Detecting Physiological Changes in Response to Sudden Events in Driving: A Nonlinear Dynamics Approach

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Abstract—In this study, we propose a novel analytic framework to detect emergency braking intentions in driving tasks by capturing the delay in human responses using multimodal biosensor data, e.g., electroencephalography (EEG) and electromyography (EMG). To quantify the response delay, we consider EEG and EMG signals as a coupled dynamic system and employ a recurrence plot (RP) based approach to characterize the nonlinear dynamics. We then apply the maximally stable extremal regions (MSER) method in computer vision for detecting transition states associated with sudden events (e.g., braking intentions in driving). Our proposed framework is tested on a publicly available dataset of driving experiments. The results demonstrate the effectiveness of our proposed approach for assessing the response delay to reflect the motor control command, which shows that the average response delays to the braking intentions are 300 milliseconds in EEG and 194 milliseconds in EMG prior to the actual emergency braking. The proposed quantification can be employed in driving assistant system for reducing or diminishing potential accidents.

I. INTRODUCTION

According to the report from National Highway Traffic Safety Administration, the deaths in car accidents in the US increased by 5.6% in 2016 comparing to 2015, and most of them stemmed from distracted driving or human misjudgment of braking [1]. Driving assistant systems, especially autonomous emergency braking systems, are designed to reduce such potential human errors or brake-related problems by constructing a human-machine interface in vehicles [2]. These systems warn drivers through acoustic signals when the accidents (e.g., rear-end crashes) are still avoidable, and an emergency braking will be triggered automatically in case of no responses from drivers within a preset time interval in the systems. As a result, car accidents could be reduced by 38% with the application of these systems [3].

Recently, some studies investigated how to accurately detect braking intentions through estimating some cues related to driving behaviors, vehicle state or surroundings, such as steering angle and brake pedal pressure [4]. Response delay between detected braking intentions and actual braking actions is considered for automatic emergency braking activation in different traffic scenarios, such as rear-end and interaction [5]. However, in real-world driving, accidents can hardly be diminished via detecting braking intentions based on driving behaviors. On the other hand, the physiological responses to emergency breaking events generate information flow among physiological subsystems (e.g., nervous and neuromuscular systems), and these responses can be monitored through biosensors such as electroencephalography (EEG) or electromyography (EMG). It was evidenced that physiological responses can be observed earlier than driving behaviors (e.g., pressure on brake pedal) following the same stimuli [6]. In particular, a previous study [7] used EEG and EMG signals for detecting emergency braking intentions prior to the subjects’ behavioral braking. However, little has been done in the previous studies to exploit the response delay between EEG and EMG signals following sudden events in driving, nor to investigate the multimodal coupling dynamics among different biological subsystems in response to the emergency braking.

In the present study, we aim to monitor and detect the response to the sudden changes corresponding to stimuli in multi-modal physiological systems, and in turn quantify the corresponding response delay between them. Such physiological systems (e.g., EEG or EMG) can be considered as a nonlinear dynamical system, which can be captured using the concept of recurrence plot (RP) [8]. We develop a new search algorithm to recognize the sudden changes using EEG and EMG signals based on maximally stable extremal region (MSER), which is a blob detection method in computer vision applications based on searching for illumination changes or other invariant transformations [9].

II. METHODOLOGICAL FRAMEWORK

Figure 1 presents our proposed framework to measure the response delays of EEG and EMG signals with respect to such sudden events while consider them as a physiological coupling system. We first segment EEG and EMG signals with a time window from pre-stimulus 60 ms to post-stimulus 240 ms, and represent the nonlinear behaviors of the EEG and EMG signals, respectively, using the RP technique. Second, MSER is applied to RPs for detecting the highlighted regions with increasing values as these regions are related to the emergency braking intentions detected by EEG and EMG signals. Finally, the time delay in response to stimuli in EEG, EMG, and behavioral braking signals is quantified for target events.

A. RP Representation of Physiological Signals

The nonlinear behaviors of dynamic systems can be quantified through representing the time-series data by RP,
which is a symmetric matrix for visualizing the recurrence patterns [10]. Suppose an n-dimension vector $v_t = (v_{t1}, v_{t2}, ..., v_{tn})^T$ represents the state of a dynamical system with n observable variables for a given time $t$. After estimating the embedding dimension $m$ and time delay $\tau$, the phase space trajectories of the dynamical system are reconstructed such that the $i^{th}$ state of the corresponding system is characterized by a vector $x_i$ with $m$ components described by:

$$x_i = (v_i, v_{i+\tau}, ..., v_{i+(m-1)\tau})^T.$$  (1)

Conceptually, RP is a visual representation of a given time period to describe where the time-delay embedded trajectory of a system revisits the same region in a phase space. Based on a Heaviside function $\Theta(\cdot)$, the RP with a threshold parameter $\varepsilon$ is presented by:

$$R_{i,j} = \Theta(\varepsilon - \|x_i - x_j\|),$$  (2)

where $\|\cdot\|$ is the distance between any points on the phase space trajectory. Unthreshold recurrence plot (URP) was first proposed by Iwanski and Bradley [11], which aims to characterize the closeness between two points on the phase space trajectory using the distance matrix:

$$R_{i,j} = \|x_i - x_j\|, \quad x_i, x_j \in R^m, \quad i, j = 1, ..., T,$$  (3)

where embedding dimension $m$ is estimated by the false nearest-neighbor (FNN) [12] method and the time delay $\tau$ is estimated as the first local minimum in the mutual information function [13]. In this study, both parameters are customized for EEG ($m=3$, $\tau=4$) and EMG ($m=5$, $\tau=2$) separately.

In this study, our basic assumption is that irruptive alterations underlying the dynamics of EEG and EMG signals will occur when participants have an emergency breaking intention during driving; consequently, these irruptive alterations may be observed in the corresponding RP visualizations. Figure 2 shows that when EEG and EMG signals are visualized using URP, some luminous regions can be observed after the braking events as the red squares highlight. These luminous regions, according to our assumption, represent the sudden increases in the distance metrics, which mark some “gap areas” in URPs as detectable signs of transitions in the system states captured by EEG and EMG signals in response to the emergency braking events. In other words, the URP helps visually characterize the sudden changes of EEG and EMG dynamics such that the task of detecting the breaking intention of participants is made feasible by localizing those luminous areas, for which computer vision algorithms can be employed as an automatic detector (to be discussed in Section II-B in detail).

### B. Computer Vision Detection Method of Luminous Regions

We hypothesize that detecting emergency brake intentions of drivers is equivalent to localizing the sudden changes in the distance matrix of phase space trajectory of systems states (URP). Given that the sudden changes in the value of URPs constructed from EEG and EMG signals can be characterized by luminous areas as shown in Figure 2, we apply the MSER algorithm for automatic detection of these illumination regions in URPs, which was originally proposed as a method for detecting stable regions in images based on affine invariant transformations [9]. The principle of MSER can be explained as follows [14]: in grey-level images, the brightness of each pixel is represented by a single value ranging from 0 (black) to 255 (white). The MSER algorithm is initialized at a pixel with extreme density of 0, and the initial threshold value $\theta_0$ is set to 0. With threshold value gradually increases, the pixels with grey levels exceeding the current threshold are set to lowest (darkest) and thus brighter pixels will appear and merge to a large and stable bright region with the increasing threshold. Let $Q_i$ denote the size of the bright region corresponding to threshold value $\theta_i$, the MSER algorithm converges when the relative growth of bright regions is maximally stable and namely, when $q_i$ has a local minimum. The mathematical formulation for this stability, denoted by $q_i$, is given as follows:

$$q_i = \frac{|Q_i+\Delta|/|Q_i| - 1|}{|Q_i|},$$  (4)

where $|\cdot|$ is cardinality of region $Q_i$ and $\Delta$ is a tuning parameter for adjusting the threshold. MSER is implemented using the built-in function in MATLAB with default settings. The step size between intensity threshold levels is predetermined as $\Delta = 2$ in Equation (4).

Figure 3 illustrates how the sudden changes, which are represented by the luminous regions in URP, are detected via MSER algorithm, while the detected regions are plotted...
as green ellipses on the top of URP plots. In Figure 3(A),
the red solid line marks braking events of the leading car
(stimulus), while the purple line marks the beginning for
the behavioral braking and the red dashed rectangular marks
when the detected emergency braking intentions take place.
When further zooming in the red dashed rectangular area
in Figure 3(B), the parallel yellow lines depict the location
of the vertical bar we apply to detect emergency braking
intentions, which is to be explained in details in the next
section.

C. Searching Algorithm for the Boundary

A searching algorithm is designed to determine the number
and density of detected luminous regions. First, a vertical
bar area (width = 5ms) is applied to scan through the URP
starting from the beginning of stimulus to the end of every
target situation. Importantly, since the URP is symmetric
about the main diagonal line, we only count all the ellipses
in the upper right triangles. The number of ellipses appear in bar
area is defined by the centroids located within the vertical
bar. Note that those centroids detected are not our actual
target, but instead the primordial brake intention begins at
the left outer boundaries of corresponding ellipses. Through
the corresponding elliptical frames, the left outer boundary
can be decided by taking the difference between location
of centroids and the corresponding minor-axis, where the
minimal difference represents the time where primordial
emergency braking intentions were triggered in EEG or EMG
signals. Zooming in the regions marked by red dashed lines
in Figure 3(B) gives us Figure 3(C), and given that URP is
symmetric, \( X_1 \) is always equal to \( Y_1 \).

III. COMPUTATIONAL RESULTS

A. Dataset Description

The dataset used in this paper was from a research
database collected during driving simulation from 18 healthy
subjects [7]. The physiological responses are recorded with
59-channel EEG, 2-channel EOG, one channel EMG and
7 other technical channels. In our study, we only used
the EEG, EMG and driving behaviors. All signals were
preprocessed and down-sampled to 200 Hz. The emergency
braking detection experiment was designed and conducted
in a customized racing system, where subjects were required
to operate a virtual racing car and instructed to follow a
virtual leading car closely, which was controlled by the
computer with a speed of 100 km/h. In addition, subjects
were instructed to respond as possible as they can to avoid
crashes by decelerating when they see the flashing of braking
lights of leading car. Next, the leading car would reaccelerate
to the speed of 100 km/h, and if the distance between these
two cars exceeds 100 meters it would also wait for the
following car to catch up. The same scenario is repeated to
create 18 trials of experiments. The driving tasks consisted
of three sections and each of them lasted for 45 minutes with
10 to 15 minutes rest between sections.

B. Primordial Braking Intention Detection of EEG Signals

Using a technical channel which recorded all emergency
braking events of the leading vehicle, we extracted target
situations from 18 subjects, with the number of target situations
varying from 169 to 238 for each subject. Notably, we
performed EEG analysis on both functional regions (frontal,
parietal, occipital, temporal) and whole brain level.

Figure 4 presents the results of detected emergency braking
intentions using EEG data across the whole brain. In overall,
the post-stimulus time detected from 18 subjects ranges from
295 ms to 540 ms, while the first responder (Subject 4)
is 245 ms faster than the last responder (Subject 18), and
the total mean and standard deviation across 18 subjects
are 369 ± 15 ms (the orange bar in Figure 4. The standard
deviations across channels for each subject range from 9
ms (Subject 9) to 28 ms (Subject 2), indicating a minor
difference in detected response time among different EEG
channels in response to stimulus.

Figure 5 presents the results of detected emergency braking
intentions across different functional brain regions
comparing to the whole brain. As shown in Figure 5(A),
the results obtained from models using different functional
regions are similar for most subjects, except for Subjects
2, 11, 14, 15 and 16. In addition, a minor difference in
response time across channels for each individual subject
is observed (the maximum standard deviation = 22 ms from
Subject 2). Figure 5(B) provides the across subjects results
for different functional regions, where the frontal channels
yield the best performance (356 ± 11 ms), and in contrast,
the parietal channels responded slowest (379 ± 12 ms). In
general, the models using channels from each functional
region performed at comparable level to the whole brain.
model, which suggests that no division of brain channels is needed for the present study.

(A) The time delay of detected response for each subject with different brain functional regions.

(B) The time delay of detected response across subjects.

Fig. 5. The detected emergency braking intentions using EEG Signals from different functional regions and individual subjects.

C. Primordial Braking Intention Detection for EMG Signals

Figure 6 shows the results of detected emergency braking intentions using EMG data, which recorded the muscle activities of right lower leg. The average response time varies from 276 ms (Subject 9) to 627 ms (Subject 2); Subject 1 has the largest (205 ms) and Subject 5 has the smallest standard deviation (62 ms). The overall mean and standard deviation of responding time across all subjects is 475 ± 145 ms. Comparing to the EEG-based model, the EMG-based model has a larger standard deviation, which suggests a less stability in EMG responses in the braking intention experiments.

D. Behavioral Braking Detection

The results of behavioral braking are shown in Figure 7. The overall response time across all 18 subjects is 669 ± 95 ms. Subject 5 is the first responder with 440 ± 328 ms and Subject 3 is the last responder with 856 ± 424 ms. The large standard deviation indicates that the braking behavioral response may not be a reliable choice for detecting the intentions (e.g., in case of Subject 3).

E. Response Delay Quantification

We further compare the differences in EMG and EEG with detected braking intentions in Figure 8. As expected, we detected the braking intentions 106 ms on average using EEG responses earlier than EMG responses for almost all subjects except for Subjects 5 and 18. The quantification of average responding time to brake was 669 ms. It demonstrates that they responded 194 ms later than EMG, and 300 ms later than EEG. EEG is the first responder to the stimulus and the response delay between them was 369 ms, and then EMG makes responses to the stimulus and the response delay between EEG and EMG was 106 ms. Finally, the behavioral braking occurs 194 ms later than EMG. Figure 9 summarizes the average percentage of successfully detected braking intentions among 18 subjects over time. Three vertical green lines mark 540, 760, and 900 ms post-stimulus, respectively. Responses in EEG and EMG have already been detected from the beginning of the stimulus to the time of 900 ms. These responses within both signals were triggered in a random pattern which covers around 900 ms later than the stimulus. In summary, EEG responded to the stimulus faster than EMG on average. However, EEG was detected later than EMG in time interval [540, 760], as shown in Figure 9. Accordingly, we applied average results of all signals to quantify the time delay between EEG and EMG systems in our case.

IV. DISCUSSIONS

In our study, EEG responses were detected 106 ms (average results among 18 subjects) earlier than EMG responses to emergency braking in driving. Likewise, EMG responses were detected 194 ms earlier than behavioral braking. Comparing to previous study which also quantified the response delays of EEG and EMG, the findings in our study confirm the earlier detection of EEG in the braking intentions, while the results for EMG were less consistent and resulted in a larger standard deviation.
delay [7], we are able to save more perception-reaction distance in emergency braking events by more timely detection (from 3.66 to 8.33 meters). Although no standardized criteria are available to characterize such response delays in driving simulation, our study is exploratory model for quantifying the response delays among different dynamical systems, which may provide some suggestions for future studies.

Notably, we observed individual variations in the response pattern to stimulus among EEG, EMG, and behavioral braking. In the response delays between EEG and EMG signals, for instance, the detected EEG responses were slower than the EMG responses only for Subjects 5 and 18. Possible reasons are inferred as follows. Firstly, some exceptional cases may exist in the individual internal reaction mechanism. We hypothesized that for most drivers, EEG response would be faster than EMG response. However, Figures 10(A) and 10(B) show that EMG response has a steep increase in the average percentage of emergency braking detection between 200 ms and 400 ms for Subjects 5 and 18, respectively. Comparing to EEG which has a gradual increase in the same range, the percentage of EMG broke out during this interval and exceeded the corresponding percentage of EEG around 300 ms and influenced the average response time accordingly. Figure 10(C) also presents a common case that EEG responded faster than EMG on average. The percentages of emergency braking detection for EEG and EMG have a stable increase during the first 900 ms. EEG is not exceeded by EMG even in the range from 200 ms to 400 ms. Secondly, our analytic framework was designed to search the pattern of sudden changes within dynamical systems, not intended to detect the specific emergency braking intentions. Consequently, some abrupt noises within signals were also regarded as the pattern of emergency braking by our method. Thirdly, data quality issue may exist in the driving simulation dataset. The experiments consisted of three sections and each of them lasted for 45 minutes, they maybe suffer from fatigue or some crashes cannot be avoided, as mentioned in [7].

Another point to be discussed for the present study is the few cases where EEG or EMG responses were detected even earlier than the occurrence of stimulus. Figure 11 provides the percentage of those situations across 18 subjects for EEG and EMG responses. Those situations were ubiquitous among subjects, especially for Subjects 2, 9 and 15 in EEG responses, with the average percentage in EEG and EMG responses are 3.45% and 0.27%, respectively. The difference may be due to the number of channels for EEG and EMG: there was only one EMG channel but 57 EEG channels, so EEG yielded a higher chance to be impacted by system or experimental errors. Besides, our searching algorithm locates emergency braking intentions by taking differences between the centroids and the minor-axis through the corresponding elliptical frames and determining left outer boundary of detected ellipses. When detected sudden changes close to the stimulus, however, the algorithm may locate the centroids on the other side of the stimulus events because the MSER is not sensitive and robust enough for detecting the precise middle point of luminary regions. Even though taking the differences between centroids and corresponding minor-axis exceeded our expectations on some cases, a few exceptional cases still exist as shown in Figure 11, especially for EMG signals.

V. CONCLUSIONS

In this study, we proposed a new analytic framework, where the RP technique was introduced to measure and quantify the state of nonlinear physiological systems of EEG and EMG signals in response to the emergency braking intentions, and the MSER method was applied to the visual representation of RP. In our experimental results for a publicly available driving dataset, we demonstrated that emergency braking intentions can be detected earlier than the behavioral braking events through monitoring EEG and EMG dynamic changes. In future work, it is suggested to emphasize on the parameter sensitivity analysis of RP and MSER methods for physiological systems of EEG and EMG signals. We will expect to apply our method to enhance the detection of sudden events in realistic driving scenarios or driving assistant systems in practice.

REFERENCES

Fig. 10. The EEG and EMG responses to detected braking intentions.

Fig. 11. Percentage of detected braking intentions before the stimuli.


