Can electroencephalography improve road safety? An EEG-based study of driver’s perception of traffic light signals in a virtual environment

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Abstract: Virtual traffic light environment was simulated by exposing the test subject to images of traffic lights to study his cognitive responses. Electroencephalogram (EEG) was collected from a driver in this environment, pre-processed and decomposed into EEG rhythms with wavelet transform. Epochs related to individual visual stimuli were extracted. Minimum and maximum values, standard deviation, skewness, kurtosis, and variance were used as feature vectors for classification with K-nearest neighbour (KNN) and neural network classifiers to discriminate between different traffic light colours. Classification accuracy was 84.05% and 86.94% for KNN and NN classifiers respectively, while the highest performance was observed for images of yellow lights. We conclude that drivers may perceive different traffic lights differently and that their perception results in distinct neurological activities reflected in EEG. Therefore, EEG-based detection of traffic lights may be possible that may be implemented in future automotive BCI systems expanding cars’ assistive driving capabilities.

Keywords: road safety; traffic lights; electroencephalogram; wavelet transform.


1 Introduction

Traffic accidents result in approximately 1.25 million deaths per year (WHO, 2016). Even though roads and modern cars are made better and safer, one critical traffic component is somewhat reluctant to improve. This component is us, the drivers. As cars are traveling faster, it may be more difficult for the driver to respond to the quickly
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changing traffic environment. Additionally, modern gadgets – such as tablets, mobile phones, and smart watches – may “provide” us with temptations to take our attention off the road while driving to attend something else. As a result, many road accidents occur due to driver’s mistakes and the lack of concentration.

We argue that studying drivers’ perception of traffic environment may play an important role in understanding and possibly mitigating driver-related road accidents. However, the key for such understanding – functioning of human brain that is perhaps the most complex organ in our body – still holds many hidden mysteries. Electroencephalography (EEG) is among the key instruments to unravel some of these mysteries, since it is a valuable tool for analysing brain activity in a non-invasive manner.

On the other hand, many modern systems depend on computers for their correct functioning. Yet, when human control or interactions are involved, safety risks arise due to human failures that may lead to severe consequences. Many traffic accidents are related to drowsiness, drunk-driving, and lack of concentration (NSF, 2016), while specific research projects attempt studying these relationships (Ali, 2012; Bayliss and Ballard, 2000; Lin et al., 2007).

The objective of present work is to quantitatively assess driver’s cognitive responses to a virtual traffic environment, while utilising wavelet analysis of his/her EEG, with the specific interest in the classification of traffic lights that a driver perceives.

2 Methods and theory

2.1 Experimental setup and EEG acquisition

The virtual traffic light environment was created in the laboratory by exposing the test subject to images of traffic lights. One male subject with normal colour vision and no reported neurological disorders participated in data acquisition. The participant was seated in a comfortable chair with his head and arms in a relaxed position during the experimental procedure. Ambient lighting was adjusted to the subject’s comfort. During each data acquisition session, the participant was instructed to avoid eye and body movement to reduce biological artefacts (Picton et al., 2000).

To simulate the traffic light environment, images of traffic light signals (red, green, or yellow) were presented on the screen at approximately 2 metres in front of the subject. The images of traffic light were presented sequentially, when each image was displayed for five seconds.

Continuous EEG was recorded with the ANT-Neuro ASALAB acquisition system. A recording montage was used with 32 electrodes embedded in the EEG cap according to the International 10–20 System. The EEG cap was fitted to the subject’s head and adjusted to ensure the correct positioning of electrodes on the scalp. The frontal lobe electrode ‘AFz’ was used as the reference. EEG was sampled at 256 Hz to provide signals with the frequency range 0–128 Hz according to the Nyquist criterion. This range usually suffices for extracting evoked potentials for BCI applications (Schnitzler et al., 1997). EEG acquisition was synchronised with images presentation via “eevoke”.
We hypothesise that the specific EEG fragments – recorded when the subject was exposed to images of traffic lights of specific colours – may contain unique features elicited by the subject’s perception of traffic lights of these specific colours. We further hypothesise that it may be possible to extract these features, analyse them statistically, and, perhaps, use them to determine the colour of traffic light that was observed by the subject. The latter is the ultimate goal of this project.

EEG pre-processing and analysis were conducted using MATLAB.

2.2 EEG pre-processing

EEG pre-processing is usually implemented, since the recorded EEG may be contaminated with non-cerebral processes related to other neural activities (Baillet, 2010), such as ocular artefacts, cardiogram artefacts, visual potentials, muscle artefacts, etc., as well as environment-related artefacts, AC power-line noise, etc. These contaminations should be minimised prior the EEG analysis.

Two techniques, DC offset removal and common average reference (CAR) special filter were implemented to reduce artefacts related to EEG electrode design and to mitigate currents propagating along the head surface (Bertrand et al., 1985).

2.3 Wavelet analysis

Due to the non-stationary nature of EEG, applicability of traditional Fourier-based methods in EEG analysis is rather limited and such methods were observed as not very successful in EEG-based diagnostics (Subasi, 2005). On the other hand, wavelet transform (WT), whose basis functions are localised in both time and frequency, may alleviate this problem. The latter has made wavelet transform popular among the biomedical engineering community (Baleanu, 2012).

WT is a tool that can represent a signal in the time-frequency domain. By wavelet transform, transient features of the signal can be accurately detected and localised in both time and frequency. Discrete WT is a multi-resolution analysis technique that can be applied to decompose EEG signal at different resolution levels (Omerhodzic et al., 2010). Parseval’s theorem can be used for energy estimation at each resolution level.

The Continuous Wavelet Transform (CWT) of a signal $x(t)$ is defined as (Omerhodzic et al., 2010):

$$
X(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t) \psi^* \left( \frac{t-b}{a} \right) dt
$$

(1)

where $\psi(t)$ is the mother wavelet function with zero average, $a$ is the scaling parameter, and $b$ is the translation parameter.

For discrete signals, Discrete Wavelet Transform (DWT) is defined with the discrete values of the scaling and the translation parameters as $a = a_0^m$ and $b = nb_0a_0^n$. Thus the discrete wavelet function is defined as follows:

$$
\psi_{m,n}(t) = a_0^{-m} \psi \left( a_0^{-m} t - nb_0 \right)
$$

(2)
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where \( m \) and \( n \) are frequency localisation and time localisation respectively. Selecting \( a_0 = 2 \) and \( b_0 = 1 \), a dyadic-orthogonal DWT is produced that specifies the basis for the multi-resolution analysis. In such analysis, a signal can be represented in the form of its approximation (a) – specified by the scaling function \( \varphi_m(t) \) – and the details (d) that are defined by the wavelet function \( \psi_m(t) \). The scaling and wavelet functions are related to the low-pass and high-pass filters respectively. Therefore, the approximation and details are the low- and high-frequency components of the signal. The energy of the detail and the approximation coefficients at each resolution level, \( E_d \) and \( E_a \), can be estimated as shown below:

\[
E_d_i = \sum_{j=1}^{N} |d_{i,j}|^2, \quad i = 1, ..., l \tag{3}
\]

\[
E_a_i = \sum_{j=1}^{N} |a_{i,j}|^2 \tag{4}
\]

Here \( i \) represents the wavelet decomposition level and \( N \) is the number of either detail or approximation coefficients at each decomposition level.

Using wavelet decomposition, the energy distribution of EEG can be estimated within different frequency bands. Such decomposition can be utilised for further analysis and classification. Selection of the appropriate wavelet function and the number of decomposition levels is important for signal analysis with DWT. Since EEG signals contain most information in the 0-45 Hz frequency range, the number of decomposition levels can be selected as 5 (Guo et al., 2009). Due to the smoothing feature of Daubechies 4-tap wavelet (db4), selecting this function is suitable for detecting changes in EEG (Subasi, 2007). EEG is first decomposed into \( d_1 \) (a high frequency component) and \( a_1 \) (a low frequency component). We assume that the frequency range of \( d_1 \) (64–128 Hz) corresponds to noise and \( a_1 \) (0–64 Hz) contains the signal of interest. \( a_1 \) is further decomposed into \( d_2, d_3, d_4, d_5 \), and \( a_5 \) that are approximately related to \( \gamma, \beta, \alpha, \theta, \) and \( \delta \) EEG rhythms respectively. Their energy can be estimated according to (3) and (4).

2.4 Segmentation, feature extraction, and classification

After DWT decomposition, EEG was represented in terms of approximation and details coefficients. Next, the EEG decomposition coefficients were segmented into epochs corresponding to the specific visual stimuli that the subject was exposed to. Therefore, we may argue that these epochs should be associated with the corresponding event-related potentials. Fifty three EEG epochs of 300 ms duration and synchronised with specific visual stimuli were selected for the analysis. All epochs started 50 ms before the corresponding stimulus presentation and terminated 250 ms after it. Sixteen epochs were related to red traffic light signals; twenty two epochs were elicited by yellow traffic lights; and fifteen epochs were extracted when exposing the subject to green traffic light signals.

To reduce the dimensionality of the feature space, the minimum and maximum values, standard deviation, skewness, kurtosis, and variance were evaluated for the coefficients corresponding to individual epochs and used as feature vectors for the classification.
Classification is a metrics-based procedure where individual groups are categorised based on the feature vector. In this project, a three-class classification was implemented using the K nearest neighbours (KNN) classifier and the neural network classifier.

KNN is a distance-based classifier where the assignment of an unknown vector to one of the classes is achieved by a majority vote of its neighbours. The vote is evaluated through the close proximity amongst datasets (training data and testing data) measured by the distance (Rahman et al., 2015). In this project, Euclidean distance was selected as the metric; 75% of data were used for training and the rest were used for testing the KNN classifier.

MATLAB toolbox was used to implement the neural network classifier. The available data were divided randomly, while 75% contributed to the training dataset, 15% to the testing dataset, and 15% to the validation dataset. Number of hidden neurons was selected as 10.

3 Results and discussion

EEG was decomposed with DWT into six sub-bands: d1, d2, d3, d4, d5, and a5 as Figure 1 illustrates for channel POz.

Figure 1 EEG signal for channel POz decomposed into the approximation (a5) and the detail (d1) components
We observe in Figure 1 that the average component, $a_5$, resembles the original signal, while the detail components depict its higher-frequency content. As seen in Figure 1, the magnitudes of decomposition components differ, thus their energy is also different. Table 1 illustrates the relative energy of EEG components shown in Figure 1.

### Table 1 Energy of DWT decomposition components of a sample EEG sequence

<table>
<thead>
<tr>
<th>Decomposition component</th>
<th>$d_1$</th>
<th>$d_2$</th>
<th>$d_3$</th>
<th>$d_4$</th>
<th>$d_5$</th>
<th>$a_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency range, Hz</td>
<td>64–128</td>
<td>32–64</td>
<td>16–32</td>
<td>8–16</td>
<td>4–8</td>
<td>0–4</td>
</tr>
<tr>
<td>EEG rhythm</td>
<td>Noise</td>
<td>$\gamma$</td>
<td>$\beta$</td>
<td>$\alpha$</td>
<td>$\theta$</td>
<td>$\delta$</td>
</tr>
<tr>
<td>Energy, %</td>
<td>0.17</td>
<td>0.05</td>
<td>0.11</td>
<td>0.19</td>
<td>0.31</td>
<td>99.17</td>
</tr>
</tbody>
</table>

Next, the decomposition components were segmented to obtain epochs elicited by specific visual stimuli. Examples of such epochs are illustrated in Figure 2 for the images of red, green, and yellow traffic lights, as indicated by the line colours. The epochs are shown as functions of latency, where zero corresponds to the visual stimulation event.

**Figure 2** Sample EEG epochs (channel POz) corresponding to red, green, and yellow stimuli and their decompositions
We observe in Figure 2 that both signals evoked by different traffic lights and the corresponding wavelet decomposition components appear somewhat different, although these differences seem rather random. To assess whether the observed deviations (hypothetically related to different stimuli) are significant, groups of features were extracted from the EEG decomposition components corresponding to the specific traffic light stimuli and assessed for the classification. Such features were extracted for all available EEG channels and, prior the classification, were subjected to the one-way analysis of variance (ANOVA) to assess whether the features produced for different stimuli were statistically different. The EEG channel POz was selected for the classification as yielding the most significant differences between the features extracted for different traffic light colours.

The KNN and neural network classifiers were implemented next. Tables 2 and 3 illustrate the corresponding confusion matrices.

### Table 2  Confusion matrix of the KNN classifier

<table>
<thead>
<tr>
<th>Predicted class</th>
<th>Red</th>
<th>Yellow</th>
<th>Green</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red</td>
<td>81.25% (13)</td>
<td>0</td>
<td>18.75% (3)</td>
</tr>
<tr>
<td>Yellow</td>
<td>0</td>
<td>90.91% (20)</td>
<td>9.09% (2)</td>
</tr>
<tr>
<td>Green</td>
<td>13.33% (2)</td>
<td>6.67% (1)</td>
<td>80.00% (12)</td>
</tr>
</tbody>
</table>

### Table 3  Confusion matrix of the neural network classifier

<table>
<thead>
<tr>
<th>Predicted class</th>
<th>Red</th>
<th>Yellow</th>
<th>Green</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red</td>
<td>87.5% (14)</td>
<td>6.25% (1)</td>
<td>6.25% (1)</td>
</tr>
<tr>
<td>Yellow</td>
<td>0</td>
<td>100% (22)</td>
<td>0</td>
</tr>
<tr>
<td>Green</td>
<td>13.33% (2)</td>
<td>13.33% (2)</td>
<td>73.33% (11)</td>
</tr>
</tbody>
</table>

The diagonal elements, indicated by the bold italic font, of the confusion matrices represent the percentages of correct classifications for the three classes (traffic lights images) in question. The numbers in parenthesis show the number of epochs assigned to each class. Evidently, the images of yellow traffic lights were classified the most accurately. We can further deduce that the overall classification accuracy was 84.05% for the KNN classifier and 86.94% for the neural network respectively.

### 4 Conclusions

This work implemented a wavelet-based offline analysis of EEG targeting on studying driver’s cognitive response to the virtual traffic light environment. After pre-processing, EEG was decomposed by DWT and segmented to extract the features evoked by the specific visual stimuli. The overall accuracy of a three-class discriminator exceeded 84%, which indicates that EEG indeed contains features elicited by the observation of traffic lights and, therefore, may be used in perception studies.

Sensitivity of EEG to artefacts was one of the main challenges in this project. To reduce muscle-related artefacts, the participant was avoiding any head motions during the
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EEG acquisition. This approach, however, would limit the real-road applications of this study, since the ability to move and turn head is essential for driving. Therefore, EEG artefact suppression techniques must be considered in the future applications.

Another limitation of the project was the inclusion of EEG-based features extracted from only one specific channel. Perhaps, utilising more channels may further improve the classification accuracy. The observation that the yellow traffic light had a higher likelihood to be detected correctly may, perhaps, be attributed to the fact that more images of yellow lights were used for the stimulation than red or green. Therefore, the number of trials and participants should be increased to produce more accurate and realistic results. Finally, the next step in this project would be to perform similar experiments in real driving conditions.

Besides advancing our understanding of visual perception mechanisms, the results of this study may be potentially implemented in future intelligent driving systems. With the advance of assistive technologies and the increased concern for traffic safety, the ability to automatically recognise traffic lights may be vital in the future.

References


