Research on the Fractal Feature Extraction Based SSVEP Idle-State Detection

Xiuquan Li and Zhidong Deng

Abstract—**Presented study investigates nonlinear feature extraction method for Electroencephalography (EEG) signal using fractal measures. The classical fractal measures of Higuchi dimension and Box-counting dimension were used and compared. This paper also introduces a new measure of approximate fractal entropy (AFE). It is applied as feature extraction in solving the problem of SSVEP idle-state detection. Comparison study was conducted between AFE and fractal dimension methods. Experimental results show the advantage of AFE-based feature extraction.**

Index Terms—**Electroencephalography (EEG), steady-state visual evoked potentials (SSVEPs), feature extraction, brain-computer interface (BCI).**

I. Introduction

Brain-Computer Interface (BCI) technology is a communication system which does not rely on the brain peripheral nerve pathways and muscle of the communication system [1]. BCI converts the information sent by brain into commands to drive external equipments, realizing information exchange between human body and the outside world, as well as external environment control. BCI technique has important application value in multiple fields of military, aerospace, transportation, entertainment and rehabilitation robots, etc [2][3]. Brain computer interface technology founded on the basis of brain nerve scientific theory, involving cognitive science, signal processing, pattern recognition, motion control, and other technology area, establishing itself an intelligent control system based on EEG data processing.

Because of its convenient signal acquisition and high time resolution, scalp EEG is widely adopted in brain computer interface study. Four kinds of brain wave signal types are commonly employed in current scalp EEG based BCI systems researches, including Steady-state visual evoked potentials (SSVEPs), P300, Event-related desynchronization/ synchronization (ERD/ERS), Slow-scalp potentials, (SCPs), etc[4]. Among them SSVEP attracted widely attention, due to its advantages of convenient experiment preparation, high information transfer rate, low training process requirement, and less affected by the individual difference [5][6][7].

SSVEPs are biological feedbacks of visual cortex to flashing stimulation in the visual center. Studies have proved that the flashing stimulation in the visual center can enhance particular neural activity mode of neurons assembly, regulating specific frequency component amplitude of recoded EEG signal. The response frequency of the SSVEP is the similar to that of visual stimulation. It is generally believed that, when visual stimulation frequency is higher than 6 Hz, SSVEPs could be induced [7][8].

There are two patterns in brain-machine interface research, saying synchronous control and asynchronous control [9]. Users of synchronous brain computer interface system need to cooperate with system, providing control commands in the period of time specified by system. For this control mode, the users are prompted by system at intervals of time, and only in this period the system can be controlled. The so-called asynchronous refers to such kind of control mode, the changes of symbols, command, signal level occur when the user has control intent (Intentional control, IC), the system output keep middle state when the user have no control purpose (no control, NC), while system is still in control at this time.

Asynchronous control mode helps to improve the user independence and practical degree of BCI. How to realize asynchronous BCI effectively is one of the key problems for developing BCI from lab to actual application [10]. Study has been conducted on how asynchronous control could be applied in BCI. The research presented in literature [11] and [12] applied respectively subspace decomposition (CSSD) method and energy accumulation method on asynchronous control of movement imagine based BCI. Literature [13] presented a SSVEP-based asynchronous BCI system employing C0 complexity metrics as feature extraction method.

The presented study investigated the SSEVEP idle-state detection problem on the basis of fractal theory. Non-linear character of fractal dimension was employed for feature extraction and its physiological implication was discussed. A new EEG feature extraction method using approximate fractal entropy as mental state metric was further proposed in this paper, and its relationship with fractal dimension was discussed as well. Both methods were then applied in SSVEP idle-state detection. Experimental results show that approximate fractal entropy method has superiority in SSVEP idle-state detection over fractal dimension.

II. Fractal-Measure Based Idle-State Detection

A. Fractal-Dimension Based Idle-State Detection

Fractal (Fractal) is a mathematics set with high geometrical complexity. Fractal theory was firstly founded by Mandelbrot in 1975, which has been widely employed to depict natural phenomenon nowadays [14]. Fractals has fine structure at any scale, while keep self-similarity between

Manuscript received July 21, 2012; revised September 2, 2012.

Xiuquan Li is with the Chinese Academy of Science and Technolgoy for Development, Beijing, 100038, China (e-mail:lixiuquan@tsinghua.org.cn).

Zhidong Deng is with the State Key Laboratory of Intelligent Technology and Systems, Tsinghua National Laboratory for Information Science and Technology, Department of Computer Science and Technology, Tsinghua University, Beijing 100084, China (e-mail: michael@tsinghua.edu.cn)

different scales. A prominent feature of fractal is the negative power law characteristics, which can be commonly observed in measurement results of different scales, or in energy spectrum of fractal time series. Fractal dimension (FD) is thus established based on fractal theory as a measure of describing the invariance character of negative power law behavior [15].

There are different methods for estimating the fractal dimension of 1-*d* signal, for example, Higuchi method [16], and the Box-counting method [17], etc. To make performance comparison of different methods in estimating time series fractal dimension, we conducted simulation study employing a standard fractal signal generated by Weierstrass cosine functions. Weierstrass cosine function is a special function with property of everywhere continuous everywhere non-differentiable. It was put forward by the German mathematician Karl Weierstrass in 1872 [18]. Weierstrass curve has proved to be a typical fractal signal when fractal theory was developed. The generation formula of Weierstrass fractal signal is.

$$W_H(t) = \sum_{k=0}^{\infty} \gamma^{-kH} cos(2\pi\gamma^k t)\,, 0 < H < 1, \gamma > 1 \qquad (1)$$

The fractal dimension of this fractal signal can be determined by the parameters of the formula, ie.$D = 2 - H$.

In the present study, we set $\gamma = 5$ and $t \in [0,1]$ for fractal signal generation. Sampling $N + 1$ points at equal interval, with $N = 4096$. Set parameter H from 0.9 to 0.1 at interval of 0.1 respectively, we got nine generated fractal signals, with fractal dimension of 1.1~1.9. These nine signals with different fractal dimension were then analyzed with Higuchi algorithm and Box-counting method to estimate the fractal dimension. The change correlation of estimated fractal dimension with Weierstrass fractal dimension is shown in Fig. 1.

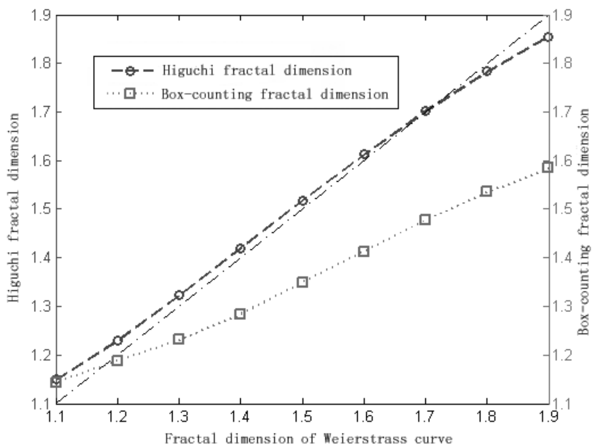


Fig. 1. Higuchi fractal dimension and box-counting fractal dimension of Weierstrass curve.

We can see from the figure, Higuchi method outperformed Box-counting method in Weierstrass fractal dimension estimation. There were also researchers compared different methods for fractal dimension estimation of EEG signals. they pointed out that for EEG signals fractal dimension estimation which has less signal length, Higuchi method could achieve more stable performance than several other methods [19][20]. Therefore, Higuchi method was employed in this study as the fractal dimension estimation method.

We have conducted a previous study on the neural physiological basis of the fractal dimension of EEG signal, the experimental results showed that the time domain fractal complexity of EEG signals correlated with the component diversity of signal spectrum. EEG fractal properties can reflect in certain sense the oscillation pattern diversity of the neurons assembly [21]. In this article, we further discuss the application of fractal dimension extraction of EEG signals in SSVEP idle-state detection.

According to the basic principle of SSVEP, most of the visual cortex area is used to dealing with the information in the central region our vision. so when stimulation target with certain frequency moves around the vision central, SSVEP of corresponding frequency will be enhanced remarkably [8]. By looking at stimulation targets coded by different frequency, different SSVEP potential can be induced at visual cortex.

To explain the SSVEP generating mechanism, researchers put forward a kind of oscillator explain theory [22]. This theory believes there are neural networks with different resonance frequency in the brain, known as oscillator. These oscillators are not synchronized with each other when no stable external stimuli received. The EEG of this status behaves disorderly. When receiving external stimuli repeatedly with certain frequency, oscillators of the stimulating frequency or harmonic frequency will produce resonance. These resonance results in significant enhancement of the corresponding spectrum component of EEG signals and harmonic signal, thus SSVEPs are observed [23].

The appearance of dominant component in EEG spectrum introduced by SSVEP remarkably reduce the component diversity, thus the temporal complexity are reduced correspondingly. This reduction in temporal complexity can then be detected by calculating the fractal dimension of EEG signal. That is to say, lower EEG fractal dimension indicates the appearance of SSVEP potential, while higher EEG fractal dimension corresponds to high diversity of neuron activity pattern, namely idle state. Thus the detection of SSVEP state was transformed into estimating the fractal dimension of EEG signal.

B. Approximate Fractal Entropy Based Idle-State Detection

Entropy is a quantitative measure for describing the randomness and disorderliness of system based on the second law of thermodynamics [24]. Shannon entropy was jointly established by Shannon and Wiener, an information theory concept defined on the basis of probability model. It provides a new measure of uncertainty or information quantity [25], [26].

Let X to be the provided discrete random variable, with value range of $\{x_{1,\cdots,}x_n\}$. Then an uncertain system is built of X and its values. Let p to be the probability density function (PDF) of X, we have the definition of Shannon entropy,

$$H(x) = -\sum_{i=1}^{n} p(x_i) log\, p(x_i)$$

In information theory, information is related to the reduction of entropy or uncertainty. The concept of information entropy has also been introduced into ecological system study, forming Shannon-Wiener index, an important indicator for measuring the diversity of species [27]. The so-called diversity is to indicate the unevenness between the components of a system. As discussed above, the fractal dimension measure of EEG signal is closely correlated with the spectrum diversity of EEG. Information entropy is thus introduced in this section to further discuss its application in complexity measure and feature extraction of EEG and also in SSVEP idle-state detection as well. For this purpose, we give the definition of Approximate Fractal Entropy (AFE) as,

For given time series $X(i), i = 1,2,\cdots,N$, we calculate the power spectrum density according to N-point Fourier transformation,

$$F_N(j) = \frac{1}{N}\sum_{k=1}^{N} X(k)e^{-2\pi(kj/N)}$$

let $$S_F = \sum_{i=1}^{N} F_N(i)$$

then the Approximate Fractal Entropy of the given time series can be defined as

$$D_0 = (-\sum_{s=1}^{N} F_N(s)/S_F \, log_2(F_N(s)/S_F))^{1/2} \quad (2)$$

Simulation experiment was also conducted for the Approximate Fractal Entropy measure employing the Weierstrass fractal signal, as conducted in previous section. Fig. 2 gives the simulation result of Higuchi fractal dimension and Approximate Fractal Entropy, when changing with the fractal dimension of Weierstrass fractal signal. Table I gives the correlation performance.

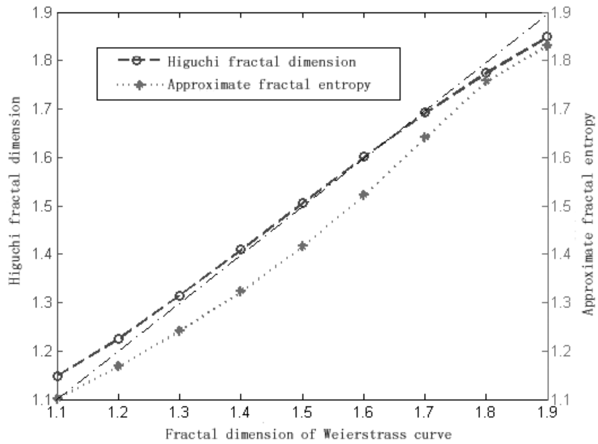


Fig. 2. Fractal dimension and approximate fractal entropy of Weierstrass fractal curve.

TABLE I: CORRELATION BETWEEN DIFFERENT MEASURES

	FD	Higuchi FD	AFE
FD	1	0.99919	0.99471
Higuchi FD	0.99919	1	0.99194
AFE	0.99471	0.99194	1

We can see from the results that both Higuchi fractal dimension and Approximate Fractal Entropy can effectively reflect the fractal property of Weierstrass fractal signal. Approximate Fractal Entropy provides an alternative measure for temporal fractal property of time series, and thus provides a new non-linear feature extraction method for SSVEP idle-state detection.

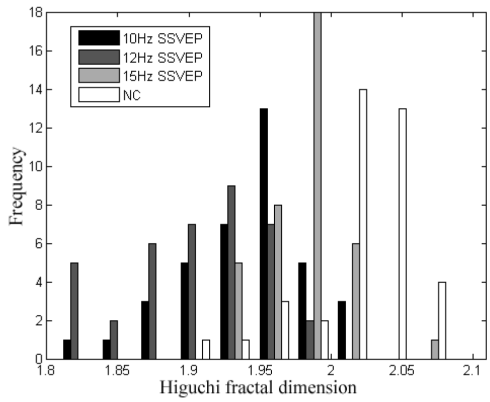
III. EXPERIMENT RESULTS AND PERFORMANCE EVALUATION

To testify and compare performance of different fractal feature extraction methods in SSVEP idle-state detection, real world SSVEP experiment was conducted and the results are presented in this section.

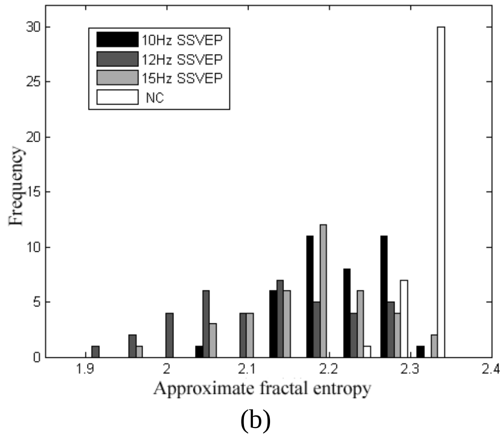
The stimulation stimuli in experiment were generated by SSVEP inducing program. White squares with side length of 200 pixels flicker at different position of a screen with resolution of 1024 x1280 pixels. In SSVEP period, experiment volunteers were required to focus on one of the flickering targets, and in NC time, participants can see any other places, or even conversation. The focusing goals were randomly determined by the system, and each period lasts 2 seconds.

Two volunteers took part in the experiment, no visual disease, normal vision after correction. The scalp EEG acquisition in the experiment was conducted by physiological signal acquisition instrument produced by Biosemi corporation, with sampling frequency of 256 Hz. The electrode A30 in the Biosemi 128 ABC positioning system was selected for the idle-state detection experiment. Three SSVEP states, including 10 Hz, 12 Hz, 15 Hz, and NC idle state were employed. Participant1 conducted 125 SSVEP experiments and 85 idle-state experiments, while participant2 126 SSVEP and 122 idle-state.

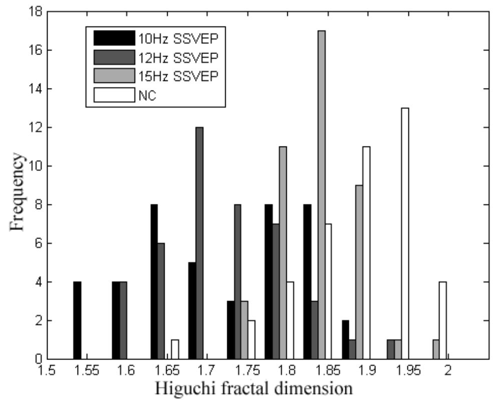
Feature extraction was then performed using both fractal dimension method and approximate entropy method, to compare the performance of the different methods in SSVEP idle-state detection. The experiment results are shown in Fig. 3.



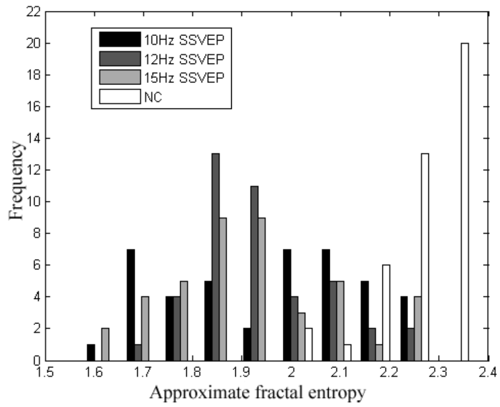
(a)



(b)



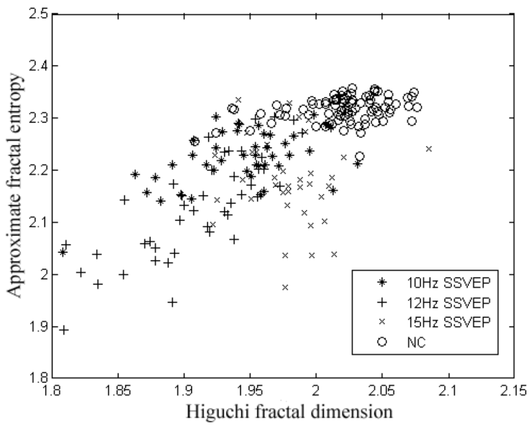
(c)



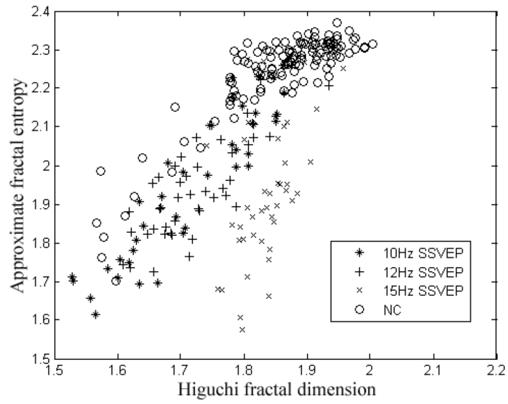
(d)

Fig. 3. Distribution of the feature values(a)FD feature value of participant 1(b)AFE feature values of participant 1(c) FD feature value of participant2(d)AFE feature values of participant2

We can see from the feature extraction results of these two methods, there is no remarkable difference can be observed within three SSVEP states for both fractal dimension method and AFE method. The feature values of different SSVEP states mixed together. For SSVEP state and NC state, effective separating capacity was manifested, which showed the effectiveness of these two methods. Compared with fractal dimension method, AFE method got higher discriminating performance with less overlap between SSVEP and NC state. To see more clearly, we drew 2-*d* distribution of the extracted feature values as Fig. 4.



(a)



(b)

Fig. 4. Scatter plot of FD feature values and AFE feature values (a)Participant 1(b)Participant 2.

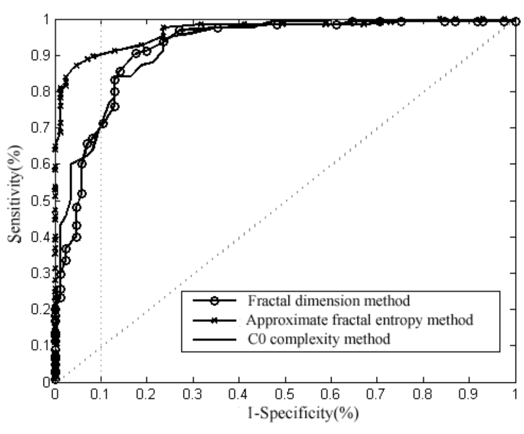
From the experiment results shown in figure 3 and figure 4, feature separating degree of AFE is obviously higher than fractal dimension method. We then conducted quantitative performance evaluation for the SSVEP idle-state detection experiment. Sensitivity and specificity are two main performance indicators for binary classification problem [28], ie.,

$$Sensitivity = 100\frac{TP}{TP+FN} \tag{3}$$

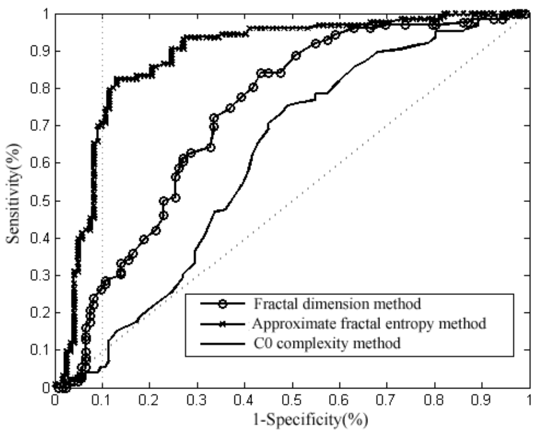
$$Specificity = 100\frac{TN}{TN+FP} \tag{4}$$

In the formula above, TP means true positive, FN false negative, TN true negative, FP false positive. Sensitivity represents the ratio of correctly identified SSVEP cases to all SSVEP cases, and Specificity refers to the ratio of correctly identified NC cases to all NC states.

Receiver operating characteristic curve (ROC), also called sensitivity curve, is a effective performance evaluation method to visualize both sensitivity and specificity results. The more the ROC approaches to the left-up corner, the better the synthesis performance of both sensitivity and specificity. In figure 5, we give the ROC curves of fractal dimension, AFE, and C0 complexity [13].



(a)



(b)

Fig. 5. ROC curves of different feature extraction methods (a)Participant 1(b)Participant 2.

It can be observed in figure 5(a), the ROC of AFE method got the best performance among the three feature extraction methods. For AFE method, if we control specificity at 90%, we can get a high sensitivity performance of above 90%. In figure 5(b), the performance evaluation result of participant 2, the ROC of AFE method also outperformed the other two methods. The experiment results demonstrated the superiority of AFE feature extraction method in the EEG SSVEP idle-state detection application.

IV. Conclusion

Brain-computer interface is an EEG-based intelligent control system, the efficiency of feature extraction method plays key role. This study investigated EEG non-linear feature extraction method employing fractal analysis theory. The correlation between EEG fractal dimension and SSVEP potential was described utilizing the sensitivity characteristic of temporal fractal dimension to the frequency components diversity. This study further gave the definition of approximate fractal entropy, and put forward a new fractal feature extraction method for SSVEP idle-state detection. The performance of both the fractal dimension and approximate fractal entropy methods was evaluated and compared through simulation and real world EEG experiments. The experiment results show that, for feature extraction of SSVEP idle-state detection, fractal measures are effective, and AFE method significantly outperformed fractal dimension. Thus the presented fractal-feature-based method provides an alternative solution for feature extraction of SSVEP-based asynchronous BCI research.

References

[1] J. R. Wolpaw, N. Birbauner, D. J. MacFarland, G. Pfurtscheller, and T. M. Vaugha, "Brain-computer interfaces for communication and control," *Clin Neurophyiol*, 2002, vol. 113, no. 6, pp. 767-791.

[2] J. J. Vidal, "Towards direct brain-computer communication," *Annu Rev. Biophys Bioeng*, 1973, vol. 2, no. 1, pp. 157-180.

[3] G. Pfurtscheller, G. R. Mueller-Putz, *et al.*, "15 years of BCI research at graz university of technology: current projects," *IEEE Trans Neural Sys. Rehab Eng*, 2006, vol. 14, no. 2, pp. 205-210.

[4] T. W. Berger, J. K. Chapin, G. A. Gerhardt, *et al.*, "International assessment of research and development in brain-computer interfaces: report of the world technology evaluation center," Berlin: Springer, 2007.

[5] L. J. Trejo, R. Rosipal, and B. Matthews, "Brain-computer interfaces for 1-D and 2-D cursor control: designs using volitional control of the EEG spectrum or SSVEP," *IEEE Trans Neural Syst Rehabil Eng*, 2006, vol. 14, no. 2, pp. 225-229.

[6] P. Martinez, H. Bakardjian, and A. Cichocki, "Fully-online, multi-command brain computer interface with visual neurofeedback using SSVEP paradigm," *Computational Intelligence and Neuroscience*, 2007, online article ID: 94561.

[7] M. Cheng, X. R. Gao, S. K. Gao, and D. Xu, "Design and implementation of a brain-computer interface with high transfer rates," *IEEE Trans Biomed Eng*, 2002, vol. 49, no. 10, pp. 1181-1186.

[8] D. Regan, "Human brain electrophysiology: Evoked potentials and evoked magnetic fields in science and medicine," New York: *Elsevier Press*, 1989.

[9] J. F. Borisoff, S. G. Mason, and G. E. Birch, "Brain interface research for asynchronous control applications," *IEEE Transactions on Neural Systems and Rehabilitative Engineering*, 2006, vol. 14, no. 2, pp. 160-164.

[10] M. A. Lebedev and M. A. Nicolelis, "Brain–machine interfaces: past, present and future," *Trends in Neurosciences*, 2006, vol. 29, no. 9, pp. 536-546.

[11] D. Zhang, Y. J. Wang, X. R. Gao, B. Hong, and S. K. Gao, "An algorithm for idle-state detection in motor-imagery-based brain-computer interface," *Computational Intelligence and Neuroscience*, 2007, Article ID: 39714.

[12] R. Leeb, D. Friedman, G. R. Mueller-Putz, D. Scherer, M. Slater, and G. Pfurtscheller, "Self-paced (asynchronous) BCI control of a wheelchair in virtual environments: a case study with a tetraplegic," *Computational Intelligence and Neuroscience*, 2007, Article ID: 79642.

[13] R. Ren, G. Y. Bin, and X. R. Gao, "Idle state detection in SSVEP-based brain-computer interfaces," *2nd International Conference on Bioinformatics and Biomedical Engineering, ICBBE08*, 2008, pp. 2012-2015.

[14] B. B. Mandelbrot, "Stochastic models for the Earth's relief, the shape and the fractal dimension of the coastlines, and the number-area rule for islands," *Proc Nat Acad Sci*, 1975, vol. 72, no. 10, pp. 3825-3828.

[15] D. L. Gilden, T. Thornton, and M. W. Mallon. *1/f Noise in Human Cognition. Science*, 1995, vol. 267, no. 5205, pp. 1837-1839.

[16] T. Higuchi, "Approach to an irregular time series on the basis of fractal theory," *Physica D*, 1988, vol. 31, no. 2, pp. 277-283.

[17] L. S. Liebovitch and T. Toth, "A fast algorithm to determine fractal dimensions by box counting," *Physics Letters A*, 1989, vol. 141, no. 8-9, pp. 386-390.

[18] K. Weierstrass, "On continuous functions of a real argument that do not have a well-defined differential quotient," in: *Edgar G A. Classics on Fractals*, New York: Addison-Wesley Publishing Company, 1993.

[19] G. Wang, H. Huang, H. B. Xie, Z. Z. Wang, and X. Hu, "Multifractal analysis of ventricular fibrillation and ventricular tachycardia," *Medical Engineering and Physics*, 2007, vol. 29, no. 3, pp. 375-379.

[20] C. H. Scholz and B. B. Mandelbrot, "Pure and applied geophysics-introduction," *Pure and Applied Geophysics*, 1989, vol. 131, no. 1/2, pp. 1-4.

[21] X. Q. Li, Z. D. Deng, and J. W. Zhang, "Function of EEG temporal complexity analysis in neural activities measurement," ISNN 2009, Part 1, LNCS 5551, 2009, pp: 209-218.

[22] R. B. Silberstein, "Steady-state visually evoked potentials, brain resonances, and cognitive processes," in *Nunez P L (Ed.) Neocortical Dynamics and Human EEG Rhythms.* Oxford: Oxford University Press, 1995, pp. 272~303.

[23] Z. H. Wu and D. Z. Yao, "Study on the selection mechanism of attention by steady-state visually evoked potential," *ACTA Biophysica Sinica*, 2006, vol. 22, no. 6, pp. 455-460.

[24] K. G. Denbigh, "Note on entropy, disorder and disorganization," *The British Journal for the Philosophy of Science*. 1989, vol. 40, no. 3, pp. 323-332.

[25] C. E. Shannon, "A mathematical theory of communication," *Bell System Technical Journal*, 1948, vol. 27, pp. 379-423 and 623-656.

[26] N. Wiener, "Cybernetics; or control and communication in the animal and the machine," New York: *John Wiley and Sons*, 1948.

[27] E. C. Piolou, "An introduction to mathematical ecology," *Translated by LU Ze-yu*. Beijing: Science Press, 1978.

[28] P. Baldi, S. Brunak, Y. Chauvin, C. A. Andersen, and H. Nielsen, "Assessing the accuracy of prediction algorithms for classification: an overview," *Bioinformatics*, 2000, vol. 16, no. 5, pp. 412-424.

Li Xiuquan was born in 1976. He received the Ph.D. degree in the field of intelligent data processing, from the Department of Computer Science and Technology, Tsinghua University, Beijing, in 2010. Before that, he received the MA degree in the field of artificial intelligence from the Department of Computer Science and Technology, East China University of Science and Technology in 2006. He is now a research associate in Chinese Academy of Science and Technology for Development, Beijing, China. His current research interests include pattern recognition, macro-economy data mining, science and technology indicators prediction, time series analysis.

Deng Zhidong was born in 1966. He received the Ph.D. degree from Harbin Institute of Technology, Astronautics School, Harbin, China, in 1991. He spent two years, from 1992 to 1994, at Department of Computer Science and Technology, Tsinghua University, Beijing, as a postdoctoral researcher. He had served as a Research Associate at the Hong Kong Polytechnic University, Kowloon, Hong Kong during 1996-1997. Currently, Dr. Deng is a professor at the Department of Computer Science and Technology, Tsinghua University. Prof. Deng's current research interests include virtual reality, IBMR, reverse engineering, fuzzy neural networks, learning control, reinforcement learning algorithms, nonlinear dynamical systems in Internet, and robot control. Prof.Deng is a member of the IEEE and the American Society of Mechanical Engineers(AMSE).