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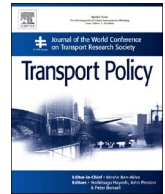
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Car following: Comparing distance-oriented vs. inertia-oriented driving techniques

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ABSTRACT

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. psychophysiological modeling streams (Brackstone and McDonald, 1999; Saifuzzaman 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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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:

$$sE_r = sH_r \times D \times V \times K \quad (1)$$

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, $\Delta V_n(t - \tau_n)$, between the subject car at time $(t - \tau_n)$, 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 Saifuzzaman & 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), maneuvering (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

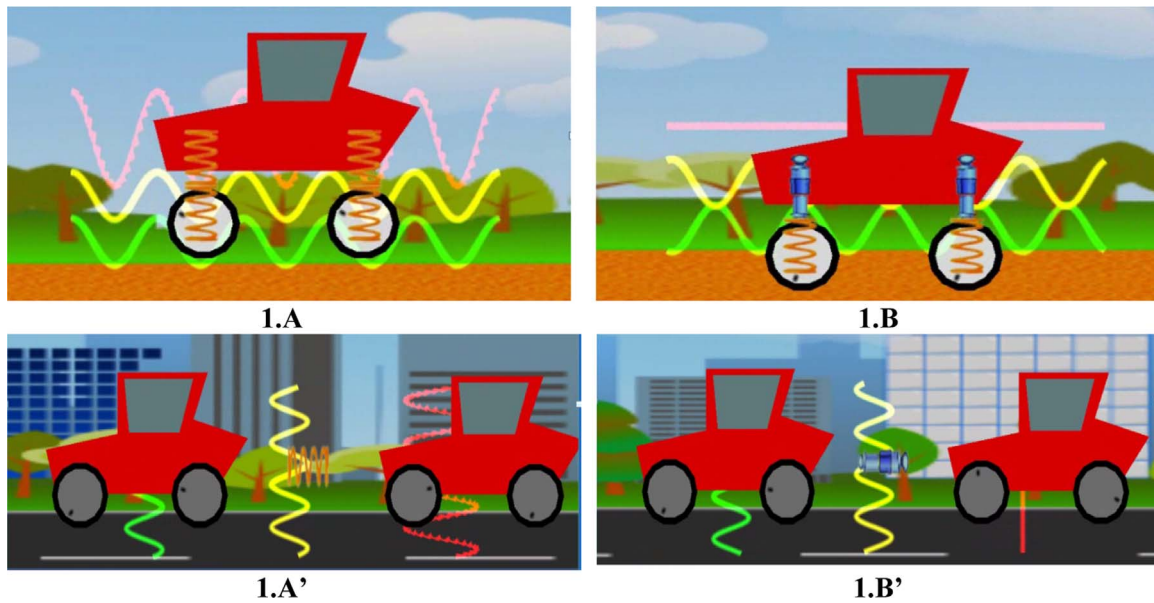


Fig. 1. Summing and offsetting waves in vertical and horizontal directions. (Videos at: https://drive.google.com/file/d/0B1F_W58F2EWPVTdYaTROWkdnbmc/view?usp=sharing, and https://drive.google.com/file/d/0B1F_W58F2EWPVTdYaTROWkdnbmc/view?usp=sharing.)

theories under the AP paradigm (e.g., close following spirals, Brackstone et al., 2002; Pariota and Bifulco, 2015; Pariota et al., 2016b; Wagner, 2011). Other models describe instability typical of transition phases between free-flow and congestion (Orosz et al., 2004), especially when the leader's speed varies (Pariota et al., 2016a). Wille's finding, reported above, was striking: the oscillatory pattern comes per se, is systematic, and is near constant in different driving contexts.

1.3. Car following: mental models

Humans are active and highly adaptive due to an ability to generate complex, internal models of their environs. In *Mental Models*, a cognitive science masterpiece, Johnson-Laird (1983) dares to explain *how* without referring to presumed, black box mental algorithms. Humans perceive real and imaginary worlds, then act by developing specific mental models of such worlds. Perception, language and general knowledge may nurture mental models about these worlds. Johnson-Laird (1983) distinguishes between two basic types of mental models, physical (the tangible, including dynamic referents) and conceptual (the abstract); for mental models to be built up, the information available must be determined and specific. According to Johnson-Laird, (1983, 2006), our minds hold more types of mental representations: images (basically portraying one recognizable facet of a mental model) and propositional representations of a verbal nature (similar to natural language) verified on a mental model. Physical mental models are structural analogs of a specific referent. If I enter a familiar maze and recall “three L-shaped left turns” to exit, a mental model is heeded. If I enter an alien maze, I am told “when possible, always turn left” to exit and I do, I am heeding a propositional representation that I verify onto a perceptual model of the maze generated dynamically.

1.4. Car following: way forward

CF theories would likely baffle most drivers. They need not hear how mathematical models portray their driving or why they drive as they do, currently, as an aggregate of drivers. But we do require a vision (also a mental model) of the basic dynamics of traffic flow and improvements for drivers to adopt. A good example of a concrete empirical manifestation of a theoretical background (Bando et al.,

1995) is the Nagoya experiment by Sugiyama et al. (2008); Tadaki et al. (2013), which found why traffic jams arise when bottlenecks (e.g., lane loss) are absent.

Examining road *capacity* may be misleading. Topologically speaking, capacity of a bucket is limited; that of a hose (like a road) is not. Road functionality relies on how flows are *ordered*. Congested roads express unreasonably scant capacity so pervasively that a metaphysical label was earned: *phantom traffic jam* (Gazis and Herman, 1992). Explaining phantom traffic jams requires a shift from modeling coupled vehicles; now “traffic flow is investigated as a dynamical phenomenon of a many-particle system” (Sugiyama et al., 2008; p. 2). The Nagoya experiment created an artificial jam. Drivers followed each other in a circle of 230 m perimeter. Subjects were instructed only: *follow the vehicle ahead in safety in addition to trying to maintain cruising velocity*. This was a propositional representation enacted dynamically (against the background of the lead vehicle). Subjects drove and kept free flow. But, when number of drivers rose to 22, fluctuations tripping backward broke the free flow and several vehicles stopped for a moment to avert crashing. It does not matter if tight couplings and platoons come from external reduction of space (adding cars to a track) or voluntary decision (e.g., driving with less than 1 s distance to the car ahead, as many really do) (Brackstone et al., 2002).

At stake here are longitudinal mechanical waves (Cromer, 1977). Keep safety distance is good advice for coupling cars on a road, but, when more than two follow, cars platoon into a near perfect medium for wave transmission (three cars may suffice, Orosz et al., 2004). As Sugiyama et al. showed, the oscillatory nature of flowing cars eventually spread, backward, to form a soliton of 25 km/h. Cars platooned so nicely that drivers, due to the instruction given, could not avoid propagating disturbances. Considering wave mechanics, we either eliminate disturbances or tackle the medium transmitting them – the car-following platoon. Controlling the former is hard, but not the latter (at least in harmonic form). In mathematics, a Fourier series can represent a (wave-like) function as the sum of simple sines. Hence, complex waves may be expressed as the sum of simple waves (French, 1971). Bringing this to our discussion is Fig. 1. Car 1. A has three elements: the ground (emitting vibrations), shock absorbers (springs linking chassis and wheels) and chassis (receiving the final sum of disturbances). The yellow and green waves sum bottom-up, yielding the pink wave: considerable oscillation of its chassis results. Car 1. B

has the same elements, but its shock absorbers, now modern and functional, compensate for disturbances coming up. A stable chassis (flat pink line) results.

Supplementary material related to this article can be found online at <http://dx.doi.org/10.1016/j.tranpol.2017.05.008>.

Consider now the horizontal waves in 1. A'. The lead car emits disturbances (green wave) as the follower receives the sum of the waves (red wave). Who manages the center yellow wave? Answer: the driving technique, in this case *Driving to keep Distance* (DD). The follower, mimicking the leader's actions, aims for a constant heading distance. But his/her reaction time intensifies the oscillatory pattern (red wave). Scenario 1. B' presents an alternative. The follower, *Driving to keep Inertia* (DI), has a stable speed that damps the leader's oscillatory pattern, thereby compensating for the leader's disturbance and becoming an easier car to follow.

To cope with a lead oscillatory car (the shockwave origin), a follower must be shockwave proof. Reversing the goal of Sugiyama et al. is the remedy: preventing jams instead of observing their cause. To this end, effectiveness of DD and DI in promoting steadier travel is compared. Proposing these orthogonal driving techniques (aim for uniform distance vs. uniform speed) opposes the NDB concept as a unique driving mode (Brackstone and McDonald, 1999) and assumes drivers can learn CF proactively by changing operative mode from automatic to controlled (Charlton and Starkey, 2011) and applying DD or DI as appropriate.

2. Overview of the studies

DD and DI were tested in three separate, but linked, studies (N = 113).

2.1. Goals

All three studies checked if: a) the same driver could adopt DD and DI when following a lead “disturbing” car; b) drivers could adopt DD and DI after a three-sentence 10 s instruction; c) DD vs. DI differences were statistically significant in behavioral, operative terms (accelerations, decelerations, crashes, speed, distance to leader, fuel usage, etc.). Study 3 also monitored space used by eight virtual “robot” DD drivers following a DD or DI subject. For psychophysiological (skin conductance) and cognitive responses (self-assessment concerning affective and personality factors), which are beyond this paper's scope, see Lucas-Alba et al. (2017).

2.2. Subjects

All subjects were licensed drivers (Table 1), mostly students plus others responding to posters in nearby shops, driving schools, restaurants, etc.

2.3. Design

The studies shared the same experimental design, a repeated measures model controlling for order. Manipulation of driving techni-

Table 1
Main demographics of subjects in the three Studies.

Variables	Study 1: Blanch (2015)	Study 2: Blanch (2015)	Study 3: Ferruz (2015)
N	44	44	25
Gender (n)	24f, 20 m	37f, 4 m	12f, 13 m
Age in years (Mean)	23.3	20.7	21.3
University education (%)	84.1%	68.2%	100%
Years driving (Mean)	4.07	2.81	2.68
Km per year (%)	59.1% < 10,000	59.6% < 10,000	44.0% < 10,000

Table 2

Means corresponding to the main variables in Studies 1–3.

Variables	Study 1		Study 2		Study 3	
	DD	DI	DD	DI	DD	DI
Accelerations (n)	147.9	90.1	158.3	106.6	230.9	55.0
Decelerations (n)	108.5	55.8	100.7	62.6	134.2	31.2
Crashes (n)	3.7	.3	2.9	.2	1.56	.36
Fuel expenditure (l)	19.4	15.0	18.6	15.1	19.7	13.9
Distance to leader (m)	6.6	11.9	7.7	17.6	9.25	19.4
Distance dispersion (m)	3.95	4.74	4.37	5.40	4.57	6.08
Speed (m/s)	3.08	3.05	3.07	3.03	3.07	3.03
Speed dispersion (m/s)	2.57	1.44	2.54	1.44	2.24	.99

que (DD/DI) was the within-subject factor. Random order (DD/DI, DI/DD) was the between-subjects factor. Dependent measures concerned performance indicators (Table 2). The controlled laboratory scenario had no roadway distractions (other cars, overtaking, merging, etc.). The task was advancing, for 4 min on a straight simulated road, behind a car accelerating and decelerating (until stopping) cyclically, like driving in congested traffic. A 4-min drive is not long, but enough for our purposes. Initial adaptation to the CF situation in terms of speed and distance to leader took from 12 to 18 s and was regular afterwards (Figs. 2 and 3). Naturalistic situations with Instrumented Vehicles consider even shorter time slots, 30–90 s, for analyzing CF parameters, (Pariota et al., 2016b).

2.4. Materials

A Spanish university faculty laboratory provided a booth for task execution and an adjoining room with two-way glass and monitor displaying the psychophysiological responses. An early goal was designing a 3D driving simulator to run remotely on a standard PC. React Follower (Impactware, 2014), based on UNITY software, was developed and customized to change parameters (speed, frequency of stop-and-go cycles, etc.) externally, via XML. The focus was on materializing study of DD/DI with a lead car's differing oscillatory patterns. Subjects saw three scenarios, always in one lane: A) driving alone on the road (in a natural position on the driver's virtual side of the car); B) driving behind another car traveling at constant speed of 3 m/s (10.8 km/h); C) driving behind another car traveling with stop-and-go cycles of a sinusoidal function built at a mean speed of 3 m/s (data is presented only from C). Subjects could control their car's acceleration/deceleration only by pressing up/down arrows on a PC keyboard. When “up” was pressed, the car accelerated and maintained constant speed. When “down” was pressed, it decelerated and maintained constant speed. Each speed change was in incremental: to accelerate or decelerate continually meant repeatedly pressing the keys. The simplest option (keyboard) was preferred to enable all subjects to use the software with basic hardware equipment, and to level differences in expertise with video game keyboards. The road had no changes in horizontal or vertical alignment; the only requirement was altering speed-distance on a straight flat lane. The driving simulator worked on an HP TouchSmart iq522es with a 23-in. screen, NVIDIA GeForce 9300 m GS video card and 4 GB RAM, Intel Core 2 Duo Processor T6400 2.00 GHz, and Windows 7 operating system. A precision Apple USB keyboard (PCB DirectIN V2012) was used. The simulator collected, among others, variables for speed, distance to leader, and fuel usage (a gross estimate obtained considering variations in speed per frame, Table 2).

2.5. Procedure

Scenarios A/B were designed as controls. Scenario C subjects were told to follow the lead car and adopt DD or DI; neither was given an

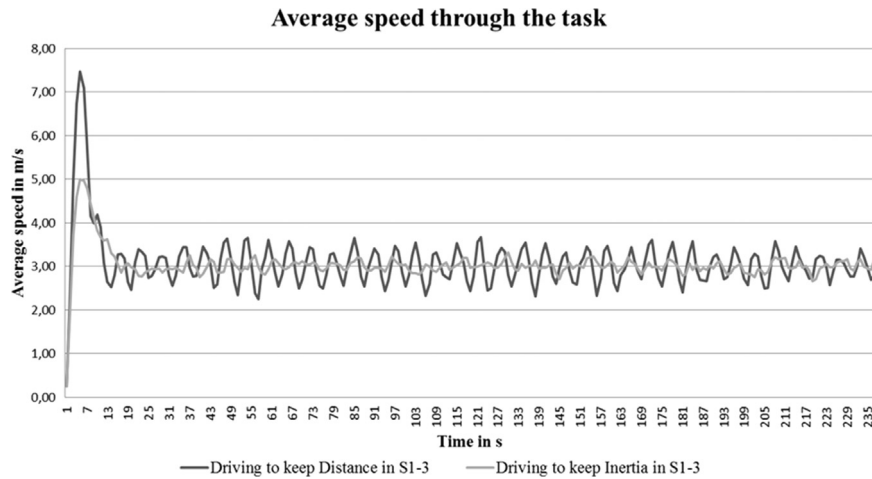


Fig. 2. Average speed of followers throughout the CF driving path under DD and DI.

explicit verbal label. The group first performing DD had this instruction first: “In the simulated driving scenario that you will enter, you will see a vehicle ahead of you and it will not move at a constant speed. Sometimes it will go faster or slower. We ask you to travel behind that vehicle as closely as possible without risking a crash.” Heeding this, they used the simulator and then were given the SAM scales. Next, the instruction for DI was provided: “In the simulated driving scenario, you will see a vehicle ahead of you and it will not move at a constant speed. Sometimes it will go faster or slower. We ask you to travel smoothly behind the vehicle and maintain a constant speed, without letting the lead vehicle move too far away.” For the group performing DI first, the instructions’ order was reversed.

3. Overview of main results

Data was subjected to a repeated measure ANOVA having two levels of driving orientation (DD/DI). Table 2 presents the main performance results. Comparing the DD/DI means for all factors (accelerations, decelerations, crashes, etc.) yielded significant differences in Study 1 ($p < .001$), Study 2 ($p < .001$) and Study 3 ($p < .005$).

Performance characterized DD mainly as preserving distance to leader (always shorter and within a smaller span) and sacrificing, notably, speed dispersion. DD replicated the leader disturbance, hence transmitting it. Performance characterized DI mainly as preserving speed dispersion while yielding on distance and distance dispersion. DI damped the leader's disturbance, rendering the subject easier to follow.

Fig. 2 summarizes average speed in Studies 1–3. During DI driving, subject's speed was more uniform throughout the whole CF path; during DD driving, the same subjects had heavier oscillation around the mean (Table 2).

With average distance to lead car in Studies 1–3, Fig. 3 shows the complementary side of DD and DI strategies. Heeding the DD instruction, follower distance to leader is shorter. Heeding the DI instruction requires a damping distance to keep a uniform speed, so more space is left. Sugiyama et al. (2008) provoked a traffic jam increasing density, as drivers could not keep the instruction concerning the uniform speed. But we see that drivers may cope with an oscillating leader by summing or offsetting so they can proactively avoid transmitting jam-causing waves.

This issue was checked in Study 3 with new simulator measurements: eight virtual cars followed subjects (who were unaware of it). These virtual drivers all practiced the traditional DD approach to follow each other (and the subject). The simulator registered distances from leader to 8th car, and from subject to 8th car. Average distance from leader to 8th car is similar under DD and DI (DD: $M = 117.3$ m, $SD = 1.93$; DI: $M = 118.95$, $SD = 8.75$). However, as Table 2 shows, distance from subject to leader is larger under DI. Most important, measuring distances from subjects' car to 8th car under DD and DI (DD: $M = 108.03$ m, $SD = 1.93$; DI: $M = 99.55$, $SD = 3.69$) yields significant differences: $F_{(1,23)} = 30.32$, $p < .001$. DI furnishes platoon stability and optimized space on the road. Overall, a good global indicator of performance in Studies 1–3 is virtual fuel expenditure, always ~ 20% lower under DI.

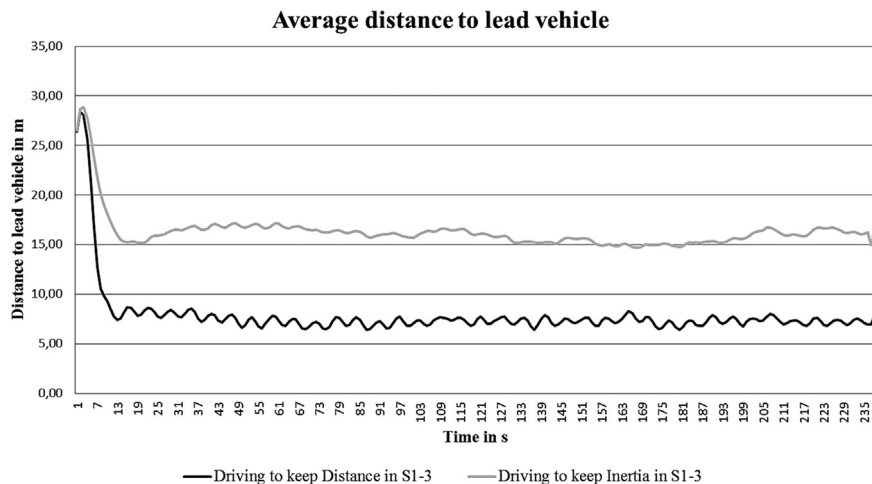


Fig. 3. Average distance from followers to leader under DD and DI.

The next section compares performance measurements based on mixed ANOVA for each as within-subject factors; DD/DI order and the Study were between-subject factors.

3.1. Measures concerning punctual actions: accelerations, decelerations, crashes

Operational scores were subjected to a repeated measure ANOVA having two levels of driving orientation (distance, inertia), two action types (accelerations, decelerations) and DD/DI vs. DI/DD order and the Study (1–3). More accelerations ($M = 131.42$) than decelerations ($M = 82.22$) occur overall, $F_{(1107)} = 71.52$, $p < .0001$, $\eta_p^2 = .401$ (Table 2), as expected considering real life acceleration/deceleration asymmetry (Saifuzzaman and Zheng, 2014). More accelerations and decelerations occur under DD ($M = 146.81$) than DI ($M = 66.83$), $F_{(1107)} = 87.39$, $p < .0001$, $\eta_p^2 = .450$. This is nuanced by an interaction of factors, $F_{(1107)} = 10.59$, $p < .005$, $\eta_p^2 = .09$: more accelerations ($M = 179.0$) than decelerations ($M = 114.6$) occur under DD than DI (Acc. $M = 83.8$; Dec.: $M = 49.8$), but decelerations differ more.

Though the factor Study's main effect is not significant ($p > .54$), former results are nuanced by it. Number of accelerations/decelerations differs significantly for DD and DI considering each Study, $F_{(2107)} = 10.3$, $p < .0001$, $\eta_p^2 = .160$. The DD/DI differences in S-1 (DD: $M = 128.2$; DI: $M = 72.9$) and S-2 (DD: $M = 129.5$; DI: $M = 84.6$) are less extreme than in S-3 (DD: $M = 182.8$; DI: $M = 42.9$). This effect yields a second order interaction, including event type – accelerations and decelerations, $F_{(2107)} = 4.30$, $p < .05$, $\eta_p^2 = .074$ (Fig. 4). DD/DI differences in accelerations and decelerations are more extreme in S-3.

More crashes always occur under DD ($M = 2.72$) than DI ($M = .31$), $F_{(1107)} = 56.7$, $p < .0001$, $\eta_p^2 = .346$ (Table 2). The factor Study presented a marginal effect on crashes, $F_{(2107)} = 2.79$, $p < .07$, $\eta_p^2 = .049$, but this is nuanced by interaction with driving technique, $F_{(2107)} = 3.35$, $p < .05$, $\eta_p^2 = .059$. Difference in number of crashes is larger in S-1 (DD: $M = 3.66$; DI: $M = .32$) and S-2 (DD: $M = 2.91$; DI: $M = .23$) than in S-3 (DD: $M = 1.59$; DI: $M = .38$).

3.2. Referential measures: distance to lead car

Average and dispersion measures of distance to leader were subjected to a repeated measure ANOVA having two levels of driving technique (DD/DI), and DD vs. DI order and the Study (1–3). Mean distance to lead cars differs according to driving technique, more under DI ($M = 16.26$) than DD ($M = 7.84$) overall, $F_{(1107)} = 138.43$, $p < .0001$, $\eta_p^2 = .564$ (Table 2). The Study also presents differences, $F_{(2107)} = 10.06$, $p < .0001$, $\eta_p^2 = .158$; S-2 ($M = 12.68$) and S-3 ($M = 14.26$)

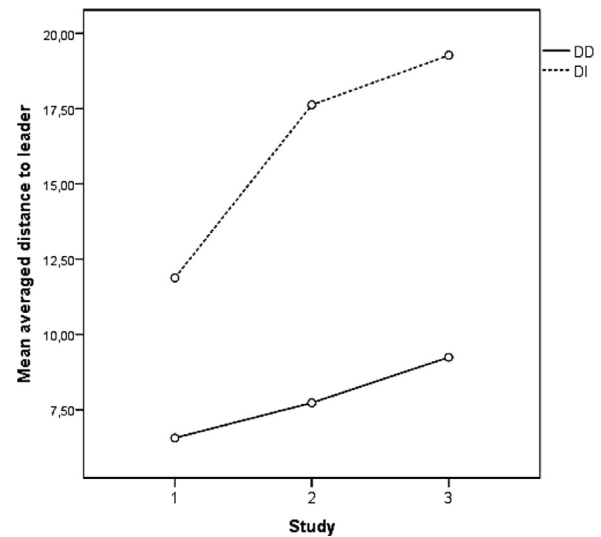


Fig. 5. Differences in distance to leader considering technique type and Study.

do not differ from each other ($p > .19$), but both differ with S-1 ($M = 9.22$; $p < .001$). The two factors give way to an interaction, $F_{(2107)} = 5.35$, $p < .01$, $\eta_p^2 = .091$: differences between S-1 vs. S-2 and S-3 are more acute for DI (Fig. 5).

Order also reveals as significant the between-subject factor, $F_{(1107)} = 4.81$, $p < .05$, $\eta_p^2 = .043$, distance being overall greater with DI/DD ($M = 13.10$) vs. DD/DI ($M = 11.01$). This effect is nuanced by interaction with driving technique, $F_{(1107)} = 7.96$, $p < .01$, $\eta_p^2 = .069$: when subjects heed the order DI-DD, distance to leader is greater under DI ($M = 18.31$) than when the order heeded is DD-DI (distance under DI, $M = 14.21$), while distance to leader when driving DD is always similar (DI-DD, $M_{DD} = 7.87$; DD-DI, $M_{DD} = 7.81$). Complementarily, dispersion of distance to leader differs according to driving technique, more under DI ($M = 5.40$) than DD ($M = 4.30$) overall, $F_{(1107)} = 28.63$, $p < .0001$, $\eta_p^2 = .211$ (Table 2). The Study also presents differences, $F_{(2107)} = 3.74$, $p < .05$, $\eta_p^2 = .065$: S-2 ($M = 4.89$) and S-3 ($M = 5.31$) do not differ from each other ($p > .25$); neither do S-1/S-2 ($M = 4.35$; $p > .08$), but S-1 and S-3 do ($p < .01$).

3.3. Referential measures: speed

Average and dispersion measures of speed were subjected to a repeated measure ANOVA having two levels of driving technique (DD/DI) and DD

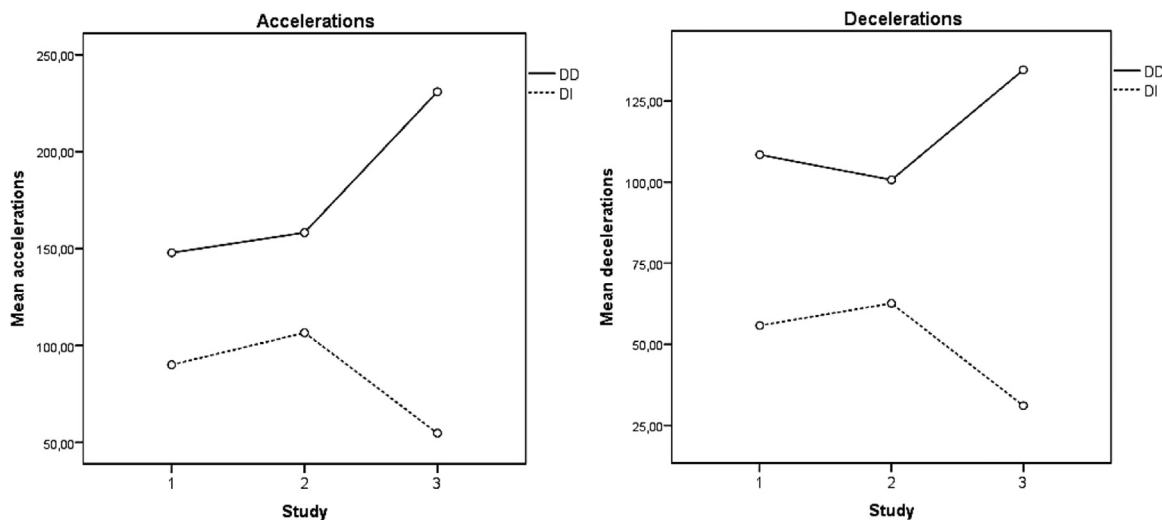


Fig. 4. Differences in operation considering technique type and Study.

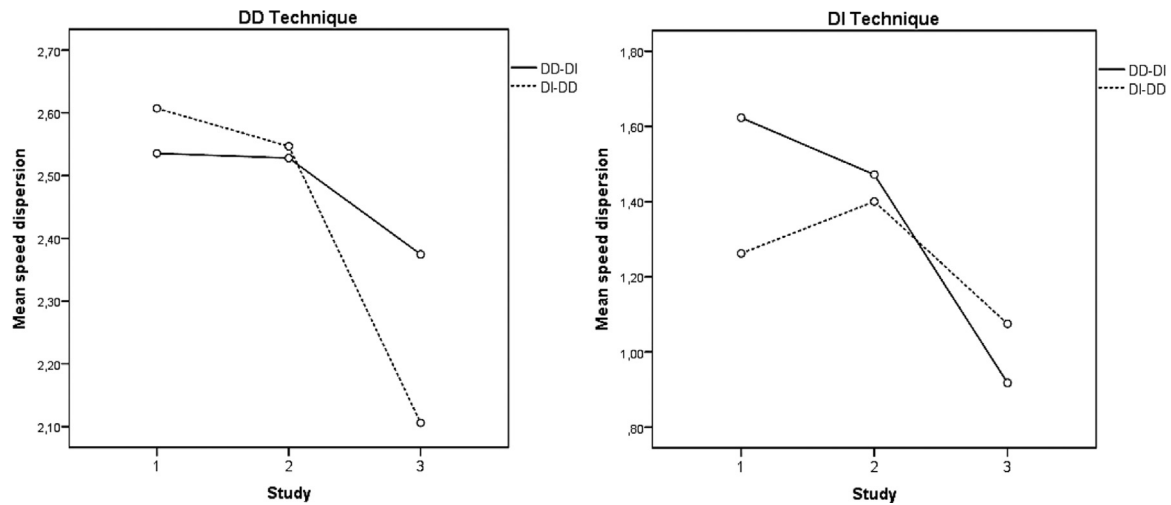


Fig. 6. Differences on speed dispersion for DD/DI considering order and Study.

vs. DI order and the Study (1–3). Mean speed differs depending on driving technique, more under DD ($M = 3.08$) than DI ($M = 3.04$) overall, $F_{(1107)} = 46.66$, $p < .0001$, $\eta_p^2 = .304$ (Table 2). The Study also presents differences, $F_{(2107)} = 5.72$, $p < .005$, $\eta_p^2 = .097$: S-2 ($M = 3.05$) and S-3 ($M = 3.05$) do not differ from each other ($p > .63$), but both differ from S-1 ($M = 3.07$; $p < .01$). And the order presents differences, $F_{(1107)} = 12.60$, $p < .001$, $\eta_p^2 = .110$: drivers starting with DD ($M = 3.07$) drove faster overall than drivers starting with DI ($M = 3.05$). This effect is nuanced by an interaction, $F_{(1107)} = 8.82$, $p < .005$, $\eta_p^2 = .076$: when subjects began with DI, speed was first low under DI ($M = 3.02$) and then higher under DD ($M = 3.07$); however, when subjects began with DD, speed was equally high under DD ($M = 3.08$) and DI ($M = 3.06$).

Dispersion measures of speed yield a strong main effect, $F_{(1107)} = 305.43$, $p < .0001$, $\eta_p^2 = .741$ (Table 2); dispersion is clearly higher under DD ($M = 2.45$) than DI ($M = 1.29$). The Study also presents differences, $F_{(2107)} = 8.51$, $p < .001$, $\eta_p^2 = .137$: S-1 ($M = 2.01$) and S-2 ($M = 1.99$) do not differ from each other ($p > .82$), but both differ from S-3 ($M = 1.63$; $p < .001$). Finally, a second order interaction of these variables is observed, $F_{(2107)} = 3.18$, $p < .05$, $\eta_p^2 = .056$ (Fig. 6).

3.4. Overall measures: fuel consumption

Liters of virtual fuel used were subjected to a repeated measure ANOVA having two levels of driving technique (DD/DI) and DD vs. DI

order and the Study (1–3). Sound differences were noted in fuel used, more under DD ($M = 19.23$) than DI ($M = 14.65$) overall, $F_{(1107)} = 429.4$, $p < .0001$, $\eta_p^2 = .801$ (Table 2). This is nearly 24% less fuel usage. This effect is nuanced by the Study, $F_{(2107)} = 8.39$, $p < .0001$, $\eta_p^2 = .136$. Fuel usage under DD and DI is more extreme in S-3 than S-1/S-2: difference in S-3 = 5.86 l; in S-2 = 3.53 l; in S-1 = 4.34 l. A second order interaction occurs too, $F_{(2107)} = 4.50$, $p < .01$, $\eta_p^2 = .078$ (Fig. 7).

4. Discussion

DI drivers perform more steadily, and are easier to follow (even for DD virtual drivers). Statistical analysis confirms the main results underlined here concerning characterization of performance and operative indicators (Table 2). All three studies show sound differences in these factors, always in the same direction depending on technique being heeded. First, all drivers can drive under DD/DI mode when following a lead swinging car and keep it permanently as requested (not return solely to DD or another “natural” way of driving after a while). Second, drivers assume these techniques easily after a 10 s instruction (a few sentences or a short video). Third, differences in behavioral, operative terms (accelerations, decelerations, crashes, speed, distance to leader, fuel usage, etc.) are statistically significant. DI and DD techniques are basically orthogonal modes.

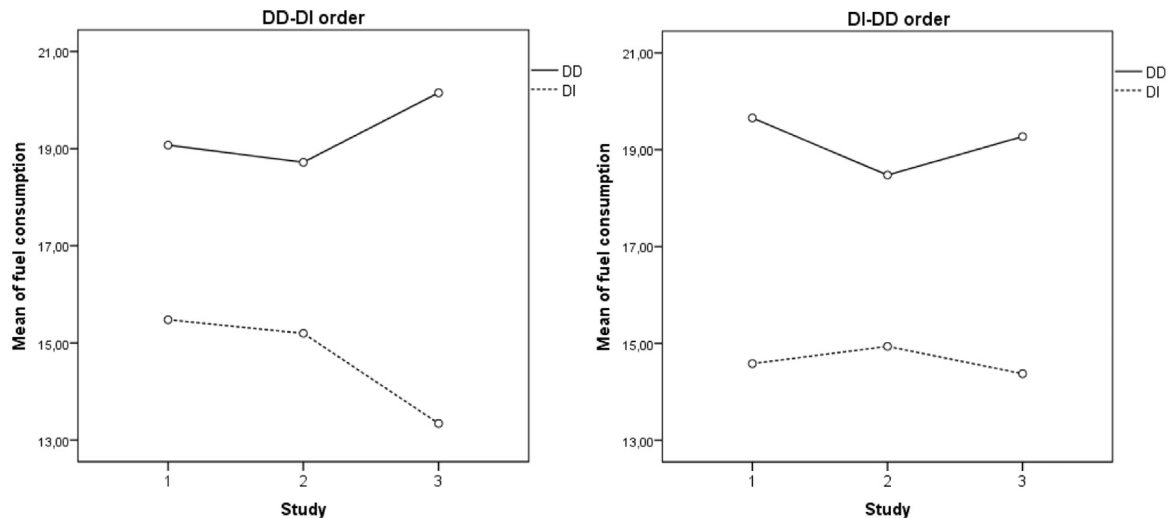


Fig. 7. Differences in fuel consumption for DD/DI considering order and Study.

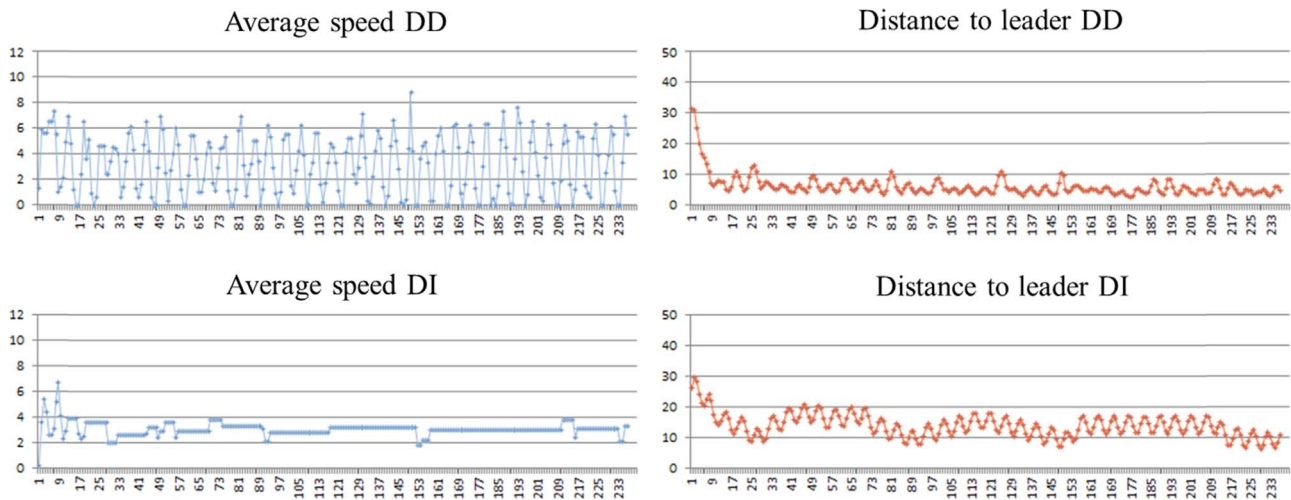


Fig. 8. Performance of a proficient driver subject under DD and DI.

Provided drivers get proper instruction, DI drivers can be a determinant and act proactively as a bottom-up element against traffic flow's oscillatory nature. In a similar vein to Wiener (1950), one may say each driver's role can be essential in bringing order to the natural entropy of such dynamic systems as traffic flow. Drivers can mentally model the present dynamics of traffic ahead and damp oscillations – not contribute to the problem, but to the solution. Henceforth, our empirical findings may be formally described as:

$$\omega_n = \omega_{n-1} + i\omega_n \quad (3)$$

where, ω_n is the wave corresponding to movement of car “n” in the platoon, ω_{n-1} is the wave corresponding to movement of the preceding car, and $i\omega_n$ is the imaginary wave enacted by mental endeavor (flow ordering strategy) corresponding to car “n” in the platoon. Human and automated drivers can move according to the same CF strategies as other animals do in Nature. For example, pine processionary larvae (*T. pityocampa*) can turn in a circle one after another for 12 consecutive hours before disaggregating (Fitzgerald, 2003).

4.1. Potential relevance of training and education in learning DD/DI

Results show differences concerning the Studies as factor and the DD-DI vs. DI-DD order. Subjects in Studies 1–3 received the same main instructions about the driving techniques. But compared with Studies 1 and 3 (short sentence describing the procedure), Study 2's instruction was a short video on how phantom traffic jams emerge and how to prevent them by applying DD or DI. The main recommendation was embedded (written) at the video's end. Also, the description in Studies 1 and 3 was direct, even more directive, than Study 2's instruction (Blanch, 2015).

Before the experiment proper, subjects in Studies 1 and 2 were invited to check distance to the lead car (some purposely crashed to verify the limit). Subjects in Study 3 were left to their own perceptions about how to follow the lead car. Although DD/DI differences were sound in all Studies, due to differences among the studies (number of crashes, distance to lead car, speed variations, fuel consumption) that seemed related to instructions, effect of instruction procedures deserve attention. More demographics may also be compared. These considerations push future efforts toward analyzing the role of the premises within the AP theoretical background (how drivers compute DI car following in perceptual and cognitive terms) and the role of expert vs. novice drivers on the technique applied.

4.2. Changes as a consequence of order followed

Though the technique type applied first may have affected assimilation or contrast of magnitudes (speed, distance), the global set we

analyzed (including psychophysiological and self-reports) points to a statistical effect that tends to compensate under different conditions (sometimes assimilation, sometimes contrast). Order, as such, is not a theoretical variable for us, just a methodological control. If perceived as relevant, this effect should be theoretically analyzed, then introduced and manipulated for better appraisal.

4.3. Limitations of the studies

The set of studies is not without limitations. Most subjects were young drivers at university. That weakness may be a strength as acquiring both driving techniques was easy despite their inexperience. Does experience (habit) improve or worsen performance (especially under DI)? Future studies should check. Another issue is driver heterogeneity. Endogenous factors (gender, age, personality and individual differences, transient states, specific travel goals and timing) may introduce considerable changes in CF (Hennessy et al., 2011; Saifuzzaman and Zheng, 2014; Wille, 2011). Though the experimental manipulation of DD and DI conditions led to sound differences, subjects were heterogeneous too. Fig. 8 shows performance of one subject under DD and DI throughout the task. Y-axis shows speed (m/s) and distance (m); X-axis shows time (s). This proficient driver performed as requested: uniform speed under DI and uniform distance under DD. Other subjects were less good, with a DI output that was a “mild” version of DD (too many ups and downs in speed, close distance to leader).

Also materials may improve. Our simulator used PC keys, not a realistic driving environment with gas/brake pedals. The leader's speed (10.8 km/h) was set up thinking of a critical, jammed situation – not so uncommon and applicable to emergency situations – to gain clear observation of the effects after the two strategies adopted to follow a swinging leader. Recently, Carrasco (2017) tested DI on a circular track (30 m radius) with six real cars, similar to the Nagoya experiment. The first was an automated car driving with cycles of acceleration (till 25 km/h) and deceleration (to a full stop); the second was the subject car (with no instruction in Trial 1, and a short DI instruction, similar to ours, in Trial 2); the other cars were followers with no instruction (driving “naturally”). In only three complete loops around the track, driving with no instruction equates to DD and reproduces the backward soliton wave instability (as in Nagoya); driving with DI instruction keeps free flow behind the subject's car (Carrasco's original sessions are at https://drive.google.com/file/d/0B1F_W58F2EWPVfHmBgGFDmWxMUms/view?usp=sharing). Like Carrasco (2017), our aim is showing as possible quicker stabilization of the following platoon; however, a wider range of speeds should be tested.

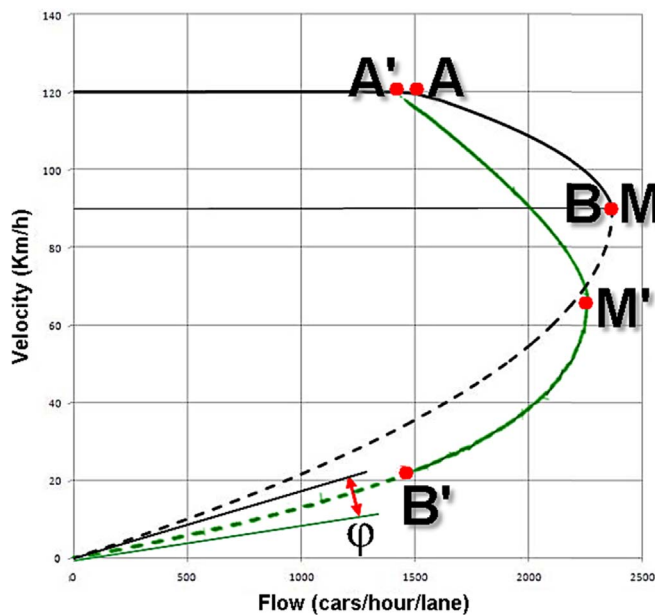


Fig. 9. Fundamental diagram of traffic flow (DD vs. DI).

Similarly, the leader's oscillation was constant (a harmonic wave) so the DD/DI instruction was easy to apply (e.g., considering the basic parameters fixed by the classic models under the AP paradigm; [Pariota and Bifulco, 2015](#); [Wagner, 2011](#)). But most studies under the AP paradigm analyze how followers adapt to a relatively stable leader. [Pariota et al. \(2016a\)](#) proposed a CF model based on two inputs: follower's desired equilibrium space and speed of leader. When this speed is non-constant, "the follower tries to achieve the desired spacing, but the process is continuously perturbed by the bias produced by the leader" (p. 1036). At present, drivers are supposed to practice CF in the "natural" (desired) way. Yet, rather than assume "naturally endowed" CF behavior, drivers are taught DD: roadway "capacity" has been designed considering couplings of speed-safety distance and number of expected drivers (per lane and kilometer) between locations, then driving schools teach DD, and road signs reinforce it as does surrounding traffic – not always safely ([Brackstone et al., 2002](#); [Hennessy et al., 2011](#)). What would result if car drivers learned DI instead, to aim for uniform speed like teamsters do? ([Ossen and Hoogendoorn, 2011](#)). Despite our studies' narrow speed range, we know drivers can learn and apply DI. The challenges now are determining driver ability to apply DI under differing speed-distance CF contexts and calculating the gains if DI becomes commonplace.

5. Concluding remarks

Modern societies face this hazard: breathing eliminates part of vehicle emissions, which has already taken more lives than road crashes ([Caiazzo et al., 2013](#)). Pollution and jams are highly linked because acceleration and deceleration are the most contaminating ([Tong et al., 2000](#)). This paper aims to frame CF models by widening their potential ties to human behavior, with our first attempts focused on how individual drivers may improve traffic flows. Drivers learn to stay close behind leaders, but changing this thinking can ease jams if drivers combine safety distance with efficiency distance needed to damp without stopping. Abstract as it seems, our subjects did it.

Inspired by [Smeed's classic accounts \(1968\)](#), Fig. 9 presents two extremes of the fundamental traffic flow diagram. The black curve shows the typical relationship between velocity and flow under DD. Point A is maximum flow at the speed limit (e.g., 120 km/h). Forced traffic begins at B. Maximum flow is attained at M. B and M are coincident. Ideally, maximum flow at the corresponding speed (90 km/

h) should be kept, but, given the oscillatory nature of traffic flows (reaction time, summing waves), this state cannot last long; a jam occurs and speed and flow decrease. The green curve represents DI. A' is maximum flow at the speed limit (e.g., 120 km/h). Forced traffic begins (~ 20–25 km/h) at B'. Maximum flow is attained at M' (~ 70 km/h). B' and M' are not coincident so M' is not as precarious as M and can last much longer. The bad news: M' is lower than M, so capacity seems undermined; but M will not last long. The good news: DI should promote a stable flow lasting longer. Angle Φ represents level of flow stability: as the efficiency factor increases the maximum flow decreases, but gets more stable (this is graphically represented by a family of curves and the Φ parameter).

Conceptual models need more physical and mathematical complexity to depict the road network (multiple lanes, curves, hills, various speeds, overtaking, merging). However such analysis progresses, and with the right driver training and education (in a growing ICT context), the role of individual drivers in modern traffic deserves review. Small, simple changes may effect global transformations if we all adopt them. Washing hands, for instance, revolutionized sanitation. Teaching drivers DI may similarly transform traffic flows. This pertains to automated cars too, which may be programed to leave extra space with the vehicle ahead. If humans grasp the basic principles of flow stability, they will also understand how automatons may drive. Longitudinal mechanical waves are instruments of Nature that serve different types of movement, and robots are not free of such allegiance. Perhaps under this common stance integrating human and automated driving will not be difficult.

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