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Low channel count montages using sensor tying for VEP-based BCI

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Abstract

Objective. Brain computer interfaces (BCIs) are slowly making their appearance on the consumer market, accompanied by a higher popularity among the general public. This new group of users requires easy-to-use headsets with robustness to non-precise placement. In this paper, an optimized fixed montage EEG headset for VEP BCIs is proposed. Approach. The proposed layout covers only the most relevant area with large sensors to account for slight misplacement. To obtain large sensors, without having them physically available, we tie multiple sensors together and simulate the effect by averaging the signal of multiple sensors. Main results. In simulations based on recorded 256-channel EEG data, it is shown that a circular center-surround configuration with sensor tying, leading to only eight channels covering a large part of the occipital lobe, can provide high performance and good robustness to misplacement. Automatically optimized layouts were unable to achieve better performance, demonstrating the utility of this manual design. Finally, the performance and benefits of sensor tying in the manual design are then validated in a physical experiment. Significance. The resulting proposed layout fulfills most requirements of an easy to use consumer EEG headset.

Keywords: EEG, electrode montage, layout optimization, BCI, visual evoked potentials

(Some figures may appear in colour only in the online journal)
2. Materials and methods

The experiments are subdivided into two parts; the first part will focus on offline analysis of high density measurements to assess performance of a parameterized concentric circle layout, inspired by previous findings about the most relevant areas for BBVEP speller, which is referred to as manual design in the rest of this paper. The performance of this manual design is then compared to a layout based on forward and backward automated search. The second part of this research will focus on the physical evaluation of the manual-design layout and the validation of sensor-tying versus single electrode measurements.

2.1. Part 1: layout optimization

Optimal fixed montages can be obtained by automatic procedures such as sparse sensor selection (Rivet et al. 2010, Chepuri and Leus 2015), convex optimization (Joshi and Boyd 2009) or simpler methods like Recursive Feature Elimination (Guyon et al. 2002). To obtain a minimal yet effective layout for the headset, in this paper, we examined two approaches by running two sets of simulations. First, inspired by the activity pattern of a BBVEP speller, we propose a manual design layout. We study the effect of size and tying pattern on the performance and robustness using offline analysis based on high density measurements. To assess how good the designed layout is, we compare it with sensor selection resulted from an automatic optimization procedure which does not include any initial assumption about the area of interest. For this purpose, we use both forward and backward greedy search to find the best combination of one up to 256 sensors.

Physically making and evaluating every possible montage is clearly impractical, in terms of both researcher resources and subject time. Thus, we first designed and evaluated possible montages in simulation by averaging the sensor measurements in each sub-region in a previously recorded offline high-density EEG experiment (256 sensors with 20 mm sensor spacing).

2.1.1. Experimental setup. Participants were seated at a distance of 60 cm from the 17 inch LCD screen. EEG data was recorded with a 256 full Biosemi cap with gel electrodes at a rate of 360 Hz. A Biosemi-active2 amplifier was used and the data was recorded based on a HQ reference system. The BBVEP speller consisted of three blocks of 36 trials. In each block the subject was instructed to attend to 36 characters in a randomized order. The order was different for each training block but the same across subjects. Each trial had a length of 4.2 s, with an inter-trial time of 0.5 s.

2.1.2. Stimuli. Stimuli consisted of a flickering matrix-layout keyboard with 36 keys presented at 60 Hz. All buttons flickered between black to white colors according to a modulated Gold code, Gold (1967). The Gold codes ensure small cross-correlations between flickering patterns. We multiply the Gold codes with a double bit clock which retains the correlation properties but removes low spectral content; hence the flickering pattern consists of two types of events; a long and a short flash.

2.1.3. Participants. Five healthy adults (age: 37.6 ± 16.6, mean ± standard deviation, one female) participated in the study after having signed written informed consent. All
participants had normal to corrected-to-normal vision and no history of epilepsy. The study was approved by and conducted in accordance with the guidelines of the Ethical Committee of the Faculty of Social Sciences at the Radboud University, Nijmegen in the Netherlands.

2.1.4. Manual design.

Layout design. The average spatial filter of the BBVEP speller, found by Thielen et al (2015), suggests that the most important areas for decoding during the BBVEP task is a classic Laplacian-derivation with circular center-surround shape at the back of the head (figure 1(a)). Therefore we propose a circular design, covering the active area with a center-surround configuration, an invention described in Desain (2018), with an inner circle and outer ring (figure 1(b)). To allow for the fact that not all subjects have an ideal circularly symmetric response, like the one captured by the atypical spatial filter of Thielen et al (2015) shown in figure 1(c), we propose different ways of breaking each area into sub-regions (figure 1(d)). Thus, to identify the ‘optimal’ center-surround montage we need to identify the best size at the best position for the center and the ring, the number of segments and the segment shapes.

Analysis. To simulate various montages, we consider each individual measuring point on the skull as one sensor, which in our experimental setting, is one out of the 256 electrodes. To simulate the arbitrary shaped sensors, we used spherical spline interpolation (Perrin et al 1989) to sample points (spaced 10 mm apart) from the area and then tie the sample points together by averaging the resulting measurements.

Assuming that all the sensors have roughly similar impedance, averaging is a reasonable approximation to electrically tying sensors. As long as the sensors are perfectly connected to the skull, they all have similar impedance, and as long as there is no strong local noise, under the assumption of spatial smoothness, the exact position of the sensors is not critical. In such condition, it is enough to make sure that the sensors are located such that the spatial Nyquist frequency is met. It also entails that in such an ideal situation, tying a group of sensors into one channel might not result in a difference in performance when compared to the use of isolated sensors. In reality however, it may happen that one sensor becomes less well connected over time, causing an increase in its impedance and therefore reducing its signal to noise ratio. For a non-adaptive classifier, such a change in a sensors signal-to-noise ratio results in a subsequent increase in the noise in the classifier predictions—potentially resulting in wrong or no predictions from the BCI. In the one sensor-one channel case this situation is common as sensor noise maps directly into channel noise. However, in the multiple-sensors tied to a single channel situation, the effect of a single bad sensor is much reduced. This is in part because the averaging over sensors reduces the relative impact of the noise (basically it is divided by the number of sensors in the group). However, it is also in part because sensor tying creates a parallel resistance circuit which further down-weights a noisy or high impedance sensor’s voltage by the inverse of the impedance allowing the parallel lower impedance (and less noisy) sensors to takeover (See figure 2 and equation (1)). The final signal-to-noise ratio will, therefore, be higher in the tied situation than in the isolated sensor case. In an even more extreme case, one of the channels can become disconnected completely resulting in a pure noise measurement in the isolated channel case, but a simple average of the remaining connected sensors in the tied case. Another non-ideal situation in which sensor tying can be beneficial is when the amplifier is not ideal in which case there is a signal loss depending on the average impedance of the electrodes relative to the amplifier input impedance (Ferree et al 2001, Chi et al 2010). As sensor tying reduces the effective impedance of each channel, The signal loss resulting from non-ideal amplifier input stage decreases.

\[ I_c = \frac{\sum X_i + n_i(R_i)}{R_i} \].

In summary, sensor tying should have similar performance to individual electrodes when all conditions are ideal. Sensor

\[ \text{In equation (1), for simplification, we have represented noise as a function of the electrode resistance. More precisely, the relation between the noise and the electrode-scalp resistance depends on the type of noise. The noise resulting from electrical interference depends upon the impedance mismatch between the measurement and the common reference electrodes (Ferree et al 2001). So the electrical noise is indirectly dependent on the electrode impedance. Magnetic noise, on the other hand, does not depend on the electrode impedance. Hence the total noise has a component which increases as the electrode impedance increases and another component that is independent of the electrode impedance.} \]
tying, however, does increase robustness against local noises and degrading sensor contact and perhaps non ideal equipments such as amplifier. As we do not model such conditions in our simulation on the high density data, the difference between sensor tying and isolated sensor montages in terms of absolute performance might be negligible. We will come back to this issue in section 2.2.2

We apply sensor tying in the circle design in two ways and we also test a third configuration in which each circle is represented by four separate sensors. Hence we have three montages:

(i) **T1–T1 montage**: Two channels in a concentric layout comprising of one filled circle in the middle surrounded by another circle (ring) which diameter is between 10 to 100 mm larger. Each circle is made by tying the sensors together into one channel located in the area covered by that circle (figure 3(a)).

(ii) **T4–T4 montage**: One filled circle in the middle divided into 4 segments, surrounded by another circle (ring) which diameter is between 10 to 100 mm larger. The second circle is also divided into 4 segments and altogether form eight channels (figure 3(b)).

(iii) **I4–I4 montage**: This is an eight-channel montage which follows the T4–T4 montage but instead of tying multiple sensors to make one circle segment, we take one single isolated sensor from each segment (figure 3(c)).

The resulting signals for the channels of each of the above montages were then fed into our standard BBVEP analysis pipeline, which is given in Thielen et al (2015). See Thielen et al (2015) for detailed information, but in outline this consisted of: spectral filtering with a pass band of 2–48 Hz followed by model-fitting using canonical-correlation analysis (CCA) to identify subject-specific spatial filters and pulse responses for each event: a long or short flash. During testing, the pulse responses are re-convolved with the stimulation pattern for each possible output to generate per-output template responses. The predicted target is then identified as the output with maximal correlation between the spatially filtered data and the template response (Desain and Farquhar 2009, Desain et al 2015). Accuracy is determined after 10-fold cross validation and defined as the percentage of trials where the predicted output was correct. This definition is used in this paper to assess the performance of a montage. The analysis presented here is done with trials of a fixed duration of 1 s, to avoid saturation effects where all subjects hit perfect performance, which would decrease the sensitivity to changes in the montage.

To study the effect of circle diameter and find the optimum diameter for the inner (center) and outer (surround) circles, the center circle diameter varies between 0 (a single sensor) and 100 mm. The surround circle diameter goes from 20 mm to 120 mm. Both circle diameters change with step size of 10 mm. In the rest of this paper, to address various configurations of each montage, we use the following names: T1\_dc and T4\_dc (for tied montages) and I4\_dc (for the isolated sensor montage), where xx is the circle diameter (dc or ds in figure 3) and T1, T4 and I4 specify the T1–T1, T4–T4 and I4–I4 montages respectively. For example T1\_dc=T1\_ds0 is the two channel montage with a single sensor as the center circle and a surround circle of 30 mm diameter. Similarly T4\_dc0–T4\_ds0 is the eight channel tied montage with a 20 mm center circle and a surround circle of 30 mm diameter.

Furthermore, effects of slight displacement of a headset are simulated by moving the center point of the montage. We
shifted the center point by 80 mm with 5 mm steps horizontally and vertically, such that the whole grid is covered. We considered the location of A22 in the Biosemi cap, which is located halfway between CZ and inion, as (0,0) coordinate, therefore, the shifted center points are $(dx, dy)$, $-4 \leq dx \leq 4$ and $-4 \leq dy \leq 4$. The simulation was repeated for each center point by tying the sensors that would be covered by the circles centered at that position. We look at the relative performance drop as the indicator of sensitivity to misplacement.

2.1.5. Automated search algorithms. In this section, we are looking for the optimal N-sensor layout that can be found using recursive forward or backward search.

**Forward search.** The forward search, as used in this paper, is done in a series of steps. In the first step, the cross validation accuracy averaged over five subjects, obtained by using each of 256 sensors separately is calculated. The sensor that results in the maximum accuracy gives the best single sensor layout. In the next step, the combination of this best sensor with each of the 255 remaining sensors is evaluated and the couple resulting in the maximum accuracy will be plotted as the best two-sensor layout. The same procedure is repeated, such that in each step one sensor that contributes the most to the accuracy is added to the layout. In order to speed up the procedure, after the 16-sensor layout, two sensors are added per step. The step size in number of sensors added increases to 10 after 36-sensor layout and up to 20 and then 30 after 106-sensors and 166-sensors respectively.

**Backward search.** In the backward search, the algorithm starts at the full 256-sensor layout and gradually eliminates the sensors that contribute the least in the cross validation accuracy averaged over subjects. To maintain computational feasibility, in the first step, the accuracy obtained by eliminating each of the 256 sensors is calculated and the first 30 sensors that contributed least are dropped. The remaining sensors would form the best 226-sensor layout. After having obtained the 166-sensor layout, we drop 20 sensors in each step. The step size keeps decreasing to 10 after 106-sensors and to 2 and then 1 after 36 and 16, respectively.

**Analysis.** Sensors are added or removed by evaluating their performance accuracy. This accuracy is calculated using the same method as the simulation of the manual design. If necessary, consult (Thielen et al 2015) for detailed information.

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Figure 4. The 3D-printed custom made EEG cap. (a) The designed layout (the green shaded areas indicate the tying pattern). (b) The 3D-printed prototype with TMSI water based electrodes ans connecting bands. (c) The n-to-1 connector used for sensor tying and (d) the experiment setup.
Comparison with manual design. The automated search results are shown by their accuracy of the optimal N-Sensor layouts. The resulting values at two and eight sensor are then compared to the best accuracy obtained from two channel (T1–T1) and the eight channel (T4–T4 and I4–I4) montages. This comparison will provide us with insights into the difference in performance between the manual and automated designs.

2.2. Part 2: physical evaluation of sensor tying versus single electrode sensor configurations

As the results in part 1, are all simulated offline, part 2 will focus on the evaluation of the proposed layout in an online test and examining sensor tying by electrically connecting the sensors. Based on the results of simulation (part 1 of this paper), we designed a custom made cap prototype of the circle shaped manual design. The sizes are chosen to be optimal or close to optimal but yet more convenient from a design perspective. The designed layout, shown in figure 4(a), has a 70 mm center circle consisting of 16 electrodes forming two concentric circles and a surround ring of 120 mm diameter containing 16 electrodes. The electrode holes are designed to fit TMSi’s water based AgCl electrodes. The layout is then 3D printed and together with the electrodes and fixing bands it forms what can be seen in figure 4(b). In this part, the designed prototype is evaluated by comparing its performance in two conditions; first using the 32 electrodes as separate channels and then reducing the number of channels by tying them into eight channels (forming the T4–T4 montage). The performance will enable evaluation of whether sensor tying is an effective way of reducing the number of channels. To examine the effect of sensor tying, we simulate the isolated eight channel montage of I4–I4 to see if reducing the number of channels by simply using eight single electrodes at the same distance of circles will reduce or increase the performance. We further validate the robustness of sensor tying by simulating temporary sensor drop-outs.

2.2.1. Physical validation of the optimal design.

Experimental setup. Participants were seated at a distance of 40 cm from a 10 inch tablet screen. EEG data was recorded with the 32 electrode custom made cap. The electrodes used were TMSi’s water based AgCl electrodes with wet cotton rolls to bridge the skull electrode gap. To reduce the contact resistance, 3 ml of 0.74% Sodium chloride eye drop was added to 100 ml of water used to soak the cotton rolls in. The EEG data is recorded at a sample rate of 360 Hz. A TMSI Porti amplifier was used and the data were recorded based on a common average reference system. The experiments were conducted in 32 and 8 channel phases. In the 32 channel phase, all the 32 electrodes were considered as separate channels and connected directly to the amplifier without any tying. In the eight channel phase however, groups of 4 electrodes shown in green shaded areas in figure 4(a), were tied by electrically connecting them using a n-to-1 tree-like connector (see figure 4(c)) to form the T4–T4 montage. The order of the 32 and eight channel phases were counterbalanced across subjects. In both phases, the BBVEP speller consisted of three blocks of 20 trials. In each block the subject was instructed to attend to
20 characters in a randomized order. The order was different for each training block but the same across subjects. Each trial had a length of 4.2 s, with an inter trial time of 0.5 s. The three blocks were followed by an online test block in which the subject was instructed to type a fixed sequence of 20 characters.

**Stimuli.** The stimuli used in experiments of part 2 were identical to the BBVEP speller used in part 1 (see section 2.1) except that the keyboard layout was the ipad layout with 33 keys (see figure 4(d)).

**Participants.** Ten healthy adults (age: 36 ± 17, mean ± standard deviation, three female) participated in the study after having signed a written informed consent. All participants had normal to corrected-to-normal vision and no history of epilepsy. All but one participant were inexperienced with visual speller. To ensure the generalizability of the results and to avoid overfitting, there was no shared participant with part 1. The study was approved by and conducted in accordance with the guidelines of the Ethical Committee of the Faculty of Social Sciences at the Radboud University, Nijmegen, The Netherlands.

**Analysis.** In the offline analysis, the same procedure explained in section 2.2.2 was followed. A 10-fold cross validation was performed on the data recorded in the three blocks and the average classification accuracy was calculated. In the online test, the classifier was trained/calibrated on the data recorded in the third offline test block and then the percentage of correctly typed characters was calculated. We performed the offline analysis of the data for four different configuration, two of which were according to the way the data was collected (32 isolated channel and eight tied channel (T4–T4)). In the other two configurations, we used the data collected in the 32 isolated channel blocks and only took eight out of 32 channels in accordance to the I4–I4 montage (figure 3(c)). As the center circle of our designed layout consisted of two rings of sensors (see figure 4(a)), there were two choices for picking the four center sensors. Therefore, the two configurations were I4(C1)–I4, where selected sensors were 1, 2, 3, 4, 17, 21, 25, 29 and I4(C2)–I4 with 5, 8, 11, 14, 17, 21, 25, 29.

### 2.2.2. Simulation of electrodes with unstable contact.
To validate the robustness of sensor tying to unstable contacts, we used the data collected in the training blocks of the physical validation test and simulated unstable contacts as follows. An extreme case is simulated by removing signal from either 1, 2 or 3 electrodes during randomized test trials. The aim of the simulation is to see whether a classifier that is trained using data of fully connected electrodes, can still classify the test trial. The classifier is trained on a fully connected cap, after which is applied to the test data where 30% of test trials has 1, 2 or 3 randomly selected sensors set to 0. The test is repeated for I4–I4 (eight isolated channel) and T4–T4 (eight tied channel) montages. For the T4–T4 case, we first drop the signal of randomly chosen electrodes and then simulate the tying by averaging signals.

### 3. Results

#### 3.1. Part 1: optimize layout based on high density measurements

#### 3.1.1. Manual design. For the manually designed layout, the average classification accuracy is reported. To make a headset usable for a large population, however, the optimal size and
configuration should be based on people with different performances. To boost the possibility for inclusion of as many users as possible, the subject with the poorest performance is examined separately. For each simulated montage, we optimize for the minimum accuracy in addition to the average accuracy. Even though the best configuration for each subject was different from the other, the same subject appeared to have the lowest accuracy in almost all the configurations. Thereby we refer to this subject as ‘The worst subject’. As results of the worst subject followed a similar trend to that of the average performance, full results are only included in the appendix of this paper.

Figure 5 shows the accuracy averaged over five subjects of the high density measurement experiment. This accuracy is defined as the percentage of correctly classified targets in a 10 fold cross validation, for the T1–T1, T4–T4 and I4–I4 montages for all the possible center and surround configurations. The numbers in brackets show the 95% confidence interval. A similar plot for the worst subject is presented in appendix (figure A1)

In figure 6, the change in relative performance defined as $P_{	ext{new}} / P_{	ext{max}}$ as a result of moving the central point is visualized for T1–T1, T4–T4 and I4–I4 montages. The center and surround size are chosen according to the optimal points of figure 5, so they correspond to T1$_{d_0}$–T1$_{d_80}$, T4$_{d_{40}}$–T4$_{d_{120}}$ and I4$_{d_{30}}$–I4$_{d_{110}}$. The first contour shows the area in which the performance drops up to 1% relative to the maximum (For example, if the maximum absolute performance is 90%, 1% relative drop is equivalent to 0.9% absolute drop, i.e. going from 90% to 89.1%). Other contours are at 2%, 5%, 10% and 20% and below. A similar contour plot for the worst subject as well as the same contour plot for all the center and surround sizes can be found in appendix (figures A2 and A3). To quantify the sensitivity of each montage to misplacement, the area in which the performance is within 1%, 2%, 5% or 10% of the maximum is measured. As the optimal center and surround size for absolute performance and robustness to misplacement do not necessarily coincide, the contour areas are calculated for all the center and surround sizes to find the size with maximum contour area as the most robust size for each montage. In table 1, the 1%, 5% and 10% areas for the most misplacement-robust center and surround sizes are listed for the three montages (T1–T1, T4–T4 and I4–I4). The most misplacement-robust layout is chosen to be the one with the largest area in which the relative performance drop is below 1%. To give an impression of horizontal and vertical shifts which causes 1%, 5% and 10% drop in performance, we include approximate dx and dy corresponding with each contour in table 1 as well.

3.1.2. Automated search. Figure 7 shows the accuracy as a function of the number of sensors for the forward and backward search together with the position of the 1, 8 and 16 sensor cases. The green pentagram and star show the best accuracy obtained with the T1–T1 and T4–T4 montages respectively.

3.2. Part 2: physical evaluation

3.2.1. Physical validation of the optimal design. In figure 8, the results of the physical evaluation experiment are presented for each subject and averaged over all the ten subjects. Figure 8(a), shows the results of cross validation on three training blocks of the data, recorded in 32 isolated and eight tied channel (T4–T4). The result for I4–I4 montages are obtained by choosing eight out of 32 channels in the 32
channel recordings. In figure 8(b), the performance of subjects in the test phase, of both 32 channel and eight channel T4–T4, are reported as the percentage of correctly spelled characters.

3.2.2. Simulation of electrodes with unstable contact. The performance of the three eight channel montages in case of simulated unstable sensor contact is presented in figure 9 as the ten-fold cross validation accuracy averaged over all the ten subjects. The accuracy is plotted as a function of the number of unstable sensors, which randomly drop out in 30% of test trials. The analysis was repeated ten times with different random seeds. The shaded areas show the 95% confidence interval.

4. Discussion

This paper examined a design of an EEG headset aimed towards the general consumer market. For general consumer use an EEG headset should meet the following (conflicting) objectives; (i) low-cost, (ii) high BCI-performance, (iii) easy-to-fit, (iv) comfortable to use, (vi) robust to inaccurate placement, (vii) robust to (temporary) poor sensor contact. The intuitive idea was inspired by the activity pattern observed for a BBVEP BCI, which resulted in a circular center-surround configuration. By tying electrodes within this design together, forming circle (or circle segment) shaped area sensors, the number of channels can be reduced while still covering a large area on the skull. It was hypothesized that this tying would induce robustness against misplacement and unstable sensor contact.

4.1. Sensor-tying and isolated sensor montages

In the first set of simulations, data from a high density EEG experiment were used to simulate the center-surround layout and evaluate it with different sizes. As can be seen in figure 5(a), increasing the surrounding circle in diameter in the T1–T1 montage up to 80 mm results in a higher performance while the surround diameter larger than 80 mm seems sub-optimal. Increasing the size of the center circle only decreases the performance even though the decrease is not
monotonic and there are non significant fluctuations. For the T4–T4 montage, however, as figure 5(b) indicate, an increase of the center circle size increases the performance. Moreover, the performance increase as a result of larger surround circle is less compared to the T1–T1 montage. Interestingly enough, the eight isolated channel montage (I4–I4) performs quite similar to the eight tied channel montage (T4–T4) and the absolute maximum accuracy is slightly (but not significant), higher than the tied version.

According to figure 5(a), the best T1–T1 two channel configuration in terms of average performance is the configuration with a single center point and a 80 mm surrounding circle (T1d50–T1d80). The eight channel configuration (T4–T4 montage) as can be seen in figure 5(b), shows higher performances with maxima reached at 40 mm center circle and 120 mm surround circle (T4d40–T4d120). In this case, both T4d40–T4d100 and T4d50–T4d80 give very similar high average performance, while the T4d60–T4d80 is the size that is preferred in terms of maximizing the worst performance (see figure A1(b) in the appendix). For the average performance of T4–T4, there are many sizes that are not performing significantly lower than the maximum (to within the 95% confidence intervals). This means that for the eight channel montage of T4–T4, there is more freedom in choosing the size, compared to the two channel montage T1–T1. The absolute maximum performance for the I4–I4 montage occurs at 30 mm center and 110 mm surround circle (I4d30–I4d110). Similar to the T4–T4 montage, I4–I4 shows rather little sensitivity to the exact size of the circles. Having freedom in choosing the size is an advantage as it gives more freedom for an ergonomic and practical headset design.

The average accuracy obtained using the full 256 channels was 92.49% ± 1.21% which did not differ significantly from the performance of the T4–T4 and I4–I4 montage (T4d40–T4d120 and I4d30–I4d110).

4.2. Two-channel and eight-channel montage

A clear result from this research is that the eight channel configurations are superior to the two channel one (especially for a bad subject). However, the average performance of the two channel configuration is good enough to make such a montage an attractive option for a low cost EEG headset. On the other hand, the similarity between the results of T4–T4 and I4–I4 montages in terms of absolute performance, suggests that in eight channel case, sensor tying does not have an advantage over isolated sensors.

The difference between the two channel T1–T1 montage and the eight channel T4–T4 and I4–I4 montages becomes more visible when the sensitivity of each montage to misplacement is examined. Figure 6 shows the contour plot of how the relative performance changes as the center of the layout with highest absolute performance moves away from the ideal point. As can be seen in table 1, the most robust layout for each montage differs from the layout with the highest average accuracy. For T4–T4 the performance of these montages is not statistically significant in terms of average performance or robustness to misplacement. Conversely, for T1–T1 and I4–I4 the performance difference is significant. Thus, for T1–T1 and I4–I4 one must trade-off average-performance and robustness, whereas with T4–T4 a single montage can achieve both.

4.3. Misplacement

From figure 6 and table 1, it can be seen that all the three montages are more robust to vertical shift than horizontal shift, specially the two channel T1–T1 montage. However, one has to be careful in interpreting the effect of negative vertical shift as in reality it might cause some sensors to be placed below the skull and capture muscle artifact while such an effect is absent in our simulation using interpolation. Therefore, in practice we will expect more drop around \(dy < -30\) for large size montages. Comparing figures 6(a) and (b) and the numbers in table 1 it is evident that the T4–T4 montage is much less sensitive to misplacement compared to T1–T1. The most robust T4–T4 layout size (T4d40–T4d100) can safely be mis placed up to ±15 mm horizontally and ±25 mm vertically, compared to \(\pm 3\) and \(\pm 18\) mm for the T1–T1 montage. The best T4–T4 looks slightly more robust compared to the T4–T4 montage as its 1% contour range is slightly larger. The T4–T4 montage, also stays within the 5% of it’s best performance within a larger area. A nonprofessional user is reasonably expected to have a placement error in the order of 1–3 cm, therefore we can claim that the design is robust to such a typical misplacement.

The sensitivity of T1–T1 montage to misplacement (which as can be seen in figure A3 in appendix, is largely influenced by the worst subject) can be an example of the effect caused by a circularly asymmetric response due to a non-radial dipole (see figure 1(c)). In this case, having very large sensors increases the chance that a single sensor is placed across the boundary between the positive and negative components and averages the signals that need to be kept separate for detection. This can also explain why the best T1–T1 configuration for the worst subject is the one with a single point sensor in the center. By splitting the channels, the risk of cancelling out the activities reduces and therefore the placement of the sensors become less difficult. Hence, in this type of design, on one hand large sensors are desirable since they save the number of required channels and on the other hand the sensor should not be too large to mix up different activities and cancel them out. The eight channel T4–T4 montage seems to provide a good trade off.

4.4. Automated search

To evaluate the maximum accuracy obtained by our circular designed headset, the accuracy of the layouts are compared that are optimized using greedy search algorithms. Forward and backward search procedures are used without enforcing any constraints on the location of sensors. As can be seen in figure 7, the forward and backward search algorithms result is similar accuracies for seven and more sensors. The backward search shows slightly but not significantly higher performance.
for two up to six sensors while the single sensor layout obtained by the forward search performs significantly better than the montage of the backward search. Looking at the location of the sensors, a few of which are shown in the figure, two directions of search result in different locations of sensors are apparent, even when the accuracies are similar (the location of sensors for all n-sensor configurations can be found in figure A4 in the appendix). The backward search seems to benefit more from the local context and as can be seen in the eight sensor layout. It has more focus on the occipital area while the forward search has selected more scattered sensors. It might be the case that for two–six sensors, the ability of the backward search to benefit from local context has caused its advantage over the forward search. This breaks at single sensor case where the single sensor resulting in the highest performance selected by forward search has been dropped long ago by the backward search because other sensors had shown more contribution in combination with other sensors. While more sophisticated automatic procedures such as sparse sensor selection (Rivet et al 2010, Chepuri and Leus 2015), convex optimization (Joshi and Boyd 2009) or combination of both forward and backward search might have resulted in better results, for the purpose of this article, the forward and backward search provides enough confidence for sanity check of our designed layout. From figure 7 it can also be seen that our eight tied channel layout (T4–T4) and the eight isolated channel one (I4–I4) perform as good as both eight sensor layouts resulting from the greedy searches. For the two channel case, however, it seems that the two tied channel circle shaped layout (T1–T1) shows significantly better performance compared to the best two-point-sensor layout resulting from search algorithms. This indicates that we can gain more advantage by tying sensors as the number of channels goes very low.

4.5. Online performance

The optimized concentric circle layout was made into a prototype and evaluated in a physical experiment with ten subjects. The results of the offline analysis of the experiment data (figure 8(a)), shows that on average the 32 channel configuration results in significantly higher accuracy compared to the tied eight channel montage. However, for seven out of ten subjects the difference between the two is insignificant. While the 32 channel configuration resulted in 90.83% ± 1.17% average accuracy, the average accuracy obtained by the eight tied channel configuration (T4–T4) was 84.71% ± 1.46%, this is still an acceptable performance for a BCI system and at the same times reduces the number of channels by a factor of four. An alternative to sensor-tying for reducing the number of channels is to use eight isolated channels. As it can be seen in figure 8(a), one of the isolated channel configurations I4(C1)–I4 evaluated by using eight out of 32 channels of the data recorded during the experiment, results in slightly but statistically significantly higher (87.83 ± 1.53%) than the eight tied channel montage. It is interesting to see that the I4(C1)–I4 configuration in which the center electrodes are closer to each other outperforms the one with wider center (I4(C2)–I4) which on average performs equal to the T4–T4. Two out of 10 subjects almost failed at the online test. For the other ones, however, the accuracy obtained in online test was comparable to the cross validation accuracy of the offline analysis. As can be seen in figure 8(b), on average, the test accuracy obtained by 32 channel and the eight tied channel configurations are not significantly different.

4.6. Channel dropout

During the evaluation of the prototype headset, low impedance and relatively stable sensors were observed as the experiment was conducted under laboratory conditions. To validate the advantage of sensor tying in more challenging conditions, transient channel drop out was simulated by randomly removing one, two or more sensors during some test trials. The T4–T4 montage was quite robust to missing sensors and shows no significant drop even after loosing nine sensors while the performance of the two I4–I4 montages drop significantly after dropping one or two sensors. This is an evidence of the advantage of sensor-tying. However, if instead of looking at the absolute number of loose contact points, we evaluate the performance of each layout as a function of the fraction of loose contacts (figure 9), the advantage of T4–T4 over I4(C1)–I4, is not permanent. In situations where between 35% and 80% of the sensors are expected to be unstable, the T4–T4 montage is significantly more robust, otherwise the 8 isolated channel montage I4(C1)–I4 outperformed the tied montage. However, the large gap between the yellow and the purple curves in figure 9, corresponding to I4(C1)–I4 and I4(C2)–I4, indicates that when using isolated sensors, the distance between the sensors is critical while in the tied version making sure that the area of interest is covered seems to be enough. In summary, the benefit of sensor tying in robustness to unstable contact depends on whether we can expect only a certain ‘number’ of sensors to go bad at test time, in which case tying helps a lot, or if we expect a certain ‘fraction’ of sensors to go bad, in which case the advantage of tying is less and depends of the fraction of loose sensors. The T4–T4 results reported in figure 9 are calculated by simulating tying with averaging signals of the 32 sensors from the 32 channels data. The performances are slightly different from the performances obtained from physical tying of the sensors, shown in figure 8(a). However, analysis shows a correlation coefficient of 0.97 between the two results (See figure A5 in appendix) indicating that averaging is a good approximation for physical tying of the sensors.

4.7. Summary and future work

In short, the eight channel T4–T4 montage seems to provide a slightly higher average accuracy than the two channel T1–T1 montage. A further advantage of the eight channel T4–T4 montage is that it is relatively robust against misplacement. This robustness increases the usability of a headset for a consumer. The only disadvantage of T4–T4 over T1–T1 is the increase in channel count and associated costs. The results of simulation
using high density data and also the data recorded with the prototype show that eight isolated channels (I4–I4) performs as well as (and in some cases better than) the tied channel version (T4–T4). However, with I4–I4 one must choose between average performance and misplacement robustness as the same design cannot achieve both. Moreover, a simulation sensor tying shows that T4–T4 is more robust than I4–I4 to unstable sensor contact. The advantage of sensor tying is more visible in the large difference between the performance of T1–T1 and the automatically optimized two channel montage showing that sensor tying can be a useful method for dramatic reduction in the number of channels.

In this paper, we used the gel based electrodes to obtain reliable high-density measurements. Later we moved to using water based electrodes to test our prototype as they are more suitable for customer use. A similar layout can be designed with dry electrodes (Lopez-Gordo et al 2014) as they are reported being as effective but much easier to put on (Di Flumeri et al 2019). The effectiveness of sensor tying in reducing the effective electrode resistance can be an interesting future investigation. As the typical resistance of different types of electrodes is quite different, according to equation (1), we expect the sensor tying to be more effective when electrodes with higher impedance are being used, such as dry electrodes.

As this study was focused on VEP-based BCIs, it is interesting to examine how the results generalize to other types of BCI. The response in VEP-based BCIs is quite strong and spatially localized. Even though we expected high sensitivity to the size of the layout and its misplacement, as can be observed in our simulation results, the performance is quite robust to the design parameters and the exact location of the layout on the head. Most other types of BCI such as P300 (Polich et al 1996, Rivet et al 2009, Mugler et al 2010), SCPs (Hinterberger et al 2004, Iversen et al 2008) and motor imagery (ERS/ERD) (Pfurtscheller and Neuper 2001, Pfurtscheller et al 2006) have weaker response which is more distributed over the head causing much lower spatial frequency (Hinterberger et al 2004, Rivet et al 2009). Therefore we expect the advantage of sensor tying to be stronger but the layout itself would perhaps need to be larger. Since in all BCIs the spatial response is either radial or dipolar, a similar layout shape with the same tying pattern would work for other types of BCI as well. The optimal placement of the layout may, however, differ depending on the modality of BCI. For example, the activity pattern of ERS/ERD is concentrated on the sensorimotor cortex (Ramoser et al 2000) requiring the measurement layout being located higher compared to VEPs. Examining these speculations by performing a layout optimization and sensor tying on another type of BCI remains future work.

5. Conclusion

In this paper a fixed montage EEG acquisition headset for cVEP-based BCIs is proposed with a focus on home-use customer product design. Such a product needs to have the following properties: high performance with minimum number of channels, robust to slight misplacement caused by non-professional home users, robust to unstable contact between the sensing points and the user’s head. The design was based on covering the most important areas of the skull with a few large sensors in an optimal layout. To evaluate the design, high density EEG recordings were made and signals from the multiple adjacent sensors were averaged to simulate larger sensors in various layouts. Simulation results show that an eight channel circular center-surround montage with center size of 40mm and surround size of 120mm, results in maximum average classification accuracy which is almost identical to what can be achieved using the full high density measurements. Such a design also provides very good robustness to misplacement such that moving it by ±15mm causes less than 1% relative drop in performance. This level of robustness is reasonably good for nonprofessional users. Simulations also showed that this design is also very robust to unstable sensor contact as it can handle loosing up to 28% of contact points without any significant drop in performance. It is also shown that it is possible to reduce the number of channels to two and still have acceptable average performance. Even though the placement of such a headset has to be more accurate, it still makes an attractive design for low budget devices (Desain 2018).

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Data availability

Before conducting the experiments, an Ethical Approval and Informed Consent of participants were obtained. This restricts us from making raw data available at a public repository. Anonymized data and the analysis scripts are available in: (http://hdl.handle.net/11633/aacssvje, http://hdl.handle.net/11633/aacssuop).

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