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Designing a brain computer interface for control of an assistive robotic manipulator using steady state visually evoked potentials

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Abstract—**An assistive robotic manipulator (ARM) can provide independence and improve the quality of life for patients suffering from tetraplegia. However, to properly control such device to a satisfactory level without any motor functions requires a very high performing brain-computer interface (BCI). Steady-state visual evoked potentials (SSVEP) based BCI are among the best performing. Thus, this study investigates the design of a system for a full workspace control of a 7 degrees of freedom ARM. A SSVEP signal is elicited by observing a visual stimulus flickering at a specific frequency and phase. This study investigates the best combination of unique frequencies and phases to provide a 16-target BCI by testing three different systems offline. Furthermore, a fourth system is developed to investigate the impact of the stimulating monitor refresh rate. Experiments conducted on two subjects suggest that a 16-target BCI created by four unique frequencies and 16-unique phases provide the best performance. Subject 1 reaches a maximum estimated ITR of 235 bits/min while subject 2 reaches 140 bits/min. The findings suggest that the optimal SSVEP stimuli to generate 16 targets are a low number of frequencies and a high number of unique phases. Moreover, the findings do not suggest any need for considering the monitor refresh rate if stimuli are modulated using a sinusoidal signal sampled at the refresh rate.**

I. Introduction

Studies show that an assistive robotic manipulator (ARM) can give tetraplegic patients more independence and improve their quality of life [1]–[3].

The best method for controlling the ARM depends on the severity of the disability; a joystick can be used if patients still have some residual motor functions in their upper extremities [1]. Similarly, the tongue can be used if all motor functions below the neck are lost [2]. However, when all motor functions are lost, the final option is a brain-computer interface (BCI) [3].

A BCI allows users to interact with a computer and/or a robot using only voluntarily produced brain activity, typically measured through electroencephalography (EEG). One of the fastest and most reliable BCI control signals is the steady-state visually evoked potential (SSVEP) [4]. In SSVEP-based BCI systems the user stimulates the brain activity by focusing on a frequency-specific flickering light which represents a specific action; this could be on a computer monitor or an LED. The EEG signals measured (at especially the occipital lobe) will adopt the flickering frequency associated with the intended action, so the power at this frequency increases. This gives a fairly simple and accurate method of detecting the user intentions [4]. It requires little to no user training to obtain BCI control with SSVEP. Thus, SSVEP may be a good choice for controlling external devices such as robotic arms or remotely controlled robots since good control is needed to control them satisfactorily [5].

The performance of a BCI is typically measured as accuracy or information transfer rate (ITR) [5], [6]. A high ITR allow the user to better exploit the functionality of the assistive devices such as an ARM with several degrees of freedom or a wheelchair [7]. Three parameters can be adjusted to improve the ITR. A decrease of the transfer time, increasing the system accuracy, and/or increasing the number of available targets/classes [5].

To fully control an ARM, a high number of targets are required which possess a technical challenge. When using Boolean logic (i.e. switching between on/off states to create the different targets), a light source can only allow frequencies which resonate with its refresh rate [8]. Thus, the available (Boolean) frequencies for a 60 Hz computer monitor is:

$$f_i = \frac{60}{i}\,\text{Hz} \qquad i=1, 2, \ldots, 60 \tag{1}$$

In the 6-16 Hz spectrum, which is the typical frequency spectrum for SSVEP [8]–[13], only 7 frequencies (i=4,..,10) are available; 6, 6.67, 7.5, 8.57, 10, 12 and 15 Hz. Furthermore, brain signals also carry higher harmonic frequencies [10], so resonating couples, such as 6 and 12 Hz, and 7.5 and 15 Hz should be avoided.

Several schemes have been proposed to increase the number of targets when keeping the number of frequencies fixed. Frequency sequential coding (presenting sequences of stimuli of varying frequencies) was used to create a unique stimuli sequence [14]–[16]. These allow for a high number of targets, but longer periods of stimulation are required.

The use of phase lag of the stimuli is yet another way to increase the number of targets in SSVEP [8]–[11], [17]. Jia et al. designed a 15 target BCI using 3 frequencies; 10, 12 and 15 Hz with 6, 5 and 4 phases, respectively [8]. The phases were determined by shifting the signal by one monitor frame period. The maximum quantity of signals within the 6-16 Hz frequency band for a 60 Hz monitor was therefore the 49 signals shown in Fig. 1.

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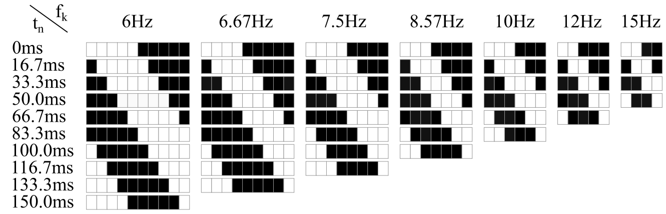
Figure 2. Frame boolean switching control for a 60 Hz monitor at frequencies f_k and timed lag t_n. The black boxes indicate an off-frame, while the white boxes indicate an on-frame.



By modulating the luminance of an LCD monitor to follow a sinusoidal signal sampled at the monitor refresh rate, rather than a Boolean on/off modulation, it is possible to achieve a much smaller phase interval [9], thus achieving even more unique targets.

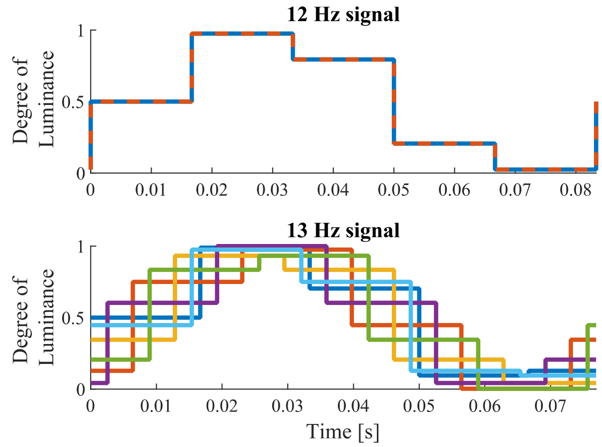
The sinusoidal sampled modulation has since been used to create stimuli which do not resonate with the monitor refresh rate [10]. With this technique, a BCI-speller with 40 targets was created wherein each target represented both a unique frequency and phase called joint frequency-phase modulation (JFPM). The BCI achieved a mean ITR of 264bits/min which is among the best performing to date.

However, while Chen et al. postulated that all frequencies can be properly stimulated [10], the consequence of using frequencies independent of the refresh rate is to the authors knowledge yet to be confirmed. Nakanishi et al. showed that the amplitude of a 12 Hz signals was enhanced when using a 120 Hz monitor opposed to a 75 Hz, which indicates that the refresh rate is indeed an important consideration [12].

This is further illustrated in Fig. 2 that shows the main difference between a 12- and 13 Hz sinusoidal signal sampled at 60 Hz. The signal is cut into consecutive segments of time length equal to the period of the signal frequency. As the 12 Hz signal is periodic within 5 periods of the 60 Hz refresh rate (i.e. all segments will be equal). This is not the case for a 13 Hz signal as 13 Hz do not resonate with 60 Hz. Each segment will in this case lag the previous with 6.4 ms for 13 Hz.

How this will influence the EEG signal is unknown; and has to the authors knowledge never been investigated. This

Figure 2. Six consecutive periods of 12 or 13 Hz stimulus, at a 60 Hz refresh rate. The 12 Hz signal is periodic within 5 periods of the 60 Hz sampling, why all 12 Hz-segments are equal. Each segment of the 13 Hz signal lags the previous with 6.4ms.



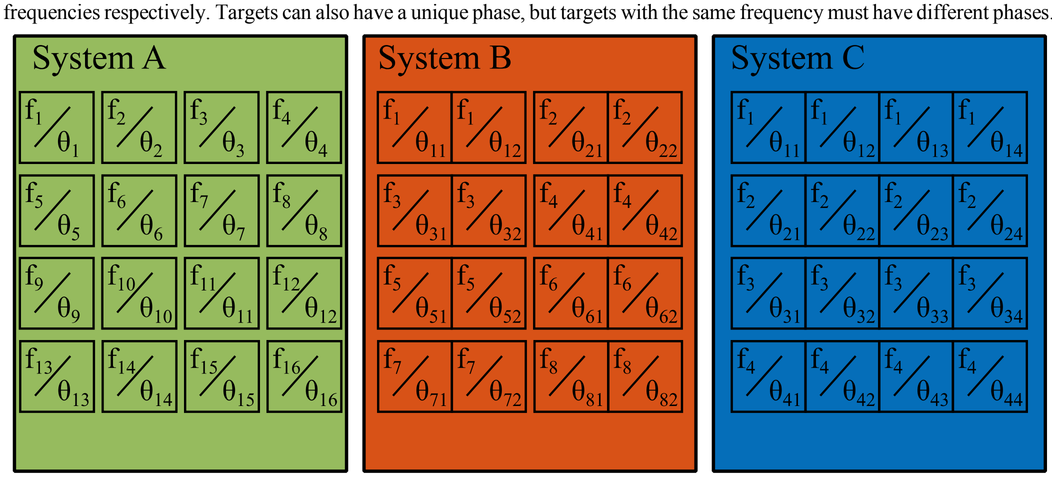
paper therefore investigates if higher accuracies can be achieved when frequencies are kept Boolean-compatible.

The developed BCI in this work will be designed with the purpose for control of a 6 DoF robotic arm with a 1 DoF end-effector; thus requiring 14 actions for full workspace control. With the inclusion of 2 menu-dedicated actions, a requirement of 16 targets for full interface control exists.

A 16-target BCI system can be build using several combinations of unique frequencies and phases. Fig. 3 shows three examples of how these combinations can be made. System A was designed as in Chen et al. with a unique frequency and phase for every target [10]. System B and C are designed with fewer unique frequencies, thus having a higher frequency interval and using phase to ensure target uniqueness. Fewer unique frequencies would lead to better discrimination between adjacent frequencies.

A shorter training time is also expected when using fewer unique frequencies as this has been shown for similar BCI systems [18]. It will be investigated if it is indeed beneficial to assign each target a unique frequency and phase as done by Chen et al. [10], or if similar results can be achieved by using

Figure 3. Three examples of a 16-target BCI system design setup. System A, System B and C have 16, 8 and 4 unique frequencies respectively. Targets can also have a unique phase, but targets with the same frequency must have different phases.



fewer unique frequencies as done by Jia et al. [8] and Wittevrongel and Hulle [11].

The aim of this study is to determine if there exist a difference in achievable BCI accuracy and ITR when varying the number of unique frequencies and unique phases, represented in this study as the three systems in Fig. 3. In addition, the effect of having monitor refresh rate resonating and non-resonating stimuli is investigated.

II. METHODS

A fourth system (system D) is created similarly to system C with the difference being that system D uses monitor refresh rate resonating frequencies. System A and system B cannot be replicated with only refresh rate resonating frequencies since they require too many unique frequencies. The four 16-target systems are investigated:

- System A: 16 targets, using 16 refresh rate non-resonating frequencies.
- System B: 16 targets, using eight refresh rate non-resonating frequencies, with at least two unique phases to differentiate between targets using the same frequency.
- System C: 16 targets, using four refresh rate non-resonating frequencies, with at least four unique phases to differentiate between targets using the same frequency.
- System D: 16 targets, using four refresh rate resonating frequencies, with at least four unique phases to differentiate between targets using the same frequency.

System A used 16 evenly spaced frequencies chosen as 7.96 to 14.86 Hz in steps of 0.46 Hz. The frequencies used in system B and C were the best performing subset of frequencies (eight and four respectively) from system A.

System D used the 60 Hz monitor refresh rate resonating frequencies; 8.57, 10, 12 and 15 Hz.

All systems have phase lags between targets. System B, C, D need this to achieve 16 unique targets while system A use it to increase discrimination between adjacent frequencies. The phase lag between the targets is simulated offline as done by Chen et al. [10].

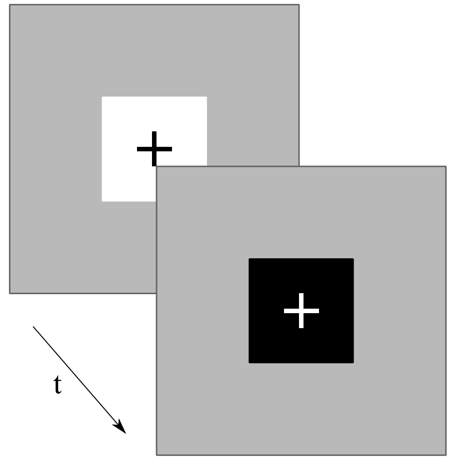
A. *Experiment*

The experiment was performed on two healthy subjects (male, 31 years and male, 25 years). Five second epochs EEG were measured at a 500 Hz sampling frequency from 9 channels [P3, Pz, P4, PO3, POz, PO4, O1, Oz, O2] using an EEG amplifier (Nuamps Express, Neuroscan). The impedance of all electrodes was below 10kΩ throughout the experiment.

The experiment was split into two tests. The first test stimulated the 16 evenly spaced frequencies used in systems A, B and C (system B and C use only 8 or 4 of these 16 frequencies, respectively). The second test stimulated the four refresh rate resonating frequencies used in system D.

A total of 20 trials were performed in each test, each consisting of all the stimulated frequencies appearing in a random sequence. The frequencies were sequentially presented as a single stimulus to avoid visual interference between neighboring stimuli. Fig. 4 shows the chosen stimulation design. It was decided to implement a fixation cross stimulating with an equivalent frequency, though having the inverted color. Each stimulus appeared for 5 seconds followed by a one second break before the next stimulus appeared. The subjects were allowed breaks between runs.

Figure 4. Stimuli design in complete on and off state.



The stimuli were created using the MATLAB addon Pscychtoolbox-3 [*http://psychtoolbox.org/*] and were displayed separately on a 17.3” LED backlit LCD monitor from a Lenovo G710 laptop, with a recorded monitor refresh rate of 60.006 Hz. It followed the sampled sinusoidal modulation procedure presented by Manyakov et al. [9].

B. *Spatiotemporal beamformer*

The spatiotemporal beamformer was chosen as classifier [11], [19], [20]. It is built on the spatial beamformer theory [21], and the stimulus-locked inter-trace correlation [13]. The beamformer is a weighted sum filter, calculated for every target k, given as:

$$y_k = \boldsymbol{w}_k^T \boldsymbol{s}_k \tag{2}$$

Where **s** denotes the investigated EEG segment of data, after transposing it to a spatiotemporal vector form, **w** is a beamformer weight value trained through a Linearly Constrained Minimum Variance problem, and y is the beamformer output representing the probability of a given target. The classification can be done by determining the target k with a maximum beamformer output.

Previous studies using the SSVEP spatiotemporal beamformer have only studied 12 and 15 Hz frequencies [8], [18], and thus only considered frequencies outside the alpha wave frequency band (8-12 Hz) where high disturbance can exist. Other classification methods, such as the modified canonical correlation method used by Chen et al. [10], use higher harmonics to account for such alpha contamination and thus allow 8-12 Hz frequencies.

This study we used frequencies in the alpha wave band; therefore, the beamformer is modified by including higher harmonic frequencies. This is done by training a spatiotemporal beamformer for every n harmonic frequency (n=1, 2, ..., N), N being the highest order of included harmonic frequencies. Eq. (2) was then modified to:

$$y_k = \frac{1}{N}\sum_{n=1}^{N} \boldsymbol{w}_{kn}^T \boldsymbol{s}_{kn} \tag{3}$$

This study used N=2, i.e. the 1st and 2nd harmonic frequencies were used.

C. Signal processing and data segment extraction

Two Butterworth zero-phase bandpass filters were used ([7-16] Hz and [15.8-32] Hz) to capture either the 1st or 2nd harmonic frequencies, respectively. The five-second epochs were cut to 0.5 seconds by removing the last 4.5 seconds of each epoch. This was done to simulate a higher potential ITR, than what could be achieved with 4.5s epochs, and is a commonly used method for analysis an SSVEP based BCI system offline [10], [11], [13], [15]–[17].

D. System optimization

As system B and C are independent of the refresh rate it is possible to select the best combination of frequencies. Similarly, an optimal phase interval between targets will be made.

1) Selection of frequencies

An algorithm was designed to determine the optimal combination of frequencies for system B and C. At each iteration the algorithm evaluates the classification accuracy after removal of one of the M available frequencies. The target that causes the highest increase in accuracy after removal was then permanently removed. Subsequently, the algorithm was recalled with M-1 targets. This continues until only eight or four targets remain for system B or C, respectively.

2) Selection of phases

An optimal phase assignment is assigned to all four systems. Note, system A only implements phase to increase variance between targets and thus the classification accuracy. The remaining systems require a phase variation between the equal frequencies to achieve 16 unique targets.

TABLE I. The phase assignment using a phase interval $\Delta\theta$ between adjacent frequencies. Targets are sorted in terms of lowest to highest frequency, such that $f_i \leq f_{i+1}$.

Target	1	2	…	16
Signal Frequency	f_0	f_1	…	f_{15}
Phase lag, θ	0	$\Delta\theta$	…	$15\Delta\theta$

A phase interval ($\Delta\theta$) between adjacent frequencies was used to create the target phase (θ). The procedure is illustrated in Tab. I; (1) the targets were first sorted in terms of lowest to highest frequency. (2) The phase lags were then assigned each target. (3) The phase lags were normalized between 0 and 2π radians.

To simulate a phase lag θ at a target with a frequency f, the 0.5-second time window was lagged with $t=\theta/(2\pi f)$ seconds. I.e. instead of removing the last 4.5 seconds of an epoch, the first t seconds and last (4.5-t) seconds were removed. The system which yield the highest accuracy at a specific phase interval is considered to be the subject's optimal system.

3) System comparison

The systems were compared in terms of accuracy and ITR. The ITR is calculated as [6]:

$$\text{ITR}= \frac{\log_2(N) + P\log_2(P) + (1\text{-}P)\log_2\left(\frac{1\text{-}P}{N\text{-}1}\right)}{T} \tag{4}$$

Where N is the number of targets, P is the system accuracy and T is the total selection time. A stimulation time window of 0.5 seconds was used on all above tests. Including a 0.5-second break between stimuli, as was done in [8]-[9], the total selection time is 1 second. The maximum theoretical ITR achievable, given a 1-second total selection time and 100% accuracy for this 16-target BCI is then 240 bit/min.

Reported results are those obtained using the optimized systems, identified using all available data.

III. RESULTS

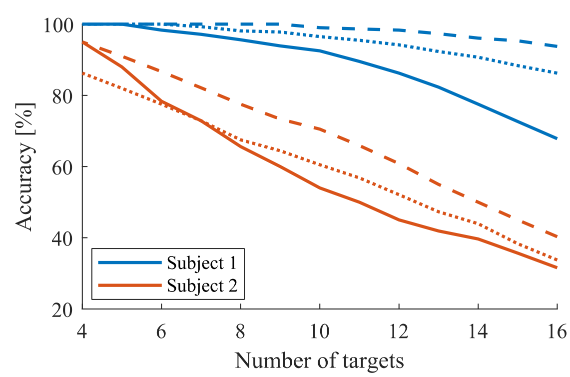
The result of the frequency selection procedure is shown in Fig. 5. Fig. 6 shows the result of the phase selection procedure. The final system performances are shown in Tab. II.

A. Frequency evaluation

Fig. 5 shows the accuracy increase after removal of a target with an assigned unique frequency. Subject 1 had a high accuracy (94%) at 16 targets which reaches 100% when the system has nine or less targets. Subject 2 had a lower performance of 40% at 16- and 95% at four targets.

The accuracy was improved by using both 1st and 2nd harmonics (dashed lines in Fig. 5) compared to only using 1st harmonics (solid lines). Using only the 2nd harmonics (dotted lines) would generally also yield a higher accuracy compared to using only the 1st harmonics.

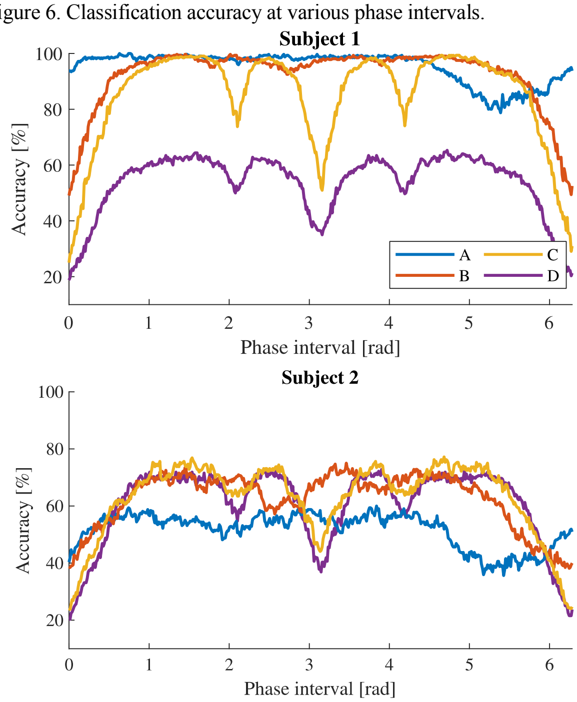
Figure 5. Accuracy versus number of targets for subject 1 and 2. Solid lines are the estimated accuracy using 1st harmonics, doted lines use 2nd and dashed use both.



B. Phase evaluation

Fig. 6 shows the accuracies for the four systems at various phase intervals. Subject 1, who had high performance at 16 frequencies, had the best performance when using System A (16 unique frequencies). Subject 2 had much greater performance using System C (4 unique frequencies). Both subjects had worse performance when using the refresh rate determined frequencies.

Figure 6. Classification accuracy at various phase intervals.



C. *Performance evaluation*

The optimal accuracies, estimated using both the 1st and 2nd harmonics, and the corresponding ITR were calculated for each system and are shown in Tab. II. The best performing system for each subject is highlighted with bold font. Subject 1 had the best performance when using system A but still had excellent performance when using either system B or C. Subject 2 had the best performance when using system C.

TABLE II. Accuracy and ITR for each of the tested systems, at the optimal phase interval. The best performing system is highlighted with bold font.

	System [-]	Phase interval [rad]	Est. Accuracy [%]	Est. ITR [bits/min]
Subject 1	**A**	**0.63**	**100.0**	**240**
	B	1.35	99.7	238
	C	4.65	99.4	235
	D	4.72	65.3	103
Subject 2	A	3.84	60.0	88.0
	B	3.46	75.0	133
	C	**4.68**	**77.2**	**140**
	D	3.90	72.8	126

IV. DISCUSSION

This study investigated some of the design considerations made when designing a SSVEP-based BCI system. It focused on a 16-target BCI with the purpose of controlling a 7 DoF ARM in its full workspace as this will be attempted in our future work.

In this study, better performance was achieved when using evenly spaced frequencies compared to the fixed resonating frequencies. The likely reason for this is that the high number of frequencies available allowed a selection of the best performing frequencies suggesting that frequencies optimized to the individual subject are more important than optimizing frequencies to the monitor refresh rate.

System C had the highest mean ITR of 187.5 bits/min across the two subjects compared to Systems A, B and D (164, 185.5 and 114.5 bits/min, respectively). While subject 1 achieved the best performance with system A, subject 2 achieved the best performance using system C. This could indicate the importance of tailoring the BCI system to the individual subject, however, due to only two subjects being enrolled in this study, any kind of generalization on these results would be inadequate. Future studies should enroll many more subjects, to more appropriately address whether there is to be made a general tendency, as to whether more unique frequencies, or less with various phase lags, are preferable. This will require more sophisticated numerical methods of determining the optimal targets and phase intervals, as the methods used in this study requires fairly heavy CPU-power due to their numerical simplicity. Chen et al. used a similar phase determination scheme, but this was generalized for all subjects rather than tailored to each individual one [10]. Wittevrongel and Hulle noted that temporal patterns are very subject-dependent, why a more subject-tailored system is assumed beneficial [11]. Future studies should therefore consider developing and testing system optimization methods able to tailor a BCI system to the individual users online.

In this study, all stimuli were presented sequentially, as it was beneficial to provide equal conditions to all stimuli. This will of course not be the case for the final interface as multiple stimuli must be available for the user at the same time. In the final 16-target BCI, neighboring targets may interfere with the target in focus, which could cause a lower accuracy. It will therefore be important to organize targets, in an effort to minimize the effect of surrounding targets, on classification accuracy. However, Chen et al. previously controlled 40 targets online [10], which makes it seem very likely that the proposed 16 target BCI is feasible. Even so, further studies should be made, to investigate the configuration of the targets best suited for control of an ARM, as some visual feedback of the ARM position should be provided to the user, while still making it feasible for subjects to focus on an SSVEP target.

A study regarding the systems online performance should also be conducted, as it is yet to be confirmed how many commands truly can be given per minute, in the online system when operating the 7 DOF ARM. It seems unlikely that the proposed 16 targets can be used to accurately control the 7 DOF ARM, with only one second to discriminate actions for novel tasks or extended periods of time, why this needs further validation. Both subjects complained regarding visual fatigue during the experiment. Higher frequencies (>30 Hz) have been shown to decrease visual fatigue [22]; therefore, the ergonomics must be considered in future studies. These frequencies typically yield lower accuracies and/or ITR; thus, it might be a trade-off between accuracy and comfort. This trade-off is likely to be subject-dependent, so such a BCI system should be able to be easily tailored to the individual end-user.

The spatiotemporal beamformer was slightly modified for this study such that higher harmonic frequencies could be included. Using both the first and second harmonics did indeed increase performance in this study. It is therefore recommended to include higher harmonics in future spatiotemporal beamformer studies.

V. Conclusion

This very exploratory study aimed to set up a framework to determine the best combinations of unique frequencies and phases for an ARM control purposed SSVEP-BCI. All systems considered in this case study achieved good performance. The study indicates that the best design for a 16-target BCI is using four unique frequencies complimented by 16 unique phase lags. The accuracies estimated with the system using refresh rate resonating frequencies was generally lower compared to systems using non-resonating frequencies. An advantage to using refresh rate resonating frequencies was therefore not observed. Future studies should focus on an intelligent solution for tailoring the BCI system to the individual users and provide a statistical analysis on the performance improvements achieved from such a solution.

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