Detecting stress using eye blinks and brain activity from EEG signals

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Abstract – **In this paper, we discuss our findings on detecting eye blink artefacts in brain activity using EEG. A test subject participated in a car driving simulation and his brain activity was captured during the experiment. While driving, stressful emotions were triggered in the participant, through steep curves and attention seeking billboards. Our research shows that detecting eye blinks is possible using a low cost EEG solution. We use the longitudal differences of two prefrontal cortex sensors in combination with amplitude maps to classify eye blinks. We correlate eye blink frequency with experienced stress, observing higher frequency of eye blinks in stressful situations. Furthermore, we show that brain activity is significantly more active when doing mental calculation with eyes open as opposed to doing them with eyes closed. Results of this research could in combination with other stress detectors lead to applications to improve transport safety and support other areas where stress levels need to be monitored.**

Index Terms – **Neural Networks, Brain Computer Interface, Cognitive Psychology**

I. INTRODUCTION

The human brain is considered a black box by many scientists. Although we are able to model and explain some phenomena, the majority of the brain's workings are still a mystery. The brain's activity can be measured using detection of electrochemical signals, blood flow and possibly others. When looking at the electrochemical signals, a large problem is linking these signals with a specific activity, such as activating motor functions or solving math equations using mental calculations. It is even harder to generalize the interpretation of these associations, since brain activity can differ between different persons. In this paper we discuss our findings on detecting eye blinks of one test subject and correlate eye blink frequency with the experienced level of stress. We also present our findings on mental calculations with open and closed eyes, and their effect on brain activity.

This line of research may be very useful to society. Human activities like driving vehicles could be made safer when being able to sense that the driver has irregular or fast eye blinks, indicating drowsiness or stress. There are numerous other applications where eye blink detection may be used to enhance stress monitoring. It also useful for the scientific EEG community since eye blink artefacts contaminate the EEG signal the most (Peterson, 1999).

For our experiment we chose EEG as the technique to capture brain activity. Its detection technique is based on the electrochemical brain activity. It has excellent temporal resolution in contrast to blood flow techniques. such as fMRI and PET (Horlings, 2008). The high temporal resolution together with the low cost make EEG a great solution for our research.

In our experiment we acquire brain activity using EEG equipment, convert and remove artifacts using software, extract and select features characteristic for eye blinks and finally classify the signal, using the selected features as eye blinks in the signal (figure 1).

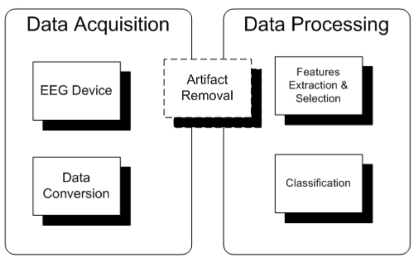


Fig. 1. Schematic overview of the research method

Two challenges have been identified for our work:

- Detecting eye blinks in EEG signal
- Isolating events to be able to link the eye blink frequency to the perceived level of stress

For the detection of eye blinks we use techniques of the signal processing field to remove unwanted artefacts (like lateral eye movement which usually effects EEG sensors F7 and F8), background noise (which is captured using EEG sensors A1 and A2) and other noise. To isolate events we use a custom car driving simulation.

1. Eye blinks

Eye-blinks are an often unwanted feature found in EEG measurements, due to the eye lid muscles' proximity to the posterior sensors Fp1 and Fp2 (Yoo et. al., 2007). The signals measured from the muscles have a magnitude much greater than the signals from the brain, and as such they often occlude essential data.

Although several methods are available for detection and removal of eye-blinks, their greater magnitude makes them more easily detectable than other features, both visually and analytically – they occur mostly in the 0.5-3 Hz range of the power spectrum (Manoilov, 2006).

This paper is outlined using the following structure. First we have a brief look at previous research in this subject. Then the set-up and tools are discussed. Following, the paper goes into the actual conducting of the experiment and present a summary of the collected data. Finally, we analyse the data, extract result and come to a conclusion.

II. Related work

A lot of research has been done on detecting eye blinks using specific features of the data, such as:

- Cross-Correlation (Yoo et.al., 2007); this method is capable of detecting and removing eye-blink artifacts through average and cross-correlation features of the independent EEG components,
- Power spectrum analysis (Manoilov, 2006); this method exploits the lower amplitude signature coming from the Fp1 en Fp2 sensors,
- EMCP (Hoffman, 2008) and ICA (Hoffman, 2009) ; the EMCP method is based on regression while ICA is a blind source separation algorithm assuming statistically independent components.

Areas in which EEG research concerning eye-blinks has been done (Dharmawan, 2006):

- Clinical Research
- Mental State Identification
- Brain computing interfaces
- Computer games

III. Tools

To conduct the experiment we used the TruScan 32 EEG system from Deymed Diagnostics (see figure 2) with 19 electrodes placed according to the 10-20 placement standards (figure 3b). This solution from Deymed provides both the Brain Computer Interface as well as the capture and analysis software. We used Matlab and the EEG toolbox to further analyze these signals.

1. Hardware

The most important hardware components are listed below. For a full list of required hardware, see (Horlings, 2008)

- *EEG Cap*, fitted with 19 electrodes, senses the brain activity,
- *Earlobe electrodes*, these measure the background noise,
- *EEG Headbox*, this box connects the cap with the computer.

2. Software

A. Data Acquisition

Deymed's TruScan Acquisition (TA) is used for the recording of the EEG signals. TA contains an overview of all electrodes and allows the test administrator to add markers and notes during a recording when significant events occur in the experiment.

B. Data analysis

Deymed's TruScan Explorer (TE) is used for loading the captured EEG data and do basic filtering and analysis. Matlab is used to perform statistical analysis on the data.

IV. Experiment

A. Set-up of the experiment

In this experiment a test participant is required to drive a race car simulator while an EEG recording is made of his brain activity. The race car simulator contains a number of predefined race tracks. These race tracks can be curved or straight, and may contain graphic billboards or not.

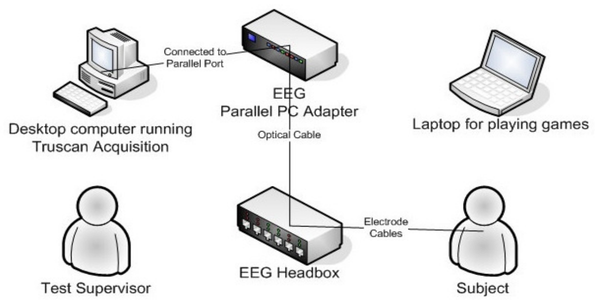


Fig. 2 Setup used for the equipment used in all the experiments

The test participant wears an EEG cap contains 19 electrodes. These electrodes are connected to the TA recording software through the headbox and a pc adapter. The software is operated by the operator, who in real-time adds markings to the recordings at moments of interest. This can for instance be when a billboard appears in the race track simulation, or when the participant crashes the car. During the analysis of the recorded EEG data, the appearance and subsequent cognitive processing of the billboard can be correlated with measured brain activity. Figure 3a shows a test participant in the experiment set-up.

(a) *(b)*

Fig. 3 The recording of an experiment in progress, with the participant wearing the TruScan 32 EEG cap (a) and the layout of the sensors (b).

B. Description of the conducted experiments

A number of experiments have been conducted, which can be divided into two groups. The first set of experiments (table I) consists of the participant driving on a track, either a 10 km long straight road, or three laps on a curved race track (figure 5), optionally with or without billboards (figure 4). There are two variables which are expected to influence the participant's performance and the resulting EEG recordings. The first variable indicates the type of track, straight or curved.

Fig. 4 Typical scene from the curved race track with billboards

The second variable denotes the presence of billboards. Both tracks contain 10 billboards. These billboards are meant to distract the participant emotionally, by either showing graphic pictures of car accidents, or, as in the case of our experiment, scarcely dressed females and shocking anti-smoking ads. Each track contained one billboard with a business ad, not containing any graphic content. On the straight road, the billboards are placed equidistantly, 100 meters apart, with the first billboard at 50 meters. At a speed of 70 km/h, billboards appear about every 50 seconds (table II). On this track, billboards can be sighted from 60 meters away (equivalent to about 30 seconds), and their contents can be distinguished from 25 meters. On the curved race track, the billboards are randomly placed, mostly near the more difficult sections of the track (figure 4, table II).

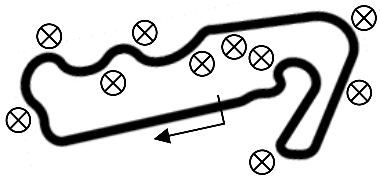


Fig. 5 The curved race track driven by the participant. Markers indicate locations of the billboards, if enabled.

TABLE I
Experiments involving the participant in driving around a track

Number	**Track**	**Billboards**
1	Straight road Max. speed: 70 km/h Length: 10000 m Time: ~8m 36s	No
2		Yes
3	Race track Max. speed: 160 km/h Length: 4258m Time: ~1m50s	No
4		Yes

TABLE II
Placement of billboards

Number	**Time (position)**	**Billboard**
Straight road		
1	00:15 (50 m)	female(s)
2	01:05 (150 m)	female(s)
3	01:55 (250 m)	female(s)
4	02:50 (350 m)	female(s)
5	03:40 (450 m)	female(s)
6	04:30 (550 m)	female(s)
7	05:20 (650 m)	anti-smoking ad
8	06:10 (750 m)	business ad
9	07:05 (850 m)	female(s)
10	07:55 (950 m)	female(s)
Curved race track		
1	00:25	female(s)
2	00:34	anti-smoking ad
3	00:39	female(s)
4	00:44	female(s)
5	00:49	female(s)
6	00:57	anti-smoking ad
7	01:06	female(s)
8	01:15	female(s)
9	01:22	female(s)
10	01:38	business ad

The second set of experiments (table III) required the participant to perform a few simple tasks. The EEG recordings from these experiments may offer additional insights to the recordings from the experiments that were mentioned previously. Experiment 5 required the test participant to drive on a straight racetrack. The test administrator would give simple commands such as 'change lane' or 'weave between the left and right lanes', and mark the recordings when these commands were given.

Experiments 6 and 7 did not require the test participant to control a racetrack simulator. The participant was asked to relax and perform a few basic multiplications (such as 23 × 15). This experiment was conducted twice, once with the eyes open (experiment 6), and again with the eyes closed (experiment 7).

TABLE III
Experiments involving the participant performing simple tasks

Number	Duration	Track	Billboards	Description
5	1m 03s	Straight	No	The test participant was required to execute commands such as 'steer left', 'steer right', or 'change lanes'
6	1m 20s	None	None	With his eyes closed the test participant is asked to multiply two numbers
7	1m 39s	None	None	With his eyes open the test participant is asked to multiply two numbers

C. Data recorded during the experiments

Different features appear in the data that have been recorded during the experiment. The data is first filtered using a bandpass filter. Following previous research, we've used a high pass filter of 2 Hz and a low pass filter at 40 Hz (Horlings, 2008). Using a high pass filter at 2 Hz makes the visual detection of the eye blinks much easier, while frequencies below this band are part of the Delta band and only occur in the brain during deep sleep (Horlings 2008). Frequencies above 40 Hz contain little to no activity, and are polluted with common interferences such as from the electrical net with AC currents at 50 or 60 Hz. For eye blink detection alone, the frequencies between 20 and 40 Hz are not relevant, but we have included them for spotting other features of brain activity presented in section 5.

The data from the first experiment is used as reference data. The straight track required minimal corrective steering adjustments and the omission of billboards ensured no emotional responses were triggered (figure 4). The steering corrections showed a temporarily increase in variance in the measured signals between sensors fp1-f7 and f7-t3 (steering to the right) and fp2-f8 and f8-t4 (steering to the left).

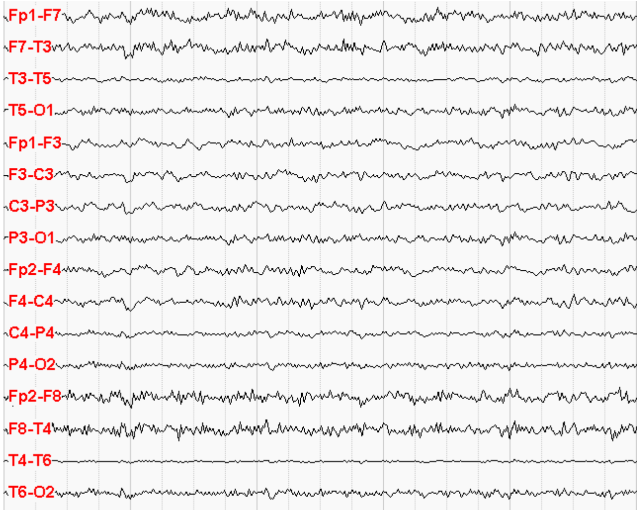
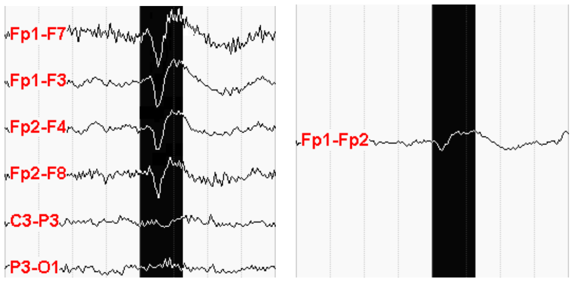


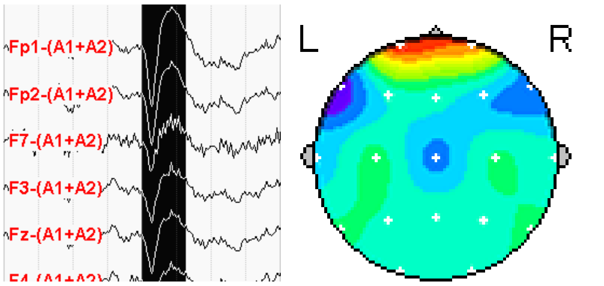
Fig. 6 Typical EEG pattern when driving on a straight road, without any billboards (experiment 1)

Important features of this experiment are the eye-blinks, as their frequency is used to measure the perceived level of stress the participant is under. Figure 7 shows a two second recording with a single eye-blink occurrence (highlighted). The potential difference between sensors Fp1 and Fp2 and their neighbors is increased during the duration of the eye blink, which is typically between 200 and 400 ms (Yoo et. al., 2007).

The longitudinal differences (figure 6a) allow easy visual identification of the eye blinks as peaks on the differences between Fp1 and Fp2 and their surrounding electrodes. The transverse differences (figure 6b) measures the potential differences between Fp1 and Fp2. Because both sensors will be triggered simultaneously during an eye blink, the eye blinks are barely noticeable. Using the earlobes as reference (figure 6c), such as the ear lobes, has the effect of eye blinks showing up on all channels, not just on Fp1 and Fp2. Even though eye blinks are easily spotted in this configuration, essential data on other channels may be masked.



(a) *(b)*



(c) (d)

Fig. 7 A two second recording with a single eye-blink highlighted, using longitudinal differences (a), traverse differences (b), and the earlobes as reference (c). Only the relevant channels are shown. Finally an amplitude map of this same moment (d).

The following tables list the occurrences of eye blinks while riding on the straight road. Table IV shows the measurements for the straight track without any billboards. The first minute of this data was not usable do to distraction of the participant, and has been removed. The has been shifted such that the first eye blink occurs at 0 seconds

TABLE IV
Eye blinks occurring while riding on the straight road without billboards

	Time				Time		
#	**min:sec**	**sec.onds**	**Diff**	**#**	**min:sec**	**seconds**	**Diff**
1	0:00	0	0	15	4:07	247	10
2	0:13	13	13	16	4:20	260	13
3	0:15	15	2	17	4:28	268	8
4	0:45	45	30	18	4:32	272	4
5	1:15	75	30	19	4:50	290	18
6	1:41	101	26	20	5:01	301	11
7	2:02	122	21	21	5:25	325	24
8	2:09	129	7	22	5:30	330	15
9	2:16	136	7	23	5:53	353	23
10	3:01	181	45	24	6:32	392	39
11	3:22	202	21	25	6:37	397	5
12	3:42	222	20	26	7:20	440	43
13	3:46	226	4	27	7:24	444	4
14	3:57	237	11	28	7:34	454	10

TABLE V
Eye blinks occurring while riding on the straight road with billboards

	Time				Time		
#	**min:sec**	**sec.onds**	**Diff**	**#**	**min:sec**	**seconds**	**Diff**
1	0:00	0	0	38	3:32	212	1
2	0:03	3	3	39	3:34	214	2
3	0:16	16	13	40	3:35	215	1
4	0:18	18	2	41	3:38	218	3
5	0:26	26	8	42	3:43	223	5
6	0:41	41	15	43	3:48	228	5
7	0:44	44	3	44	3:53	233	5
8	0:47	47	3	45	3:58	238	5
9	0:49	49	2	46	4:00	240	2
10	0:53	53	4	47	4:12	252	12
11	0:56	56	3	48	4:20	260	8
12	1:01	61	5	49	4:34	274	14
13	1:05	65	4	50	4:42	282	8
14	1:11	71	6	51	4:49	289	7
15	1:21	81	10	52	4:50	290	1
16	1:24	84	3	53	5:16	316	26
17	1:32	92	8	54	5:18	318	2
18	1:34	94	2	55	5:21	321	3
19	1:39	99	5	56	5:24	324	3
20	1:40	100	1	57	5:28	328	4
21	1:46	106	6	58	5:32	332	4
22	1:47	107	1	59	5:41	341	9
23	1:54	114	7	60	5:50	350	9
24	1:58	118	4	61	5:52	352	2
25	2:03	123	5	62	5:57	357	5
26	2:09	129	6	63	6:02	362	5
27	2:18	138	9	64	6:08	368	6
28	2:20	140	2	65	6:17	377	9
29	2:35	155	15	66	6:24	384	7
30	2:36	156	1	67	6:32	392	8
31	2:40	160	4	68	6:38	398	6
32	2:42	162	2	69	7:01	421	23
33	2:50	170	8	70	7:06	426	5
34	2:54	174	4	71	7:23	443	17
35	3:06	186	12	72	7:41	461	18
36	3:22	202	16	73	8:00	480	19
37	3:31	211	9	74	8:03	483	3

TABLE VI
Eye blinks occurring while riding on the curved without billboards

	Time				Time		
#	**min:sec**	**sec.onds**	**Diff**	**#**	**min:sec**	**seconds**	**Diff**
1	0:00	0	0	24	4:05	245	3
2	0:35	35	35	25	4:06	246	1
3	0:36	36	1	26	4:08	248	2
4	1:09	69	33	27	4:12	252	4
5	1:21	81	12	28	4:30	270	18
6	1:50	110	29	29	4:41	281	11
7	1:51	111	1	30	4:42	282	1
8	2:11	131	20	31	4:43	283	1
9	2:13	133	2	32	4:47	287	4
10	2:14	134	1	33	5:40	340	53
11	2:16	136	2	34	5:57	357	17
12	2:21	141	5	35	5:58	358	1
13	2:45	165	24	36	5:59	359	1
14	2:46	166	1	37	6:00	360	1
15	3:06	186	20	38	6:01	361	1
16	3:08	188	2	39	6:02	362	1
17	3:09	189	1	40	6:03	363	1
18	3:24	204	15	41	6:04	364	1
19	3:40	220	16	42	6:06	366	2
20	3:42	222	2	43	6:07	367	1
21	3:57	237	15	44	6:08	368	1
22	3:58	238	1	45	6:09	369	1
23	4:02	242	4	46	6:12	372	3

TABLE VII
Eye blinks occurring while riding on the curved with billboards

	Time				Time		
#	**min:sec**	**sec.onds**	**Diff**	**#**	**min:sec**	**seconds**	**Diff**
1	0:00	0	0	14	2:55	175	2
2	0:09	9	9	15	3:28	208	33
3	1:01	61	52	16	3:30	210	2
4	1:48	108	47	17	3:47	227	17
5	1:57	117	9	18	3:48	228	1
6	2:16	136	19	19	4:01	241	13
7	2:28	148	12	20	4:39	279	38
8	2:29	149	1	21	4:40	280	1
9	2:30	150	1	22	4:45	285	5
10	2:41	161	11	23	5:46	346	61
11	2:43	163	2	24	5:47	347	1
12	2:47	167	4	25	5:49	349	2
13	2:53	173	6				

TABLE VIII
Crashes on the curved track

Without billboards			With billboards		
#	min:sec	sec.onds	#	min:sec	seconds
1	0:33	33	1	2:28	212
2	1:49	109	2	2:41	214
3	2:42	162	3	4:24	215
4	3:55	235	4	4:40	218
5	4:26	266	5	5:46	223
6	4:40	280			
7	5:54	654			

V. ANALYSIS

A. Eye blink frequency in stressful situations

We first analyzed basic statistical properties. Figure 8 shows the distributions of the time between the eye blinks. The graph for the curved race track without billboards (figure 8c) has been clipped. The last 20 seconds of the data showed continuous blinking. Although this has been removed from the distribution, we will include this data in the remainder of our analysis.

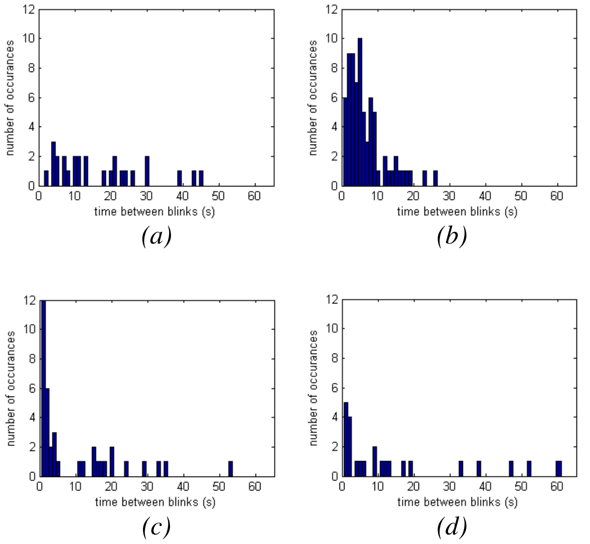


Fig. 8 The distribution of eye blink intervals (seconds) for each of the driving simulations; straight road, no billboards (a), straight road, with billboards (b), curvy race track, no billboards (c) and curvy race track with billboards (d).

All distributions show properties of the Gamma distribution, which could be expected (Dekking et al, 2005). It is immediately obvious that the presence of billboards has an effect on the emotional state (figures 8a and b). The mean time between two eye blinks is much shorter, which is to be expected given many more eye blinks in the same amount of time. The same does not happen for the curvy race track, though. The distributions are similar, and in fact the track without billboards shows a higher count of blinks, and a lower mean time between blinks. This can only partly be explained to the stress experienced of having to steer the vehicle, and control the throttle to stay on the track.

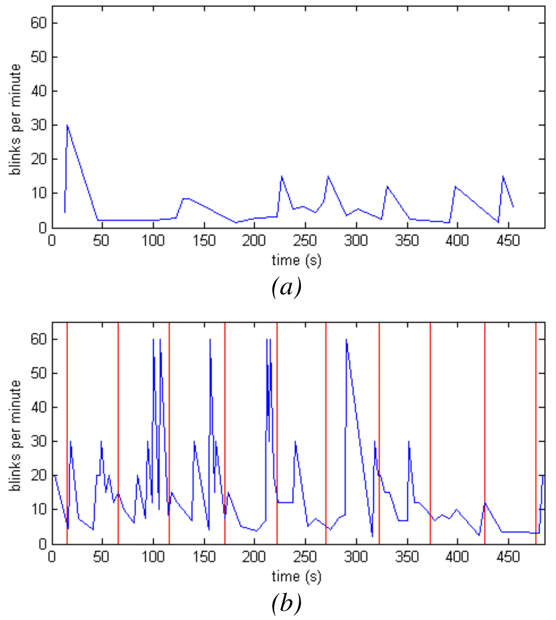
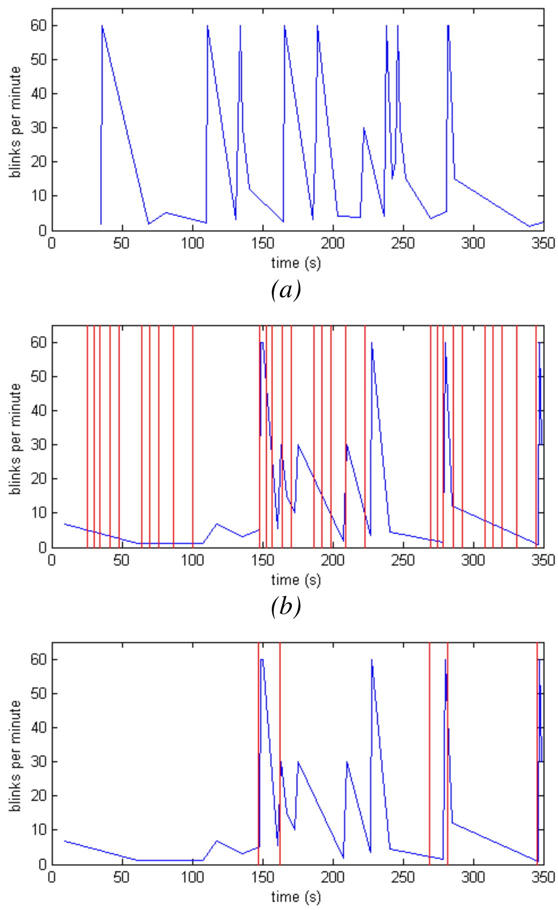


Fig. 9 Projected eye blinks per minute for the straight road, without billboards (a), and with billboards (b). The billboards are marked in red.



(c)

Fig. 10 Projected eye blinks per minute for the curvy race track without billboards (a), and with billboards (b and c). The billboards are shown as markers in (b), the crashes are shown as markers in (c).

While on the straight road the presence of emotion stimulating billboards has an obvious effect, there is no significant difference in the perceived emotions on the curvy race track. To support this notion, we have marked both the billboards and crashes onto the eye blink data. If we plot the billboards on the data (figure 10b), there appears no connection between the location of a billboard and the perceived emotion. But if we mark the crashes (figure 10c), we see an immediate increase in eye blink frequency after a crash, indicating a strong correlation between the two. This shows that in fact the crash, even though only simulated, causes an immediate emotional response.

This still leaves the issue of the higher eye blink on the curvy track without billboards as opposed to the one with billboards. This is probably due to the fact that more crashes occurred during this run, as well as the fact that the participant still had to adapt to the curvy track, and was more emotionally tense when driving the first few laps.

B. Brain activity under mental load

Figure 7 shows an EEG pattern of the participant during experiment 3, while passing through a sharp turn in the race track. The amount of variation in the EEG signals seems to be related to the psychophysical load of the steering task at the moment. Sharp curves in the racetrack require more cognitive processing and exertion of physical control than gentle ones. For instance gentle curves can be completed without adjusting the speed of the race car, with little steering and with little danger of the race car slipping and potentially becoming uncontrollable.

Some of the curves in the race track show activity such as in figure 7, while others do not show any increase in brain activity, and the EEG patterns look like those in figure 5. Another noticeable situation is the EEG pattern that emerges when the participant loses control over the race car and it crashes into the sidewall of the track. The EEG pattern then reflects all the psychophysical activity that must be done in order to get back in control of the race car.

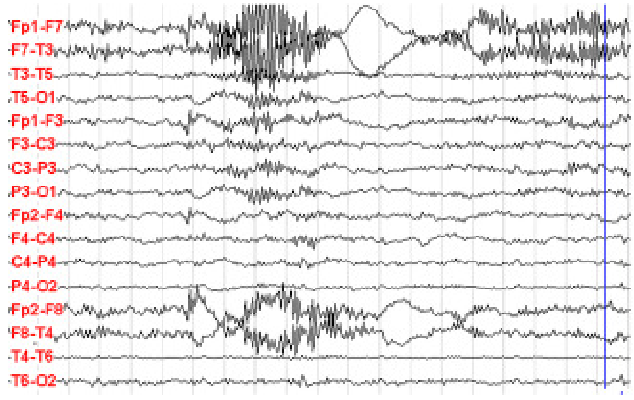
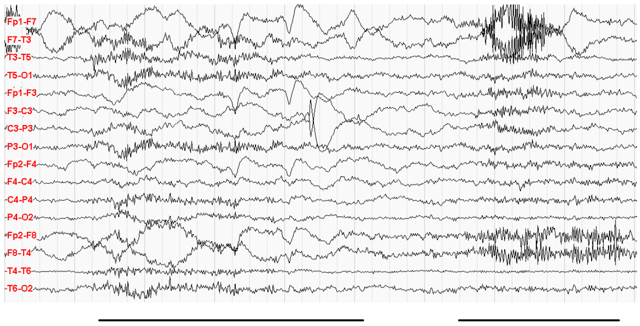


Fig. 11 EEG pattern when driving through a curve that required relatively much control adjustments



(a) *(b)*

Fig. 12 A 10 second EEG clip showing brain activity while the car becomes uncontrollable and crashes (a) and during recovery (b).

The second set of experiments that were conducted also revealed some EEG patterns of interest. From figure 13 and 14 the difference is visible between the participant's brain activity when his eyes are open and when they are closed. In both cases the participant was asked to perform relatively simple calculations, which were done correctly. However, it appears that the brain is much busier when the eyes are opened, possibly because it is engaged in subconsciously processing what the eyes see, even when the participant's attention is not focused on his surroundings. It is interesting to notice that the occipital lobe (responsible for vision) activates when the participants eyes opened briefly (figure 15).

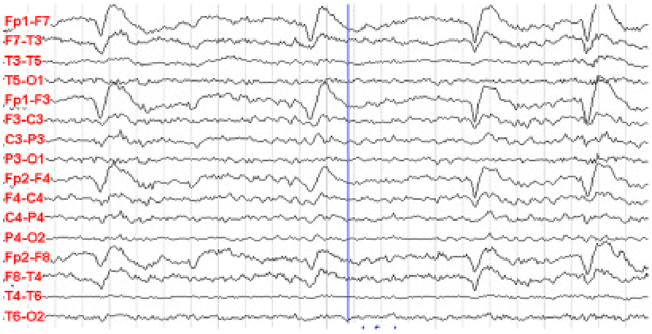


Fig. 13 EEG pattern from experiment 7 – the participant has his eyes open and is asked to calculate 90 × 6.

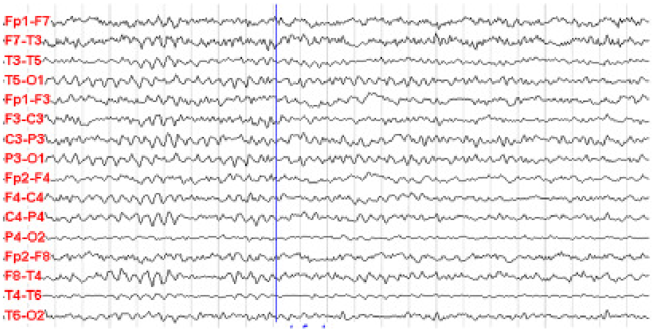


Fig. 14 EEG pattern from experiment 8 – the participant has his eyes closed and is asked to calculate 19 × 8.

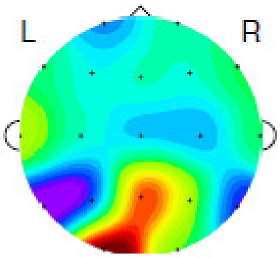
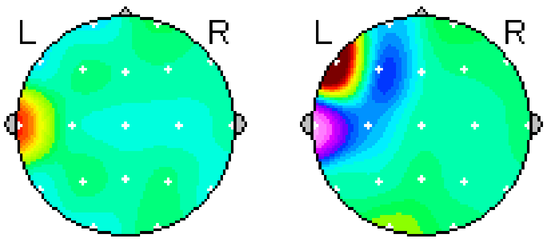
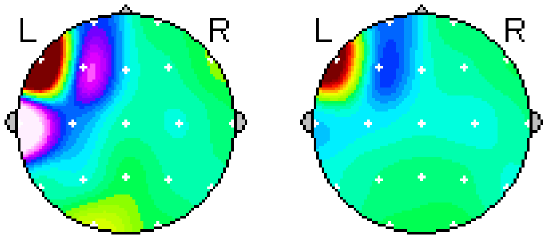


Fig. 15 Brain activity after opening the eyes, clearly showing activity in the occipital lobe.

Another observation was the activation of the left frontal lobe. Earlier studies show that exact math is mostly done in the left frontal part of the brain (Spelke et al., 1999). Figure 16 shows a time lapse of 4 amplitude maps 8ms apart.



(a) *(b)*



(c) *(d)*

Fig. 16 Brain activity during performing mathematical exercises, clearly showing activity in the left frontal lobe. Each map is taken 8 ms apart.

VI. RESULTS

There seems to be an obvious connection between eye blink frequency and the perceived level of stress. Both artificially triggered emotional responses by using billboards, and more natural emotional responses occurring after crashing the car in the drive simulator cause a temporary increase in the eye blink frequency.

Unfortunately the results from the classification of emotions from the recorded EEG signals cannot be strongly correlated with the data. The participants were not interviewed or otherwise asked to state which emotions they perceived during specific event of the experiment. Additionally, short dummy sessions could be held on the straight track to make the participant more comfortable with the experiment.

In the second set of experiments we noticed that specific brain areas were being activated after certain events. The occipital lobe was highly active when opening the eyes and the frontal lobe was highly active when doing the mental calculation. Although this is expected according to other studies (ie. Spelke and Dehaene), this reseach is not able to connect stated brain areas with mentioned events. This would require a different experiment set-up

A weakness of using EEG signals for combined eye blink and brain activity detection is that both occlude each other. Firstly, only relatively strong electric potential at the outer edge of the scalp only are recorded. The origins of the emotional brain however are not limited to the outer edge alone. Secondly, the generated electrical potential from brain activity, and the electrical potential from muscle activity from the eye lids tend to occlude each other.

To remedy these problems, we would recommend using separate eye lid sensors. This allows much more accurate eye blink detection and removal of these artefacts from the EEG data.

VII. Conclusion

Our results show that there is a strong correlation between eye blink frequency and emotional stress. This was even more apparent during more confronting situations, such as the simulated car crashes Although the temporal increase in eye blink frequency can already be used as a measure of stress, our method is not accurate enough to be used in commercial applications. Further isolating the eye blink from the EEG signal using other features and possible enhanced stress detection using additional sensors, for example attached to the eye lids, are interesting research topics.

The detection of eye blinks in an EEG signal is easily done visually, using the longitudal differences of sensors Fp1 and Fp2, presenting eye blinks as unique peaks. When displaying the amplitude map, a clear active area of the prefrontal cortex is shown. Automatic detection of eye blinks using these two characteristics possible.

During the analysis of the mental calculation we noticed an active left frontal lobe. This confirms the theory of increased brain activity in the left frontal lobe during mental mathematical processing, as stated by Spelke and Dehaene. We further noticed significant less variation in the EEG signal when the subject's eyes were closed and detected a spike in the occipital lobe when opening the eyes, indicating increased visual prosessing. This confirms that brain activity is heavily influenced by visual information. We noticed no correlation of math performance and eyes closed or open.

References

[1] Horlings, R. (2008), "Emotion recognition using brain activity", Man-Machine Interaction Group, Delft University of Technology, Delft, Netherlands

[2] Dharmawan, Z. (2007), "Analysis of Computer Games Player Stress Level Using EEG Data", Man-Machine Interaction Group, Delft University of Technology, Delft, Netherlands

[3] Yoo, K., Basa, T., and Lee. W. (2007), "Removal of Eye Blink Artificats From EEG Signals Based on Cross-Correlation", Chung-Ang University, Seoul, Korea

[4] Dekker, F.M, Kraaikamp, C., Lopuhaä, H.P. and Meester, L.E. (2005), "A Modern Introduction to Probability and Statistics", Springer, Delft, Netherlands

[5] Peterson, D.A,Anderson (1999), C.W, "EEG-based cognitive task classification with ICA and neural networks", Springer, Berlin, Germany

[6] Manoilov, P (2006), "EEG Eye-Blinking Artefacts Power Spectrum Analysis", Journal CompSysTech '06

[7] Hoffman, S.,Falkenstein, M. (2008), "The correction of Eye Blink Artefacts in the EEG: A comparison of two prominent methods", published online:

http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=2500159

[8] Spelke, E.S.,Dehaene, S.(1999), "Biological foundations of numerical thinking", Trends in Cognitive Sciences, 3, page 365-366