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禪定腦電波之研究(2/3)

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行政院國家科學委員會補助專題研究計畫 期中報告

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※ **禪定腦電波之研究（2/3）** ※
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計畫類別：■個別型計畫　　□整合型計畫

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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

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一、中文摘要：

過去一年多的『禪定腦電波』研究，已觀察到不同禪定劇本，我們以不同方法進行多通道腦電波分析與詮釋，包括小波分析、參數模型、分頻量化、模糊理論分類、非線性動態分析…等， 並依據其空間－時間－頻域之特性變化，歸納出幾種不同的禪定腦電波變化劇本，並已將結果撰寫成三篇學術論文投稿於國際期刊，目前正在審查中。

關鍵字：禪定腦電波、禪定劇本、小波分析、參數模型、分頻量化、模糊理論分類、非線性動態分析、空間－時間－頻域之特性

二、英文摘要：

During the past years, we have observed a variety of meditation scenarios based on the meditation EEG analysis. A number of methods applied to multi-channel EEG analysis and interpretation include the wavelet analysis, parametric modeling, subband spectral quantification, fuzzy clustering, nonlinear dynamical analysis, etc. Results of quantifying the spatio-temporal-spectral characteristics are shown to correlate with different meditation scenarios. Three manuscripts reporting our research work have been submitted to the international journals.

Keywords: Meditation EEG (electroencephalogram), meditation scenario, wavelet analysis, parametric modeling, subband spectral quantification, fuzzy clustering, nonlinear dynamical analysis, spatio-temporal-spectral characteristics.

三、前言：

Zen-Buddhist meditation originated more than 2,500 years ago, and had been proved to benefit the health while on the way toward the ultimate "Buddhahood" state. Meditation process reflects a brain state completely differing from the normal consciousness or the sleep states. Different meditating techniques have been studied for several decades [1]-[9]. They are mostly the TM (transcendental meditation), Yoga, and Japanese Zen meditation, with the focus mainly on the physiological and psychological effects of meditation. This paper presents a systematic approach for meditation EEG interpretation and firstly reports the results of investigating meditation scenarios of the orthodox Zen-Buddhist practitioners.

A number of papers have reported the EEG findings for experimental subjects under meditation [3]-[5] [8]-[9]. EEG has been recognized to be an important clinical tool for diagnosing and monitoring the nervous system [10]-[12]. In the meditation EEG study, West [5] summarized the EEG findings and made three major comments including: slower alpha with larger power at the meditating beginning, occurrence of the rhythmic theta trains for experienced meditators at the mid session, and very rarely, bursts of high-frequency beta (above 20Hz) observed for meditators capable of achieving deep meditation, the so-called *samadhi* or *transcendence*. Thus, it was suggested that the beta dominated pattern characterized the EEG under deep meditation stage.

In spite of the extensive study on meditation EEG since 1960, no report was found regarding the meditation scenario based on the EEG features. This paper proposes a strategy of establishing an overview of the meditation EEG record. The strategy involves a robust approach in consideration of the inter-subject variation. We extract the subject-oriented prototypes from meditation EEG, without a pre-specified, prototypical base, to characterize the meditation process. The first approach mainly applies the FCM clustering to the feature vectors derived from the wavelet coefficients. Thus, the feature prototype is oriented towards the particular EEG patterns of each individual meditator. The second approach is based on parametric modeling and subband spectral quantification. Details of both approaches were illustrated in [13] and [14].

四、研究方法：

A. Experimental protocol

The meditation EEG signals were recorded using 8-channel SynAmps amplifiers (manufactured by NeuroScan, Inc.) connected to the Pentium MMX-166 (MHz) PC. We applied the 8-channel unipolar recording montage of which the common reference was the linked MS1-MS2 (mastoid electrodes). The 8-channel EEG electrodes were placed at F3, F4, C3, C4, P3, P4, O1, and O2. The sampling rate was 400Hz. Each recording lasted for 45 minutes, including the first 5-minute background EEG (the subject sat in normal relaxed position with eyes closed) and the rest 40-minute meditation EEG. During the meditation session, the subject sat, with eyes closed, in the full-lotus or half-lotus position. Each hand formed a special mudra (called the Grand Harmony Mudra), laid on the lap of the same side. The subject focused on the Zen Chakra and the Dharma Eye Chakra (also known as the “Third Eye Chakra”) in the beginning of meditation till transcending the physical and mental realm [13]. The Zen Chakra locates inside the third ventricle, while the Dharma Eye Chakra locates at the hypophysis.

B. Feature vector derived from Wavelet coefficients

For the past two decades, Wavelet analysis has been extensively studied and proved to be a useful tool in biomedical signal processing. Appropriate selection of scales and wavelet bases enables it to characterize the EEG rhythmic patterns. According to our study, wavelet prototype of appropriate duration has little effect on the quantitative feature vector. We employ db5 wavelet prototype in this study. In consideration of computational efficiency, the discrete Wavelet transform (DWT) is often applied. The DWT scales D4 ~ D7 are approximately matched to those well-defined EEG rhythmic bands, assuming a sampling rate of 400 Hz. The feature vector is thereafter constructed from these DWT coefficients. The procedure is depicted below.

Firstly, the 2-second running window, moving at a step size of 1 second, is employed. And the entire meditation EEG record is divided into L segments. Consider a discrete-time signal $x[n]$, $0 \le n \le N-1$ (N=800), representing the lth running EEG epoch. The $a_j[n]$ and $d_j[n]$ indicate, respectively, the coarse and detailed sequences after j's decompositions.

The lth running feature vector, $v_k[l]$, is extracted from the selected detailed-scale coefficients by computing their powers. The feature vector of the lth EEG epoch accordingly is

$$v[l] = \{v_4[l], v_5[l], v_6[l], v_7[l]\}.$$

Finally, $\underline{\boldsymbol{V}} = \{v[l] | 0 \le l \le L-1\}^T = \{v[0], \ldots, v[L-1]\}^T$ is an $L \times 4$ feature matrix of which each row indicates the running feature vector.

C. FCM-merging strategies

Automatic interpretation algorithm often involves three strategies: derivation of feature basis, feature clustering, and scoring (interpretation) based on the feature clusters. Feature extraction aims at transforming the input data into a form (feature vector) appropriate for the clustering algorithm to identify the clusters. Each feature vector, after processed by the FCM, belongs to a cluster to some degree that is specified by a membership matrix. According to our experience in EEG feature classification, conventional FCM algorithm, without the background knowledge of EEG characteristics, cannot effectively classify and interpret the EEG record in comparison with the naked-eye examination. We thus developed a novel approach, with three cluster-merging strategies, for the meditation EEG analysis. The main attribute is its knowledge-based processing of EEG record, that is encoded into an easily comprehensible chart of meditation scenario. Fig. 1(a) illustrates the overall strategy developed according to our experiences on meditation EEG characteristics. The *FCM-merging strategies* involving three cluster-merging subroutines (Fig. 1(b), 1(c), and 1(d)) are designed particularly to solve the problem of blind clustering by simple FCM algorithm [13].

Fig. 1(a) Flow chart of FCM.

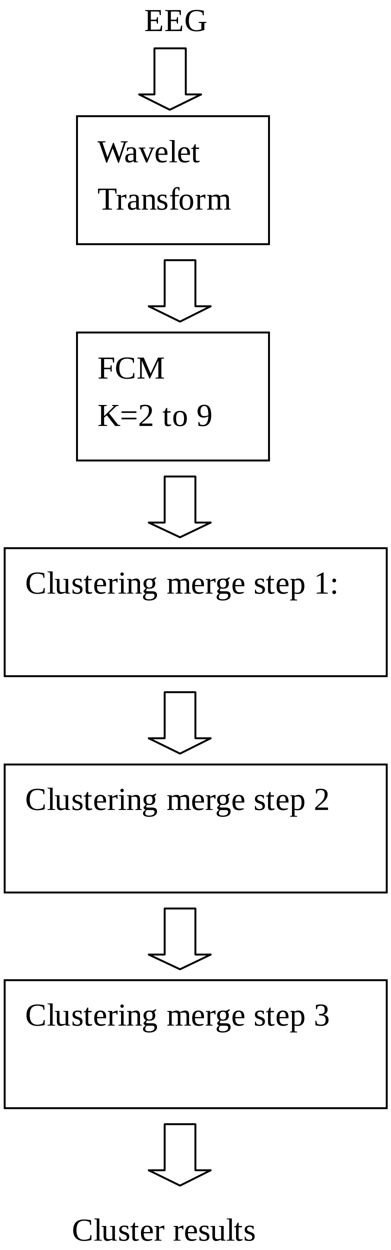


Fig. 1(b) Clustering merge step 1.

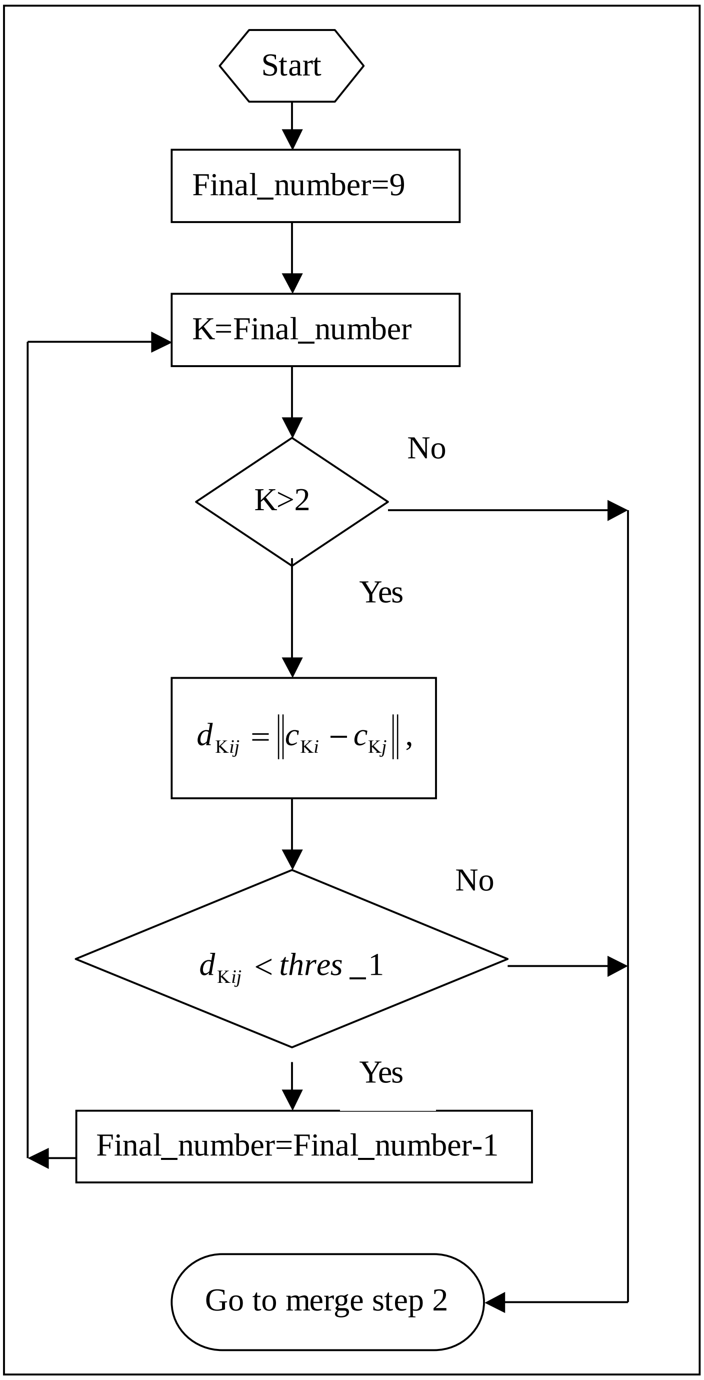


Fig. 1(c) Clustering merge step 2.

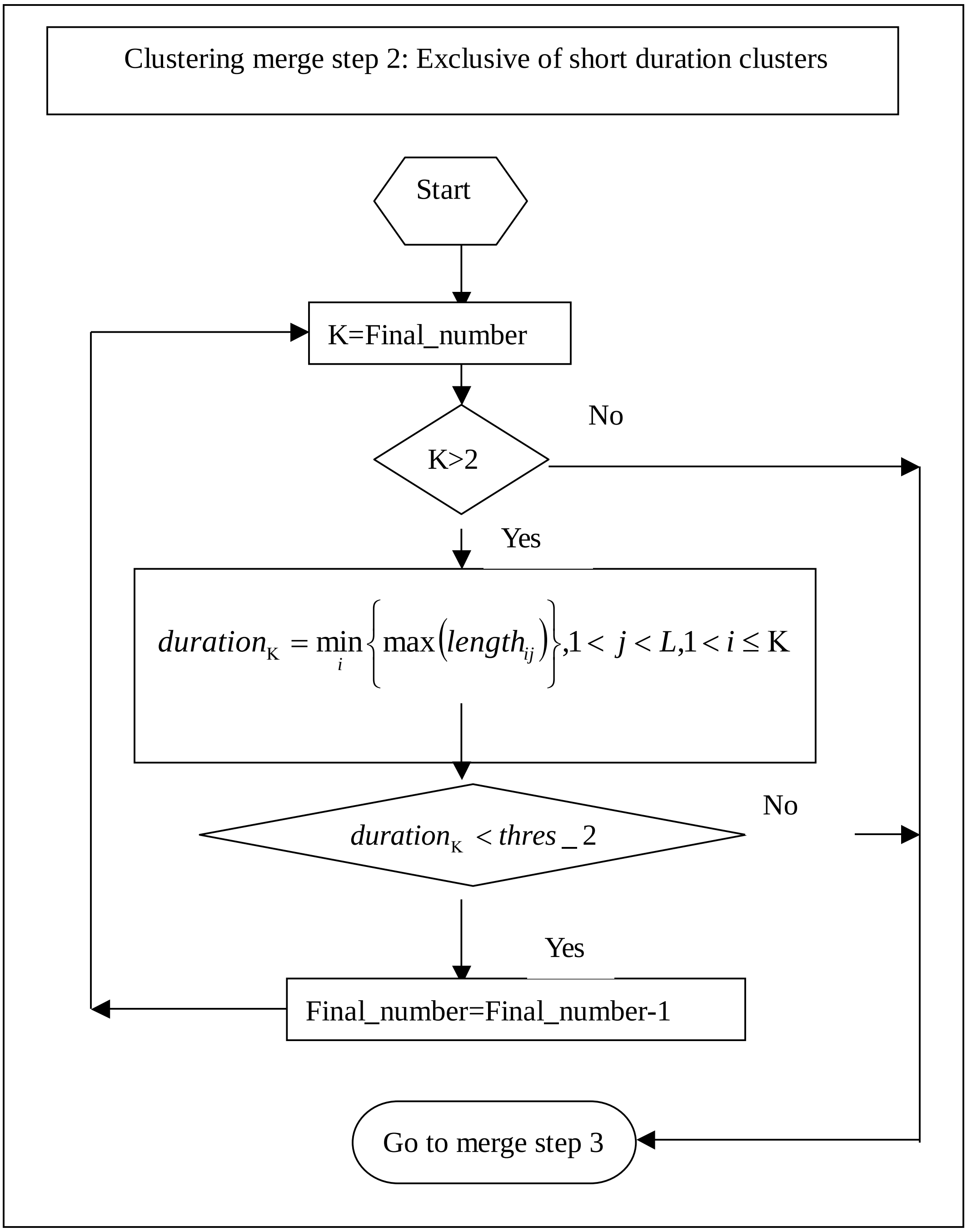
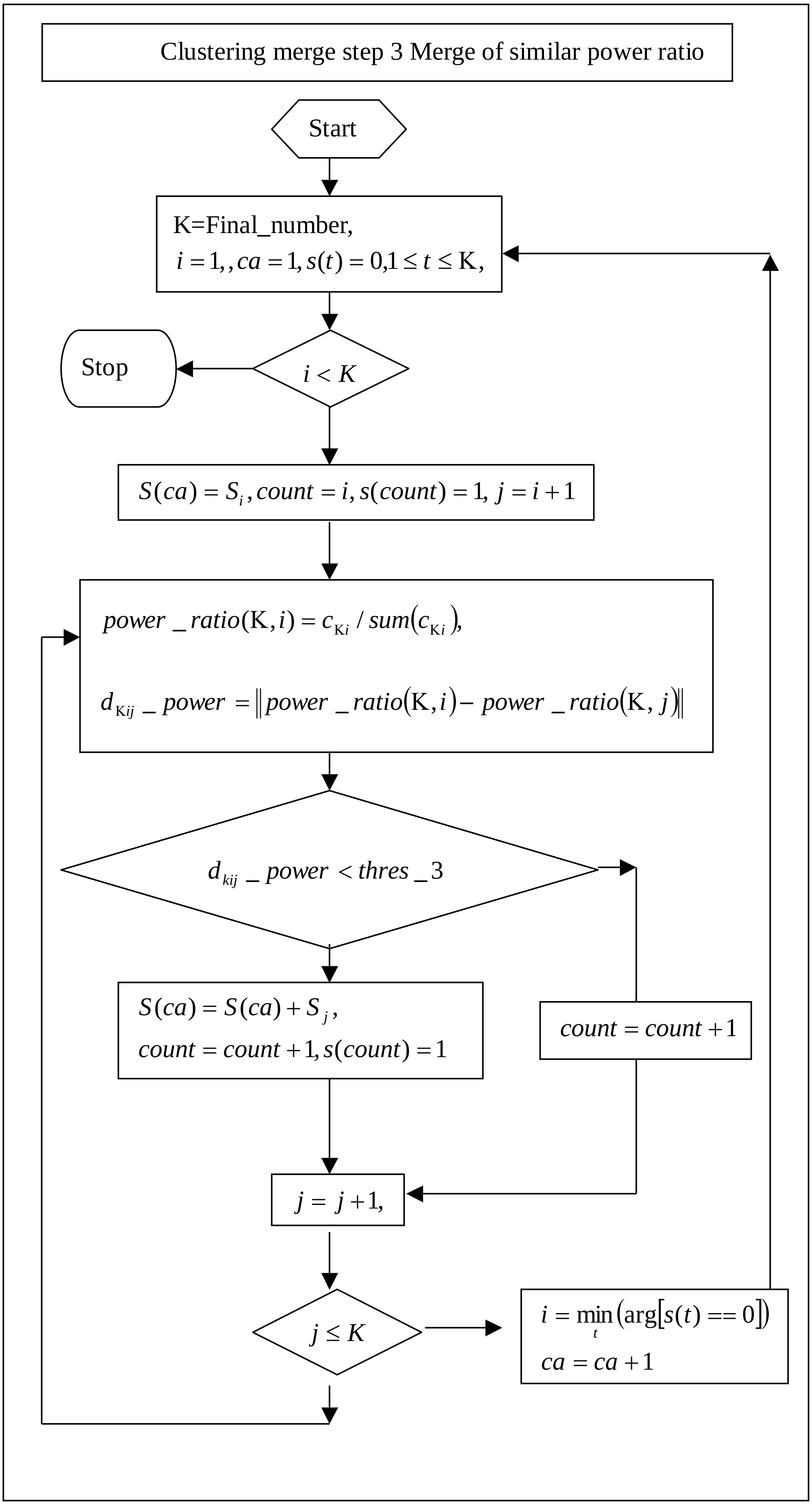


Fig. 1(d) Clustering merge step 3.



The FCM function described above blindly classifies the EEG patterns based on quantitative features. Consequently, the result of interpretation often appears to be away from satisfaction. We accordingly developed sophisticated cluster-managing strategies, the *FCM-merging strategies*, based on background knowledge of meditation EEG characteristics, for achieving an interpretation closer to the result of naked-eye examination. Figs. 1(b)-1(d) illustrate, respectively, three cluster-merging stages. In the *cluster-merge* A subroutine (Fig. 1(b)), number of clusters (K) is justified by having the inter-distance between cluster centers (D_{ij}) no less than a pre-specified threshold $D_{th,1}$. The goal of *cluster-merge* B is to eliminate the tedious work of interpreting those insignificant transient activities, which tend to complicate the result.

In EEG, considerable variation in amplitude often obscures identification of certain rhythmic pattern. For instance, FCM function tends to output multiple clusters for α rhythm classified according to the squared wavelet coefficients. This situation also occurs to Δ and θ rhythms. *Cluster-merge* C subroutine hence reexamines and corrects the fault by computing the subband power ratios as follows. Firstly, we modify the $L\times4$ feature matrix $\underline{\boldsymbol{V}}$ that is expressed by

$$\underline{\boldsymbol{V}'} = \{v'[0], v'[1], \ldots, v'[L-1]\}^T ,$$

where $v'[l]$ is the new (1×4) feature vector of the lth EEG epoch:

$$v'[l] = \{v'_4[l], v'_5[l], v'_6[l], v'_7[l]\} .$$

Elements in $v'[l]$ are derived from $v[l]$ by

$$v'_k[l] = \frac{v_k[l]}{v_t} \times 100\ \%,\ 4 \le k \le 7 \text{ , where}$$

$$v_t = \sum_{k=4}^{7} v_k[l] .$$

Based on the modified feature matrix $\underline{\boldsymbol{V}'}$, FCM function outputs a set of new cluster centers $\{c_i', 1\le i\le K\}$. If cluster j has a center c_j' close enough to the center of cluster i (i.e., $D'_{ij} = \|c'_i - c'_j\| < D_{th,3}$), the coding vector $\underline{\boldsymbol{S}}$ (output of *cluster-merge* B) will be modified by re-encoding cluster j as cluster i. In this way, different clusters actually containing feature vectors of the same EEG rhythm (e.g., α or θ) are to be identified and interpreted as the same one via an adequate choice of $D_{th,3}$.

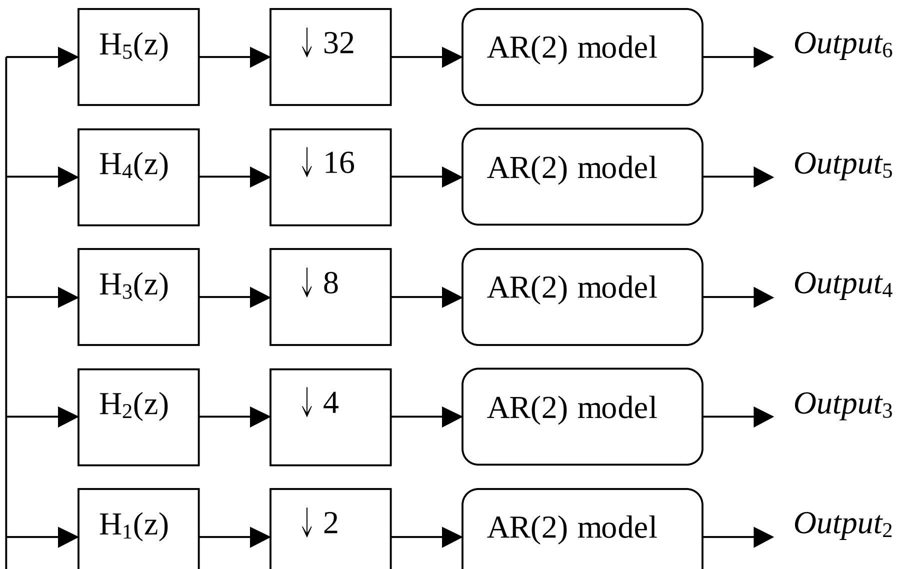
The FCM-merging strategies, systematically and effectively encoding the quantitative EEG features, were also proven to be robust to implementing parameters. Moreover, a wide range of mother wavelet prototypes can be used without changing the interpreting result should the wavelet duration be long enough.

D. AR coefficients of subband component

The method proposed is focused on monitoring the time-varying characteristic frequency in meditation EEG. The AR model is applied to the subband component to quantify the characteristic frequency. The autoregressive (AR) spectrum estimation is one of the widely used methods for examining the time-varying spectral activities due to its advantage of obtaining more accurate estimate with better resolution. Nevertheless, the AR estimates of low frequencies are less reliable than those for high frequencies. However, EEG is a low-frequency signal in the range between DC and 30 Hz. The AR method often fails to provide accurate estimate of low-frequency spectral components. To solve this problem, one can use a higher order AR model to estimate the spectrum, yet, at the cost of heavy computation load.

To deal with the problems mentioned above, we developed a systematic strategy, combining multiresolution concept with parametric modeling, to facilitate the long-term meditation EEG analysis. Main idea of the proposed strategy is to establish an adequate criterion for classifying the windowed segment, based on the characteristic frequency extracted from subband components, and for eventually providing an overview of the entire meditation EEG record. EEG signals are firstly decomposed into different subband components by downsampling and filtering. Then the characteristic frequency (root frequency) of each subband component is estimated by AR(2) model. The entire scheme is called the *Subband-AR EEG Viewer* (Fig. 2).

Fig. 2 Subband-AR EEG Viewer.



The cutoff frequencies of $H_1(z)$, …, $H_5(z)$ are, respectively, 30Hz, 15Hz, 7.5Hz, 3.75Hz, and 1.875Hz (sampling rate: 200Hz).

Note that the cutoff frequencies approximate the upper boundaries of the four well-known EEG rhythms— β (13~30Hz), α (8~13Hz), θ (4~8Hz), and Δ (below 4Hz). Therefore, changes of the characteristic frequency in meditation EEG can be traced by quantifying the root frequency (f_r) of each subband filtered component. For example, when f_r's of $output_1$, $output_2$ and $output_3$ are all within the range 8~12 Hz, the dominated pattern of this windowed segment is identified, to a great degree, as the α rhythm. When f_r's of $output_1$ and $output_2$ are greater than 15Hz and f_r of $output_4$ is between 4Hz and 7Hz, the particular segment most likely contains the θ intermixed with β rhythm. After the subband decomposition, the AR(2) model coefficients are computed. The model coefficients are directly computed by

$$a_2[1] = -\left(\frac{r_x[1]}{r_x[0]}\right) + \left(\frac{r_x[1]}{r_x[0]}\right)\left(\frac{r_x[0]r_x[2] - r_x[1]^2}{r_x[0]^2 - r_x[1]^2}\right), \text{ and}$$

$$a_2[2] = -\left(\frac{r_x[0]r_x[2] - r_x[1]^2}{r_x[0]^2 - r_x[1]^2}\right),$$

where $\gamma_x[k]$ is the autocorrelation function. Finally, the characteristic frequency f_r, also called the "root frequency," of $output_i$ can be estimated by

$$f_r = \sin^{-1}\left(\frac{\sqrt{\dfrac{4a_2[2] - a_2^2[1]}{4}}}{\sqrt{a_2[2]}}\right) = \sin^{-1}\left(\sqrt{1 - \frac{a_2^2[1]^2}{4a_2[2]}}\right) \approx \sqrt{1 - \frac{a_2^2[1]}{4a_2[2]}}\ .$$

五、結果與討論：

A. Five meditation EEG scenarios

During the past three years, we have collected the EEG and other electrophysiological signals for more than fifty meditators. Their experiences on Zen-Buddhism meditation range from a few months to sixteen years. Substantial meditation training leads them into the true Zen realm, that is, the spiritual world beyond the Alaya consciousness (the 8th consciousness). We thus are able to observe a variety of EEG changes during meditation session.

Quantitative illustration of whole meditation EEG record portrays a distinctive scenario for each particular meditator. To provide a long-term legible illustration, five meditation EEG prototypes are displayed by different gray-scales. As illustrated in Fig. 3, the gray-scales from the darkest to the brightest colors indicate, respectively, the α^{+}, Δ, $\Delta+\theta$, $\theta+\underline{\alpha}$, and Φ prototype. Based on the running gray-scale chart quantifying the evolution of meditation EEG, we have observed five distinct meditation scenarios (Figs. 3(a)-3(e)).

Fig. 3 Five meditation scenarios (a)-(e) and the control-group scenario.

Alpha delta delta-theta theta-alpha flat

Fig. 3(a) Meditation scenario A

Fig. 3(b) Meditation scenario B

Fig. 3(c) Meditation scenario C

Fig. 3(d) Meditation scenario D

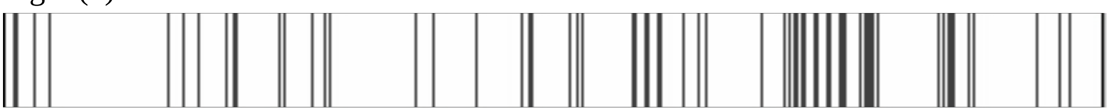


Fig. 3(e) Meditation scenario E

Fig. 3(f) Control group scenario E

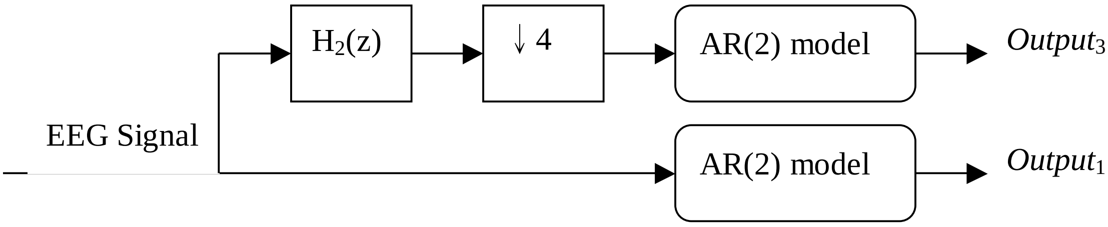
Each meditation scenario was explained in details in [13]. The interpreted result highly correlates with that of the naked-eye examination. Among all, one particular meditator exhibits a unique meditation scenario (Fig. 3(e))— the Φ prototype dominates since the beginning of meditation, and no other activity is observed to be significant. Another interesting observation is the correlation between the occurrence of Φ prototype and the feeling of blessings by most experimental subjects.

The running gray-scale chart derived from the control group tells quite another story. As shown in Fig. 3(f), the entire meditation scenario was dominated by the α rhythms, while Δ+θ or θ appeared occasionally. Note that Δ and θ emerged because the subjects fell asleep.

B. Extraction of slow alpha rhythm

Frequency of α rhythm ranges from 8Hz to 12Hz. The slow α is a particular pattern, normally below 10Hz, that is observed in some experimental subjects at the mind-focusing stage of meditation. The *Subband-AR-EEG-Viewer*, designed to track the slow-α, can be reduced to the structure shown in Fig. 4.

Fig. 4 The slow-α detector derived from the reduced structure of *Subband-AR-EEG-Viewer*.



According to analytical reasoning and practical experience, $output_1$ in combination with $output_3$ highly enhances the effectiveness of slow-α detection. The algorithm developed in [14] depicts that slow-α pattern is detected when both root frequencies satisfy the following criteria:

$f_{r,1} < 14$Hz, and

8Hz $< f_{r,3} <$10Hz.

While only examining $output_1$ (up to 30Hz) with the criterion 8Hz $< f_{r,1} <$10Hz, the model often fails to identify the noise-contaminated slow-α activities. Figure 5 demonstrates the noise-immunization capability of our model. When a pure 9Hz sinusoid (Figure 5(a)) is partially contaminated by a uniformly distributed random noise (Figure 5(b)), the *AR* model does not recognize the noise-contaminated slow-α segment based on the criterion 8Hz$<f_{r,1}<$10Hz (Figure 5(c)). Note that the epoch identified as the slow α is indicated by a black bar above the signal. Result in Figure 5(d) shows that the proposed model successfully detects the slow α under poor environment (SNR=8dB).

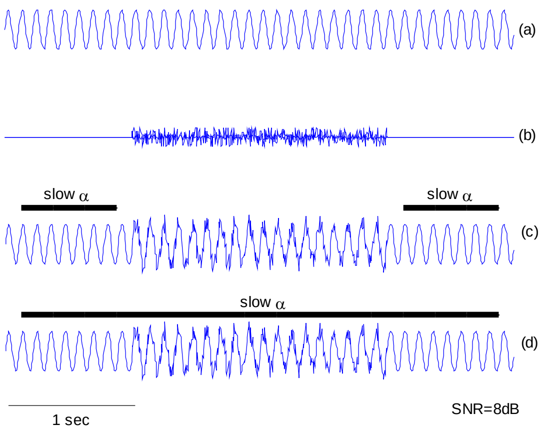


Fig. 5

To justify the performance, we first analyze a simulated signal of 4-second duration. The signal shown in Figure 6(d) is generated by connecting three short-duration, amplitude-modulated sinusoids, respectively, with frequencies 9Hz, 15Hz, and 5Hz (Figure 6(a)~(c)). The window length is 0.5 second (100 samples), moving at a step of 0.25 second. As shown in Figure 6(d), the algorithm effectively detects the occurrence of slow-α pattern.

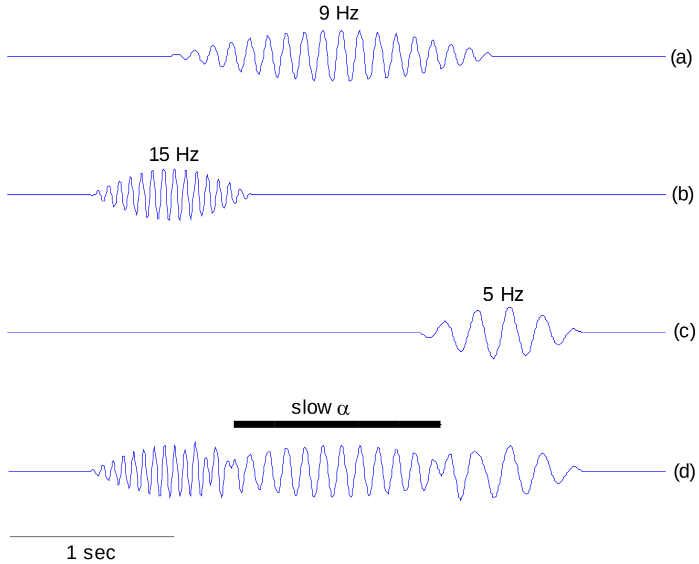


Fig. 6

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七、計畫成果自評：

During the past year, results of our research work have been reported in conferences and symposiums. In addition, these results were organized into four manuscripts and submitted to well-known international journals. As listed below, one is in press, the other three are in reviewing process. Our research work is pioneering and promising. Especially motivated by the multiform benefits of Zen-Buddhist meditation in promoting health, investigation of brain dynamics under meditation and various consciousness states become more and more significant. From the threat of SARS since March of this year, we should make a self examination of our health-care problem. We believe that this research study will lead to more understanding of the mechanism of how people can keep younger and healthier via Zen meditation practice.

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