A Comparison of Pseudo Noise Coding and Mixed Frequency Phase Coding for Visual Evoked Potential Brain Computer Interface

Jun-ichi Sato

Washizawa Lab.

January 27, 2017

Outline

Last seminar

- Online experiment : c-VEP vs m-SSVEP
  - 32 targets
  - Data length : 1s or 4s
  - Spatial filter (c-VEP, m-SSVEP): CCA
- c-VEP exhibited higher accuracy than m-SSVEP
- Calculation using remote server
  - Socket communication
- It was hard to find the input target in the online
- The number of subjects was not enough

This seminar

- Introducing of the paper [1]
- Offline experiment using cross validation
- Three subjects participated.

A Comparison of Pseudo Noise Coding and Mixed Frequency Phase Coding for Visual Evoked Potential Brain Computer Interface

Jun-ichi Sato and Yoshikazu Washizawa

Graduate School of Informatics and Engineering, The University of Electro-Communications
1-5-1 Chofugaoka, Chofu, Tokyo 182-8585 Japan, Phone:+81-42-443-5976
E-mail: j.sato015@gmail.com, washizawa@uec.ac.jp

Abstract

Brain Compute Interface (BCI) controls a computer or device by brain signals. In this study, we focus on the stimulus-driven BCI using the visual evoked potentials (VEP) and compare coding methods for VEP-BCIs, the pseudo noise (PN) coding and the mixed frequency-phase coding (mixed coding). These two coding methods have reported high information transfer rate (ITR) compared with conventional EEG-based BCIs. However, these two codings have not yet compared in the same condition. Therefore, we conduct an experiment to compare PN and mixed coding to prove which coding has better ITR.

1. Introduction

Brain Compute Interface (BCI) is a communication pathway by discriminating brain signals without a user making any muscle movements. BCI is a promising communication tool for severely disabled people who lost control of any muscle movements such as amyotrophic lateral sclerosis (ALS) patient [1]. BCI is categorized into self-actuated or stimulus-driven type. In self-actuated BCI, the user performs a mental task such as imagery right/left-hand movement. On the other hand, stimulus-driven BCIs requires some stimuli such as visual, auditory, tactile. In this study, we focus on the stimulus-driven BCI which utilizes the visual stimulus.

Visual evoked potential (VEP) is a response to visual stimulus (e.g., LED flashing). VEP-based BCIs show higher communication speed than the other stimulus-driven BCIs. VEP based BCIs are categorized into time modulated VEP (t-VEP), code modulated VEP (c-VEP), or frequency modulated VEP (f-VEP).

In c-VEP BCI, the pseudo noise (PN) sequence is used for the stimulation. PN sequence has low autocorrelation in analogy with noise. This property is useful to improve the performance of the input target detection. c-VEP BCI exhibited higher ITR than t-VEP and f-VEP BCIs [2]. The authors have proposed spatial filters for c-VEP to improve the performance [3, 4]. They exhibited the higest ITR among c-VEP BCIs.

Steady State VEP (SSVEP) is a kind of f-VEP, and evoked by flicker stimuli at a fixed frequency. SSVEP BCI requires no training data. Therefore many practical BCI applications adopt SSVEP. However, the refresh rates of the liquid crystal display (LCD) restricts the number of the targets of SSVEP BCI. In 2010, the approximation approach to render the visual flickers was proposed to overcome the limitation [5]. This method has been extended to mixed frequency-phase coding (mixed coding). The mixed coding realizes the phase coding of SSVEPs. The mixed coding method exhibited an average of 166.91 ± 18.50 bit/min ITR [6]. This result exceeds the highest c-VEP record (144 bits/min) [7]. However, further experiments in the same condition are required to prove which coding has better ITR.

In this study, we show experimental results to compare PN and mixed coding in the same condition. We discuss the performance, such as communication speed, training computational complexity.

2. Code modulated VEP BCI

M-sequence is a kind of PN sequence whose elements are 1 or 0. The visual stimuli of c-VEP are code modulated by 63-bit M-sequences which are generated by 2-bit shifting of the M-sequence. The binary digits 0 and 1 represent black or white color respectively (Figure 1). In the calibration of c-VEP, The EEG signal is filtered by bandpass-bandstop filters to reduce noise. The signal is extracted features by a spatial filter. The template matching method is used for the target detection.

2.1 Spatial filter

Many BCI systems adopt multichannel EEG. The spatial filter integrates the multichannel EEG to reduce the redundant dimensions and the signal noise. The spatial filter is given by

$$y[n] = \sum_{i=1}^{M} w_i x_i[n], \quad (1)$$

[1] J. Sato and Y. Washizawa, A comparison of pseudo noise coding and mixed frequency phase coding for visual evoked potential brain computer interface, 2017 RISP International Workshop on Nonlinear Circuits, Communications and Signal Processing (NCSP'17), 2017.

code modulated VEP (c-VEP) BCI

- The VEP based BCI
- The visual stimuli modulated by the PN sequence
  - PN sequence has low autocorrelation
  - The evoked EEG also has low autocorrelation
    $\rightarrow$ Improving the performance of the target detection
- c-VEP exhibited higher ITR than t-VEP and f-VEP (G. Bin, 2009)

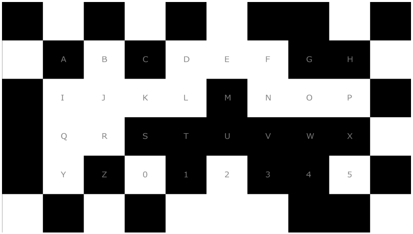


Fig. 1: The display of the 32 target c-VEP BCI

Spatial filter

- Integrating the multichannel EEG to reduce redundant dimensions and the signal noise
- $x_i[n]$: the signal of the i-th electrode
- w_i : the weight for the spatial filter

$$y[n] = \sum_{i=1}^{M} w_i x_i[n] \tag{1}$$

- In c-VEP BCI, the weight w_i is given by canonical correlation analysis (CCA).

CCA spatial filter

- $\boldsymbol{X} \in \mathbb{R}^{M \times KN}$: the EEG signal for K trials
  - M : the number of electrodes
  - KN : the number of sampling
- $\boldsymbol{Y} \in \mathbb{R}^{M \times KN}$: the averaged EEG obtained by replicating of the averaging of $\boldsymbol{X}$
- CCA finds the weights $\boldsymbol{w}_x, \boldsymbol{w}_y$ which maximizes the following canonical correlation,

$$\max_{\boldsymbol{w}_x \, \boldsymbol{w}_y} \frac{\boldsymbol{w}_x \boldsymbol{X} \boldsymbol{Y}^\top \boldsymbol{w}_y}{\sqrt{\boldsymbol{w}_x \boldsymbol{X} \boldsymbol{X}^\top \boldsymbol{w}_x \cdot \boldsymbol{w}_y \boldsymbol{Y} \boldsymbol{Y}^\top \boldsymbol{w}_y}} \tag{2}$$

Template matching

- The c-VEP experiment is separated into training and testing.
- The data of any target is generated by cyclic-shifting of one target data.
- $y_{t_0,k}[n]$ $(k = 1, \ldots, K)$: the spatial filter output of k-th target t_0
- The template $T_{t_0}[n]$ of the target t_0 is given by

$$T_{t_0}[n] = \frac{1}{K} \sum_{k=1}^{K} y_{t_0,k}[n]. \tag{3}$$

  - τ_t : the delay time of the t-th target
- The desired target t is estimated by the largest correlation coefficient between test $y[n]$ and template $T_t[n]$

Phase synchronization

- In the case of the experiment that is not separated into training and testing
- we can increase the number of averaging by the synchronization
- The synchronization of the target t to t_0 is defined by

$$y_{t_0,k}[n] = y_{t,k}[n + (\tau_t - \tau_{t_0})] \tag{4}$$

Mixed frequency-phase coded SSVEP (m-SSVEP) BCI

- m-SSVEP has the fixed frequency and phase
- The row and columns correspond the frequency $(8, \ldots, 15$ Hz) and the phase (0, 90, 180, 270 dgrees).

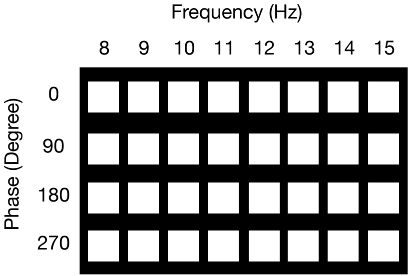


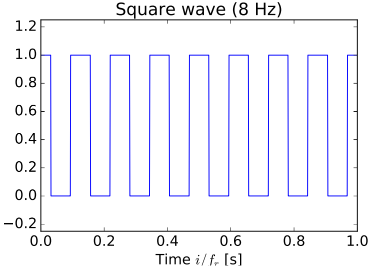
Fig. 2: The display of m-VEP BCI

Visual Stimuli

- The stimuli sequence are generated by

$$s(f, \phi, i) = \text{square}[2\pi f(i/f_r) + \phi] \tag{5}$$

  - square$[\cdot]$ generates a square wave
  - f_r : the monitor refresh rate
  - i : frame index



Ensemble classifier based CCA (1)

- $\boldsymbol{X}_{t,k} \in \mathbb{R}^{M \times N}$: the training EEG signals where t and k
  - t : the target label
  - k : the trial index
- $\boldsymbol{Y}_{f_t} \in \mathbb{R}^{2N_h \times N}$: an artificial reference signals

$$\boldsymbol{Y}_{f_t} = \begin{bmatrix} \sin(2\pi f_t/f_s \cdot n) \\ \cos(2\pi f_t/f_s \cdot n) \\ \vdots \\ \sin(2\pi N_h f_t/f_s \cdot n) \\ \cos(2\pi N_h f_t/f_s \cdot n) \end{bmatrix} \tag{6}$$

  - N_h : the number of harmonics
- $\bar{\boldsymbol{X}}_t$: The averaged training EEG signals

$$\bar{\boldsymbol{X}}_t = \frac{1}{K} \sum_{k=1}^{K} \boldsymbol{X}_{t,k} \tag{7}$$

Ensemble classifier based CCA (2)

- The correlation coefficients of the target t is defined as follows,

$$\rho_{1,t} = \rho(\boldsymbol{X}^\top \boldsymbol{w}_x, \boldsymbol{Y}_{f_t}^\top \boldsymbol{w}_y) \tag{M1}$$

$$\rho_{2,t} = \rho(\boldsymbol{X}^\top \boldsymbol{w}_{\boldsymbol{X}\bar{\boldsymbol{X}}_t},\ \bar{\boldsymbol{X}}_t^\top \boldsymbol{w}_{\boldsymbol{X}\bar{\boldsymbol{X}}_t}) \tag{M2}$$

$$\rho_{3,t} = \rho(\boldsymbol{X}^\top \boldsymbol{w}_{\boldsymbol{X}\boldsymbol{Y}_{f_t}},\ \bar{\boldsymbol{X}}_t^\top \boldsymbol{w}_{\boldsymbol{X}\boldsymbol{Y}_{f_t}}) \tag{M3}$$

$$\rho_{4,t} = \rho(\boldsymbol{X}^\top \boldsymbol{w}_{\bar{\boldsymbol{X}}_t\boldsymbol{Y}_{f_t}},\ \bar{\boldsymbol{X}}_t^\top \boldsymbol{w}_{\bar{\boldsymbol{X}}_t\boldsymbol{Y}_{f_t}}) \tag{M4}$$

$$\rho_{5,t} = \sum_{i=1}^{4} \mathrm{sign}\left(\rho_{i,t}\right) \cdot \left(\rho_{i,t}\right)^2 \tag{M5}$$

$$\rho_{6,t} = \sum_{i\in\{1,3,4\}}^{4} \mathrm{sign}\left(\rho_{i,t}\right) \cdot \left(\rho_{i,t}\right)^2 \tag{M6}$$

- $\boldsymbol{w}_x$, $\boldsymbol{w}_y$: the CCA weights of $\boldsymbol{X}$ and $\boldsymbol{Y}_{f_t}$ in (2)
- $\boldsymbol{w}_{AB}$: the weight w_x in (2) and the subscript A and B describe $\boldsymbol{X}$ and $\boldsymbol{Y}$ in (2), respectively.

Experiment setup (1)

- Offline experiment
- Three healthy subjects (males)
- The target position is randomly selected and emphasized yellow.
- The coding type (c-VEP/m-SSVEP) is selected randomly.

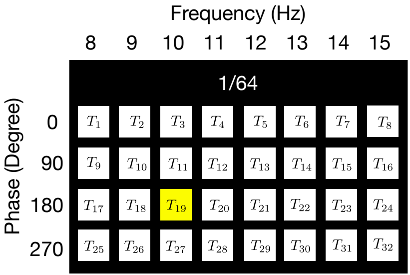


Fig. 3: The display of the offline experiment

Experiment setup (2)

- Both codings presented for 4.2 ($63/60 \times 4$) s.
- All 64 (32×2) targets were presented in one run.
- Three runs were carried out for each subject.
- 16 electrodes (P1, PZ, P2, PO3, POZ, PO4, PO7, O1, OZ, O2, PO8, PO9, O9, IZ, O10, and PO10)

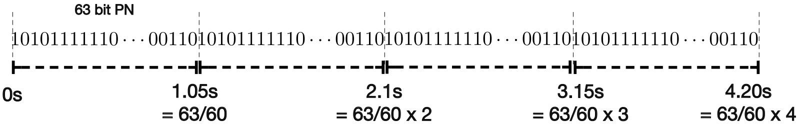
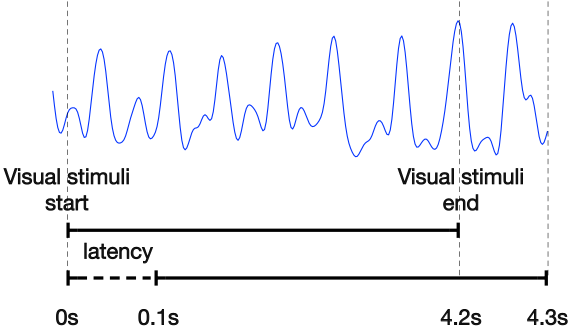


Fig. 4: The time of visual stimuli

Preprocessing

- Assuming that the latency of the VEPs is 0.1
- We extracted the signals in [0.1s, 4.3s]
- The EEGs were samples at 600 Hz
- 2-50 Hz Butterworth bandpass, 49-51Hz bandstop, 60 Hz lowpass filter
- EEG was downsampled from 600 Hz to 120 Hz



Evaluation

- Comparison of m-SSVEP (M1 $\sim$ M6) and c-VEP (CCA)
- Leave one out cross validation
- Data length : 1.05, 2.10, 3,15, 4.20 s
- Averaged classification accuracy and ITR ovr the three subjects.

Result : classification accuracy

- c-VEP exhibited higher accuracy than the m-SSVEP methods

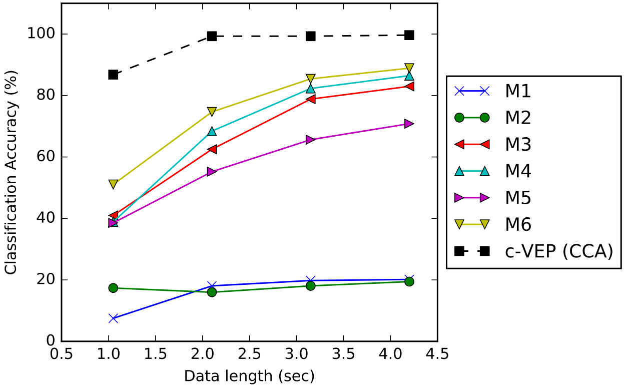


Fig. 6: The averaged classification accuracies

Result : ITR

- c-VEP exhibited higher ITR than the m-SSVEP methods

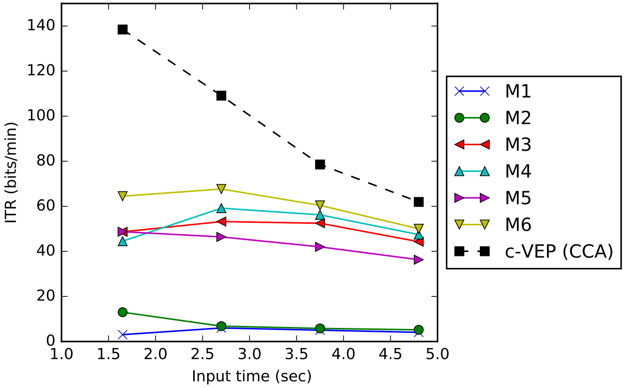


Fig. 7: The averaged ITRs

Discussion

- c-VEP achieved 100 % at 2.1s
- The highest : 138.5 (bits/min), (c-VEP, 1.05s)
- M2 was the lowest in the m-SSVEP.
  - M1 only detects the frequency (max 25
- M5 received a bad influence from M2
- M6 was the highest in the m-SSVEP
- Conv. m-SSVEP (M. Nakanishi, 2014) : 166.91 bits/min
  - They did not consider the latency delay (0.12 s) in the calculating of ITRs.
  - Averaged ITR cosidering the latency : 154.5 (bis/min)

Signal analysis

- I analyzed the signals using frequency spectrum to find the following reasons
  - Why c-VEP was better than m-SSVEP ?
  - Why M2 was the lowest performance ?
- Comparing sequence of visual stimuli and EEGs
  1. M sequence (63 bit)
  2. m-SSVEP stimuli (15 Hz)
  3. The EEG of no visual stimuli (spontaneous brain activity)
  4. The EEG of m-SSVEP (15 Hz)
  5. The EEG of c-VEP
- The three EEGs were measured in the same minutes to avoid the effects of the measuring time

M sequence (63 bit)

- M sequence has the property of white noise
  $\rightarrow$ The same power at all frequencies

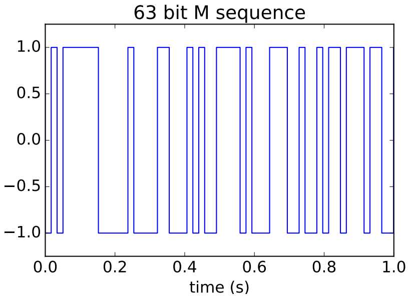


Fig. 8: M sequence (1s)

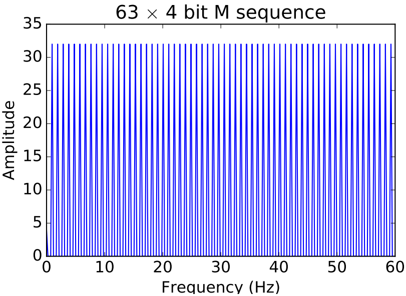


Fig. 9: freq. spectrum (4.2s)

m-SSVEP stimuli

- The peaks are at 15 Hz and 45 (15×3) Hz

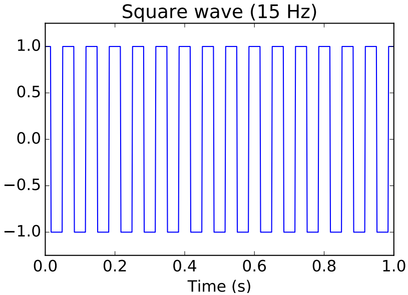


Fig. 10: m-SSVEP stimuli (1s)

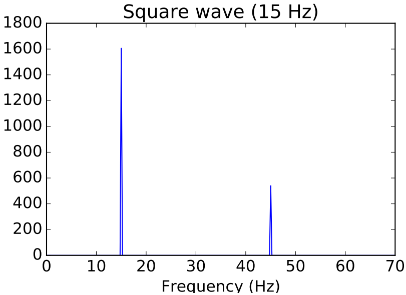


Fig. 11: freq. spectrum (4.2s)

No visual stimuli

- Subject 2, channel Oz

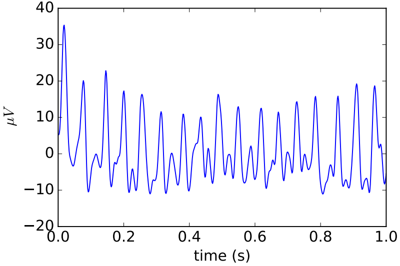


Fig. 12: EEG (1s)

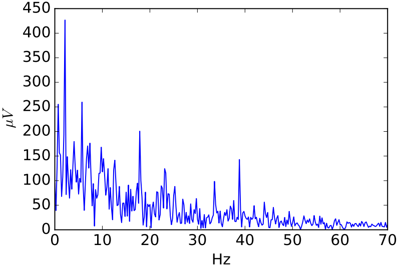


Fig. 13: freq. spectrum (4.2s)

m-SSVEP (15 Hz)

- Subject 2, channel Oz

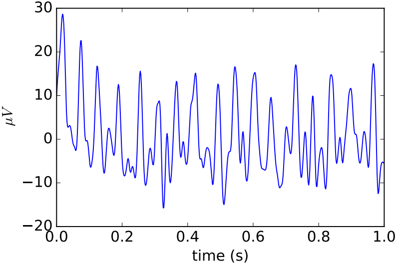


Fig. 14: EEG (1s)

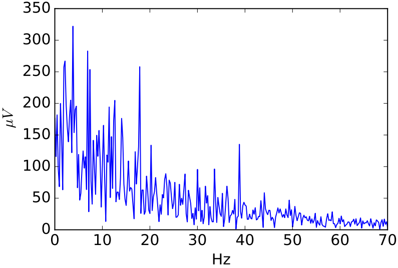


Fig. 15: freq. spectrum (4.2s)

c-VEP

- Subject 2, channel Oz

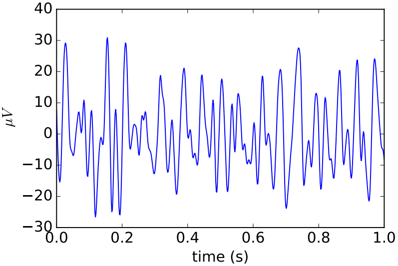


Fig. 16: EEG (1s)

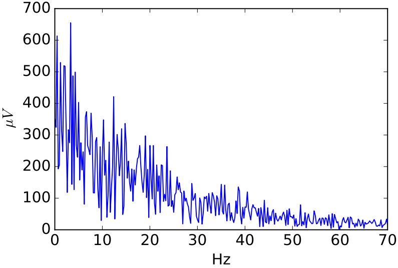


Fig. 17: freq. spectrum (4.2s)

Discussion

- Our EEG signal contained some noises in the specific narrow frequency.
- The spatial filter of M1, M3 and M4 have a feature of bandpass filter.
    - These filer are derived from $\boldsymbol{Y}_{f_t}$.
- M2 is easily effected by the noise.
- c-VEP has a wide frequency band than SSVEP
  $\rightarrow$ c-VEP is robust to the noise

Conclusion

- I compared m-SSVEP and c-VEP BCI in the same experimental condition.
- c-VEP BCI exhibited better performance than m-SSVEP BCI.
- Some noises that have specific narrow frequency were mixed in the EEGs.
- c-VEP is robust to the measuring situation.

Future works

- Re-experiment in the no noise effect environment.
- Comparing the proposed filters with parameter tuning
  - proposed filter were overfitted with no paramter tuning