腦波訊號分析與應用
EEG Fundamentals and Applications

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老鼠嵌晶片測癲癇 成大生奪獎

全國大學校院前瞻晶片系統設計3項競賽今天舉行聯合頒獎典禮，成功大學學生大
以老鼠做試驗，設計出即時癲癇偵測與抑制系統，奪得嵌入式系統設計競賽…

即時偵測抑制癲癇 成大晶有效

2010-07-09　中國時報　【洪榮志／台南報導】

成軍三年的成功大學心腦福祉團隊，成功研發「即時癲癇偵測與抑制系統」，已在癲癇老鼠中驗證成功。這套犧牲五十條鼠命換來的無線晶片嵌入系統，未來不僅希望能造福癲癇患者，還期盼能擴大應用到其他類似的腦部疾病。

據了解，該團隊學生成員廖益誠、陳怡均、黃郁馨、許宇成等人，對於在實驗鼠頭部裝上無線晶片系統的過程，都留下極為深刻的印象。尤其是負責「開腦」的黃郁馨，更難忘耗費六個小時辛苦完成「手術」後，實驗鼠卻突然暴斃的經驗。

成大心腦福祉（BMW）團隊係結合資訊工程、醫學資訊與社會科學等跨領域專家組成，該團隊研發的即時癲癇偵測與抑制系統，除榮獲「二○一○全國大學校院嵌入式系統設計競賽」創意應用組特優獎外，成果也將刊登於知名的《儀器與量測》（Instrumentation and Measurement）期刊上。

團隊主持人之一的認知科學研究所長蕭富仁表示，癲癇是最常發生的神經疾病之一，全世界的盛行率約一%。然而卻有約有二五%的癲癇病患，無法透過現有的服藥或手術方法控制，生活品質受到嚴重干擾。

蕭富仁認為，閉迴路深部顱內電刺激，近來被視為抑制癲癇病發的有效替代方案，只要能在偵測到癲癇發作時，立刻給予顱內電刺激，就能有效抑制癲癇發作。

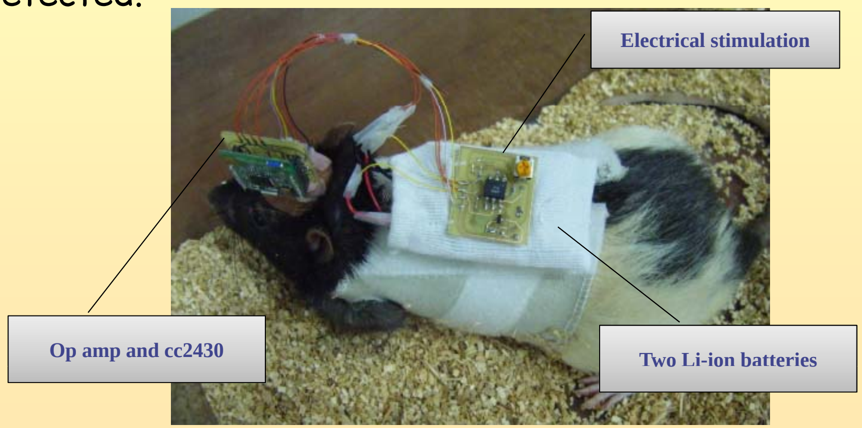
不過，此種方式面臨的挑戰，在於除需成功偵測癲癇發作外，更要克服清醒、睡眠、日常活動等不同狀態的干擾，盡量減低誤判率，並能在可攜式系統即時運算。

資訊工程研究所助理教授梁勝富說，癲癇偵測與控制系統整合腦波感測器、電刺激器、運算單元與無線傳輸模組，處理方式類似於心臟節律器的設計原理，可即時偵測與抑制失神性與藥物誘發癲癇，並在癲癇發作零點六秒內給予電刺激，具有高偵測率、低誤判率，快速電刺激反應與微小化的特點。

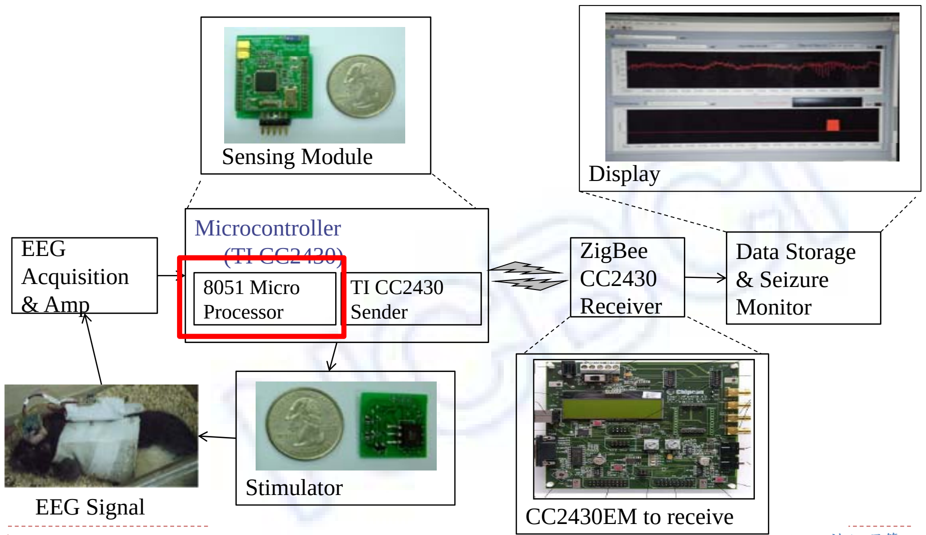
另外一方面，資工所助理教授張大緯指出，未來還希望能進一步將整個系統縮小為單一系統晶片，並與花蓮慈濟醫院合作進行臨床試驗。一旦測試成功並推廣在人體應用上，對癲癇病患將是一大福音。

Closed-loop Seizure Controller

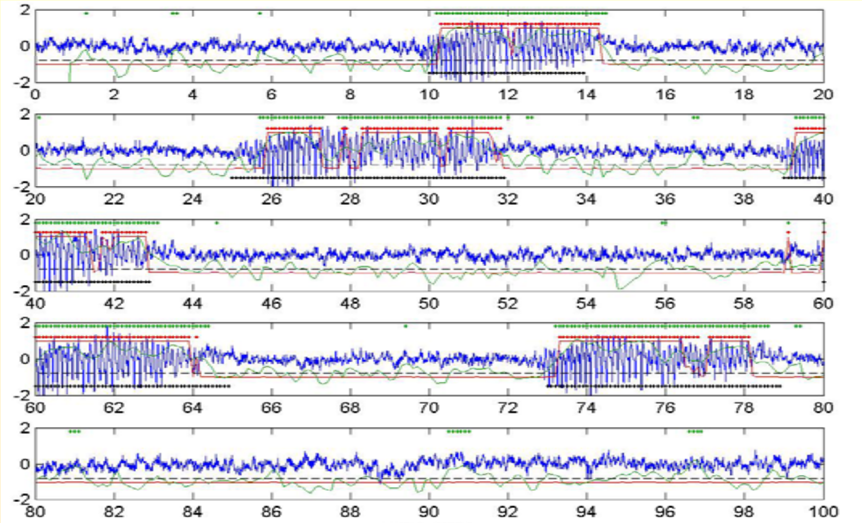
- It can perform on-line EEG monitoring and provide the electrical stimulation when a seizure event is detected.



Block Diagrams of the System

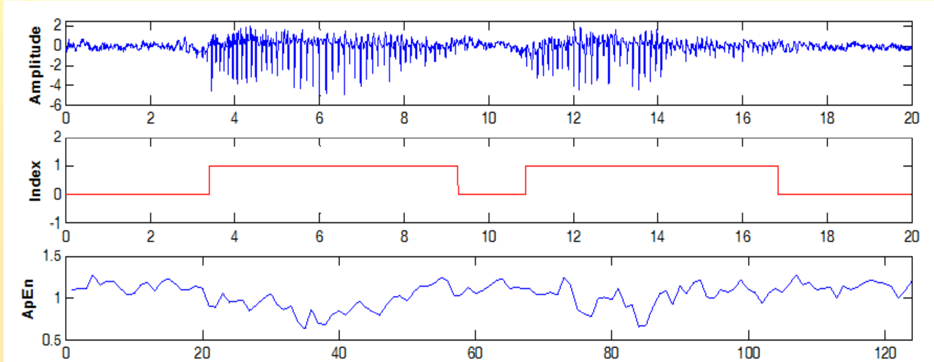


On-line Seizure Detection



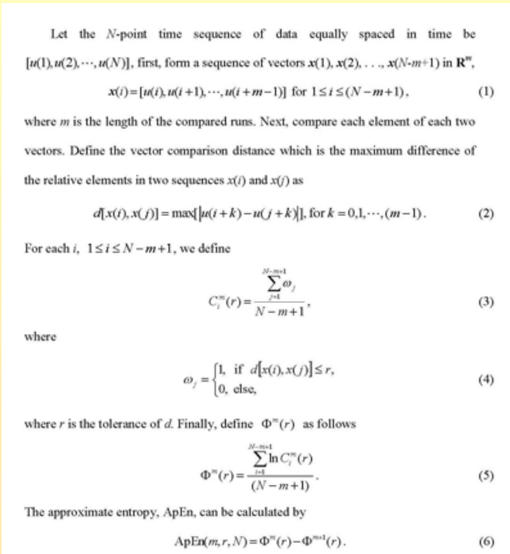
Approximate Entropy (ApEn)

- Approximate entropy (ApEn) is a measure that quantifies the regularity or predictability of a time series (Pincus, 1994).
- It counts the similarity of a vector and it's shifting version.



Approximate Entropy (ApEn)

- Srinivasan et al. (2007) successfully combined ApEn analysis with neural networks to discriminate between normal and ictal EEG signals, and the overall accuracy was as high as 100%.



Let the N-point time sequence of data equally spaced in time be $[u(1), u(2), \cdots, u(N)]$, first, form a sequence of vectors $x(1), x(2), \ldots, x(N-m+1)$ in $\mathbf{R}^m$,

$$x(i) = [u(i), u(i+1), \cdots, u(i+m-1)] \text{ for } 1 \le i \le (N-m+1), \quad (1)$$

where m is the length of the compared runs. Next, compare each element of each two vectors. Define the vector comparison distance which is the maximum difference of the relative elements in two sequences $x(i)$ and $x(j)$ as

$$d[x(i), x(j)] = \max[|u(i+k) - u(j+k)|], \text{ for } k = 0, 1, \cdots, (m-1). \quad (2)$$

For each i, $1 \le i \le N-m+1$, we define

$$C_i^m(r) = \frac{\sum_{j=1}^{N-m+1} \omega_j}{N-m+1}, \quad (3)$$

where

$$\omega_j = \begin{cases} 1, & \text{if } d[x(i), x(j)] \le r, \\ 0, & \text{else,} \end{cases} \quad (4)$$

where r is the tolerance of d. Finally, define $\Phi^m(r)$ as follows

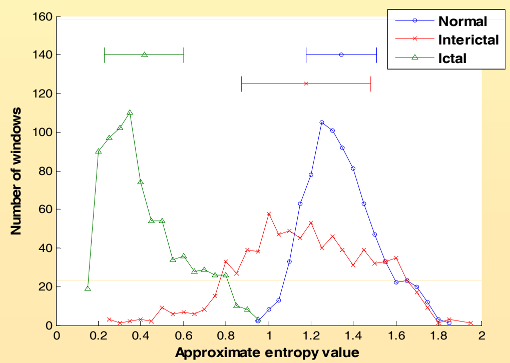
$$\Phi^m(r) = \frac{\sum_{i=1}^{N-m+1} \ln C_i^m(r)}{(N-m+1)}. \quad (5)$$

The approximate entropy, ApEn, can be calculated by

$$\mathrm{ApEn}(m, r, N) = \Phi^m(r) - \Phi^{m+1}(r). \quad (6)$$

Approximate Entropy (ApEn)

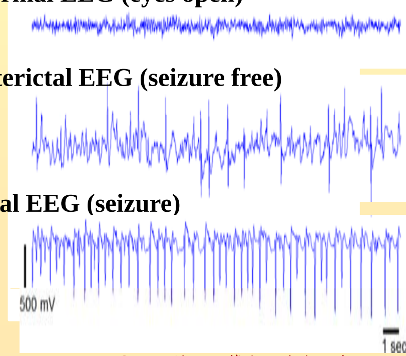
- ApEn is a useful feature to discriminate normal and siezure EEGs.
- However, ApEn values of the interictal EEGs overlapped with those of the normal and the ictal EEGs.



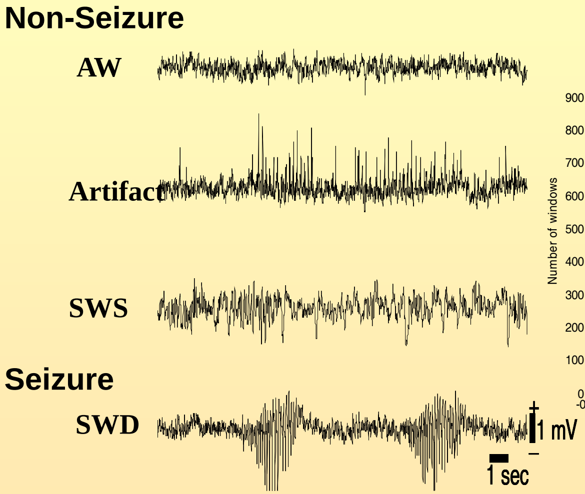
Normal EEG (eyes open)

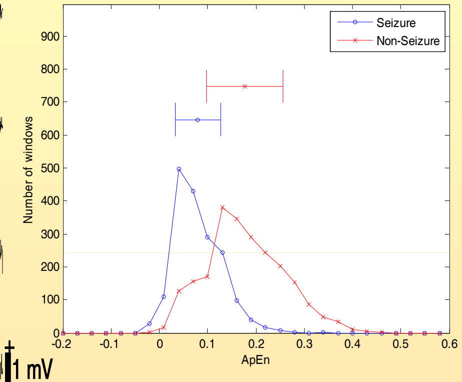
Interictal EEG (seizure free)

Ictal EEG (seizure)



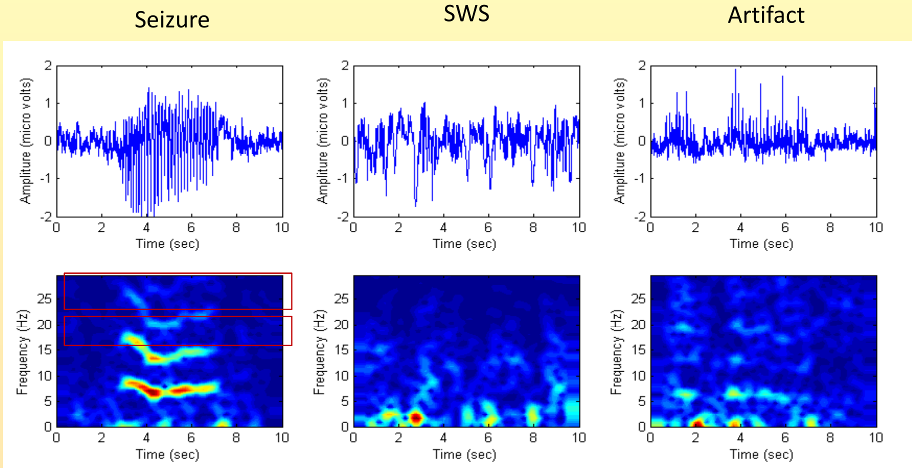
Continuous EEG Recordings





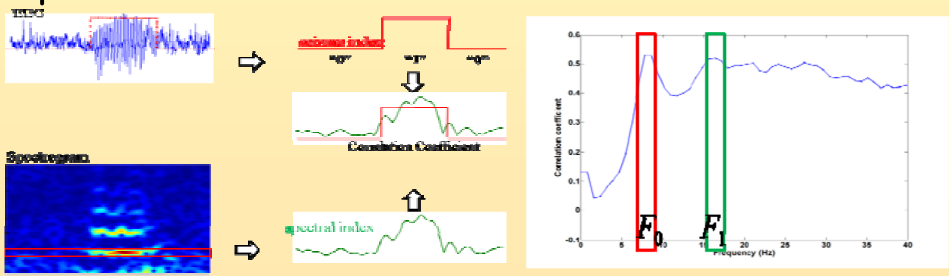
Time-Frequency Analysis

- The EEG power spectrum was utilized as the complementary feature of ApEn.



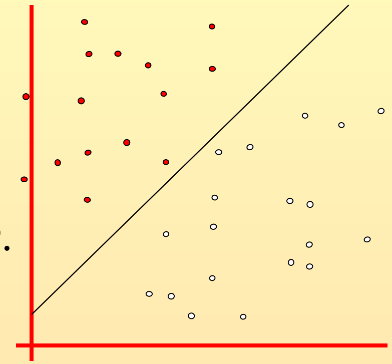
Spectral Features-FFT

- Fast Fourier Transform was used for spectral analysis.
- Frequency bands corresponding to the top two correlation coefficients were extracted as the spectral features.

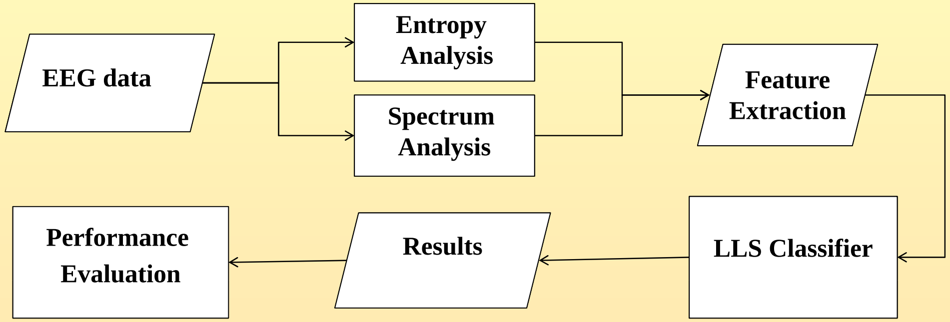


Classification-LLS

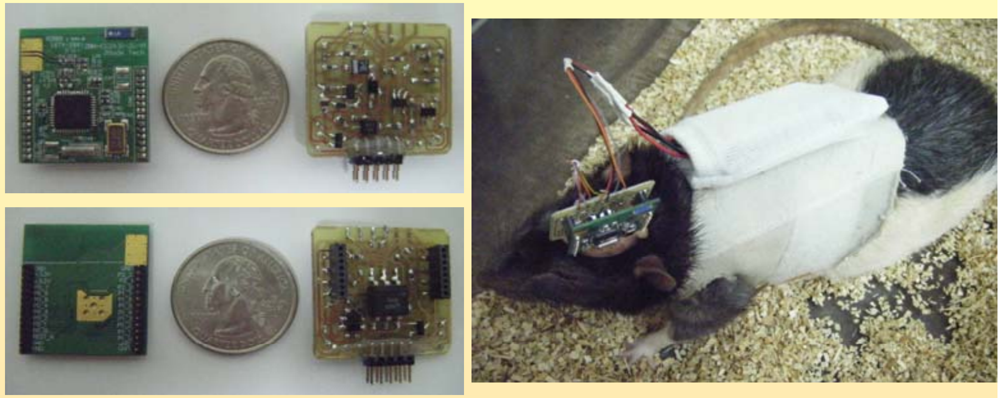
- One entropy value and the powers of two selected frequency bands were used for classification.
- A linear classifier called linear least squares (LLS) was utilized as the classifier.



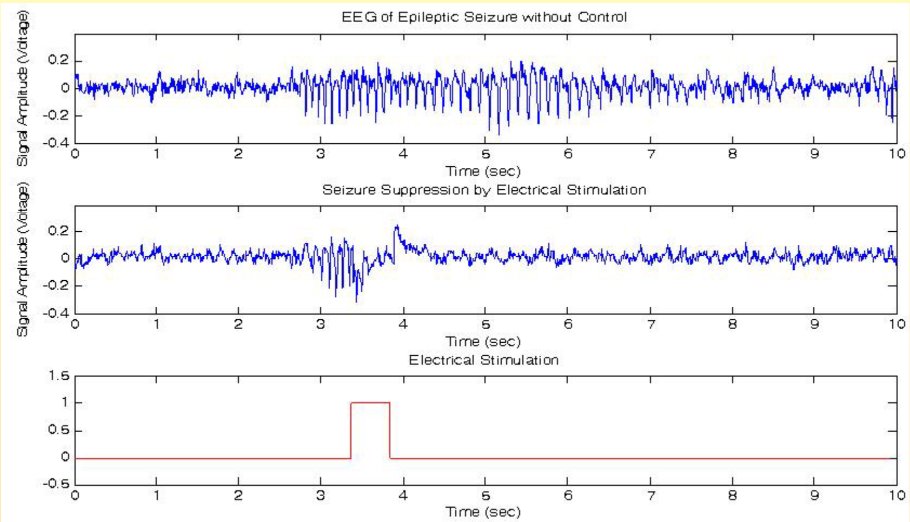
The Seizure Detection Method



Closed-loop Seizure Controller



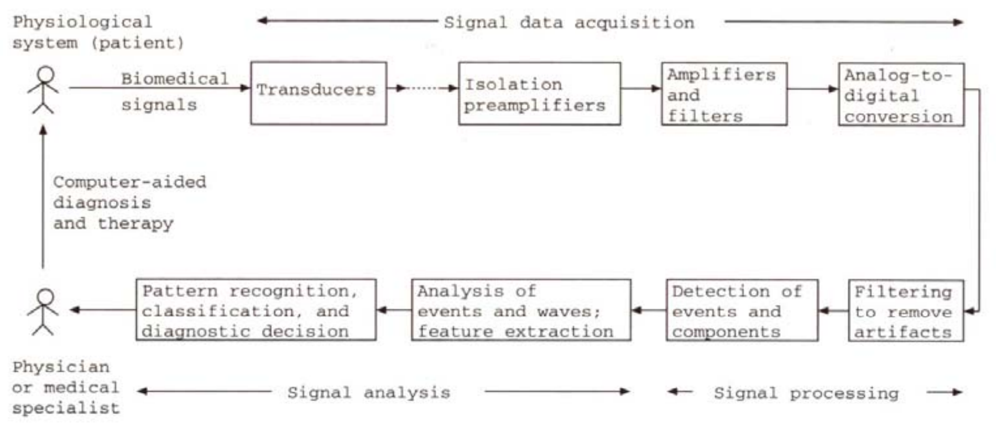
Electrical Stimulation



Performance Evaluaiton

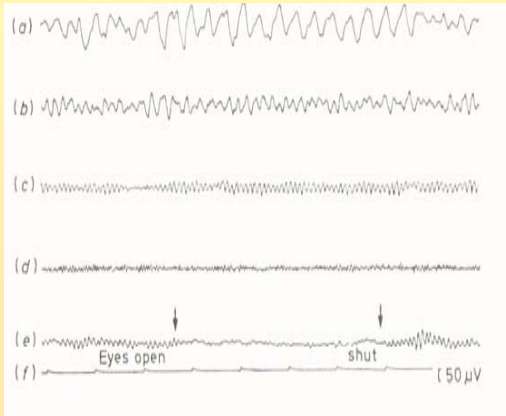
Subjects			SWD	Detected SWD	Accuracy	False stimulation	Detection delay (s)
#1	Light-on (2 hours)	Awake	349	343	97.7%	1	0.536
		Sleep	46	43		8	0.545
	Light-off (2 hours)	Awake	248	247	99.1%	0	0.491
		Sleep	100	98		9	0.567
#2	Light-on (2 hours)	Awake	250	230	92.0%	0	0.547
		Sleep	4	2		0	0.599
	Light-off (2 hours)	Awake	246	235	95.2%	4	0.540
		Sleep	26	24		2	0.556
#3	Light-on (2 hours)	Awake	644	627	97.3%	17	0.471
		Sleep	0	0	---	0	n/a
	Light-off (2 hours)	Awake	449	442	99.1%	8	0.485
		Sleep	0	0	---	0	n/a

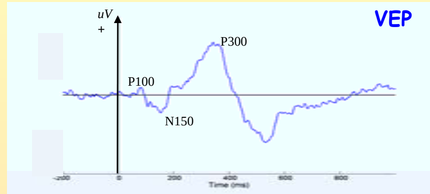
Computer-Aided Diagnosis and Therapy System

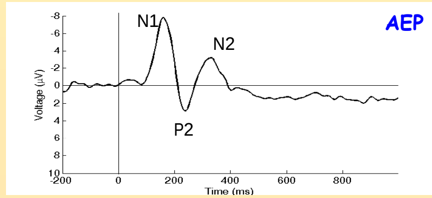


Multi-Channel EEG for Cognition Study

- EEG rhythms
- Event related potentials





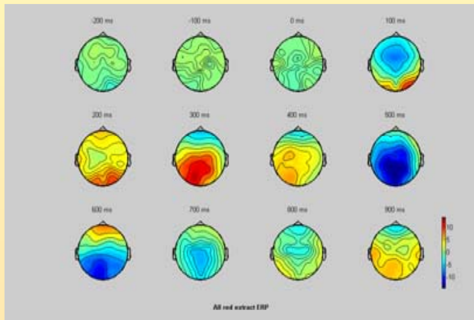


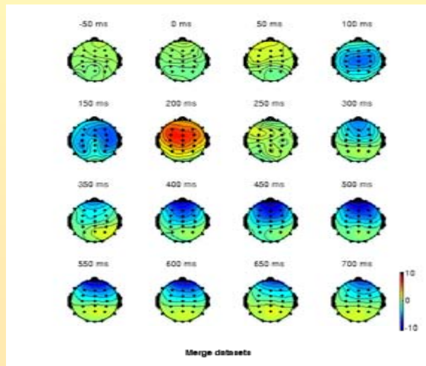
Scalp EEG

- Scalp EEG is the average of multifarious electrical activities of many small zones of the cortical surface beneath the electrode.

Brain Areas

- VEP
- AEP



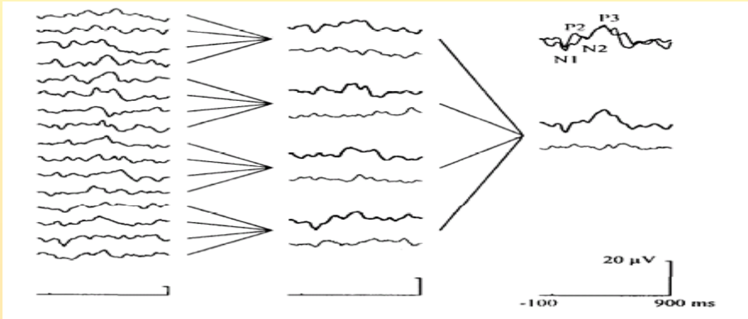


Event-Related Potentials (ERP)

- Event-related potential (ERP) represents the EEG in response to visual (light), auditory (sound), electrical, or other external stimuli.
- ERPs are weak signals buried in ongoing activity of associated systems
- Signal-to-noise ratio (SNR) improvement is usually improved by synchronized averaging and filtering.

Ensemble Averaging for ERP

- Visual event related potential (VEP)
- Time-locked and phase locked



(From Chapter 1, Handbook of Neuropsychology, Volume 10, editor: R. Johnson, Elsevier, ISBN: 0-444-89979-02.)

Applying ICA to ERP

- **Stimulus Sequence:**
  - Total stimulus of one experiment (400 sec) are 150 events
  - Stimulus rate: Red=30%, Green=60%, Yellow=10%
    i.e., R=45, G=90, Y=15
  - Stimulus (RGY) interval: random {1.7, 2.1, 2.3} (sec)
  - Duration of each stimulus is fixed in 300 ms. (300~800 ms)
  - Sampling rate = 1 KHz, 32 Channels
- **Reactions of the subject:**
  - Red --- Right Button
  - Green --- Nan
  - Yellow --- Left Button

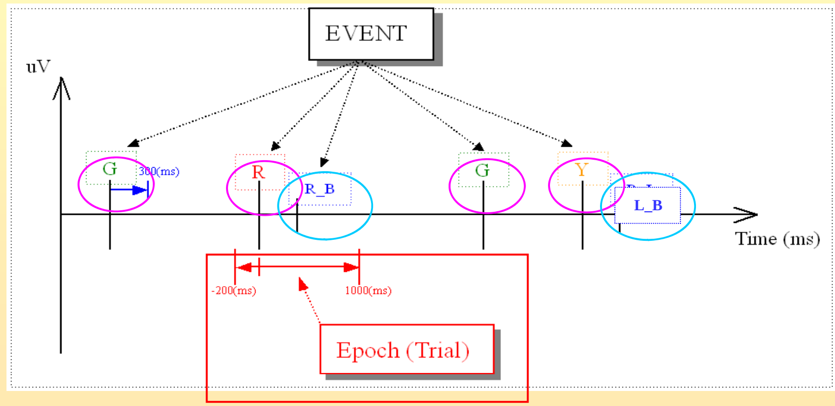

IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 54, NO. 7, JULY 2007

Communications

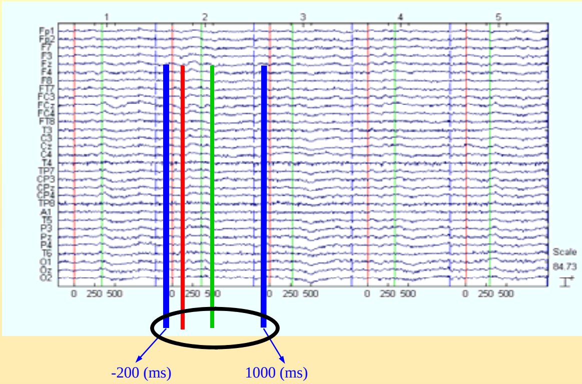
EEG-Based Assessment of Driver Cognitive Responses in a Dynamic Virtual-Reality Driving Environment

Chin-Teng Lin*, I-Fang Chung, Li-Wei Ko, Yu-Chieh Chen, Sheng-Fu Liang, and Jeng-Ren Duann

Events

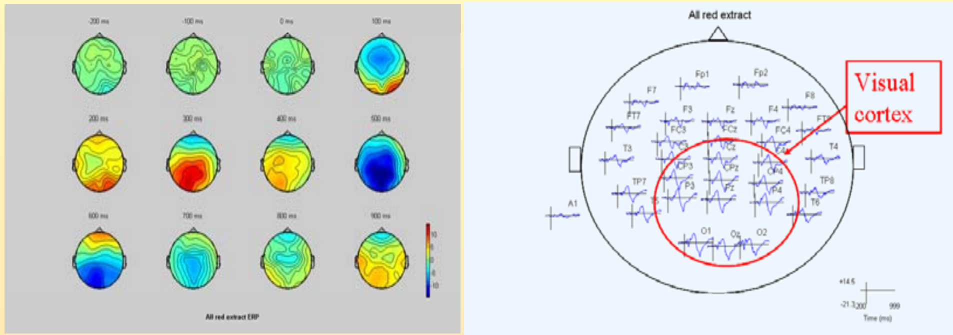


ERP Trials



- Each epoch (trial) is included in the **blue** interval, the **red** line represented the time point of given stimuli, the **green** line represented the time point of subject's response.

Spatial Maps of Averaged ERP



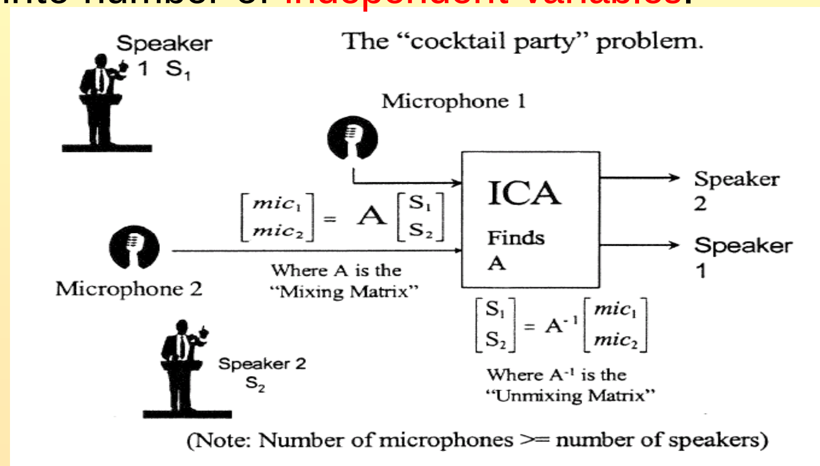
Independent Component Analysis

- Consider a situation where there are a number of signals emitted by some physical objects or sources. These physical sources could be, for example,
  - people speaking in the same room, thus emitting speech signals;
  - different brain areas emitting electric signals;
  - or mobile phones emitting their radio waves.

(Chapter 9, Biosignal and Biomedical Image Processing, John L. Semmlow, Marcel Dekker, ISBN: 0-8247-4803-4 3.)

ICA

- ICA seeks to transform the original data set into number of independent variables.



ICA

- The ICA model assumes that the measured signals $x_i(t)$ are the product of instantaneous linear combination of the independent sources $s_i(t)$.

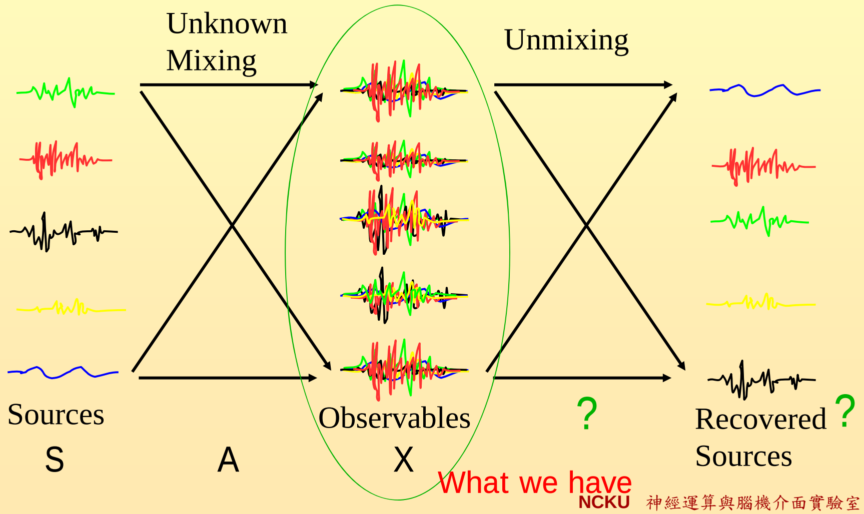
$$x_1(t) = a_{11}s_1(t) + a_{12}s_2(t) + \ldots + a_{1N}s_N(t)$$
$$x_2(t) = a_{21}s_1(t) + a_{22}s_2(t) + \ldots + a_{2N}s_N(t)$$
$$\vdots$$
$$x_i(t) = a_{i1}s_1(t) + a_{i2}s_2(t) + \ldots + a_{iN}s_N(t)$$
$$\vdots$$
$$x_N(t) = a_{N1}s_1(t) + a_{N2}s_2(t) + \ldots + a_{NN}s_N(t)$$

$$\mathbf{x=As}$$

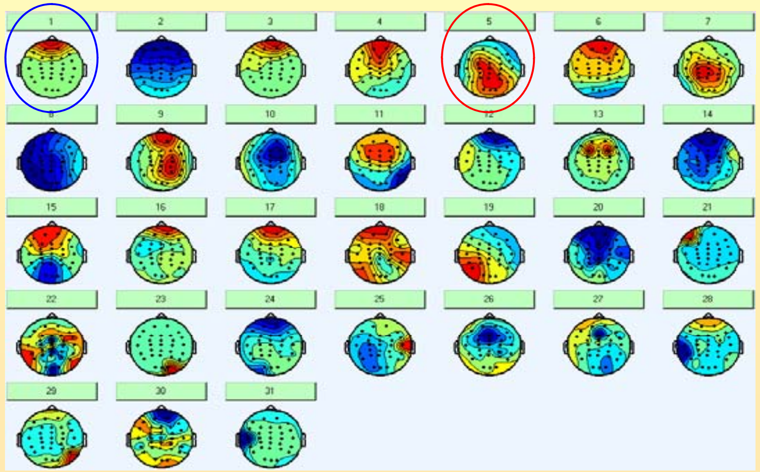
$$\mathbf{s=A^{-1}x}$$

$$\mathbf{s'=Bx}$$

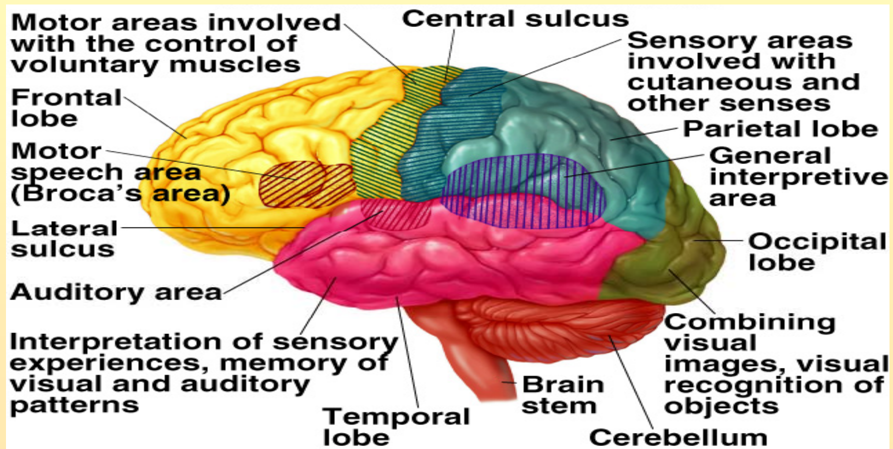
Mixing and Un-Mixing Matrices



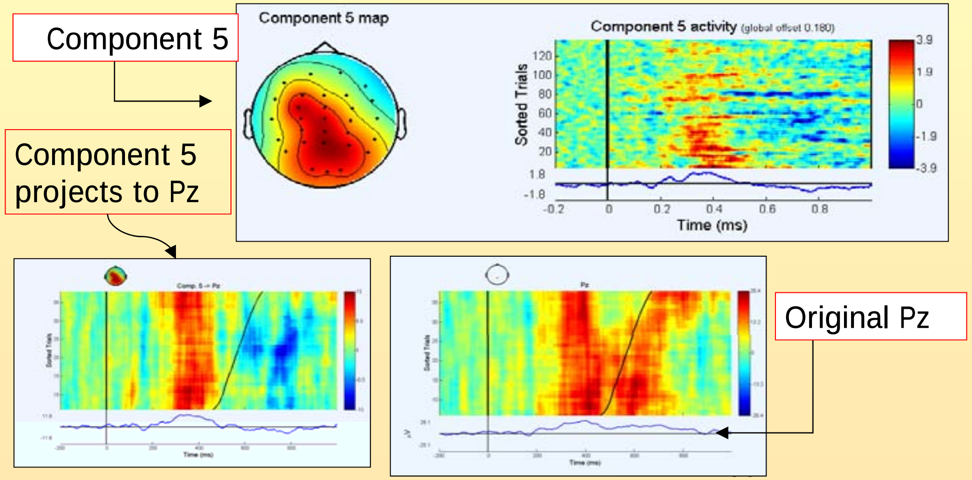
ERP/EOG after ICA Analysis



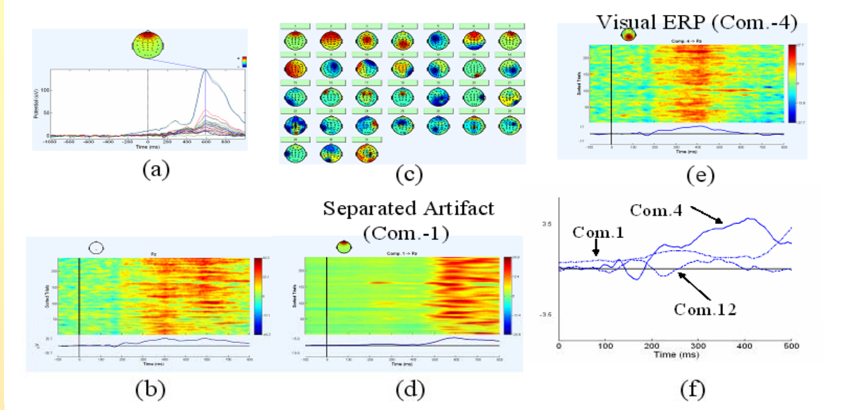
Brain Functions and Regions



ICA Component 5 (S_5) & Its Contribution to Pz Channel)



Source Component Decomposition



(a) Averaged EEG signal for 31 channels. (b) Single-trial EEG signal in Pz channel. (c) The topographic maps on scalp of ICA components. (d) Separated artifacts in ICA Component 1. (e) Separated noise-free ERP in ICA Component 4. (f) Average ERP of component 1, 4 and 12.

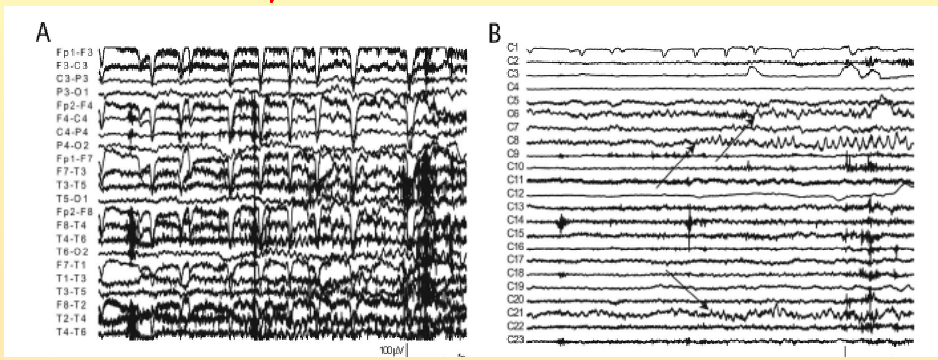
Seizure Analysis by ICA

- ICA has been used in ictal recordings to show the possibility of isolating the ictal activity.
- ICA can also be applied to analyze focal seizures for decomposing the elements of the seizures to understand their genesis and propagation.

Seizure Analysis by ICA-focal seizure

Decomposition of an anterotemporal seizure.

- Ictal components 6, 8, and 21 contain by rhythmic theta activity.

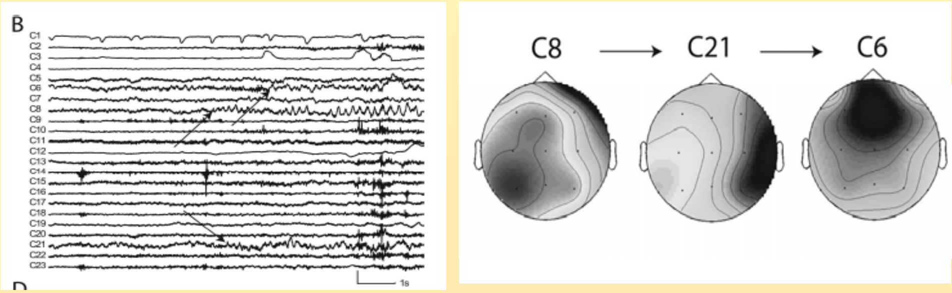


(Jorge Iriarte et al., J Clin Neurophysiol., 23:6, 551–558, 2006)

Seizure Analysis by ICA-focal seizure

Propagation:

1. Right anterotemporal region (C8)
2. Posterior right temporal areas (C21)
3. Bilateral frontal (C6)

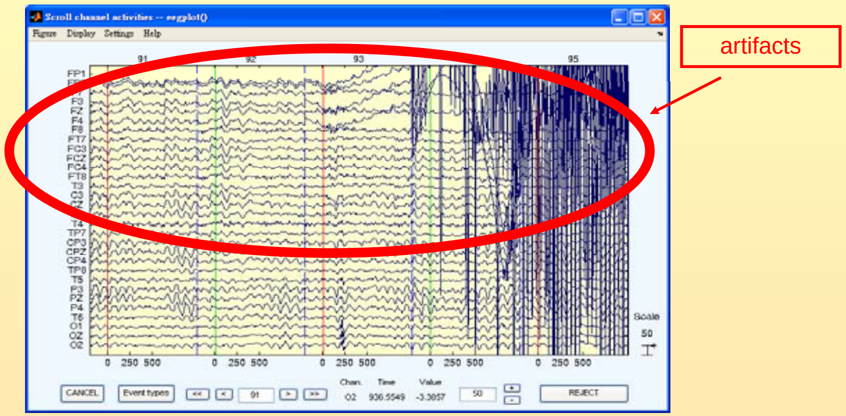


(Jorge Iriarte et al., J Clin Neurophysiol., 23:6, 551–558, 2006)

Ambiguities of ICA

- We can not determine the variance (energies) of the independent components.
- We don't know the sign of the source.
- We can not determine the order of the independent components.

ICA?



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- Collaboration
  - Dr. C.T. Lin and BRC, NCTU
  - Drs. Peter Wu, J.C. Chiou and BSRC, NCTU
  - Dr. W.T. Liu (UCSC), Dr. T.P. Jung (UCSD)