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Modeling driver control behavior in both routine and near-accident driving

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Building on ideas from contemporary neuroscience, a framework is proposed in which drivers' steering and pedal behavior is modeled as a series of individual control adjustments, triggered after accumulation of sensory evidence for the need of an adjustment, or evidence that a previous or ongoing adjustment is not achieving the intended results. Example simulations are provided. Specifically, it is shown that evidence accumulation can account for previously unexplained variance in looming detection thresholds and brake onset timing. It is argued that the proposed framework resolves a discrepancy in the current driver modeling literature, by explaining not only the short-latency, well-tuned, closed-loop type of control of routine driving, but also the degradation into long-latency, ill-tuned open-loop control in more rare, unexpected, and urgent situations such as near-accidents.

INTRODUCTION

There is a wealth of existing models that describe the steering and pedal behavior exhibited by drivers to control their vehicles (Plöchl & Edelmann, 2007; Markkula et al., 2012). Such models can provide great advantages in many simulation-based approaches to the study of traffic, not the least concerning road safety (van Auken et al., 2011; Markkula et al., 2012). However, as will be described here in a brief literature review, driver models have so far taken rather different forms when accounting for routine driving behavior on the one hand, and near-accident behavior on the other. To date, there have been no models that predict the differing characteristics of control behavior in these two contexts, based on a single set of underlying assumptions. The aim of this paper is to present a framework which could be capable of doing so, partially with the help of some recent results from the neurobiological study of sensorimotor behavior. The argument for the proposed assumptions will be based on explanations of how the resulting framework is capable of predicting typical properties of both routine and near-accident behavior, complemented with reconsideration of some existing results from the driver behavior literature.

REVIEW

Most models of routine driving (Plöchl & Edelmann, 2007) assume that drivers engage in *closed-loop control*, continuously updating steering and pedals in response to the traffic situation, limited only by a constant *neuromuscular delay* of about 0.2 seconds. In contrast, typical models of near-accident control (van Auken et al., 2011; Kusano & Gabler, 2012) posit single *open-loop* braking or steering maneuvers of a shape that many closed-loop models have a hard time reproducing (Markkula et al., submitted), occurring after a long *reaction time* of about 1-2 seconds. Near-accident maneuver amplitudes have been modeled as basically random, with reports of both overreactions (Malaterre et al., 1988) and under-utilization of vehicle capabilities (Adams, 1994), whereas in routine driving, control has been assumed to be well-tuned to vehicle and situation dynamics, sometimes to the point of *optimal control*. Many routine driving models posit the use of *perceptual cues*, such as the movement of sight points for lateral control (Salvucci & Gray, 2004), or, for longitudinal control, the optical size θ and expansion $\dot{\theta}$ of a forward obstacle, the optically defined estimate of time to collision $\tau = \theta/\dot{\theta}$ (Lee, 1976; Flach et al., 2011) or its inverse $1/\tau$ (Kiefer et al., 2003). When such cues have been considered in near-accident control, it has been to discuss *detection thresholds*, the minimal stimuli at all discernible to a driver (Maddox & Kiefer, 2012). On the other hand, if thresholds have been applied in modeling of routine driving, it has mainly been to account for the *satisficing* nature of non-critical control: To limit expended effort, drivers postpone control until conflict-describing cues get large enough (Kiefer et al., 2003; Gordon & Magnuski, 2006; Flach et al., 2011), reaching levels orders of magnitude above typical thresholds for detection.

Considering the above, one could posit two distinct classes of behavior, mediated by different neural circuitry altogether. However, there are clear difficulties to this approach: Isn't there a continuum of traffic situations between "routine" and "near-accident"? And from where does the, albeit limited, near-accident ability of handling pedals and steering wheel come, if not from routine driving experience?

NEW CONTRIBUTION

Driving control as a series of open-loop adjustments

The first key assumption of the proposed framework is that, at a basic level, driving control is to a large extent

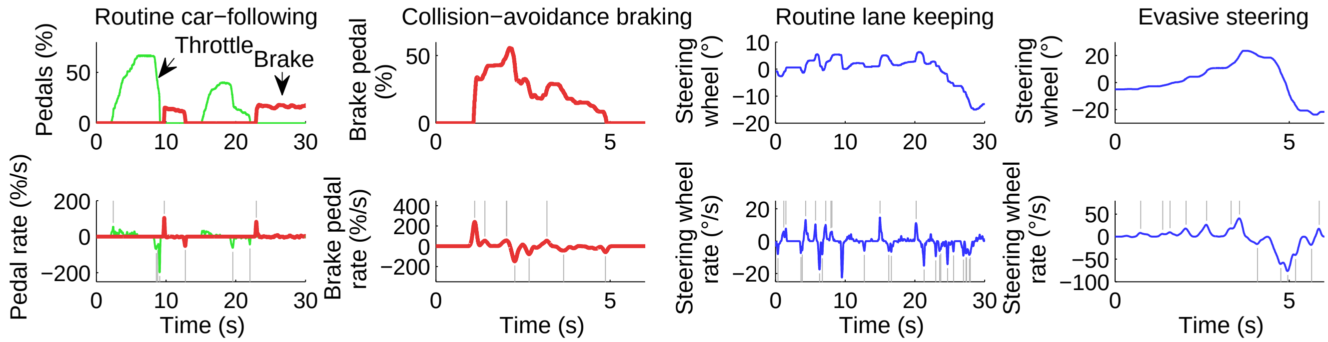

Figure 1. Example steering and pedal use in routine and near-accident situations, all from heavy truck driving in real traffic.

constructed from individual, discrete *control adjustments*, each of which is open-loop in the sense that the shape of the adjustment over time is predetermined already at its onset. Fig. 1 provides examples, from a data set of naturalistic driving, of human driving control in both routine and near-accident maneuvering. The lower row of panels show rates of change of pedal and steering wheel positions. These rates stay close to zero throughout, except for intermittent upward or downward pulses of activity (highlighted with vertical gray lines), interpretable as the hypothesized individual control adjustments. Previously, it has been observed that amplitude and maximum steering rate of severe evasive maneuvers are linearly correlated (Breuer, 1998; Markkula et al., submitted), suggesting a constant maneuver duration. Recently, Benderius and Markkula (2014) have shown that this correlation exists also for routine steering adjustments. These were found to follow bell-shaped profiles of movement speed, similar to what is consistently observed in laboratory experiments on reaching (Franklin & Wolpert, 2011). Short bell-shaped bursts of movement have been suggested to serve as spinal-level building blocks that can be combined and superpositioned to construct complex movement (Giszter, 2009).

It is proposed, here, that driving control adjustments are typically both small and frequent in occurrence, explaining why routine driving can nevertheless be well characterized as a continuous closed-loop activity. This would be especially true in situations like curve-taking (see the third panel from the left in Fig. 1, from about 20 s), where overall control is large in duration and amplitude, compared to the individual adjustments. However, in more urgent situations, where large changes in pedal or steering command are needed quickly, the underlying open-loop nature of control comes to the fore.

Additionally, when specific sequences of movement bursts are used recurrently, these can be established as higher-level movement primitives in their own right (Giszter, 2009). Such learning could be hypothesized for longer-duration control maneuvers that are recurrently useful in traffic, such as gradual changes in pedal position (visible for the throttle at 5 and 15 s in the leftmost panel of Fig. 1), intersection turning, or lane changes, which human drivers can perform blindfolded with some, but not complete, accuracy (Cloete & Wallis, 2009).

Some previous models of driving have considered intermittent control, occurring either at satisficing thresholds (Gordon & Magnuski, 2006) or as a result of bottlenecks in information processing (Bi et al., 2012). Here, another means of accounting for adjustment timing is adopted.

Timing distributions from noisy evidence accumulation

The second key assumption is that one needs to consider *distributions* of control timing, not only in near-accident control, but also in routine driving, and that these distributions are affected by, among other things, situation kinematics and expectancy. Specifically, it is suggested here that (a) late timing of control in unexpected critical situations and (b) satisficing timing of control in non-critical routine situations, are governed by the same underlying mechanisms.

A strong candidate for such a mechanism is available from *accumulator* models of action timing. These models, which assume that action occurs after integration to threshold of sensory evidence for an action's suitability, have been shown to account well for timing distributions in a large number of laboratory tasks, and through microelectrode recordings in behaving animals, likely neural correlates of this process have been identified (Purcell et al., 2010). Recently, Ratcliff and Strayer (2013) have successfully fitted this type of model to distributions of reaction time to one important fixed-intensity stimulus in traffic: brake lights.

In order to account for the satisficing patterns of behavior in routine driving, one would need to consider also variable-intensity stimuli, such as the perceptual cues used in many driver models. As a first indication that driver response timing can be understood as accumulation of such perceptual evidence, consider the experiment reported by Lamble et al. (1999), on how detection thresholds for optical expansion rate $\dot{\theta}$ vary with gaze eccentricity and initial lead vehicle headway: Test subjects, instructed to decelerate as soon as they detected a closing headway, consistently did so at lower $\dot{\theta}$ values for longer initial headways. This is precisely what would be predicted by an accumulator model where $\dot{\theta}$ is considered the stimulus intensity, since integration of a small quantity over a long time is equivalent to integration of a large quantity over a short time. To see this in more detail, consider the following simple accumulator:

$$\frac{\mathrm{d}A(t)}{\mathrm{d}t} = C \cdot P(t) - M + \varepsilon(t) \tag{1}$$

Where $P(t)$ is a stimulus, C and M are model parameters, and $\varepsilon(t)$ is noise, and where detection occurs when $A(t) \geq A_0$. This specific formulation is inspired by Purcell et al. (2010). In line with their interpretation of A as a neuron firing rate, this quantity is constrained to $A(t) \geq 0$.

The upper panels of Fig. 2 illustrate the behavior of this model, with $P(t) = \dot{\theta}(t)$, $C = 1$, and zero noise, parameter-fitted ($M = 0.000554$ rad/s; $A_0 = 0.00143$ rad) to reproduce the detection thresholds reported by Lamble et al. (1999) for zero gaze eccentricity. With a longer initial headway, $\dot{\theta}$ grows more slowly, meaning that A will reach threshold later in time, but at a lower final $\dot{\theta}$ value, just as observed in the experiment. The lower panels of Fig. 2 hint at how the same model could also account for the observed increasing thresholds and variance with increasing gaze eccentricity, by including a non-zero noise term $\varepsilon(t)$, and making C a nonlinear function of eccentricity (not pursued further here).

The experiment of Lamble et al. (1999) was not intended to approximate satisficing driver behavior. For a step in that direction, consider the results reported by Kiefer et al. (2003). These authors instructed drivers to wait to the last second deemed possible before applying "normal" or "hard" braking, in response to a set of test track scenarios with a lead vehicle mockup. This is also a rather artificial task, but arguably at least the normal braking condition could come somewhere close to routine, satisficing headway control. It is interesting to note, then, that the observed pattern of inverse times to collision (TTC) at response, in the normal-braking scenarios with lead vehicle deceleration, can be well explained ($R^2 = 0.91$) by an accumulator model with $P(t) = \dot{\theta}(t)/\theta(t) = 1/\tau(t)$; see Fig. 3 ($M = 0.00155$ s^{-1}; $A_0 = 0.0888$). For the scenarios without deceleration, on the other hand, the same model predicts a much earlier response than what was observed. This could mean that there is some fundamental flaw to the accumulator approach, but it could also be that the drivers were using some other perceptual cue than just $1/\tau$, or that the "last-second normal braking" task was further from routine driving behavior in the scenarios without deceleration.

In any case, in real traffic, driver behavior is not based solely on responding to graded perceptual quantities such as $1/\tau$. Fig. 4 provides an illustration of how Eq. (1) can be understood in this broader context. For example, braking may be triggered without optical expansion, based on other evidence for its need, such as a brake light onset, or a red traffic light ahead of the lead vehicle. Conversely, braking may not occur despite optical expansion due to counter-evidence such as the traffic light shifting to green, or the lead vehicle's turn indicator activating.

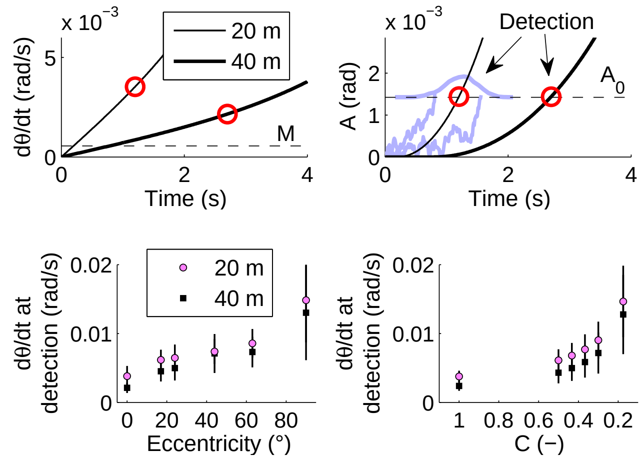

Figure 2. The 20 m and 40 m headway scenarios of Lamble et al. (1999). Top left: Growth of $\dot{\theta}$ over time. Top right: Accumulator model fitted to detection thresholds observed for zero gaze eccentricity, and illustration of model with noise (light blue trajectories and detection distribution). Bottom left: Detection thresholds (mean and standard deviation) as a function of gaze eccentricity, as observed by Lamble et al. Bottom right: Prediction from model with noise, at values of C selected to roughly match the data in the left panel.

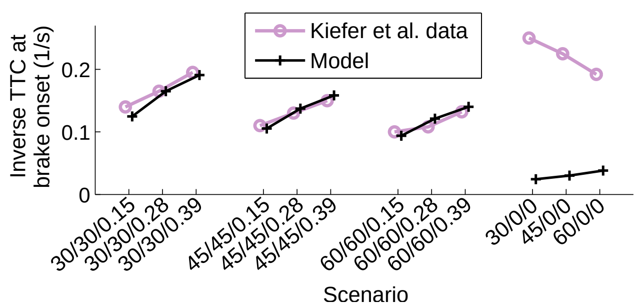

Figure 3. Accumulator model fit of "normal" last-second braking onset data from Kiefer et al. (2003), for decelerating and stationary lead vehicle scenarios (own speed in mph/lead vehicle speed in mph/lead vehicle deceleration in g).

With Fig. 4 in mind, the perceptual quantity $P(t)$ in Eq. (1) can be interpreted as being one piece of evidence for a possible need of control adjustment, and the $-M$ term as being the sum of a negative gating (corresponding to a minimum level of input activation for accumulation to begin; again inspired

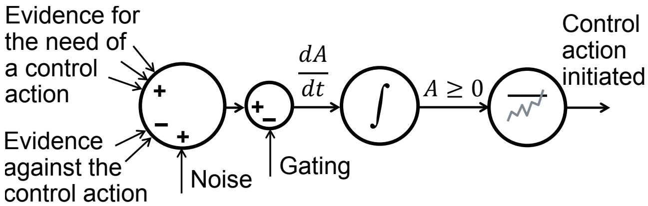

Figure 4. Schematic illustration of the proposed accumulator account of control adjustment timing.

by Purcell et al., 2010) together with all the other available evidence for and against the control adjustment. If so, the parameter M should vary with expectancy: In situations where the driver would normally not at all expect a need for a control adjustment, M will be larger, $\mathrm{d}A/\mathrm{d}t$ will be smaller, the driver will be correspondingly desensitized to the perceptual quantity P, and the time to response will be prolonged.

Magnitude of adjustments tuned to sensory inputs

Another important assumption, which may not be surprising given what has been said so far, is that the magnitude of each control adjustment is affected by the situation at hand. Specifically, it is suggested here that in routine, steady state driving, each control adjustment aims to resolve the situation that triggered it. A steering adjustment caused by a moving far point aims to immobilize the far point, a brake application caused by a looming lead vehicle aims to stop the looming. For often-encountered driving situations, drivers will have had ample time to learn suitable mappings from sensory input to control adjustment, acquiring a near-optimal trade-off between effort and performance, and what can be interpreted as a thorough understanding of their vehicle's dynamics. See (Markkula, 2013) for a sketch of how the far point control law suggested by Salvucci and Gray (2004) could be understood in this way. However, in more critical situations, typically previously unexperienced by the driver, the same mappings may no longer be as well-tuned to the situation or to the vehicle (Markkula et al., submitted), and this could explain reports of driver overreactions or underreactions in near-accident maneuvering. Furthermore, a possibly relevant neurobiological phenomenon in this context is *motor noise*, inherent variability in motor output which typically scales with movement amplitude (Franklin & Wolpert, 2011), such that large pedal or steering movements will be more likely to turn out far from what was intended by the driver.

Forward-model prediction of sensory input

An important follow-up question to what has been said so far is: When a control-adjusting burst of activity has been generated, how long time must pass before the next one can occur? To begin with, the previously cited work on motor primitives (Giszter, 2009) as well as Fig. 1 suggest that one does not have to await the completion of the first burst; control adjustments can be additively superpositioned. But if each control adjustment aims to completely resolve the situation that triggered it, such as suggested above, then superposition should not be needed. Rather, it would seem inappropriate to generate any further control until the vehicle has fully responded, with its inherent delays, to the first adjustment.

One possibility here is that the accumulator is simply reset to zero or some intermediate value after reaching threshold, and that during the time after the first control adjustment, when the original situation is still not fully resolved, the delays of the accumulation process in itself is enough to withhold further control response. A more elegant solution, with neurobiological support, would be that when the motor command for the first control adjustment is generated, an *efference copy* of this command is sent to parts of the brain (especially the cerebellum), which are capable of generating *forward model* predictions of the effect of the motor action on future sensory input (Franklin & Wolpert, 2011). It is thus proposed here that after each control adjustment, a prediction $P_p(t)$ is formed of how $P(t)$ will respond, e.g. by gradually falling to zero. $P_p(t)$ is then included as an inhibitory input to the accumulator, such that what is driving the accumulator is actually not $P(t)$, but $P(t) - P_p(t)$.

Fig. 5 illustrates the behavior of the brake reaction model fitted to the Kiefer et al. (2003) data (Fig. 3), complemented with (a) a linear mapping from $1/\tau$ at brake adjustment onset to adjustment amplitude, well-tuned for moderate levels of lead vehicle braking, and (b) a simple forward model of how $1/\tau$ will respond to such adjustments. Full details of these simulations are beyond the scope here; they are shown merely as a qualitative illustration of the proposed framework principles. Specifically, it can be noted how an unusually high lead vehicle deceleration causes an initial underreaction, followed by increases in pedal position later on.

DISCUSSION

Many testable predictions can be made based on the framework proposed here. For example, in both routine and near-accident situations, control timing should be affected by the dynamics of both traffic situation and evidence accumulation, such as preliminarily suggested here for the Kiefer et al. (2003) data set. To test this prediction in more detail, controlled experiments are needed, where situation dynamics are varied while keeping constant any other evidence to the driver for or against the need of control adjustments.

If the suggested framework principles can be corroborated, they can be used for developing improved simulation models of driver behavior. Near-accident models can be extended with situation-dependent distributions for both response time and maneuver amplitudes. Routine driving

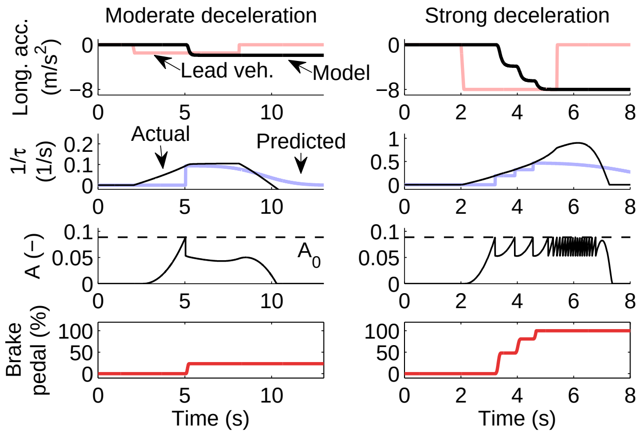

Figure 5. A braking model based on the proposed framework, in two scenarios with lead vehicle deceleration.

models can be extended to better account for control, most immediately in situations where longer-duration learned maneuvers should be rare, such as keeping in a lane with low curvature, or car-following at roughly constant speed.

It should be noted that several factors important for driving control have been left out of the scope here, such as arousal, cognitive control, and sensorimotor learning (Engström et al., 2013). However, the proposed framework seems highly amenable to extensions in these directions, probably more so than alternative frameworks based on for example control theory.

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