



Electro-Acupuncture Stimulation (EAS) Control by Imaginary Movement with Feedback Based on Electroencephalograph (EEG) Sensing

Hao Ding, * Dong Ming, Shuang Qiu, Rui Xu, Lu Wang, Minpeng Xu,
Wen Li, Weibo Yi, Hongzhi Qi, Baikun Wan

College of Precision Instruments and Optoelectronics Engineering, Tianjin University,
Tianjin 300072, P. R. China

Tel.: +86-022-27408718, fax: +86-022-27406726

E-mail: richardming@tju.edu.cn

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Abstract: Electro-acupuncture stimulation (EAS) technique applies the electrical nerve stimulation therapy on traditional acupuncture points to restore the muscle tension. The rapid promotion and development of brain-computer interface (BCI) technology makes the thought-control of EAS possible. This paper designed a new BCI-control-EAS (BCICEAS) system by using event-related desynchronization (ERD) of EEG signal evoked by imaginary movement. The change of EEG signal was observed in the training and stimulation experiments with visual feedback. The Fisher parameters were extracted from feature frequency bands of EEG and classified into EAS control commands by Mahalanobis distance (MD) classifier. A feedback training technique was employed to correlate the enhancement of relevant EEG feature through a visual interface with a virtual liquid column, whose height varied along with EEG power spectral feature. According to the statistics analysis of 12 subjects, experimental results revealed the effective improvement of feedback training on signal feature and reliable control of EAS. It is expected that the proposed control method can explore a new way for EAS system design and help people who suffer from severe movement dysfunction. *Copyright © 2013 IFSA.*

Keywords: Electro-acupuncture stimulation, Brain-computer interface, Event-related desynchronization, Imaginary movement, Mahalanobis distance classifier.

1. Introduction

Acupuncture originated from ancient China has been used in the orient to treat various clinical muscle disorders for thousands of years, with recognized as a complementary medical method by NIH Consensus in 1997 [1-2], which has been gaining popularity among practitioners of modern medicine [3]. Among the previous studies, electro-acupuncture stimulation (EAS) was widely used as a substitute for classical acupuncture. It is demonstrated that EAS produces

reflex changes in muscle motor nerve activity and successful treatments of patients with clinical muscle disorders, providing this highly credible method [4-8]. The traditional usage of EAS was found to improve lower limb motor function of patients with paralyzed arms [5]. However, the poor autonomy for the patient to control EAS device restricts its application and makes it a technical bottleneck for further popularization. This template provides authors with most of the formatting specifications needed for preparing their articles.

Nowadays, the rapid promotion and development of brain-computer interface (BCI) technology makes it possible for the EAS to be controlled by imaginary movement. The option for restoring function to those with motor impairments is to provide the brain with a new, non-muscular communication and control channel, a direct brain-computer interface (BCI) for conveying messages and commands to the external world. In a variety of methods for monitoring the brain activity, noninvasive EEG-based BCI provides an augmented communication channel for individuals who do not have the motor function capabilities that are necessary to interact with the external world [6, 9].

This research proposed a BCI-controls-EAS (BCICEAS) system to stimulate upper limbs action based on event-related desynchronization (ERD) of EEG signal evoked by imaginary movement. Three modules were contained in this system: signal acquisition module, signal processing module and EAS stimulator module, as shown in Fig. 1. A feedback training technique was designed to correlate the enhancement of relevant EEG feature through a visual interface with a virtual liquid column, whose height varied along with EEG power spectral feature.

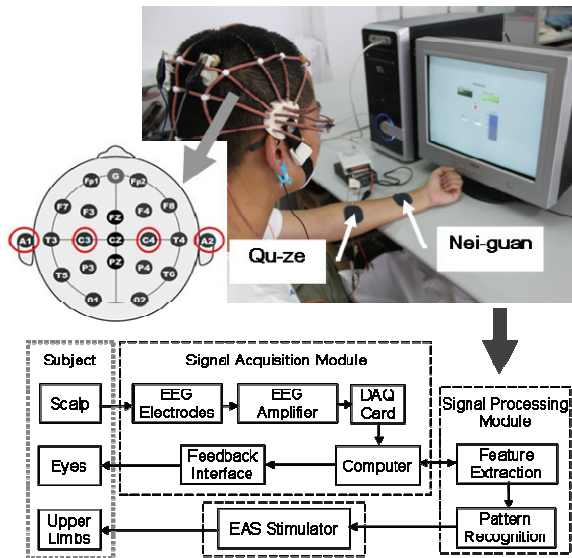


Fig. 1. BCICEAS experimental environment and control platform.

2. Signal Processing Algorithm

2.1. Short Time Fourier Transform (STFT)

Considering that specific frequency bands and a fixed time delay of ERD, we introduce the method of Short Time Fourier Transform. STFT is one of the classic Time-frequency analyses in the EEG signals under study [9]. The STFT positions a window function $\psi(t)$ at τ on the time axis, and calculates the Fourier transform of the windowed signal as

$$F(w, \tau) = \int_{-\infty}^{\infty} f(t)\psi^*(t-\tau)e^{-jw t} dt, \quad (1)$$

when the window $\psi(t)$ is a Gaussian function, STFT is called a Gabor transform. The basis functions of this transform are generated by modulation and transformation of the window function $\psi(t)$, where w and τ are modulation and translation parameters, respectively. The fixed time window $\psi(t)$ is the limitation of STFT as it causes a fixed time-frequency resolution [10].

2.2. Matching Pursuit (MP)

The method of algorithm of matching pursuit (MP), introduced by Mallat and Zhang (1993), decomposes any signal into a linear expansion of waveforms that belong to a dictionary of functions [11]. There are several restrictive conditions of its basics. In the first step of the MP, the waveform g_{r0} which best matches the signal $f(t)$ is selected from a redundant dictionary D . In each of the following steps, the waveform g_m is matched to the signal $R^n f$ which is the residual left after subtracting results of previous iterations:

$$\begin{cases} R^0 f = f \\ R^n f = \langle R^n f, g_m \rangle g_m + R^{n+1} f \\ g_m = \arg \max_{g_i \in D} |\langle R^n f, g_i \rangle| \end{cases}, \quad (2)$$

MP decomposition of a signal $f(t)$ is carried out by successive approximations of the signal $f(t)$ with its orthogonal projections on the atoms chosen from the dictionary in order to best match the local structure of the signal. After m iterations, a matching pursuit decomposes a signal f into

$$f = \sum_{n=0}^{m-1} \langle R^n f, g_m \rangle g_m + R^m f, \quad (3)$$

where $R^m f$ is the residual vector after $f(t)$ is approximated by m atoms, and $\langle R^n f, g_m \rangle g_m$ characterizes the projection of $R^n f$ onto an atom g_m [11].

The orthogonality of $R^n f$ and g_m in each step implies energy conservation:

$$\|f\|^2 = \sum_{n=0}^{m-1} |\langle R^n f, g_m \rangle|^2 + \|R^m f\|^2, \quad (4)$$

For a complete dictionary, the procedure comes together to

$$f = \sum_{n=0}^{\infty} \langle R^n f, g_m \rangle g_m, \quad (5)$$

We compute an estimation of the time-frequency density of the signal's energy, which is free of cross-terms, by adding Wigner distributions W of selected functions:

$$Ef(t, w) = \sum_{n=0}^{\infty} |\langle R^n f, g_m \rangle|^2 Wg_m(t, w), \quad (6)$$

2.2. MP-Fisher

However, MP decomposition does not represent signals with time-frequency modulations correctly. Thus, MP-Fisher is the advance of MP algorithm. In this paper, the MP method based on Fisher criterion for optimization of movement-related EEG power features is proposed to provide a theoretical guide for selecting the most relevant EEG frequency components. Given the time-frequency distribution of the EEG power features, we calculate the parameters, called MP-Fisher ratio (MFR) combined with Fisher criterion in the following procedures

The time-frequency distribution $F_{f_f}(t, f)$ of the EEG power features is found by the MP algorithm. Sample mean and variances is determined according to the patterns of imaginary and non-imaginary motor. Based on Fisher criterion, we may estimate MP-Fisher parameters $s(t, f)$ defined by

$$s(t, f) = \frac{[M_{f_f(1)}(t, f) - M_{f_f(2)}(t, f)]^2}{S_{f_f(1)}(t, f) + S_{f_f(2)}(t, f)}, \quad (7)$$

where $M_{f_f(1)}(t, f)$ and $M_{f_f(2)}(t, f)$ stand for the corresponding range of mean, while $S_{f_f(1)}$ and $S_{f_f(2)}$ are variances of elements in two $F_{f_f}(t, f)$. The bigger $s(t, f)$ is, the higher the level of separability is.

2.3. Mahalanobis Distance

In statistics, Mahalanobis distance (MD) is a distance measure introduced by P. C. Mahalanobis (1936), and based on correlations between variables by which different patterns can be identified and analyzed. It is a useful way of determining similarity of an unknown sample set to a known one, in order to explore the classification procedures. The MD becomes an evaluation between two data points in the space defined by relevant features. Accounting for unequal variances as well as correlations among features, it will adequately evaluate the distance by assigning different weights or important factors to the features of data points [6].

Formally, the Mahalanobis distance from a group of values with mean $\mu = (\mu_1, \mu_2, \mu_3, \dots, \mu_p)^T$ and covariance matrix \sum_p for a multivariate vector $x = (x_1, x_2, x_3, \dots, x_p)^T$ is defined as:

$$D_M^2(x) = (x - \mu)^T \sum_p^{-1} (x - \mu), \quad (8)$$

The formula of Mahalanobis distance can also be defined as distinction with the following equation:

$$d^2(\vec{x}, \vec{y}) = (\vec{x} - \vec{y})^T \sum_p^{-1} (\vec{x} - \vec{y}), \quad (9)$$

where two random vectors \vec{x} and \vec{y} of the distribution with covariance matrix \sum_p

Given two data total sets G_1, G_2 and sample point x , their Mahalanobis distance can be restricted by the discrimination formula:

$$w(x) = \frac{d^2(x, G_1) - d^2(x, G_2)}{2}, \quad (10)$$

where sample point x exists three patterns: if $w(x) < 0$, $x \in G_1$; if $w(x) > 0$, $x \in G_2$; if $w(x) = 0$, sample point x can not be certain.

3. Experimental Design

In this study, EEG training experiment was induced by imaginary movements. 12 healthy adult subjects participated in the experiment were divided into two groups by with or without feedback with 3 males and 3 females for each group separately. For individuals, there are three stages in the experiment. Each stage lasts about 40 minutes and comprises of four sets (30 trials of imaginary movement for one set), including preparation, tips, imaginary movement and resting. The rest time between two trial-sets is about three minutes and each trial lasts about nine seconds.

EEGs were recorded by an EMS Phoenix Digital EEG Equipment at electrode positions C3, C4 and A1, A2 of the international 10-20 system (as marked with red circle in Fig. 1). The research of neural electrophysiology showed that either an actual body movement or an imaginary movement can increase obvious intensity changes in the power spectral density (PSD) of some characteristic band components in evoked potentials [12]. The decrease of power spectrum ratio is called as event-related desynchronization (ERD), while the enhancement is called as event-related synchronization (ERS). In addition, both the characteristic bands and spatial cortex regions of ERD/ERS are related to the kind of actual or imaginary movements. It indicates that the

ERD/ERS induced the brain imaginary movements can be used as an effective means for EEG feature detection and pattern recognition.

There are many definition and calculation methods for ERD/ERS, such as Hilbert transformation, band power spectrum, and power spectral decomposition [13-15]. Therefore, we adopt the definition of band power spectrum proposed by Pfurtschella and Aranibar [16]. The percentage values for ERD are obtained by the following equation:

$$C_{ERD} = \frac{A - R}{R} \times 100(\%), \quad (11)$$

where A represents the power spectral density within the frequency band of interest in the period after the event happens, whereas that of the preceding baseline or reference period is given by R [16].

Under aforementioned study, the training experiments are applied to electro-acupuncture stimulation (EAS), in which the subjects can self-control their upper limbs in an on-line system test with feedback training. The electrodes are placed in the acupuncture Qu-Ze and Nei-Guan, which are the sensitive points of stimulation for lifting the fore-arm, as shown in Fig. 1.

4. Results

In this study, the PSD was applied to analyze the EEG activity of hand imaginary and non-imaginary movements, and discriminated between two stages by ERD on 12 subjects. All of them were aged between 20 and 30 years old, and divided into two groups by with or without feedback. For the group of subjects with feedback, the feedback adjustment of imaginary movement state can be carried out by a visual interface of a virtual liquid column representing EEG power spectral value on feedback tache, as shown in Fig. 1, and by a visual interface of a virtual liquid column representing EEG power spectral value on feedback tache, as shown in Fig. 2.

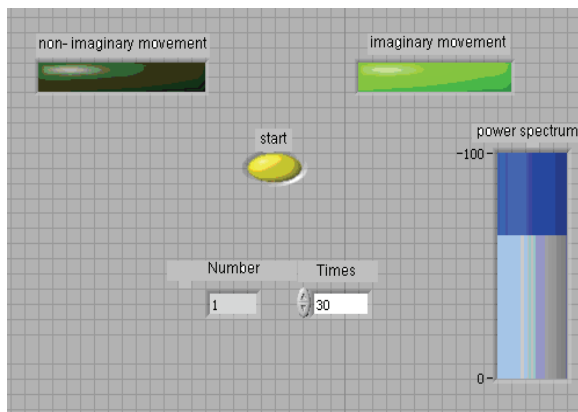


Fig. 2. Visual feedback interface of a virtual liquid column.

For MP method based on Fisher criterion, the value of the frequency bands of ERD feature was calculated for all subjects, as it shows in Fig. 3. For MP -Fisher criterion, the characteristic frequency bands of each subject firstly are extracted according to Fisher parameter criterion. PSD is averaged in the corresponding characteristic bands and time periods. After the data being normalized, ERD value of each imaginary movement can be got according to equation (10).

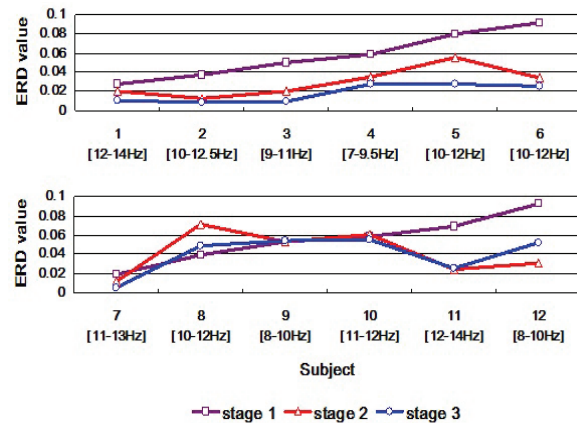


Fig. 3. ERD value calculated from 6 subjects with feedback (Subject 1-6) and without feedback (Subject 7-12).

The mean of ERD value is from 0.0561 in stage 1 down to 0.0181 in stage 3 for the group with feedback, while from 0.0548 down to 0.0393 for the group without feedback, as shown in Fig. 4. Comparing the first stage data with the third ones, the ERD value is defined as the ratio of the difference between imagination and resting period, so the EEG feature of imaginary movement increases following lower ERD values. Fig. 4 shows obvious enhancement phenomenon of EEG, after the participants in the two groups complete the training process. It is also concluded that feedback training has a more improvement of EEG feature in comparison to no feedback training. By comparing the ERD value of 2 stages through t test, P value which reflects the extent of difference was shown in Fig. 5. The remarkable dissimilarity exists when P is less than 0.05, as marked with red star. For the group with feedback, there are significant differences in the data between the stage 1 and next two stages. For the groups without feedback, only the distinctions between stage 1 and 3 are obvious. Therefore, we can see the significant enhancement phenomenon of EEG by feedback training process. Importantly, feedback training is necessary for BCICEAS system to overcome the problem, which results from strangeness to influence imaginary movement efficiency for the first use of the system. The similarity between stage 2 and 3 indicates a saturation situation resulting from feedback training which reflects that the feedback system decreases the training time significantly for the

voluntary control by the patients using BCI, and proves a suitable method for medical rehabilitation. Thus, there is no significant improvement when training reaches certain intensity. The training process is of importance for each individual in the experiment. Thus, clear enhancement phenomenon of EEG can be achieved by training. Further more, the enhancement of EEG feature in the test with feedback is higher than that of non-feedback. Fig. 3 shows the curves of the mean ERD value for all subjects with and without feedback. Compared with the group without feedback, there is more remarkable increase of ERD value and more significant enhancement of EEG feature in the test with feedback. These results prove that the feedback training can effectively improve the intensity of EEG feature.

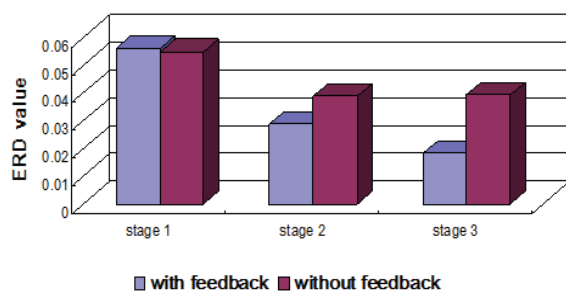


Fig. 4. ERD value comparison during trainings with and without feedback in different stages.

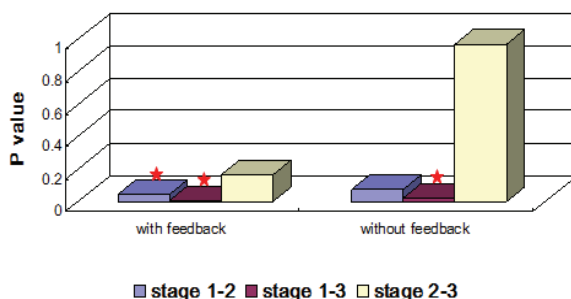


Fig. 5. P value comparison by T-test between two stages during trainings with and without feedback in different stages. (☆: $P < 0.05$).

Mahalanobis distance was used to evaluate accuracy of imaginary and non-imaginary. Imaginary accuracy is considered that the disposed signals of imaginary movement stimulate the upper limb correctly, whereas non-imaginary accuracy denotes movement without real stimulus signals. The recognition accuracy in stimulus experiment for non-imaginary task in EAS experiment is more than 90.9 % while that for imaginary task is just more than 76.7 %. The experimental accuracy in non-imaginary task is higher than those in imaginary task. It is the reason that the delay comes out in the process of collecting EEG signals, which can not generate ERD phenomenon.

5. Discussion

In this research, our aim was to develop a BCI-controls-EAS (BCICEAS) system to modulate movement of upper limbs by electroacupuncture and EEG. An imaginary movement can induce obvious intensity changes in the power spectrum density (PSD) of some characteristic band components in evoked potentials Event-related desynchronization (ERD) of EEG signal was observed by the decrease of power spectrum ratio, which is evoked by imaginary movement. Moreover, the change of EEG signal was observed in the training and stimulation experiments with visual feedback. The Fisher parameters were extracted from feature frequency bands of EEG and classified into EAS control commands by Mahalanobis distance (MD) classifier. A feedback training technique was employed to correlate the enhancement of relevant EEG feature through a visual interface with a virtual liquid column, whose height varied along with EEG power spectral feature. According to the statistics analysis of 12 subjects, experimental results revealed the effective improvement of feedback training on signal feature and reliable control of EAS.

Several previous studies have shown the benefit of acupuncture for motor improvement in stroke rehabilitation [17-20]. However, the effectiveness of acupuncture on motor functional recovery has been seriously challenged by the results reported in recent clinical trials [21-22]. The poor autonomy for the patient to control EAS device restricts its application and makes it a technical bottleneck for further popularization. In the current study we targeted a self-control electroacupuncture system for clinical needs. Our results in the present study are promising. Acupuncture stimulation offered important benefits of limbs' motor when combined with BCI training.

Additionally, previous studies have shown that these applications of the matching pursuit (MP) method to EEG recordings demonstrate the ability of this method to provide continuous detailed decompositions of captured activity into component waveforms [23]. In our study MP-Fisher is a valuable tool for time-frequency analyses of dynamic activity of EEG as the advance of MP algorithm, which is consistent with previous results.

Previous studies have demonstrated that the Mahalanobis classifier based on the use of the full covariance matrix of features is able to classify EEG patterns during imagination of left and right hand movements [24]. Such recognition has been performed by using data from few EEG electrodes at a high level of accuracy. The classification performance by using data from the C3 and C4 electrodes of such method are statistically equivalent to those obtained by using four recording electrodes (C3, C4, P3, P4) [24]. Thus, it was used to apply for our study.

After extracting the PSD from the recorded EEG data, the value of ERD can be acquired. This paper made use of ERD phenomenon evoked by imaginary movement to observe the change of EEG signal in the

training process and two EEG experiments (with feedback and without feedback). Against the absence of this exploration of the relativity of EEG features for training, especially relative research problems about how training effects the change of these features, the feature of EEG can be strengthened using the training process and feedback tache. It is proved that training can intensify EEG features and the EEG features after the whole training process for subjects of both groups show significant enhancement. In addition, the introduction of feedback tache can improve the effect of training; the EEG features of the subjects in the group with feedback were obviously better than those in the group without feedback. Beside, the subjects were tested by an on-line system after feedback training and the highest experimental accuracy rate of them could reach above 76.7 % equally, with highest one at 90.9 %. Thus, it can be realized that the function of transforming imaginary movement into self-acupuncture stimulization and possess higher application prospects of serving disabled people to recover their upper limbs, which was worth making further research and extension.

6. Conclusions

The development of a scientific electrical acupuncture stimulization has made it possible to consider a wide variety of clinical applications that have been demonstrated. Acupuncture has a great potential of being used for rehabilitation. This research provides the basis for the development of BCI-control-EAS system which might help patients with severe paralysis to regain control over their body, which is worth making further research and extension. Using the fMRI, however, the neurobiological evidence of specificity of the acupuncture has been provided by EAS [25]. The important next step in acupuncture research is to have a better understanding of the neurophysiologic mechanism of acupuncture in order that the therapeutic effectiveness of acupuncture can be further increased.

Acknowledgments

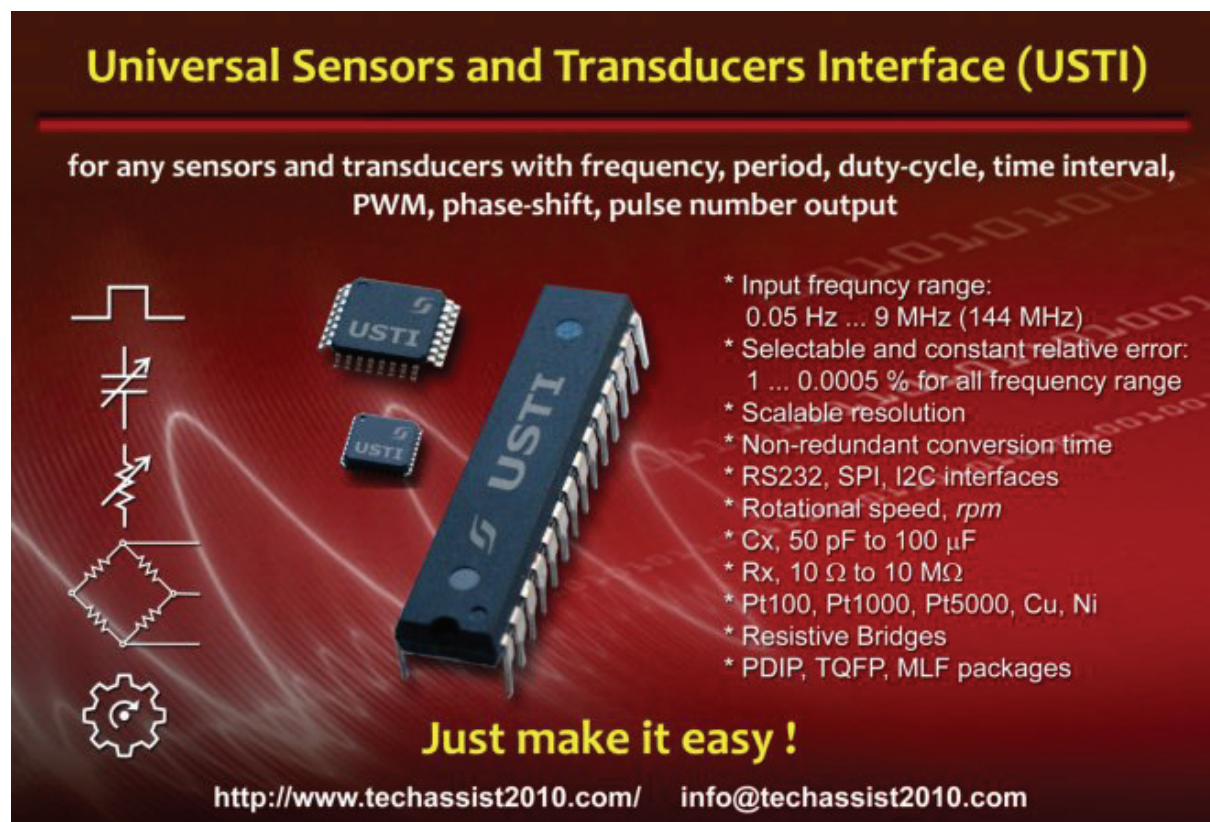
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References

- [1]. J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, Brain- computer interfaces for communication and control, *Clinical Neurophysiology*, Vol. 113, Issue 6, 2002, pp. 767-791.
- [2]. K. Qian, P. Nikolov, D. Huang, D. Y. Fei, X. Chen, and O. Bai, A motor imagery-based online interactive brain-controlled switch: paradigm development and preliminary test, *Clinical Neurophysiology*, Vol. 121, Issue 8, 2010, pp. 1304-1313.
- [3]. NIN Consensus Development Panel on Acupuncture, NIH Consensus Conference Acupuncture, *Journal information: The Journal of the American Medical Association (JAMA)*, Vol. 280, Issue 17, 1998, pp. 1518-1524.
- [4]. W. T. Zhang, Z. Jin, G. H. Cui, K. L. Zhang, L. Zhang, Y. W. Zeng, F. Luo, A. C. Chen, and J. S. Han, Relation between brain network activation and analgesic effect induced by low vs. high frequency electrical acupoint stimulation in different subjects: a functional magnetic resonance imaging study, *Brain Research*, Vol. 982, Issue 2, 2003, pp. 168-178.
- [5]. T. Yan, C. W. Hui-Chan, Transcutaneous electrical stimulation on acupuncture points improves muscle function in subjects after acute stroke: a randomized controlled trial, *Journal of Rehabilitation Medicine*, Vol. 41, Issue 5, 2009, pp. 312-316.
- [6]. S. M. Xiang, F. P. Nie, and C. S. Zhang, Learning a Mahalanobis distance metric for data clustering and classification, *Pattern Recognition*, Vol. 41, Issue 12, 2008, pp. 3600- 3612.
- [7]. J. M. Peets, B. Pomeranz, CXBK mice deficient in opiate receptors show poor electroacupuncture analgesia, *Nature*, Vol. 273, Issue 5664, 1978, pp. 675-676.
- [8]. B. J. Na, G. H. Jahng, S. U. Park, W. S. Jung, S. K. Moon, J. M. Park, and H. S. Bae, An fMRI stud of neuronal specificity of an acupoint: electroacupuncture stimulation of Yanglingquan (GB34) and its sham point, *Neuroscience Letters*, Vol. 464, Issue 1, 2009, pp. 1-5.
- [9]. W. D. Zhou, Y. Y. Li, EEG real-time feedback based on STFT and coherence analysis, in *Proceedings of the 23rd Annual Interactional Conference of the IEEE Engineering in Medicine and Biology Society*, Istanbul, Turkey, 25-28 October 2001, Vol. 2, pp. 1869-1871.
- [10]. M. K. Kiyimik, I. Güler, A. Dizibüyük, and M. Akin, Comparison of STFT and wavelet transform methods in determining epileptic seizure activity in EEG signals for real-time application, *Computers in Biology and Medicine*, Vol. 35, Issue 7, 2005, pp. 603-616.
- [11]. X. L. Shi, B. D. Bai, Y. F. Zhang, H. H. Ma, and J. H. Chen, Extraction of mean frequency information from Doppler blood flow signals using a matching pursuit algorithm, *Signal Processing*, Vol. 88, Issue 11, 2008, pp. 2720-2730.
- [12]. P. Zhuang, EEG event-related desynchronization/synchronization activities and sports-related operations, *Chinese Journal of Clinical Rehabilitation*, Vol. 8, Issue 1, 2004, pp. 152-154.
- [13]. M. Barry Stermann, David A. Kaiser and Bettina Veigel, Spectral analysis of event-related EEG responses during short-term memory performance, *Brain Topography*, Vol. 9, Issue 1, 1996, pp. 21-30.

- [14]. A. P. Burgess, J. H. Gruzelier, The reliability of event-related desynchronization: a generalisability study analysis, *International Journal of Psychophysiology*, Vol. 23, Issue 3, 1996, pp. 163-169.
- [15]. G. Florian, G. Pfurtscheller, Dynamic spectral analysis of event-related EEG data, *Electroencephalography and Clinical Neurophysiology*, Vol. 95, Issue 5, 1995, pp. 393-396.
- [16]. G. Pfurtscheller, Lopes da Silva FH, Event-related EEG/MEG synchronization and desynchronization: basic principle, *Clinical Neurophysiology*, Vol. 110, Issue 11, 1999, pp. 1842-1857.
- [17]. H. H. Hu, C. Chung, T. J. Liu, R. C. Chen, C. H. Chen, P. Chou, W. S. Huang, J. C. Lin, and J. J. Tsuei. A randomized controlled trial on the treatment for acute partial ischemic stroke with acupuncture, *Neuroepidemiology*, Vol. 12, Issue 2, 1993, pp. 106-113.
- [18]. K. Johansson, I. Lindgren, H. Widner, I. Wiklund, and B. B. Johansson. Can sensory stimulation improve the functional outcome in stroke patients?, *Neurology*, Vol. 43, Issue 11, 1993, pp. 2189-2192.
- [19]. A. Kjendahl, S. Sällström, P. E. Osten, J. K. Stanghelle, and C. F. Borchgrevink, A one year follow-up study on the effects of acupuncture in the treatment of stroke patients in the subacute stage: A randomized, controlled study, *Clinical Rehabilitation*, Vol. 11, Issue 3, 1997, pp. 192-200.
- [20]. J. Pei, L. Sun, R. Chen, T. Zhu, Y. Qian, and D. Yuan, The effect of electro-acupuncture on motor function recovery in patients with acute cerebral infarction: A randomly controlled trial, *Journal of Traditional Chinese Medicine*, Vol. 21, Issue 4, 2001, pp. 270-272.
- [21]. B. B. Johansson, E. Haker, Von M. Arbin, M. Britton, G. Långström, A. Terént, D. Ursing, and K. Asplund, Acupuncture and transcutaneous nerve stimulation in stroke rehabilitation: A randomized, controlled trial, *Stroke*, Vol. 32, Issue 3, 2001, pp. 707-713.
- [22]. F. K. Sze, E. Wong, X. Yi, and J. Woo, Does acupuncture have additional value to standard poststroke motor rehabilitation?, *Stroke*, Vol. 33, Issue 1, 2002, pp. 186-194.
- [23]. P. J. Franaszczuka, G. K. Bergeya, P. J. Durkac, and H. M. Eisenberg, Time-frequency analysis using the matching pursuit algorithm applied to seizures originating from the mesial temporal lobe, *Electroencephalography and Clinical Neurophysiology*, Vol. 106, Issue 6, 1998, pp. 513-521.
- [24]. F. Babiloni, L. Bianchi, F. Semeraro, J. del R. Millin, J. Mourillo, A. Cattini, S. Salinari, M. G. Marciari, and F. Cincotti. Mahalanobis Distance-Based Classifiers Are Able to Recognize EEG Patterns by Using Few EEG Electrodes, in *Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (Cat. No. 01CH37272)*, Istanbul, Turkey, 25-28 October 2001, Vol. 1, pp. 651-654.
- [25]. P. Liu, Y. Zhang, G. Zhou, K. Yuan, W. Qin, L. Zhuo, J. Liang, P. Chen, J. Dai, Y. Liu, and J. Tian, Partial correlation investigation on default mode network involved in acupuncture: an fMRI study, *Neuroscience Letters*, Vol. 462, Issue 3, 2009, pp. 183-187.

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