EEG-based Emotion Recognition with Brain Network using Independent Components Analysis and Granger Causality

CHEN Dongwei[1, 2], Wu Fang[2], Li Haifang[1], CHEN Junjie[1], Wang Zhen[2], Zhuo QiuSheng[2]
[1]College of Computer and Software
Taiyuan University of Technology
Taiyuan, China
[2]College of Computer
Beijing Institute of Technology, Zhuhai
China
[3]University of Technology, Taiyuan, China, 030024
chendwzhbit@sina.cn, {lihf, chenjj}@tyut.edu.cn, zhbitwufang@gmail.com, {chavez.w, 305082800}@qq.com

ABSTRACT: *With the continuous development of brain network technology, it has become a hot area of neuroscience and information technology to research the human emotion changes, cognitive status and psychiatric disorders by means of brain network. In recent years, any smart device can be used as a terminal sensor in the Internet of Things for information interaction. It will be the new research aspect for brain-computer Interface (BCI) to regard the human brain (the most intelligent "device") as a terminal sensor in the Internet of Things and to construct a network based on the human brains (we name it as Internet of Brains). In this paper, a causal connectivity brain network (CCBN) was firstly constructed based on multivariate autoregressive (MVAR) modeling, independent component analysis (ICA) and partial directed coherence (PDC). Then the different features of three emotional states (positive, neutral, negative) were respectively extracted by graph theoretical analysis based on the CCBN estimated by granger causality analysis. The relationship between characteristics of EEG pattern and emotional states was disclosed. Result suggested that a classification rate of about 88.75% was achieved in the human subject studied, thus it is feasible to discriminate emotional states with causal connectivity brain network and is a promising non-invasive approach for studying the model of affective computing. Furthermore the model of wearable affective computing was estimated based on above relationship with the portable EEG acquisition device, and prototype system of Internet of Brains would be achieved for BCI.*

Keywords: Causal Connectivity Brain Network, Multivariate Autoregressive Modeling, Independent Component Analysis, Granger Causality Analysis, Wearable Affective Computing, Internet of Brains

Received: 12 November 2012, Revised 23 December 2012, Accepted 30 December 2012

1. Introduction

Emotion is an inseparable part of human intelligence, and it plays an important role in the human brain cognition, reasoning, decision-making, diagnosis and treatment of mental illness [1, 2]. Affective Computing will acquire the physical and behavioral characteristics of physiological signal caused by the human emotion through a variety of sensors, then establish emotional model, and give intelligent, sensitive, friendly response to users' emotion. The wearable computer is the best platform for affective computing. Internet of Things [3] is booming today, any smart device can be used as terminal sensor for information exchange. While the human brain, as the most intelligent "*device*" terminal of the Internet of Things, can provide powerful support in real-time monitoring of human emotional changes, cognitive status, and mental disease. Thus it provides the opportunity for us to make the wearable computer to be fulfilled for affective computing.

Human brain consists of different functional regions which are interconnected to flow the interactive information. Thus, brain network is constructed with the graph theory according to the different brain regions and information flow. Furthermore, we could detect the different biomarkers of diverse brain cognition functions according to brain network. While emotion is the unstable process for brain cognition, thus it is the key problem to explore the characteristics of dynamic interaction for human brain. Dynamic brain network is defined to reflect the causal connectivity and transient transmission of human brain. It is the physiological basis for human emotional response, as the characterization of the human brain emotional recognition, reasoning, decision-making and mental diseases. It will become a hotspot issue for BCI [4] in the Internet of Things to explore executable mechanism and information processing of dynamic brain network and to construct the Internet of Brains according to the mechanism above.

To sum up, it will be trend to combine the neural feedback technology, data acquisition of real-time brain imaging, characteristics of dynamic brain network and wearable affective computing model for the application of BCI. However, there is still no consistent conclusion about how to construct dynamic brain network and wearable affective computing model, especially in the area of emotion recognition; until now, to our knowledge, there is also no report to apply the dynamic brain network to extract the characteristics of different emotions, while there is still no review to regard human brains as terminal sensor in Internet of Things and to construct the model of wearable affective computing for Internet of Brains.

2. Theory

2.1 Multivariate Autoregressive Modeling

Multivariate Autoregressive (MVAR) Modeling is a linear multivariate time series model which has a long history of application in econometrics. The MVAR model characterizes inter-regional dependencies within data, specifically in terms of the historical influence one variable has on another. Consider d time series generated from d variables within a system such as a brain network and where m is the order of the model. A MVAR (m) model predicts the next value in a d-dimensional time series, y_n as a linear combination of the m previous vector values

$$y_n = \sum_{i=1}^{m} y_{n-i} A(i) + e_n$$

where $y_n = [\, y_n(1), y_n(2), \ldots\, \ldots, y_n(d)\,]$ is the n^{th} sample of a d-dimensional time series, each $A(i)$ is a d-by-d matrix of coefficients (weights) and $e_n = [\, e_n(1), e_n(2), \ldots\, \ldots, e_n(d)\,]$ is additive Gaussian noise with zero mean and covariance R. We have assumed that the data mean has been subtracted from the time series.

2.2 Independent Components Analysis

Independent components analysis (ICA) is an unsupervised statistical method used for decomposing a complex mixture of signals into independent sources [5]. It is especially suitable for preprocessing multichannel EEG data in BCI research because of the capacity for removing a number of different artifacts, such as electromyogram (EMG) or electrooculogram (EOG) signals [6, 7]. It can also be used to separate different rhythmic EEG components, such as right- and left-hemispheric mu rhythms, from ongoing EEG [8].

2.3 Graph Theory

Methods for analyzing causal connectivity of human brain are especially powerful when applied in combination with graph-theoretic and network-theoretic techniques, which allow their quantitative characterization [9]. In causal networks, nodes represent variables or system elements and directed edges represent causal interactions among nodes. There is wide range of graph theory concepts that may find useful application to causal networks.

The causal density and causal flow [9] are the central concerns of this work. Causal density refers to the total amount of causal interactivity sustained by a network. It is a useful measure of dynamical complexity because high causal density reflects integration and differentiation in network dynamics. In this case, nodes (functional brain regions or Independent Components) are both globally coordinated in their activity (useful for predicting each other's activity) and dynamically distinct (so that different elements contribute in different ways to these predictions). Causal flow refers to the difference between its out-degree (number of outgoing connections) and its in-degree (number of incoming connections). Causal flow can identify nodes that have distinctive causal effects on network dynamics: a node with a highly positive flow is a causal '*source*'; a node with a highly negative flow is a causal '*sink*'.

2.4 Brain Network

With the development of study for the structure and function of human brain, it is not only limited to search and locate the region with the specific cognitive task-related cortex function, but also focus on connectivity among brain regions and construction of brain network for the research of human brain function. For example: Friston et al. divided the connection among brain regions into functional connectivity and effective connectivity [10]. Functional connectivity is used to determine whether exist connectivity among brain regions and the strength for relationship among connectivity; Effective connectivity refers to measure the pattern of information transfer among brain regions, and to establish the causal interactive relationship between neurons, and to reflect the dynamic process of neural activity and the dynamics characteristics properties of brain networks. These characteristics are similar to the real mechanism of human brain. Petra proposed "*BrainModes*" [11] plan, which was used to detect the mechanism of human brain and to reveal relationship among the multi-modal neuroscience dataset. Valdés-Sosa introduced the ICA-STTONNICA [12] model which demonstrates the EEG source localization and dynamic network connectivity; Chen proposed large-scale causal model by means of conditional Granger Causal [13], and applied it to the study for resting-state dynamic brain network.

2.5 Granger Causality Analysis

Granger causality (GC) is a method for inferring certain types of causal dependency between stochastic variables based on reduction of prediction error of a putative effect when past observations of a putative cause are used to predict the effect, in addition to past observations of the putative effect. The concept was first introduced by Norbert Wiener in 1956 and later reformulated and formalized by C.W. Granger in the context of bivariate linear stochastic autoregressive models. The concept relies on two assumptions:

Granger Causality Axioms

(1) Causes must precede their effects in time;

(2) Information in a cause's past must improve the prediction of the effect above and beyond information contained in the collective past of all other measured variables (including the effect)

Assumption (1) is intuitive from basic thermo dynamical principles: the arrow of causation points in the same direction as the arrow of time – the past influences the future, but not the reverse. Assumption (2) is also intuitive: for a putative cause to truly be causal, removal of the cause should result in some change in the future of the putative effect – there should be some shared information between the past of the cause and the future of the effect which cannot be accounted for by knowledge of the past of the effect. The theory and application of *GC* (and its extensions) to neural system identification has been elaborated in a number of other articles and texts.

2.6 Affective Computing

Since 1995, Professor Picard defined the term "*affective computing*" and many scholars followed the study and proposed a variety of emotion models. 1988, Ortony et al. divided the emotion into 22 categories according to three aspects of the evaluation criteria of the goals, events and actions, then proposed the OCC emotion model [14] in the point of view of emotional cognition. In 2002, Kshirsagar introduced the multilayer emotion model of "*personality-mood-emotions*", and had a well relation with personality and emotion, and successfully applied it to the synthesis of facial expressions of virtual human [15]. In 2005, Gebhard extended the work of Kshirsagar, proposed the ALMA (A layered model of affect) [16] model. Yong Chen, from University of Shandong, constructed a fuzzy set of emotion model [17], this model provided a novel method to combine fuzzy sets and Markov chain, and described the dynamic changes in process of emotion and static emotional space. In 2006, Hernández, et al. established an emotional model that combined the OCC model and dynamic decision network, then applied it to the intelligent tutoring system with mobile robots (the Intelligent tutoring System ITS) [18].

3. Experiment and Dataset

3.1 Experimental Paradigm

3.1.1 Subject

As part of a study to investigate the relative mechanism between "*inner*" emotion and EEG pattern at the level of CCBN characteristics, a twenty-eight-year-old-right-handed male was paid for his participation. Written informed consent was obtained and the protocol was approved by the Research Ethics Board.

3.1.2 Stimulus

Ninety pictures were taken from International Affective Picture System (IAPS) [19], depicting 30 unpleasant events (e.g. spiders, mutilations, etc.), 30 pleasant events (e.g. attractive infants, gracious old man, etc.) and 30 neutral events (e.g. neutral faces household objects, etc.). The content groups were selected so that there was almost no overlap in IAPS normative affective valence ratings, i.e. the three stimulus contents were distinct and representative of affect type: mean valence (nine-point scales, pleasant high) for pleasant pictures, 7.4; neutral pictures, 5.0; unpleasant pictures, 2.7. All neutral pictures had lower standard emotional arousal ratings (mean 2.9) than the pleasant (mean 5.8) and unpleasant (mean 6.4) pictures. The distributions of arousal ratings for pleasant and unpleasant pictures were overlapping. Both contents were anchored at the high end by similar high arousal exemplars; because of the natural picture distribution of the IAPS, the low arousal end of the unpleasant pictures range was somewhat less extended than for pleasant pictures.

3.1.3 Procedure

The experiment paradigm was illustrated in Figure 1. After arrival at the laboratory, participants read and signed an informed consent form and filled out several questionnaires, then was briefly introduced to the experiment protocol and the use of self-assessment questionnaire. Participants were then seated in a recliner in a dimly lit room, and electrodes were attached. The participant was told that a series of slides would be presented and that he should attend to each picture the entire time it appeared on the screen. The pictures were presented as color slides, arranged in the random sequence and presented for 1000ms in the computer. In order to promote a stable mental set, the participant was asked to try to maintain the image of the slide for a short period after its presentation (terminated by a keyboard number button). The participant was then asked to judge their emotional reactions while viewing the picture on bi-polar scales measuring affective valence and arousal. The subject was asked to quantify the valence and arousal for nine-point scales. A 30s resting baseline was initiated at the beginning of the experiment to facilitate laboratory adaptation, and 30s resting after thirty trials.

3.2 Data acquisition

EEG data were recorded using a 32-channel EEG system (actiCHamp, Brain Products, Munich, Germany). The EEG cap consisted of 28 scalp electrodes distributed according to the 10–20 system and two additional electrodes, one of which was attached approximately 2 cm below the left collarbone to record the ECG, while the other was attached below the left eye for measurement of the electrooculogram. TP9 and TP10 were reference electrodes. Data were sampled at 500Hz.

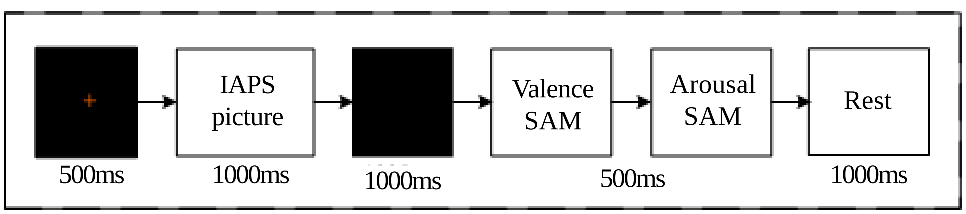

Figure 1. Experiment paradigm for emotion-induced

4. Methods and Results

4.1 Data Preprocessing

The data collected in our experiment using the 32-channel EEG device was analyzed to characterize EEG patterns for positive, negative and neutral emotion. EEG data were referenced to the common average, resampled to 128 Hz, and high-pass filtered with a 1-Hz cutoff-frequency using EEGLAB. Eye movement and blinking artefacts were removed with a blind source separation technique from the AAR toolbox for EEGLAB. 1 to 40 Hz band-pass filter was applied to the raw data as the major EEG waves (theta, delta, alpha, beta, and gamma) lie in this band [20, 21].

4.2 Causal Connectivity Brain Network

A useful property of any network consisting of multiple nodes is its Topology. The topology of a network describes the way network nodes are connected to each other. That is, it describes the pattern of network edges. In the case of a MVAR model, the Topology property describes how the nodes of the model, the $y_i(d)$, send or receive information from/to other nodes. We referred to the elements of vector $y(d)$ as the nodes of the model. The term "*nodes*" was used because each time-series $y_i(d)$ can be understood as the temporal activation pattern of a network node. Then, nodes may or may not be connected to each other by directional edges.

4.2.1 Nodes Definition

ICA described above was applied for discriminating brain and non-brain activity from brain components to determine the nodes of brain network. In this paper, the specific ICA algorithm employed was FastICA. One of the reasons for this choice was the large number of successful applications in various fields of data mining, particularly medical signal processing. The other factors were the broad availability of the algorithm and the diversity in the way the unmixing matrix is estimated.

The FastICA algorithm [22] extracts independent components by separately maximizing the negentropy $J(y)$ of each mixture. FastICA has two algorithmic approaches available for the estimation of the unmixing matrix: one is the symmetric approach and the other is the deflationary approach where independent components are estimated one by one like in projection pursui [23]. There are a number of parameters available that can be tuned in order to optimize the performances of FastICA. For this study, FastICA was using a tangent hyperbolic as its non-linearity instead of the default third order polynomial, which was not found to be a robust parameter, because it is only recommended when there are no outliers. This was not the case for the data analyzed in this paper, because all trials were retained and no artifacts were rejected. Moreover, the deflationary approach was used in favor to the symmetric approach.

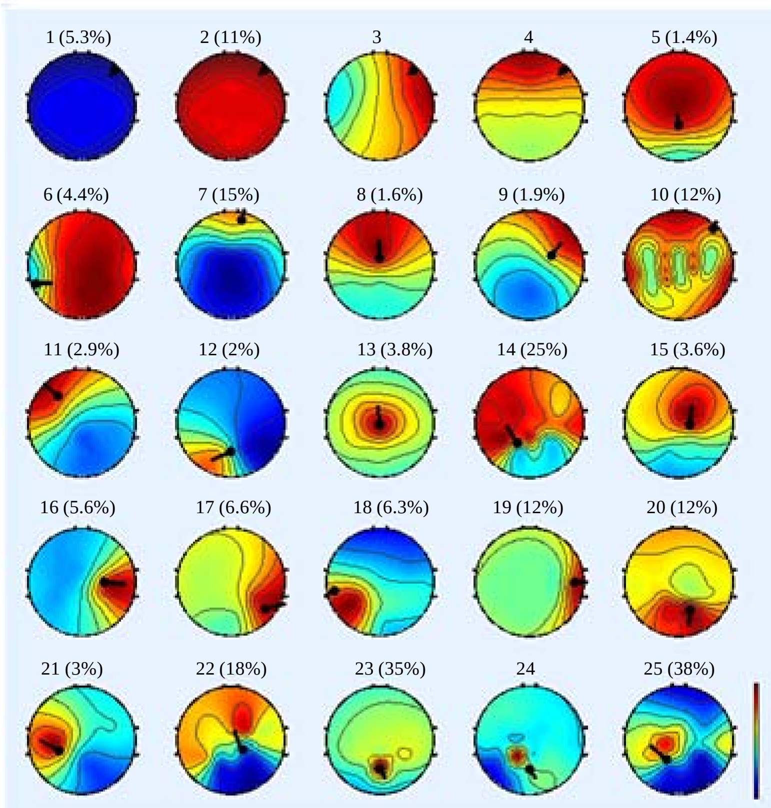

Figure 2. Dipole locations and ICs on scalp maps

Finally, ICA linearly decomposed EEG data into 25 maximally independent components. We implemented FastICA for 20 times with random initialization. To determine which components were common across implementations, we performed cluster analysis using mutual information between components and got greatly successful at this task. Since the activities of cortical and other EEG sources are not perfectly independent, after performing ICA a low level of dependence still exists between the returned maximally independent Component (ICs). This residual mutual information can be used to infer relations between different ISs. Figure 2 below showed the scalp maps 25 ICs returned for the positive emotion dataset (neutral and negative also have similar 25 ICs). Figure 3 showed a 3-D representation in which closer ICs have higher mutual information or activity dependence. Components are colored according to their respective cluster.

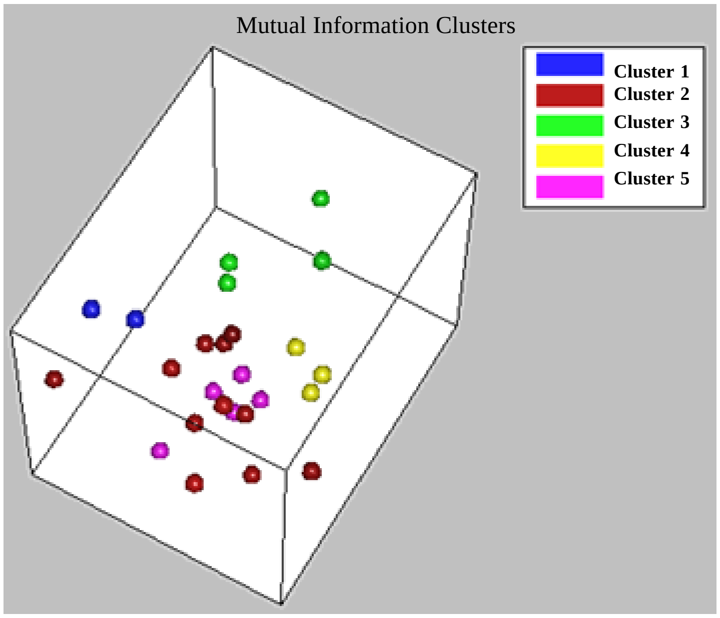

Figure 3. 3-D representation in which closer ICs have higher mutual information

4.2.2 Edges Definition

Once determine the nodes of brain network, here we will focus primarily on edges, which multivariate extensions of the granger-causal for connectivity estimates computed.

In this paper we proposed a study on the application of the PDC technique, already used for the assessment of information flows between ICs, to the source activity estimated by using realistic models of head. The PDC analysis started by fitting a VAR model to the EEG data of different emotional states, and the AR model underlying the computation of PDC was estimated using the ARFIT package. A global measure of interaction was obtained by averaging the scores related to all frequency bins for PDC. Since the PDC was just estimates, it was affected by random estimation errors. Therefore, it was necessary to assess how large a PDC value needs to in order to consider it significantly larger than 0. This could be done using a one-tailed one sample t-test ($P < 0.05$). Finally, the significant flows were defined as edges among ICs.

4.3 Characteristics of CCBN

Based on the Granger causality network estimated by GCA, graph features of the brain network were quantitatively characterized by GTA.

For now, a simple classification rule can be defined based on causal connectivity brain network

(1) For causal density analysis, the classification is correct if the causal density of positive or negative emotion is higher than neutral emotion over all independent sources; while the causal density for positive and negative is different from the special independent source.

(2) For causal flow analysis, the classification is correct if the causal flow of positive or negative emotion has more '*source*' or '*sink*' than neutral emotion over all independent sources; while the causal flow of positive, compare to negative, has different '*source*' and '*sink*' with the special independent source.

The classification accuracy was defined as the ratio of the number of trials the present casual connectivity brain network method for which the different emotion was classified correctly over the total number of trials. Based on these two criteria, we obtained 88.75% classification accuracy in the human subject studied.

4.4 Wearable affective computing model

The causal density and causal flow of causal connectivity brain network under different emotional states were computed by independent components (nodes) and effective connectivity among ICs (edges). Thus, the common characteristics of EEG signal pattern in the specific emotion were identified. Then the different emotional states could be discriminated according to the special EEG pattern, and the model of affective computing was built by means of statistical analysis and classified algorithm based on the EEG pattern for different emotions. Furthermore, with the portable EEG signal acquisition device, such as Emotiv [25] or self-designed EEG device, we could build the model of wearable affective computing based on the relationship between common characteristics of EEG pattern and emotional states of human brain. Then the portable EEG signal acquisition devices were connected to the Internet with wireless/wired devices, and we developed a web-based application that would enable users to upload their encrypted EEG data to Internet. Finally, the web-based application could process EEG data from the Internet and the wearable affective prototype system (we named it as Internet of Brains) was achieved for BCI.

5. Conclusion

In this paper, we proposed a promising methodology for constructing EEG-based casual connectivity brain network (CCBN) and a novel concept to build model of wearable affective computing underlying Internet of Things (name it as Internet of Brains).The CCBN was constructed by Multivariate Autoregressive Modeling, Independent Component Analysis (ICA) and Granger Causality Analysis (GCA) to discriminate emotional states of human brain with the characteristics of CCBN. The results showed that ICA could be applied to decomposed different independent components of EEG data under different emotional states, furthermore determined the nodes of CCBN. Then we identified the causal relations among independent components via Granger causality analysis and determined the directed edges of CCBN which was constructed based upon PDC. Finally, the corresponding relationship between common characteristics of EEG pattern and emotional states of human brain were explored, therefore affective computing model was constructed based on the causal density and causal flow characterized by GCA. By means of portable EEG acquisition device, the wearable affective computing model was fulfilled. The promising results we have obtained in this pilot study suggest that characteristics of causal connectivity brain network could be the biomarker for discriminating different emotional states of human brain, and EEG-based Internet of Brains will be the future for BCI.

6. Acknowledgment

The authors would like to thank Prof. Chen Junjie, Li Haifang, Xiangjie of Taiyuan University of Technology and Dr. Lei Xu of Southwest University for hosting this research and providing valuable comments. This work was financed by National Natural Science Foundation of China (Grant No.61170136 and No.61070077).

References

[1] Rosalind W. Picard. (1997). Affective computing. USA: MIT Press.

[2] Chen, J-J., Li, H-F., Xiang, J., Zhao, J-J. (2011). Emotional Analysis Technology based on Graphics. *Publising House of Electronics Industry*.

[3] Luigi Atzori, Antonio Iera, Giacomo Morabito. (2010). The Internet of Things: A survey. Computer Networks.

[4] Niels Birbaumer, Leonardo G. Cohen (2007). Brain–computer interfaces: communication and restoration of movement in paralysis, *The Journal of Physiology*, 579 (3) 621–636.

[5] Vigario, R., Sarela, J., Jousmaki, V., Hamalainen, M., Oja, E. (2000). Independent component approach to the analysis of EEG and MEG recordings. *IEEE Trans. Biomed. Eng*. 47, 589–593.

[6] Jung, T. P., Makeig, S., Humphries, C., Lee, T. W., McKeown, M. J., Iragui, V., Sejnowski, T. J. (2000a). Removing electroencephalographic artifacts by blind source separation. *Psychophysiol*. 37, 163–178.

[7] Jung, T. P., Makeig, S., Westerfield, M., Townsend, J., Courchesne, F., Sejnowski, T. J. (2000b). Removal of eye activity artifacts from visual event-related potentials in normal and clinical subjects. *Clin. Neurophysiol*. 111, 1745–1758.

[8] Makeig, S., Debener, S., Onton, J., Delorme, A. (2004). Mining eventrelated brain dynamics. *Trends Cogn. Sci*. 8, 204–210.

[9] Seth, A. (2005). Causal connectivity of evolved neural networks during behavior. *Network: Comput Neural Syst*, 16, 35–54.

[10] Büchel, C., Friston, K. J. (1997). Modulation of connectivity in visual pathways by attention: cortical interactions evaluated with structural equation modelling and MRI. *Cerebral Cortex*, 7 (8) 768-778.

[11] John R. Terry, Petra Ritter, Andreas Daffertshofer. (2011). BrainModes: The role of neuronal oscillations in health and disease. *Progress in Biophysics and Molecular Biology*, 105 (1-2) 1-4.

[12] Valdés-Sosa, Mayrim Vega-Hernández, aría Antonieta Bobes. (2009). EEG source imaging with spatio-temporal tomographic nonnegative independent component analysis. *Human Brain Mapping*, 30 (6)1898–1910.

[13] Wei Liao, Jurong Ding, Daniele Marinazzo, Huafu Chen. (2011). Small-world directed networks in the human brain: Multivariate Granger causality analysis of resting-state MRI. *NeuroImage*, 54 (4) 2683-2694.

[14] Ortony, A., Clore, G. L., Collins, A. (1988). The Cognitive Structure of Emotions. Cambridge, UK: Cambridge University Press.

[15] Kshirsagar, S, Magnenat-Thalmann, N. (2002). A Multilayer Personality Model. *In*: Proceedings of the 2nd International Symposium on Smart Graphics, ACM Press, 107-115.

[16] Gebhard, Patrick. (2005). ALMA-A layered model of affect. *In*: Proceedings of AAMAS 05, Utrecht, Netherlands,177-184.

[17] Yong Chen, Tong He. (2005). Affective computing model based on rough sets. *In*: Proceedings of ACII 2005, Beijing, China: 606-613.

[18] Yasmín Hernandezl, Julieta Noguez, Enrique Sucar. (2006). Incorporating an Affective Model to an Intelligent Tutor for Mobile Robotics. *In*: Proceedings of 36th ASEE/IEEE Frontiers in Education Conference, San Diego, CA, 22–27.

[19] Lang, P. J., Bradley, M. M., Cuthbert, B. N. (1999). International affective picture system (IAPS): instruction manual and affective ratings. Technical Report A-4, The Center for Research in Psychophysiology, University of Florida.

[20] Sanei, S., Chambers, J. (2007), EEG signal processing. Chichester, England ; Hoboken, NJ: John Wiley & Sons.

[21] Sammler, D., Grigutsch, M., Fritz, T., Koelsch, S. (2007). Music and emotion: Electrophysiological correlates of the processing of pleasant and unpleasant music, *Psychophysiology*, 44, 293-304.

[22] Hyvarinen, A., Oja, E. (1997). A fast fixed-point algorithm for independent component analysis. *Neural Comput*. 9, 1482–1492.

[23] Hyvarinen, A., Oja, E. (2000). Independent component analysis: Algorithms and application. *Neural Networks*, 13, 411–430.

[24] Efron, B., Tibshirani, R. (1994). Introduction to the bootstrap. Monographs on statistics and applied probability. New York, NY: Chapman & Hall.

[25] Emotiv, Available: http://www.emotiv.com.

Author Biography

CHEN Dongwei received the B.Sc. and M.Sc. degrees in Computer Science from Taiyuan University of Technology, in 2004 and 2007, respectively. He is currently a PHD student (2010-) with the College of Computer and Software at Taiyuan University of Technology. His research interests lie in the area of affective computing, brain-computer interface and pattern recognition.

CHEN Junjie received his Ph.D. degree in Beijing Institute of Technology, in 2003. He is senior fellow of CCF and president of Shanxi Computer Federation. He is currently a professor and PhD supervisor in the College of Computer and Software Engineering, Taiyuan University of Technology, Taiyuan. His main research interests include brain informatics, data mining and artificial intelligence.