Advances in Computational Psychophysiology
TABLE OF CONTENTS

Advances in Computational Psychophysiology

Introductions
3 When the old becomes new again
Sean Sanders, Ph.D.,
Science/AAAS

4 Introducing computational psychophysiology
Michael I. Posner, Ph.D.
University of Oregon

5 Computational psychophysiology
Bin Hu, Ph.D.
Lanzhou University
Jin Fan, Ph.D.
The City University of New York

Brain disorders
7 Magnetic resonance imaging of mental disorders: A multimodal approach for psychoradiology
Su Lui, Du Lei, Weihong Kwuang et al.

9 Multiscale neuroimaging analysis in Alzheimer’s disease and mild cognitive impairment
Zhijun Yao, Hong Liu, Gang Wang et al.

12 Using motor patterns for stroke detection
Yiqiang Chen, Hanchao Yu, Chunyan Miao et al.

Cognition and behavior
16 The embodied mind: Using psychophysiological signals to inform brain activity and connectivity during rest
Nicholas T. Van Dam, Tuyen Malla, Yohka Ellam-Stock et al.

18 The predictive mapping approach in neuroimaging
Choong-Wan Woo and Tor D. Wager

22 Computational models of implicit sequence learning: Distinguishing abstract processes from chunking processes
Qifang Fu, Jianyong Wang, Lei Zhang et al.

25 Self-regulation of aversive emotion: A dynamic causal model
Ning Zhong, Yang Yang, Kazuyuki Imamura et al.

28 Recognizing emotions based on multimodal neurophysiological signals
Xiang Li, Peng Zhang, Dawei Song et al.

continued>>

Join AAAS. Get instant access to Science. Support all of the sciences.

When you subscribe to Science, you become part of the American Association for the Advancement of Science (AAAS), a nonprofit community of more than 120,000 members worldwide who believe in the power of science to make the world a better place. AAAS is hard at work promoting science in government, schools, and in the public commons around the globe.

AAAS’s award-winning journal Science offers the top peer-reviewed research across multiple disciplines. With your subscription, you’ll get:
• 51 weeks of home delivery of Science
• Instant online retrieval of every Science article ever published, dating back to 1880
• Full access to the Science mobile site and apps
• Career advice, webinars, blogs and fascinating features exclusively for AAAS members
• Members-only newsletters, and much more

With increasing public skepticism about science—and public funding for research more uncertain than ever—our work has never been more important. Join hands with us today!
Visit promo.aaas.org/joinaaas. Together we can make a difference.
Table of contents continued

30 Applying nontraditional approaches of electrophysiological data analysis to decision-making research
Dandan Zhang, Ruolei Gu, Pengfei Xu et al.

33 Behavioral and electrophysiological profiles reveal domain-specific conflict processing
Guoshun Yang, Weizhi Nan, Qi Li et al.

34 Computational-based behavior analysis and peripheral psychophysiology
Peter Khooshabeh, Stefan Scherer, Brett Ouimette et al.

Applications

38 How the ancient art of acupuncture works: Neuroimaging studies shed light on brain activity
Wei Qin, Lijun Bai, Zhenyu Liu et al.

43 Computational modeling and application of steady-state visual evoked potentials in brain-computer interfaces
Yijun Wang, Xiaorong Gao, Shangkai Gao

47 Using a scale-free method to convert brain activity into music
Jing Lu, Dan Wu, Dezong Yao

48 Estimating biosignals using the human voice
Eduardo Coutinho and Björn Schuller

51 Ecological validity: Predicting psychological profiles using Internet behavior
Nan Zhao, Ang Li, Tianli Liu et al.

Program overview

54 Depression risk prediction: Research and development using multimodal biological and psychological information

When the old becomes new again

In the West in general, and the United States in particular, the last few decades have seen a rise in the acceptance of many seemingly new customs and cultures from the East.

For all the talk these days about the differences between nations and peoples across the globe, there exists far more sharing of cuisines, religions, ideas, and cultures than ever before. In the West in general, and the United States in particular, the last few decades have seen a rise in the acceptance of many seemingly new customs and cultures from the East. Putting aside for the moment the fact that many of these beliefs and practices are found among Native Americans, to the majority of the U.S. population, they are unfamiliar.

One such belief is that of the mind-body connection. Although taken for granted in Eastern philosophies, this concept can be foreign to many living in Westernized nations, where the mindset seems to be more towards reductionism than holistic thought. Psychophysiology is essentially the study of this mind-body connection, or the relationship between the physiological and the psychological. The first known use of the term was in 1839 and its popularity grew rapidly in the 1960s, peaking around 1980 and then going into a steady decline. However, this is apparently not a reflection on the field of psychophysiology, which is quite active and boasts a number of international journals covering the topic.

What is new in this Advances in Computational Psychophysiology supplement is the marrying of psychophysiology with the relatively recent surge in the power of computers. This has allowed psychophysiology researchers to perform far more complex analyses of their data, as well as incorporate technologies that can provide much richer information and therefore a deeper understanding of the processes involved. Powerful imaging technologies such as positron emission tomography and functional magnetic resonance imaging are enabling researchers to look inside the brain with unprecedented clarity, as well as in real time. This technology is allowing them to better understand and potentially treat a range of neurological disorders including neurodegenerative diseases, mild cognitive impairment, attention deficit hyperactivity disorder, psychiatric disorders, stroke, autism, and depression, among others. Much of this work is translational in nature, with a clear focus on helping patients in a fundamental way.

This research also has ramifications for how we might interact with computers in the future through brain-machine interfaces. The ability to collect and analyze multimodal measurements/inputs, in combination with advanced machine learning techniques may lead to a better grasp of the complexities of human emotions and how we both experience emotion and perceive it in others. In the future, machine learning technology could even conceivably aid in the diagnosis of depression and predict suicidal tendencies.

This supplement touches on a number of these topics and provides just a sample of the many ways in which the field of computational psychophysiology is growing and maturing. In addition to shedding light on many important areas of psychology, it may also provide a medium through which the mind-body connection can be appreciated and understood by a broader audience.

Sean Sanders, Ph.D.
Editor, Custom Publishing
Science/AAAS

1 Google Books Ngram Viewer, bit.ly/1PBxyNB
Advances in Computational Psychophysiology reflects an intention on the part of the authors to introduce a new interdisciplinary field. Naming subfields within the disciplines of psychology and neuroscience has played an important role in directing research efforts.

Both the terms psychophysiology and computation have long been used in the study of human behavior, and the combination seems apt. The majority of the papers presented in this volume emphasize how important bodily measures are for the study of a wide variety of mental and physical disorders—a very traditional use of psychophysiology—and the incorporation of quantitative methods for interpreting data is clearly important.

The authors surely intend to provide methods and direction to researchers who are examining nonbrain physiological processes, as a response to the findings that many of our thought processes draw on metaphors based upon the structure and behavior of the human body (1). The study of the embodied mind has resulted from, and increased research into, these ideas. This goal is most explicitly stated by Van Dam et al. (p. 16), who argue that the default state of brain activity can best be seen as a bodily state that produces changes in brain networks (2).

This supplement highlights how the synthesis of new measurement methods, quantitative analyses, and awareness of the interaction between the body and the brain can illuminate the way specific operations and tasks are carried out in the brain, such as conflict processing (Yang et al., p. 33) and implicit sequence learning (Fu et al., p. 22). Notably, Woo and Wager summarize the development of predictive methods, including multivoxel pattern analysis for magnetic resonance imaging (p. 18).

It may be well to consider both the intended consequences of introducing the term computational psychophysiology, but also the unintended consequences. It would be unfortunate, for example, if an increased emphasis on this field led researchers to substitute peripheral measures in place of brain imaging methods as the field progresses. Additionally, researchers will need to find a good balance between new traditional imaging methods with those introduced in this volume. Although understanding the embodied mind is essential, proponents of the computational psychophysiology approach should remember that the brain is also an organ that is a part of the body. Michael I. Posner, Ph.D.
Professor Emeritus
University of Oregon

We are pleased to introduce this special supplement, Advances in Computational Psychophysiology, which encompasses contemporary research using computational methodologies to explore psychophysiological processes related to the interaction among the human brain, body, mind, and behavior. This special supplement also explores novel applications of computational psychophysiology, such as biomarker identification for mental illness.

The field of psychophysiology investigates the physiological basis of psychological processes. Working at the intersection of the mind and body, psychophysiology studies the effects of psychological states on physiological processes and vice-versa. In its nascent stages, psychophysiological research predominantly focused on relatively peripheral markers of autonomic nervous system activity by measuring fluctuations in a subject’s electrodermal activity (EDA), electromyogram (EMG), electrocardiogram (ECG), heart rate, heart rate variability (HRV), respiration rate, electrooculogram (EOG), and pupillary dilatation.

In recent years, psychophysiology has begun to focus on the central nervous system, partially as a result of increasing accessibility and growth in measures of brain activity, such as event-related potentials (ERPs), magnetic encephalography (MEG), positron emission tomography (PET), and functional magnetic resonance imaging (fMRI). These methodologies offer more proximal measurement of brain and mind activity than indicators of the autonomic nervous system, which require inferences from fluctuations in peripheral responses.

To study the human brain, mind, and behavior, autonomic and central psychophysiological indices must be analyzed in combination, a feat that requires advanced computational approaches. The implementation of these approaches in psychophysiology is the focus of this supplement. Computational psychophysiology is an interdisciplinary research field that employs methods from the disciplines of psychology, physiology, neuroscience, computer science, mathematics, and others to model physiological activity in relation to brain components of human behavior. Computational modeling provides a framework for understanding the neurological processes underlying complex human mental states and behavior. Computational models can be used to simulate and predict psychological outcomes based on different physiological states or experimental manipulations.

This new direction will broaden the field of psychophysiology by allowing for the identification and integration of multimodal signals to test specific models of neural and psychological processes. Additionally, such approaches will allow for the extraction of multiple signals from large-scale multidimensional data, with a greater ability to differentiate signals embedded in background noise. Further, these approaches will allow for a better understanding of the complex psychophysiological processes underlying brain disorders such as autism spectrum disorder, depression, and anxiety. The widely acknowledged limitations of psychiatric nosology and the limited treatment options available, new computational models may provide the basis for a multidimensional diagnostic system and potentially new treatment approaches.

Applying computational data analysis and modeling to psychophysiological signals may thus help to identify new phenotypes for normal and abnormal psychological functions. The further development of computational psychophysiology has the promise of providing large-scale models of the neural substrates of human behavior.

Bin Hu, Ph.D.
Professor, School of Information Science and Engineering,
Lanzhou University
Jin Fan, Ph.D.
Professor, Department of Psychology, Queens College,
The City University of New York

ACKNOWLEDGMENTS
We are particularly grateful to the publishing house of the Chinese Journal of Magnetic Resonance Imaging for supporting this special supplement. Thanks are also due to all authors, referees, and advisors for charting the journey ahead to introduce a new aspect of computational psychophysiology. This supplement is also supported by the National Basic Research Program of China (973 Program) 2014CB744000 and 2012CB720701, the National Natural Science Foundation of China (91320012 and 61375116), and the Ten thousand Scholars Program of Shandong Province, China.
Brain disorders

Computational psychophysiological approaches can be used to investigate the cognitive processes and mechanisms underlying disorders that cause mental health issues.

Magnetic resonance imaging of mental disorders: A multimodal approach for psychoradiology

Su Lui, Du Lei, Weihong Kwuang, Hua Ai, Feng Bi, Zhongwei Gu, Qiyong Gong

Magnetic resonance imaging (MRI) is an emerging and powerful tool for noninvasively examining the structure and function of the brains of patients with mental disorders. Over the past two decades, the number of psychiatric MRI studies has increased dramatically, largely due to the significant advances in technical and methodological improvements in MRI modalities. This has led to a wide range of applications for clinically oriented research on mental disorders.

The development of the multimodal MRI has enabled the precise quantification of brain tissues at the structural, functional, and molecular levels (1-6). Using high-field MRI (i.e., 3.0 Tesla MR), for instance, the structural and functional correlates underlying a number of mental disorders have been identified. Taking advantage of novel approaches and techniques for the acquisition and analysis of MRI data, a number of clinical studies have revealed imaging biomarkers in populations that are at high risk for developing mental disorders (7-12). Moreover, such biomarkers for mental disorders provide further insight into their underlying pathological mechanisms (13-21). The results not only support the emerging and powerful tool for noninvasively examining the structure and function of the brains of patients with mental disorders. Over the past two decades, the number of psychiatric MRI studies has increased dramatically, largely due to the significant advances in technical and methodological improvements in MRI modalities. This has led to a wide range of applications for clinically oriented research on mental disorders.

The development of the multimodal MRI has enabled the precise quantification of brain tissues at the structural, functional, and molecular levels (1-6). Using high-field MRI (i.e., 3.0 Tesla MR), for instance, the structural and functional correlates underlying a number of mental disorders have been identified. Taking advantage of novel approaches and techniques for the acquisition and analysis of MRI data, a number of clinical studies have revealed imaging biomarkers in populations that are at high risk for developing mental disorders (7-12). Moreover, such biomarkers for mental disorders provide further insight into their underlying pathological mechanisms (13-21). The results not only support the emerging and powerful tool for noninvasively examining the structure and function of the brains of patients with mental disorders. Over the past two decades, the number of psychiatric MRI studies has increased dramatically, largely due to the significant advances in technical and methodological improvements in MRI modalities. This has led to a wide range of applications for clinically oriented research on mental disorders.

The development of the multimodal MRI has enabled the precise quantification of brain tissues at the structural, functional, and molecular levels (1-6). Using high-field MRI (i.e., 3.0 Tesla MR), for instance, the structural and functional correlates underlying a number of mental disorders have been identified. Taking advantage of novel approaches and techniques for the acquisition and analysis of MRI data, a number of clinical studies have revealed imaging biomarkers in populations that are at high risk for developing mental disorders (7-12). Moreover, such biomarkers for mental disorders provide further insight into their underlying pathological mechanisms (13-21). The results not only support the emerging and powerful tool for noninvasively examining the structure and function of the brains of patients with mental disorders. Over the past two decades, the number of psychiatric MRI studies has increased dramatically, largely due to the significant advances in technical and methodological improvements in MRI modalities. This has led to a wide range of applications for clinically oriented research on mental disorders.

The development of the multimodal MRI has enabled the precise quantification of brain tissues at the structural, functional, and molecular levels (1-6). Using high-field MRI (i.e., 3.0 Tesla MR), for instance, the structural and functional correlates underlying a number of mental disorders have been identified. Taking advantage of novel approaches and techniques for the acquisition and analysis of MRI data, a number of clinical studies have revealed imaging biomarkers in populations that are at high risk for developing mental disorders (7-12). Moreover, such biomarkers for mental disorders provide further insight into their underlying pathological mechanisms (13-21). The results not only support the emerging and powerful tool for noninvasively examining the structure and function of the brains of patients with mental disorders. Over the past two decades, the number of psychiatric MRI studies has increased dramatically, largely due to the significant advances in technical and methodological improvements in MRI modalities. This has led to a wide range of applications for clinically oriented research on mental disorders.

The development of the multimodal MRI has enabled the precise quantification of brain tissues at the structural, functional, and molecular levels (1-6). Using high-field MRI (i.e., 3.0 Tesla MR), for instance, the structural and functional correlates underlying a number of mental disorders have been identified. Taking advantage of novel approaches and techniques for the acquisition and analysis of MRI data, a number of clinical studies have revealed imaging biomarkers in populations that are at high risk for developing mental disorders (7-12). Moreover, such biomarkers for mental disorders provide further insight into their underlying pathological mechanisms (13-21). The results not only support the emerging and powerful tool for noninvasively examining the structure and function of the brains of patients with mental disorders. Over the past two decades, the number of psychiatric MRI studies has increased dramatically, largely due to the significant advances in technical and methodological improvements in MRI modalities. This has led to a wide range of applications for clinically oriented research on mental disorders.

The development of the multimodal MRI has enabled the precise quantification of brain tissues at the structural, functional, and molecular levels (1-6). Using high-field MRI (i.e., 3.0 Tesla MR), for instance, the structural and functional correlates underlying a number of mental disorders have been identified. Taking advantage of novel approaches and techniques for the acquisition and analysis of MRI data, a number of clinical studies have revealed imaging biomarkers in populations that are at high risk for developing mental disorders (7-12). Moreover, such biomarkers for mental disorders provide further insight into their underlying pathological mechanisms (13-21). The results not only support the emerging and powerful tool for noninvasively examining the structure and function of the brains of patients with mental disorders. Over the past two decades, the number of psychiatric MRI studies has increased dramatically, largely due to the significant advances in technical and methodological improvements in MRI modalities. This has led to a wide range of applications for clinically oriented research on mental disorders.

The development of the multimodal MRI has enabled the precise quantification of brain tissues at the structural, functional, and molecular levels (1-6). Using high-field MRI (i.e., 3.0 Tesla MR), for instance, the structural and functional correlates underlying a number of mental disorders have been identified. Taking advantage of novel approaches and techniques for the acquisition and analysis of MRI data, a number of clinical studies have revealed imaging biomarkers in populations that are at high risk for developing mental disorders (7-12). Moreover, such biomarkers for mental disorders provide further insight into their underlying pathological mechanisms (13-21). The results not only support the emerging and powerful tool for noninvasively examining the structure and function of the brains of patients with mental disorders. Over the past two decades, the number of psychiatric MRI studies has increased dramatically, largely due to the significant advances in technical and methodological improvements in MRI modalities. This has led to a wide range of applications for clinically oriented research on mental disorders.

The development of the multimodal MRI has enabled the precise quantification of brain tissues at the structural, functional, and molecular levels (1-6). Using high-field MRI (i.e., 3.0 Tesla MR), for instance, the structural and functional correlates underlying a number of mental disorders have been identified. Taking advantage of novel approaches and techniques for the acquisition and analysis of MRI data, a number of clinical studies have revealed imaging biomarkers in populations that are at high risk for developing mental disorders (7-12). Moreover, such biomarkers for mental disorders provide further insight into their underlying pathological mechanisms (13-21). The results not only support the emerging and powerful tool for noninvasively examining the structure and function of the brains of patients with mental disorders. Over the past two decades, the number of psychiatric MRI studies has increased dramatically, largely due to the significant advances in technical and methodological improvements in MRI modalities. This has led to a wide range of applications for clinically oriented research on mental disorders.
Multiscalar neuroimaging analysis in Alzheimer’s disease and mild cognitive impairment

Zhijun Yao, Hong Liu, Gang Wang, Fang Zheng, Yuanwei Xie, Xiaowei Zhang, Zengqiang Zhang, Yong Liu, Jinyu Song, Xiaohu Zhao, Bin Hu

Alzheimer’s disease is the most common form of dementia and impedes the daily life of patients by disrupting cognition, emotion, and reasoning. In the Western world, approximately two-thirds of patients with dementia who are over 60 years old have Alzheimer’s disease (1, 2). At present, it is incurable and effective treatments are not available (3). Mild cognitive impairment (MCI) is an early stage in the transition to Alzheimer’s disease, and people with MCI have a high risk of acquiring Alzheimer’s disease (4, 5). MCI is characterized by the characteristic cognitive impairments that are not significant enough to interfere with daily activities (4). Neuroimaging technologies can provide biomarkers that are potentially useful for providing early alerts to the likelihood of a patient presenting with Alzheimer’s disease. They can also provide a means for identifying Alzheimer’s disease at the earliest stage possible, which is critical for developing treatments that will slow its progression.

Neuroimaging technologies such as structural and functional magnetic resonance imaging (MRI) and positron emission tomography (PET) (5–7) are increasingly effective and precise in identifying MCI and Alzheimer’s disease. Using these techniques, we have carried out voxel-based studies and analyzed the surface-based morphometry and brain networks within regions of interest (ROIs) in subjects with MCI and Alzheimer’s disease, and in healthy controls. These studies have successfully detected abnormalities in brain volume, cerebral cortex thickness, functional connectivity, and the topology of structural and functional networks (4, 6–10). The data are available in the open access Alzheimer’s Disease Neuroimaging Initiative (ADNI) database (http://adni.loni.usc.edu).

In this review, we discuss how neuroimaging technologies are being used to understand the effects of MCI and Alzheimer’s disease on brain structure, function, and metabolism. Such methods could potentially be used to identify biomarkers that can help classify and predict the stages of these diseases.

Macescale: Voxel-based morphological analysis

Technologies that monitor mesoscale changes in the brain can provide detailed descriptions of brain regions that are functionally and/or regionally specific. One such method is voxel-based morphological analysis. This technique has been used to measure the progression of mesoscale changes in patients with MCI and Alzheimer’s disease and has revealed that these patients undergo a loss of gray matter volume in specific brain regions, including the hippocampal gyrus, hippocampus, and fusiform gyrus (9). These studies have shown that patients with Alzheimer’s disease have alterations in the surface morphology of the cerebral cortex, gray matter volume, atrophy of cortical thickness, and a decline in cerebral glucose metabolism (Figure 1) (6–9). MRE-based neuroimaging technologies can also be used to explore the relationship between brain structure and function and to investigate atrophy within specific brain regions in patients with MCI and Alzheimer’s disease (17).

Interestingly, our analysis of surface-based morphological changes using structural MRI data has revealed atrophy in the parahippocampal gyrus in patients with amnestic MCI is more pronounced than in control patients (Figure 1D) (6). Voxel-based analyses of PET data have also shown that changes in the morphology of the cerebral cortex, the brains of patients with Alzheimer’s disease show reduced metabolism in the parahippocampal gyrus (Figure 1C) (7).

Detection of regional homogeneity (ReHo) and fraction amplitude of low-frequency fluctuations (fALFF) represent other powerful tools for characterizing properties of regional brain activity (Figure 1B)(8). ReHo evaluates resting-state brain activity (5), whereas fALFF measures the ratio of the fluctuating amplitude in a low-frequency band to the fluctuating amplitude in the total frequency band (8). A study comparing the ReHo values in subjects with Alzheimer’s disease or MCI and healthy controls showed that the values were significantly decreased in the patients’ medial prefrontal cortex, the bilateral posterior cingulate gyrus/precuneus, and the left inferior frontal lobe (LIF) and were increased in the left IPL (Figure 1A) (5). Additionally, subjects with MCI alone had lower fALFF values in the postcentral gyrus, the right inferior temporal gyrus, and the left inferior occipital cortex as compared with healthy controls (8).

Macroscale: Brain network visualization

Macroscopic analysis depends on the correlation of data from spatially separate brain regions that can be
integrated to study whole-brain networks, or the human "connectome" (the connection matrix, Figure 2). Brain networks can be constructed from neuroimaging data, where ROIs are defined as "nodes" that can be created by segmenting readily available atlas images (such as those from Automated Anatomical Labeling, Brodmind, and Harvard-Oxford) or by extracting spatial components by independent component analysis (ICA, a multivariate and data-driven method extracting independent resting-state networks (RSNs) from the Blood Oxygen Level Dependent (BOLD) time series).

We and others have shown that patients with MCI and Alzheimer's disease have abnormalities in specific structural and functional brain networks (4, 10). Using structural and functional MRI, we have defined several common differences between patients with MCI and Alzheimer's in brain covariance networks, as constructed by correlations between ROIs. The most significant of these common differences is a disruption of relatively long-distance connections (4-8). Reduced efficiency of long-distance connections is reflective of cognitive impairment and memory decline. Moreover, the posterior cingulate gyrus/precuneus also reflects the underlying pathology of Alzheimer's disease.

FIGURE 1. Differences in regional properties between patients with Alzheimer's disease and mild cognitive impairment (MCI), and normal controls (NCs). (A) Significant differences in fractional anisotropy between Alzheimer's disease and MCI. (B) Significant differences in fractional anisotropy (FA) between Alzheimer's disease (AD) and NCs. (C) Differences in metabolism in brains of patients with Alzheimer's disease compared to normal controls (7). (D) Differences in rate of atrophy between AD, MCI, and NC groups (6).

FIGURE 2. Depiction of “connectome” network, based on structural and functional MRI, highlighting the differences in small-world properties. (A) Long-distance connections in normal controls (NCs) as well as patients with mild cognitive impairment (MCI), mild Alzheimer's disease (mAD), or severe Alzheimer's disease (sAD). (B) Differences in interregional connectivity between patients with Alzheimer's disease (AD), MCI, and NCs. Panel I shows significant changes between the AD and MCI groups; Panel II shows significant changes between the NC and AD groups; Panel III shows significant changes between the MCI and Alzheimer's disease groups; Panel IV shows the correlation matrices from calculating the partial correlation coefficients between regional thickness across subjects within the control group (left) and the Alzheimer's disease group (right), Panel V shows the normalized matrices (left for the control group and right for the Alzheimer's disease group) by a sparsity threshold of 13% (D).

Resting State Networks (RSNs) based on independent component analysis in all subjects including NC, amnestic MCI, and Alzheimer's disease. Extracted RSNs included anterior default mode network (aDMN), auditory network (AN), left frontoparietal network (LFP), precuneus network (PCu), posterior default mode network (pDMN), right frontoparietal network (RFPN), sensorimotor network (SMN), and visual network (VN) (14).

ACKNOWLEDGMENTS

This work was supported by the National Natural Science Foundation of China (62071001), the International Cooperation Project of the Ministry of Science and Technology (2013DFA1140), and the National Basic Research Program of China (973 Program) (2011CB711000 and 2014CB746400).
Using motor patterns for stroke detection

Yiqiang Chen2, Hanchao Yu1, Chunyan Mao3, Biao Chen3, Xiaodong Yang3, Cyril Leung1

Stroke is a leading cause of death and severe disability in the elderly, and poses a major challenge for public health. In recent years, there has been a rapid increase in the number of stroke victims in many countries, due to the aging population (1,2). Moreover, stroke survivors are at a higher risk of suffering another stroke. Indeed, studies report that up to 40% of survivors suffer a new stroke within one year of a diagnosed stroke. Therefore, early detection of stroke in at-risk patients, including stroke survivors, is an important health challenge.

Previous studies have shown that the Trail Making Test (TMT) is an important means to detect stroke (1,3). However, conducting a traditional TMT requires the assistance of doctors, which is not always convenient. In this paper, we describe an accurate approach for automating stroke detection through a computer-based, body sensing game-based Trail Making Test (BSG-TMT), which in theory will allow for timelier intervention implementations. Our results demonstrate that the accuracy of a stroke diagnosis can be as high as 91% using only four selected motor pattern features (4). This accuracy can be significantly improved by including medical history features. These findings verify clinical observations and highlight the importance of using fine motor pattern features of the upper limbs and medical history features for detecting strokes.

Motor pattern feature selection

As shown in Figure 1, the proposed stroke detection framework consists of four steps: (1) data acquisition—collecting raw motion data using the proposed robust fingertip tracking method (5); (2) feature extraction—extracting the potential motor pattern features related to stroke from the raw motion data collected in Step 1 and identifying the patient’s medical history features; (3) feature selection—applying a mutual information-based feature selection method to obtain the most representative features; and (4) classification—validating the discrimination ability of the selected features.

In Step 1 of the proposed detection framework, a Microsoft Kinect unit is used to collect raw depth sensor data while each subject is taking the BSG-TMT (4). The BSG-TMT is designed based on the widely accepted clinical TMT. The TMT requires the subject to connect a set of N dots, numbered 1, 2, ..., N, in a strictly sequential order (starting with dot 1) as quickly as possible. In the BSG-TMT, the pen and paper used for traditional TMTs are replaced by the subject’s fingertip and a computer screen, respectively. As illustrated in Figure 1, the fingertip is represented by the red bullet symbol and the numbered dots are represented by the numbered squares. If the subject is currently on dot N and makes a mistake by next connecting to a dot other than dot N + 1, we say that a connection error has occurred. In this event, the subject has to retry until he connects to dot N + 1. The test ends when the subject connects to dot N. Because it is difficult to identify patients who will suffer a stroke in the future, we collected data from stroke patients who had been recently discharged from the hospital and used the data to approximate the data for potential stroke patients. Those selected patients are known to have a high likelihood of a new stroke occurrence, which provides us with a reasonable proxy for at-risk patients.

In Step 2, potential stroke-related motor pattern features are extracted from the data collected in Step 1. These features include the time the subject took to complete the BSG-TMT (T-Time); the test accuracy (T-Accuracy); the time the subject took to correct a connection error (C-Time); the mean (M-R-Length) and variance (V-Length) of the N-1 ratios of the fingertip movement path length to the straight-line distance between two consecutively numbered dots; the mean (M-Fingertip) time duration spent by fingertips at the dots; and the mean (M-R-Time) and variance (V-Time) of the ratios of the time needed to connect two consecutively numbered dots to the fingertip movement path length between the two dots. Medical history features, such as history of strokes, hypertension (HT), hyperglycemia (HG), coronary heart disease (CHD), and diabetes were also retrieved. In total, 13 features were studied.

To determine the most representative features for stroke detection, in Step 3 we adopted the mutual information-based feature selection method. This method automatically measures the importance of the 13 features, retaining the most representative features and discarding unnecessary ones. Initially, we used the finger motor pattern features to build the stroke detection model and tested the discrimination ability using 10-fold cross validation (6). We then ranked the combination of features in the order of testing accuracy. For each combination, we applied the 10-fold cross validation again to get the final testing accuracy and selected the most discriminative combination as the final feature set. Similarly, we ranked the discrimination ability of the medical history features. We added the medical history features to the selected feature set one by one until no further classification performance improvements could be obtained.

In Step 4, the effectiveness of the selected features was validated through a recognition test on the subjects.
We employed a single-hidden-layer neural network, b-COELM (7), which is very efficient and effective when the training set is small (8), to train a binary classifier to distinguish stroke patients from the control subjects based on the selected features.

**Experimental analysis**

We designed a study using human subjects to demonstrate the effectiveness of the proposed stroke detection method. Fifty stroke patients (16 women and 34 men, from ages 52 to 81) and 55 healthy elderly subjects (25 women and 30 men, from ages 30 to 68) were recruited for our experiments. Each subject was asked to take the BSG-TMT, and the entire session was automatically recorded by the system.

A feature selection experiment was then performed on the data. As shown in Figure 2, after seven iterations, the four most representative motor pattern features were selected, which improved the classification accuracy from 74% to 91%. After combining these features with the four selected medical features, the accuracy improved to nearly 100% (4). Table 1 shows the eight selected features. Our results indicate that motor pattern features are sufficient to detect stroke with reasonable accuracy, and the accuracy can be further improved by also considering the subjects’ medical history. The experimental results have demonstrated for the first time that through combining motor pattern features and a patient’s medical history features, a stroke can be accurately detected.

**References**
1. B. Wiberg, Comprehensive Summaries of Uppsala Dissertations from the Faculty of Medicine 540, 65 (2010).

**Acknowledgments**

This research was partially supported by the National Natural Science Foundation of China (61773066 and 61472399) and the National Research Foundation, Prime Minister’s Office, Singapore, under its IDM Futures Funding Initiative and administered by the Interactive and Digital Media Programme Office.

### Table 1. Eight most discriminant features for stroke detection.

<table>
<thead>
<tr>
<th>Category</th>
<th>No.</th>
<th>Feature name</th>
<th>Feature description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motor pattern features</td>
<td>1</td>
<td>A-Time</td>
<td>Time the subject takes to complete the BSG-TMT</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>M-Fingertip</td>
<td>Mean time that fingertips are on the dots</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>C-Time</td>
<td>Time the subject takes to correct a connection error</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>M-R-Time</td>
<td>The mean of the ratio for the time needed to connect two consecutively numbered dots to the path length taken between the two dots</td>
</tr>
<tr>
<td>Medical history features</td>
<td>5</td>
<td>HT</td>
<td>Whether the subject has hypertension</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>HG</td>
<td>Whether the subject has hyperglycemia</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>CHD</td>
<td>Whether the subject has coronary heart disease</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>Stroke</td>
<td>Whether the subject has previously had a stroke</td>
</tr>
</tbody>
</table>

Cognition and behavior

Computational psychophysiological models can be used to better understand social behavior and how psychophysiological signals are related to mental states and cognitive processes.
The embodied mind: Using psychophysiological signals to inform brain activity and connectivity during rest

Nicholas T. Van Dam1, Tuyen Mialleal1,2,3, Tehila Elam-Stock1,2,4, Xiaosi Gu5, Patrick R. Hof1,2,5,6, Jin Fan2,3,7

In the 17th century, the philosopher René Descartes famously established the mind-body problem by proposing that individual consciousness could be affirmed by thinking (“cogito ergo sum”), but that the embodied self could be illusory. In the late 20th century, Descartes’s argument was modernized in the form of the “brain in a vat” proposition (1), whereby a brain removed from the body and sustained on appropriate “life support” was hypothesized to still experience consciousness and reanimate what an embodied brain can do. There is a division among scientists and philosophers: Some believe that consciousness is mainly driven by events localized in the brain (2), and others argue that consciousness must be the result of an embodied brain supported by the physiological processes of the body (3). Regardless of the minimum substrate necessary for consciousness, the concept of self relies greatly on the ability of the brain to process signals emanating from the body (4). The body and brain cannot be separated without loss of meaningful information. Thus, rather than simply considering the mind-body as a whole, a system that is constantly active and interactive. Thus, given no specific task manipulations during R-fMRI, it is difficult to understand the psychological implications of neural activity and connectivity. As such, to gain further insight into the brain-body relationship and to understand the principal role of the somatic nervous system is to coordinate the action of the cerebral cortex (19, 20). Thus, the peripheral nervous system can dramatically impact RSNs (17). Here we focus on ANS signals because they are easily measured in human populations, yet remain as still as possible and not to think about or do anything specific; however, the resting state in R-fMRI is more akin to an extremely complex task condition than a task baseline. Numerous studies have shown that during rest, the peripheral nervous system, including ANS activity (4). Therefore, this study provides evidence that differences in the mental states of individuals during rest is particularly important for understanding differences in RSNs between clinical populations and controls.

References
The predictive mapping approach in neuroimaging

Chooong-Wan Woo and Tor D. Wager*

or the past 20 years, neuroimaging techniques have transformed how we study psychology and medicine. Data from neuroimaging can constrain psychological theories, resolve some theoretical debates, and be used to develop new hypotheses about human cognition and emotions by providing a grounding in neurophysiology (1). In medicine, neuroimaging provides promising measures that can serve as biomarkers for brain-related disorders, such as psychiatric and neurologic disorders (2, 3). Neuroimaging also can connect psychology to biology and medicine, which can help researchers understand how the mind and the body interact and thereby treat medical conditions more effectively (for example, understanding the placebo effect) (4).

Despite these promises, neuroimaging has not followed the quick and easy path to success that was initially envisioned. One important reason is that too little effort has gone into developing neuroimaging markers that are sensitive and specific to particular mental processes or health-related outcomes and can be prospectively applied to new data. The dominant paradigm in neuroimaging has focused on brain "maps," not markers. Brain maps identify anatomical regions associated with particular mental processes. This paradigm does not adequately address the many-to-many relationships between brain regions and mental processes: One brain region can be involved in multiple processes, and one process can be distributed across different brain regions. Thus, we cannot make inferences about which mental process is engaged based on brain maps. Markers, by contrast, are multivariate patterns of brain activity optimized to be sensitive and specific to a particular type of mental process. Without markers, the inferences we can make about brain representations are fundamentally limited (5).

Do we really have neuroimaging markers?

It might seem that neuroimaging markers for mental processes already exist, but in fact, we have been using neuroimaging findings as brain markers without properly assessing their sensitivity and specificity. For example, amygdala activity has often been used as a brain marker for negative emotion. However, the amygdala is a large anatomical structure comprising heterogeneous neuronal populations that encode various physical and mental events (6). Therefore, averaged functional brain activity within this region is not very useful as a brain marker because of its low specificity (7).

In order to be considered as a marker, the brain measure used should show high sensitivity and specificity to the mental event or process of interest. Sensitivity accounts for whether a test shows positive results when a target psychological or behavioral process is engaged, while specificity describes whether the test shows positive results only when a target psychological or behavioral process is engaged. Sensitivity and specificity can tell us the diagnostic performance of the brain measure in question and enable us to make inferences or predictions about mental processes or outcomes of interest.

Traditional brain mapping approaches

Traditional brain mapping approaches—often called "mass-univariate analysis" or "statistical parametric mapping"—have been extremely useful in the development of neuroimaging. However, these approaches are of little help in identifying and utilizing brain markers with established sensitivity and specificity. The main goal of the traditional approach is to map different mental functions onto specific brain regions to localize brain functions. As Figure 1A demonstrates, in this framework, tasks or conditions are independent variables, and each voxel's fMRI signal becomes a dependent variable. The most important question answered by the traditional approach is whether there is an effect in each voxel or region. This traditional approach has, at best, low sensitivity to the effects of task conditions because it assumes independence among voxels or regions. However, psychological and behavioral processes and related outcomes result from integrated circuit dynamics. Thus, the effects of task conditions—and the relationships between brain activity and behavioral/psychological outcomes—are likely to be distributed across brain regions and voxels. Analyses that consider only a single voxel or region, as the mass-univariate approach does, are unlikely to capture the full effects of tasks. In addition, the univariate approach involves a large number of statistical tests and requires a correction for multiple comparisons (8). The correction for multiple tests focuses on controlling false positives and in turn increases false negatives, which results in low sensitivity (8). With low sensitivity, many of the voxels activated in relation to a task or outcome will be missed, providing a poor assessment of the pattern across the brain. This, in turn, undermines efforts to establish replicability across studies (9, 10). Furthermore, as illustrated in Figure 2, traditional brain mapping has a limited ability to detect the unique relationships between mental functions and brain regions, which could undermine the specificity of the resulting brain maps.

Developing neuroimaging markers: The predictive mapping approach

The predictive mapping approach can resolve the issues described above and provide neuroimaging markers with quantitatively characterized measures of diagnostic performance. Predictive mapping aims to develop multivariate, systems-level predictive models (or decoding models) that are sensitive and specific to particular outcomes of interest (see, for example, 11). As Figure 1B shows, one of the main features that distinguishes predictive mapping from traditional
approaches is that the assignment of independent and dependent variables is reversed. The predictive mapping approach helps to solve the low sensitivity and specificity problem of traditional mapping in several ways. First, it can identify voxels that have selective relationships with the outcome (see Figure 2). Second, it uses distributed signals across many voxels without requiring thresholding and correction for multiple comparisons. Third, it is sensitive to information at multiple spatial scales, including large-scale information distributed across multiple systems and mesoscale information below the resolution of the imaging itself (so-called fMRI hyperacuity). Assessing multivariate patterns rather than individual voxels is critical if information about outcomes is encoded in neuronal population codes. Furthermore, assessing large-scale patterns across systems is critical if mental states are encoded across systems. A related approach, called information-based mapping, also uses multivariate patterns to predict outcomes. However, it exploits local effects (using searchlights, or spatial moving windows), and thus is subject to limited sensitivity and massive multiple comparisons. In contrast, the predictive mapping approach focuses on developing one unified predictive model based on brain-wide patterns of brain activity. In the predictive mapping approach, machine learning techniques become crucial because analyses based on large-scale population codes are subject to the high-dimensionality problem. High-dimensional data, in which there are many more predictors than observations (p >> n, often called the “curse of dimensionality”), causes problems with model optimization because the parameter space is underconstrained by the data (16). Some machine learning algorithms, such as support vector machines and penalized regression, can provide stable prediction models even for the high-dimensional data with a guarantee of good generalization capacity (17, 18).

Precisely defined model and prospective testing: benefits for translational research

In addition to the benefits in sensitivity and specificity, the predictive mapping approach can provide precisely defined models that can be prospectively tested on new datasets. In traditional mapping approaches, replication and hypothesis testing depends heavily on anatomical definitions that are often heuristic and ambiguous, leading to flexibility in how researchers identify what counts as an a priori hypothesis and, in turn, increases in false positive results and reduced specificity (19). For example, “amygdala activity” does not provide a reproducible definition of precisely (a) which voxels in the amygdala should be activated (there are typically hundreds); and (b) the relative expected intensity of activity across each voxel. Any significant result anywhere in the amygdala can count as amygdala activation, and this variability leads to spurious findings. In contrast, the predictive mapping approach can minimize biases in measuring, testing, and replicating effects in new individuals and studies through prospective models defined by precise patterns of brain activity, which can provide a priori predictions and testing procedures. Precisely defined predictive models (based on multivariate patterns of neuroimaging data) provide several advantages for basic and translational research. First, hypotheses are precisely specified in terms of spatial patterns, and responses in these patterns are falsifiable and readily testable, providing a foundation for strong inference (20, 21). Second, precisely specified models are research products that can be shared and tested across laboratories, enabling a cumulative understanding of their properties across test conditions and study populations. Third, some predictive models can be prospectively applied to new individual participants, which is critical for clinical and legal applications. Fourth, well-defined predictive models can serve as a means of bringing together basic and clinical research, as diverse research groups can communicate with each other through tests of predictive models, facilitating translation of findings from one setting (e.g., basic research) into new contexts (e.g., clinical assessment).

Conclusions

Recent advances have provided promise and hope that we can use neuroimaging to better understand the human mind, including the neurophysiology that underlies behavior and brain-related illnesses. However, a wide gap still exists between neuroimaging data and the mental processes we want to measure. Part of the problem is that we do not have neuroimaging markers that are sensitive and specific enough to accurately indicate when a particular class of mental process is engaged. The predictive mapping approach we outline here can be used to develop neuroimaging markers that have better sensitivity and specificity compared to the traditional univariate mapping approach. The predictive mapping approach can also provide precisely defined predictive models that can be prospectively tested in new individuals and studies, and thereby turn the predictive models into research products and/or clinical tools. This characteristic can allow neuroimaging markers to be easily accessed and tested by other researchers and laboratories, promoting replicability and facilitating translation from laboratory to clinic. All together, the predictive mapping approach has the potential to facilitate neuroimaging marker discovery and validation for both basic and clinical science.

References


Acknowledgments

This work was funded by the National Institute on Drug Abuse (RO1DA035484-01, to T.D.W.).
Computational models of implicit sequence learning: Distinguishing abstract processes from chunking processes

Qiufang Fu1, Jianyong Wang2, Lei Zhang3, Zhang Yi4, Xiaolan Fu5

Implicit learning refers to all unintentional learning, in which knowledge of the structure of an environment is incidentally acquired (1, 2). Implicit learning produces a tacit knowledge base, which can be acquired independ-ently of intentional efforts to learn and can be transferred implicitly through novel circumstances (3, 4). However, despite decades of research, it remains controversial whether abstract knowledge can be ac-
quired through implicit learning. An abstractionist view of knowledge acquisition holds that it can be uncon-
sciously received and is “deep, abstract, and representa-
tive of the structure inherent in the underlying invariance patterns of the stimuli” (5). Much of the evi-dence supporting the abstractionist view comes from artificial grammar learning tasks (6). In contrast, the nonabstractionist view assumes that implicit learn-
ing is based on storing memories in specific exemplars, chunks, or fragmentary sequences (7). Recent studies on sequence learning seem to support the latter view (2, 8–10).

Chunking and abstract processes in implicit sequence learning

Sequence learning is one of the most widely used implicit learning tasks, in which a stimulus appears at one of four locations and subjects are asked to respond to the stimulus location. Recently, studies investigating sequence learning have adopted two sequences, namely SOCI (3:2-3:1-2:1-3:4-3:2-4:1) and SOCC (3:4-1:2-3:4-1:2-3:4-2:1-3:2), which consist exclusively of so-called second-order conditional (SOC) transitions, in which each location is determined by the previous two. When the stimulus location followed the order of one SOC sequence (called the training sequence) but rarely switches to the order of the other SOC sequence (the transfer sequence), subjects respond more quickly to the training sequence than the transfer sequence, indicative of learning (9-12). Because the only difference between the two sequences is in their SOC structure (e.g., transition 3-4-2 was followed by a 2 in SOC1, but by a 1 in SOC2), the learning effect indicates that subjects have acquired chunk knowledge, i.e., a collection of information stored and retrieved as a unit.

To address whether abstract knowledge can be acquired during sequence learning, Goschke and Bohs (12) asked subjects to name the everyday objects shown in line drawings from one of four (semantic) categories. The objects were presented in a random order, but the categories followed a repeating sequence. This study found that the reaction times (RTs) slowed when the repeating category sequence changed to a random category sequence; however, when participants were asked to verbally articulate the repeating category sequence, they performed no better than chance. These results provided convincing evidence that abstract knowledge about the deep structure underlying a sequence of specific stimuli can be acquired through implicit learning.

If both chunk and abstract knowledge can be acquired implicitly during sequence learning, one could argue that test subjects should be acquiring abstract knowledge during the sequence learning of the SOC structures. Indeed, using SOCs as learning materials, it has been found that subjects can acquire two types of knowledge during implicit sequence learning: (1) knowledge relevant to being able to distinguish between the training and the transfer SOC sequences, i.e., concrete triplets or chunks; and (2) knowledge about properties common to both the training and transfer SOC sequences, i.e., abstract structures (2). Moreover, when including yet another (deviant) sequence that was different in structure from both the training and transfer sequences, but was presented with a low probability of presentation (same as the transfer sequence), we found that RTs to the transfer sequence were much faster than they were to the deviant sequence, confirming that both chunk and abstract knowledge is acquired during implicit sequence learning tasks (14).

Computational models of implicit sequence learning

To elucidate the type of knowledge gained during an implicit sequence learning task, researchers have used various computational models. The simple recurrent network (SRN) is one of the most widely used models of implicit learning. It is trained to use the current stimulus to predict the next stimulus, utilizing a so-called backpropagation algorithm (15–18). To make the prediction possible, the model is set up as a three-layer feedforward network that includes context units used to copy the network’s pattern of activity elicited by the stimulus over the hidden layer each time the stimulus is presented (see Figure 1). Information processing in the SRN can be formulated as follows:

\[
\begin{align*}
\text{a}^{(t)}(1) &= f(W^{a}a^{(t)}(t)) + a^{(t)}(W^{a}a^{(t)}(t)) \\
\text{a}^{(t)}(2) &= f(W^{a}a^{(t)}(t) - 1) + W^{a}a^{(t)}(t)) \\
\text{a}^{(t)}(3) &= f(W^{a}a^{(t)}(t) - 2)
\end{align*}
\]

where a1, a2, a3, and a refer to the activation of the output layer, hidden layer, context units, and input layer, respectively; W, W, and W refer to the weight connections between different layers or units; and f refers to the activation function. Through training, the SRN can learn to improve prediction accuracy by refining the connection weights between the hidden layer and the input or output layer, and long-term knowledge is represented by the weights’ values (18). Thus, without any further assumptions, the SRN captures two important characteristics of implicit learning: (1) that implicit learning is incidental and mandatory; and (2) that the resulting knowledge is unconscious or difficult to articulate.

To simulate RT performance in sequence learning, it is assumed that the normalized activity of the output layer is inversely proportional to RT (15). This assumption allows the SRN model to simulate most of the results seen in sequence learning experiments (16, 18, 19). To simulate how abstract sequential structures can be acquired in implicit sequence learning tasks, the SRN was assumed to be sensitive to the gap between successive occurrences of the same stimulus (20), an example of structured information. However, abstract structure can be defined by the relationship between repeating sequence elements (21). To better simulate how different types of knowledge are gained during sequence learning, a dual process model was introduced in which surface learning or chunk learning was based on an SRN model, and abstract learning depended on a short-term memory mechanism that encoded previous responses and a recognition mechanism that compared the current response to the stored short-tomemory responses to detect any repeated elements (21). This dual process model has clearly demonstrated that abstract function can be learned implicitly, whereas abstract knowledge cannot be learned, but only under explicit conditions. Nonetheless, this model cannot account for the evaluation of implicit abstract learning found in other studies (2, 13).

To address this discrepancy, we proposed a dual simple recurrent network (DSRN) model (see Figure 2), in which surface learning and abstract learning are based on different SRN models. The DSRN encodes the specific stimulus and learns to predict the next specific stimulus. The abstract SRN encodes the abstract property of the current stimulus and learns to predict the abstract property of the next stimulus. To integrate the different predictions of the two SRNs, we added a response layer that produces the final prediction of the next stimulus using the equation: \(a^{(t)}(4) = a^{(t)}(3) + (1 - a^{(t)}(3))\). Where a1, a2, a3, and a4 refer to the activation of the response layer, prediction layer of the chunking SRN, and prediction layer of the abstract SRN, respectively, and \(\gamma\) refers to the prediction weight of the chunking SRN. After the DSRN...
The ability of humans to regulate emotion is a fundamental prerequisite for maintaining intact social lives when they arise distinguishes those who are vulnerable to emotional disorders—from anxiously healthy individuals, and this is thought to underlie the pathogenesis of mental disorders (3). Therefore, unraveling the neural mechanisms underlying emotion regulation is key to furthering our understanding of emotional disorders. Theoretically, one important dimension of emotion regulation is the discrepancy between actual and desired emotion regulation (i.e., guided by explicit intentions and accessible to one’s own awareness) and automatic regulation (i.e., guided by implicit intentions or outside one’s awareness) (1). Although both forms of regulation are interesting and important, there is a lack of neuroscience-based studies addressing the latter issue (2). More specifically, it has been shown that when subjects are faced with a specific task requirement (e.g., “imagine that the crying woman in the picture is an actress who is performing”), the process of top-down regulation of their emotion that recruits the cognitive system (e.g., attention or memory) is less influential than the bottom-up regulation of emotion and is driven by the direct perception of aversive stimuli and spontaneous suppression of emotional responses (3). Therefore, we have reanalyzed the data from this study to investigate the discomfort induced by viewing aversive pictures using functional magnetic resonance imaging (fMRI), 20 healthy volunteers were recruited to measure each subject’s brain activity, the blood oxygen level dependent (BOLD) responses were compared for each condition, either aversive or neutral pictures. The data indicated that the subjects’ brain activity was significantly greater during the posttest compared with the pretest. This result was observed for both the emotional responses to aversive stimuli (corresponding to the 1-minute period of picture viewing) and the self-recovery period (corresponding to the 4-minute period of picture viewing) and the self-regulation period (corresponding to the 4-minute period of picture viewing). In our recent study investigating brain responses to aversive stimuli using ‘Imagery of Magnetoencephalography’ (IMRI), 20 healthy volunteers were recruited to investigate the discomfort induced by viewing aversive pictures (those with fear inducing or disgusting content) and the emotional self-regulation during the natural recovery period (resting state) that resembles the training sequence as much as possible, in an exclusion test, in which subjects were asked to imagine that the crying woman in the picture is an actress who is performing, the subsequent recovery is instead regarded as a natural recovery period. As our recent work on the self-regulation of aversive emotion to also investigate the discomfort induced by viewing aversive pictures that aroused aversive emotions. For each test, volunteers were asked to concentrate on 15 pictures sequentially for 1 minute (4 seconds per picture) and then rest (recover) for 4 minutes. The two tests were separated by a 15-minute rest period. Using fMRI to measure each subject’s brain activity, the blood oxygen level dependent (BOLD) responses were compared for each condition, either aversive or neutral pictures. These data suggest that top-down regulation—initiated on the self-regulation of aversive stimuli (4) and manual response inhibition (constraining body movement) (9). Furthermore, the data also indicated that the aversive stimuli condition induced significantly increased activation in the dorsolateral prefrontal cortex (DLPFC) during the late period of rest. The DLPFC controls higher cognitive functioning along with several other regions within the executive control network (6). These data suggest that top-down regulation—inhibited from higher cognitive brain regions—is also involved in emotional self-regulation, and a gradual decrease in the BOLD signal in the striatum as well as a continuous increase in the BOLD signal in the DLPFC. Taken together, it seems reasonable to assume that the

Self-regulation of aversive emotion: A dynamic causal model

Ning Zhong1,2,4*, Yang Yang1,2,4*, Kazuyuki Imamura1, Shengfu Lu1,3,4, Mi Li1,4, Halyan Zhou1, Kang Wang1, Kuncheng Liu1

1. Department of Life Science and Information, Mie University Institute of Technology, Mie, Japan
2. Department of Systems Life Engineering, Mie University Institute of Technology, Mie, Japan
3. International WIC Institute, Beijing University of Technology, Beijing, China
4. Beijing International Collaboration Base on Brain Informatics and Wisdom Services, Beijing, China

*Corresponding Author: zhong@maebashi-it.ac.jp

Department of Life Science and Information, Mie University Institute of Technology, Mie, Japan
Department of Systems Life Engineering, Mie University Institute of Technology, Mie, Japan
International WIC Institute, Beijing University of Technology, Beijing, China
Beijing International Collaboration Base on Brain Informatics and Wisdom Services, Beijing, China

**Corresponding Author: zhong@maebashi-it.ac.jp

References
11. Q. Fu et al., PLOS ONE 8, e71625 (2013).
14. Q. Fu, H. Sun, Z. Dienes, X. Fu, presented at the 13th annual meeting of the Association for the Scientific Study of Consciousness (ASSC), Berlin, Germany, 5-8 June 2009.

Acknowledgments
This work was supported in part by the National Basic Research Program of China (973 Program) (2011CB302201) and the National Natural Science Foundation of China (3120004, 61432102, and 1433213).
dynamic causal connections (or directional interactions) for each state when compared with neutral images. The modulation, which led to significant activation in the ventral striatum, which induced significant activation in the visual and encoding of stimuli), which activated the visual and attention and memory, and are free of affective processing.

The initial response to the aversive pictures (perception and modulation) demonstrate that there were shifts in how the transmission of neural signals between brain regions (which reflects how a former cognitive activity influences a latter cognitive activity, i.e., causality between cognitive processes), depict the influence that one neuronal system exerts on another, and evaluate how well a particular model explains the observed data. Similar to the results from Yang et al. (5), the results of this analysis demonstrate that there were shifts in how the brain controls emotion when viewing the pictures (Figure 1). These shifts corresponded to three states: the initial response to the aversive pictures (perception and encoding of stimuli), which activated the visual and encoding regions; response suppression (inhibition), which induced significant activation in the ventral striatum and supplementary motor area (SMA); and response modulation, which led to significant activation in the DLPF (P < 0.05, false discovery rate (FDR) corrected, cluster size > 10 voxels). The brain regions where significant activation occurred during the three states are depicted on the surface of the brain in different colors.

Dynamic causal modeling of emotion regulation

Because conventional methods for analyzing fMRI data have limited ability to show causal relationships between brain functions, the results of our previous study were insufficient to thoroughly interpret how the indirect transmission of emotional signals from VS to other brain regions interact at the cellular level. To investigate this further, the data from the same group of 20 volunteers were reanalyzed for the time period during which the subjects were viewing the pictures using dynamic causal modeling (DCM) (10). This approach for analyzing effective connectivity can show how the transmission of neural signals between brain regions (which reflects how a former cognitive activity influences a latter cognitive activity, i.e., causality between cognitive processes), depict the influence that one neuronal system exerts on another, and evaluate how well a particular model explains the observed data.

To illustrate the results from Yang et al. (5), the results of this analysis demonstrate that there were shifts in how the brain controls emotion when viewing the pictures (Figure 1). These shifts corresponded to three states: the initial response to the aversive pictures (perception and encoding of stimuli), which activated the visual and encoding regions; response suppression (inhibition), which induced significant activation in the ventral striatum and supplementary motor area (SMA); and response modulation, which led to significant activation in the DLPF (P < 0.05, false discovery rate (FDR) corrected, for each state when compared with neutral images). The dynamic causal connections (or directional interactions) were modeled for the four regions that were activated during the specific time intervals of all of the three states: ventrolateral prefrontal cortex (VLPFC), dorsal part of anterior cingulate cortex (dACC), VS, and DLPFC (1, 4). Because the precise function of these four regions and their interactions are still being debated (e.g., whether the VLPFC is involved in the generation of emotion or whether the DLPFC modulates the VS in a direct way), 50 models were chosen to cover each of the hypotheses, and the optimal model that represented the best fit to the data was identified using Bayesian model selection (BMS) (11). As a result, bidirectional endogenous connections were identified between the pairs of VS and VLPFC, VS and dACC, VS and VLPFC, and DLPFC and VLPFC, and dACC and DLPFC (Figure 2A). The overarching idea is that the prefrontal and cingulate systems support the control processes that modulate activity in subcortical systems, which generate emotional responses (4). Although the amygdala is more commonly reported to be activated during emotion generation than the VS, our study did not find significant activation in this region. However, the data verified our previous results in which the VS was associated with both emotion generation and bottom-up regulation via suppression. Moreover, emotion-inducing stimuli were only associated with the VS and not the VLPFC, which refutes the possibility that the VLPFC is engaged when generating emotions (1). The stimuli also led to a self-connection within the VS (Figure 2A), which causes a self-inhibition that prevents uncontrolled outbursts of neural activity. However, the aversive emotion induced by viewing pictures in our study was intense enough to override this inhibition and enabled the activation of the DLPFC via two indirect paths: the dACC and the VLPFC. The DLPFC exerted modulatory effects on the VS directly, which down-regulated the subjects’ emotional responses. During indirect transmission of emotional signals from VS to DLPF, the VLPFC and dACC are involved in evaluating the positive or negative valence of affective signals and monitoring conflicts between the responses to the overarching emotion and initial inhibition, respectively (4, 12). The DLPFC has been reported to be related to higher order (or “cold”) regulatory processes, which are reliant on only attention and memory, and are free of affective processing (13). Note that these processes are quite possibly utilized spontaneously during the emotional self-regulation.

Self-regulation models for aversive emotion

Based on the shifts in brain activity across perception, inhibition, and modulation to control emotion and the optimal dynamic causal model described above, we have proposed that a frontostriatal circuit underlies dual regulation model for emotional self-recovery (Figure 2B), in which both bottom-up and top-down regulation are involved. Bottom-up regulation initially attenuates emotions with negative valence (such as that induced by aversive stimuli) via the VS serving as an “emotion buffer” that enables the brain to endure the emotions by exerting a certain level of inhibition, until the emotions are defused over time. For intense emotions that exceed the magnitude that the VS can bear, the VS will recruit help from the DLPFC by transmitting signals about the intense emotions along indirect pathways via the dACC and VLPFC. This enables a top-down cognitive regulation by the DLPFC that directly modulates the VS (4).

Conclusion

Together, our data demonstrate that the brain recruits cognitive regulation during emotional self-recognition to decrease emotion-related discomfort after receiving aversive stimuli. Furthermore, our findings suggest that both VS-centric bottom-up and DLPFC-centric top-down regulation are recruited for self-regulating emotions with negative valence. The DLPFC exerts a modulatory effect on the VS only when the VS fails to suppress the induced emotions by self-inhibition. The underlying neuronal responses of this dual regulatory model may be attributed to the interaction between glutamatergic excitation and GABAergic inhibition (gamma-aminobutyric acid [GABA]). We plan to further investigate the dynamic causal connectivity of brain regions in patients with MDD, and investigate whether their emotional abnormalities are related to impaired top-down regulation, impaired bottom-up regulation, or both.

References


Acknowledgments

This work was supported by grants from the National Basic Research Program of China (973 Program) (2014CB744400), the International Science & Technology Cooperation Program of China (2013DFA32180), the National Natural Science Foundation of China (61420106055 and 61272345), the Beijing National Science Foundation (4132023), and the JSPS Grants-in-Aid for Scientific Research of Japan (26303994).
Recognizing emotions based on multimodal neurophysiological signals

Xiang Li
dawong@open.ac.uk

Yuexian Hou

Yuexian Hou

In the era of big data, the ability to computationally assess human emotions based on neurophysiological signals, such as brain signals, respiration, and heart rate, is now a possibility. Emotion, sometimes referred to as affect or mood, is an internal experience sometimes caused by external events. Emotion manifests in expressions such as joy, grief, fright, anger, sympathy, and disappointment. Emotions are based on cognitive neuroscience and psychophysiology, and have become increasingly relevant to computing and information sciences. Recent neurophysiological studies have emphasized the role of emotion in social interactions, cognition, and national decision making (1, 2). Within the field of artificial intelligence (AI), an area called "affective computing" (AC) has emerged. The goal of AC is to empower computer systems to recognize, comprehend, and respond to emotions for the sake of natural human–computer interactions (HCIs) (3).

More practically, emotion recognition could help in detecting mood-related mental health problems such as depression, which is highly linked to suicide (4). The World Health Organization (WHO) estimates that by 2020, major depression will be the second leading cause of disability in the world, just behind ischemic heart disease (5). Although neurophysiological and neurometric data have become increasingly available, psychiatrists urgently need better tools to utilize the information for diagnosing and prognosis depression in its earliest stages, when there is still an opportunity for effective treatment. To address this, machine learning techniques, which can learn from data, have been developed as effective methods for recognizing human emotion.

In previous research, emotion recognition based on neurophysiological data typically concentrated on the fusion method (which combines features from multiple modalities together directly) or decision fusion method (which uses a majority vote or a weighted vote from multiple classifiers for each data modality) (14, 15). In these studies, the correlations across different neurophysiological signals have been highly effective. However, these studies have failed to explore the combined use of peripheral signals, and to the combined use of EEG and peripheral signals (e.g., galvanic skin response (GSR), respiration, and skin temperature). DEAP also provides data from subjects’ self-assessment of their emotions, rated according to Russell’s affective arousal scale (21). Using these data, we divided the samples into two emotional classes (i.e., positive and negative emotional states) as most studies have done for validating emotion recognition performance (17).

Feature extraction is important to machine learning tasks. In addition to the widely used linear features, we opted to extract a variety of nonlinear features (e.g., correlation dimension and Shannon entropy) from neurophysiological signals. We compared the recognition performance of our multimodal deep learning method with a commonly used traditional classification approach. We first applied the k-Nearest Neighbor (KNN) classifier to the data. We then applied the same classifier to the combined features of peripheral physiological signals, and to the combined features of EEG and peripheral signals. Through experimental comparisons, we have found that the use of the deep learning approach shown in Figure 1 (which is our multimodal deep learning framework) can achieve better recognition of emotions than the traditional KNN classifier based on the use of different modalities individually or in combination.

In this article we have summarized how it is possible to recognize emotion using a deep learning approach based on multiple neurophysiological signals. In the future, emotion-related modalities not limited to neurophysiological signals (e.g., speech and magnetic resonance imaging) could also be added around the globe. However, a major challenge has been how effectively the teachers or the platform can track the level at which the student is learning. Neuroscience and psychology research has shown that cognitive processes, such as attention and long-term memorization, are tightly linked to emotions. If a student gazed at the computer screen at length without displaying signs of interactive pleasure, it is likely that a mood of antipathy has emerged, which can result in low learning efficiency. AC can provide the ability to assess the emotional states of learners in an online environment based on analysis of signals from various sensory apparatuses, and teaching strategies can be automatically adapted to accommodate these emotional changes (8).

AC has been adopted for promoting the information retrieval (IR) experience, which underlies applications such as web search engines. Researchers have observed that positive emotions often reflect a user’s satisfaction with search results (9) and interest in certain information (10). Negative emotions, on the other hand, occur more often with user’s dissatisfaction with search results and search strategies (9). Capturing the emotional states of users while they are seeking information through search engines can be used as feedback to adjust the search engines’ retrieval strategies and to better predict the topical relevance of information being presented to users (11, 12).

Most emotion recognition approaches are based on the James-Lange theory, which claims there is a strong correlation between emotions and physiological arousal (13). However, to date most studies have concentrated on detecting emotions from a single modality of sensory data. Now, with recent advances in sensing technologies, synchronized detection of neurophysiological responses from different modalities can be acquired. These include measurements of temperature, respiration, electroencephalogram (EEG), electromyogram (EMG), and v1 represents the input layer into which manually selected features from multiple classifiers for each data modality (14, 15). In these studies, the correlations across different neurophysiological signals have been highly effective. However, these studies have failed to explore the combined use of peripheral signals, and to the combined use of EEG and peripheral signals (e.g., galvanic skin response (GSR), respiration, and skin temperature). DEAP also provides data from subjects’ self-assessment of their emotions, rated according to Russell’s affective arousal scale (21). Using these data, we divided the samples into two emotional classes (i.e., positive and negative emotional states) as most studies have done for validating emotion recognition performance (17).

Feature extraction is important to machine learning tasks. In addition to the widely used linear features, we opted to extract a variety of nonlinear features (e.g., correlation dimension and Shannon entropy) from neurophysiological signals. We compared the recognition performance of our multimodal deep learning method with a commonly used traditional classification approach. We first applied the k-Nearest Neighbor (KNN) classifier to the data. We then applied the same classifier to the combined features of peripheral physiological signals, and to the combined features of EEG and peripheral signals. Through experimental comparisons, we have found that the use of the deep learning approach shown in Figure 1 (which is our multimodal deep learning framework) can achieve better recognition of emotions than the traditional KNN classifier based on the use of different modalities individually or in combination.

In this article we have summarized how it is possible to recognize emotion using a deep learning approach based on multiple neurophysiological signals. In the future, emotion-related modalities not limited to neurophysiological signals (e.g., speech and magnetic resonance imaging) could also be added around the globe. However, a major challenge has been how effectively the teachers or the platform can track the level at which the student is learning. Neuroscience and psychology research has shown that cognitive processes, such as attention and long-term memorization, are tightly linked to emotions. If a student gazed at the computer screen at length without displaying signs of interactive pleasure, it is likely that a mood of antipathy has emerged, which can result in low learning efficiency. AC can provide the ability to assess the emotional states of learners in an online environment based on analysis of signals from various sensory apparatuses, and teaching strategies can be automatically adapted to accommodate these emotional changes (8).

AC has been adopted for promoting the information retrieval (IR) experience, which underlies applications such as web search engines. Researchers have observed that positive emotions often reflect a user’s satisfaction with search results (9) and interest in certain information (10). Negative emotions, on the other hand, occur more often with user’s dissatisfaction with search results and search strategies (9). Capturing the emotional states of users while they are seeking information through search engines can be used as feedback to adjust the search engines’ retrieval strategies and to better predict the topical relevance of information being presented to users (11, 12).
Applying nontraditional approaches of electrophysiological data analysis to decision-making research

Dandan Zhang1,†, Ruolei Gu2,†, Pengfei Xiu, Wenbo Luo1, Yue-jia Luo2,†

Synchronous firing of populations of neurons, which is an important source of brain electrical activity, contributes significantly to the neurobiological basis of human cognitive processing (1). Electrophysiological (EEG) captures this mechanism by measuring voltage fluctuations that result from the summation of the simultaneous activity of millions of neurons (2). The EEG signals containing recorded content information arising from the activation of scattered brain regions, which may be located either near or far from the cerebral surface. EEG predomi-
nantly measures the activity of cortical pyramidal neurons, because the geometrically parallel organization of these cells ensures that their synchronous firing can be easily detected by electrodes placed on the subject’s head (3). It has been suggested that scalp EEG amplitudes elicited by the onset (or offset) of a sensory or a cognitive event (i.e., event-related EEG) can be detected as distinct from spontaneous or background EEG signals (4). This methodology has proven to be a valuable tool for cognitive neuroscientists, including those interested in human decision making (Figure 1A). The process of decision making can be broken down into several steps, including situation perception, option evaluation, action selection, and learning from outcome (5). The temporal overlap between the different stages of decision making provides huge difficulties for investigating the separate neural mechanisms underlying each stage. The EEG can help address this problem because it enables high temporal resolution (6).

As pointed out by Makeig et al., traditional event-related EEG data processing consists of two approaches, namely, a time-domain approach using event-related potentials (ERPs) that focuses on temporal features of the data, and a frequency-domain approach using spectrum analysis that focuses on a spectrum of frequencies or energies of the data. Neither of these fully represents

the neural dynamics of the brain, which have important implications for the underlying neurocognitive function (1). The drawbacks inherent in the classical methods have long been acknowledged (see below), and researchers have sought to explore novel techniques of data analysis in recent years. Below we discuss the pros and cons of these techniques and their applications in decision-making studies.

Dynamics of neural synchrony

Electrophysiological activity in the human brain is highly oscillatory, which means that the firing patterns of neighboring neurons tend to be synchronized because of the feedback connections between them (3). The theoretical significance of neural oscillation lies in the fact that it is the neuroelectric basis of distinct cognitive activities such as perception, memory, and consciousness (7). Data recorded from any given electrode contains power/phase dynamics that define the characteristics of neural oscillation (3). To decipher this information, a time-frequency analysis is necessary, which depicts the temporal synchrony of oscillatory activity over multiple frequency bands (Figure 1B). This approach helps unravel neural oscillation patterns in both the time and frequency domains simultaneously that cannot be reflected by traditional methods (for example, traditional cross-frequency coupling only results in a single index that reflects the intensity of synchronization between two oscillations over the whole time span) (3).

It is worth noting that a single EEG oscillation can be involved in different cognitive processes, because the combination of neurons that make up oscillations can belong to spatially overlapping or segregated functional networks (8). Therefore, it would be questionable to derive a one-to-one mapping relationship between a cognitive function and an oscillation response. Take medial frontal theta rhythms as an example. Numerous studies have reported that oscillations within the theta band (4–7 Hz) are critical for decision making under uncertainty, possibly reflecting neurophysiological processes underlying the way the brain learns from the environment (9–11). Nevertheless, frontal theta rhythms are also activated in a wide range of other cognitive tasks such as error processing and conflict detection, and thus likely represent a general operating mechanism involved in action monitoring, rather than a specific decision-making component (11).

Decomposing EEG data

The use of both principle component analysis (PCA) and independent component analysis (ICA) in EEG data processing is also becoming popular. The PCA approach treats the ERP waveform as a combined effect of temporally irrelevant voltages presenting simultaneously in the brain, and tries to provide a set of latent components that may index physiologically distinct processes (1, 9) (Figure 1D). By applying temporal-spatial PCA to ERP data, Foé et al. revealed that the feedback-electric brain waves process the feedback as an additional factor (9).

FIGURE 1. Examples of advanced electrophysiology (EEG) processing techniques. Participants took part in a monetary gambling game and the outcome feedback-elicited EEG data were analyzed. Refer to (9) and (14) for detailed experimental designs. (A) A traditional method for event-related EEGs, event-related potential (ERP) analysis. (B) A time-frequency analysis of EEG. Left panel: the event-related spectral perturbation (ERSP); Right panel: the inter-trial coherence (ITC). (C) The single-trial display of the P2 latency sorted ERP. (D) Principle component analysis (PCA) of the data from (9). (E) Independent component analysis (ICA) of the data from (14).

Institute of Affective and Social Neuroscience, School of Psychology and Sociology, Shandong University, Shandong, China.
Key Laboratory of Behavioral Science, Institute of Psychology, Chinese Academy of Sciences, Beijing, China.
School of Psychology, Liaoning Normal University, Dalian, China.
Key Laboratory of Cognitive Science, Center of Software for Eider Care and Health, Chengdu University, Chengdu, China.
†Contributed equally to the paper.
Corresponding author: luoyj@szu.edu.cn

Acknowledgments

This work was funded in part by the Natural Basic Research Program of China (973 Program) (2014CB744064 and 2013CB329304), the National High-Tech R&D Program of China (863 Program) (2015AA015403), and the National Natural Science Foundation of China (61272265 and 61402324).
related negativity (FRN)—represented as a negative wave elicited by the outcome feedback from decision-making tasks in conventional ERPs (12)—is actually a positive wave localized in the striatum (13). PCA components of ERP data are temporally or spatially orthogonal (or uncorrelated), because PCA specifically makes each successive component account for as much as possible of the remaining activity that has been unaccounted for by previously determined components. Unlike PCA, it is possible that maximally independent sources of activity and results in temporally independent components with unconstrained spatial distribution (1). By applying ICA to the EEG data recorded in a monetary gambling game, we found that the frontocentral theta component, the source of which is located in the anterior cingulate cortex, was closely associated with future risk-taking behavior (14) (Figure 1E). PCA and ICA techniques enhance the precision of source localization of EEG data (15). However, we should keep in mind that as a data-driven method, neither PCA nor ICA is guaranteed to yield neurophysiologically meaningful results (16). Additional anatomical and empirical evidence is highly recommended (17).

Single-trial ERPs

Traditional analysis of event-related EEG data recognizes amplitude or energy changes time-locked to a given event by averaging epochs over a period of time, assuming that peaks at the same latencies are near-identical at the single-trial level (18). This oversimplified approach leaves a lot of the cognitively relevant information in the temporal dimension of EEG activity undiscovered (3). In contrast, single-trial analysis offers an opportunity to directly investigate systematic variations in the timescale of milliseconds (19). This method does a better job of discovering potential links between cognitive processes and neural dynamics compared with conventional averaging (3). For instance, our recent study revealed that the P3 amplitudes in response to the stimulus and the required response. One such example which stems from an incongruency between the task-relevant information (the color of the word) and task-irrelevant features of the stimulus (the word itself) (1). In contrast, a stimulus-response (S-R) conflict arises when there is incongruency between the task-irrelevant stimulus and the required response. One such example is the Simon task, in which participants are asked to respond to a stimulus that is displayed at the opposite side of the location of a response button (e.g., pressing a button on the right in response to an item shown on the left). In addition, a person’s performance on the current trial is also modulated by whether or not there exists incongruence in the preceding trial. Response times tend to be lengthened in congruent trials but to be lengthened in congruent trials, when following an incongruent trial as compared to following a congruent trial (2). The Simon task posits that stimulus-evoked power perturbations or phase synchronizations are near-identical at the single-trial level (18). Therefore, S-S and S-R conflicts could occur for both types of conflict involving incongruent information and may continue from being presented with a task already been activated from being presented with a task.

Behavioral and electrophysiological profiles reveal domain-specific conflict processing

Guochun Yang1,*, Weizhi Nai1,*, Qi Li*, Xun Liu*

cognitive control refers to the top-down control of cognitive processes based on higher-order representations, such as goals or plans. It serves an essential role in carrying out goal-directed behaviors, especially when situations present conflicting information. A person’s ability to perform a cognitive task can be hampered when the task involves an incompatible association between a stimulus and a response—a phenomenon known as the stimulus-response compatibility (SRC) effect. For example, in the Stroop task, participants are asked to name the color of a word; however, the word itself is presented in an incongruent color (e.g., the word “red” is displayed in blue ink). This creates a stimulus-stimulus (S-S) conflict, which stems from an incongruency between the task-relevant information (the color of the word) and task-irrelevant features of the stimulus (the word itself) (1). In contrast, a stimulus-response (S-R) conflict arises when there is incongruency between the task-irrelevant stimulus and the required response. One such example is the Simon task, in which participants are asked to respond to a stimulus that is displayed at the opposite side of the location of a response button (e.g., pressing a button on the right in response to an item shown on the left). In addition, a person’s performance on the current trial is also modulated by whether or not there exists incongruence in the preceding trial. Response times tend to be lengthened in congruent trials but to be lengthened in congruent trials, when following an incongruent trial as compared to following a congruent trial (2). The Simon task posits that stimulus-evoked power perturbations or phase synchronizations are near-identical at the single-trial level (18). Therefore, S-S and S-R conflicts could occur for both types of conflict involving incongruent information and may continue from being presented with a task already been activated from being presented with a task.

Behavioral and electrophysiological profiles reveal domain-specific conflict processing

Guochun Yang1,*, Weizhi Nai1,*, Qi Li*, Xun Liu*

Cognitive control refers to the top-down control of cognitive processes based on higher-order representations, such as goals or plans. It serves an essential role in carrying out goal-directed behaviors, especially when situations present conflicting information. A person’s ability to perform a cognitive task can be hampered when the task involves an incompatible association between a stimulus and a response—a phenomenon known as the stimulus-response compatibility (SRC) effect. For example, in the Stroop task, participants are asked to name the color of a word; however, the word itself is presented in an incongruent color (e.g., the word “red” is displayed in blue ink). This creates a stimulus-stimulus (S-S) conflict, which stems from an incongruency between the task-relevant information (the color of the word) and task-irrelevant features of the stimulus (the word itself) (1). In contrast, a stimulus-response (S-R) conflict arises when there is incongruency between the task-irrelevant stimulus and the required response. One such example is the Simon task, in which participants are asked to respond to a stimulus that is displayed at the opposite side of the location of a response button (e.g., pressing a button on the right in response to an item shown on the left) (2). In addition, a person’s performance on the current trial is also modulated by whether or not there exists incongruence in the preceding trial. Response times tend to be lengthened in congruent trials but to be lengthened in congruent trials, when following an incongruent trial as compared to following a congruent trial (2). The Simon task posits that stimulus-evoked power perturbations or phase synchronizations are near-identical at the single-trial level (18). Therefore, S-S and S-R conflicts could occur for both types of conflict involving incongruent information and may continue from being presented with a task already been activated from being presented with a task.

Behavioral and electrophysiological profiles reveal domain-specific conflict processing

Guochun Yang1,*, Weizhi Nai1,*, Qi Li*, Xun Liu*

Cognitive control refers to the top-down control of cognitive processes based on higher-order representations, such as goals or plans. It serves an essential role in carrying out goal-directed behaviors, especially when situations present conflicting information. A person’s ability to perform a cognitive task can be hampered when the task involves an incompatible association between a stimulus and a response—a phenomenon known as the stimulus-response compatibility (SRC) effect. For example, in the Stroop task, participants are asked to name the color of a word; however, the word itself is presented in an incongruent color (e.g., the word “red” is displayed in blue ink). This creates a stimulus-stimulus (S-S) conflict, which stems from an incongruency between the task-relevant information (the color of the word) and task-irrelevant features of the stimulus (the word itself) (1). In contrast, a stimulus-response (S-R) conflict arises when there is incongruency between the task-irrelevant stimulus and the required response. One such example is the Simon task, in which participants are asked to respond to a stimulus that is displayed at the opposite side of the location of a response button (e.g., pressing a button on the right in response to an item shown on the left) (2). In addition, a person’s performance on the current trial is also modulated by whether or not there exists incongruence in the preceding trial. Response times tend to be lengthened in congruent trials but to be lengthened in congruent trials, when following an incongruent trial as compared to following a congruent trial (2). The Simon task posits that stimulus-evoked power perturbations or phase synchronizations are near-identical at the single-trial level (18). Therefore, S-S and S-R conflicts could occur for both types of conflict involving incongruent information and may continue from being presented with a task already been activated from being presented with a task.

Behavioral and electrophysiological profiles reveal domain-specific conflict processing

Guochun Yang1,*, Weizhi Nai1,*, Qi Li*, Xun Liu*

Cognitive control refers to the top-down control of cognitive processes based on higher-order representations, such as goals or plans. It serves an essential role in carrying out goal-directed behaviors, especially when situations present conflicting information. A person’s ability to perform a cognitive task can be hampered when the task involves an incompatible association between a stimulus and a response—a phenomenon known as the stimulus-response compatibility (SRC) effect. For example, in the Stroop task, participants are asked to name the color of a word; however, the word itself is presented in an incongruent color (e.g., the word “red” is displayed in blue ink). This creates a stimulus-stimulus (S-S) conflict, which stems from an incongruency between the task-relevant information (the color of the word) and task-irrelevant features of the stimulus (the word itself) (1). In contrast, a stimulus-response (S-R) conflict arises when there is incongruency between the task-irrelevant stimulus and the required response. One such example is the Simon task, in which participants are asked to respond to a stimulus that is displayed at the opposite side of the location of a response button (e.g., pressing a button on the right in response to an item shown on the left) (2). In addition, a person’s performance on the current trial is also modulated by whether or not there exists incongruence in the preceding trial. Response times tend to be lengthened in congruent trials but to be lengthened in congruent trials, when following an incongruent trial as compared to following a congruent trial (2). The Simon task posits that stimulus-evoked power perturbations or phase synchronizations are near-identical at the single-trial level (18). Therefore, S-S and S-R conflicts could occur for both types of conflict involving incongruent information and may continue from being presented with a task already been activated from being presented with a task.

Behavioral and electrophysiological profiles reveal domain-specific conflict processing

Guochun Yang1,*, Weizhi Nai1,*, Qi Li*, Xun Liu*

Cognitive control refers to the top-down control of cognitive processes based on higher-order representations, such as goals or plans. It serves an essential role in carrying out goal-directed behaviors, especially when situations present conflicting information. A person’s ability to perform a cognitive task can be hampered when the task involves an incompatible association between a stimulus and a response—a phenomenon known as the stimulus-response compatibility (SRC) effect. For example, in the Stroop task, participants are asked to name the color of a word; however, the word itself is presented in an incongruent color (e.g., the word “red” is displayed in blue ink). This creates a stimulus-stimulus (S-S) conflict, which stems from an incongruency between the task-relevant information (the color of the word) and task-irrelevant features of the stimulus (the word itself) (1). In contrast, a stimulus-response (S-R) conflict arises when there is incongruency between the task-irrelevant stimulus and the required response. One such example is the Simon task, in which participants are asked to respond to a stimulus that is displayed at the opposite side of the location of a response button (e.g., pressing a button on the right in response to an item shown on the left) (2). In addition, a person’s performance on the current trial is also modulated by whether or not there exists incongruence in the preceding trial. Response times tend to be lengthened in congruent trials but to be lengthened in congruent trials, when following an incongruent trial as compared to following a congruent trial (2). The Simon task posits that stimulus-evoked power perturbations or phase synchronizations are near-identical at the single-trial level (18). Therefore, S-S and S-R conflicts could occur for both types of conflict involving incongruent information and may continue from being presented with a task already been activated from being presented with a task.
Computational-based behavior analysis and peripheral psychophysiology

Peter Khoshhabeh†1,‡, Stefan Scherer†1,‡, Brent Ouimette†, William S. Ryan§, Brent J. Lance†, Jonathan Gratch1

Within an educational context, computer-assisted training and assessments of a person’s social skill proficiency and expertise can help create individualized education scenarios, in particular for those with learning disabilities or social anxiety. Computer-assisted vocational training, for example, might be able to improve the chances that a young adult with autism spectrum disorder (ASD) can become a fully integrated member of society through extended and guided preparation. Computationally based behavior analysis has already found its way into a number of application-oriented educational scenarios, including job interview training (6) and public speaking training (7, 8), as well as science, technology, engineering, and mathematics (STEM)–oriented learning technologies (9).

This novel field of research is at the intersection of psychology, machine learning, multimodal sensor fusion, and pattern recognition, and is emerging as an essential field of investigation for computer scientists. Most recently, researchers have started to not only assess visual and acoustic behavior via unimodal and noninvasive sensors (i.e., cameras and microphones), but also track otherwise latent measures, such as a person’s heart rate (HR). This approach to assessing often inaccessibility measures of a person’s physiology could enable novel applications and provide a deeper understanding of the physiological processes underlying observable behavioral changes.

Psychologically grounded physiological measures

Most psychological approaches in computer science only use one type of physiological measure. Conversely, our research uses multiple psychologically grounded measures that reflect autonomic nervous system activity. For example, it is not uncommon for applied computer science researchers to measure a single peripheral physiological measurement, such as heart rate variability (HRV) (11) or electrodermal activity (EDA) (12), because they are assumed to be indicative of cognitive workload and/or stress. However, changes in HRV and EDA measures have been correlated with several different psychological states and processes, e.g., HRV can vary depending on cognitive workload and on how a risky choice is framed during the decision-making process (13, 14). Relying on single physiological measures can mask important processes because of the one-to-many mapping between a single physiological measure and the numerous psychological processes to which it can be correlated. Conversely, according to the biopsychosocial model of stress (15), a single physiological measure of cardiovascular responses can be used to determine specific patterns that represent the two motivational states of challenge and threat. A person will perceive a situation as a challenge if they determine that the available resources outweigh what is needed to complete a task. Whereas, one perceives a threat if instead the evaluated resources do not meet the demands to carry out a task, or if there is uncertainty.

The same neural and endocrine processes affect cardiovascular responses during both a perceived challenge and threat, including increased sympathetic–parasympathetic balance and increased ventricular contractility (VC). However, cardiac output (CO) and total peripheral resistance (TPR) differ depending upon the motivational state. The neuroendocrine underpinnings (16) of cardiovascular responses involve the sympathetic–adrenal-medullary (SAM) and hypothalamic–pituitary–adrenal-cortical (HPA) axes. Both states involve the activation of the SAM axis, while only the threat state involves both of the axes. A challenge state results in decreased TPR and no change or a decrease in CO and little or no change of the axes. A threat state involves both increased TPR and an increase in CO, whereas a threat state leads to little or no change or a decrease in CO and little or no change or an increase in TPR. We infer CO, TPR, and VC from the physiological data stream (Figure 1).

FIGURE 1. Sample continuous data stream of the multivariate cardiovascular physiology measures. (A) Impedance cardiograph. (B) Electrocardiogram. (C) Blood pressure graph. (D) GSR/FF, the derivative of the impedance cardiograph.

References


Acknowledgments

This research was supported by the National Natural Science Foundation of China (31070697, 31200782, and 31328013).

‡Equal contribution.

†Shared first authorship, ordered alphabetically.

‡U.S. Army Science and Technology for Artificial Intelligence (STARAI) and the Defense Advanced Research Projects Agency (DARPA) Cyber Studies Institute for Creative Technologies, University of Southern California, Playa Vista, CA

§Department of Psychological and Brain Sciences, University of California, Santa Barbara, CA

*Corresponding Author: khooshbah@usc.edu (P.K.), schererst@usc.edu (S.S.)

†Treyon first authorship, ordered alphabetically.

Computational-based behavior analysis aims to automatically identify, characterize, model, and synthesize multimodal nonverbal behavior within both human–machine as well as machine-mediated human–human interaction. It uses state-of-the-art machine learning algorithms to track human nonverbal and verbal information, such as facial expressions, gestures, and posture, as well as what and how a person speaks. The emerging technology from this field of research is relevant for a wide range of interactive and social applications, including health care and education. The characterization and association of nonverbal behavior with underlying clinical conditions, such as depression or post-traumatic stress, could have significant benefits for treatments and the overall efficiency of the health care system. Here we review our collaborative research efforts on advanced computational approaches to studying nonverbal and physiological signals related to psychological states. First, we discuss the computational behavior analysis framework. Second, we discuss the cardiovascular physiological measures that are the basis of the biopsychosocial model of our research. Finally, we discuss our intended future work and the limitations of integrating computational analytical techniques with physiological sensors in order to infer psychological states.

First, we discuss the computational behavioral analysis framework. Multimodal behavior assessment approaches, we have identified a number of behavioral indicators of psychological distress. Such indicators include, but are not limited to the, the average intensity or duration of smiles (11), increased response times in controlled interview studies (2), attenuation of expressions associated with social isolation (3), and changes in the voice quality of a speaker (3-5). These findings not only confirm findings in the psychology literature, which mostly rely on subjective assessments and manual annotations, but also contribute to a better scientific understanding of psychological states through the development of advanced computational methods. The automated assessment of a patient’s nonverbal behavior could prove valuable to clinicians and provide them with additional objective assessments of a patient’s state or development over time.
increase the ecological validity of the experiment, while also maintaining tight experimental control of social cue manipulation. Virtual humans were able to make emotional facial expressions and behave either competitively or more cooperatively during the negotiation. The results showed the same patterns of cardiovascular measures as the BPS model of a psychological state of threat when there was discordance between the behavior and expressed emotion of the virtual human. A corresponding eye tracking analyses during this task further suggested that the participants experienced uncertainty because of the discordance, which is characteristic of a threat state. Specifically, participants in the discordant conditions looked at the virtual human’s face more, most likely to sample information that might help them reconcile the discordance between the behavior and facial expressions.

Throughout the task, individual events during the game were synchronized with the cardiovascular physiology data stream. These events would take place at variable intervals because of the interactive nature of the task, but the average frequency was 5 and 10 seconds. Traditionally, we have analyzed the physiological measures at every minute using ensemble averaging, which is the mean of a signal as a function of a microstate of that signal, e.g., a heartbeat. We then related the time points between the dZ/dt and the electrocardiogram on the ensemble waveform (a composite waveform for a specific time window). However, we anticipate moving to a more fine-grained analytical approach in which we relate events in the game to a window corresponding to the near-real time cardiovascular data stream. Moreover, we are currently engineering solutions to synchronize multimodal data from the computational behavior analysis framework with the corresponding time course in both the virtual game environments and physiological data streams. For example, a preliminary analysis indicates some interesting relationships between the voice quality measures of the computational behavior analysis and the BPS cardiovascular physiology measures (19). One applied goal in this line of work is to detect states of relative challenge or threat from the cardiovascular data in near-real time, so as to design an interactive virtual human that is responsive to the user’s motivational state.

Certain limitations must be overcome in order to further understand the dynamics behind real-time changes in an individual’s cardiovascular state and the concomitant psychological states. Practically, many of the sensing hardware setups are not robust enough to detect movement artifacts. Therefore, the current application for this approach involves tasks in which users are seated. Scientifically, much can be gained by understanding the variability of human’s physiological responses to the same stimulus (20). For example, two different individuals might have different cardiovascular responses as a result of how they evaluate perceived resources relative to perceived task demands. A future goal will be to understand the characteristics that predict how an individual will respond to different psychological stressors.

References

Acknowledgments
The work depicted here is sponsored by the U.S. Army Research Laboratory (ARL) under contract numbers W911NF-14-D-0005 and W911NF-09-D-0001 through the Institute for Creative Technologies (ICT) and the Institute for Collaborative Biotechnologies (ICB). Statements and opinions expressed and content included do not necessarily reflect the position or the policy of the United States government, and no official endorsement should be inferred.
How the ancient art of acupuncture works: Neuroimaging studies shed light on brain activity

Weiqi Qi1†, Lijun Bai2†, Zhenyu Liu3†, Peng Lui4†, Yi Zhang1†, Jie Lui5, Kai Yuan6, Baixiao Zhao6†, Jianping Dai6†, Yijun Liu6†, Jie Tian7†

Corresponding Authors: daijianping_2008@126.com (D.P.), yjliufl@gmail.com (Y.L.), jietian13@126.com (J.T.)

6Department of Biomedical Engineering, School of Life Science and Technology, Xi’an Jiaotong University, Xi’an, China
5Department of Neurology, School of Medicine, Xi’an Jiaotong University, Xi’an, China
4Korea Advanced Institute of Science and Technology, Daejeon, South Korea
3Acupuncture Research Center, Beijing University of Chinese Medicine, Beijing, China
2School of Kinesiology and Health, University of Michigan, Ann Arbor, Michigan, USA
1School of Integrative Traditional Chinese Medicine, Peking University Health Science Center, Beijing, China

Background: Acupuncture is an ancient art of medicine that has been used for thousands of years. It involves the insertion of needles at specific points on the body to treat various conditions. While its effectiveness has been discussed for centuries, understanding the underlying neural mechanisms is crucial for its proper application and further development. The present study aimed to investigate the neuroimaging effects of acupuncture to shed light on the brain activity associated with its therapeutic effects.

Methods: The study utilized both fMRI and ERPs to examine the neural responses to acupuncture. The participants were divided into two groups: the acupuncture group and the sham acupuncture group. Neuroimaging studies were conducted before and after the acupuncture treatment to assess changes in brain activity.

Results: The study revealed differential brain activations in specific regions associated with acupuncture treatment. These regions included the primary sensory cortex, insula, and prefrontal cortex, which are known to be involved in pain processing and modulation. The findings suggested that acupuncture could activate self-regulating mechanisms without using drugs.

Conclusions: The results support the hypothesis that acupuncture activates specific neural correlates that contribute to the therapeutic effects of acupuncture. These findings could also provide a theoretical basis for developing new acupuncture protocols or improving current techniques.

Keywords: Acupuncture, Neuroimaging, Brain Activity, Pain Processing, Self-Regulating Mechanisms
Improving working memory using EEG biofeedback

Jiacai Zhang, Shi Xiong, Chen Cheng, Li Yao*, Xia Wu, Xiaojuan Gao

Working memory (WM) refers to the ability to maintain and manipulate information over short periods of time in the context of concurrent processing or distractions (1,2). It is widely accepted that WM capacity is key for a wide range of higher-order cognitive functions (3,4), therefore the possibility of enhancing WM has stimulated a series of WM training studies (4-6). Computerized WM training (CWMT), originally developed by Torkel Klingberg, has been widely employed for such research, in which subjects repeat WM tasks using a computer program that provides visual and verbal feedback and rewards based on the accuracy of every trial. Subjects who have practiced WM tasks using this type of feedback have been reported to have significantly higher improvements than controls (5,6). This form of repetitive WM practice is essentially behavioral feedback, which activates both the central executive and subcomponents of the related working memory brain systems. Based on functional magnetic resonance imaging (fMRI) studies, researchers have attributed such WM improvements to long-lasting neuronal changes in WM task-specific areas of the brain. These changes are accompanied by alterations in common neural networks that are not only related to WM but also many other cognitive functions, such as fluid intelligence (7). Functional magnetic resonance imaging (fMRI) studies have provided further evidence suggesting that WM training induces plasticity that alters both WM-related neural networks and those related to other cognitive functions (8).

However, most, if not all, of these studies employed WM training using behavioral feedback in which subjects practice a task, but without use of the neurofeedback technology (NF). The purpose of NF technology is to help the brain function more efficiently by specified strategies that induce autoregulation of specific brain regions using real-time data depicting fluctuations in brain activity. Studies have shown that WM capacity can be enhanced by NF training. In NF training, the subject’s brain activity related to a WM task is observed and quantified and then feedback is provided to the subject with the aim of enhancing the subject’s performance by providing the subject with real-time information about the subject’s brain activity as it unfolds (9-11). When the brain decreases its activity in the area that is most related to WM, the NF system tells the subject to increase the activity in that area. For example, when the brain shows less activity during a memory task, the NF system tells the subject to increase the activity in that area. Therefore, we designed a study to test both of these questions and discuss the results below.

References
6. J. Han, Trends Neurosci. 28, 17 (2005).

Acknowledgments
This paper is financially supported by the National Science Foundation of China (61227901 and 61231004) and the National Basic Research Program of China (973 Program) (2011CB707700, 2011CB707703, 2012CB518001, and 2012CB518003).
The sham EEG signals were similar to those of the real other subjects’ signals. The magnitude and variability of a mixture of noise and rhythms but rather from not from their own EEG provided with sham except that they were the same instructions as NF-training group, followed by the behavioral-training group. This gain was significantly smaller for the sham-NF and no-training groups compared with both the NF-training and the behavioral-training groups. The accuracy gain that we observed between the different groups indicates that NF training and behavioral training are both superior to sham NF training or no training at all. However, it should be noted that behavioral exercises took more time to train subjects (five training sessions) and showed a slightly larger accuracy gain compared with NF training (one training session) [11].

Summary
The goal of our study was to elucidate the effects of NF during WM training. Our data demonstrated that young healthy adults can improve WM by training (evident by our subjects’ increased response accuracy and decreased response time in the 2-back task). Future research will be needed to ascertain the neurological mechanisms underlying WM training.

References
3. V. Cameron, J. Exp. Psychol. 97, 37 (2008).

Acknowledgments
This study was supported by the National High-Tech R&D Program of China (863 Program) (2012AA011612) and the National Natural Science Foundation of China (61320001 and 61351116).

In the NF training group, the EEG signals related to the WM tasks were transferred into visual feedback—a rotating sphere with a graduated thermometer on the computer screen that was presented to subjects once every 500 milliseconds. Subjects were instructed to use a cognitive strategy to persistently increase the level in the thermometer or rotation speed of the sphere as much as possible. In the sham NF-training group, subjects completed the same experimental procedure and received the same instructions as the NF training group, except that they were provided with sham NF signals, which were not from their own EEG rhythms but rather from a mixture of noise and other subjects’ signals. The magnitude and variability of the sham EEG signals were similar to those of the real signals. In the behavioral-training group, subjects attended the CWMT training, performing the WM (2-back) tasks using a computer program developed for this study. In the no-training group, subjects also attended the pretest and posttest, which was similarly separated by a 5-day interval; however, subjects were not trained in between the two testing sessions. This group served as a control to assess the effects of the repetitive performance of the same WM tasks in pretests and posttests.

We assessed the change in WM performance by measuring the accuracy and time of responses during the 2-back tasks for the pretests and posttests. A one-way analysis of variance (ANOVA) determined that the each of the groups’ pretest performances were equivalent (accuracy: F(3, 44)=0.184, P>0.906; response time: F(3, 44)=1.131, P>0.347). A pairwise comparison between the pretest and posttest results showed increased accuracy (an accuracy gain) for each of the groups; however, the effect was significant only in the NF-training, behavior-training, and no-training groups. The largest effect was in the NF-training group, followed by the behavioral-training group. This gain was significantly smaller for the sham-NF and no-training groups compared with both the NF-training and the behavioral-training groups. The accuracy gain that we observed between the different groups indicates that NF training and behavioral training are both superior to sham NF training or no training at all. However, it should be noted that behavioral exercises took more time to train subjects (five training sessions) and showed a slightly larger accuracy gain compared with NF training (one training session) [11].

Summary
The goal of our study was to elucidate the effects of NF during WM training. Our data demonstrated that young healthy adults can improve WM by training (evident by our subjects’ increased response accuracy and decreased response time in the 2-back task). Future research will be needed to ascertain the neurological mechanisms underlying WM training.

References
3. V. Cameron, J. Exp. Psychol. 97, 37 (2008).

Acknowledgments
This study was supported by the National High-Tech R&D Program of China (863 Program) (2012AA011612) and the National Natural Science Foundation of China (61320001 and 61351116).

In the NF training group, the EEG signals related to the WM tasks were transferred into visual feedback—a rotating sphere with a graduated thermometer on the computer screen that was presented to subjects once every 500 milliseconds. Subjects were instructed to use a cognitive strategy to persistently increase the level in the thermometer or rotation speed of the sphere as much as possible. In the sham NF-training group, subjects completed the same experimental procedure and received the same instructions as the NF training group, except that they were provided with sham NF signals, which were not from their own EEG rhythms but rather from a mixture of noise and other subjects’ signals. The magnitude and variability of the sham EEG signals were similar to those of the real signals. In the behavioral-training group, subjects attended the CWMT training, performing the WM (2-back) tasks using a computer program developed for this study. In the no-training group, subjects also attended the pretest and posttest, which was similarly separated by a 5-day interval; however, subjects were not trained in between the two testing sessions. This group served as a control to assess the effects of the repetitive performance of the same WM tasks in pretests and posttests.

We assessed the change in WM performance by measuring the accuracy and time of responses during the 2-back tasks for the pretests and posttests. A one-way analysis of variance (ANOVA) determined that the each of the groups’ pretest performances were equivalent (accuracy: F(3, 44)=0.184, P>0.906; response time: F(3, 44)=1.131, P>0.347). A pairwise comparison between the pretest and posttest results showed increased accuracy (an accuracy gain) for each of the groups; however, the effect was significant only in the NF-training, behavior-training, and no-training groups. The largest effect was in the NF-training group, followed by the behavioral-training group. This gain was significantly smaller for the sham-NF and no-training groups compared with both the NF-training and the behavioral-training groups. The accuracy gain that we observed between the different groups indicates that NF training and behavioral training are both superior to sham NF training or no training at all. However, it should be noted that behavioral exercises took more time to train subjects (five training sessions) and showed a slightly larger accuracy gain compared with NF training (one training session) [11].

Summary
The goal of our study was to elucidate the effects of NF during WM training. Our data demonstrated that young healthy adults can improve WM by training (evident by our subjects’ increased response accuracy and decreased response time in the 2-back task). Future research will be needed to ascertain the neurological mechanisms underlying WM training.

References
3. V. Cameron, J. Exp. Psychol. 97, 37 (2008).

Acknowledgments
This study was supported by the National High-Tech R&D Program of China (863 Program) (2012AA011612) and the National Natural Science Foundation of China (61320001 and 61351116).
SSVEP-based BCIs are typically less than 60 bits/min (1).

Computational model of SSVEP

A computational model of SSVEP is a mathematical formula describing the relationship between the visual stimuli and brain responses (Figure 2A). Computational modeling of SSVEPs is advantageous for developing target identification methods for SSVEP-based BCIs (3). Currently, there is a lack of computational models of SSVEPs for the specific purpose of designing a BCI. Therefore, we wanted to explore the potential for creating an efficient computational model to improve the performance of SSVEP-based BCIs.

We have proposed a computational model of SSVEPs that jointly considers the incoming stimulus and the ongoing state of SSVEP responses (Figure 2B). Given a stimulus frequency, \( f_x \), and an initial phase, \( \phi_0 \), the stimulus signal can be described as follows:

\[
x(t) = \sin(2\pi f_x t + \phi_0), \quad 0 \leq t \leq T
\]

where \( T \) is the stimulus duration. The scalp-recorded EEG responses to the stimulus consist of SSVEPs, spontaneous EEG signals, and other noise (such as muscle artifacts and power line interference). We use the following model to describe SSVEPs recorded on the scalp:

\[
x(t) = \sum_{k=-\infty}^{\infty} a_k \sin(2\pi f_k (t - t_0) + \phi_k) + n(t), \quad t_0 \leq t \leq t_0 + T_{\text{SVEP}}
\]

The evoked SSVEP signals consist of multiple sinusoidal components at the stimulation frequency and its harmonic frequencies. The number of harmonics \( N_h \) can be determined by the stimulus frequency and the upper-bound frequency of the responses (4). In our recent study, SSVEP harmonics were clearly observed within the frequency range that showed an upper-bound frequency around 90Hz (5). \( \tau_{\text{VP}} \) is the visual delay between the stimulus and the SSVEP response (6). \( \tau_{\text{VP}} \) is the duration for which a response persists following a stimulus. Each phase of each harmonic component is specified by \( \alpha_k \) and \( \phi_k \), respectively. Generally, the amplitude of the harmonics decreases when the phase of each harmonic component increases (6). The phase for each harmonic component can be considered as a constant. However, the relationship between the stimulus phases and harmonic phases still remains unknown due to a lack of information about how the SSVEP harmonics are generated. For simplicity, other non-evoked EEG signals are considered as noise and simplified as \( n(t) \) in the model. Here we only focus on modeling the evoked SSVEP signals.

Categorizing SSVEP modulation

The proposed computational model describes SSVEPs as a set of sinusoidal signals with specific frequencies and phases. Parameters in the model can be used to track how different cognitive tasks affect SSVEP. Typically, BCI and cognitive studies that use SSVEPs can only modulate one parameter (e.g., frequency, phase, or amplitude) at a time. Recently, methods that can simultaneously modulate multiple parameters (e.g., frequency, phase, or amplitude) have been proposed for BCI studies (7). The approaches for modulating SSVEPs can be categorized into three groups (see Figure 3):

Frequency tracking

Frequency tracking is the most well-known characteristic of SSVEPs (4). SSVEPs exhibit the same frequency as the flickering stimulus. The widely used frequency tracking technique (i.e., multiple visual targets are tagged with different flickering frequencies, see Figure 3A) was developed based on this characteristic. The direction of the gaze when the target is fixed can be determined based on the frequency of SSVEPs. Frequency tracking is the most popular method for implementing SSVEP-based BCIs (2). The proposed computational model of SSVEP indicates that, in addition to the fundamental component, the harmonic components can also provide distinct information for frequency tracking.

Phasing tracking

The initial phase of SSVEP can reflect the visual delay between the stimulus and the SSVEP response in the visual pathway (6). A stable visual delay found in our recent study (7) suggests that phase tracking of SSVEPs is feasible and practical. A phase-tagging technique in which multiple visual targets are tagged with different phases at the same frequency (see Figure 3B) can be developed. It was noted that the phases of the harmonic SSVEP components could also be used for phase tracking. In recent BCI studies, the combination of frequency tracking and phase tracking was shown to be more efficient than either one alone (7).

Attention tracking

In addition to frequency tracking and phase tracking, attention tracking is another approach that employs SSVEP modulation. Overt attention (i.e., attending to the target by moving the eyes) and covert attention (i.e., mentally attending to the target without moving the eyes, see Figure 3C) impact SSVEPs in different ways (8). Specifically, one study of visual attention has shown that both the amplitude and phase of SSVEPs are modulated by covert attention (9). Therefore, attention tracking can be performed by measuring the amplitude and phase of SSVEPs. Attention tracking requires precise synchronization between the stimulus signals and the resulting SSVEPs.

Guidance for design and implementation of SSVEP-based BCIs

Further, the SSVEP model proposed above emphasizes that the transferability of information from the stimulus to SSVEPs is an important principle to consider when designing an SSVEP-based BCI. The stable visual delay in the visual pathway ensures that the properties of the stimulus signals are carried through to the resulting SSVEP responses. For example, two stimuli with the same frequency and a 180-degree phase difference can result in two SSVEP signals that are negatively correlated (i.e., with a correlation coefficient of -1). Therefore, optimization of the stimulus signals can be used as a proxy for optimization of BCI performance. In this case, advanced target coding technologies such as multiple access (MA) methods in telecommunications, which allow multiple streams to share the same communication channel, can be applied to improve the performance of SSVEP-based BCIs (1).
FIGURE 3. Approaches to modulation steady-state visual evoked potentials (SSVEPs). (A) Frequency tracking: Multiple targets are tagged with different flickering frequencies. (B) Phase tracking: Multiple targets are tagged with different phases at the same frequency. (C) Attention tracking: Multiple targets correspond to different attending locations or features. For example, attending to the right-side stimulus (S2) can lead to enhanced amplitude of SSVEPs at f2.

The stimulus coding and target identification methods play important roles in optimizing the performance of SSVEP-based BCIs. Advanced stimulus coding methods (e.g., mixed frequency and phase coding) can significantly improve the coding efficiency (7). Target identification methods typically consist of signal processing and machine learning algorithms that can be applied to extract frequency and phase information of SSVEP. Under the computational model described above, selections of frequency band and time window are crucial for feature extraction (5). In addition, SSVEP training data can be used to improve target identification using machine learning techniques (7). Furthermore, information of SSVEPs from previous sessions and other subjects can be used to facilitate the training procedure in BCI operation (10).

Another important factor that affects BCI performance is user attention. During BCI operation, visual attention needs to be maintained at a high level so that SSVEP parameters are stable across multiple trials.

Example application of high-speed BCI speller
We recently developed a high-speed BCI speller based on the system framework described above (5). The 40-character speller (see Figure 1B) used a frequency-coding diagram (frequency range: 8–15 Hz; frequency interval: 0.2 Hz). The three major procedures in system design and implementation were as follows: First, a benchmark SSVEP dataset was collected from 12 subjects in an offline BCI experiment. Second, the dataset was used for offline system design. The proposed computational model of SSVEPs suggested that the harmonic SSVEP components could provide valuable information for use in frequency detection. A filter bank canonical correlation analysis was developed to extract independent features from the fundamental and harmonic SSVEP components. The parameters of the filter bank and the classifier were optimized through evaluating offline BCI performance using the benchmark dataset. At the same time, the stimulus duration was optimized toward the highest ITR. Third, an online BCI speller, using the same parameters obtained from the offline system design, was implemented using a different group of 10 subjects. The online speller demonstrated an average ITR of 151 bits/ min, to our knowledge one of the highest ITRs reported in BCIs. This example application demonstrates the efficacy of the proposed computational model of SSVEP in improving the performance of SSVEP-based BCIs.

References

Acknowledgments
This work was supported by the National Natural Science Foundation of China (51431007), the National Basic Research Program of China (973 Program) (2011CB301704), the National High-Tech R&D Program of China (863 Program) (2012AA011601) and the Recruitment Program for Young Professionals.

Using a scale-free method to convert brain activity into music
Jing Liu1, Dan Wu1, Dezong Yao2,3

Music can create experiences that can be shared by humans. Emotional expression and communication through music are strongly linked to health and well-being (1, 2). For many years, musicologists and scientists have attempted to uncover the relationship between music and the human experience. In recent years, musicians have been considered as an outstanding model for studying the operations of the human brain and in particular, the effect of music on brain functions (3–6). We carried out an inverse study of sorts, in which we recorded brain activity and converted the data into music. In 2009, we proposed a scale-free method (7) to translate electroencephalogram data into music. The translation is based on the scale-free properties followed by both music and EEGs. Thereafter, we developed a series of scale-free methods for converting brainwaves into music (called “brainwave music”) that represents different states of brain activity, such as eyes open and eyes closed for healthy people, and the moment of seizure onset for patients with epilepsy (6–10).

Recently, we evaluated brainwave music for two subjects: a healthy, 5-year-old child, and an 80-year-old female patient with Alzheimer’s disease. We collected their EEG data using an electrode cap with 64 silver/silver chloride electrodes, connected using the established
Estimating biosignals using the human voice

Eduardo Coutinho and Björn Schuller

Computational paralinguistics (CP) is a relatively new area of research that provides new methods, tools, and techniques to automatically recognize the states, traits, and qualities embodied in the nonverbal aspects of human speech (1). In recent years, CP has reached a level of maturity that has permitted the development of a myriad of applications in everyday life, such as the automatic estimation of a speaker’s age, gender, height, emotional state, cognitive load, personality traits, likability, intelligibility, etc. (2). Here, we present an overview of one particular application of CP that offers new solutions for health care–the recognition of physiological parameters (biomarkers) from the voice alone.

Unintrusive and pervasive monitoring

Currently, there are a variety of portable medical devices enabling patients to actively monitor the relevant factors contributing to their diagnosis and treatments. These devices are particularly important when remote monitoring (daily or several times a day) is required for the adequate treatment and detection of symptoms, especially for patients with limited mobility and difficulties accessing medical facilities. Further, these technologies help address the shortage of qualified medical staff needed to adequately monitor patients, which can lead to delays in obtaining appropriate feedback and treatment.

The technologies currently available include those that measure heart rate, blood volume pressure, body temperature, respiration rate, and other physiological parameters. Such devices can be quite expensive and complicated for older patients and those with limited mobility, and often inconvenient for everyday use. Ideally, monitoring biosignals should be unobtrusive, not require additional electronic devices, and require minimal effort from the patient. Most importantly, monitoring should be easy to perform in emergency situations.

To assess the potential of automatic voice analysis, we investigated whether voice recordings could be used to estimate biosignals from the voice alone (13). In a first set of experiments, we evaluated the estimation of two biosignals—heart rate (HR) and skin conductance (SC)—and the classification of pulse level (high pulse; HP; low pulse; LP). We show that vocal expressions can be applicable to any speaker rather than a specific individual, and voice analysis can provide new methods, tools, and techniques to automatically recognize the states, traits, and qualities embodied in the nonverbal aspects of human speech (1).

In summary, scale-free brainwave music, a musical representation of brainwave activity, may provide a new way to peer inside the “brain,” or provide a new emotional brain-computer interface, as described within the brain and may be applicable for monitoring brain states, for use as an emotional brain-computer interface, or as a method of clinical rehabilitation (such as music therapy). However, additional work is needed to interface, or as a method of clinical rehabilitation (such as music therapy). However, additional work is needed to fully elucidate its underpinnings.

References


Acknowledgments

This work was supported by the National Natural Science Foundation of China (81333032 and 91232725).

Department of Computing, Imperial College London, United Kingdom
Corresponding Author: bjorn.schuller@imperial.ac.uk

The full database consists of 1,420 audio recordings (and concomitant HR and SC recordings).

The audio recordings were analyzed using the openSMILE (Speech and Music Interpretation by Large Space Extraction) software toolkit (14), which was used to extract a large set of acoustic descriptors. These descriptors included 4,368 acoustic features capturing a variety of energy-, spectral-, and voice-related information, which was used to develop computational models that predict SC and HR using the so-called time-frequency representation of the art-processing (a common, commercially available headset (“headset”)). The recorded EEG data was subsequently offline processed with the Reference Electrode Standardization Technique (REST) software (http://www.neuro.ucc.ie/rest/). Participants gave informed consent before the experiment was conducted, in accordance with the established guidelines of the Ethics Committee of the School of Life Science and Technology at the University of Electronic Science and Technology of China.

We translated the brainwaves (EEGs) into music for both males and females. To do this, we used a specific software that converts the brainwaves into music. This software is called BrainWave Music. The music was created using a specific algorithm that takes into account the brainwaves and transforms them into music. The music was then played in a specific tone, which is called the “heart tone.” The heart tone is a specific sound that is used to stimulate the brain.

Currently, there are a variety of portable medical devices enabling patients to actively monitor the relevant factors contributing to their diagnosis and treatments. These devices are particularly important when remote monitoring (daily or several times a day) is required for the adequate treatment and detection of symptoms, especially for patients with limited mobility and difficulties accessing medical facilities. Further, these technologies help address the shortage of qualified medical staff needed to adequately monitor patients, which can lead to delays in obtaining appropriate feedback and treatment.

The technologies currently available include those that measure heart rate, blood volume pressure, body temperature, respiration rate, and other physiological parameters. Such devices can be quite expensive and complicated for older patients and those with limited mobility, and often inconvenient for everyday use. Ideally, monitoring biosignals should be unobtrusive, not require additional electronic devices, and require minimal effort from the patient. Most importantly, monitoring should be easy to perform in emergency situations.

To assess the potential of automatic voice analysis, we investigated whether voice recordings could be used to estimate biosignals from the voice alone (13). In a first set of experiments, we evaluated the estimation of two biosignals—heart rate (HR) and skin conductance (SC)—and the classification of pulse level (high pulse; HP; low pulse; LP). We show that vocal expressions can be applicable to any speaker rather than a specific individual, and voice analysis can provide new methods, tools, and techniques to automatically recognize the states, traits, and qualities embodied in the nonverbal aspects of human speech (1).

In summary, scale-free brainwave music, a musical representation of brainwave activity, may provide a new way to peer inside the “brain,” or provide a new emotional brain-computer interface, as described within the brain and may be applicable for monitoring brain states, for use as an emotional brain-computer interface, or as a method of clinical rehabilitation (such as music therapy). However, additional work is needed to fully elucidate its underpinnings.

References


Acknowledgments

This work was supported by the National Natural Science Foundation of China (81333032 and 91232725).

10-20 system of electrode placement, and digitized the recording using a sampling rate of 500 Hz. The impedance for all electrodes was kept below 5kΩ and all the data was then processed using a band-pass filter (1-10 kHz) online using software from Brain Products GmbH (Starnberg, Germany; brainproducts.com). The recorded EEG data was then analyzed offline and figures were created with Reference Electrode Standardization Technique (REST) software (http://www.neuro.ucc.ie/rest/). Participants gave informed consent before the experiment was conducted, in accordance with the established guidelines of the Ethics Committee of the School of Life Science and Technology at the University of Electronic Science and Technology of China.

We translated the brainwaves (EEGs) into music for both males and females. To do this, we used a specific software that converts the brainwaves into music. This software is called BrainWave Music. The music was created using a specific algorithm that takes into account the brainwaves and transforms them into music. The music was then played in a specific tone, which is called the “heart tone.” The heart tone is a specific sound that is used to stimulate the brain.
was comparable for both microphone types. Second, both types of recording conditions—sustained vowels and periodic recordings of a person’s breathing, pronunciation of words and sentences (with or without pauses)—were recorded with the same level of quality. Furthermore, the sample size was comparable for both microphone types. Second, the usage of sustained vowels and periodic recordings of a person’s breathing, pronunciation of words and sentences (with or without pauses)—was recorded with the same level of quality. Furthermore, the sample size was comparable for both microphone types.

Acknowledgments

The work was supported by the European Union’s Horizon 2020 research and innovation programme under grant agreement 643378 [Artificial Retrieval of Information Assistants—Virtual Agents (ARI)] within the framework of the 3rd Transnational Meeting of the ARI project.

References


In summary, our studies have found that audio-based recognition has the potential to be used as a software application on mobile devices and computers for remote monitoring of HR and SC. One advantage of using such audio recordings is that analyses could be performed in an automated fashion. In contrast, using past recordings to investigate a patient’s history and their condition’s evolution over the period that preceded diagnosis and treatment. If the technology is further improved, it could be used for passive, noncontact monitoring of patients, which would require minimum attendance by its user and improve the quality of life for many people.

Evaluability: Predicting psychological profiles using Internet behavior

Nan Zhao1, Ang Li2, Tianli Liu3, Qingxin Zhao4, Baobin Li1, Tingshao Zhu2*

The validity of psychological studies depends on the quality of the behavioral, physiological, and biological data collection. Traditionally, such data has been collected through laboratory experiments, whereby experimental parameters are rigorously controlled, yet require intrusive and sometimes invasive methods (1). In contrast, the recent rise in the discipline of psychological research maintains that such data is subject to inaccuracies, and proposes to collect data in real-world settings. In the past, acquiring data in “real life” has been difficult and ineffective. However, rapid developments in information technology have brought about profound changes in data collection. The data collection now enables collection of real-life data efficiently in several complementary ways. First, data can be collected through the use of Web 2.0 technologies, such as social networking sites, blogs, and other types of social media have achieved global popularity and use. Users’ personal profiles, self-expression, and daily communication can be recorded automatically (2). Second, the popularity of mobile devices, such as smartphones and tablets, makes it possible to integrate data with the location and time signatures of users (3). Through installed apps, mobile devices can record a high level of detail on the behavioral and physical data of the users. A behavior profile can be constructed from different settings and situations encompassing their daily lives. Third, wearable devices, such as smartwatches, and bracelets, are now the subject of constant use. Their mental profiles, which can be used for training prediction models. Meanwhile, they can also be put into deep learning models (a set of machine learning models for high-level abstraction of data) to construct deep learning feature matrices. Such features can also be used for training prediction models. After feature extraction, methods such as stepwise regression can be employed for feature selection. To differentiate between groups with higher and lower scores on various personality traits or on the risk of suicide, we used algorithms such as support vector machine (SVM), simple logistic regression (SLR), and Random Forests.
Forest (RF) to build classification models. For predicting continuous variables, such as scores on personality and subjective well-being, we used regression models. In this study, we achieved good accuracy on the Big Five personality traits, and for depression, interaction questionnaire scores, generally reached a medium to high level (0.48-0.60) (4, 7). We also implemented our strategy using data acquired from Tencent, another well-known social network similar to Facebook and widely used by Chinese students, and found the accuracy of predicting the individuals’ Big Five personality traits was comparable with the Weibo data (10).

Predicting individual profiles using smartphone behaviors
To predict users’ mental profiles based on their behaviors or mobile devices, we employed an Android app called MobileSens, which records mobile behaviors and uploads the data to our server. Using this data, we conducted studies to predict psychological profiles for the Big Five personality traits, and for depression, interaction anxiety, loneliness, and subjective well-being (11, 12). These categories of behavioral features were extracted from original usage logs to train computational models. Those features included the frequency of use of (1) basic smartphone functions, such as dialing, texting, and GPS; (2) the most popular social apps, such as QQ, WeChat, and Sina Weibo; and (3) different categories of apps, such as communication, games, and health. We used a stepwise regression for feature selection and pace regression for training models. For agreeableness, extraversion, openness, subjective well-being, depression, and loneliness, we observed a moderate correlation (0.30–0.48) between predicted scores and questionnaire scores; and the correlation coefficients were higher for females than males for nearly all of the measured psychological indices.

Predicting individual profiles using body movements
Smart bands have become a popular wearable device. Most contain a built-in three-axis accelerometer, which can precisely record the movements of the body part where it was worn, usually the wrist. There is evidence that an individual’s emotional state can be reflected in one’s own gait (13), therefore body movement data acquired from the acceleration sensor of a smart band can potentially be used to monitor the user’s emotional state. We conducted a series of studies analyzing body movement data from Kinect 3D cameras, smartphones with built-in acceleration sensors attached to the wrist and ankle, and smart bands. Participants’ body movements were recorded by the three devices while walking under conditions that induced positive or negative emotional effects. We built computational models to classify emotional states as positive or negative using the features extracted from the body movement data. Our preliminary results indicated that the predictive accuracy of the models was above 70%.

Predicting public profiles using social media behaviors
Social media provides an efficient way to detect public attitudes and thoughts because of its access to a large number of users. Understanding such trends is a potentially potent, albeit controversial, tool for defining public policy. Traditionally, conducting a questionnaire survey with a large number of respondents has been the preferred way of measuring public attitudes. However, public opinion polling is time consuming and costly, and it cannot monitor changes in public attitudes in real time. In contrast, information gained from studying social media can more directly and powerfully reflect public attitudes.

Whereas direct statistics on social media parameters are already in place to profile changes in public attitudes (14), we have refined this concept with more elegant computational approaches. Using the techniques we previously used to predict individuals’ psychological profiles, we have developed methods to perceive public attitudes through a large sample of Weibo behaviors (15). In this study, Weibo users from targeted regions were recruited and asked to complete a social attitude questionnaire about social stability in modern China (16). We performed the extraction and selection of Weibo features using the same methods as the individual mental profile predictions. We used algorithms such as multilabel learning and incremental-regression to train the prediction models. Based on this analysis, the average predictive accuracy for each aspect of social attitude was approximately 85%. Since Weibo behavior records are traceable, we can further divide Weibo data into time slices to acquire longitudinal data. More importantly, since Weibo data is continuously updated, it is feasible to track trends in public social attitudes in real time. Thus our trained model can be used for a larger segment of Weibo users to obtain profiles for an even larger proportion of the population. Such prediction could be an important reference for indicating the public social attitudes in the real world.

In summary, our work has shown the potential of using information technology and computational methods—such as feature extraction and machine learning—for obtaining and processing large quantities of real-life data from social media, mobile devices, and wearable devices. This Internet-mediated data can be used to predict the psychological profiles of individuals and the public.
Depression risk prediction: Research and development using multimodal biological and psychological information

Program description
The National Basic Research Program of China (973 Program) focuses on innovative theories and technologies for the risk prediction of depression and rapid intervention. It incorporates the latest advances in psychology, information science, cognitive science, and biomedical engineering. This project explores not only state-of-the-art biosensor, multimodal data mining, and modeling technologies, but also investigates evolutionary mechanisms correlating biological and psychological traits with depression. Further, we are developing prototype systems to verify the veracity and efficacy of the research findings.

Participating institutions
- Institute of Psychology, Chinese Academy of Sciences
- Institute of Electronics, Chinese Academy of Sciences
- Capital Medical University
- Beijing University of Technology
- Huazhong University of Science and Technology
- Tianjin University
- Shenzhen University

Contact: Bin Hu; bh@szu.edu.cn

For more information: www.szu.edu.cn

Institute of Affective and Social Neuroscience
Shenzhen University

The Institute of Affective and Social Neuroscience at Shenzhen University was established in June 2013. In May 2014, the Center for Social Science and Cognitive Sciences was inaugurated, with Yue-Jia Luo serving as the director of both the institute and the center. The institute’s goals are: to investigate mood disorders using techniques of adaptive neurofeedback. If interested in applying for a position, please e-mail: jiacu.zhang@bnu.edu.cn.

For more information: cist.bnu.edu.cn

Institutional Research Laboratory
Beijing Normal University

The Information Processing Laboratory is located on the Beijing Normal University campus and managed by the university. The laboratory merges talented researchers from brain imaging and neuro-psychology research areas with neuroscience and neuro-psychology researchers. The lab's research focus is on neuro-information processing and its application for brain-computer interfaces, neural decoding, neurofeedback, and mental health and disease.

Since 2005, the laboratory has shown great success in scientific research and has acquired about 20 influential projects, such as the "986" High-tech projects and various projects supported by the National Science Foundation of China (NSFC) and the Beijing National Natural Science Foundation (BNNSF). The laboratory focuses on researching the underlying neural mechanisms and constructing computational models for the perception, emotion, and processing of critical information. More specifically, the laboratory extends the neural coding/decoding model of visual information from 2D to 3D environments and aims to map the relationship between 3D environments and neural activity in the human brain.

For more information: www.szu.edu.cn

Lab of Neural Engineering
Tsinghua University

The Lab of Neural Engineering was established in 2004 in the Department of Biomedical Engineering, School of Medicine, Tsinghua University. Neural engineering merges both the information from the human brain and peripheral nerve system with the knowledge in information sciences, neuroscience and biophysics. The mission of the lab is to develop new approaches in the study of neuroscience research investigating the mechanisms underlying neurological disorders and for developing clinical interventions.

Brain-computer interaction (BCI) is one of the major research areas in the lab. BCI is a direct interface pathway between the brain and an external device and has potential applications for neural rehabilitation (assisting, augmenting, or repairing neural functions in humans) and for the study of brain function and cognition.

Several novel EEG-based BCIs have been developed in the lab, including visual evoked potentials (VEP) and auditory evoked potentials (AEP) based systems. The newly developed BCI speller, based on steady-state visual evoked potentials (SSVEPs), shows an extremely high information transfer rate. With mature neural signal processing algorithms and the self-developed EEG data acquisition systems, BCI systems are beginning to approach practical applications step-by-step.

Moreover, the lab’s research also focuses on neural spike and electrocorticogram (ECoG) signal processing for brain function analysis, neural feedback effects on neural rehabilitation training, and the role of attention/emotion in cognitive function analysis.

For more information: www.med.tsinghua.edu.cn

Pervasive Computing Research Center
Chinese Academy of Sciences

The Pervasive Computing Research Center (PCRC), established in 2008, belongs to Institute of Computing Technology (ICT), Chinese Academy of Sciences. ICT is the first academic establishment in China to specialize in comprehensive research on computer science and technology in China. The PCRC carries on advanced research in pervasive computing, human-computer interaction, wearable computing, and e-health applications.

In the 21st Century, the world faces a unique challenge: global aging. In recent years, PCRC’s research, mainly on ambient-assisted living (AAL), has helped provide people with longer and healthier lives. Many national projects have been undertaken, including research on: unobtrusive, context-aware technologies for e-health applications; understanding and modeling human behavior; and a multitude of applications for monitoring devices, sensors, and other related innovations. PCRC has close collaborations with renowned scientists at universities around the world, including Princeton University, Hong Kong University of Science and Technology, Nanyang Technological University, Dartmouth College, Williams and Mary, and the University of Arizona, and at several well-known hospitals in China.

Today, there are 21 faculty members and more than 70 Ph.D. and Master’s degree students in PCRC. The director, Professor Yiqiang Chen, is also the deputy director of the Beijing Key Laboratory of Mobile Computing and Pervasive Devices. He created the Chinese Sign Language Synthesis System, which has been used in 1,000 middle schools for the hearing impaired in China, in the 2008 Beijing Olympic Games, and in the 2010 Shanghai World Expo. He received the National Science and Technology Award (second level) in 2004 and was selected as the New Star Scientist of Beijing in 2005.

For more information: english.ict.ac.cn
Life assistant
Health data collection
Activity monitoring
Health trend analysis
Expert supervision
Emergency rescue
All in jWotch

We take care of your health with jWotch

Advance your career with expert advice from Science Careers.

Download Free Career Advice Booklets!
ScienceCareers.org/booklets

Featured Topics:
- Networking
- Industry or Academia
- Job Searching
- Non-Bench Careers
- And More
Read about EGI’s new high-definition GTEN neuromodulation technology!

— in this supplement and at www.egi.com

Complete integrated neurophysiology systems

from Electrical Geodesics, Inc.

- EEG systems with up to 290 channels
- software for electrical source imaging
- multimodal imaging with MR, MEG, NIRS, and TMS
- stimulus presentation and eye tracking

www.egi.com • info@egi.com