Towards EEG-Based Eye-Tracking for Interaction Design in Head-Mounted Devices

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***Abstract*—Augmented Reality (AR), Mixed Reality (MR) and Virtual Reality (VR) have an increasing impact on our daily lives. They improve workers' performance in industry and medicine. In addition gaming and entertainment profit from these innovations. The enabling devices are often head-mounted. New intuitive interaction methods must be developed to control application, because conventional input devices such as keyboards, touch screens or classical touch pads cannot be used. This paper introduces electroencephalographic (EEG) eye-tracking as an additional interaction channel. Ocular artefacts (EOG) in the EEG signal are used to detect eye positions. A Brain-Computer Interface (BCI) is used to capture the data. Data is processed and EOG artefacts are extracted to compute the position of the pupil. The first test runs confirm that ocular artefacts in the EEG signal are strongly correlated with the position of the pupils. Extreme positions of the pupils (horizontal left, horizontal right, vertical up and vertical down) can be detected with high accuracy (true-positive-rate of up to 96,6%). In future tests, we successively refine the direction and speed of eye movement and verify their usage under real-time conditions.**

Keywords—Brain-Computer Interface (BCI), Electroencephalography (EEG), Electrooculography (EOG), Eye-Tracking, Human-Computer Interaction (HCI), Head-Mounted Device (HMD), ocular artefacts

I. Introduction

Augmented, Mixed and Virtual Reality have experienced an enormous technical development in recent years. They represent the fourth wave of disruptive digital technology [1] and have now arrived in everyday use. Smart glasses already support workers in remote maintenance by sending blueprints of the product to be repaired directly into the field of view. Planned products can be virtualized and customized before they are physically created. Tele-support, training videos and videoconferencing are further applications that will save time and money in the future [2]. In medicine, the use of Augmented Reality is increasingly being researched, too. X-ray images are matched with real images and visualized by a Head-Mounted Display (HMD). Even remote operations are already possible in part [3].

The gaming and entertainment industries benefits from these innovations as well. In tandem with the hardware suppliers, they produce and deliver contents that make use of novel media modalities. One common goal of innovation of consumer media is to make the mapping of real and artificial worlds as immersive as possible. An important part of this immersion is intuitive interaction. Current developments focus on the optimization of content and innovative control [4]. Producers of HMDs introduced additional hardware to control applications. 3D mice, digital gloves, tracking sticks or integrated electromagnetical sensors provide new ways to interact with applications.

One research area is the development and evaluation of hands-free applications, which should enable the user to interact in a natural way without additional hardware. Using smart glasses, the eyes as primarily involved organs offer an interesting possibility for intuitive interaction. This paper presents a novel eye-tracking approach. It interprets ocular artefacts in the EEG signal, which are caused by movements of the eyeball. A major difference to camera-based eye-tracking systems lies in that the measurements are not made directly at or next to the eye but at different positions on the head. Therefore, we can place non-invasive electrodes anywhere on the head, which results in technology that can be easily integrated into common HMDs.

II. State of the Art

A. Interaction

Uchino et al. [5] utilize speech recognition and gestures to interact between avatars and manipulate 3D-objects in real-time. Gestures, which are captured by 2D-cameras, are also used to interact with a 3D-model [6]. Achibet et al. [7] combined passive haptics and pseudo-haptics and added them to gestures to provide force-feedback. Seeking enhanced player interaction, Krompiec et al. [8] use a motion controller in addition to a head-tracking system. This controller tracks the controller's acceleration and button events, which are two individual actions in games.

Brain-Computer Interfaces (BCI) establish an additional, direct channel between a human and a computer. Faller et al.

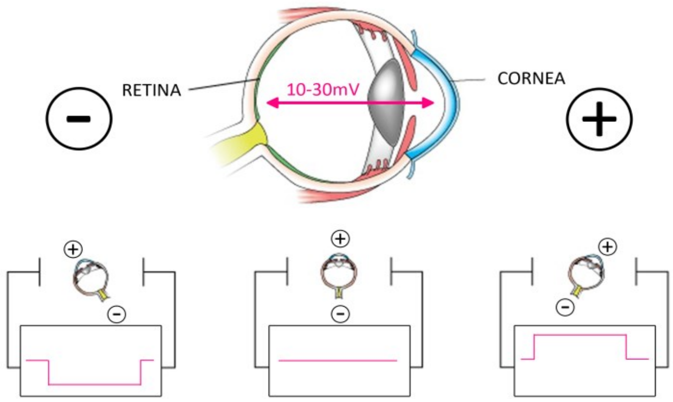

Fig. 1. Graphical illustration of the corneo-retinal standing potential of the eyeball.

[9] introduced a system, which uses steady-state visually evoked potentials (SSVEP) to finish navigation tasks in Virtual and Augmented Realities. Motor imagery is also processed by BCI and combined with eye-tracking to select content and objects [10]. Positions and movements of both eyes can be detected by cameras (binocular eye-tracking). An image processing software then recognizes the position of the pupils and thus conveys conclusions about the direction of view (gaze) and focus.

B. *Eye-tracking*

Virtual Reality applications use such information mainly for foveated rendering or foveated imaging [11]. This allows to preserve valuable resources, such as computing power and energy consumption [12]. Eye-tracking in Augmented Realities is used to determine the user's attention and to guide the user through the application purposefully [13]. In addition, patterns of eye movements can be interpreted and supported, for example while reading [14]. Further areas of using the information of eye positioning and movement are spatial navigation, menu control or authentic depth blurring in 3D and light-fields. Also conceivable is the verification of embedded hints or warning alerts by monitoring gazing and length of stay.

At present, only conventional camera-based eye-tracking systems are used. However, due to the technical conditions, these systems can only be conditionally integrated into Head-Mounted Devices. Infrared diodes and camera technology can only be positioned directly at or below the eye, which forces a wider mounting depth of the displays. Additional to the increasing weight and power consumption, this construction also develops heat, which has to be exhausted and a cooling system has to be provided. This is a main problem on closed HMDs, such as VR goggles. Therefore, an eye-tracking system has to be developed which is not based on camera technology, but is equally measurable and can be installed more flexibly in HMDs.

C. *EOG and Ocular Artefacts in EEG*

The principle of electrooculography (EOG) - and thus the ocular artefacts in the EEG signal - is based on the electric dipole of the eyeball (bulb), in which the cornea is positively and the retina negatively charged (corneo-retinal standing potential, Fig. 1). The electric field, which can be measured by electrodes around the eye, changes by the movement of the bulb [15]. The voltage for horizontal and vertical eye movements is 16μV respectively 14μV per one degree of gaze angle and is nearly linear for the entire viewing range of ± 50° horizontally and ± 30° vertically [16].

In the past, the EOG signal has only been exploited in niche areas. Kumar et al. [17] used the EOG signal to control applications by means of eye movements. Similarly, Yamagishi et al. [18] detect horizontal and vertical eye movements to control writing aids. However, they focused on people with physical limitations and used electrode positions above and below the eyes to record the signal.

In electroencephalography, ocular artefacts are used to diagnose sleep phases for clinical and physiological purposes. Thus, Mohammadie et al. [19] used the EOG components in the EEG signal to distinguish rapid eye movement (REM), non-rapid eye movement (NREM), and awake status. Outside of sleep research, ocular artefacts are seen as interfering signals, that adversely affect brain activity studies [20].

EOG signals are also perceived as interfering signals in Brain-Computer technologies. Maddirala et al. [21] used combined techniques to remove ocular artefacts from the EEG signal. However, ocular artefacts in the EEG signals have to the knowledge of the authors never been used to control applications (BCI).

III. METHODOLOGY AND RESEARCH QUESTION

At the core of our approach lies the insight that an electroencephalogram not only captures brain activities of thought, expectations and emotions. Rather, these values are superimposed by other signals, for instance from power networks, radio waves or light flashes. In addition to such external factors, the EEG also captures internal factors. In particular, these can be the movement of one’s nose, mouth throat, one’s heartbeat or the movement of one’s eyes.

In a first experiment, extreme positions of the eyes are analyzed in horizontal (left, right) and vertical (top, bottom) as well as neutral (centered) direction. Extreme eye positions, which have to be consciously executed, can then be used to switch binary states. The approach of this research work is to determine, whether EOG can be extracted from the EEG and whether the extracted signal correlates with the position of the eyes.

A second contribution are the findings of electrooculography, where eye movements are measured via electrodes directly next to the eyes on the nose, forehead and temple. The subsequently analyzed electrical potential, which is also the cause of the ocular artefacts in the EEG signal, provides information about the position and movement of the eye. This method approximates the accuracy of camera-assisted systems and is mainly used in medical applications.

Brain-Computer Interfaces use EEG signals to control applications. The respective processing pipeline steps through five stages: It starts with the data acquisition, leads to the classification (machine learning) via filtering and feature

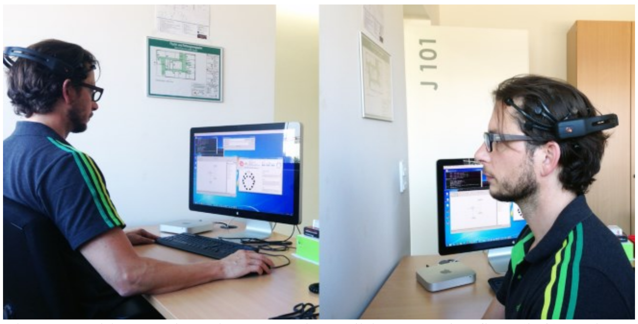

Fig. 2. Subject and environmental conditions on the first (left) and seccond (right) session.

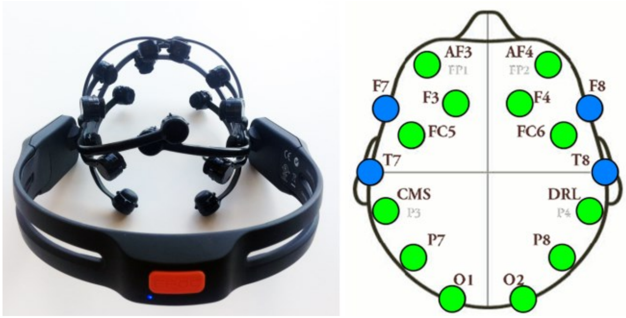

Fig. 3. EEG-headset Emotiv EPOC (left) and its electrodes positions (right).

evaluation and arrives at controlling the application. An evaluation of the application feedback might enforce an improvement of one or any of those steps.

IV. MATERIAL AND METHOD

A. *Subjects and Environmental Condition*

A single 38 years old male person is engaged in this experiment. He is healthy and had no significant head injuries or brain surgery in the past. There is a slight visual weakness of -1.0 diopters on the left eye and -0.75 diopters on the right eye. A pair of glasses is worn during the experiment.

The test environment is a room at daylight with a large window measuring 1.25m x 3.00m (height x width) at the back of the workplace. Placed on an office desk with a height of 72cm is a 27-inch monitor, the display center point of which is 30cm from the table top. To the left of the monitor is an Apple Mac Mini as a computing unit, to the right an IP-phone.

The subject is sitting upright and relaxed on an office chair at the workplace in front of the monitor, the head tilted slightly downwards so that the distance from face to monitor is about 70cm and the eyes look at a height of about 40cm from the table. This corresponds to a viewpoint of 10cm above the monitor center. In the second recording situation, the subject is at the same place, but turns 90 degrees to the left and looks at a white wall at a distance of 40cm with the head straight forward (Fig. 2).

B. *Experimental Design*

In the first session results of four different gaze targets are captured: Right, left up, down are displayed in a given sequence. After the subject has positioned himself, he starts the recording with a mouse click. At the same time, he observes the session, which is displayed directly in the central view field. After the start, he waits for two seconds, looking at the screen's center to record a baseline. Then the eyes are moved as fast and far (full swing) as possible to the appropriate direction. After one second, the eyes quickly return to the central starting position. Finally, two seconds later, the recording is stopped. This procedure is repeated ten times per action, which results in 40 recordings.

Two other actions (straight-ahead and closed eyes) will be included in a second session on another day, but under the same conditions. This time, a second person (operator) starts and stops the session. The operator waits until the subject has positioned himself and the subject looks straight ahead at the wall without blinking. The operator then starts the recording. After five seconds, the recording is stopped and the test person relaxes. The sequence is repeated ten times. After this, ten more records follow, where the subject closes his eyes. He first looks at the wall and closes the eyelids. Only then the recording is started. Meanwhile, the test person does not try to move or twitch his eyes. A total of 20 additional data records are created.

C. *Experimental Devices and Data Recording*

An Emotiv EPOC (Fig. 3, left) is available for data acquisition. It has 14 non-invasive wet electrodes (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4) and two reference electrodes (CMS, DRL). All electrodes are applied to the frontal, temporal and occipital cortex according to the international 10-20 system (Fig. 3, right). The integrated acceleration sensor is not used. The EEG device operates with an internal sampling rate of 2048Hz and a resolution of 14Bit. Before the transmission, the EEG signal is sampled down to 128Hz and then transmitted via Bluetooth to a USB dongle, which is connected to the recording computer.

The Emotive Control Panel software ensures that the Emotive EPOC is connected to the computer, the signal strength is sufficient and all the electrodes are in good contact. The RAW signal is recorded with the OpenSource software OpenViBE. For this purpose, the OpenViBE Acquisition Server v1.1.0 is started with the driver for the Emotive EPOC, the connection port 1024 selected and a number of 32 samples per block is sent. All data from the 14 channels are stored in a CSV file and the electroencephalogram is displayed simultaneously by means of a display window.

D. *Pre-processing and Filtering*

Each of the ten records of a specific gazing direction (e.g. to the right) are imported individually into MATLAB 2016a via its import wizard and grouped into matrices of the type Number. Subsequently, the vectors are shortened to the smallest common length, since not all records could be

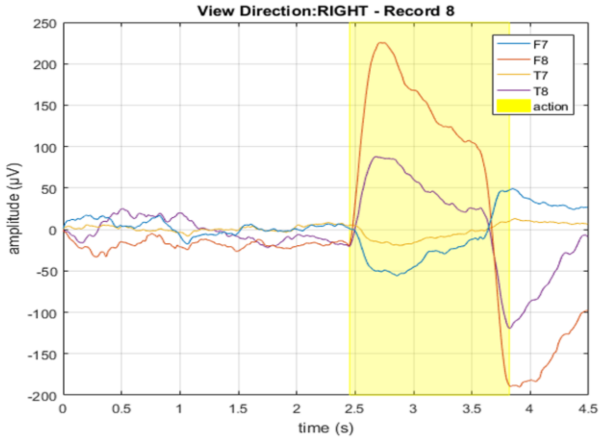

Fig. 4. Example of a pre-processed time signal of the four electrodes F7, F8, T7 and T8 of the eighth record gazing to the right. The yellow area marks the time, when the user moved quickly the eyes to the extreme right position and after one second back to the center.

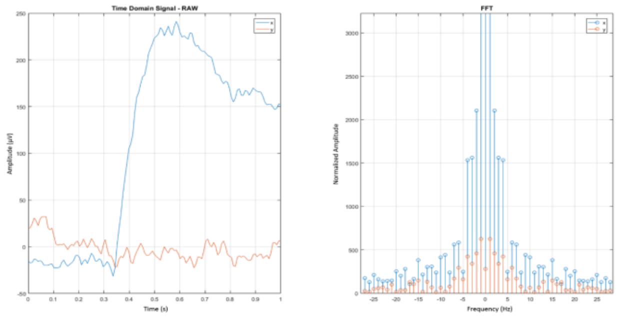

Fig. 5. Time signal (left) and frequency spectrum (right) of a centered gaze (red, y) and an extreme eye position (blue, x).

stopped precisely at five seconds. The shortening does not affect the quality of the data, because the most important data, i.e. the movement of the eye, does not occur at the end of the recording during the first recording sequence and the second recording sequence is a continuous viewing direction.

All records are passed through the MATLAB function detrend() to remove continuous linear displacements on the amplitude axis and to normalize the values. Thereafter, a notch filter at 50Hz and a Butterworth low-pass filter with a cut-off frequency at 13Hz and an order of five are applied. In addition, a fast Fourier transform (FFT) is used to analyze the frequency spectrum.

E. Feature Extraction and Classification

The features are extracted manually by viewing the time signals visualized as graphs. We first concentrate on the four measuring points F7, F8, T7 and T8 (Fig. 4), since these points are more likely integrated into HMDs. In a separate vector, the time signals are given a numeric action-ID, namely 0,1,2,3,4,5 and 6 for the viewing directions not defined, right, left, up, down, centered with open eyes and centered with closed eyes.

To prepare the classification, all the selected data sets (vectors) from the feature extraction are combined in a specific and unchanged sequence and the resulting matrix is converted into a table. The classification is done by the MATLAB Classification Learner Toolbox, with the values of the four measuring points F7, F8, T7 and F8 as predictors and

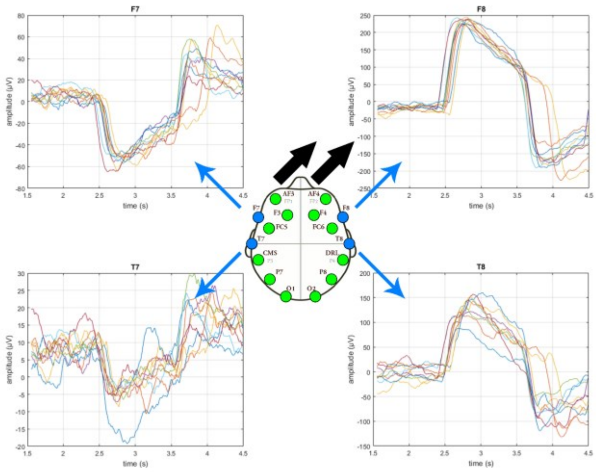

Fig. 6. Overlaying all ten time signals of the electrodes F7, F8, T7 and T8 with the eye position to the extreme right. In this case, the amplitudes on the left hemisphere are negative and on the right hemisphere are positive.

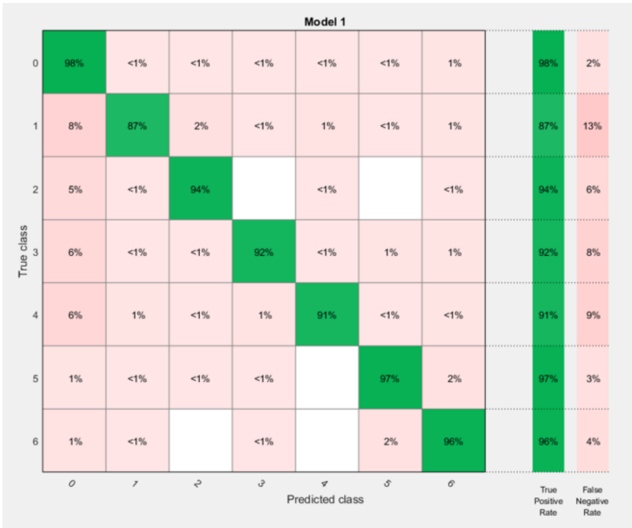

Fig. 7. Confusion matrix of the fine KNN with all data and a holdout of 10% done by the MATLAB 2016a Classification Learner Toolbox.

the action-ID as a response. A total of 156 combinations of classifiers (tree, discriminant, K-Nearest-Neighbor, Ensemble, Support-Vector-Machine), cross validation (2, 5, 10, 15, 20, 30) and holdouts (10%, 20%, 25%) are tested (Table I).

V. Results

The signals show clear negative and positive amplitude deflections, consciously carried out eye movements for the duration of one second (Fig. 4, Fig. 6). They are also clearly recognizable even in the case of poor signal quality, and differ in their characteristics depending on the region of the brain. Measured to the basic potential of the EEG signal, the magnitudes reach values of up to 300µV. The temporal offset of up to 0.5s is due to the reaction time of the subject. The reduction of the records from originally 5.0s to 4.5s is due to data preprocessing.

TABLE I. RESULTS OF TESTED CLASSIFIER SETTINGS

	Classifier	K-Fold						Holdout		
	Type	***2***	***5***	***10***	***15***	***20***	***30***	***10%***	***20%***	***25%***
Tree	Complex Tree	79.6	79.8	80.1	80.0	79.9	80.8	80.9	79.6	79.2
	Medium Tree	70.5	70.2	70.3	70.2	70.2	70.3	69.8	70.1	69.9
	Simple Tree	58.3	58.2	58.2	58.3	58.3	58.3	58.4	58.1	57.9
	Linear Discriminant	50.4	50.4	50.4	50.4	50.4	50.4	50.3	50.3	50.3
	Quadratic Discriminant	40.7	40.8	40.8	40.8	40.8	40.9	40.7	40.9	41.5
KNN	Fine KNN	95.3	96.2	96.3	96.3	96.3	96.3	96.6	96.3	96.0
	Medium KNN	90.8	92.8	93.2	93.3	93.4	93.4	93.2	92.8	92.2
	Coarse KNN	82.5	84.3	84.7	84.8	84.9	85.0	85.1	84.0	83.9
	Cosine KNN	85.5	87.3	87.9	88.1	88.2	88.2	87.9	86.7	86.8
	Cubic KNN	90.9	92.8	93.2	93.2	93.4	93.4	93.2	92.7	92.7
	Weighted KNN	94.4	95.2	95.4	95.4	95.5	95.5	95.5	95.3	95.0
Ensemble	Boosted Trees	71.4	71.5	71.2	71.2	71.2	71.2	70.7	70.9	71.2
	Bagged Trees	93.5	94.8	95.1	94.9	95.2	95.1	95.2	94.8	94.6
	Subspace Discriminant	49.7	49.7	49.8	49.5	49.6	49.6	49.1	49.6	49.6
	Subspace KNN	81.5	81.0	80.7	81.0	80.5	80.9	79.4	80.8	78.8
	RUSBoosted Trees	66.2	66.8	66.0	66.5	66.2	66.0	66.2	64.4	65.2
SVM	Linear SVM	-	58.7	-	-	-	-	-	-	58.4
	Quadratic SVM	-	69.5	-	-	-	-	-	-	75.3
	Cubic SVM	-	63.1	-	-	-	-	-	-	38.6
	Fine Gaussian SVM	-	87.3	-	-	-	-	-	-	87.3
	Medium Gaussian SVM	-	79.1	-	-	-	-	-	-	79.2
	Coarse Gaussian SVM	-	62.1	-	-	-	-	-	-	62.7

There is an interesting correlation between the direction of view and the amplitude deflections of the hemispheres. They behave in a binary way. If the view goes to the right, the peak is positive in the right hemisphere and negative in the left hemisphere (Fig. 6), on the look to the left the peaks in the hemispheres are the other way round. If the eyes move up and down, the peaks in both hemispheres are positive respectively negative. So the direction of view can be detected with one measure point on each half of the head only.

Splitting the filtered EEG signal into the individual EEG frequency bands, the main components of the ocular artefacts appear in the range of the low-frequency delta waves from 0Hz to 4Hz. Further signal peaks can be measured in the range of theta waves (4Hz-8Hz) and alpha waves (8Hz-13Hz). This is consistent with the findings from EOG. Correspondingly, the FFT of the data confirms this. There are high values on the low frequencies from 0Hz up to 4Hz and more on the frequency pairs 6Hz/7Hz, 9Hz/10Hz and 12Hz/13Hz (Fig. 7). The very high peak at 0Hz turns out to be a DC offset.

All algorithms of type K-Nearest-Neighbor (KNN) perform well with a positive recognition rate of over 80%. The Fine KNN and a holdout of 10% achieved the highest value of 96.6%. Complex trees, bagged trees and subspace KNN show the same ratio. Among the Support Vector Machines (SVM), the Fine-Gaussian SVM method is at a comparable level with more than 87.3% (Table I). The methods according to the principle of discriminants with a maximum true-positive-rate of 50.4% are unsatisfying. The computing time of the classifiers takes from at least 2s (decision trees, KNN) up to 3.5h (SVM).

Centered eye positions are very well recognized with 97% (open eyes) and 96% (closed eyes). The initial position 0 (not defined), which is also centered, is similarly well predicted at 98%. Horizontal eye movements are correctly classified with 87% (right) and 94% (left), vertical with 92% (up) and 91% (down). Viewing directions against one another are very well distinguished with an error rate of less than 1%. There is a small range false-negative-rate of 5% to 8%, when predicting the eye position 0 (not defined) instead of one of the four extreme eye positions 1 (right), 2 (left), 3 (up) or 4 (down) (Fig. 7). Correspondingly, the area under curve of the receiver operation characteristic curve is 0.97.

VI. DISCUSSION

With regard to prevent noise on the EEG-signal, computers, mobile phones, telephones and other sources should be avoided in the immediate environment. The monitor from the first session also interfered with the EEG signal in the high frequency range (50Hz). It is also necessary to investigate the extent to which the electronics in HMDs affect the EEG signal and how the light of displays affects the ocular artefacts.

A low-pass filter is not suitable, since frequency components are present at 0Hz (DC offset) and 0.5Hz, which are not caused by ocular artefacts. A band-pass filter from 0.5Hz to 13.0Hz seems more appropriate. Due to the necessary rate of change, it is recommended to combine a high-pass filter with a cut-off frequency at 0.25Hz and a low-pass filter with a cut-off frequency at 15.0Hz. Increasing the filter order may cause a temporal shift, which is not usable for real-time applications.

The feature extraction was done by hand, which caused an inaccuracy in detection of the eye position. Thus, the feature extraction has to be automated, e.g. via peak detection or a signal (action-ID) should be provided by the sequence. In addition, the eye positions and eye movements should be monitored and verified by a third-party system (e.g. camera-based eye-tracking). Furthermore, a proportion of undefined states (eye position 0) has to be avoided.

KNN has the best performance. However, KNN does not build classification models, but the classification is done by matching the input data with instances from training data one by one. Neither a windowing nor a batch processing for observing trends was used, which could mitigate overfitting and improve performance. To prevent an overfitting of the classifier, several data sets from different subjects have to be taken and proven by a control group. The consideration of frequency components as well as the first derivation as a trigger can further improve the true-positive rate. Potential time delays of ocular artefacts on different measure points should be analyzed, too.

VII. Conclusion and Further Steps

In this paper, the approach of a new EEG-based eye-tracking System is presented, which is based on the findings of EOG. Experimental results show that extreme eye positions to the left, right, up and down as well as the centered eye position can be detected with four measuring points and a true-positive rate of 96,6%. To distinguish the viewing direction, at least one corresponding measuring point per hemisphere is required, which allows simple and flexible integration in Head-Mounted Devices.

In the future, we want to extend our preliminary tests to large test groups. This will allow us to train generalized classifiers based on potentially diverse data sets. In addition, we want to test the applicability of our new tracking approach under real-time and under different lighting conditions.

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