TO WHAT EXTENT CAN DRY AND WATER-BASED EEG ELECTRODES REPLACE CONDUCTIVE GEL ONES?

A Steady State Visual Evoked Potential Brain-Computer Interface Case Study

Vojkan Mihajlović, Gary Garcia Molina
Brain, Body and Behavior Group, Philips Research, High Tech Campus 34, Eindhoven, The Netherlands
vojkan.mihajlovic@philips.com, gary.garcia@philips.com

Jan Peuscher
Twente Medical Systems International, Zutphenstraat 57, Oldenzaal, The Netherlands
jan.peuscher@tmsi.com

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Abstract: Recent technological advances in the field of skin electrodes and on-body sensors indicate a possibility of having an alternative to the traditionally used conductive gel electrodes for measuring electrical signals of the brain (electroencephalogram, EEG). This paper evaluates whether water-based and dry contact electrode solutions can replace the gel ones. The quality of the obtained signal by three headsets, each using 8 electrodes of a different type, is estimated on the steady state visual evoked potential (SSVEP) brain-computer interface (BCI) use case. The stimuli frequencies in the low (12 to 21Hz) and high (28 to 40Hz) frequency domain were used. Six people, that had different hair length and type, participated in the experiment. SSVEP response in terms of power spectra across different electrodes is compared and the impact of noise on temporal characteristics of the response is discussed. For people with shorter hair style the performance of water-based and dry electrodes comes close to the gel ones in the optimal setting. On average, the classification accuracy of 0.63 for dry and 0.88 for water-based electrodes is achieved, compared to the 0.96 obtained for gel electrodes. The theoretical maximum of the average information transfer rate across participants was 23bpm for dry, 38bpm for water-based and 67bpm for gel electrodes. Furthermore, the convenience level of all three setups was seen as comparable. These results demonstrate that, having optimized headset and electrode design for dry and water-based electrodes for people with different hair length and type, dry and water-based electrodes can replace gel ones in BCIs and Neurofeedback applications where lower communication speed is acceptable.

1 INTRODUCTION

Brain computer interface (BCI) technology has not yet reached wider adoption except for the few cases where it was utilized by severely impaired patients (for a recent review see (Kübler and Birbaumer, 2008)). A number of research groups are trying to bring this technology to a more advanced level, mainly focusing on the most convenient of brain sensing solutions - the electroencephalogram (EEG) - which measures electrical activity of the brain.

Despite numerous advances, both in technological and ergonomic aspects, all three predominant BCI modalities, namely, steady state visual evoked potential (SSVEP), motor imagery (or event related desynchronization / event related synchronization – ERD/ERS), and P300 are still bound to laboratory settings and do not indicate the potential to enter mass markets in coming years. Among the many problems that EEG-based BCI systems face, the most important ones are:

1. Cumbersome and inconvenient procedures to prepare the user before BCI operation, low comfort during the BCI operation, and issues in detaching the system at the end of the usage.
2. Lower accuracy of the BCI command classification algorithms, especially when deployed outside lab conditions, leading to a lower information transfer rate (ITR).
3. Long time required for the user to adapt and learn to use the BCIs, including the time required for the BCI to learn specific user parameters, i.e., long calibration procedure.

4. Unpleasant and intrusive interaction with a BCI system that results in users being aversive to the use of BCIs.
5. High number of users that cannot learn to use the BCI, i.e., a so-called BCI illiteracy.

While the first problem is common to all BCIs, except that the number and positioning of electrodes used in a particular system can change, the latter ones have different impact depending on the BCI modality. In addressing these problems, we consider the SSVEP BCI as a promising solution because, when compared to other BCIs, it can provide high level of detection accuracy (i.e., high ITR), requires short calibration time, and has low BCI illiteracy (Cheng et al., 2002; Garcia-Molina et al., 2010).

The steady state visual evoked potential (SSVEP) refers to the response of the cerebral cortex to a repetitive visual stimulus (RVS) oscillating at a constant stimulation frequency. The SSVEP manifests as peaks at the stimulation frequency and/or harmonics in the power spectral density (PSD) of EEG signals (Regan, 1989). Because of their proximity to the primary visual cortex, the occipital EEG sites exhibit a stronger SSVEP response. SSVEP based BCIs operate by presenting the user with a set of repetitive visual stimuli (RVSi). In most of current implementations, the RVSi are distinguished from each other by their stimulation frequency (Gao et al., 2003; Lalor et al., 2005; Friman et al., 2007; Garcia-Molina and Mihajlović, 2010). The SSVEP corresponding to the RVS receiving user's attention is more prominent and can be detected in the ongoing EEG. Each RVS is associated with an action or a command which is executed by the BCI when the corresponding SSVEP response is detected.

The majority of current SSVEP-based BCIs use stimulation frequencies in the 4 to 30Hz frequency range (Zhu et al., 2010). RVS at these frequencies, as compared to higher frequencies, have several disadvantages that underpin the fourth problem defined previously: they are prone to visual fatigue which decreases the SSVEP strength, they entail a higher risk of photic or pattern induced epileptic seizure (Fisher et al., 2005), and they overlap with the frequency bands of spontaneous brain activity. Higher stimulation frequencies are, thus, preferable for the sake of safety and comfort of the BCI user (Garcia-Molina et al., 2010).

The major aspect addressed in this paper is the first problem of the inconvenient and uncomfortable preparation, usage, and detachment of a BCI. This problem stems from the fact that EEG recording procedures remained very similar than that of the early EEG days. The EEG is recorded using Ag/AgCl electrodes that are in contact with the skin (i.e., scalp) through electrolytic gel (Webster, 1997). The electrolyte performs dual task, it bridges the ionic current flow from the scalp and the electron flow in the Ag/AgCl electrode and 'glues' the electrode to the scalp. To further improve signal quality the scalp is frequently cleaned and, especially in clinical applications, skin on the scalp is abraded.

The abrasion process, as well as the usage of conductive gel (electrolyte) makes the whole EEG setup inconvenient for practical application, especially for consumer applications. The application of electrolyte and the electrodes, even when typical EEG caps are used, cannot be performed by a user, requiring expert assistance. The setup process is lengthy as it includes preparing the skin, applying the gel, positioning the electrodes (or the cap) and ensuring that the EEG signal quality level is acceptable. Additionally, the user (or expert) has to remove the electrolyte and clean the user's head afterwards, and also clean and dry the electrodes (and the cap) that were used. This also takes time and requires additional effort. This paper aims at addressing these issues, focusing on two alternative solutions, water-based and dry contact electrodes. It also addresses the issue of safe interaction in BCI applications using the high frequency RVSi.

The paper is organized as follows. An overview of the alternative approaches for EEG acquisition systems in BCI is given in the next section. Section 3 details the setups for measuring EEG, using dry, water-based, and gel electrodes. The methods we used to evaluate the quality of the obtained signal in SSVEP BCI domain are also detailed in Section 3. Evaluation of the three setups with respect to signal quality is presented in Section 4. This section starts with the evaluation of baseline classification approaches and then investigates the impact of noise on the classification accuracy achieved with different electrode types, and the usefulness of first harmonics. Section 5 addresses the potential practical application of water-based and dry electrodes in SSVEP BCIs, focusing on the impact of stimuli duration, replacing the conductive gel ground electrode with the dry or water-based one, and looking into convenience and comfort level of used setups. Results of the evaluation are discussed in Section 6. Section 7 concludes the paper.

2 EEG ACQUISITION SYSTEMS IN BCI: OVERVIEW

Few research laboratories realized the problem of cumbersome EEG acquisitions systems and engaged in developing more convenient techniques for acquiring brain signals. The approaches range from developing hydrogel-based electrode (Alba et al., 2010) to numerous versions of dry electrodes. Dry electrode solutions include electrodes that are integrated into the wearable material (contactless electrodes) or affixed on top of the scalp (insulated electrodes) (Alizadeh-Taheri et al., 1996; Harland et al., 2002; von Ellenreider et al., 2006; Sullivan et al., 2007; Fonseca et al., 2007; Chi et al., 2009), electrodes that penetrate the outer layer of the skin (Ruffini et al., 2006; Ruffini et al., 2008; Griss et al., 2002; Gramatica et al., 2006; Chiou et al., 2006; Matteucci et al., 2007; Lin et al., 2008; Chang and Chiou, 2009; Ng et al., 2009; Dias et al., 2010), and dry contact electrodes that exhibit galvanic contact to the skin without the usage of additional electrolyte (Taheri et al., 1994; Matthews et al., 2007; Gargiulo et al., 2010). Due to skin damage they can cause, users might be exposed to a higher risk of infection and skin irritation (Ferree et al., 2001) for all dry electrode types except the last one – dry contact electrodes. That is why we consider dry contact electrodes as the desired technology for convenient BCIs.

Addressing the SSVEP BCI field, in a recent publication (Volosyak et al., 2010), a successful BCI application of electrodes that use cotton soaked in water to replace the conductive gel is demonstrated. User investigation confirmed that so called 'water-based' electrodes are preferred over gel-based ones, and that no significant performance drop is reported. Also, several papers addressed the usage of dry contact electrodes for acquiring brain signal for SSVEP BCI applications (Popescu et al., 2007; Sellers et al., 2009; Luo and Sullivan, 2010).

Despite the advances in convenient (SSVEP) BCIs, to the best of our knowledge, none of the research publications have systematically characterized the performance of the new BCI acquisition systems in terms of signal quality in different electrodes, and the impact of signal quality, electrode selection, and classification algorithm parameters on the accuracy and ITR of the SSVEP BCI system. Furthermore, the impact of variety of users, having a different hair length and type on the signal quality is often omitted. In this paper we explore how headset setups using dry contact electrodes, water-based electrodes (replicated setup from (Volosyak et al., 2010)), and conductive gel electrodes compare to each other considering above mentioned aspects. We also evaluate the convenience levels for the end users, as well as the time required for preparing participants for the experiment.

We believe that robust BCI systems with dry and water-based electrode solutions would greatly simplify the usage, increase acceptance by users in certain clinical applications, and enable wider adoption of BCIs in consumer applications. Therefore, we emphasize the importance of a *practical EEG signal acquisition system* which does not require expert assistance, can be setup and removed by the user himself in a short period of time, and is designed to be ergonomic, convenient, unobtrusive, and comfortable during the measurement process.

3 MATERIALS AND METHODS

In this section we present the brain signal acquisition technology consisting of an EEG signal amplifier and three different electrode setups, followed by presenting the details of the study design, data processing, and evaluation methods.

3.1 Amplifier technology and data acquisition

The EEG data was recorded using the Twente Medical Systems International (TMSi) Porti system with 24 EEG channels. The Porti uses bipolar amplifier technology that amplifies the difference of the two inputs (so-called instrumentation amplifier technology) with a gain of 20 and includes a common mode rejection in the second stage of amplification. This technology prevents the issues caused by different gain in operation amplifiers and amplifies the input signal against the average reference of the incoming signals, i.e., the common mode signal. The common mode range is -2V to 2V, and the common mode rejection ratio is higher than 100db.

The Porti is used in a battery powered mode and it was connected to a PC via an optical cable. The highest possible sample rate of 2kHz was used (bit rate of 7.168Mbit/s). As the Porti system requirements include the usage of shielded cables for EEG electrodes and ground electrode with low impedance ($< 1\text{k}\Omega$), we used shielded cables for all electrodes and gel electrode as a ground for all three setups.

3.2 EEG setups with three different electrode types

For all three setups we used 8 electrodes positioned at the occipital and parietal sites where the SSVEP exhibits the strongest response. The 8 electrode locations selected were O1, O2, Oz, PO3, PO4, POz, P1, and P2, according to the International 10-20 System. For all setups (except two configurations discussed in

(a) (b) (c)

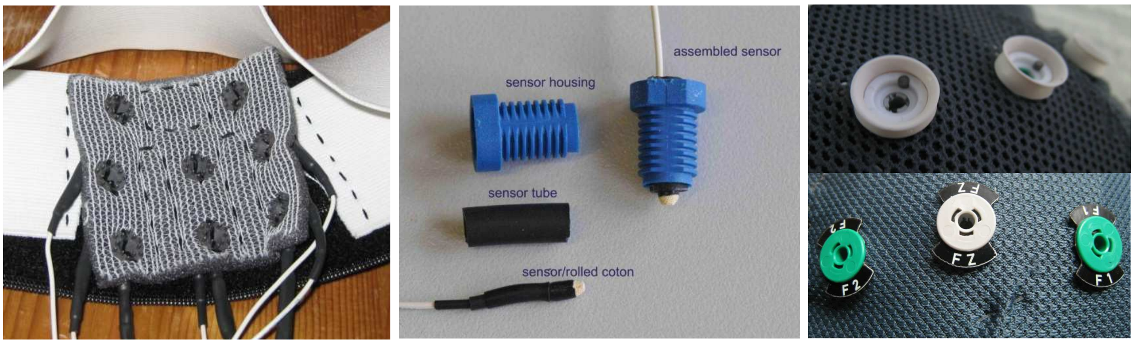

Figure 1: EEG setups: a) Dry contact electrodes with pins integrated in the EEG headband; b) A water-based electrode and its components; c) Inner and outer side of the head cap with electrodes that need to be filled with conductive gel.

Section 5) conductive gel ground electrode was positioned at the participants right collar bone.

The dry electrode setup is constructed using 8 commercially available sintered Ag/AgCl ring electrodes (with 10mm outer and 5mm inner diameter) that have twelve 2mm long rigid pins. These electrodes are attached to a soft textile patch which is connected to the elastic head band using six Velcro straps, three at each side, as depicted in Figure 1a. Velcro straps are used to accommodate for head sizes and head shapes of different participants. The electrodes are connected using shielded cables to the TMSi Porti acquisition system. The setup is mounted on a participant's head similarly as a normal headband. To the best of our knowledge this is the first 'easy-to-mount' EEG setup with multitude of dry contact electrodes aimed at measuring SSVEP response. The first evaluation of the performance of this setup is described in the paper.

For water-based setup we used electrodes that require tap water instead of electrolytic gel. These electrodes are developed within the framework of BRAIN project and first tests are reported in (Volosyak et al., 2010). They are made from a silver-chloride pallet and rolled up cotton, as shown in Figure 1b, and are connected to the Porti system via shielded cables. Commercially available EEG head cap with the screwing mechanism was used to position the water-based sensors on the head.

The setup for measuring brain signals using conductive gel was prepared using a standard 32 channel head cap (depicted in Figure 1c) for the usage with the TMSi Porti EEG acquisition system. Shielded cables were also used as in the case of dry and water-based electrodes. From the 32 channels only the 8 selected channels were filled with conductive gel (Signa gel from Parker Laboratories). In the preparation step we did not used any skin abrasion or clean up procedure in order to reproduce as closely as possible the setup in daily life applications.

3.3 Methods

This section describes the design of the experimental evaluation, the algorithms we used for handling artifacts, the estimation of the magnitude of the SSVEP response, and the manner in which we estimated the performance and comfort of different setups.

3.3.1 Study design

Six participants (4 males and 2 females) aged 24, 26, 28, 29, 31, and 32, were recruited for the experiment. Participants were selected to cover the hair characteristics ranging from short, sparse, and thin hair, to long, dense, and thick hair. The participants were informed about the experiment and they all signed an informed consent before the start of the study. Special emphasis was put on verifying that the participants did not had any history of epileptogenic episodes or discomforts due to the exposure to oscillating light. For their participation in the experiment participants received a small reward.

Experiment was performed in a laboratory where only artificial light was present (the light screens were closed). The room was not specially shielded or controlled against environmental noise (to resemble real-life situation). Participants sat in a comfortable chair, at a distance of roughly 60cm from the screen. The RVS was rendered using an LED panel with 4 LEDs positioned at its corners, measuring 25cm on the diagonal. The LEDs were switched on and off simultaneously. The experimenter had an extensive experience in EEG measurement and analysis.

The study comprised two sessions per participant. Each session lasted for about two hours and consisted of a preparation segment, dry electrode evaluation segment, water-based electrode evaluation segment, gel electrode evaluation segment, and debriefing segment. The order of evaluation segments was chosen to enable testing of all three setups in a single session. Having to remove the gel after the usage of gel electrodes, or to dry the hair after the usage of water-based electrodes in a different order of segments, would make the study design more complex and lengthy. Also this stresses further the impracticality of especially gel solutions for daily applications.

During the preparation segment the procedure was explained to the participants and the three setups were shown to them. The participants then filled in the questionnaire expressing their perception of different electrode types and EEG acquisition systems that will be used in the investigation. This procedure was only done during the first session.

Dry electrode evaluation segment consisted of positioning the textile patch with dry electrodes on participant's head. The experimenter visually inspected the EEG signal quality (high-pass filtered at 1Hz) and in case of no signal, larger impact of noise, and/or severe presence of artifacts in some of the channels, the headband was adjusted to improve the contact and achieve better EEG signal quality level. A chronometer was used to record the time required for this activity. Then the EEG signal was recorded while the participant was focusing on one of the 4 LEDs oscillating at 28, 32, 36, and 40Hz in one of the runs and 12, 15, 18, and 21Hz in the other run. The order of these runs was randomly selected for both sessions. This procedure was repeated for all 4 frequencies per run, each having segments of 5 seconds where LEDs were switched on, interspersed with segments of 4-6 seconds (randomized) where LEDs were switched off. The participants were instructed not to blink during the segments while the LEDs were on. The recorded EEG data, sampled at 2048Hz, for all frequencies were stored. At the end of this segment the headband with electrodes was removed.

For the water-based electrode evaluation segment, the experimenter soaked the water-based electrodes into the cup with tap water 5-10 minutes before the start of the setup. The setup consisted in positioning the EEG cap on a participants head and attaching the water-based electrodes to the EEG cap. In case the signal quality was not good enough according to the experimenter, more water was added to some of the electrodes and/or the electrode positioning was adjusted. The time required to perform this procedure was recorded (excluding the time required to water the electrode before the setup procedure). Then the EEG signal was recorded in two runs, the same way as explained in the previous paragraph for the dry electrodes. After the recording the head cap and the electrodes were removed.

For the gel electrode evaluation segment, the experimenter positioned the EEG cap on a participants head and filled the holes (electrodes) in the cap with conductive gel. The experimenter controlled the EEG signal quality and if needed added more gel to improve the contact and achieve desired EEG signal quality level. This activity was also timed. Then the EEG signal was recorded in the two runs, the same way as for water-based and dry electrodes. After the recording, the EEG cap was removed from the participants head. On completion of this session, a hair wash coupon was given to the participant.

In the debriefing segment (only at the end of the second session) participants had to fill in a questionnaire about their experience with the different electrode types and mounting systems. They were also encouraged to give general comments on the setups and the study design.

3.3.2 Signal analysis

In the SSVEP BCI framework, the goal of signal processing methods is to detect the presence of an SSVEP at a given stimulation frequency in the EEG. In general, the problem consists of deciding if within a certain time window, the attention of the subject on an RVS has been sufficient to elicit an SSVEP response. The main challenge is to avoid the impact of various artifacts on the SSVEP, as well as the selection of the best components (e.g., electrodes, temporal segments) that contribute the most in the SSVEP response. These two aspect correspond to artifact handling methods and algorithms for optimal SSVEP detection.

To minimize the impact of severe artifacts, expected when using dry (and water-based) electrodes, we employed an algorithm for rejecting epochs with artifacts. We selected the epoch duration of 1s with 75% overlap. The algorithm excluded the epochs where the absolute amplitude peak inside the epoch was larger than the empirically selected threshold. The thresholds were estimated based on the standard deviation within the recorded segment. We used a numeric value that is 5 times larger than the standard deviation of the signal in each electrode. Such threshold was used for all three electrode types. In addition, the standard deviation of the recording was used in estimating the level of noise in a particular channel (see Section 4).

The strength of SSVEP can be estimated using various methods, ranging from univariate based power spectral density (PSD) estimation to the use of multivariate spatial filtering (Zhu et al., 2010). Since our intention was to compare the SSVEP strength measured with different electrode setups and to infer the difference in performance we employed the simplest method of PSD estimation using the Welch al-

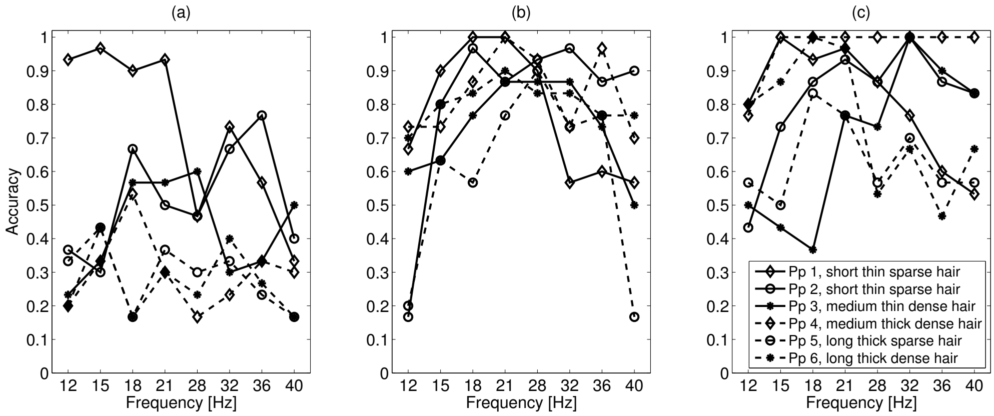

Figure 2: Classification accuracy for three different setups with 6 participants (Pp 1 to Pp 6)) when using PSD at the occipital sites (i.e., O1, O2, and Oz): a) Dry contact electrodes; b) Water-based electrodes c) Conductive gel electrodes.

gorithm (Welch, 1967), which also provided us with easily traceable and interpretable results. The PSD was estimated on one-second long epochs with 75% overlap (that do not contain artifacts). For selecting the best channels, the absolute PSD value across the 1 to 40Hz frequency spectra is used to estimate the presence of (white) noise in the EEG (see Section 4).

3.3.3 Evaluation protocol

BCI performance is usually assessed in terms of classification accuracy, classification speed, and the number of available choices. In SSVEP-based BCIs, the classification accuracy is primarily influenced by the strength of the SSVEP response, the signal-to-noise ratio (SNR), and the differences in the properties of the stimuli. That is why we focus on reporting the accuracy of three setups. As the classification speed depends on the time it takes for the SSVEP to be of sufficient strength, we also report the information transfer rate (ITR). ITR is estimated using the approach detailed in (Dornhege et al., 2007).

In addition to the bit rate, it is also important to consider the safety and comfort of SSVEP-based BCIs. That is why participants had to rate the comfort level of each of the setups, and provide additional information on whether and under what circumstances would they use a particular setup.

4 SIGNAL QUALITY AND PERFORMANCE

This section discusses the performance of dry, water-based, and gel-based setups considering the presence of noise in the EEG signal, usage of harmonics, and the optimal selection of electrodes.

4.1 Baseline performance and the presence of noise

4.1.1 Accuracy when using occipital electrodes

We expected that the SSVEP response is strongest in the occipital sites and therefore as a baseline measurement we selected three electrodes at occipital sites, namely, O1, O2, and Oz. Figure 2 depicts the classification accuracy when maximum PSD in these electrodes is used for each of the participants and for each of the setups. The accuracy for dry electrodes (Figure 2a) is rather low, ranging from the chance level, i.e., 25% for participants with long and/or thick hair (Participant 4, 5, and 6) to more than 50% for participants with shorter and/or tinner hair (Participant 1, 2, and 3). These baseline results demonstrate at the first stage of our analysis the problem of measuring the SSVEP response, and EEG in general, using dry electrodes with people with long and thick hair.

The detection of 12Hz response shows to be a challenge for water-based and gel electrodes, as illustrated in Figure 2b and Figure 2c. This demonstrates the problem of distinguishing the changes in the alpha power domain due to the overlap with the dominant alpha frequency. Similar issues can be seen with the 40Hz response, which is mainly due to the decrease in the SSVEP strength at the very high frequency.

As expected, the overall performance of the water-based electrodes was much higher than for the dry electrodes. The surprising result was that the overall accuracy obtained with gel electrodes was comparable to the one obtained with water-based ones. Although this coincides with the results obtained in (Volosyak et al., 2010), as we did not used any advanced algorithm for SSVEP response estimation, these results were unexpected. To better understand

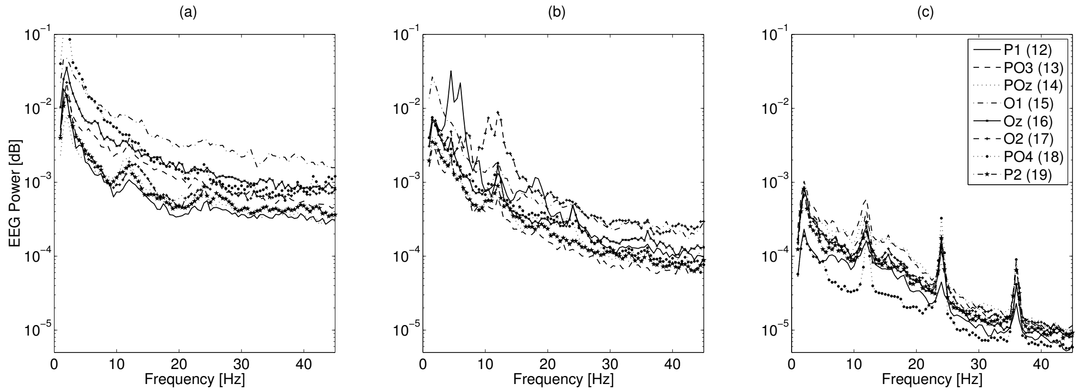

Figure 3: Spectral power across 8 electrodes for different setups measured for Participant 6 (second run) when he was attending 12Hz RVS: a) Dry contact electrodes; b) Water-based electrodes c) Conductive gel electrodes.

these results we analyzed the impact of noise on the signal, and the signal quality in different electrodes.

4.1.2 Spectral content across electrode types and positions

By comparing the raw signal and the power spectra obtained within different EEG channels we observed the following (also illustrated in Figure 3):

1. The noise component in the EEG signal, being environmental or physiological, can be observed for all setups.
2. The severity of noise contribution in the signal and the number of EEG channels contaminated by the noise is higher for the dry setup than the water-based setup, and for the water-based than the gel setup.
3. The impact of noise per electrode can vary throughout a single recording session and it is differs for different recording sessions.
4. In most cases, the higher the level of noise in an EEG channel, the lower the SSVEP response.

The first observation can be explained by the environment which was not specially shielded for such kind of experiment and was contaminated by electromagnetic waves coming from the environment. Also, motion artifacts stemming from muscle tension and head and body movements were present, due to the lengthy recording procedure. The second observation was expected due to the type of the skin-electrode contact. The third one was not expected for gel electrodes, although it can be partially explained by the fast preparation procedure that did not include skin cleaning and de-greasing before the measurement. It was expected for water-based and especially dry electrodes. Finally, the last observation was a learning point for us and we wanted to incorporate this fact in devising the electrode selection algorithm that will improve the accuracy levels obtained with different setups, as explained below.

4.2 The impact of noise estimation on the electrode selection

To estimate the noise level in the signal, we used two simple approaches. The first one was based on the standard deviation (STD) of each channel, i.e., we assumed that the lower the STD in the channel, the lower the noise. The second one used the amount of white noise in each channel, estimated in the frequency range of 1Hz to 40Hz. In both cases the estimations were performed using the EEG segments where stimulation was not presented. To keep the results comparable to the baseline ones in terms of the number of electrodes, we used the 3 electrodes with the lowest noise. The comparison of the achieved accuracy is depicted in Figure 4. The figure clearly illustrates the benefits of using the channels with the lowest noise for dry and gel electrodes, irrespective of the approach used for noise estimation. The effect for water-based electrodes is not so pronounced.

4.3 SSVEP discrimination power and electrode selection

The second feature that we explored for optimal electrode selection was the discrimination level of the PSD of the RVS during the stimuli period versus PSD of the RVS during the non-stimuli period. For each stimuli period we selected the three electrodes with the higher discrimination power for all 4 stimuli. The extent to which this approach compares to the baseline and noise estimation approaches is also depicted

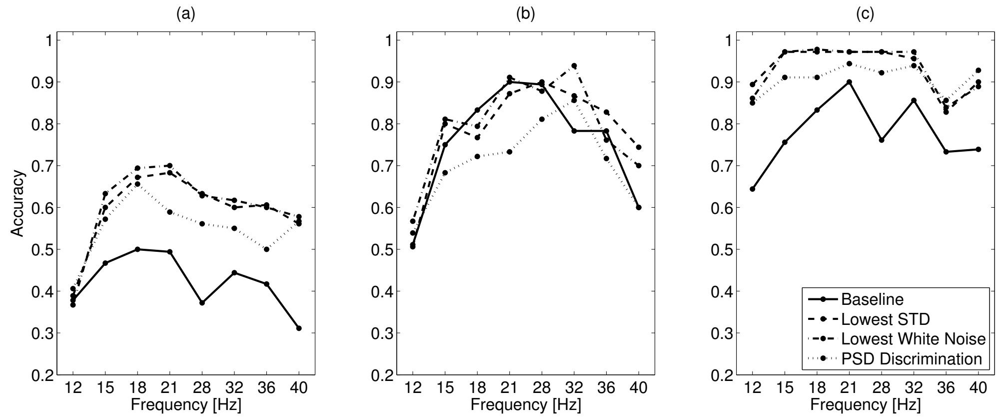

Figure 4: Classification accuracy for three setups with the optimal selection of 3 electrodes for PSD computation: a) Dry contact electrodes; b) Water-based electrodes c) Conductive gel electrodes.

in Figure 4. Although it outperformed baseline results for dry and gel electrodes, the accuracy was lower than for the noise estimation approaches across all three setups and even lower than the baseline run for the water-based setup (see Figure 4b). Consequently, we infer that for the optimal electrode selection it is of high importance to select the EEG channels that have the lowest impact of noise in order to make a good estimation of the SSVEP power. That is why for the rest of the paper we use the optimal selection of electrodes with the lowest white noise component.

4.4 Usage of first harmonics

Figure 5 illustrates the effect of using first harmonics in the noise estimation as well as PSD estimation on classification accuracy. For dry electrodes, significant increase was observed only for the high frequencies, while the improvements of accuracy are significant for both low and high frequencies of water-based and gel setups. With the use of harmonics, the mean accuracy across subjects can be increased to more than 60% for dry setup (except for 12Hz stimuli frequency), to more than 70% accuracy for water-based electrodes, and to more than 88% accuracy for gel electrodes.

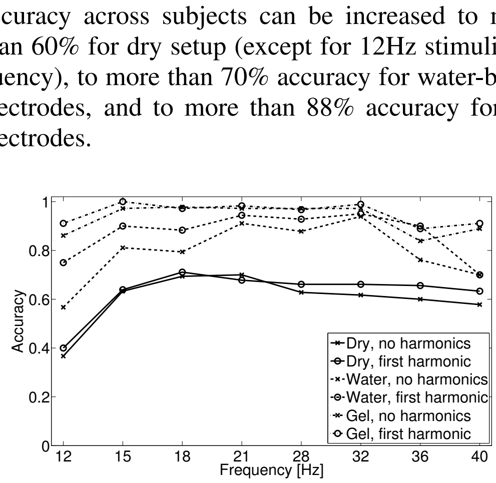

Figure 5: The effect of the usage of first harmonics on the classification accuracy across three different setups.

4.5 The impact of the number of electrodes on the performance

So far in the analysis we have used 3 electrodes as we reckoned that this number would be sufficient to achieve good SSVEP detection performance. To test this hypothesis and to investigate the impact of the number of electrodes used in the analysis, we applied PSD-based algorithm (that uses harmonics) to the cases of one to eight electrodes. The results are illustrated in Figure 6. The figure shows that on average the accuracy is stable across all setups, if 3 to 6 electrodes were used. Also the accuracy level when using 2 electrodes is not much lower indicating that even a setup with 2 dry (or water-based) electrodes with a low noise contamination might be sufficient for SSVEP classification, as also shown in (Luo and Sullivan, 2010; Garcia-Molina and Zhu, 2011).

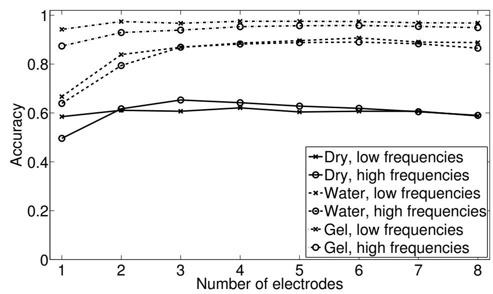

Figure 6: The effect of the number of electrodes used in the PSD computation on classification accuracy across three different setups in the low and high frequency domain.

5 PRACTICAL APPLICATION

This section illustrates the potential of applying the presented setups in the real life situations. The effect of stimuli duration on the classification rate is addressed in terms of finding the highest ITR. Then, the impact of replacing the conductive gel ground electrode with the dry and water-based one is demonstrated. The section finishes with the discussion on user comfort, convenience and time required to prepare different setups for practical use.

5.1 Stimuli duration and ITR

The increase of average accuracy across three setups when using longer stimuli duration times is illustrated in Figure 7. In contrast to our expectation, the decrease of accuracy was minor when shortening the stimuli period from 5s to 3s and not so steep from 3s to 0.75s. This resulted in very high theoretical bit rates (shown in Figure 8), going up to 26bpm (1s stimuli duration) for low frequencies and 21bpm (0.875s stimuli duration) for high frequencies with dry setup, 41bpm (1.5s stimuli duration) for low frequencies and 40bpm (0.875s stimuli duration) for high frequencies with water-based setup, and 69bpm (1.125s stimuli duration) for low frequencies and 65bpm (1.125s stimuli duration) for high frequencies with gel setup.

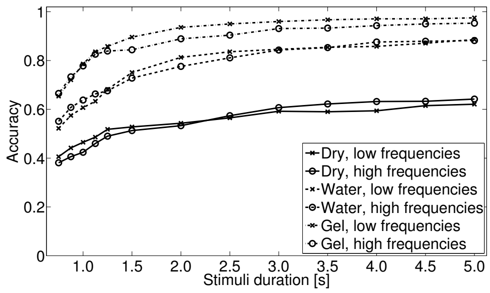

Figure 7: Average classification accuracy across three different setups in the low and high frequency domain having stimuli duration ranging from 0.75s to 5s.

Although this transfer rates cannot be achieved in practice due to the time required for a person to refocus from one stimuli to the other, this result indicate that even with the technology such as dry or water-based electrodes, quite good communication speed can be reached, i.e., 23bpm for dry and 38bpm for water-based electrodes, when averaged over low and high frequency bands. Furthermore, the decrease of the ITR in high frequency range is only minor compared to the low frequency range ITR.

5.2 Using dry and water-based electrode as a ground

To test whether we can design a complete EEG acquisition system using dry or water-based electrodes

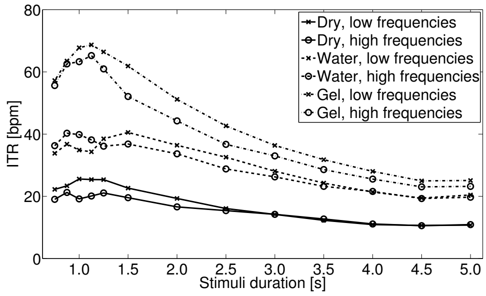

Figure 8: ITRs across three different setups in the low and high frequency domain having stimuli duration ranging from 0.75s to 5s.

we performed additional experiments with Participant 1 where we replaced the conductive gel ground electrode with the dry or water-based one, respectively. The comparison of classification accuracy using different stimuli duration for dry electrode setup is shown in Figure 9. The figure illustrates that the accuracy when using gel and dry electrodes as a ground is almost the same for both, low and high frequencies. Moreover, for this participant (short thin hair), the accuracy is higher than the 90% leading to the maximum theoretical bitrate of 86bpm (1s stimuli duration) for low and 65bpm for high frequencies (1.25s stimuli duration). Similarly, Figure 10 illustrates the comparison of water-based setups when using gel and water-based electrode as a ground. In this case, the usage of water-based ground electrode results in improved accuracy, leading to bitrates of 88bpm (1.25s stimuli duration) for low and 61bpm (1.125s stimuli duration) for high frequencies.

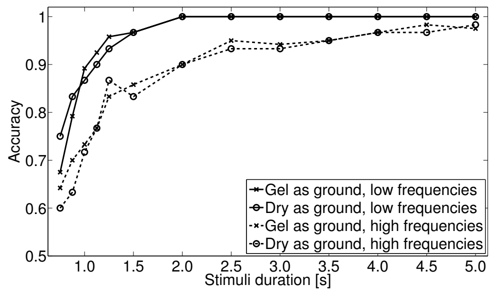

Figure 9: Comparison of classification accuracy levels with dry contact electrodes when using gel and dry electrode as ground, using different stimuli duration.

In conclusion, although we cannot infer statistical significance of the presented results, we can hypothesize that using acquisition setup that is completely based on dry or water electrodes would not significantly decrease the achieved classification accuracy over the setup that uses conductive gel as a ground.

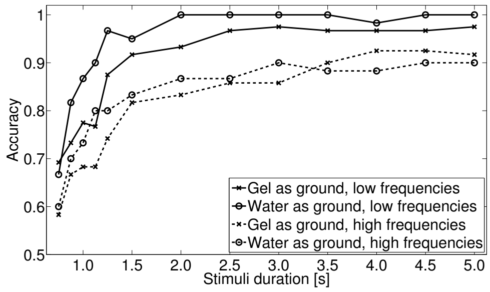

Figure 10: Comparison of classification accuracy levels with water-based electrodes when using gel and water-based electrode as ground, using different stimuli duration.

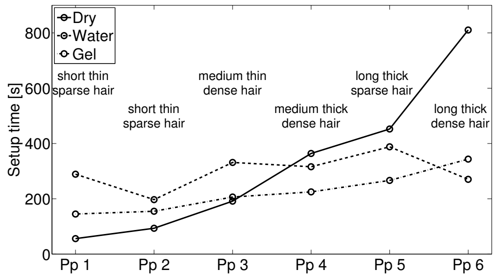

Figure 11: Time (averaged over two sessions) required for the experimenter to prepare the participant for the recording.

5.3 Convenience and setup time

Before and after the usage of the headsets, participants reported their anticipated and experienced convenience level (see evaluation protocol detailed in Section 3). Although participants expected that the dry electrode setup will be the least convenient one with the median score of 3.5 on the scale of 1 (unconvenient) to 10 (convenient), compared to 4.5 and 6 for water-based and gel ones respectively, this was not reflected in the rating after the usage of the electrodes. The final median score was 5 for dry, 6 for water-based, and 5 for gel electrodes. These results also indicate that the water-based solution would be preferred over the gel one. Note that the users were asked to rate not only the perceived comfort, but also the practicality of the headsets and the effort required to use them.

Based on the comments and the discussion with participants we learned that the participants with shorter hair had the preference for using the dry electrodes, over water-based and gel ones, while for the participants with the longer hair water-based electrodes were preferred as the procedure for positioning the dry headset was too long (see also Figure 11) and/or the headband was too tight. Most participants did not like the feeling of gel in their hair and the fact that they had to wash the hair after the usage of gel setup.

Direct comparison of the preparation time, depicted in Figure 11, shows that water-based electrodes require more preparation time than gel ones, while dry electrodes require less time than the other two for people with shorter and thiner hair style and more time for people with longer and/or thick hair style. The former can be partially explained by the cumbersome 'screwing' procedure required for placing the water-based electrodes in the EEG headset holes, which had to be redone in case the signal was not good enough. For the gel setup the procedure required adding more gel between the scalp and the electrode until the signal was at the acceptable level, which was much faster. The latter can be explained by the design of the dry electrodes themselves. The length and the rigidness of the pins was a major problem for obtaining a good signal for participants with longer hair. The amount of hair under the electrode was in many cases preventing the pins from getting in contact with the skin on the scalp. Not only this problem increased the preparation time. The quality of the signal obtained was much lower compared to the participants with shorter and thin hair types (see, e.g., Figure 2)

6 DISCUSSION

The question we aim to answer in this paper is whether and to what extent can dry contact and water-based electrodes replace the conductive gel ones for EEG measurements. As a means to test the performance we selected the SSVEP, since this is a well understood phenomena and as it is one of the most popular neural sources in BCI applications. The analysis has revealed that both electrode types can replace the gel-based configuration, but at the expense of performance. The mean accuracy rate drops $10-25\%$ when using water-based electrodes and $35-45\%$ when using dry electrodes, while the information transfer rate in the optimal case is one half of water-based and one third of dry electrodes ITR.

The baseline evaluation where we used only the occipital sites (i.e., O1, O2, and Oz) demonstrated low accuracy levels for dry electrodes, and lower than expected values for gel electrodes which were comparable to the water-based ones (see Figure 2). Our hypothesis that the selection of 3 electrodes that have the lowest contamination by noise would improve the accuracy for dry electrodes, showed to be true, as it can be seen in Figure 4. The same was observed when using gel electrodes. However, contrary to our expecta-

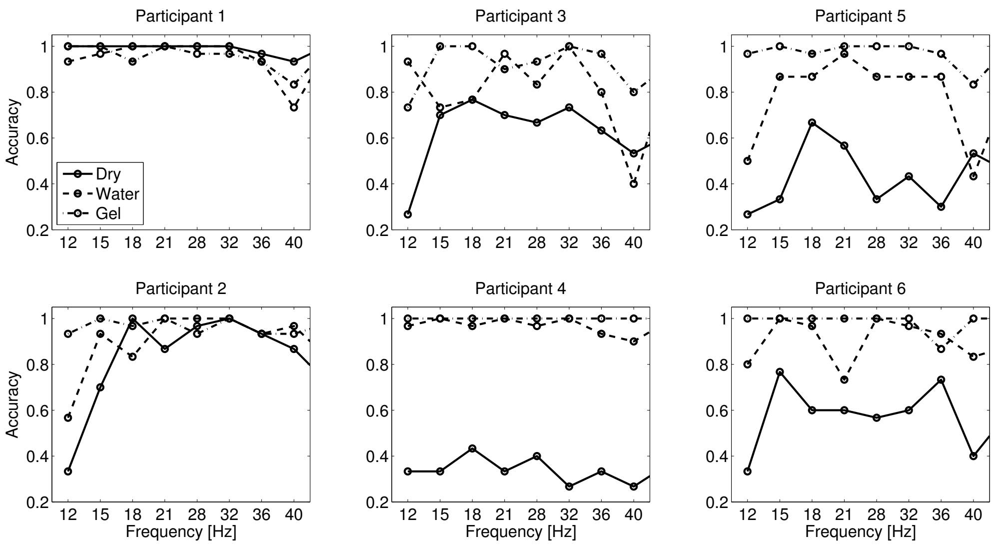

Figure 12: Comparison of optimal classification accuracy in three setups for each participant.

tions this was not the case for water-based electrodes. Further investigation is required to fully understand this effect. Nevertheless, we can infer that the step of selecting the electrodes with the 'cleanest EEG signal' is crucial in achieving higher performance in the SSVEP classification task.

Although we expected that using the discriminative spectral power around the peak of the RVS frequency would be also beneficial for selecting the optimal set of electrodes, this was proven wrong. The accuracy improved for dry and gel electrodes compared to the baseline, but for water-based ones this was not the case. The accuracy for all three setups was lower then when using 3 electrodes with the lowest noise contamination (see Figure 4). It is worth noting that we used two simple algorithms that compute the presence of white noise and the standard deviation in the EEG channels which resulted in similar performance. We argue that using algorithms that have better characterization of environmental or motion artifacts, tailored to the used electrode and amplifier technology, could further improve the performance.

The utilization of first harmonics increased the accuracy in all the cases, except for the dry electrodes in the low frequencies, as shown in Figure 5. This result, and the small increase in the accuracy levels for dry electrodes overall, still remain an effect that requires further investigation. However, the performance of different setups when using different number of optimal electrode positions confirmed that the maximum accuracy is reached when using $3-7$ electrodes. Furthermore, slight drop in performance when using two electrodes suggests that systems with two electrodes at optimal positions that contain less noise, might be sufficient for practical SSVEP BCI applications.

Maximum accuracy across different setups is achieved when using 4 electrodes with the lowest presence of white noise and when the harmonics were used. The performance per participant in this optimal case is depicted in Figure 12. The figure illustrates that the comparable accuracy to the gel solution can be achieved with dry and water-based electrode solutions for users with short thin hair (Participants 1 and 2). However, for participants with medium and long hair, the performance of water-based electrodes slightly decreases, and exhibits a significant drop of accuracy for dry electrodes. The results are in favor of our hypothesis that better design and integration of dry and water-based electrodes in a headset solution is a prerequisite for good performance in a wide range of users, having different hair type and length.

Looking into practical aspects of the proposed alternatives to gel electrodes that are discussed in Section 5, we can infer that users do not perceive dry and water-based electrodes as less convenient than the gel ones, especially having in mind that they do not require gel removal after the usage. Given the potential short preparation time, i.e., having optimized electrode and headset design such as the one for dry electrodes presented in (Mihajlović et al., 2011), and having the possibility to use only dry or only water-based electrodes without additional loss in signal quality as shown in Figure 9 and Figure 10, practical EEG acquisition systems are achievable. Such systems can provide ITRs of 40bpm for water-based and of 20bpm for dry electrodes, and with the optimized design and application of better signal processing and classification algorithms, potentially even higher transfer rates for SSVEP BCI applications.

7 CONCLUSION

This paper demonstrates that EEG systems that use water-based electrodes and dry contact electrodes with tailored electrode and headset design can be a viable alternative to traditionally used conductive gel systems. These two systems are successfully applied to the SSVEP BCI. Although the mean information transfer rate in the optimal case, estimated on 6 participants, droped from 67bpm for gel electrodes to 38bpm for water-based and 23bpm for dry electrodes, water-based and dry electrodes ease the setup procedure, have the potential to reduce the setup time with the proper design of dry and water-based headset and electrodes, and enable usage of the system without expert assistance. Therefore, dry and water-based electrodes can provide an alternative to gel ones in situations where practical aspects of the EEG system are preferred over communication speed. We believe that, having the advantage of greater practicality, with the advances in the water-based and dry electrode design, improvements in the amplifier technology, and the usage of more advanced signal analysis methods, the signal quality and overall performance of water-based and dry EEG systems would reach the performance of the gel-based ones.

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