehicle speed and thus the gap, ii) during these times THW errors build up, iii) to correct these large errors when they return to the driving task, drivers need to respond faster and stronger, iv) this would considerably increase the driving workload and jeopardize safety, v) to reduce this workload, a larger tolerance margin in THW needs to be adopted, vi) this can be accomplished by either allowing for shorter than comfortable THWs (i.e. adopt an undesirable safety compromise) or by increasing THW (i.e. desirable because it maintains safety and lowers workload), vi) a longer THW allows for a slower and weaker response to lead vehicle decelerations because now the larger gap absorbs THW changes across the look away time such that the minimum THWs remains relatively constant between normal driving and driving while performing in-vehicle tasks (this is why the expected deceleration rate and duration is also expected to impacts drivers' target THW choice). In summary: i) drivers are hypothesized to adopt a *longer target THW* that affords them to adopt a lower bandwidth or equivalently low control effort strategy of *ii) lower gains* and *iii) longer delays in the distance and relative speed control loops*; it is also expected that: *iv) drivers' response becomes more nonlinear* (i.e. a linear model fit to observed driver behavior will degrade). To test these hypotheses, a car following experiment was conducted.

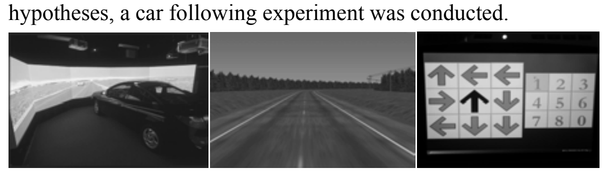

Fig. 3 Left panel: Picture of the UMN HumanFIRST 8-channel simulator (210 degree front FOV) with small actuators under the front axel to render road roughness induced vibrations onto the whole vehicle (greatly enhances speed perception and control) as well as small pitch and roll in response to acceleration and deceleration which is expected to increase the bandwidth of the speed and gap control loops. Middle panel: the scene that subjects experienced in the car following experiment. Right panel: a picture of the arrow task LCD display that subjects interacted with during secondary task trials (see text for details).

3. EXPERIMENTAL DESIGN

Subjects drove a rural Minnesota highway in the UMN HumanFIRST driving simulator (Fig. 3) with two 10-minute periods of car following (Fig. 3). In the second period, subjects had the opportunity to engage in a secondary task as frequently and comfortably as they felt they were able to perform (Fig. 3).

The main subject sample was comprised of 25 subjects (11 male, 14 female) with a mean age of 26.4 years (range 19 to 40 years). All subjects held a valid Minnesota driving license and had corrected vision of 20/40 or better.

The secondary task was devised to represent the generic demands of common in-vehicle tasks including (a) visual search, (b) target matching, (c) working memory, and (d) response input. It emulates destination entry in a navigation device or searching through a complex menu structures of a telematics system. As shown in Fig. 3 (right panel), the task is comprised of a matrix of arrows around a central "target" arrow. The task becomes active when the target arrow is pressed. This user selection initiates the rotation of each arrow in a different direction and at different speeds. After a random period (up to 1.5 seconds), the rotation cycle is automatically stopped to set the orientation of each arrow. The task is completed by then pressing the number button corresponding to the correct number of peripheral arrows in the matrix that match the orientation of the central target arrow. Fig. 4 shows how frequently subjects initiated the task.

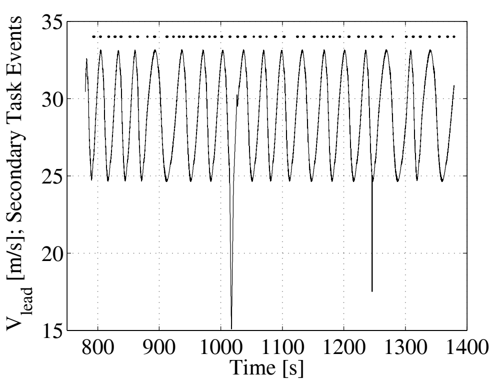

Fig. 4. Lead vehicle profile during the free driving and secondary task driving segment. During each 10min segment, the lead car would at a random location brake hard once at a deceleration of 3.5 m/s². The asterixes along the top axis indicate when a typical subject requested to perform a new secondary task.

As dictated by the coherence technique around which the experiment was originally designed, the lead vehicle speed fluctuated randomly around a nominal speed of 25m/s as described by:

$$v_n^l = \{29 + 4\sin(2\pi f(n) n T_s)\} m/s$$

where the frequency *f(n)* randomly shifts between 0.02 to 0.04 Hz as a function of time step *n*.

4. VEHICLE DYNAMICS MODEL

The vehicle dynamics model is constructed around the steady state speed that is reached for a given gas pedal depression (see Fig. 6 for the identified relationship) and an acceleration or deceleration rate that depends on how far the gas pedal depression deviates from the one that corresponds to the pedal depression associated with the current speed (i.e. if it were the steady state speed). The vehicle model is described by the following equation when the pedal value g_n is positive (a single pedal signal is used; it is negative when the brake is pressed and positive when the gas pedal is depressed; the delay to go from gas to brake pedal is ignored in this version of the model):

$$v_n^h(ss) = \alpha_0 + \alpha_1 g_n + \alpha_2 g_n^2$$
$$v_n^h = v_{n-1}^h + \lambda\left(v_n^h(ss) - v_{n-1}^h\right)$$

where

$$\lambda = \begin{cases} c_0^+, & g_n \geq 0 \wedge \left(v_n^h(ss) - v_{n-1}^h\right) \geq 0 \\ c_0^-, & g_n \geq 0 \wedge \left(v_n^h(ss) - v_{n-1}^h\right) < 0 \end{cases}$$

This is an intuitive simple model that is sufficient for human vehicle interaction car following research.

If the brake pedal is depressed (i.e. g_n has become negative), the following vehicle dynamics equations are used:

$$v_n^h = a_1 v_{n-1}^h + b_0 g_n$$

where the vehicle speed decays (i.e. engine, air and road friction) even when the brake is not depressed and it is assumed that the brake signal magnitude is linearly related to deceleration rate.

The tight fit as exemplified in Fig. 5 shows that the model is very reasonable and that it also accurately represents the hard braking event around 1040s.

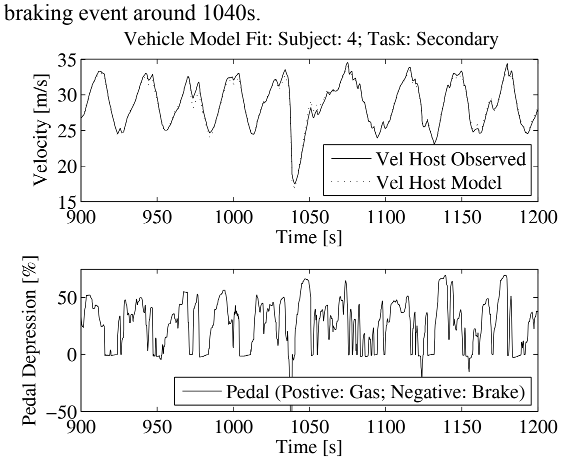

Fig. 5. Representative fit between predicted and observed host vehicle speed based on observed gas pedal input only.

4.1 Identification

The vehicle model was identified based on all data from all subjects and both segments (i.e. baseline and secondary task trials). First, the state variables of the model (i.e. host vehicle speed) were initialized with the observed values. Second, the model was simply run with the model coefficient

$$\alpha_0, \alpha_1, \alpha_2, c_0^+, c_0^-, a_1, b_0$$

estimates from a gradient decent search algorithm (Matlab 6.5's "fminsearch" with default settings) and the observed pedal signal (i.e. gas pedal and brake pedal combined into bipolar signal).

This was repeated for each subject; the fit was computed for each subject, and all the fit values were summed and handed back to the gradient search algorithm for the next iteration of a coefficient estimate. The fit was simply the sum of the squared differences between the model predicted and observed host vehicle speeds. Note, the model was run with one initialization at time step 1 only and then was run through all 10min with just the observed gas pedal input. This differs substantially from the standard least squares approaches (2). The standard least squares approach could not be applied because the model was non-linear and could not be assumed linear over the entire range of gas pedal depressions and speeds. One benefit from the adopted approach is that the final result is by definition a model that can be run stably, which is not always the case with the results from a least squares identification especially if linearity assumption can not be ignored. The resulting model coefficients are:

$$\alpha_0 = 18.1087, \alpha_1 = 61.8777, \alpha_2 = -34.7402$$
$$c_0^+ = 0.0134, c_0^- = 0.0273,$$
$$a_1 = 0.9937, b_0 = 1.7563$$

Note that these values and are based on a time step of 200ms (i.e. 4 times the original sampling rate) and that they change for different sampling intervals. A fit for typical subject 4's secondary task segments is shown in Fig. 5. The average std prediction error between observed and model predicted lead vehicle speed across all subjects is about 1m/s. For most subjects it is about 0.2 and for a few with very high bandwidth pedal fluctuations the fit is much worse.

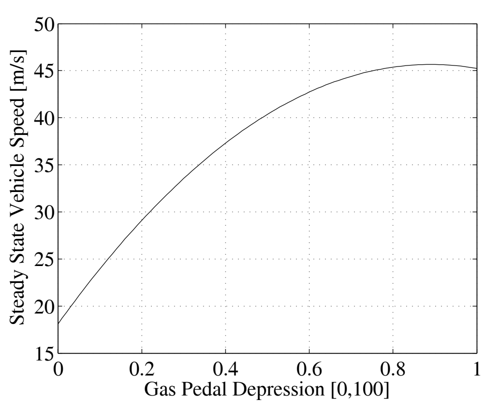

Fig. 6. Relationship between gas pedal position and steady state vehicle speed. Not expected to be representative outside experimental speed range of 15-40m/s.

4.2 Steady State Speed per Gas Pedal Depression

The steady state relationship between gas pedal position and host vehicle speed were identified as part of the overall vehicle model identification (Fig. 6). The fact that the curve drops down a little at high gas pedal depression is due to the fact that only pedal depressions up to about 0.8 were observed thus the steady state speed at higher gas pedal depressions can not be trusted.

5. DRIVER MODEL

The driver model shown in Fig. 2 is a straight forward PD controller on distance deviation from target distance (i.e. v_{lead} THW*) and a PD controller on relative velocity. The error free gas pedal depression is based on the current lead vehicle speed using the inverse of the relationship shown in Fig. 6. The driver's control goal is assumed two fold: i) maintain THW within a tolerance range around a target THW to prevent the minimum THW to become too low, and ii) maintain the relative velocity within a tolerance range around zero. The complete set of equations that comprise the driver model are:

$$x_n^h = x_{n-1}^h + v_{n-1}^h T_s$$
$$x_n^v = x_{n-1}^v + v_{n-1}^v T_s$$
$$d_n = x_n^v - x_n^h$$
$$e_n^d = \tau^* v_{n-1}^l - d_{n-1}$$
$$\Delta g_n^d = k_0 e_n^d + k_1 e_{n-1}^d$$
$$e_n^v = v_{n-1}^l - v_{n-1}^h$$
$$\Delta g_n^v = c_0 e_n^v + c_1 e_{n-1}^v$$
$$g_n^{ss} = \frac{-\alpha_1 + \sqrt{\alpha_1^2 - 2\alpha_2(\alpha_0 - v_{n-1}^l)}}{2\alpha_2}$$
$$g_n = g_n^{ss} + \Delta g_{n-\delta}^d + \Delta g_{n-\delta}^v$$

For a typical subject (Subj.2 baseline), the coefficient values are:

$$k_0 = 0.0006, k_1 = -0.0112, c_0 = 0.0114,$$
$$c_1 = 0.0553, \delta = 0, \tau^* = 1.9058$$

Note that the three alpha coefficients values are simply those obtained in the car model. Essentially it is assumed that the subject has the equivalent of a perfect internal model of the relationship between gas pedal and steady state vehicle speed.

To avoid a significant impact of signal noise on the identification results, a time step of 200ms was used (i.e. 4 times the original data collection sampling rate).

An example of how well the driver model fits the data is shown in Fig. 7.

5.1. Driver Model Identification

The model was identified for each subject for each 10min segment (i.e. baseline and secondary) separately. First the target THW was simply set to the median observed THW. Identification of the 4 gain coefficients and the delay coefficient (i.e. same delay was assumed in both error loops) was achieved by first initiating the model's state variables (i.e. host vehicle speed and gap) to the observed ones, the error gain coefficients to zero, and the delay to a value between 0 and 10 time steps (i.e. 0 and 2s). Second the model was run and the fit computed between model produced output (i.e. time series of host vehicle speed, gap, and pedal) and the observed corresponding time series. Then the 4 error gain coefficients were adapted with a gradient search algorithm (Matlab 6.5's "fminsearch" function with default setting) to reduce the fit as much as possible. Note that the delays were kept constant during the search for the 4 gain coefficients. This was repeated for all delays between 0 and 10 time steps and the coefficients for the delay that yields the best fit are selected. For an example fit, see Fig. 7.

Five subjects were removed from the analysis because of missing data (2), an extremely large and fluctuating target THW (1), and extremely low correlation between lead vehicle speed and gas pedal depressions (2) suggesting extremely low motivation (i.e. behavior so inconsistent that model assumptions did not apply).

5.2. Driver Model Identification Fit Function

The fit is simply the following function, which roughly normalizes each term by scaling it by the inverse standard deviation or the observed signal in question.

$$\psi = \sum_{n=1}^{N} \frac{\left|\hat{g}_n - g_n\right|}{\sigma_{\{g\}}} + \frac{\left|\hat{d}_n - d_n\right|}{\sigma_{\{d\}}} + \frac{\left|\hat{v}_n^h - v_n^h\right|}{\sigma_{\{v^h\}}}$$

where the ^ sign signifies model prediction. To avoid a chattering controller, a 4th fit term that penalizes fast pedal fluctuations was added.

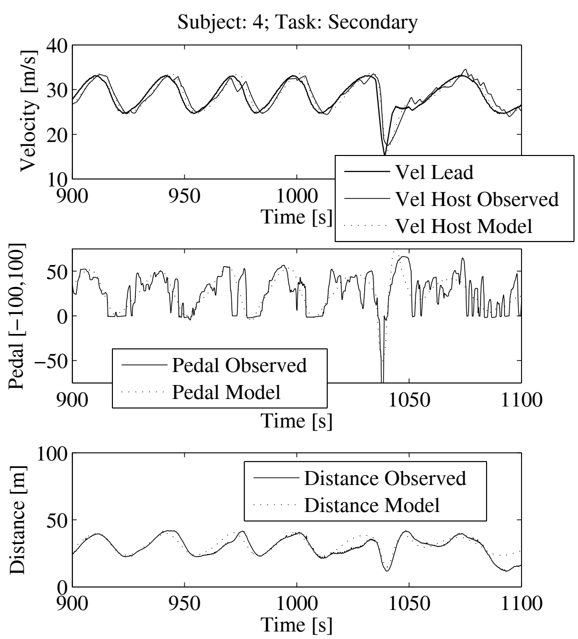

Fig. 7. Model fit for subject 2's baseline task trial The fit is shown for host vehicle speed (top panel), pedal position (middle panel), and gap (bottom).

6. RESULTS AND DISCUSSION

The results indicate that drivers indeed adapt their behavior in response to the need to perform an in vehicle task as frequently as comfortably and safely possible as hypothesized in section 2.2. We observe that subjects adopt a significantly longer THW as shown in Fig. 8. Below the figures the significance values are given for each panel. The significance is computed with the Wilcoxon signed rank test which performs a paired, two-sided test of the hypothesis that the difference between the subject-matched samples between baseline and secondary trials come from a distribution whose median is zero.

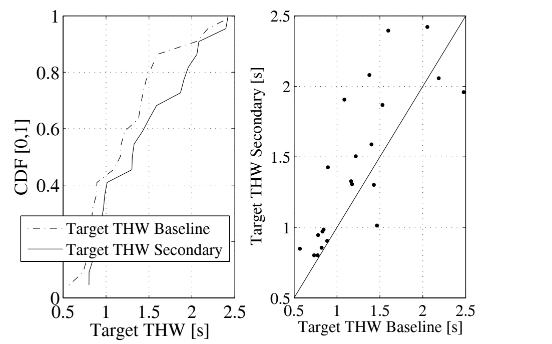

Fig. 8. Demonstration that the adopted target THW is significantly (alpha=0.0143) larger under secondary task conditions. The right panel shows per subject how their target THW changed between baseline (abscissa) and secondary trial (ordinate).

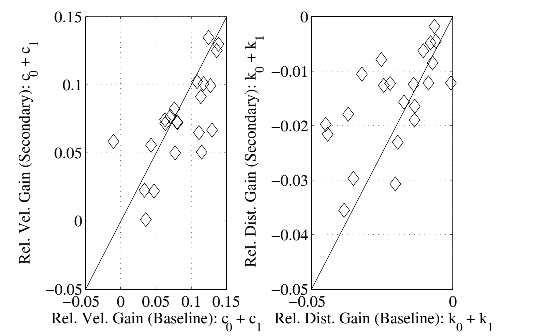

Fig. 9. The dc-gains decrease significantly (alpha=0.0680 for relative velocity dc-gain and alpha=0.0918 for the relative distance dc-gain) for most subjects when they perform a secondary task.

As hypothesized, subjects adopt lower dc-gains when performing the secondary task (Fig. 9). Fig. 10 shows clearly the correlation between THW and dc-gains (i.e. lower gains for longer THWs). The lower dc-gains result in a significant increase in the lag between the lead vehicle and host vehicle speed fluctuations as shown in Fig 11. The lag was computed based on model simulation runs with the observed lead vehicle profile. These lags and other predictions can also be computed analytically for any frequency separately (i.e. bodeplot).

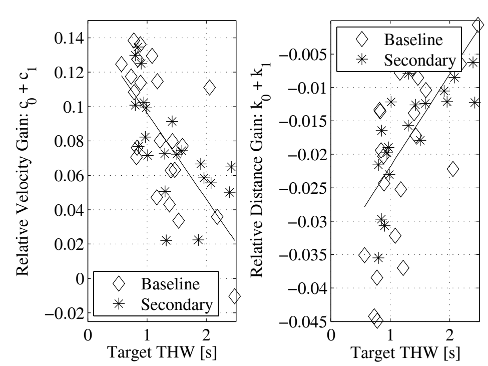

Fig. 10. The dc-gains in gap and speed error loops are lower when drivers adopt longer target THWs.

Because the control gains are lower, the lags are greater (note that delay and lag can not be separated for the relatively narrow bandwidth input signal) and the variability in THW is expected to be greater; this is confirmed in Fig 12.

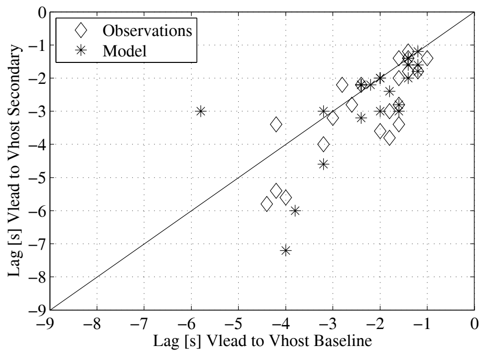

Fig. 11. Demonstration that the lag is significantly larger when subject perform a secondary task (alpha=0.0031 for observation and alpha=0.0228 for model prediction).

Finally, it was hypothesized that the driver behavior would become more nonlinear with the introduction of the secondary task. In Fig. 13 it is shown that indeed the lead vehicle speed profile is not matched as accurately (low correlation) and that the model does not predict the pedal activity as accurately (right panel). The latter is attributed to two hypothesized factors that will be confirmed in later studies: i) subjects overreact to errors causing unnecessarily strong and frequent pedal actions (i.e. from the model's perspective), and ii) subjects release the gas pedal slightly upon initiation of an attention diversion to momentarily increase their safety margin (i.e. a strategy not modeled and thus contributing to a higher remnant; the part of observed behavior not predicted by the model).

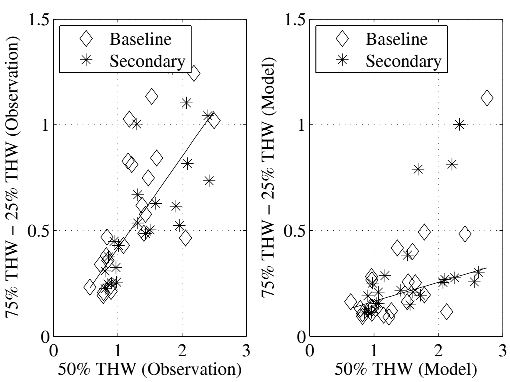

Fig. 12. Demonstration that subjects in general allow for a larger variation in THW as their target THW (abscissa) increases (left panel). This phenomenon is reproduced by the model except to a lesser degree (right panel).

7. CONCLUSIONS

In summary, subjects adapt to the need to perform the secondary task by: i) primarily increasing their safety margin (i.e. increasing their target THW), ii) secondarily enabling a decrease in their gains to lower workload and avail attentional and control resources for the secondary task (leads to high lags in velocity and distance error response loops), and iii) adopting some reactive or anticipatory pedal movement that result in a deviation from what a linear model predicts. The model theoretic assessment of driver behavior offers an easily interpretable framework for gaining an understanding of the mechanisms that underlie drivers' adaptation performing demanding in vehicle tasks. Less demanding tasks may not result in driver adaptation, which this approach would also show.

The proposed simple driver model fits the data encouragingly well and has demonstrated to offer a useful tool in complementing the standard performance assessment techniques with the model based approach presented in this paper.

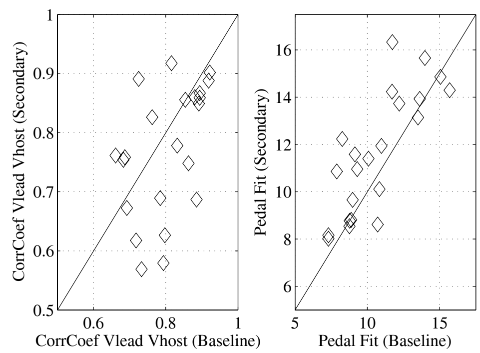

Fig. 13. Left panel: Demonstration that subjects are less able to match the lead vehicle speed profile when performing a secondary task (i.e. lower cross covariance between lead vehicle speed and host vehicle speed). Right panel: Worse pedal prediction fit when performing secondary task (i.e. magnitude of first term in equation in section 5.4. is larger).

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