

Driver Lane Change Prediction Using Physiological Measures

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ABSTRACT

Side swipe accidents occur primarily when drivers attempt an improper lane change, drift out of lane, or the vehicle loses lateral traction. Past studies of lane change detection have relied on vehicular data, such as steering angle, velocity, and acceleration. In this paper, we use three physiological signals from the driver to detect lane changes before the event actually occurs. These are the electrocardiogram (ECG), galvanic skin response (GSR), and respiration rate (RR) and were determined, in prior studies, to best reflect a driver's response to the driving environment. A novel system is proposed which uses a Granger causality test for feature selection and a neural network for classification. Test results showed that for 30 lane change events and 60 non lane change events in on-the-road driving, a true positive rate of 70% and a false positive rate of 10% was obtained.

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1. INTRODUCTION

Many driver assist features and functions continue to be introduced into vehicles to help drivers operate their vehicles safely and comfortably, e.g. systems for forward collision warning, blind spot monitoring, adaptive cruise control, and lane keeping assistance. It is reported that lane change maneuvers account for over 10% of all accidents [1, 13, 29]. Early detection of a lane change can be beneficial to systems that involve vehicle-to-vehicle (V2V) communications [2, 23]. Also, such a system, with its capability of anticipating a lane change, could be integrated into automatic activation of the turn signal.

Most published studies of lane change detection have focused on detecting lane change events based on large-scale vehicle trajectory data, i.e. steering angle, velocity, and acceleration. In this approach, the earliest a lane change event can be detected is when the driver begins to make the lane change. In the present study, we use driver physiological signals to study whether it is possible to detect a lane change **before** the event actually occurs. It has been observed, and reported in the literature, that changing lanes is reflected in several electroencephalographic (EEG) indicators which, in turn, are reflected in and correlated to other physiological signals [3]. It may be inferred that a driver's intention to change lanes may be reflected

in observable changes in brain activity and anticipatory body movements. The driver decides whether it is safe to change lanes and also synchronize the event with the flow of traffic. The relationship between brain waves and different types of activities has been reported in several studies [4, 5, 6]. However, an EEG signal is not easy to obtain from a driver in a moving vehicle on the road. Instead, studies have shown that brain activity can also be reflected by other signals such as the electrocardiographic (ECG) signal, the galvanic skin response (GSR), and respiration signals [7], [8], [9], [10], [11]. Hence we take the approach of directly using physiological signals, other than EEG, to determine if lane changes can be predicted. Of eight physiological measures investigated in earlier stages of this research, three were selected for being most representative, and easy to record [32].

The remainder of this paper is organized as follows. In [Section 2](#), we briefly review related work. [Section 3](#) discusses data collection, and in [Section 4](#), several state-of-the-art methods for signal selection and feature extraction are discussed. In [Section 5](#), a multilayer perception (MLP) neural network is used to map the features to one of two classes: either there is, or there is not, a lane change event. Experimental results are presented in [Section 6](#).

2. RELATED WORK

In various studies [20, 21, 23, 24, 25, 27], vehicle sensor data was used to construct models of driver intent. Various types of models were used including neural networks [19, 21, 24], support vector machines [19, 22, 25], Bayesian networks [16, 22], a decision fusion model [15], and the ACT-R cognitive architecture model [25, 30]. Both [21] and [24] use a multilayer perceptron (MLP) network trained on past vehicle path data to predict the future path of a vehicle that was changing lanes. In [25], support vector machines are used along with vehicle sensor data, namely heading, lead car distance, longitudinal acceleration, lateral acceleration, and lane position. Study [19] used three different models: a recurrent neural network, a feedforward neural network, and a set of support vector machines with lane offset, curvature set, and derivative of lane offset, lateral acceleration, and steering angle as inputs.

In study [15], the authors developed a decision fusion algorithm based on Dempster-Shafer theory [31]. The algorithm can predict unintentional lane changes by using information from multiple sources such as inertial sensors, radar, and cameras. But no physiological data were used. Four systems were proposed in this study: a system with only one input variable, a system with equally-trusted input sources, a system using all variables combined with a Weighted Dempster-Shafer (WDS) rule, and a system using all variables combined with a Modified Dempster-Shafer (MDS) combination rule. The first three systems gave a large number of false alarms, while the fourth system gave no false alarms but missed several lane changes.

In study [20], an interactive multiple model (IMM)-based method was proposed for predicting lane changes in highways, based on a set of low-cost global positioning system/inertial measurement unit (GPS/IMU) sensors. In studies [15, 23], a Bayesian extension to the popular support vector machine model, called a relevance vector machine (RVM), was used to predict lane changes. The feature vector, of approximately 500 dimensions, is constructed from real-time sensor data, including vehicle signals, adaptive cruise control (ACC) signals, side warning assist (SWA) signals, lane departure warning (LDW) signals, and head tracking signals.

The system proposed in [25] uses steering-wheel angle, accelerator depression, as well as environmental data (lateral position and time headway), to build a cognitive model of driver behavior [31] using the ACT-R cognitive architecture.

Other studies employ computer vision techniques to predict lane changes [16], [17], [18]. In study [16], the authors demonstrate an intent inference system which consists of a lane position tracking system, driver head motion estimation module, vehicle parameter collection system, and lane change intent classifier, which uses sparse Bayesian learning.

3. LANE CHANGE DETECTION FROM PHYSIOLOGICAL SIGNALS

3.1. Modeling Lane Changes

The lane change detection problem is formulated as follows. At each time t , we begin with a set of signals:

$$\mathbf{x}(t) = [x_1(t), x_2(t), \dots, x_n(t)]$$

The task is to classify $\mathbf{x}(t)$ as representing a *lane change event* (LC) or a *non-lane change event* (NLC). For this study, the signal set $\mathbf{x}(t)$ consists of a set of physiological signals collected from the driver, as described in the following section. In order to train and test the system, in addition to acquiring the driver physiological data $\mathbf{x}(t)$, we also acquired a video of the driver's view of the road. A schematic of the lane change maneuver is shown in Figure 1. We hand classify each frame of the video as either LC (target 1) or NLC (target 0). To do this, we first identify all lane change events in the video for the duration of the drive. If there are m such events in the video, we identify the time stamp for each t_{0i} , $i = 1, 2, \dots, m$ at which the driver crosses the center lane (Figure 1).

The time t_c is the *critical time* where we consider a lane change event to be anticipated by the driver and/or is actually in the process of occurring i.e., occurring before the center line is crossed. The target for each time sample in the range $(t_{0i} - t_c) \leq t \leq t_{0i}$ is set to 1 to represent a lane change event (LC). For all samples outside this region, the target is set to 0 to represent a non-lane change event (NLC). For each lane change, t_{0i} was determined manually from inspection of a video obtained from a front facing camera mounted on the dashboard during an individual's on-road drive, and reviewed at 30frames/sec. In particular, t_{0i} is the estimated time when the center of the vehicle crosses the center line between two lanes. A value $t_c = 2$ sec was selected for the critical time, based on the average value over lane change events in the data collected.

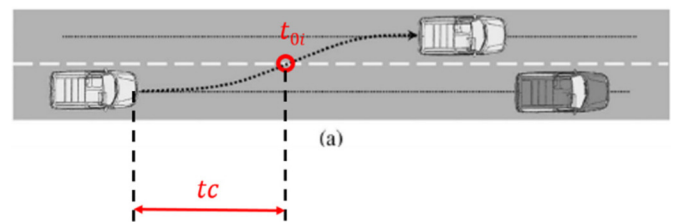


Figure 1. The lane change event model. Here, t_{0i} represents the crossing time for the i th lane change. All time samples in the video have the target set to 0 except for the regions $(t_{0i} - t_c) \leq t \leq t_{0i}$, where the target is set to 1.

During normal driving, for the vast majority of time, the driver is not changing lanes. Hence, the training set will be unbalanced and will contain many more target 0 samples than target 1 samples. Since there are many more non-lane change data points, as compared to data points associated with lane changes, we could be selective about the choice of training data. In particular, we chose NLC training samples that are at least 5 minutes from any given lane change time t_{0i} . This allowed sufficient time for any physiological signals that were perturbed during a lane change event to return to normal.

3.2. Physiological Data

Three physiological signals were recorded in real-time during each on-road drive: electrocardiogram (ECG), galvanic skin response (GSR), and respiration rate (RR). The rationale for choosing these signals is the subject of earlier work reported by the authors [32]. Briefly, from an initial recorded list of eight physiological signals in on-the-road driving, these signals were found to be the most representative of subjective human response in driving [32]. A summary of these raw signals, including sample rate for each, is given in Table 1.

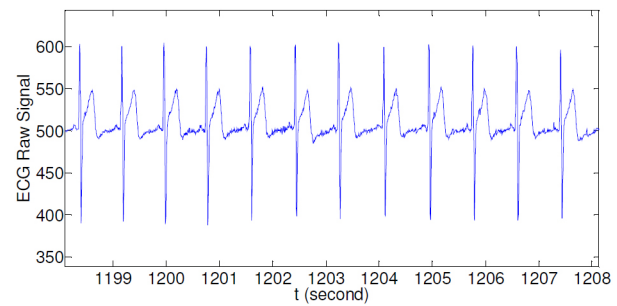
Figure 2 shows the data acquisition equipment. A chest belt (model: Equivital Chest Belt B2) is used to collect ECG and respiration data; skin conductance sensors are attached to two fingers and connected to the belt, a sensor electronics module (SEM) is connected to the belt and coordinates the data acquisition. The SEM is connected by USB to a laptop to store all the real-time physiological data [33]. Typical physiological signals collected from a driver (over a brief period of time) are shown in Figure 3.

Table 1. Categories of raw physiological signals collected from driver.

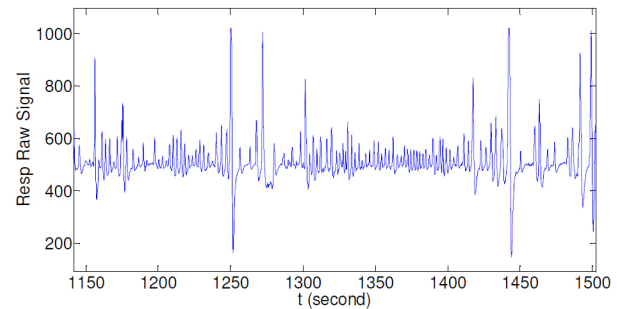
Raw Signal Type	Sample Rate	Description
ECG	256Hz	Electrical activity of the heart (ECG raw has the highest sample rate)
GSR	25.6Hz	Galvanic skin response (GSR) measures the conductance of the skin in response to discrete stimuli
Respiration	25.6Hz	Measures the volume of breath-to-breath variability



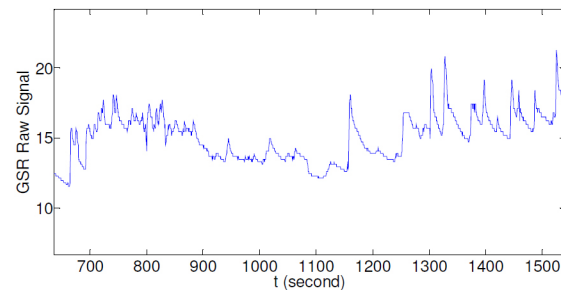
Figure 2. Physiological signal acquisition equipment.



(a). ECG signal



(b). Respiration signal



(c). Galvanic skin response signal

Figure 3. Typical raw physiological signals.

Based on the three raw signals listed in Table 1, a set of biologically meaningful signals can be computed. For example, a typical ECG waveform of the cardiac cycle consists of up to five visible waveform components, the so-called *P*, *Q*, *R*, *S*, and *T*-waves. The time between successive *R*-waves is an important cardiac measure. Similarly, the raw skin conductance and respiration signals contain biologically meaningful signals that can be computed and used for driver analysis. Table 2 shows the computed physiological signals used in this study. Note that these derived signals were computed by the *VivoSense* software, which is a part of the data acquisition package [28, 33].