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Analysis of the Relationship Between Physiological Signals and Vehicle Maneuvers During a Naturalistic Driving Study

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Abstract— **As a driver prepares to complete a maneuver, his/her internal cognitive state triggers physiological responses that are manifested, for example, in changes in *heart rate* (HR), *breath rate* (BR), and *electrodermal activity* (EDA). This process opens opportunities to understand driving events by observing the physiological data of the driver. In particular, this work studies the relation between driver maneuvers and physiological signals during naturalistic driving recordings. It presents both feature and discriminant analysis to investigate how physiological data can signal driver's responses for planning, preparation, and execution of driving maneuvers. We study recordings with extreme values in the physiological data (high and low values in HR, BR, and EDA). The analysis indicates that most of these events are associated with driving events. We evaluate the values obtained from physiological signals as the driver complete specific maneuvers. We observe deviations from typical physiological responses during normal driving recordings that are statistically significant. These results are validated with binary classification problems, where the task is to recognize between a driving maneuver and a normal driving condition (e.g., *left turn* versus *normal*). The average F1-score of these classifiers is 72.8%, demonstrating the discriminative power of features extracted from physiological signals.**

I. Introduction

In recent years, *advanced driver-assistance systems* (ADAS) have been introduced in the market to improve the safety on the roads. Earlier generations of ADAS mainly focused on vehicle maneuvers such as *adaptive cruise control* (ACC), *lane keep system* (LKS), *automated emergency brake* (AEB), and *lane departure warning* (LDW). Recent efforts for modeling and understanding the behaviors of the drivers are getting increasingly important. While many studies on driver's behavior have used direct measurements from the road scene [1]–[4], the vehicle [5], [6], or the head and body movements of the driver [7]–[9], the study of physiological signals can provide useful information about the driver's intentions (e.g., planning, preparation, and execution of driving maneuvers). Studies have shown that physiological signals are important indicators of stress and mental states [10]–[12]. Therefore, we expect that physiological signals of the drivers can provide valuable information when we study their behaviors, especially, with new commercial wearable devices with physiological sensors (e.g., Apple watch, Fitbit).

The main contribution of this paper is to explore the relationship between driver's physiological signals and vehicle maneuvers. While planning and completing a maneuver, the drivers experience physiological reactions due to stress and increased cognitive load (e.g., increasing heart rate, holding breath, increasing skin conductance). Are distinctive physiological patterns observed in the presence of driving maneuvers? Is it feasible to create machine learning algorithms for maneuver detection using physiological signals? This paper investigates these questions, building upon previous studies that have demonstrated a connection between physiological data and driver maneuvers [13]–[15]. While these previous studies considered smaller corpora, this paper analyzes a set of 76 hours of naturalistic recordings from the *Honda Research Institute driving dataset* (HDD), which includes highways and rural roads.

First, the analysis considers extreme changes on the driver's physiological data. We identify segments with high or low values for *heart rate* (HR), *breath rate* (BR), and *electrodermal activity* (EDA). During these segments, we evaluate the presence of driving maneuvers and specific objects on the road, which were manually annotated. The analysis reveals that about 80% of these segments with extreme values of physiological data cooccur with events annotated in the corpus. Second, the analysis compares the values of physiological data while completing specific driver maneuvers. The analysis reveals that the values for physiological data are statistically different during specific driver maneuvers, demonstrating the important relationship between these variables. Finally, these results are validated with discriminant analysis, where we conduct binary classification tasks for maneuver detection (e.g., normal versus a given maneuver), using only physiological features. These classification tasks are implemented with *support vector machine* (SVM), and *random forest* (RF) classifiers. We consider *right turn* (RT), *left turn* (LT), *U-turn* (UT), *intersection passing* (IP), *left lane change* (LLC), and *right lane change* (RLC). The analysis reveals stronger differences in the BR and EDA signals during driver maneuvers. When the features from HR, BR and EDA are combined, the average F1-score of the classifiers across maneuvers is 72.8%.

II. Related Work

Many studies have shown that human's physiological signals are closely related to the human's autonomous nervous system [10], [16], [17]. Changes in the physical, mental and cognitive state of a person are reflected in his/her physiological signals. Rompelman et al. [10] showed that physiological signals are closely related to the individual's stress level and demonstrated that people experiencing anxiety can exhibit sustained periods with high HR and low variability. Taelman et al. [17] used the ratio between *low frequency* (LF) components and *high frequency* (HF) components of the HR power spectrum to estimate the stress level of an individual,

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showing that an increase in this ratio was associated with an increase in his/her mental stress level. Similar to HR, BR is also an important indicator of the cognitive state of an individual. For example, Begum et al. [16] showed that the respiration rate changes when the participants' mental states change from relaxed to stressed.

Studies have used physiological sensors in the vehicle given their role as indicators for cognitive and mental states. For example, previous studies analyzing the stress level and cognitive workload of a driver have relied on physiological signals. Driving a vehicle can increase the driver's stress level [18], [19], which increases the HR, BR and EDA signals. Other studies have correlated an increase in the drowsiness level of a driver with a decrease of HR and BR [20].

Before conducting a maneuver, a driver needs to carefully plan the action, evaluating the risks, and deciding for the best timing. This process increases the cognitive load which is reflected in physiological signals. These observations have motivated previous studies to analyze the relation between the driver's physiological signals and driving maneuvers [13]–[15]. Li et al. [14] extracted features from the HR and BR signals to cluster the physiological data into three classes: "normal", "event", and "noise". The class "event" included different maneuvers (lane change, turns, starts and stops). This study showed the important relationship between physiological data and driving maneuvers. Likewise, Murphey et al. [13] used features extracted from physiological data to predict lane change actions. A similar study was conducted by Li et al. [15], which demonstrated that physiological signals are useful for driving maneuver classification when combined with features extracted from the *controller area network* (CAN) bus data. In their study, they compared the classification performance of two SVM classifiers, trained using either only CAN-bus data, or CAN-bus data with physiological data. The classifiers had a better performance when trained with features extracted from both modalities.

While these studies have showed the benefits of physiological data in the study of understanding the driver' intentions, it is still not clear how driver's physiological signals change according to different driving maneuvers. Follow this direction, this study focuses exclusively on HR, BR and EDA signals, studying their relationship with specific driving maneuvers. We investigate whether different driving maneuvers trigger specific changes on the driver's physiological signals, which can lead to machine learning solutions to understand better the drivers' intentions.

III. Honda Research Institute Driving Dataset

The analysis in this study relies on the *Honda Research Institute driving dataset* (HDD) [21], [22], which was collected by the Honda Research Institute, USA between February 2017 and February 2018 in the San Francisco Bay Area. The recordings include both urban areas and highways. The corpus has 159 driving sessions corresponding to around 180 hours. We used the latest 46 sessions of the data collection, which considered physiological data (76 hours of naturalistic driving recordings). Three drivers wore a compact physiological monitoring module (Zephyr BioHarness 3 chestband) and a wristband sensor (Empatica E4). The physiological signals include *electrocardiogram* (ECG), respiration wave and skin conductivity, which are collected at 250 Hz, 25 Hz, and 4 Hz, respectively. They are synchronized at 30Hz. From these signals, we obtain the *heart rate* (HR), *breath rate* (BR), and *electrodermal activity* (EDA) of the driver.

This corpus has been manually annotated with driving events using the software ELAN. The annotations are grouped into a four-layer representation used to describe driver behaviors: goal-oriented actions, stimulus-driven actions, causes and attentions. Table I provides the specific annotations within each layer. Misu and Chen provides further details about this corpus [21].

TABLE I: Annotations of the HDD corpus, which includes a four-layer representation with several relevant annotations to characterize driver distractions. Further details are given in Misu and Chen [21].

	Annotations
Goal-driven Action	Intersection passing; Left turn; Right turn; Left lance change; Right lance change; Crosswalk passing; U-turn; Left lane branch; Right lane branch; Merge
Stimulus-driven Action	Stop; Deviate
Cause	Sign; Congestion; Traffic light; Pedestrian; Parked car
Attention	Crossing vehicle; Crossing pedestrian; Red light; Cut-in; Sign; On-road bicyclist; Parked vehicle; Merging vehicle; Yellow light; Road work; Pedestrian near ego lane

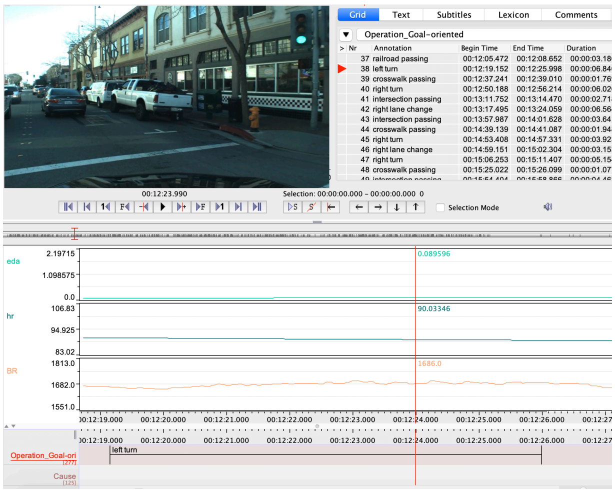


Fig. 1: Annotation interface. The open source software ELAN is used to annotate different driving maneuvers. The interface also provides visualization of physiological data.

IV. Extreme Values of Physiological Signals

We analyze extreme values of physiological data (i.e., BR, HR, and EDA). The objective is to understand some of the underlying factors that make physiological data to increase or decrease, especially as they related to driving maneuvers. We are interested in meaningful local extremes, since the goal is to relate sudden changes in the values of the physiological data to driving events. This is important since the recordings include urban routes and highways, which we

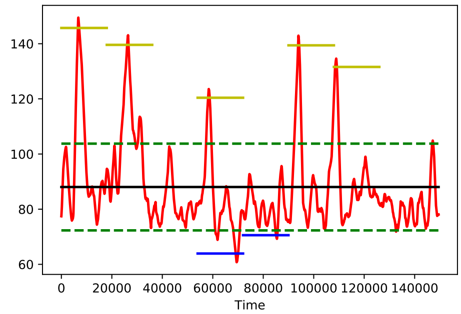


Fig. 2: Selection of regions with extreme values for HR, which are identified by selecting data in the 5% and 95% quantiles during 10-minute windows. We only select extreme segments that are outside the range defined by the global thresholds (green dashed lines).

expect to affect the baseline values for the physiological data. Therefore, we split the sessions into 10-minute windows, finding the local extremes within each segment. We define the local extremes as the segments included in the 5% quantile (low values) and 95% quantile (high values) of the physiological data within the 10-minute intervals. We observed that the range of values of the physiological data for certain 10-minute intervals were low, and the selected extremes were very close to average values across the entire session. To obtain meaningful extreme segments, we define global thresholds that need to be satisfied for a segment to be considered as a extreme. These thresholds are obtained by estimating the *mean* (μ) and *standard deviation* (σ) across the entire session. The lower and upper thresholds are defined as $t_{Lower} = \mu - \sigma$ and $t_{Upper} = \mu + \sigma$, respectively. Figure 2 illustrates this process for HR during one session, where the solid lines correspond to its mean value (black line) and the thresholds (green dashed lines). For each detected extreme, we extend the segments to account for delays in physiological state responses, starting eight seconds before and four seconds after the detected extreme. The analysis considers the manual annotations overlapping with these segments of interest. We label the segments as *normal* when we do not observe any driving event during these segments. Notice that a segment may include more than one event.

Table II shows the number of selected segments identified for each case. The table lists the segments with or without driving events during the duration of the segments. As a reference, we randomly select 1200 12-second segments to evaluate how likely is to have an annotation by chances in these windows (chances is about 43%). The table shows that driving events often cooccur with extreme values of physiological data. 89.4% of the selected segments for HR have at least one driving event. This percentage is similar for EDA (91.2%). For BR, the percentage is lower, but still important (49.1%). These results suggest that extreme changes of physiological data often cooccur with events related to driving maneuvers.

Figure 3 shows the results with the events annotated during the selected segments. The figure provides the results for low (5% quantile) and high (95% quantile) values for HR, BR, and EDA. Altogether, the most common events are *congestion* (1106), *left turn* (902), *intersection passing* (898), *red light* (758), *right turn* (431), *stop for sign* (367), and *stop for congestion* (335). *Intersection passing*, *congestion*, and *red light* are the three most frequent events for segments with extreme values in HR. For recordings with extreme values in BR, *left turn* and *right turn* are prominent events. For low extremes (5% quantile) of BR, we observe several instances with *right turns* (Fig. 3(c)). For high extremes (95% quantile) of BR, we observe several *left turns* (Fig. 3(d)). Most segments with low values (5% quantile) for EDA have an event. The top three events are *left turn*, *intersection passing*, and *congestion* (Fig. 3(e)). Another prominent event is *U-turn*. Notice that there are very few instances of *U-turn* in the database (Table IV), so it is interesting that many of these cases trigged the driver to decrease its EDA signal.

We also notice that *congestions* and *red light* account for many of the events, which suggests that traffic on the roads and waiting during red lights are associated with extreme values of physiological signals. We hypothesize that the driver's anxiety during these events triggers these physiological responses.

While some selected segments overlap with annotations of driving events, there are others without any event. This result indicates that within those segments, physiological data present extreme values for reasons that are likely not related to driving events (e.g., restlessness, moving around, changing position, mind wandering or suddenly remember something). This result is important to keep in mind, as it signals that changes in physiological signal are not always related to driving events.

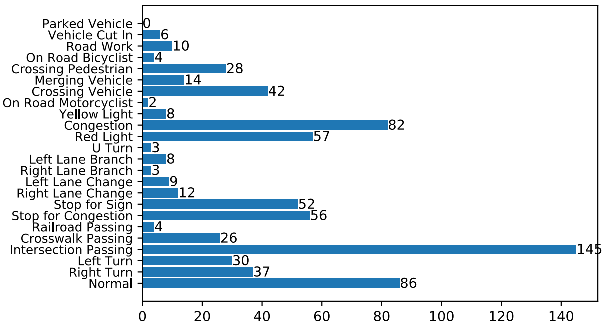
TABLE II: Number of the selected segments with extreme values in the physiological data. Number of segments with and without driving events overlapping with the selected recordings.

	HR		BR		EDA		Random
	5%	95%	5%	95%	5%	95%	
With Events	638	709	287	444	2456	465	516
Without Events	86	74	395	364	74	207	684
Total	724	783	682	808	2530	672	1200

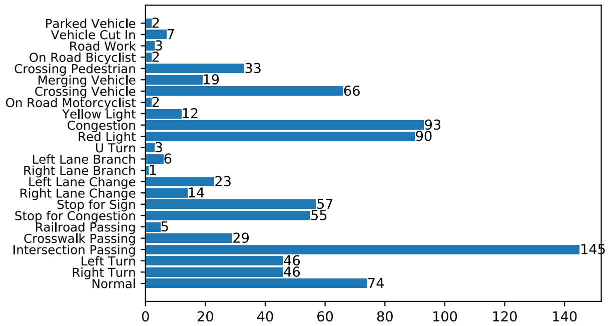
V. Physiological Signals and Maneuvers

From the driving events discussed in Section IV (see Table I), we are particularly interested on six driving maneuvers from the goal-oriented actions: *right turn* (RT), *left turn* (LT), *U-turn* (UT), *intersection passing* (IP), *left lane change* (LLC), and *right lane change* (RLC). The rest of the study will focus on the relationship between these driving maneuvers and the driver's physiological signals. While the analysis in Section IV considers only the recordings with extreme values of the physiological signals, the analysis in this section evaluates all the recordings annotated with these six driving maneuvers on the database.

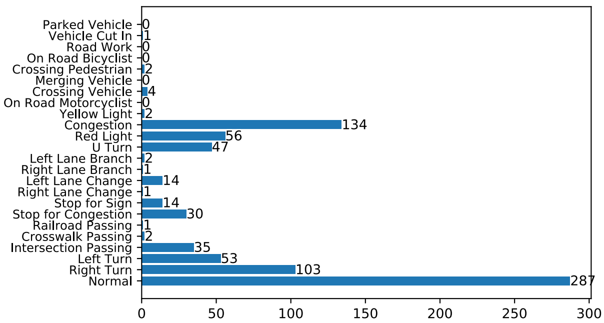
Since the recordings of the HDD corpus are collected over different sessions by multiple drivers, it is important to normalize the physiological signals before we can directly



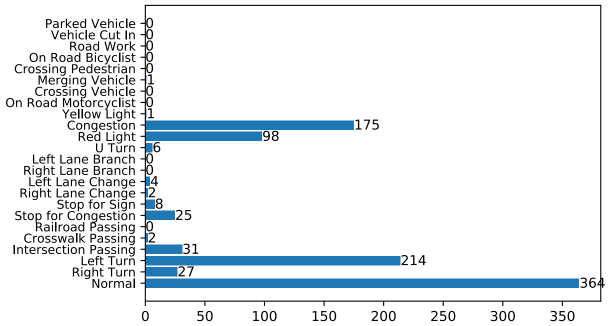
(a) *heart rate* (HR) – 5% quantile



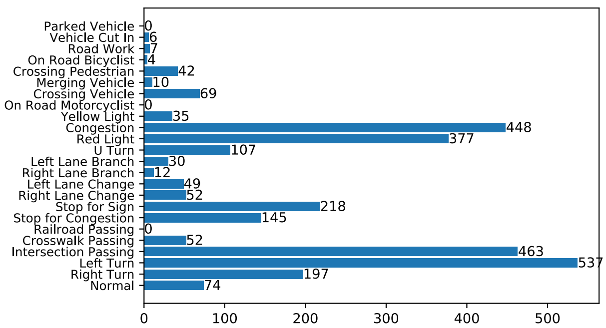
(b) *heart rate* (HR) – 95% quantile



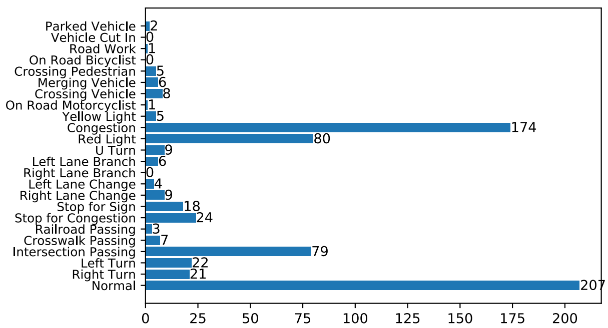
(c) *breath rate* (BR) – 5% quantile



(d) *breath rate* (BR) – 95% quantile



(e) *electrodermal activity* (EDA) – 5% quantile



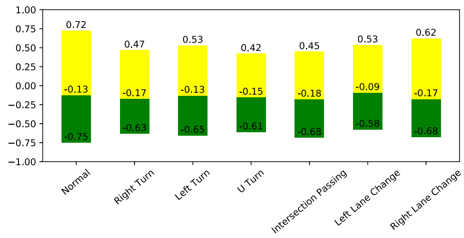
(f) *electrodermal activity* (EDA) – 95% quantile

Fig. 3: Histogram with the driving events observed during the segments with extreme values in the physiological signal. The results are presented for low extremes (5% quantile) and high extremes (95% quantile) for HR, BR, and EDA.

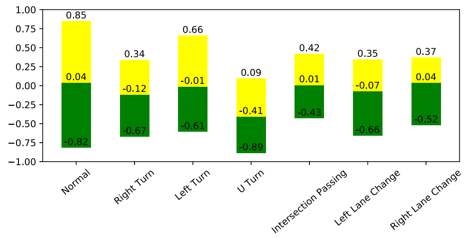
compare their values across sessions. This is important since previous studies have shown differences in physiological signals across individuals [18], [19]. We use the Z-normalization in this study ($z = \frac{x-\mu}{\sigma}$), where μ and σ are the mean and standard deviation estimated from the entire session.

The analysis evaluates the BR, HR, and EDA signals as a function of the driving maneuvers. For this analysis, we also use a 12-second window around the annotated driving maneuvers, with four seconds before and eight seconds after the beginning of the maneuver. The selection of the analysis window for this evaluation is different from the one used in Section IV. In Section IV, our reference point was the values of the physiological signal, so it was important to extend the window before the detected extreme segments. In this section, and in Section VI, the reference point is the annotation, so we extend longer the analysis window after the beginning of the maneuver to account for delays in the physiological responses. The selection of the analysis window is also justified by the duration of the events in the database, which is often between four to nine seconds [21].

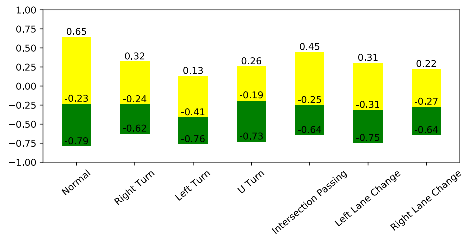
Figure 4 shows bars with the 25%, 50%, and 75% quantiles of the normalized values for BR, HR, and EDA as a function of driver maneuvers. We evaluate whether the differences in the physiological signals are statistically significant using a one-way *analysis of variance* (ANOVA). The ANOVA test is conducted over the mean value of the physiological signals during the 12-second analysis windows, reducing the degree of freedom in the test. The evaluations indicate that the physiological signals change depending on the given maneuver: $F(6,10176) = 2.719$, $p = 0.012$] for HR; $F(6,10176) = 15.484$, $p = 0.0019$] for BR; and $F(6,10176) = 12.124$, $p = 0.0013$] for EDA. Asserting significance at p-value = 0.05, all these differences are statistically significant. The differences are more clear with BR and EDA signals.



(a) HR Quantiles



(b) BR Quantiles



(c) EDA Quantiles

Fig. 4: Distribution of the physiological data as a function of driving maneuvers. Each bar provides the 25% quantile, 50% quantile (e.g., median) and 75% quantile. The information is separately presented for HR, BR, and EDA.

We use the Tukey's *honestly significant difference* (HSD) test to identify the maneuvers for which the physiological signals deviate from typical responses during normal driving conditions. For HR, the only driving maneuver with significant differences is *right turn* (Fig. 4(a)). In contrast, the physiological data for EDA present significant differences for four maneuvers: *left turn*, *U-turn*, *intersection passing* and *left lance change* (Fig. 4(c)). The analysis indicates that features extracted from EDA may be more discriminative in the detection of driving maneuvers. For BR, we observe statistical differences in the physiological data for *right turn*, *U-turn* and *left lance change* (Fig. 4(b)). BR also provides discriminative information for driving maneuvers.

VI. Discriminant Analysis of Physiological Data

To validate the discriminative power of physiological signals, we conduct classification experiments to detect driver maneuvers from normal conditions using features extracted from HR, BR, and EDA. We extract time and frequency domain features from physiological signals during the same 12-second analysis windows used in Section V. The time-domain features consists of four statistics calculated over the windows: mean, standard deviation, maximum, and minimum. The frequency domain features consist of the energy in the following five frequency bands: [0-0.04 Hz], [0.04-0.15 Hz], [0.15-0.5 Hz], [0.5-4 Hz], and [4-20 Hz]. The selection of these bands is inspired by the work of Li et al. [15]. Altogether, we extract nine features per analysis window for each physiological signal. The evaluation also considers fusing these signals, creating a 27 dimensional feature vector.

TABLE III: Discriminant analysis of physiological signal to recognize driving maneuvers (F1-score) [RT= right turn; LT = left turn; UT = U-turn; IP = intersection passing; LLC = left lane change; RLC = right lane change].

	Support Vector Machine			
	HR [%]	BR [%]	EDA [%]	Combined [%]
Normal vs. RT	62.0	69.8	65.5	70.1
Normal vs. LT	41.8	53.4	65.7	66.9
Normal vs. UT	50.6	71.5	71.8	76.1
Normal vs. IP	61.4	74.3	66.5	74.8
Normal vs. LLC	46.3	60.5	53.7	65.0
Normal vs. RLC	39.2	62.6	47.0	64.1
Average	50.2	65.3	61.7	69.5
	Random Forest			
	HR [%]	BR [%]	EDA [%]	Combined [%]
Normal vs. RT	59.9	70.9	65.8	75.5
Normal vs. LT	53.4	65.1	67.6	74.2
Normal vs. UT	57.5	72.7	69.1	75.5
Normal vs. IP	53.3	71.9	60.6	73.8
Normal vs. LLC	53.8	63.4	56.9	70.5
Normal vs. RLC	47.9	62.6	54.8	67.4
Average	54.3	67.7	62.5	72.8

This study uses two classifiers: *Support Vector Machine* (SVM) with linear kernel, and *random forest* (RF). The tasks are binary classification problem between each driving maneuver and normal conditions. Table IV shows that the maneuvers are not balanced. The majority class is always *normal*. We deal with unbalanced classes using random undersampling, where we randomly select samples from the majority class until matching the number of samples in the minority class. We repeat this process 10 times selecting different samples in each iteration. The evaluation relies on a 5-fold cross-validation approach to maximize the use of the dataset. We estimate the performance using the F1-score, reporting the performance across all the folds.

Table III gives the results for the classifiers trained with HR, BR, or EDA features. It also estimates the results when we combined all the features. The results indicate that physiological data provide valuable information about the driving maneuvers. We observe that RF classifiers often give better performance than SVMs. On average, the maneuvers can be detected with 72.8% using RF, trained with all the features (HR, BR and EDA). The fusion of the features across physiological sensors is useful, providing complimentary information with classification performances that are always better than the results obtained with classifiers trained with only one type of data. We are able to obtain these classification performance using only physiological features, without any CAN-BUS information (e.g., steering wheel angle). This result suggests that physiological signals can be useful in understanding the driver intentions during (hands-off) level 2 of driving automation.

The discriminant analysis confirms the findings in Section V, indicating that BR and EDA signals are more informative about driver maneuvers than HR signals. In fact, the performance are close to chances using features extracted

TABLE IV: Number of annotations for each of the driving maneuver included in this study.

	Number of
Normal	1245
Right Turn	1342
Left Turn	1155
U-Turn	131
Intersection Passing	5440
Left Lane Change	502
Right Lance Change	377

from HR signals. The average performances of classifiers trained with BR features are better than the ones obtained with classifiers trained with other physiological signals. The best performance is obtained with the classifier for *U-Turn*. *U-Turn* is a stressful maneuver that requires patience and good timing. BR and EDA features are useful for this task.

VII. Conclusions

This study investigated the relationship between physiological signals (HR, BR, and EDA) and driving maneuvers. The analysis considered 76 hours of naturalistic recordings of the HDD corpus, where physiological signals of the drivers were collected. The analysis leveraged the rich set of manual annotations of driving events in the corpus. The study evaluated recordings with extreme values of physiological data. The study demonstrated that most of the segments with extreme values in the physiological data overlap with driving events. We considered six specific driving maneuvers: *right turn*, *left turn*, *U-turn*, *intersection passing*, *left lane change*, and *right lane change*. The study showed that these driving maneuvers affects the physiological responses of the drivers. This result was validated with discriminant analysis, showing that driving maneuvers can be recognized from normal recordings with an average classification F1-score of 72.8% (chances performance is 50%).

This study opens several research directions. An important question is to study the complementary information provided by physiological data over other modalities commonly used to detect driving maneuvers. Li et al. [15] provides indications about the benefits of fusing physiological data with CAN-Bus signals. We are also interested in analyzing other driving events such as *stop for sign*, *stop for congestion* and *merge*. Similar events were often observed during extreme values of physiological signals (e.g., *congestion* and *red light*), indicating that driving states such as anxiety may be possible to estimate using these physiological sensors.

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