ARTICLE IN PRESS

Transport Policy xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Transport Policy

journal homepage: www.elsevier.com/locate/tranpol

Car following: Comparing distance-oriented vs. inertia-oriented driving techniques

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A R T I C L E I N F O

Keywords:
Car-following models
Driver behavior
Driving techniques
Psychological paradigms

A B S T R A C T

The rationale behind most car-following (CF) models is the possibility to appraise and formalize how drivers *naturally* follow each other. Characterizing and parametrizing Normative Driving Behavior (NDB) became major goals, especially during the last 25 years. Most CF models assumed driver propensity for constant, safe distance is axiomatic. This paper challenges the idea of safety distance as the main parameter defining a unique (or natural) NDB. Instead, it states drivers can adapt to reactive and proactive car following. Drawing on recent CF models close to the Nagoya paradigm and on other phenomena (e.g., wave movement in Nature), we conceived car following by Driving to keep Inertia (DI) as an alternative to Driving to keep Distance (DD). On a driving simulator, three studies (N = 113) based on a repeated-measures experimental design explored the efficiency of these elementary techniques by measuring individual driver performance (e.g., accelerations, decelerations, average speed, distance to leader). Drivers easily grasped and applied either technique and easily switched back and forth between the two. As an overall indicator, all the studies revealed DI trips use about 20% less fuel than DD trips do.

1. Introduction

Our goals are to point out the empirical fact that the same driver can follow the same swinging motion of a lead car in two different ways and to detect which car-following (CF) technique is more efficient. This empirical fact deserves broader examination, beyond the classic stimulus-response framework most engineering models adopt to describe CF behavior. To do so, we review analysis of CF behavior by considering three stages in the development of psychology: stimulus-response frame (e.g., Hull, 1943), TOTE unit (Miller et al., 1960) and mental model concept (Johnson-Laird, 1983).

CF literature divides into Newtonian (or engineering) vs. psycho-physiological modeling streams (Brackstone and McDonald, 1999; Saiffuzaman and Zheng, 2014; Pariota et al., 2016b). During more than 60 years of modeling efforts, their complexity grew and, in part, converged by embedding psychophysiological processes into engineering models. Valuable analytical insights were gained (Brackstone et al., 2002; Wilson, 2008; Wagner, 2011; Pariota et al., 2016b). That division is, however, artificial and unbalanced, at least for human factors. Efforts focused on modeling driver behavior forsook the issues behind the need for CF models: to rationalize traffic flows and ease congestion. This state of affairs is partly due to misconceiving driving behavior as an essential or "nature" issue, also embedded in the concept of Normative Driving Behavior (NDB). Contrarily, how a driver follows another is "nurtured" in many ways (Hennessy et al., 2011; Saifuzzaman and Zheng, 2014). A choice then arises: act as if nothing can alter the resulting CF heterogeneity, and try to model the mix mathematically (and adopt top-down measures), or find the specific knowledge drivers must learn to create a better traffic flow bottom-up.

1.1. Car following: the stimulus-response frame

At the start of the 20th century, scientific psychology ditched the instinct paradigm and embraced behaviorism, the new paradigm of

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http://dx.doi.org/10.1016/j.tranpol.2017.05.008
Received 31 July 2016; Received in revised form 28 March 2017; Accepted 31 May 2017

mainstream psychology till the early 1960s (Reeve, 2008). From then on, human behavior was explained considering exposure to patterns of stimulus configurations; behaviorists were optimists: given adequate stimuli, behavior would be predictable. General Motors researchers made the first attempt to model CF behavior in the early 1950s (Brackstone and McDonald, 1999). Though not commonly stated, that model likely held influences from contemporary mainstream physiology and psychology. Note that, in 1943, Hull's classic *Principles of Behavior* expressed the main parameters concerning human response:

$$ {}_{s}E_{r} = {}_{s}H_{r} \times D \times V \times K \quad (1)$$

This may be phrased as "the excitatory potential (E), or the likelihood that the organism would produce response *r* to stimulus *s*, depends on the habit strength (H) linking them, the drive strength (D), the stimulus intensity (V) and the incentive (K)" (Hull, 1943). Applying this formula to the CF situation would yield the classic *stimulus-response frame*. For example, the simplest form of the Gazis-Herman-Rothery (GHR) model, one of the most studied and influential ones, adopts the expression (Chandler et al., 1958):

$$ a_n(t) = \lambda \Delta V_n(t - \tau_n) \quad (2)$$

This may be phrased as "the response – i.e., acceleration, $a_n(t)$ – of the subject car *n* at time *t* is computed as the speed difference, ΔV_n ($t-\tau_n$), between the subject car at time (t - τ_n), where τ_n denotes the reaction time and λ is a sensitivity parameter" (cf., Brackstone and McDonald, 1999). Follower drivers are sensitive to stimulus-variables from the car in front and this determines their behavior (most often, acceleration). Though considered now too simple, Eq. (2) was the seed for continuous improvement in the GHR frame plus the reference for critical and alternative visions for CF modeling. For example, the main stimulus drivers respond to in the GHR model is velocity, but that response is nuanced by other elements enriching the model, such as memory (of speeds over a period of time), heterogeneity of reaction time, asymmetries between acceleration and deceleration and drivers' focus on more than one vehicle ahead and on traffic density (Saifuzzaman and Zheng, 2014).

During 1958–1963 the core CF theories and models were born. The essential issue was choosing the right variables to model the stimuli that follower drivers respond to. For example, in 1959 Kometani and Sasaki (cf. Saifuzzaman and Zheng, 2014) proposed that followers do not try to equal the leader's speed, but instead keep a minimum *safety distance*; this idea, later improved by Gipps (1981), assumed drivers modulate their speed to stop safely if the driver in front suddenly brakes. In 1959 Helly set up a family of models ascribing driver acceleration to *desired headway space* (e.g., to avoid a front-end crash; cf. Saifuzzaman and Zheng, 2014). The desired measures concept was taken farther by Treiber and colleagues in a series of changes to the Intelligent Driver Model (Treiber and Kesting, 2013), including desired speed and desired headway space. The *Optimal Velocity* model branch first introduced by Bando et al. (1995) opposed the classic, core *follow-the-leader* theories (drivers obey regulations to avoid crashes by keeping safety distance to the leader) with the principle that driver compliance is based on legal velocity. Drivers will keep the right distance to leaders, and increase speed accordingly and smoothly, never above the maximum speed limit.

The CF core period yielded another major development: the Action Point model (Barbosa, 1961; Todosiev, 1963; Michaels, 1963; cf. Pariota and Bifulco, 2015). Todosiev first used "AP" to describe two basic points of discontinuity correlating to start of CF acceleration and deceleration phases. In 1963 Michaels was first to propose a specific psychophysical mechanism to explain the discontinuity: a lead vehicle's visual extent (size) is the specific stimulus for drivers during CF. Drivers are good at estimating time to crash based on visual angles subtended by a lead vehicle (Gray and Regan, 1998). In 1974 Wiedemann issued a more sophisticated AP paradigm (cf. Pariota and Bifulco, 2015), upgraded to four APs (CLDV, OPDV, also suggested by Barbosa and Todosiev, plus ABX, SDX); though some researchers obtained empirical evidence in favor of Wiedemann's model (Brackstone et al., 2002), others found the earlier, simpler paradigms by Barbosa and Todosiev account for the same data more succinctly (Pariota and Bifulco, 2015).

After the core period such new models as Fuzzy-logic (Kikuchi and Chakroborty, 1992; cf. Brackstone and McDonald, 1999) and Cellular Automata (see Zheng, 2014) were produced and also improvements, realism, sophistication and integration in the core models, especially by embedding the psychophysiological AP paradigm in engineering models (Pariota and Bifulco, 2015; Pariota et al., 2016a; Wagner, 2011). The excellent revision by Saiffuzaman & Zheng (2014) enabled a nuanced yet easy tracking of the historical betterment of each branch of models, including aspects of driver heterogeneity (e.g., reaction time, desired spacing, speed, acceleration or time headway, driver errors), multi-vehicle interaction and, notably, introduction of predictions for free flow, CF, congestion phases and their transitions.

Overall, engineering models expect *rational driver* behavior during CF (Bando et al., 1995; Wilson, 2008), "drivers typically increase their acceleration when there is an increase in the spacing…and reduce it in the opposite situation. The same happens with respect to relative speed." (Pariota et al., 2016a; p. 1033). As the general *response = sensitivity x stimulus* frame posits, rational drivers are coherent, *reactive*-prone drivers.

1.2. Car following: the TOTE unit

Early assumptions for CF modeling were rooted in the classic, behavioristic perspective for which mental life was irrelevant. Yet, when core CF models originated, psychology's new paradigm, cognitivism, emerged. The classic *Plans and the Structure of Behavior,* analyzing how plans motivate behavior, by Miller et al. (1960) marked that change. Its main premise is humans have mental representations of *ideal* behavior (events and the environment) and of *current* behavior (events and circumstances). The ideal-real incongruence motivates behavior, and the cognitive mechanism doing that work is the Test-Operate-Test-Exit (TOTE) unit.

TOTE is a homeostatic, cybernetic control unit viewing humans and machines as a complex system of hierarchical control loops (Carver and Scheier, 2012; Wiener, 1950). Classic models in traffic psychology, Risk Homeostasis Theory (Wilde, 1982) and Zero-Risk Theory (Summala, 1997), describe speed control based on a feedback loop comparing input (perceptions while driving) and reference values (e.g., target speed). Consistent with these models, speed variations may be seen as due to a change in task demand, risk perception or enforcement of speed limits. Criticism of engineering CF models may be framed here (Boer, 1999; Ranney, 1999).

To analyze the regulation process (concerning speed, acceleration), we refer to the tracking-loop idea, based on the closed loop of physical action (Adams, 1971). Most hierarchical models of driving behavior describe three performance levels: top-down navigation (e.g., route selection), maneuvring (e.g., reaction to traffic, speed choice, control of longitudinal guidance) and control (use of gas/brake pedals to achieve the previous level's target action) (Horst, 2013). With no adverse external factors (heavy traffic, curves, fog), driver speed systematically oscillates around a mean value due to the regulation process. This oscillation, consubstantial to driving, expresses itself when driving alone, when car following at constant speed, for high or low speed, and for high or low visibility. Data shows that stable oscillatory pattern at 1 m/s around the mean speed adopted (Wille and Debus, 2005; Wille, 2011).

TOTE brings two insights to CF analysis. First, drivers can be more than reactive followers. They set up and undertake a hierarchy of actions, and how they stabilize their driving paths links to guidance strategies; nothing should prevent *proactive* following. Second, drivers move amidst a perennial oscillation. This was implicit in early CF