Neural Correlates of Mental States In Traffic Scenarios In Simulated Driving

Introduction

In the modern day traffic, driving is becoming riskier day by day. Due to road conditions, traffic volume etc., the drivers are set on emotional upheaval (with lot of surprises and anger) while driving to achieve personal timeline goals. This might lead to collisions which may impose a life threat. If we observe the driver's mental state in real time, it will help us to take appropriate actions before a potential mishap. Our goal is to study neural correlates of driver's mental states in traffic conditions. The three prime traffic scenarios that we are going to consider are *Normal Driving, Braking and Collision*. There are three neural processes that we are going to observe during each of the mentioned driving scenarios (I) The *Alpha Band Power* representing *relaxed yet conscious mental state*. (II) Local and *Long Distance (global) synchrony* which represents the cognitive context of mind. In other words, it represents a *prepared mental state* to face a situation (III) High *Gamma Band Power* also represents prepared mental state.

We predict that a high alpha band power values can be measured during *normal driving* which is relaxed yet conscious. We also predict that the Local and Long Distance Synchrony can be observed during *normal driving* as well as *braking*. The gamma band power can be higher for *normal driving and braking*.

Resources (The EEG Dataset)

We are going to use the dataset *Emergency Braking During Simulated Driving* by Stefan Haufe et all, on the site http://bnci-horizon-2020.eu/database/data-sets.This is a dataset of 18 subjects. It gives us 150 to 200 *normal driving points* per subject. It gives us approx 150 to 200 *braking points* per subject. And it gives us **xxxx** *collision points* per subject. We are planning to analyze 10 subjects and around 40 points for each of the scenario (Normal Driving, Braking and Collision) across the subjects before coming to a conclusion.

Possible Data Discrepancies

The following parameters may differ across the work related to neural correlates:

- The number of electrodes
- Electrodes positioning
- Sampling Rate of EEG

Offline Methods to gauge Local and Long Range Synchrony

Local Synchronies are short range synchronies found within the same brain region (Left Frontal, Right Frontal, Left Posterior, Right Posterior, Midline) of electrodes. Long Range Synchronies are synchrony between two regions. There are various methods to measure synchrony: Time domain methods, frequency domain methods, statistical domain methods. We are going to focus on *Granger's Causality measures,* which belongs to statistical domain*,* for measuring Long Range Synchrony. Also, we are going to focus on *Phase Synchrony* to measure local synchrony. We are going to describe both the methods below. We will also illustrate the way we apply the measures to EEG signals.

Granger's Causality (GC)

Weiner N defined causality as, "For two simultaneously measured signals, if one can predict the first signal better by incorporating the past information from the second signal than using only information from the first one, then the second signal can be called causal to the first one". Granger later gave this a mathematical formulation by using univariate and bivariate autoregressive models (AR). Suppose X_1 and X_2 can be represented by univariate AR models:

$$X_1(t) = \sum_{j=1}^{m} a_j X_1(t-j) + \epsilon_{11}(t)$$

$$X_2(t) = \sum_{j=1}^{m} b_j X_2(t-j) + \epsilon_{22}(t)$$

In the above models, a_j and b_j are estimated univariate AR coefficients for AR model of order m. ϵ_{11} and ϵ_{22} are prediction errors or residuals of AR process.

Similarly for a bivariate AR model

$$X_1(t) = \sum_{j=1}^{m} a_j^* X_1(t-j) + \sum_{j=1}^{m} b_j^* X_2(t-j) + \epsilon_{12}(t)$$

$$X_2(t) = \sum_{j=1}^{m} \widehat{a}_j X_1(t-j) + \sum_{j=1}^{m} \widehat{b}_j X_2(t-j) + \epsilon_{21}(t)$$

In the above models, a_j^*, $b_j^*, \widehat{a}_j$ *and* $\widehat{b}_j$ are estimated bivariate AR coefficients for AR model of order m. ϵ_{12} and ϵ_{21} are *prediction errors or residuals* of AR process. a_j^*, $b_j^*, \widehat{a}_j, \widehat{b}_j$, ϵ_{12} and ϵ_{21} can be derived by multivariate Yule-Walker equations. Granger Causality is then given by the log-ratio of variance of residual in univariate process to that in bivariate process.

$$F_{X_2 \to X_1} = \ln\left[\frac{var(\epsilon_{11})}{var(\epsilon_{12})}\right]$$

Apply Granger Causality to EEG Data

1. For all the three traffic scenarios *Normal, Braking and Collision,* the EEG data will be epoched in 1s segments (across all subjects).
2. These segments will then be set to zero mean and unit variance.
3. We will then use Yule-Walker equations to derive model order for EEG segments across different brain regions (For Example: X_1 will belong to a channel in Left Frontal and X_2 will belong to a channel in Right Posterior).
4. For each of the channel pair, GC will be calculated based on the log-ratio mentioned above.
5. We will have a Matrix of GC across all the channel-pairs for each EEG segment. Since there are 59 channels in the dataset, this matrix will be of size 59×59 per segment.
6. We will repeat this procedure for 40 Normal Segments, 40 Braking Segments and 40 Collision Segments, across 10 subjects. That will give us 120 segments per subject and 1200 segments to be analyzed across all subjects. This means that we have to analyze 1200 matrices for this project.
7. We might use averaging technique across the three different kinds of matrices: Normal, Braking and Collision. This exercise will let us know about the difference in the synchrony in these three scenarios.

Phase Synchrony

Phase Synchronization analysis has been independently proposed by Lachaux et all and Mormann et all. There are two fundamental steps in Phase Synchrony estimation: Instantaneous phase estimation and Phase-locking quantification. We are going to use the analytic signal approach which goes as follows.

For any arbitrary scalar signal $x(t)$, the analytic signal is formed as

$$x_a(t) = x(t) + ix_{HT}(t) \; = \; A_X(t)exp\big(i\o_x(t)\big)$$

$x_{HT}(t)$ is the Hilbert transform of $x(t)$. $A_X(t)$ = $\sqrt{x^2(t) + \; x_{HT}^2(t)}$ is an instantaneous amplitude and $\o_x(t)$ = $\tan^{-1}\{(x_{HT}(t)/x(t)\})$ is an instantaneous phase of signal $x(t)$. The phase difference can be defined with instantaneous phase $\o_x(t)$ and $\o_{\mathrm{y}}(t)$ (where $\mathrm{y}(t)$ is another scalar signal) as:

$$\Delta\emptyset_{xy}(\mathrm{t}) = \emptyset_x(t) - \emptyset_y(t)$$

The phase locking value (PLV) is then defined at time t as average value

$$PLV_t = \; \frac{1}{N} \; \left| \sum_{\mathrm{n}\,=\,1}^{\mathrm{N}} exp\;(j\Delta\emptyset_{xy}\,(t)\right|$$

Here, N is the number of trials. If two scalar signals are in synchrony, the PLV value is close to 1. It is close to zero otherwise.

Apply Phase Synchrony to EEG Data

1. For all the three traffic scenarios *Normal, Braking and Collision,* the EEG data will be epoched in 1s segments (across all subjects). Each of the segment is considered as a trial.
2. For each of the channel pair, PLV will be calculated based on the equation mentioned above.
3. We will have a Matrix of PLV across all the channel-pairs for each EEG segment. Since there are 59 channels in the dataset, this matrix will be of size 59×59 per segment.
4. We will repeat this procedure for 40 Normal Segments, 40 Braking Segments and 40 Collision Segments, across 10 subjects. That will give us 120 segments per subject and 1200 segments to be analyzed across all subjects. This means that we have to analyze 1200 matrices for this project.
5. We might use averaging technique across the three different kinds of matrices: Normal, Braking and Collision. This exercise will let us know about the difference in the synchrony in these three scenarios.

Offline Method to calculate the alpha and gamma band power of EEG data

1. For all the three traffic scenarios *Normal, Braking and Collision,* the EEG data will be epoched in 1s segments (across all subjects).
2. We will then use MATLAB *bandpower* method to calculate average power in each segment of the EEG signal, given the sampling frequency and frequency range.
3. Since we have 1200 segments across the three different driving scenarios, we will use averaging technique to calculate average bandpower across each scenario.

Future Work

1. Consider the effect of other neural signals/bands (Delta band, P300) on the driving scenario
2. Take appropriate actions while driving based on the neural states

References

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