行政院國家科學委員會專題研究計畫 成果報告

結合生物反饋之新世代腦機介面及其在移動載具控制之應用--子計畫三：運動想像腦電波之腦機介面系統(I)
研究成果報告(精簡版)

計 畫 類 別 ： 整合型
計 畫 編 號 ： NSC 97-2221-E-009-139-
執 行 期 間 ： 97 年 08 月 01 日至 98 年 07 月 31 日
執 行 單 位 ： 國立交通大學資訊工程學系（所）

計 畫 主 持 人 ： 陳永昇
共 同 主 持 人 ： 陳麗芬
計畫參與人員： 碩士班研究生-兼任助理人員：王億婷
碩士班研究生-兼任助理人員：郭柏志
碩士班研究生-兼任助理人員：王清偉

報 告 附 件 ： 出席國際會議研究心得報告及發表論文

公 開 資 訊 ： 本計畫可公開查詢

中 華 民 國 98 年 10 月 18 日

行政院國家科學委員會補助專題研究計畫 ■ 成果報告 □期中進度報告

結合生物反饋之新世代腦機介面及其在移動載具控制之應用—

子計畫三：運動想像腦電波之腦機介面系統(I)

計畫類別：□ 個別型計畫　　☑ 整合型計畫
計畫編號：NSC 97-2221-E-009-139
執行期間：2008 年 8 月 1 日至 2009 年 7 月 31 日

計畫主持人：陳永昇
共同主持人：陳麗芬
計畫參與人員：郭柏志、王億婷、王清偉

成果報告類型(依經費核定清單規定繳交)：☑精簡報告　□完整報告

本成果報告包括以下應繳交之附件：
□赴國外出差或研習心得報告一份
□赴大陸地區出差或研習心得報告一份
☑出席國際學術會議心得報告及發表之論文各一份
□國際合作研究計畫國外研究報告書一份

處理方式：除產學合作研究計畫、提升產業技術及人才培育研究計畫、
列管計畫及下列情形者外，得立即公開查詢
□涉及專利或其他智慧財產權，□一年□二年後可公開查詢

執行單位：國立交通大學 資訊工程系

中　華　民　國　2009 年　7 月　31 日

摘要

腦機界面系統(BCI)提供一個腦部和電腦直接做溝通的管道。為了達到降低訓練時間和降低使用者的負擔，我們使用一個三選項的界面實作以P300 為基礎腦機系統。為了增進線上系統溝通的效能和效率。我們提出一投票策略來達到系統可自動且即時的依使用者做調整，以增進線上系統的效能。更具體來說，我們結合步進線性鑑別分析和活動窗口(moving window)來產生時序特徵做投票。透過這些時序特徵我們可以決定門檻值使得線上系統可以在維持一定的分辨率的條件下動態決定結果。三個健康的受試者和七個健康的受試者分別被邀請參與離線和線上的實驗。研究結果顯示，我們的系統比 Sellers 和 Donchin 在 2006 所發表的四選項腦機系統有更好的效能。在離線分析我們達到 7.7 bits/min 的資訊轉移率，而當線上系統達到 5.23 bit/min 的轉移率時則有 100%的分辨率。這些結果都證明了比四選項系統 1.8 bit/min 資訊轉移率有更好的效能，也顯示了適應性在腦機界面系統上的優點。

關鍵詞：腦機介面系統、事件相關腦電波、P300、逐步線性區別分析

Abstract

Brain–computer interface (BCI) provides a channel for direct communication between brain and computer. To reduce training time and subjects' burden, our P300-based BCI system is implemented by using a three-choice paradigm. In order to improve the performance and efficiency of online BCI system, we propose a voting strategy to automatically make the online system adaptable to users. More specifically, we combine stepwise linear discriminant analysis (SWDA) with moving window to produce the temporal features for voting. Through the automatic threshold detemination, the online system can dynamically make decision while maintaining the accuracy of classification. Three and seven healthy subjects are recruited to participate in the offline and online experiments, respectively. In offline analysis, the transfer rates can achieve up to 7.7 bits/min, while the transfer rates of online testing can achieve up to 5.28 bits/min. These results suggest that the performances of our system are better than Sellers's four-choice system in which transfer rate is 1.8 bits/min, thus indicating the advantage of the adaptability in BCI system.

Keywords —Brain-computer interface system; Event related potentials; P300; Stepwise linear discriminant analysis

Proceedings of 2009 CACS International Automatic Control Conference
National Taipei University of Technology, Taipei, Taiwan, Nov. 27-29, 2009

Three-choice Brain-computer Interface System through Classification and Voting of Temporal Features

Liang-Wei Chen
Department of Computer Science
National Chiao Tung University
Hsinchu, Taiwan
e-mail:nova.iie96g@g2.nctu.edu.tw

Yong-Sheng Chen*
Department of Computer Science
National Chiao Tung University
Hsinchu, Taiwan
e-mail: yschen@cs.nctu.edu.tw

Li-Fen Chen
Institute of Brain Science
National Yang-Ming University
Taipei, Taiwan
e-mail: lfchen@ym.edu.tw

Abstract—**Brain–computer interface (BCI) provides a channel for direct communication between brain and computer. To reduce training time and subjects' burden, our P300-based BCI system is implemented by using a three-choice paradigm. In order to improve the performance and efficiency of online BCI system, we propose a voting strategy to automatically make the online system adaptable to users. More specifically, we combine stepwise linear discriminant analysis (SWDA) with moving window to produce the temporal features for voting. Through the automatic threshold determination, the online system can dynamically make decision while maintaining the accuracy of classification. Three and seven healthy subjects are recruited to participate in the offline and online experiments, respectively. In offline analysis, the transfer rates can achieve up to 7.7 bits/min, while the transfer rates of online testing can achieve up to 5.28 bits/min. These results suggest that the performances of our system are better than Sellers's four-choice system in which transfer rate is 1.8 bits/min, thus indicating the advantage of the adaptability in BCI system.**

***Keywords* —Brain-computer interface system; Event related potentials; P300; Stepwise linear discriminant analysis**

I. INTRODUCTION

Brain-computer interface (BCI) provides a channel to communicate with external world only through cerebral activity, thus replacing the normal pathway of communication by using muscles [1]. The electroencephalography (EEG) is commonly used in the BCI system. When a subject is performing specific tasks, the EEG signals induced by the subject's neuronal activities are recorded and analyzed. Then, the analyzed EEG signals will be translated to the corresponding commands to control prosthesis or cursor, spell words, and answer questions. Nowadays, there are many developments of BCI systems such as motor-imagery based and ERP-based BCI systems. In the existing BCI studies, P300-based BCI systems are commonly conducted, because P300 ERP can be reliably measured without initial user training.

Farwell and Donchin presented the first P300-based BCI speller [2] [3]. Since the work of Farwell and Donchin several researchers have proposed extensions and modifications of the basic speller paradigm. In addition, other applications of P300 ERP have been proposed such as virtual apartment [4], cursor control [5] and brain-controlled wheelchair [6].

*Corresponding author.

In order to provide a realistic application for ALS patients in daily life, Seller and Donchin proposed a four-choice paradigm which is tested on three healthy subjects and three ALS patients [7]. Four words included "Yes", "No", "Pass" and "End" were presented randomly as auditory, visual, or auditory and visual stimuli. In their system, eye movement is not necessary because of the smaller field of view. Under this paradigm, the P300 response remained stable in healthy subjects and ALS patients. However, a practical online BCI system should have real time response and flexibility in various situations. In the past studies of P300 BCI systems, most of them focused on the improvement of discriminant accuracy with fixed number of stimulus, but pay less attention to the adaptability of online BCI system. Serby [8] proposed the thresholding technique that is able to dynamically adapt to stop, and the threshold is designed based on the classification score. The performance of the system is improved by this technique.

The purpose of our system is to develop techniques that can determine the amount of acquired data by estimating whether the embedded information is enough. Thus, the voting method is to compute the standard of reliability by temporal features produced by a moving window and SWDA, and the votes can be derived from the temporal features. Additionally, we can use the percentage of votes to be the standard of reliability. Compare to the system using fixed number of trials to predict the result, our system using voting method can save time of predicting while the standard of reliability show that the number of recorded trials is enough to make a correct prediction. In this sense, if the predicted result has low standard of reliability, we can record more data to reduce the probability of errors through this technique. In this study, we perform two parts, offline analysis and online testing. In offline analysis, we use performance evaluation to examine the technique. Additionally, we validate the system performance by way of online testing.

II. MATERIALS AND METHOD

A. Participant

We invited three subjects (two males and one female) and seven subjects (four males and three females) in offline and online experiments, respectively, all aged between 22 and 24. All subjects were healthy college students. Subjects are asked to wear the EEG cap and sit on a comfortable chair, putting his/her hands on the lap.

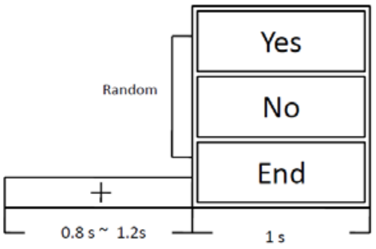


Figure 1. Experiment paradigm. This figure shows one trial of the experiment paradigm. The time intervals separately indicate the duration of stimulus and fixation which are shown on the screen.

B. Stimuli and Procedure

The experiment paradigm is shown in Figure 1. At the beginning of each stimulus, a fixation appears on the screen indicating the subjects to focus. The fixation was presented for 800 ms to 1200 ms, and then one of the stimuli (Yes, No, End) was presented randomly. The duration of three stimuli was 1000 ms. Each trial consists of one stimulus with probability of 0.33. Subjects were asked to pay attention to a specific stimulus, either Yes, No or End. The specific stimulus, the so-called target, is presented infrequently in a random sequential series. In this case, the P300 response would be elicited while the subject focuses on the stimulus series. In our paradigm, the specific stimulus is the rare event with 0.33 probability of occurrence, and the other event could be seen as the non-target with 0.66 probability of occurrence. In order to help subjects focus on the target stimulus, subjects were asked to do mental counting while the target was shown on the screen, and did not respond to another stimulus. In offline experiment, each subject participated three offline experiments sessions. Each session consisted of nine runs, and each run consisted of 20 trials. We asked these subjects to participate one offline experiment session every week. In online experiment, seven subjects participate nine runs of online experiments. Before online experiment, subjects had to participate in a training session. The session is the same as offline experiment. In this session, three runs of each target (Yes, No, End) are included. Subjects were asked to focus on a specific target that was indicated before hand, and three runs of data were used as the training data.

C. Data acquisition

The EEG was recorded using a cap containing 32 electrodes distributed over the entire scalp, and digitized with a NuAmps amplifier. The sampling rate was 1000Hz, and it is recorded at the seven channels (Fz, Fcz, Cz, Cpz, P3, Pz and P4). We start to acquire EEG data after the impedances of all 7 channels were below 5k ohm. We applied the EOG rejection to avoid eye blinking and eye movement in our data. In addition, we used a Butterworth bandpass filter to filter the data from 1Hz to 40Hz. This will eliminate the 60Hz power line interference on the signal, the low frequency heart beating (ECG), and the high frequency electromyography (EMG) effects. Before the further analysis on the discriminate analysis, we filtered the data from 1Hz to 8Hz.

D. P300 analysis

1) SWDA

SWDA was presented by Draper and Smith in 1981 [9]. It is a technique to select suitable predictor variables to be included in a multiple regression model. Additionally, it can reduce the data size but keep the most useful features in the model.

The standard stepwise selection procedure begins with the empty regression model, and subsequently adjusts the variables in the equation until the stopping rule is reached. At first, the standard procedure does forward selection to select variables. At each step the variables derived the computed F-to-enter. If one variable has the highest computed F-to-enter which is greater than the preselected significance level, the variable would be included in the regression model. After all the variables are entered, the F-to-remove is computed for all variables in the model. Furthermore, the variable with the minimum F-to-remove which is less than preselected significance level is removed. Repeat forward and backward procedure until no variables can be deleted or added. The regression coefficients were computed after the process of forward and backward procedure. We derive the regression coefficients as the weights, and the weights are applied to the prediction model.

2) Voting strategy

Voting strategy is used to estimate the standard of reliability of the discrimination result. We use moving window to produce the combination of trials. Through averaging each combination of trials and applying SWDA, the discrimination results are computed. One discrimination result can be seen as one vote to make the decision.

In other word, the votes represent the classification results which are Yes, No, or End. By moving window, the votes are derived from the trials with different window sizes. The windows size means the number of trials which are included to average and compute the vote.

In this procedure, the first vote V_1 will be computed when the first trial is recorded. After the first trial, the vote V_2 and $V_{1\text{–}2}$ are derived while the second trial is recorded. V_2 is derived from the trial 2, and $V_{1\text{–}2}$ is derived from averaging trial 1 and trial 2. In addition, V_3,

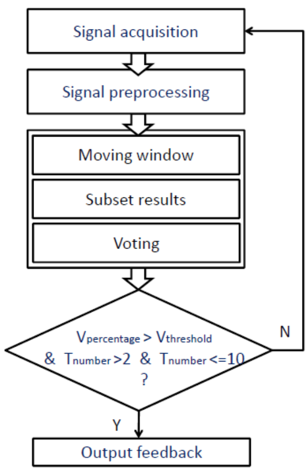
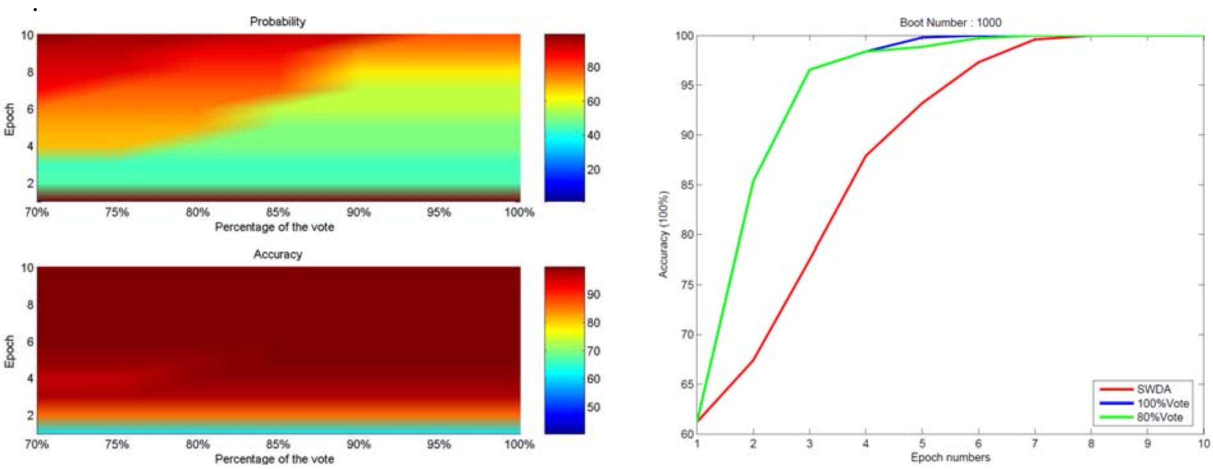


Figure 2. System flowchart



. Figure 3. Analysis results in different percentage of votes. The left figure show the probability of achievement and discriminant accuracy in seven threshold (70, 75, 80, 85, 90, 95, 100 percentage of votes), and the epoch number range from 1 to 10. The colors in the figure are defined in the color bar which shows the degree. The right figure show the comparison of accuracy of the threshold is set to 80%, 100% and only using SWDA.

V_{2_3}, and V_{1_3} are derived while trial 3 is recorded. On the analogy of this procedure, the process continues until a stopping rule is satisfied. For equipollence, the vote subsets of the same windows size represent one vote to make the decision. In other words, all the votes of the same window size have to gather statistics and produce one result. For instance, the V_{s1} is computed from gathering statistics of the vote sets V_1, V_2…, V_n. Finally, n votes V_{s1}, V_{s2}…, V_{sn} are derived while n trials are recorded. Additionally, the n votes can be seen as n temporal features to make a decision. The percentage of votes of three condition results could be seen as the standard of reliability. Thus, if we have the prior knowledge, a decision can be made only after a predefined threshold is reached; otherwise, the next trial is recorded.

The procedure of our online system is shown in Figure 2. After signal preprocessing, all the epochs are derived with different moving window size according to each recorded epochs. Additionally, all votes are observed while computing the score of each feature epochs. At the next step, the percentage of votes in accordance with three conditions is used to make the decision. If the percentage of votes is over the threshold and over 3 trials, a decision is made and the feedback would be presented on the screen. Otherwise, the next trial would be recorded until reaching the threshold. However, the decision must be made while 10th trial is recorded even though not reached the threshold.

III. Results

In offline experiment, we use bootstrap method to evaluate the performance from the recorded data. We examine the probability of achievement and accuracy in different voting thresholds (Figure 3). In addition, we also compare the accuracy of SWDA with or without voting method. The performance is actually improved by the proposed voting method. Through our method, less epochs are needed to predict the result with higher classification accuracy.

Additionally, we simulate the offline data as online recorded data. In this procedure, we test the data trial-by-trial until the threshold is reached. We evaluate the performance in different threshold settings. Moreover, eighteen data of each subject are examined in this procedure. In this analysis, the communication rate is speeded up as shown in Table 1.

We also use bit rate to evaluate the performances of three recruited subjects in offline analysis, and the maximum and average information transfer rate are shown in Table 1. For instance, subjects 3 has the maximum transfer rate 5.74 with 76.9% accuracy by using SWDA, and the average transfer rate is 1.65 with 64.9% accuracy. Furthermore, the maximum transfer rate 7.09 with 97.93% accuracy by setting the threshold to 80%.

The online testing results are shown in Table 2. The accuracy rate of three subjects are higher than 89% (eight correct and one incorrect). Furthermore, the accuracy rate of five subjects are higher than 78% (seven correct and two incorrect). We believe that the voting method has its effectiveness and stability.

Table 1. The maximum bit rate/min and average bit rate/min of three subjects by the discrimination only SWDA, voting threshold is set to 80
, and testing in online simulation procedure.

	Bit rate/min	Subject 1	Subject 2	Subject 3
Bootstrap analysis result (SWDA)	Max	7.70 (83.40%)	3.64 (82.10%)	5.74 (76.90%)
	Average	2.45 (66.69%)	1.63 (68.01%)	1.65 (64.98%)
Bootstrap analysis result (80% votes)	Max	7.70 (83.40%)	4.88 (78.40%)	7.09 (97.93%)
	Average	3.24 (84.15%)	2.75 (89.03%)	2.67 (73.82%)
Online simulation (80% votes)	Max	5.28 (100.00%)	5.28 (100.00%)	2.26 (100.00%)

Table 2. The maximum bit rate/min and total accuracy in online testing.

	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7
Max bit rate/min	5.28	5.28	3.96	5.28	3	5.28	5.28
Total accuracy	100% (9/9)	89% (8/9)	56% (5/9)	89% (8/9)	78% (7/9)	78% (7/9)	67% (6/9)

IV. Discussion

In Serby's system, the threshold is designed by way of the classifier score, and it significantly improves the speed of communication rate in online system. Thus, we test the thresholding technique based on the scores computed by SWDA, the scores could be regarded as the standard of reliability. Another idea is using sequential results as the temporal features which can be seen as the standard of reliability. Sequential results are gathered from all of the classification results while every new epoch is recorded. From the analysis result, we find the voting method has the best performance. The result of score based technique shows high classification accuracy by large threshold but has very low probability of achievement. Moreover, the probability of achievement by using sequential results to vote is similar to the voting by moving window, but using sequential result has worse classification accuracy. Thus, we prove that the voting method proposed is a better way to implement adaptability.

The best information transfer rate of Sellers's system in offline analysis are 1.8 (97.0%), 1.04 (82.1%) and 0.74 (73.2%). However, in our work, the best information transfer rate of three subjects in offline analysis are 7.7 (83.4%), 3.64 (82.1 %) and 5.74 (76.9%), and in online testing is 5.28 (100%).

Furthermore, we also test the three-choice system and four-choice system on the same subject. The comparisons of performance show that the information transfer rate of four-choice system is actually improved by voting. Moreover, the performance of three-choice system is better than four-choice system. Thus, we believe that our system significantly improve the performance in two ways. First, even though the probability of the target stimulus in three-choice paradigm is larger than the probability of the target stimulus in four-choice, the results show that the P300 response still can be reliably elicited by the three-choice paradigm. Second, the stimulus duration is shorter in our system. These two factors largely influence the performances. In addition, most answers to questions or choices in daily life are binary. Thus, we believe that the three-choice system is more practical and more efficient.

In this study, we focus on a BCI system using P300 ERP, and design a three-choice paradigm in the BCI system. Furthermore, we have used the voting strategy to develop an adaptive and efficient online BCI system. We have proved that a practical BCI system can be implemented by a simple interface, and require no complex tasks. In offline analysis, we have combined SWDA and moving window to produce temporal features, the so-called vote, and compute the percentage of votes. By way of bootstrap procedure, the percentage of votes as the standard of reliability can be proved to have high discriminating accuracy. Moreover, the online simulation result can prove that this technique can efficiently adapt to subjects, and also adapt to each run of experiments performed by the same subject. In online testing, automatically adapting to stop actually speeds up the online communication rate with high discrimination accuracy. The proposed BCI system does not have the disadvantages commonly existed in most other BCI systems. For instance, Speller has the disadvantage that subjects have to do more eye movements. Also, the motor-based BCI has longer training time and requires subjects' initial training. In conclusion, our system has the few eye movements to reduce subject's burden, and requires no subjects' initial training. In this regard, it is more practical for a BCI system.

Acknowledgments

This work was supported in part by the National Science Council, Taiwan, under Grant NSC 97-2221-E-009-139.

References

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland *et al.*, "Brain-computer interfaces for communication and control," *Clinical Neurophysiology*, vol. 113, no. 6, pp. 767-791, 2002.

[2] L. A. Farwell, and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," *Electroencephalogr Clin Neurophysiol*, vol. 70, no. 6, pp. 510-523, 1988.

[3] E. Donchin, K. M. Spencer, and R. Wijesinghe, "The mental prosthesis: assessing the speed of a P300-based brain-computer interface," *Rehabilitation Engineering, IEEE Transactions on [see also IEEE Trans. on Neural Systems and Rehabilitation]*, vol. 8, no. 2, pp. 174-179, 2000.

[4] J. D. Bayliss, "Use of the evoked potential P3 component for control in a virtual apartment," *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, vol. 11, no. 2, pp. 113-116, 2003.

[5] F. Piccione, F. Giorgi, P. Tonin *et al.*, "P300-based brain computer interface: reliability and performance in healthy and paralysed participants," *Clin Neurophysiol*, vol. 117, no. 3, pp. 531-537, 2006.

[6] B. Rebsamen, E. Burdet, C. Guan *et al.*, "Controlling a Wheelchair Indoors Using Thought," *IEEE Intelligent Systems*, vol. 22, no. 2, pp. 18-24, 2007.

[7] E. W. Sellers, and E. Donchin, "A P300-based brain-computer interface: initial tests by ALS patients," *Clin Neurophysiol*, vol. 117, no. 3, pp. 538-548, 2006.

[8] H. Serby, E. Yom-Tov, and G. F. Inbar, "An improved P300-based brain-computer interface," *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, vol. 13, no. 1, pp. 89-98, 2005.

[9] N. Draper., and H. Smith., "Applied Regression Analysis (2nd ed.): New York: Wiley," 1981.

出席國際學術會議心得報告

計畫編號	NSC 97-2221-E-009-139
計畫名稱	結合生物反饋之新世代腦機介面及其在移動載具控制之應用－子計畫三：運動想像腦電波之腦機介面系統(I)
出國人員姓名 服務機關及職稱	陳永昇　助理教授 國立交通大學 資訊工程學系
會議時間地點	May 26-29, 2009, Wuhan, China
會議名稱	The Sixth International Symposium on Neural Networks
發表論文題目	Lead Field Space Projection for Spatiotemporal Imaging of Independent Brain Activities

參加會議經過與與會心得：

International Symposium on Neural Networks 涵蓋類神經網路基礎研究及其應用，以及人腦神經科學研究之相關技術發展，今年會議在中國武漢市舉行，大會邀請的 Keynote Speech 相當精彩，包括前 IEEE Transactions on Biomedical Engineering 的 Editor in Chief、Department of Electrical and Biomedical Engineering, University of Florida 的 Professor Jose Principe，與波蘭 Department of Computer Engineering, Czestochowa University of Technology 的 Professor Leszek Rutkowski，這些優秀的演講讓我們滿載而歸。

我們在5月29日發表了研究論文：“Lead Field Space Projection for Spatiotemporal Imaging of Independent Brain Activities”。這篇論文的重點在我們發展出一個演算法，可以利用 Lead Field 空間投影的方法，針對獨立成份分析法所解析之獨立腦波成份來計算其相對應的腦皮質區活動分布。這個方法的優點在於計算十分簡便，也具相當高的準確度。

Lead Field Space Projection for Spatiotemporal Imaging of Independent Brain Activities

Huiling Chan[1], Yong-Sheng Chen[1], Li-Fen Chen[2,3], Tzu-Hua Chen[1], and I-Tzu Chen[1]

[1]Department of Computer Science, National Chiao Tung University

[2]Institute of Brain Science, National Yang-Ming University

[3]Integrated Brain Research Laboratory, Taipei Veterans General Hospital

Abstract

Magnetoencephalography and electroencephalography are non-invasive instruments that can record magnetic fields and scalp potentials, respectively, induced from neuronal activities. The recordings are superimposed signals contributed from the whole brain. Independent component analysis (ICA) can provide a way of decomposition by maximizing the mutual independence of separated components. Beyond the temporal profile and topography provided by ICA, this work aims to estimate and map the cortical source distribution for each component. The proposed method first constructs a source space using lead field vectors for vertices on the cortical surface. By projecting the specified components to this source space, our method provides the corresponding spatiotemporal maps for these independent brain activities. Experiments using simulated brain activities clearly demonstrate the effectiveness and accuracy of the proposed method.