

Semi-Autonomous Car Control Using Brain Computer Interfaces

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Abstract—In this paper we present an approach to control a real car with brain signals. To achieve this, we use a brain computer interface (BCI) which is connected to our autonomous car. The car is equipped with a variety of sensors and can be controlled by a computer. We implemented two scenarios to test the usability of the BCI for controlling our car. In the first scenario our car is completely brain controlled, using four different brain patterns for steering and throttle/brake. We will describe the control interface which is necessary for a smooth, brain controlled driving. In a second scenario, decisions for path selection at intersections and forking are made using the BCI. Between these points, the remaining autonomous functions (e.g. path following and obstacle avoidance) are still active. We evaluated our approach in a variety of experiments on a closed airfield and will present results on accuracy, reaction times and usability.

I. INTRODUCTION

Autonomous cars play an important role in current robotics and A.I. research. The development of driverless cars started in the late '70s and '80s. Ernst Dickmann's Mercedes Benz achieved a travel velocity of 100 km/h on restricted highways without traffic [3]. In the DARPA Grand Challenge 2005, autonomous cars drove off-road on desert terrain, several of them reaching the finish line [9]. DARPA's Urban Challenge of 2007 demonstrated that intelligent cars are able to handle urban scenarios and situations with simulated traffic [10]. Lately, autonomous cars have been driving through real world traffic for testing purposes in urban and rural areas alike [8].

This research lead to the introduction of various driver assistance systems for street cars. One key aspect for driver assistance systems is how the interface between human and machine affects usability. This interface question is more important for people without full bodily control. Brain Computer Interfaces can be a solution here. Recently, BCI-systems have become relatively affordable and allow people to interact directly with their environment [5]. Another big field lies in human interaction within computer games, e.g. in the research game "Brain Basher" [1] or in [6]. As a sub-field of BCI research, BCI using motor imagination brain patterns has become popular, where the user has to think of a motion instead of performing it physically [4]. In other work, users could control mechanical devices with EEG patterns [7]. In this paper we want to present a solution where a human controls a car just by using brain signals, i.e., without need for any physical interaction with the car.

In a first application, computer-aided free driving allows the passenger to claim steering- and speed-control in special areas. The car prevents traffic rule-violations and accidents by reclaiming control before they happen. The second application implements a semi-autonomous path-planning, where a car drives autonomously through a road-network until it arrives at so called decision points. Typically located at crossings, decision points require the passenger to choose which way to drive next.

The paper is structured as follows: Section II introduces the autonomous car "MadeInGermany" and the applied BCI hardware. In Section III we describe the training process and the classification approach used. Section IV presents the developed usability interface which enables a human to easily and safely control the car using brain patterns, followed by Section V, which shows experimental results of the presented approach. Section VI summarizes the paper and suggests future work.

II. AUTONOMOUS CAR AND BCI HARDWARE



Fig. 1. The autonomous car "MadeInGermany"

A. Autonomous Car

Our autonomous car "MadeInGermany" served as a test platform c.f. Fig. 1: a modified Volkswagen Passat, equipped with a variety of different sensors and a drive by wire control via CAN bus. An introduction to these sensors is necessary

at this stage, as they are used in the here-described semi-autonomous mode. The platform is equipped with six laser scanners, three at front and three at the back. Additionally, on top of the car a rotating laser scanner from Velodyne scans the near environment, c.f. Fig. 2. Further, the car has different radar sensors for obstacle detection and cameras, which are used for 3D feature extraction, lane and traffic light detection. The car actuators, i.e., gear shifting, motor and brake control are manipulated via CAN bus.

A modular architecture allows separate software-components for the different sensors and actuators on each car, while utilizing the same modules for decision-making and other higher level functions. Besides GPS and CAN data, the car relies on camera, lidar and radar sensors.

Besides, the authors want to mention, that the architecture described in this paper is also applied to a semi-autonomous wheelchair, c.f. Fig. 3, but in this paper we want to focus on the application to the semi-autonomous car.

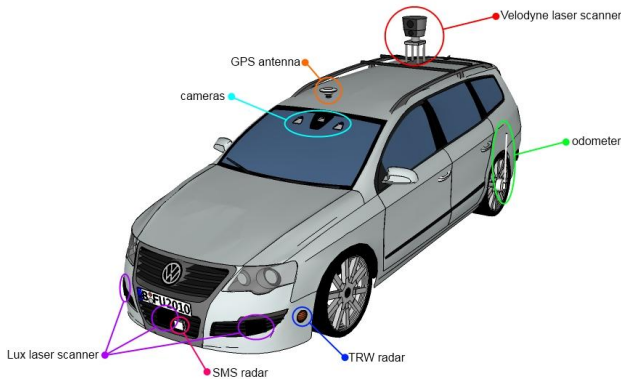


Fig. 2. Sensor configuration of “MadeInGermany”



Fig. 3. Autonomous wheelchair equipped with Kinect and lidar sensors.

B. Brain Computer Interface

The brain computer interface used in this approach is a commercial product, the Epoc cap from Emotive. It has 16 EEG sensors which measure potential differences on the scalp. A contact fluid is necessary for good recognition. As a first step, the device has to be trained to the brain patterns of a user. The 16 sensor readings are mapped to four different direction classes or to the neutral class. Unfortunately we had no access to the sensor readings of the head sensors, thus, the first classification process was not transparent. The classification result is used by the controller module to generate throttle, brake and steering commands.



Fig. 4. Epoc neuroheadset from Emotive. The cap is connected wirelessly to the computer.

III. TRAINING AND CLASSIFICATION

In the training phase the user can decide whether to control the steering only (two classes) or to also control steering and velocity (four classes). The classification program then asks the user to sequentially think of the different direction schemes. Many users tend to think of different motions, i.e. they think of moving the right arm, without really performing those motions. Thus, certain motor images do activate different regions in the brain, but not necessarily the same regions as would be activated during real motions [2]. The corresponding electric brain patterns are measured by the BCI. Usually, this method is called “Motor Imagery”.

The training process must be executed every time the user puts the cap on his head. After some time, a retraining can be necessary. After the training process, the user can estimate the quality of classification by performing an evaluation test. If classification is not sufficiently correct, a retraining is necessary; sometimes the user must choose other patterns, e.g. to think of other motions or images.

IV. INTERFACE DESIGN

A. Requirements

With the free drive controller and BrainChooser alike, design of interface is essential for BCI usability. Important aspects we focused on were

- stability and smoothness of executed actions,
- robustness to falsely classified brain patterns,
- safety of executed maneuvers with respect to physical limitations and to the surrounding area,
- minimality of necessary actions for maneuvers.

. Two solutions were developed and tested on the closed Tempelhof airfield, for which we designed a demonstration course, see Fig. 5.

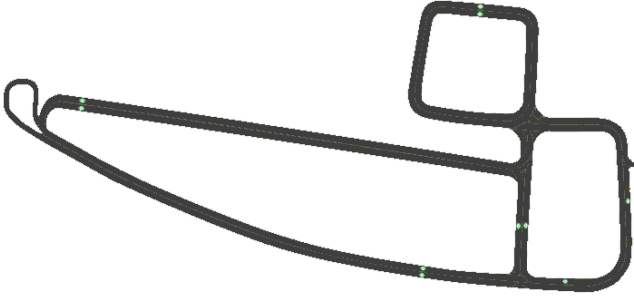


Fig. 5. Test parcours on closed Berlin-Tempelhof airfield.

B. Free Drive

In free drive mode the operator has access to steering and speed control. Accidents are prevented by constantly monitoring the operator’s decisions. If a collision is imminent or if the car is about to leave the free drive zone, the computer immediately stops the car.

a) Control Actions.: The four brain commands (“left”, “right”, “push”, “pull”) are mapped to steer and velocity commands as follows: Commands “left” and “right” increase or decrease the current steering wheel angle. Commands “push” and “pull” increase or decrease the desired velocity. This solution proved superior compared to giving direct throttle or brake commands, as it is easier to maintain a certain speed. When none of the four commands is detected, the velocity stays constant. The steering angle stays constant for one second, and then is reduced (or respectively increased) towards zero position, in which the car moves straight.

b) Control Frequency.: Steering a car requires the driver to be able to execute steering motion with slow response times. To allow filtering of noisy brain signals, we allowed only one steering command per second in earlier tests. Then, a large steering angle was added to the current position. In this solution the driver had problems to execute small steering angles, the response times were shown to be too long. In further tests a control frequency of 5 Hz and a steer step of 0.6 rad proved to be a good solution, meaning that one revolution of the steering wheel takes about two seconds. The velocity can be increased or decreased by 0.15 m/s in each step. The steering angle is limited to $\pm 2.5\pi$. Velocities are cropped between 0 and 10 m/s.

c) Steering.: When no “left” or “right” command is received for more than one second, the steering wheel returns to neutral position. At higher velocities (>2 m/s), the steering wheel turns more slowly and the steering angle limits are reduced. This prevents excessive centrifugal forces and allows the driver to stay on a desired trajectory without causing oscillations. The steering angle ω , depending on the velocity of the car v in m/s is limited to the following values (in rad):

$$\omega = 2.5\pi * \min(1.0, 2.0/v) \quad (1)$$

Accordingly, the steering angle change $\delta\omega$ within each time step is:

$$\delta\omega = 0.6\pi * \min(1.0, 2.0/v) \quad (2)$$

When the driver is accelerating or decelerating (“pull” or “push” commands), we also reduce the steering angle.

d) Steer Angle Smoother.: Sending steering angle commands to the steering controller with 5 Hz only causes non-smooth steering maneuvers. The steer controller works with 100 Hz, therefore we implemented a steering angle smoother, which linearly extrapolates 20 desired angle values (one value for each 10 ms) for the controller. The result was a very soft turning steering wheel.

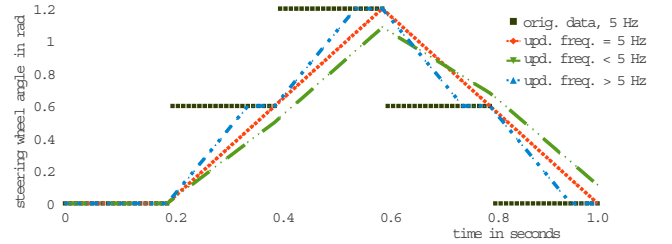


Fig. 6. Steer Angle Smoother, black dotted curve shows the raw angle values at 5 Hz; blue, red and green curves show interpolated values for interpolation frequencies higher, equal or lower than 5 Hz.

e) Velocity Controller.: The desired velocity is input to a PID-controller. The PID-controller generates positive or negative output values. Positive outputs are weighted and mapped to throttle commands, negative outputs are similarly mapped to brake commands.

As experiments will show later, staying on a given trajectory can be hard at higher velocities, so an application on open traffic is far away. Therefore we implemented and tested another solution for the BCI, in which it assists the human in deciding which direction to take; all driving and safety relevant decisions are made by the car.

C. BrainChooser

While the autonomous car usually plans the best trajectory through the road network to reach its destination, the Brain-Chooser application allows the passenger to modify the route at certain decision points by using the BCI device.

The road network is presented as a directed graph of way-points which are connected by lanes. Curved lanes are approximated by spline interpolation over the way-points. Fig. 7 shows the spline interpolation of the road network graph with the car at a decision point for two possible directions.

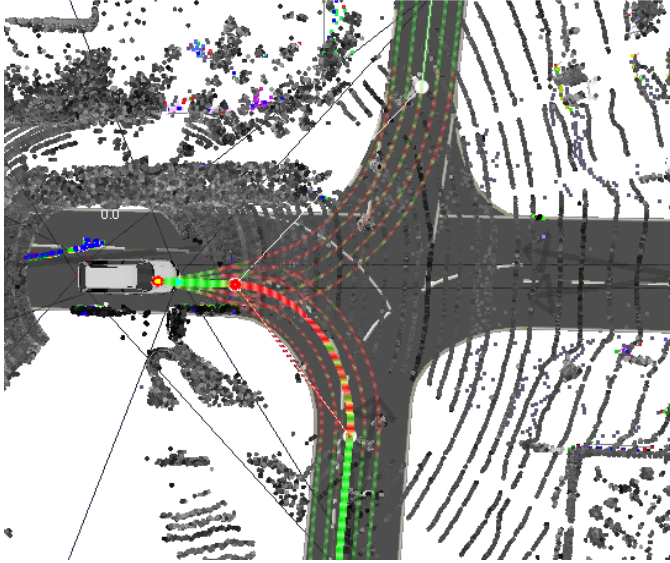


Fig. 7. A spline interpolation of the road network with a point cloud from the lidar-scanner for detecting obstacles. A path along the right lane has been chosen at the decision point in front of the crossroad, as indicated by the highlighted red-green line.

To find a desired trajectory in the road network, weights are assigned to lanes representing the distance, speed-limit and obstacles on the lanes, if necessary. When the car reaches a decision point where an operator's choice is required, e.g. an intersection, the operator is requested to choose a direction. The request is executed with the help of a synthetic voice recording. Once a choice was made, the chosen trajectory on the road network is processed and executed by the steering and velocity controller.

At decision points, the operator is requested by voice recording to input a direction with the BCI. Since it's usually not possible to hold a brain pattern steady over a long period of time, messages with detected patterns arrive at irregular intervals and include false positives. To robustly classify the brain pattern into one of the four categories, four variables (one for each possible pattern) accumulate the detection-probabilities. The variable which first passes a certain threshold defines the operator's decision. This method proved to be relatively robust to false detections. It also gives the operator the required time to enter the desired direction. To prevent distraction, no audio-feedback is given during the selection. However, a display presents the currently detected pattern, resulting in faster decisions.

A. Benchmarks

We conducted different experiments on the former Tempelhof airport in Berlin.

Experiment 1: At first we measured the accuracy of control. The first task was to keep the car on an infield course, see Fig. 5, using "left" and "right" patterns for steering only. The velocity was set to 2 meters per second. The driver had to drive the track for three laps to see whether the accuracy remained constant over time. The resulting traces are depicted in Fig. 8; the errors are shown in Fig. 13.

Experiment 2: In the second experiment the driving person had to control throttle and brake in addition to the steering commands for left and right. The car was now able to accelerate from 0 to 3 meters per second. The resulting trace is shown in Fig. 11, the errors are shown in Fig. 13.

Experiment 3: To check the lateral error to the lane at higher speeds, we designed another track with long straight lanes and two sharp corners. The velocity was fixed to 5 meters per second and like in the first experiments, the driver had to steer left and right only, trying to stay at the reference lane. The resulting trajectory is shown in Fig. 12, the errors in Fig. 13.

Experiment 4: We checked the response time of the test person. The test person received different commands, such as "left", "right", "push" or "pull" from another person and had to generate the corresponding brain pattern - this had to be recognized by the control computer. The time from the command until the recognition within the control computer was measured. We also measured falsely classified patterns.

Experiment 5: In this experiment, we tested the second module, the BrainChooser. Here, at intersections, the operator was asked to decide for the left or the right route. Then the test person had about ten seconds to decide for left or right direction. This long decision phase helps to filter out noise and ensures that the test person was generating the desired pattern over a longer time, reducing the risk of coincidentally generated patterns.

B. Experimental Results

Experiment 1: At the beginning of the first experiment we marked the desired lanes on the airfield. As we found, on a flat surface those lanes are hard to see from greater distances. Moreover, it is difficult for a human driver to estimate his distance to the middle of the lane with centimeter accuracy. Therefore the test person had access to a computer monitor, which displayed a model of the car on the virtual track from bird's eye perspective. The test person succeeded in keeping a close distance to the desired trajectory, while only having to steer the car. We performed three tests to observe the variance between different laps. The standard deviation of the lateral error function over time was 1.875 meters for one lap, the error function is shown in Fig. 9. One lap lasted for about 10 minutes. In the following laps this error did not diverge by more than 0.2 m. The angular error standard deviation was 0.20 rad. The traces of the driven laps are shown in Fig. 8. Fig. 13 comprises the results of the first three experiments.

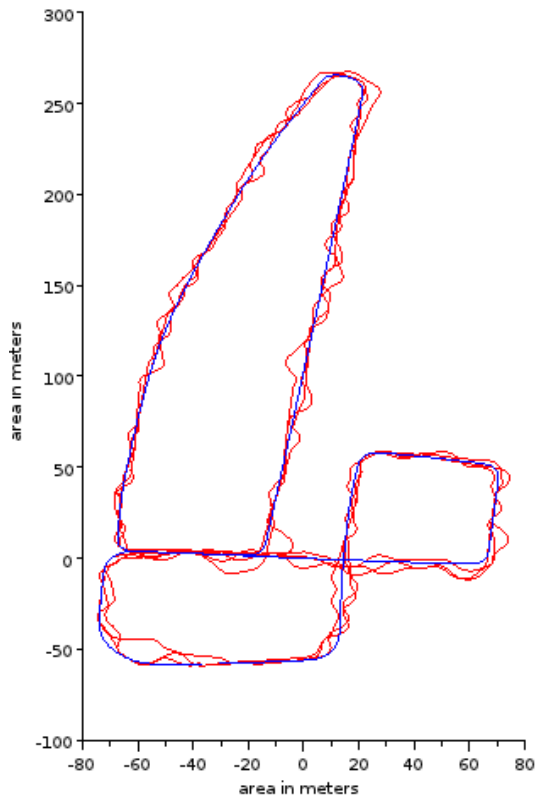


Fig. 8. Experiment 1: Infield test course. The test person had to control the car with two steering commands (“left” and “right”). Velocity was set to 2 meters per second. The traces of all three driven laps are depicted (red). Reference trace of the original track in blue.

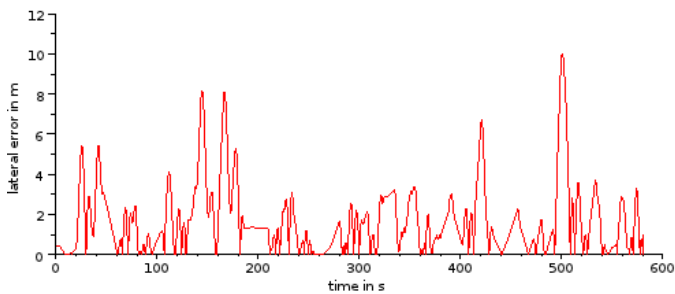


Fig. 9. Experiment 1: Lateral error of the car to the reference trajectory.

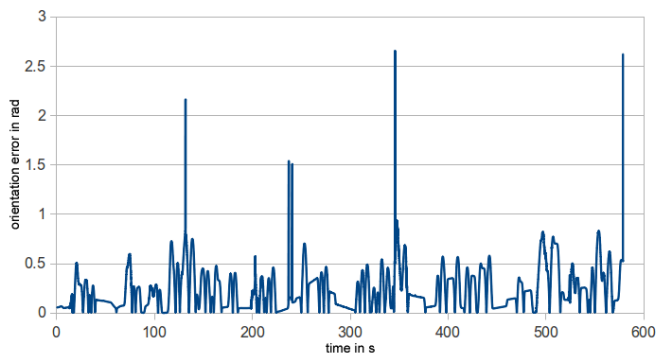


Fig. 10. Experiment 1: Orientation error of the car to the reference trajectory.

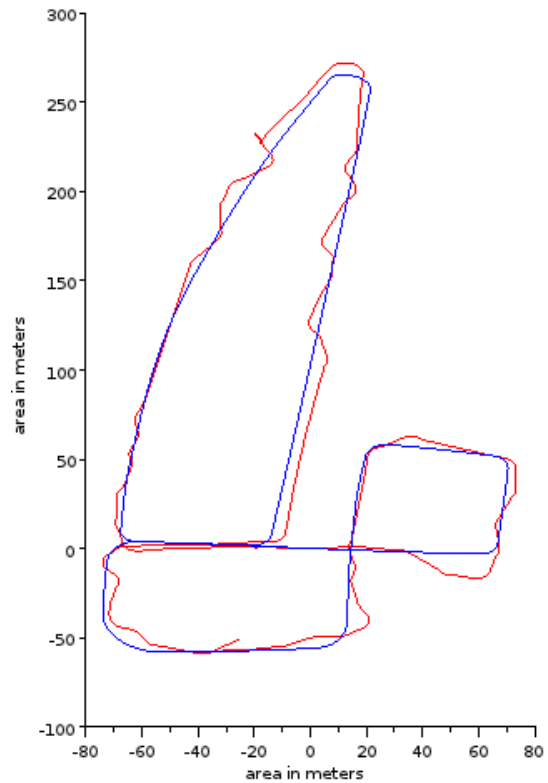


Fig. 11. Experiment 2: Infield test course. The test person had to control the car with four commands (“left”, “right”, “push”, “pull”) to steer the car and to adjust the velocity, 0-3 meters per second. The traces of the car (red) and of the original lap (blue) are depicted.

Experiment 2: The test person managed to control the car, controlling the velocity and the steering wheel. However, the accuracy of steering control was reduced, compared to Exp. 1, resulting in a larger standard deviation of the lateral error, which was 2.765 m. The standard deviation of the orientation was 0.410 rad and, thus, larger as well.

Experiment 3: The lateral error became even greater on the speedway. The speed was set to 5 meters per second and the test person tried to focus on heading in the right direction (keeping the orientation error small) rather than reducing the lateral distance. This is due to the fact that at higher speeds, the target point for orienting the car is displaced forwards. The standard deviation of the lateral error was 4.484, the standard deviation of the orientation error was 0.222 rad. The results are contained in 13.

Experiment 4: In this experiment we measured the time it takes to generate a pattern with the brain and to classify it. Results are shown in Fig. 14. Over 60 percent of the brain commands could be generated within 5 or less seconds, about 26 percent even within two seconds or less. In 20 percent of all cases the generated pattern was wrong. This was usually due to concentration problems of the test person. After a while, at latest after one hour a new training of the brain patterns is necessary. Further, after using the BCI for 90 minutes we experienced some tiredness of our test subject, which results

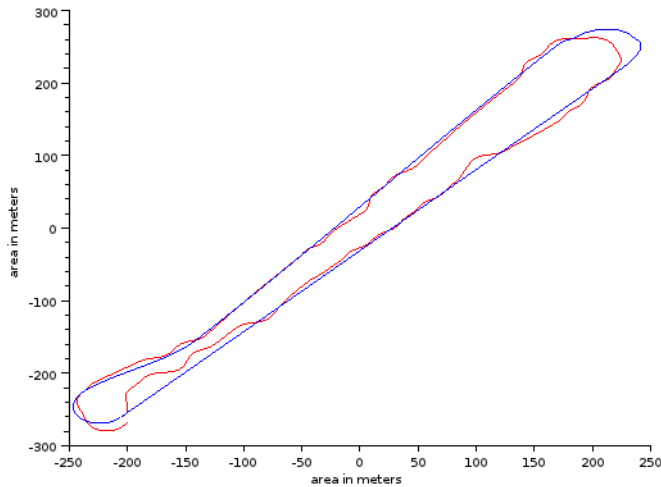


Fig. 12. Experiment 3: Speedway test course. As in the first experiment, the test person had to control the car with two steering commands. Velocity was set to 5 meters per second. The traces of the car (red) and of the original lap (blue) are depicted.

	σ_{lateral} [m]	σ_{angle} [rad]
Infield 2m/s, 2 DOF	1.875	0.200
Infield 3m/s, 4 DOF	2.765	0.410
Speedway 5m/s, 2 DOF	4.484	0.222

Fig. 13. Error measurements: Lateral distance to reference trajectory in meters and orientation error in rad. 2 or 4 DOF refer to the two or four patterns, the test person has to generate.

in longer response times or higher inaccuracies.

Experiment 5: In this experiment for the BrainChooser the test person achieved correctly classified directions in more than 90 percent of cases.

VI. CONCLUSION AND FUTURE WORK

Brain-computer interfaces pose a great opportunity to interact with highly intelligent systems such as autonomous vehicles. While relying on the car as a smart assistance system, they allow a passenger to gain control of the very essential aspect of driving without the need to use arms or legs. Even while legal issues remain for public deployment, this could already enable a wide range of disabled people to command a vehicle in closed environments such as a parks, zoos, or inside buildings.

Free drive with the brain and BrainChooser give a glimpse of what is already possible with brain-computer interfaces for commanding autonomous cars. Modifying the route of a vehicle with a BCI is already an interesting option for applications

	2s or less	2 - 5 s	5 - 10 s	10 s or more	falsely class.
percent	26 %	36 %	10 %	9 %	20 %

Fig. 14. Experiment 4: Reaction times. The test subject is told to generate a certain pattern. A pattern counts as recognized, when the computer recognizes the correct class.

that help disabled people to become more mobile. It has been proven that free driving with a BCI is possible, but the control is still too inaccurate for letting mind-controlled cars operate within open traffic. The semi-autonomous BrainChooser overcame this weakness, and decisions were performed with a high precision. Improvements of the BCI device could have multiple positive effects. One effect, of course, would be a more accurate control of the car, i.e., a more accurate steering and velocity control in free drive mode. Further, it is desirable to be able to distinguish more than four brain patterns in the future. This would enable the driver to give further commands, e.g., switching lights off and on, or setting the onboard navigation system to the desired location by thought alone.

More detailed experiments regarding this decline of concentration over time and within the context of car driving will be future work as well.

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REFERENCES

- [1] D. O. Bos and B. Reuderink. Brainbasher: a bci game. In P. Markopoulos, J. Hoonhout, I. Soute, and J. Read, editors, *Extended Abstracts of the International Conference on Fun and Games 2008, Eindhoven, Netherlands*, pages 36–39, 2008.
- [2] J. Decety. Do executed and imagined movements share the same central structures? In *Cognitive Brain Research*, volume 3, pages 87–93, 1996.
- [3] E. Dickmanns, R. Behringer, D. Dickmanns, T. Hildebrandt, M. Maurer, F. Thomanek, and J. Schiehlen. The seeing passenger car 'vamors-p'. In *IVS94*, pages 68–73, 1994.
- [4] B. V. D. Laar, D. O. Bos, B. Reuderink, and D. Heylen. Actual and imagined movement in bci gaming. In *Adaptive and Emergent Behaviour and Complex Systems (AISB 09)*, 2009.
- [5] R. Leeb, F. Lee, C. Keinrath, R. Scherer, H. Bischof, and G. Pfurtscheller. Brain-computer communication: Motivation, aim, and impact of exploring a virtual apartment. In *IEEE Transactions on Neur Sys. and Rehab. Eng.*, volume 15, pages 473–482, 2007.
- [6] A. Nijholt, D. Tan, B. Allison, J. Milan, , and B. Graimann. Brain-computer interfaces for hci and games. In *CHI '08: CHI '08 extended abstracts on Human factors in computing systems*, pages 3925–3928, 2008.
- [7] J. Pineda, D. Silverman, A. Vankov, and J. Hestenes. Learning to control brain rhythms: making a brain-computer interface possible. *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, 11/2:181–184, 2003.
- [8] S. Thrun. Official Google Blog: What we're driving at. <http://googleblog.blogspot.com/2010/10/what-were-driving-at.html>, Oct 2010.
- [9] S. Thrun, M. Montemerlo, H. Dahlkamp, D. Stavens, A. Aron, J. Diebel, P. Fong, J. Gale, M. Halpenny, G. Hoffmann, K. Lau, C. Oakley, M. Palatucci, V. Pratt, P. Stang, S. Strohband, C. Dupont, L.-E. Jendrossek, C. Koelen, C. Markey, C. Rummel, J. van Niekerk, E. Jensen, P. Alessandrini, G. Bradski, B. Davies, S. Ettinger, A. Kaehler, A. Nefian, and P. Mahoney. Stanley: The robot that won the darpa grand challenge. *Journal of Field Robotics*, 23(9):661 – 692, September 2006.
- [10] C. Urmson, J. Anhalt, D. Bagnell, C. Baker, R. Bittner, J. Dolan, D. Duggins, D. Ferguson, T. Galatali, C. Geyer, M. Gittleman, S. Harbaugh, M. Hebert, T. Howard, A. Kelly, D. Kohanbash, M. Likhachev, N. Miller, K. Peterson, R. Rajkumar, P. Rybski, B. Salesky, S. Scherer, Y. Woo- Seo, R. Simmons, S. Singh, J. Snider, A. Stentz, W. Whittaker, J. Ziegler, H. Bae, B. Litkouhi, J. Nickolaou, V. Sadekar, S. Zeng, J. Struble, M. Taylor, and M. Darms. Tartan racing: A multi-modal approach to the darpa urban challenge. Technical report, Tartan Racing, April 2007.