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Quantifying attentional demand of a lane-keeping task as the minimum required information in predictive processing

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ABSTRACT

There is no clear consensus about the theoretical definition and operational criteria of inattention or distraction in traffic, which may lead to conflicting conclusions in research [1]. The scientific community should have a consensus on the definition and operationalization of driver inattention in order to provide strong guidance, for instance, in the planned distraction assessment incorporated into EuroNCAP ratings, the new distraction legislation, and development of driver attention monitoring systems.

Some researchers may consider any competing glance away from the forward driving scene as distraction (e.g., [2]), whereas others have stressed that often drivers have spare visual capacity in driving (e.g., [3]). There is also no agreement on if a certain off-forward glance duration (e.g., 2 seconds [4]) can be considered as a general time threshold for visually distracted driving. The most popular definitions (e.g., [1][5]) suggest that glancing away from the forward driving scene is visual distraction only if it prevents the driver to perform "activities critical for safe driving". However, these taxonomies have not offered clear guidance on how this criticality should be defined or measured for different driving scenarios. Kircher and Ahlström [6] as well as Regan et al. [1] discuss hindsight bias in defining and measuring inattention. The bias refers to defining drivers as being inattentive based on the observed outcomes of a situation (e.g., a crash or a lane excursion). This is an inappropriate way to operationalize inattention, as we should know if the driver is attentive towards the driving task regardless of the outcome.

The proper way to operationalize driver inattention would require a baseline of attentive driving, that is, to define to which driving-relevant targets attention and how much, should a driver allocate for successful task performance in a given scenario (i.e., the attentional demands of driving). For scientific, engineering and regulatory purposes, it would be highly useful to have well-founded and quantifiable metrics of attentional demand and inattention applicable for various driving scenarios and, for instance, different simulations of the driving task. This contribution continues the construction of a computational framework for quantifying attentional demands of driving presented at DDI2018 [7] based on the valuable feedback from the audience.

Quantification of attentional demand of driving-relevant event states

The presented approach for modelling the dynamic information requirements of a human driver is based on the predictive processing frameworks of cognition [8][9] and relative entropy as a measure of potential information gain (i.e., Bayesian surprise [10]). The predictive processing framework of cognition [8] stresses the importance of prediction uncertainty and its resolution in human attention allocation and behaviour. Uncertainty of a belief distribution (i.e., prediction) can be computationally modelled by its entropy [10]. However, entropy of a driver's belief distribution of an upcoming driving-relevant state (e.g., distance to lead car) cannot be used directly as a measure of the *normative* attentional demand for the driver, as drivers may have inaccurate beliefs and false confidence on these [11]. This is why the attentional demand is better to be quantified with relative entropy [10]. Here, relative entropy refers to the potential information gain (i.e., potential surprise, S) for a driver's belief distribution Q of state x relative to a task-critical threshold T(x), if the driver samples the information at time t (i.e., Kullback-Leibler divergence: $S(x>T(x),t) = D_{KL}[P(x>T(x),t)||Q(x>T(x),t)]$). Zero S indicates no attentional demand towards x. This definition of attentional demand of a driving-relevant event state is dependent on task-critical threshold(s) and volatility of the state behaviour, which is affected by driver's actions based on subjective belief distribution of the state. It is well in line with the theoretical frameworks of the brain as an adaptive Bayesian prediction machine (e.g., [8]), which are currently popular in cognitive neuroscience. In this framework, inattention is a form of *inappropriate uncertainty* [9] in relation to the volatility of a task-relevant state and task goal(s).

Example: Quantification of attentional demand and inattention in lane keeping

Here, the application of this framework for the operationalization and measurement of attentional demand and inattention is illustrated for a simple lane-keeping task. The oral presentation will also review empirical evidence on the feasibility of the framework in this task, collected in a driving simulator. Figure 1 illustrates what the definition means for a simplified lane-keeping task under occlusion [12][13] and with a constant speed.

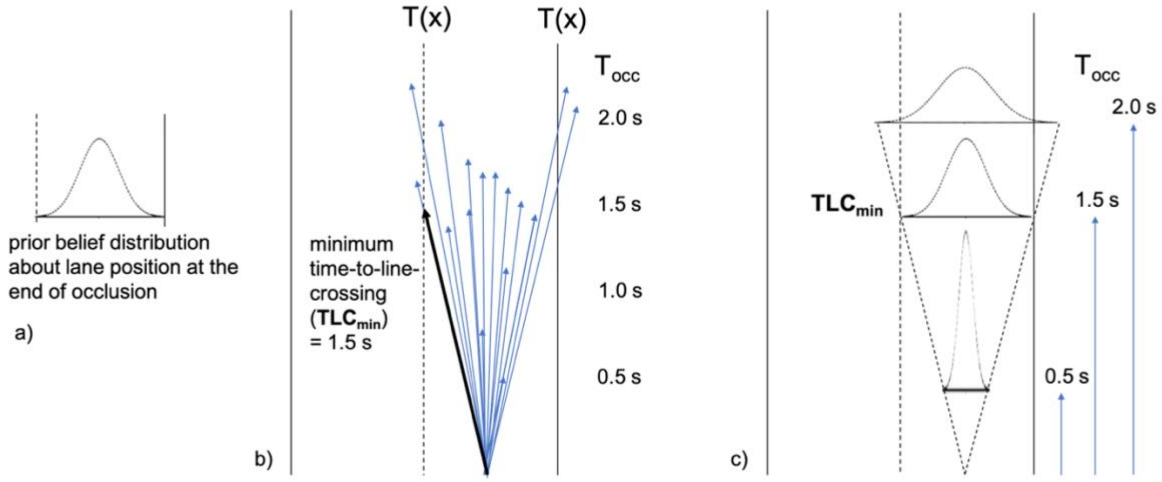

Figure 1. a) Driver's assumed prior belief distribution about lane position (x) at the end of each occlusion [$Q(x,T_{occ})$]. b) Measurements of the driver's true paths during repeated occlusions and the minimum time-to-line-crossing (TLC_{min}). c) Probabilities of lane position at three time points based on the measurements [$P(x,T_{occ})$]. Potential surprise relative to a task-critical threshold T(x) for the lane position belief starts to grow at 1.5 seconds.

In this task, the driver is instructed to keep the own lane while driving occluded, and to end the occlusion at the moment when feeling it is possible the car is leaving the lane. At each sampling, we can therefore assume driver's prior belief distribution about the lane position to resemble Fig. 1 a) (as an example), with minimum and maximum subjectively possible values at the lane boundaries (i.e., "extreme hypotheses"). Fig 1. b) illustrates measurements of the driver's true paths during repeated occlusions and the minimum time-to-line-crossing (TLC_{min} [14]) while occluded. Fig. 1 c) indicates probabilities of lane position at three points in time based on the measurements. In this example, potential surprise (S) relative to the lane boundaries T(x) for the lane position belief starts to grow rapidly after TLC_{min} (1.5 s), corresponding to a minimum sampling requirement of once per 1.5 s, to (probably) succeed in the task (NB. Reaction time and time required for corrective steering are not included in this example.). Sampling the lane position less than once per 1.5 s in similar future situations would then indicate inattention (i.e., inappropriate uncertainty), regardless of the outcome of the situation. If we knew all the relevant variables that affect this minimum sampling threshold (e.g., lane width, curvature, speed, TLC, steering amplitude), and how much, we would be able to estimate the normative situational minimum information sampling frequency in this particular task for the driver at any situation. Note that in this exactly same task, the minimum required information sampling frequency can vary between drivers and for a driver, depending on the situational and driver-specific variables (e.g., steering input). The illustration is highly simplified but the same principle applies to more winding paths and driving in curves.

Discussion

The introduced framework seems to work well for the studied part-task of driving, that is, lane keeping with fixed speed. A simplified driving task may suffice as a well-founded baseline for, for instance, in-car tasks' visual distraction potential benchmarking in controlled simulator environments. The framework should work well also for other continuous tracking-based part-tasks, such as longitudinal control, for which the occlusion method [12] can be applied to. Applicability of the approach to more realistic driving with multiple concurrent and interacting demands should be evaluated. Furthermore, its generalization to discrete driving-relevant events based on more static demands of the road environment or infrastructure (see e.g., [6]) should be further studied. At least, as opposed to a more frequentist approach, the framework suggests that the attentional demand of looking at both directions while approaching a T-crossing is independent of the traffic density in the crossing and never zero, as there is always a possibility of an approaching vehicle.

The proposed operationalization and quantification of attentional demand and inattention is probabilistic, and thus, free of hindsight bias [1][6]. The approach may also be accepted even if one is not a supporter of the predictive processing approach to human cognition [8]. The sole cognitive assumption that must be accepted is that drivers can have mental representations of driving-relevant event states and that they are able to drive based on these, at least for limited periods of time. There is empirical evidence available that supports this assumption (e.g., [15]). In future studies, it will be interesting to study the generalizability of this approach to quantify attentional demands of tasks beyond manual driving and to develop driver (in)attention monitoring algorithms (cf. [16]) based on it.

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