Human Performance Profiling While Driving a Sidestick-Controlled Car

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Abstract We have established a metric for measuring human performance while operating a sidestick-controlled car and have used it in conjunction with a known environment type to identify unusual steering trends. We focused on the analysis of the vehicle's offset from the lane center in the time domain and identified a set of this signal's features shared by all test drivers. The distribution of these features identifies a specific driving environment type and represents the essence of the proposed metric. We assumed that the driver performance, while operating a sidestick-controlled car, is determined by the environment type on one side and the driver's own mental state on the other. The goal is to detect the mismatch of the assumed driving environment, gained from the introduced metric, and a ground truth about the actual environmental type, which can be obtained through map and GPS data, in order to identify unusual steering trend possibly caused by a change in driver fitness.

1 Introduction

The most recent basic guidelines for the considerations on the driving context data were provided by the European AIDA project. The main identified context features were:

- Goal of the current voyage as provided by the navigational component
- Basic traffic information extended with car to infrastructure and car-to-car communication

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B. Lausen et al. (eds.), *Data Science, Learning by Latent Structures, and Knowledge Discovery*, Studies in Classification, Data Analysis, and Knowledge Organization, DOI 10.1007/978-3-662-44983-7_40

- Assessment of driver's current state, both mental and physical
- Assessment of vehicle's current state

This work represents the effort to indirectly assess the driver's current mental state, by measuring his driving performance when operating a sidestick-controlled vehicle. The optimal input device for the primary driving task in road vehicles is a very debatable subject. In the scope of the project Diesel Reloaded, sidestick has been proposed as the future input modality in the automotive domain (Mercep et al. 2013). As compared to a central stick, where the input device is located between the driver's or pilot's legs, a sidestick is located to the left or to the right (or both) of the driver. One advantage is the integration of longitudinal and lateral vehicle dynamics' control in one single physical device, saving space and reducing the amount of physical force necessary to operate the vehicle. Another advantage is accessibility, since the device can be operated by people with a wide range of physical impediments. However, one of the key assumptions for the acceptance of sidestick-controlled vehicles is a reliable and affordable drive-by-wire system (Spiegelberg 2005). Therefore, the acceptance of the new input device might not be a question of ergonomics, but rather of engineering and regulatory changes taking place in other vehicle subsystems. Vehicle information and communication architecture is one of the key enabling technologies for innovation in the area of human–machine interaction and driver assistance (Buckl et al. 2012).

In this work, we propose analyzing the lane keeping task as the primary factor describing the successful performance of the driving task. A blind analysis of the vehicle's offset from the lane center over the course of time is performed. The goal is to find a lane offset-based metric which describes the driver's performance in a specific environment. The focus is on the definition and the validation of the metric through experimental data. Once the driver performance in a specific environment is sufficiently described by the metric, we assume that any sudden change in this description directly relates to a new and unusual steering trend in a specific environment. The fact that the driver suddenly altered his driving performance is therefore directly attributed to the change in its mental state. This result can be used as an input for other driver assistance systems. It should be noted that this work remains plagued by the absence of any related research, since the lane following task has mostly been analyzed from the driver intention, collision avoidance, or autonomous driving point of view. The assessment of the driver performance for sidestick-controlled vehicles seems to be a novel domain, what is not surprising considering the non-existing market share of such vehicles. Nevertheless, the more general task of target following with a sidestick represents a very interesting field of research for different vehicle types and different lower-level applications.

This work is organized as follows. In Sect. 2 we describe the proposed method for obtaining the necessary metric. The experiment design is described in Sect. 3. Pre-processing methods used on the data gathered during the experiment are described in Sect. 4. Results are presented in Sect. 5. Finally, we conclude and elaborate on future work in Sect. 6.

2 Method

In this section, we describe the method used to obtain the metric for the driver's performance. Based on the previous work in the area of driver steering prediction, we opted for an approach which reduces the driving task to a lane following task, in which the driver uses his previous knowledge, current state and future predictions to keep the vehicle from leaving the road margins (MacAdam and Charles 1981). We assume that a perfect lane detection exists and that it provides the lateral vehicle offset from the middle of the lane. The lateral offset was taken as the sole input of the method. The driver's sidestick input directly changes the lane offset, but the key difference between analyzing the sidestick input and the lane offset is the suppression of the influence of the road profile. A driver following a very dynamic road at high speeds produces a relatively large amount of lateral sidestick activity, but if he still manages to follow the road profile, the activity of the lane offset will be reduced to under- and over-steering. Driver's input for the longitudinal vehicle control, i.e. throttle and brake, is only used as an additional parameter in the further analysis.

Let offset(n) represent the time series containing the lateral vehicle offset from the middle of the lane. Let $\delta(n)$ be the first differential of the function offset(n). The set Δ_0 can be defined as:

$$\Delta_0 := \{\delta_x \in \Delta \mid |\delta_x| < \epsilon_0\}. \tag{1}$$

meaning that Δ_0 contains the segments of $\delta(n)$ where the lane offset signal underwent a trend change with a magnitude described by ϵ_0. Δ_0 is a set of subsegments of $\delta(n)$ of various lengths, in which the differential fell beneath the ϵ_0. Let us now define a so-called trigger set T as a set containing the first and last element of every subsegment in Δ_0 . In a case of a subsegment which is one point wide, meaning that the first and the last element are the same, the trigger set T includes it only once. An example of the trigger set is given in Fig. 1.

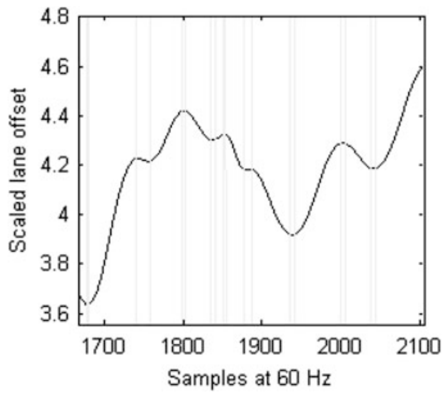

Fig. 1 Trigger set contains points in which signal started to rapidly change, here denoted with *vertical lines*

In the next step, we generate an alternative description of the trigger set, based on average densities of the triggers in a fixed time window. Inside of a larger time window, we iterate a smaller N-points time window, in which the number of triggers is counted. The counter value is added to an appropriate bin, i.e. N-point window containing four triggers increases the counter value of the bin number four. After the entire larger window has been processed, it is fully described by the final value of all the bins. Our hypothesis is that for a fixed sidestick sensitivity and a fixed sidestick sampling rate, a fixed number of bins will take on a typical average value for a specific driver and environment. The shapes of the bins' values and their relation to each other might also prove advantageous in the driver performance assessment. We propose that each environment will impose upon (or require from) the driver a specific behavior of the road offset signal, which we try to capture with the proposed metric. The static values of the bins as well as the perturbations between the bins should behave in a same manner for the same environment and for the same driver. Such perturbations can also be imagined as spectral shifts of the road offset in the frequency domain, even though we did not engage in spectral analysis in the scope of this work.

2.1 Trivial Solutions

There are, of course, trivial ways of identifying the environment based on the lateral component of the sidestick input. Long and extreme turning will signify an urban environment. Average number of sidestick corrections can trivially differentiate between inside and outside of city. The problem with these "summarizing" approaches is that they do not provide any possibility of further analysis, since most of the useful data is discarded in the averaging process.

3 Experiment Design

A total of 23 participants, all in possession of a valid driver license inside the European Union, took part in the experiment (19 male and 4 female). Mean age was 26.48, minimal 18 and maximal 36 years. A pre-experiment survey was filled out in order to determine possible alcohol or caffeine intake. The Virtual Test Drive (VTD) software from the company VIRES was used for the data collection. It was integrated into an automobile mock-up, a complete chassis of a Smart automobile, as shown in Fig. 2. A sidestick was mounted on the right of the driver, at the location usually taken by the gear shift. The sidestick did not provide force feedback. A simulation of the driving environment was shown on a large screen in front of the vehicle mock-up. Simulated vehicle dynamics were those of a typical personal automobile.

Fig. 2 Virtual Test Drive driving simulator with a complete vehicle mock-up

The experiment started with a target following game which was played with the sidestick inside the vehicle simulator. The goal was to learn the sensitivity and the behavior of the sidestick prior to the driving phase. Even though the sidestick is almost completely absent from the current road vehicles, all the participants possessed experience of using a common joystick, which lessened the learning curve. The participants were required to keep an object shaped as a circle in the middle of a large moving rectangular target for as long as possible. Penalty points were gathered when the circle failed to keep up with the rectangle. A randomly generated target following scenario was executed in each 30-s run. The game lasted no more than 3 min.

In the next step, the driving simulation was started. This step consisted of a new learning phase and, finally, the real driving phase. The learning phase lasted no more than 5 min. Participants were able to explore the simulation and further increase their grip on the sidestick skills. In the second phase, all the participants started from the same position inside the simulated world and the data was collected using the VTD RDB interface shown in Fig. 3. The participants started the drive on the outskirts of a virtual city and proceeded to drive towards and finally into the city, continuing on the city roads. Most of the participants chose to take the same route out of the city and back to the original starting position, but this was not strictly required in order to complete this phase. The real driving phase and the respective data collected lasted around 7 min.

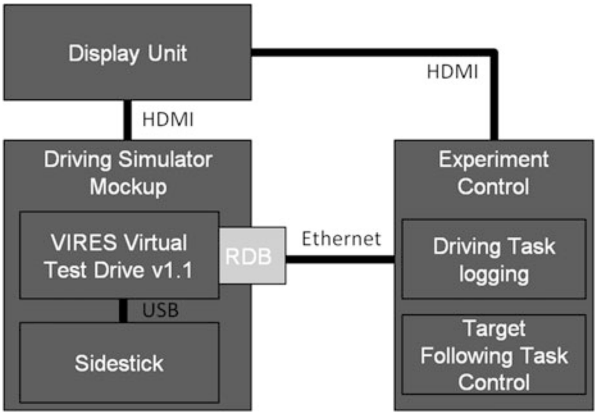

Fig. 3 Data flow between software and hardware components used in the experiment

4 Preprocessing Collected Data

The lane offset data collected in the experiment had to be pre-processed before being fed to the previously described method. Additionally, the window sizes and the ϵ_0 had to be defined. All of these values are directly dependent on the sidestick device and had to be derived from the data.

A value of 15-s has been chosen for the previously defined larger sliding window, while the smaller sliding window was fixed to 200-points (about 3 s). This has been chosen by a brute force analysis of the impact different window sizes have on the observed features and remains in direct connection with the sidestick sensitivity and sample rate. These parameters and their further refinement remain an open question and were not covered further the scope of this work.

A value of ϵ_0 of 0.3 was chosen on the same terms.

In order to eliminate the bouncing artifacts of the collected lane offset signal, present when the sidestick is switching from one discrete position to another we iterate a 3-phase 15-point moving average smoothing over the signal. The artifacts removed are rapid oscillations around a stable or steadily transient (ramp) sidestick position. They can be removed with a low-pass frequency filter, but the result has proven to be generally worse during the experiment: As the smoothing effect approaches the level of a simple average smoothing, the filter progressively removes more of the important signal features.

5 Results

After applying the binning procedure, two bins started to contain relatively large and stable signal features which stayed similar for all participants. These bins were bin number 4 and bin number 5, which count the number of 200-point windows containing, respectively, 4 and 5 triggers in larger 15-s time window. Lower bins have not been deemed useful for classification and started to fill bottom-up only during long steering maneuvers. The bins higher than 5 were almost always empty and would appear only in the most erratic and non-realistic driving situations, when the participants opted for a short chase through the streets (even though they were advised not to beforehand). The emerging signal features in bins 4 and 5 differed in two ways throughout a course of every experiment.

The first difference was the relative difference of the same bin value between different environments. Driving inside the city, as well as driving outside the city as higher speeds, trivially raised the value of bins 4 and 5 throughout all test subjects. In addition, any sudden increase in speed was intuitively countered with over-steering in the following curves, which would create significant spikes in the bin 5. This type of differences was only marginally useful for classifying environments, since the average value can drift through a large value range inside the same environment without being classified as another environment, but still denoting a change in driver performance. In other words, too much data about the driver performance is discarded by only focusing on the values of bins. This is, in fact, a version of the previously mentioned trivial solution.

The second type of differences focuses on the shapes of the bins 4 and 5 and their mutual ratio. This has proven to be the most valuable approach and it mostly tied to the surges in value of the bins 4 and 5. There were four identified sub-types, presented in Figs. 4 and 5, which are further denoted as F0, F1, F2, and SW.

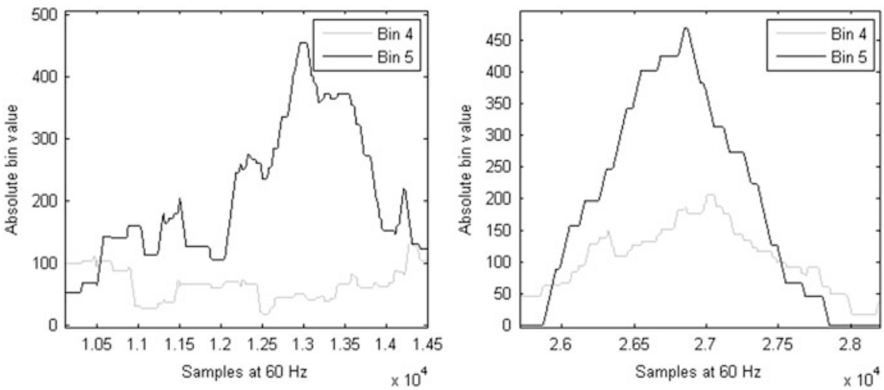

Fig. 4 Sub-type F0 on the *left*, sub-type F1 on the *right*

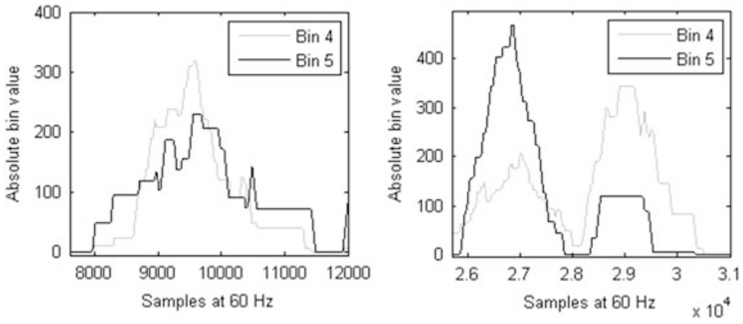

Fig. 5 Sub-type F2 on the *left*, sub-type SW on the *right*

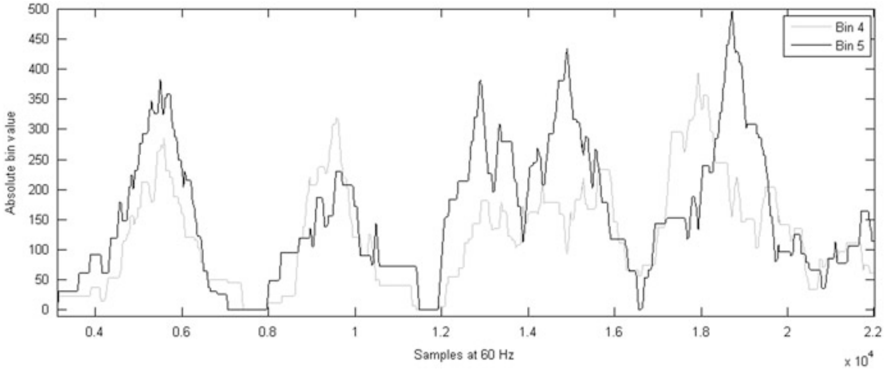

Fig. 6 Typical form of the bin 4 and bin 5 signals during the drive

Table 1 Occurrence of sub-types for different environments

Environment	SW	F0	F1	F2
Inside the city	3	3	67	14
Transition between environments	18	0	4	2
Outside the city	1	0	13	29

The SW sub-type represents a switch of absolute values between the bins 4 and 5 and was mostly observed on the borders of two environments and during a change of driving style inside a certain environment. The F0 sub-type represents a surge of bin 5 which is not followed by the bin 4. The F1 sub-type represents a surge of bin 5 which is moderately followed by the bin 4. The F2 sub-type represents a surge of bin 5 followed by a same or similar surge by the bin 4.

Figure 6 demonstrates the appearance of the sub-types during a drive in which the participant first drove outside the city (F2), than inside (F1) and than began leaving the city (SW).

Table 1 demonstrates the occurrence of sub-types in different environments for different drivers.

The relatively large amount of collected data (160 min of driving sampled at 60 Hz) resulted in a relatively low amount of detected sub-types, due to their size (some are formed over a period of 60 s) and due to the presence of other signal forms, which did not take a stable form. Nevertheless, the data clearly shows a correlation between the environment type and the signal features based on the proposed metric.

6 Conclusion

A metric for measuring driver performance for a sidestick-operated road vehicle was proposed. The driving task was first reduced to lane following task, taking the lane offset as the main element of the metric. Binning of the average number of trend changes inside the road offset signal produced several signal features which can be used for classification of the driving environment. The assumption is that each environment requires a specific performance of the lane keeping task. In this sense, we have identified the signal features which correlate with the performance and performance changes of the lane keeping task.

Future work involves classifying additional environment types and comparison with other sidestick devices, with their own sensitivity and sampling rates. Additionally, we will compare how the metric fares in more generic target following tasks, joystick being the main input method.

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