Decoding of Multichannel EEG Activity from the Visual Cortex in Response to Pseudorandom Binary Sequences of Visual Stimuli

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Abstract

Electroencephalography (EEG) signals have been an attractive choice to build non-invasive brain computer interfaces (BCI) for nearly three decades. Depending on the stimuli there are different responses which one could get from EEG signals. One of them is the P300 response which is a visually evoked response that has been widely studied. Steady state visually evoked potential (SSVEP) is the response to an oscillating stimulus with fixed frequency, which is detectable from the visual cortex. However there exists some work on using an m-sequence with different lags as the control sequence of the flickering stimuli. In this study we used several m-sequences instead of one with the intent of increasing the number of possible command options in a brain computer interface setting. We also tested 2 different classifiers to decide between the m-sequences and study the performance of multi channel classifiers versus single channel classifiers. The study is done over two different flickering frequencies, 15 and 30 Hz to investigate the effect of flickering frequency on the accuracy of the classification methods. Our study shows that the EEG channels are correlated and although all the channels contain some useful information but combining them with a multi channel classifier based on the assumption

of having conditional independence will not improve the classification accuracy. In addition we were able to get reasonably good results using the 30 Hz flickering frequency comparing with 15 Hz flickering frequency which will give us the ability of having a shorter training and decision making time.

Introduction

Brain computer interfaces (BCI) establish a communication channel between the brain and the external world and allows the subject to communicate and control devices without the need to move a muscle, using brain signals only. So the immediate beneficiaries of this technology will be individuals with mild to severe disabilities (e.g., locked-in individuals) whose mobility are very limited or cannot move at all. Healthy individuals can also use a BCI to interface with computers and devices or to improve their performance in some tasks. For example, an individual can potentially use hands to manipulate one device while simultaneously using a BCI system to control another application. Over the recent decades there have been increasingly intense attempts to build a practical and easy to use BCI system (see for instance Sutter's work [Sutter 1984] among many others from that decade and before). Today's BCI systems use a variety of electrophysiological signals to determine the intent of the user. Slow cortical potentials, P300 potentials, mu or beta rhythms recorded from the scalp, and cortical neuronal activity recorded by implanted electrodes are examples of such signals [Wolpaw 2002]. Depending on how the BCI system captures signals from the brain, these systems are categorized into three groups: invasive, partially invasive, and non-invasive. In an invasive BCI, microelectrode arrays are inserted into the brain to measure neuronal spike activity and local field potentials. In a partially invasive BCI, the electrocorticogram arrays are placed under the skull, but on the surface of the brain. In non-invasive BCI, on the other hand, the electrodes are

only in electrical contact with the scalp using a conductive paste or gel. Among all the BCI methods, those based on electroencephalography (EEG) are most attractive due to their noninvasive nature enabling a wide range of applications benefiting diverse populations.

P300 and steady state visually evoked potentials (SSVEP) are two major responses from the brain which could be detected using EEG signals.[1] There has been substantial amount of research on the P300 response of the brain to flashing stimuli [Pfurtscheller 2000, Wolpaw 2002, Pfurtscheller 2010]. P300-Speller system and its variations [Pfurtscheller 2000, Wolpaw 2002, Treder 2010], and P300 cursor movement control [Gao 2007] are examples of such P300 based BCI systems. Different methods of stimulating the brain to produce a P300 response has also been studied [Horki 2010]. In general certain conditions should hold for a system to produce a P300 response: events must be presented randomly, a separation rule must exist to separate the events into two categories, one category of events must be presented infrequently, and finally the subject's response must be based on a pre-defined rule [Farwell 1988, Donchin 2000].

SSVEP refers to the response of the visual cortex induced by periodically flickering visual stimuli such as checkerboards consisting of two patterns with opposite colors [Pfurtscheller 2000, Allison 2008]. Other stimulation methods have also been studied [Danhua 2010], but checkerboards remain the more common choice and they are known to exhibit EEG signals that are more consistent across subjects than block flickering stimuli. SSVEP response is mainly observable for stimulus frequencies in the interval of 3 to 75 Hz [Herrmann 2001]. In this method the subject needs to focus his gaze on the stimulus of interest to produce the strongest SSVEP response [Sutter 1992]. Focusing on the stimulus causes oscillations in the visual cortex matched with the frequency of the flickering stimulus and its harmonics. These oscillations could

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[1] Motor imagery induced cortical activity is the third popularly exploited brain signal in EEG-based BCI design.

be quantitatively studied by observing the power density spectrum of the EEG signals from the electrodes placed on the visual cortex [Cheng 2002, Mast 1991, Horki 2010]. Gao and others [Gao 2002, Ortner2010, Gao 2010] have studied this phenomenon to build BCI systems with numerous options. However, since the response contains the 2nd, 3rd 4th, and maybe higher harmonics of the stimuli, it is difficult to find a set of distinct frequencies for which the leakage of power from harmonics due to system nonlinearity and signal sampling insufficiency do not overlap [Muller 2005]. Mukesh proposed double stimulation to produce more options and was able to achieve 6 options by using three different frequencies [Mukesh 2006]. Jia also proposed a method of mixed frequency and phase coding, which provides more options from each frequency [Jia 2010]. However, the number of choices for stimulus frequencies is very limited.

Among all BCI systems the ones based on SSVEP are probably the easiest to develop and most reliable. As a result, SSVEP methods are receiving more attention these days [Danhua 2010]. Despite the advantages of SSVEP, successful application of this method involves certain complications, such as the limited number of choices for the frequencies, and keeping the subjects focused throughout the experiment as they get experience fatigue due to the flickering checkerboards (or other patterns). To solve the problem with limited number of choices for frequencies, Sutter proposed a method to build an SSVEP BCI using m-sequences [Golomb 1967] as the control sequence for pattern flickering instead of just flickering checkerboards with constant frequencies [Sutter 1984, Sutter 1992]. Different phase offsets of one m-sequence are nearly orthogonal to each other by design. This property is used to enhance linear classification performance. The classifier is built by templates which are obtained during a training session. A template represents the average response of the subject to a stimulus. During the test phase, the classifier calculates the correlation between the EEG signal and templates corresponding to

different offsets of the m-sequence. The template with the highest correlation will be chosen. This is basically a matched filter signal detector. Gao and colleagues recently tried to recreate this procedure [Gao 2009], but were not able to achieve the same throughput. Yun proposed a similar approach using coded VEP to increase the number of choices for stimulus [Yun 2010]. In Sutter's approach, the number of options for stimuli increases to nearly equal to the number of variations (offsets) of the m-sequence. However, as the number of choices increases, the length of the m-sequence should increase too. Using a longer m-sequence, however, increases the time that is needed to calculate the correlation, and to classify the desired option. Although there have been a lot of work on SSVEP BCI systems, still there are many open considerations in designing an SSVEP-based intent classifier. Some of these complications are the length of the training session, the total time needed to make a reliable decision, the performance of the classifier, and of course, the overall cost of the system [Gao 2009].

Combinations of SSVEP and P300 methods have also been proposed in literature [Dornhege 2003, Gert 2010]. Leeb proposed a system combining EEG and EMG [Leeb 2010]. Allison proposed a method of combining EEG with event-related desynchronization (ERD) [Allison 2010]. Using multiple methods with the option of turning on and off one method may help to increase the number of choices for the stimuli, and the accuracy of the measurements, but it increases the training time and the complexity of the overall system.

In this paper, we study the idea of using multiple m-sequences as the control sequences of stimuli flickering activity. The motivation behind using multiple m-sequences instead of shifted versions of one m-sequence is to eventually eliminate the need for perfect synchronization of the display and the EEG signal trace for classification purposes. The classifiers which use shifted versions of one m-sequence need perfect synchronization to discriminate between different

offsets of the m-sequence [Sutter 1984, Sutter 1992]. In this study, we still assume that the timing information is available so that a basic template matching classifier can be. We will use two classifiers: (1) a basic template matching classifier using the best channel, and (2) a naïve Bayesian fusion classifier which has the ability of using one or multiple channels to make the final decision. The goal behind using the Bayesian fusion classifier is to extract information from the channels with low accuracy, and combine with the information from better channels to improve the overall accuracy. The fusion is naïve in the sense that it assumes contributions from each channel are statistically independent; future work will explore more advanced and accurate graphical models for statistical channel connectivity. We also studied the effect of two different flickering frequencies on the accuracy of classification. If the classification turns out to be at least equally successful, we can simply use the higher frequency of flickering the m-sequences, which in our case corresponds to a doubling of the bandwidth of the BCI system at no cost. In addition to faster classification in test mode, higher flickering frequency has the advantage of yielding a shorter training session.

Methods

a) **Data acquisition**

As the visual stimulus, we use two inverted checkerboard patterns with 1.75cmx1.75cm black-white blocks centered on the screen covering a 14cm x 14cm area. The subject is seated such that the checkerboard is approximately centered in the field-of-view and the eye to screen distance is approximately 60cm away, leading to an approximate visual angle of 20⁰. Figure 1 part a and b show different patterns of a checkerboard according to a '0' or a'1' bit in the m-sequence and part c shows a sample m-sequence of length 31. The subjects are not restricted to maintaining the visual or viewing angle during data acquisition. The binary sequence that is

presented on the screen was also measured and recorded using an optical sensor synchronously with the EEG using a g.USBamp and g.TRIGbox acquisition system from G.tec (Graz, Austria). The two inverted versions of the checkerboard are arbitrarily assigned the bit labels 0 and 1 and the appropriate checkerboard was sent to the screen using the Matlab Psychophysics Toolbox in the first possible monitor refresh cycle consistent with the desired flickering frequency (measured in Hz or bits per second). As monitor refresh rate is set to 60Hz, our frequency selections for bit presentation rate are guided by this limitation and we try 15Hz and 30Hz bit rates in order to ensure that visual stimulus transitions occur precisely at the intended times.

For this study, the m-sequence set consists of 4 elements, each one with 31-bits. The sequences are selected from among all 31-length m-sequences in order to approximately minimize the pair wise cross correlations. During an experimental session, for each trial one of the four sequences is selected randomly in an independent identically distributed fashion according to a uniform probability distribution. The session consisted of 80 trials and each trial contained 12 periods of the designated m-sequence. For a given session, the bit presentation rates were fixed at either 15Hz or 30Hz. Each trial begins with a one second fixation period during which the subject is instructed to focus the gaze on the + sign at the center of the screen in preparation for the upcoming trial. Between consecutive trials (each of which approximately lasts 25s or 13s) the subject can rest as much as needed and initiates the next trial with a button press at will.

EEG signals, along with the optical sensor data, are captured from the scalp using active g.Butterfly electrodes using a g.Gammabox and a g.USBamp by G.tec. A nonabrasive conductive gel is used to provide conductivity between the scalp and the electrodes. Since the goal is to detect modulated P100 signals from the visual cortex, EEG sites were selected to have

a higher spatial density around the visual cortex. The channel numbers 16 to 1 in decreasing orders refer to sites O2, Oz, O1, PO4, POz, PO3, P4, P2, Pz, P1, P3, Cp2, Cp1, C4, Cz, C3, respectively.

There were 5 subjects participating in this study. Each of them had 2 sessions, one with the m-sequences presented at the frequency of 15Hz and the other one with the presentation frequency of 30Hz. The subjects were all healthy with normal eye sight from 22 years old to 28.

b) Classification methods

In this study we used two different classifiers. The first one is single channel template matching classifier which uses the best channel to make the final decision based on the correlation of the EEG from that channel with the template response at that channel for the 4 different m-sequences. The second classifier uses a naive Bayesian fusion method with the assumption of channels being independent. This classifier is able to make the final decision based on the results of a single channel or multiple channels.

1) Template matching single channel classifier

This is a correlation based classifier. Each EEG trace to be evaluated receives 4 scores for 4 m-sequences and the sequence with the maximum score is chosen as the shown sequence. The scores for each channel are the correlations between the EEG signal from each channel and the m-sequence response templates for the corresponding channel. The templates are built using the training data collected at the beginning of each session separately using the sample mean of the EEG signal for each channel in response to one period of the appropriate sequence, which leads to 4 templates for each channel in this case. We will use the name *template order* to refer to the number of response periods used to built the template; in other words, if we build a template

using the EEG signal in response to presentation of one sequence for 10 periods then the order of

that template is 10. To build the template, the EEG signals are aligned according to the start of

the presentation of each sequence period using the optical sensor, and they are split in parts

whose length is equal to the length of the presentation of one sequence for one period. Clearly

templates with higher order will be smother and less noisy (noise power inversely proportional to

the template order), but they will need a longer training session. We used sample averaging to

obtain the maximum likelihood templates under the assumption of Gaussian measurement and

background noise. The decision for channel c is $d^c = argmax_i \, \rho_i^c$ where ρ_i^c is the correlation

score between the $\mathbf{t}_i^c$ template for the ith m-sequence for channel c and the $\mathbf{y}^c$ the windowed

EEG signal for that channel time-locked to period onset, given by $\rho_i^c = \mathbf{y}^{cT}\mathbf{t}_i^c$.

2) Naïve Bayesian fusion single channel classifier

The motivation to use a Bayesian fusion classifier is to complement the best channel by

leveraging useful information from other EEG channels, in order to increase the accuracy of the

BCI classifier. Independence of the channels is the key assumption behind this method, hence the

descriptor *naive*. The naïve Bayesian fusion classifier uses the same scores from the template

matching classifier described above; this allows for a simple linear dimension reduction in the

overall feature vector though certainly this aspect could be improved and will be investigated in

future work. For the training data correlation scores for each channel and m-sequence pair, a

Gaussian Kernel Density Estimate (GKDE) is obtained. The bandwidth parameter for the

Gaussian kernel is calculated using the Silverman rule of thumb specified below. During the test

session, after receiving all scores for channel and m-sequence pairs for the new EEG trace under

consideration, using the estimated GKDEs, a new probabilistic score for each correlation score is

obtained. Using the channel-score conditional independence assumption (given the m-sequence)

and taking the logarithm of the likelihood to obtain log-likelihood, the overall decision is obtained based on conditional a posteriori likelihood calculations; these are the summation of the logarithm of the individual channel/m-sequence probabilities. The sequence which has the highest a posteriori likelihood (assuming uniform priors for m-sequences) will be the winner. The decision criterion is $d^c = argmax_l \, p(l|\rho_l^1, \dots, \rho_l^C)$ where C is the number of channels, ρ_l^c is the correlation score for channel c and template for sequence l defined as given above in the template matching. The GKDE for the probabilistic distribution of these correlation scores, obtained using training set data is given by $p(\rho_l^c|i) = \frac{1}{N^i} \sum_{s=1}^{N^i} G_{\sigma_i^2}(\rho_l^c - \rho_{i,s}^c)$ where $\rho_{i,s}^c = \mathbf{y}_s^{cT} \mathbf{t}_i^c$. Under the assumption of conditional independence of the channels given the sequence, the decision d_c will be simplified as

$$d_c = argmax_i \sum_{c=1}^{C} \log p(y_c^l|i) = argmax_i \sum_{c=1}^{C} \log\left(\frac{1}{N^i} \sum_{s=1}^{N^i} G_{\sigma_i^2}(\rho_l^c - \rho_{i,s}^c)\right)$$

where ρ_l^c is the new correlation score from the test data and $\rho_{i,s}^c$ is the correlation score from the training data sample s for channel c and m-sequence i.

In this GKDE model, the bandwidth parameter is calculated using Silverman's rule of thumb (Silverman 1986)

$$\sigma_i^2 = \frac{1}{n} \text{tr}\left(\text{Cov}(\{\rho_{i,s}^c\})\right) \left(\frac{4}{(2n+1)N^i}\right)^{\frac{2}{n+4}}$$

where $n = 1$ is the dimension of the data, set to unity in this case. The covariance also reduces to standard deviation due to the unit dimension of correlation score data.

This classifier could use one or multiple channels up to the total EEG channels. By adding more channels which contains some information to the Bayesian fusion classifier, the overall results would improve as long as the assumption of having individual conditionally independent channels holds. In the cases where the channels have some correlation, adding the more channels with the independence assumption may decrease overall classification accuracy, especially if these correlated channels are poor performers themselves.

Results

In this study we used templates of order 60 for all the subjects, however the needed template order to achieve a certain accuracy differs from subject to subject and our best subject was able to achieve the accuracy of more than 95% with templates of order 20. Also we did not include the results of our fifth subject in the analysis, because the subject reported after the session that he was not actively paying attention to the flickering checkerboards and occasionally visualizing other thoughts. Consequently, his data analysis results shows 40% accuracy in classification of 4 m-sequences. This is an experiment which shows that although the SSVEP response is in visual cortex and is expected to be strongly influenced by the external stimulus, internal thoughts and visualization processes can inhibit and reduce the effect of the external visual stimulus leading to poor BCI performance.

The results from the template matching classifier show that the Oz channel, which is placed right on the center of the occipital lobe where the visual cortex is located, has the maximum accuracy among the 16 scalp locations used. As it was expected, the channels located farther from this site, hence the visual cortex, contain less information about the visual stimulus and yield lower accuracy. Figure 2 shows the test classification accuracy for each channel on the individual m-sequences with chance level of 25% using the template matching classifier and the flickering frequency of 15Hz for one of the subjects. Figure 3 shows the same for 30Hz flickering   frequency.

Table 1 shows the performance results in(%) for the template classifier for different channels averaged over subjects and four m-sequences in the session with 15Hz flickering frequency. Table 2 shows the same results from the template matching classifier for the 30Hz flickering frequency. We have visualized the overall template classifier accuracy for each channel as a scalp distribution in Figure 4. This figure clearly shows that probability of correct decision increases as the EEG acquisition is made closer to the occipital areas. This is more explicitly observed by investigating the confusion matrices of the template classifiers for each channel.Table 3 shows the mean performance in percent and the standard deviation of the confusion matrix entries across subjects for different channels for the session with 15Hz flickering frequency. Table 4 shows the mean performance in percent and the standard deviation of the confusion matrices for the session with 30Hz flickering frequency. From channels 14, 15, and 16, which correspond to the best-performing O-sites, we see that sequence 4 is most confused with another and sequence 1 receives most erroneous decision labels from other sequences. Our m-sequence selections attempted to maintain a maximum correlation coefficient of 0.3 between pairs and this result indicates the importance of sequence design in SSVEP and code-VEP based BCI configurations. It is also interesting that the accuracy of the template classifier is consistently higher for the 30Hz flickering rate than 15Hz. This is encouraging as faster bit presentation allows for increased decision speed (hence bandwidth) and these results demonstrate that it also helps improve performance for this particular classifier.

We now investigate the performance of the naïve Bayesian fusion approach. Figure 5 shows the accuracy of the overall classification accuracy across 4 m-sequences using the naïve Bayesian fusion of best-m channels (best-m for each m taking values 1 to 16 are obtained using brute force combinatorial search to provide the best possible results). Figure 6 shows the same

performance results for 30Hz flickering frequency. These results clearly demonstrate that the naïve Bayesian fusion approach is not effectively combining information from different channels; this can be attributed to the likely fact that EEG signals, therefore correlation scores extracted from them via template projections, are correlated with each other especially between neighboring and nearby sites. As a result the accuracy of this classifier begins with the same accuracy of the previous classifier and goes down as the number of channels included in the fusion increases. Consequently, a Bayesian fusion approach such as the one attempted here must utilize graphical models that allow for higher order connectivity between features from different sites.

Discussion and future work

Looking at the accuracy results from both classifiers the overall performance is better for flickering frequency of 30Hz. Also the subjects notified us about being subjectively more comfortable with the experimental paradigm for which the flickering frequency was 30Hz. Another benefit of using higher bit presentation frequency is shorter BCI decision time. To make a decision the classifiers based on templates wait for one period of a sequence to be shown; considering the sequence length of 31 bits in our examples, this takes roughly one second at 30Hz and 2 seconds at 15Hz. For this reason, besides test mode decision time, training data collection duration is also shorter for the 30Hz case, which is a great advantage for practical BCIs.

Although the performance of the classifiers differ from one subject to the other, both of the classifiers was able to classify with good accuracy using the best channel (Oz). The performance results for naïve Bayesian fusion show that the performance decreases as the number of channels used in the classifier increases. Our attempt to use naïve Bayesian fusion classifier to use the information from the other channels was not successful, which shows that the key assumption of

correlation scores for channels being conditionally independent is very likely not true. As future work we will pursue several enhancements: (1) use graphical models to take into account the higher order correlations between EEG sites in order to be able to extract the information from neighbor channels, (2) replace template based linear dimension reduction with an information theoretic nonlinear feature projection mechanism in order to extract the most relevant and discriminative information from each channel's signal, (3) develop a methodology to design improved stimulus control sequences that will enhance discriminability of EEG responses, (4) utilize a better statistical signal model that allows for nonstationarities in EEG signal statistics by allowing period to period variability in the visual cortex response, using hierarchical Bayesian models such as mixed effects approaches and (5) learning artifact models during the training session and rejecting or reducing them during classification.

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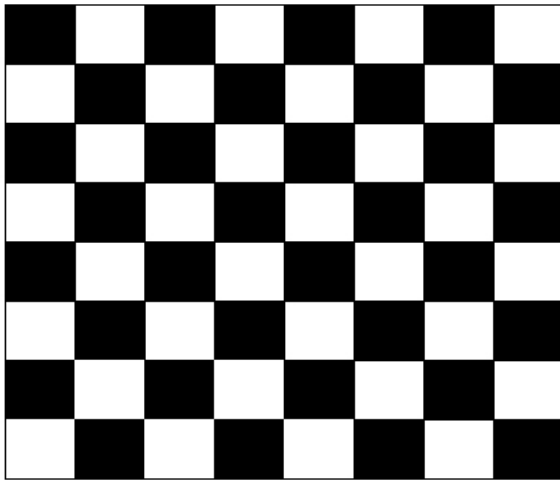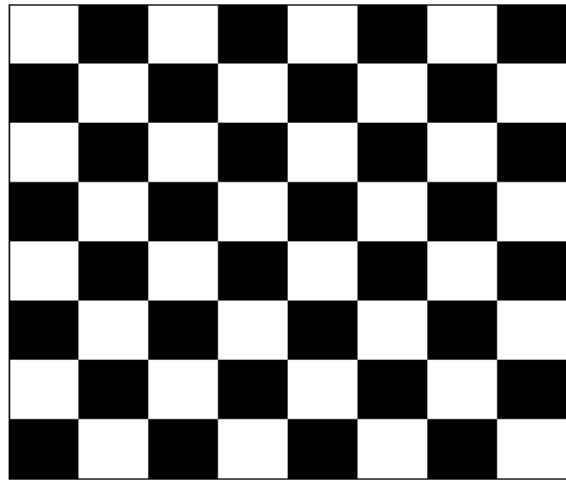
(a)   (b)

(c) 1,1,1,0,1,0,1,0,0,0,0,1,0,0,1,0,1,1,0,0,1,1,1,1,1,0,0,0,1,1,0

Figure 1:(a) Checkerboard pattern according to '1' bit (b) Checkerboard pattern according to a '0' bit (c) a sample m-sequence of length 31 bit
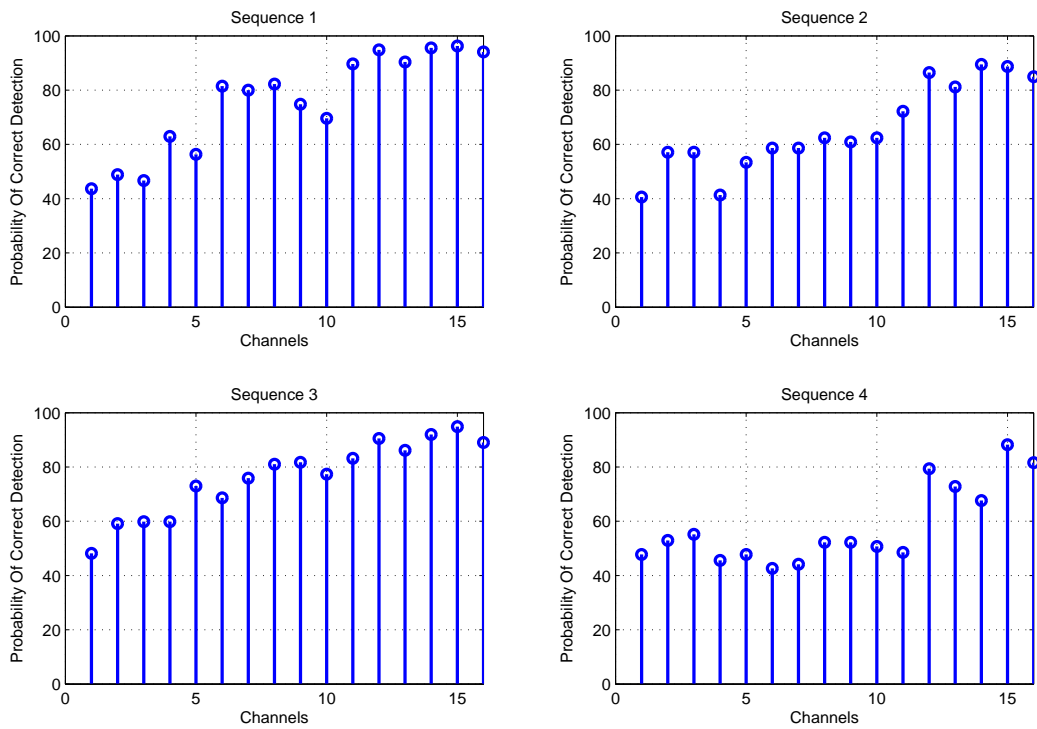
Figure 2: Template matching performance in percent for 15Hz flickering frequency.
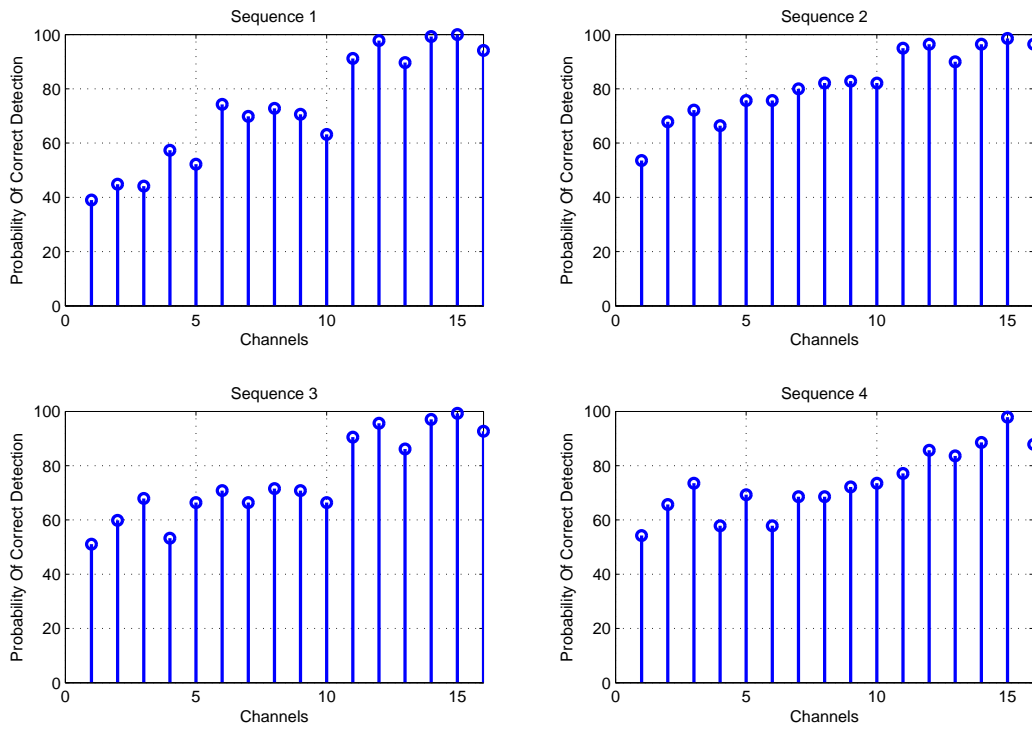
Figure 3: Template matching performance in percent for 30Hz flickering frequency.

Table 1: Template classifier performance in percent for 15Hz flickering of checkerboards				
Channel Placement	Min	Max	Mean	Std.
C3	36.5	84.5	55.5	7.39
CZ	44.75	63.75	53	7.13
C4	38.5	83.75	55.75	6.20
CP1	39.5	56.25	47.25	11.67
CP2	23.5	57.25	43	6.27
P3	19	84.25	51.25	10.16
P1	22.75	67	45	10.15
PZ	47.75	79.75	64.25	10.21
P2	40	99	63.75	6.30
P4	36.75	68	53.25	5.64
PO3	39.75	73.25	52.5	12.28
POZ	48	87.75	66	10.15
PO4	44.75	82.5	58.5	7.34
O1	50.75	99.25	77	10.48
OZ	48	95	73.25	3.96
O2	25	89	65	6.09

Table 2: Template classifier performance in percent for 30Hz flickering of checkerboards				
Channel Placement	Min	Max	Mean	Std.
C3	33	82	55.75	9.31
CZ	36.75	69.25	55.5	10.73
C4	38	87.75	61.25	10.09
CP1	34	61.25	50.5	8.73
CP2	32.75	65.75	48.75	8.65
P3	31	83.5	56	10.56
P1	37	71	54.25	8.00
PZ	42	86.25	65.25	7.50
P2	41	96.75	66.5	6.47
P4	40	72.25	60.5	7.67
PO3	41.75	88.25	59	9.29
POZ	51	94	67.25	8.13
PO4	41	87.25	61	6.92
O1	52.25	96.75	77.25	6.32
OZ	55.75	99	74.75	1.71
O2	37.25	92.75	67.75	7.40
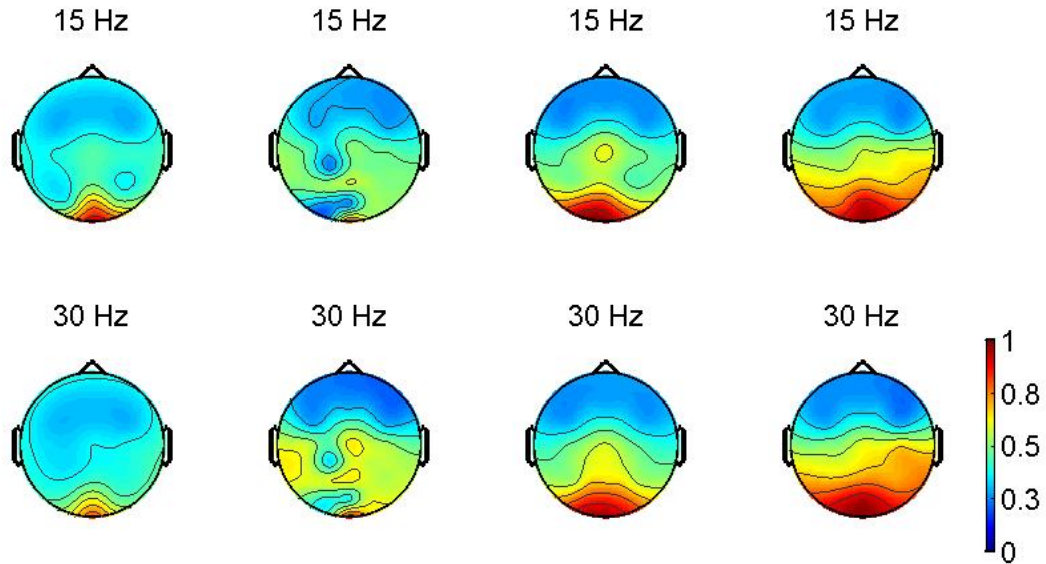
Figure 4: Probability of correct decision among 4 m-sequences as a spatial scalp distribution at 15 and 30Hz flickering frequencies for subjects 1 to 4 from left to right.

Table 3: Confusion matrices for all 16 channels at 15Hz flickering frequency.

Channel 1	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
1	37.16	7.04	22.22	4.01	21.66	8.20	18.97	5.76
2	16.19	2.16	49.95	5.19	18.03	3.80	15.82	5.51
3	19.37	4.99	16.33	3.85	47.46	5.78	16.84	1.92
4	19.08	2.64	20.60	5.38	21.62	3.43	38.69	8.35

Channel 2	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
1	45.23	3.70	20.56	4.30	19.68	4.22	14.53	0.86
2	14.13	4.16	57.61	6.12	16.00	3.38	12.26	1.17
3	15.91	4.46	8.89	5.12	56.16	6.48	19.05	2.48
4	15.60	5.83	13.62	6.19	19.83	2.78	50.96	13.37

| Channel 3	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
1	44.67	6.32	19.45	8.83	21.38	8.98	14.50	3.07
2	19.67	5.16	48.24	10.27	17.07	4.77	15.02	6.61
3	19.25	5.30	11.05	2.87	51.16	9.61	18.54	5.50
4	19.42	6.06	16.51	0.76	18.54	1.95	45.54	7.81

Channel 4	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
1	44.58	13.31	17.42	6.93	16.91	12.18	21.09	13.60
2	21.40	13.68	42.53	18.95	14.93	10.02	21.13	14.36
3	22.28	6.95	12.46	5.68	41.51	27.99	23.74	16.76
4	21.36	9.87	16.94	6.67	17.13	11.83	44.57	9.52

Channel 5	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
1	46.92	9.05	20.53	8.29	19.70	9.72	12.85	2.62
2	18.76	5.89	51.16	4.55	17.28	5.63	12.80	2.92
3	17.80	7.71	10.19	3.05	54.61	13.60	17.41	3.01
4	19.83	2.58	16.70	5.07	18.85	5.73	44.62	5.24

Channel 6	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
1	52.37	25.60	15.55	10.20	20.16	12.27	11.92	4.66
2	16.55	3.57	54.83	11.61	16.76	5.17	11.85	5.55
3	17.54	2.62	16.19	9.39	51.89	12.39	14.37	5.07
4	15.77	3.14	19.88	7.20	20.53	5.62	43.82	10.46

Channel 7	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
1	56.94	21.67	12.81	8.03	18.14	12.21	12.11	4.18
2	12.86	5.77	58.16	9.37	18.23	3.64	10.75	3.62
3	17.56	2.95	13.59	8.29	56.65	14.08	12.20	3.90
4	14.14	5.32	14.55	6.40	21.84	2.56	49.47	10.74

Channel 8	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
1	58.78	21.41	12.62	8.26	17.22	10.94	11.38	4.01
2	12.27	0.93	60.99	4.51	17.46	2.67	9.29	2.17
3	16.47	5.25	9.67	5.72	63.34	12.42	10.52	2.88
4	14.14	2.06	15.08	6.20	19.47	2.84	51.32	10.82

Channel 9	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
1	55.25	16.47	15.01	7.78	18.56	7.69	11.18	5.98
2	15.03	2.41	54.89	7.44	18.01	2.93	12.07	5.09
3	15.51	5.41	12.08	6.59	57.09	17.42	15.32	6.88
4	15.58	3.66	17.43	5.53	17.98	1.87	49.02	7.14

Channel 10	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
1	52.85	14.86	16.31	7.06	18.04	6.76	12.81	8.06
2	18.36	4.93	51.94	11.61	19.32	3.56	10.38	6.46
3	17.19	5.98	13.53	5.81	50.25	19.22	19.03	8.42
4	20.36	4.58	17.41	3.83	16.49	3.58	45.74	8.11

Channel 11	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
1	61.06	31.26	8.77	8.42	12.81	15.23	17.36	17.60
2	17.68	16.74	57.78	33.03	8.61	7.13	15.94	18.48
3	16.40	8.33	10.46	9.57	54.15	37.11	19.00	21.10
4	14.80	14.14	15.66	8.07	13.16	11.09	56.37	19.77

Channel 12	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
1	67.65	25.70	5.29	7.43	12.45	13.24	14.61	18.34
2	11.87	18.86	68.68	35.83	4.82	2.58	14.63	18.53
3	13.67	10.94	7.30	6.80	62.04	40.04	16.98	22.61
4	11.34	15.49	10.17	10.98	5.28	3.98	73.22	22.63

Channel 13	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
1	65.22	20.03	9.15	7.25	14.65	10.89	10.98	6.09
2	10.74	6.68	71.06	11.66	9.30	1.61	8.89	4.54
3	16.39	8.20	9.47	6.68	61.37	18.41	12.76	7.87
4	10.15	7.66	12.64	6.30	15.38	3.81	61.84	13.59

Channel 14	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
1	73.16	29.46	5.47	7.57	7.31	10.70	14.05	19.29
2	12.06	18.93	72.34	38.99	2.43	1.87	13.17	19.86
3	12.04	12.78	5.32	8.70	66.75	44.18	15.89	23.04
4	11.34	15.69	10.56	11.05	6.40	7.00	71.69	24.58

Channel 15	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
1	94.33	5.30	1.09	1.40	2.75	1.61	1.82	2.42
2	2.97	4.99	94.06	9.03	1.85	2.80	1.12	1.28
3	4.45	2.18	2.10	4.20	90.07	8.48	3.38	3.97
4	2.61	4.74	2.97	3.23	6.11	6.62	88.32	14.38

Channel 16	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
1	80.80	15.28	4.01	7.09	10.06	5.87	5.12	4.16
2	5.92	8.05	83.32	16.59	5.40	2.68	5.36	6.49
3	13.23	6.58	5.44	5.91	73.52	16.90	7.81	5.53
4	7.43	9.56	6.44	3.49	12.86	5.85	73.28	17.62

Table 4: Confusion matrices for all 16 channels at 30Hz flickering frequency.

Channel 1	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
Sequence 1	37.19	5.70	24.69	3.01	21.09	4.63	17.03	5.28
Sequence 2	12.80	5.16	54.55	9.99	15.50	5.75	17.15	2.46
Sequence 3	20.69	10.45	16.17	5.49	50.81	9.78	12.33	3.38
Sequence 4	16.92	9.23	24.92	9.33	17.61	5.27	40.55	14.36

Channel 2	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
Sequence 1	42.98	8.33	19.77	2.35	23.45	5.56	13.80	5.36
Sequence 2	9.93	8.00	62.29	13.85	12.80	2.85	14.97	4.57
Sequence 3	13.36	10.84	14.17	3.16	61.75	15.46	10.72	2.82
Sequence 4	15.63	4.81	19.45	11.13	15.83	4.84	49.08	15.31

Channel 3	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
Sequence 1	44.26	4.04	19.60	5.92	21.11	6.30	15.03	4.70
Sequence 2	14.41	9.54	57.98	13.93	10.82	2.90	16.79	6.02
Sequence 3	18.42	13.64	13.46	4.52	52.87	14.29	15.25	2.36
Sequence 4	20.93	9.74	18.04	6.29	17.31	7.97	43.72	20.17

Channel 4	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
Sequence 1	49.22	11.74	16.34	3.27	19.25	7.88	15.20	3.88
Sequence 2	22.31	22.41	47.55	23.41	14.80	3.46	15.33	2.71
Sequence 3	25.28	9.24	14.00	0.98	48.19	9.21	12.53	4.63
Sequence 4	24.25	15.35	19.81	6.94	16.55	5.48	39.39	16.37

Channel 5	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
Sequence 1	47.58	4.12	15.54	7.31	20.19	4.41	16.69	4.45
Sequence 2	13.35	7.61	59.58	14.72	11.19	2.40	15.87	6.49
Sequence 3	17.33	12.36	12.91	2.91	59.05	15.20	10.71	1.93
Sequence 4	18.00	7.09	17.30	6.42	15.84	7.44	48.86	15.92

Channel 6	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
Sequence 1	52.44	16.40	16.62	7.67	16.30	6.59	14.64	7.50
Sequence 2	14.43	8.71	61.20	14.15	11.55	4.42	12.82	1.24
Sequence 3	17.35	10.17	11.61	3.51	61.26	16.32	9.78	4.55
Sequence 4	17.63	9.29	17.44	3.74	19.83	4.32	45.10	16.04

Channel 7	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
Sequence 1	54.93	12.78	15.92	5.18	17.22	6.98	11.93	4.87
Sequence 2	13.90	9.01	63.91	18.40	10.10	6.40	12.09	3.21
Sequence 3	15.02	9.93	11.81	1.10	64.28	11.03	8.89	1.81
Sequence 4	16.55	8.76	13.63	4.63	15.64	6.62	54.18	17.79

Channel 8	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
Sequence 1	58.37	12.59	13.00	5.82	15.44	5.45	13.19	6.58
Sequence 2	12.82	8.97	64.62	18.89	9.56	7.12	12.99	3.56
Sequence 3	13.91	10.60	11.09	2.74	65.56	10.48	9.45	1.50
Sequence 4	17.08	6.52	13.83	5.59	13.63	6.67	55.45	13.41

Channel 9	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
Sequence 1	60.16	9.77	12.99	8.19	13.81	5.17	13.04	5.73
Sequence 2	14.63	8.68	63.90	18.01	7.57	3.23	13.89	7.49
Sequence 3	18.07	12.30	10.54	1.44	60.13	13.70	11.27	3.59
Sequence 4	19.09	7.42	12.74	2.76	14.02	6.85	54.15	14.90

Channel 10	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
Sequence 1	52.89	7.07	17.53	9.72	14.73	3.91	14.85	6.00
Sequence 2	17.69	10.12	57.06	20.08	9.37	3.34	15.87	7.66
Sequence 3	18.45	9.69	11.08	3.15	56.30	13.01	14.17	2.85
Sequence 4	17.45	5.90	10.75	3.98	16.76	7.54	55.05	15.76

Channel 11	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
Sequence 1	68.06	19.58	8.86	6.95	14.79	10.55	8.28	5.87
Sequence 2	20.87	22.69	65.02	32.86	8.69	8.04	5.43	3.39
Sequence 3	17.40	15.35	7.83	4.36	68.39	23.09	6.38	4.72
Sequence 4	19.90	16.31	10.55	6.72	16.19	7.46	53.36	27.57

Channel 12	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
Sequence 1	73.89	19.19	6.84	4.72	10.43	10.82	8.84	5.96
Sequence 2	21.95	22.88	65.22	31.54	7.60	6.75	5.23	5.36
Sequence 3	15.07	14.73	7.11	7.31	72.73	24.58	5.09	3.59
Sequence 4	17.55	17.01	6.04	7.28	13.29	4.99	63.12	27.60

Channel 13	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
Sequence 1	72.02	14.49	9.01	6.38	7.78	4.16	11.19	8.36
Sequence 2	12.99	10.22	69.86	20.80	8.31	3.76	8.84	7.26
Sequence 3	14.44	13.10	6.19	4.26	68.82	20.21	10.55	6.01
Sequence 4	12.18	6.51	9.11	7.19	15.85	6.42	62.86	18.07

Channel 14	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
Sequence 1	76.62	22.30	4.50	3.98	10.62	10.30	8.26	9.04
Sequence 2	19.61	24.23	68.28	33.06	7.59	8.20	4.53	3.99
Sequence 3	13.26	15.55	4.55	4.19	77.62	25.24	4.57	5.96
Sequence 4	16.46	18.94	6.00	5.45	8.00	3.76	69.54	25.24

Channel 15	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
Sequence 1	89.73	10.09	1.08	1.73	4.70	7.12	4.49	4.49
Sequence 2	4.34	4.82	90.78	8.76	3.26	2.98	1.62	1.36
Sequence 3	4.49	6.65	1.63	1.92	90.77	10.35	3.10	4.51
Sequence 4	2.73	2.54	1.63	1.91	5.47	3.19	90.16	7.19

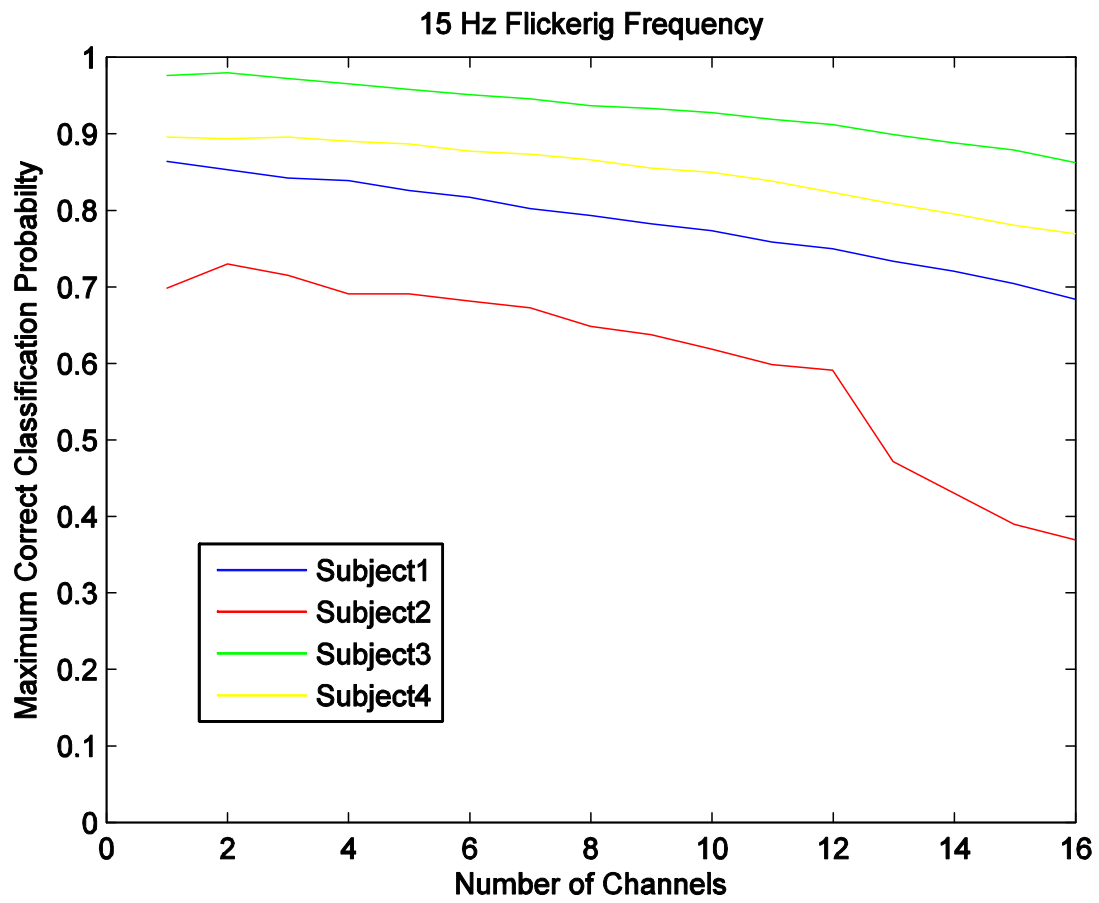| Channel 16	Sequence 1 mean	(std.)	Sequence 2 mean	(std.)	Sequence 3 mean	(std.)	Sequence 4 mean	(std.)
Sequence 1	79.62	12.40	4.88	1.86	7.22	5.86	8.28	6.41
Sequence 2	11.20	11.73	77.78	18.59	5.78	4.12	5.24	3.61
Sequence 3	12.81	14.14	3.84	4.90	74.42	23.70	8.93	8.50
Sequence 4	6.74	3.00	6.00	5.22	10.02	3.02	77.24	8.77

Figure 5: Classification accuracy of naïve Bayesian fusion of best-m channels for m from 1 to 16 at 15Hz flickering rate.
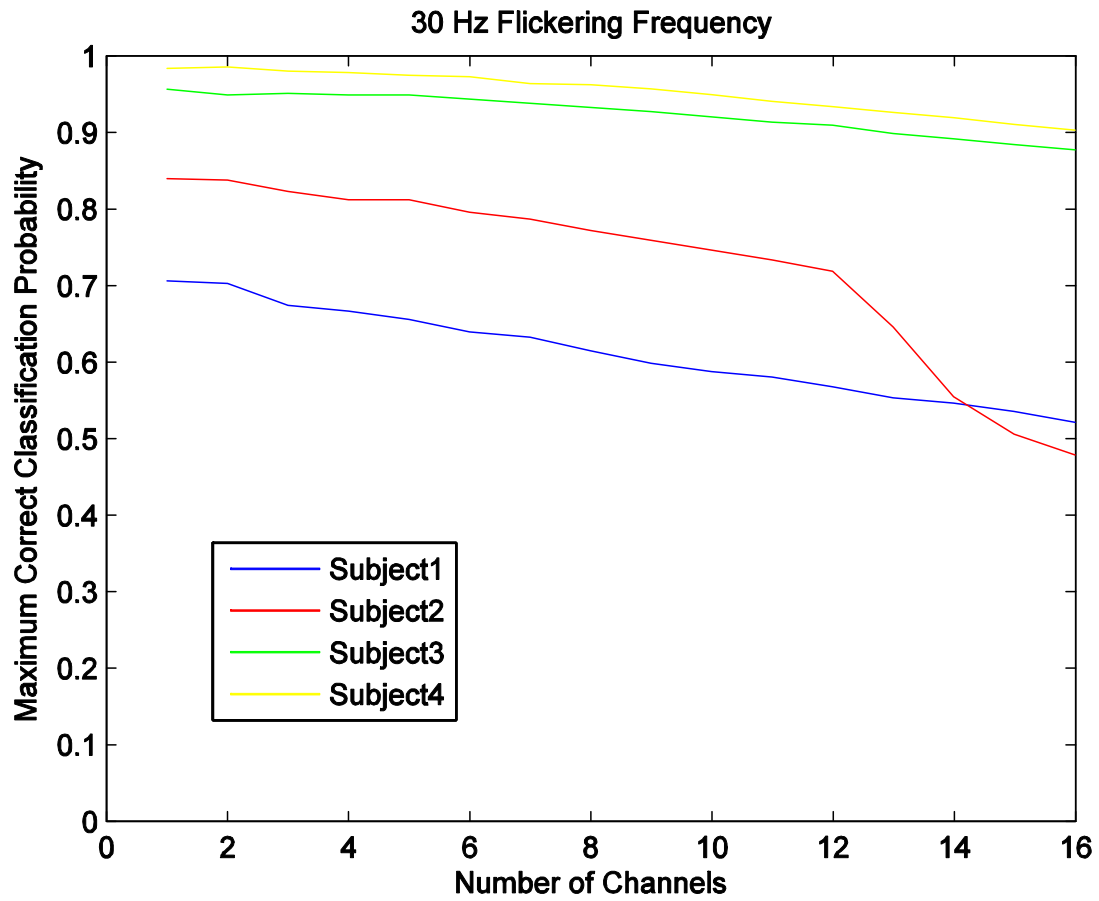
Figure 6: Classification accuracy of naïve Bayesian fusion of best-m channels for m from 1 to 16

at 30Hz flickering rate.