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EEG-based Real-time Dynamic Neuroimaging

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Abstract—**In the present paper, an electroencephalography (EEG)-based real-time dynamic neuroimaging system, which was recently developed by the authors, is introduced and its potential applications are presented. The real-time system could monitor spatiotemporal changes of cortical rhythmic activity on a subject's cortical surface, not on the subject's scalp surface, with a high temporal resolution. The developed system can be potentially applied to various practical applications such as neurofeedback based motor imagery training, real-time diagnosis of psychiatric brain diseases, online monitoring of EEG experiments, and neurorehabilitation, of which some examples are presented herein.**

I. Introduction

RECENTLY, an increasing number of neuroscientists are becoming interested in the cortical rhythmic activity since various *in-vivo* studies in both humans and animals have revealed that cortical rhythmic activity at various frequencies might be closely related to information encoding in brain [1-7]. For instance, cortical rhythmic activity might reflect specific body movements and behavioral states. The alpha rhythm peaking at around 10 Hz becomes strongest when the subject has his eyes closed and is suppressed when the subject is exposed to visual stimuli [1]. The mu rhythm, with both 10 Hz and 20 Hz components, is dampened by limb movements or tactile stimulations [2]. It has been also revealed by numerous studies [3-5] that gamma-band activity (30 – 100 Hz) can be modulated by various behavioral states such as attention, working memory, and associative memory. Moreover, changes of cortical rhythmic activity are believed to be involved in various brain diseases such as schizophrenia [6] and Alzheimer's disease [7].

EEG and MEG are excellent tools to investigate the human cortical rhythmic activity noninvasively thanks to their superior temporal resolutions to the other noninvasive brain mapping techniques such as functional magnetic resonance imaging (fMRI), positron emission tomography (PET), near infra-red spectroscopy (NIRS), and so on. Many studies have been performed to evaluate coherence between signals acquired at different scalp EEG electrodes or MEG sensors, and investigate spatial signal power patterns appearing in the scalp potential maps or magnetic field maps on the sensor plane [1–7]. However, the EEG or MEG topographies cannot be directly attributed to the underlying cortical regions since sensors may contain information from multiple brain sources, some of which might overlap, and the topographic maps might be distorted due to the inhomogeneous conductivity distributions in the human head. A deep tangential source might generate two distinct peaks on the topographic map, which are hard to be distinguished from two radial sources around the peak locations. Moreover, a very small cortical activation in some cortical areas could yield widespread field distribution in the topographic maps, preventing one from identifying correct location of the actual cortical source and investigating coherence between different sensors. Therefore, to overcome these limitations, source imaging of rhythmic activity at the cortical level is necessary.

In the previous study of our research group, we introduced a real-time cortical rhythmic activity monitoring system, which we call a real-time dynamic neuroimaging system hereafter [8]. The real-time dynamic neuroimaging system could visualize spatiotemporal changes of cortical rhythmic activity of a specific frequency band on a subject's cortical surface, rather than the subject's scalp surface, with a high temporal resolution. More recently, it was successfully applied to a motor imagery training system that can help individuals easily get the feel of motor imagery tasks [9].

In the present article, we first review the concepts of the real-time dynamic neuroimaging system briefly, and then present its potential applications with some examples.

II. EEG-based Real-time Dynamic Neuroimaging

An EEG-based real-time dynamic neuroimaging system [8] consisted of pre-processing and real-time processing parts. In the pre-processing part, a linear inverse operator was constructed in which the subject's anatomical information was reflected. Once the linear inverse operator had been constructed and saved to a data-storage unit, spatiotemporal changes of cortical rhythmic activities were monitored in real-time by means of a unified processing scheme consisting of three independent programs: an FFT program, a frequency domain minimum norm estimation (FD-MNE) solver [8], and a 3D visualization program, which were executed sequentially at each time slice.

To reconstruct the cortically distributed brain sources, we used a linear estimation approach. The expression for the inverse operator $\mathbf{W}$ is

$$\mathbf{W} = \mathbf{R}\mathbf{A}^{\mathrm{T}} (\mathbf{A}\mathbf{R}\mathbf{A}^{\mathrm{T}} + \lambda^2 \mathbf{C})^{-1}, \qquad (1)$$

where $\mathbf{A}$ is a lead field matrix, $\mathbf{R}$ is a source covariance matrix, and $\mathbf{C}$ is a noise covariance matrix. Once a specific frequency

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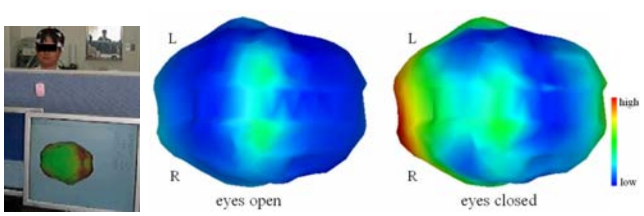
band is determined, the FFT program calculates real and imaginary components at all discrete frequencies within the predetermined frequency band. Then, the FD-MNE solver is executed and load the Fourier transformed signals $\mathbf{B}(f_i)_{Re}$ and $\mathbf{B}(f_i)_{Im}$, i = 1, 2, …, n, where *Re* and *Im* represent real and imaginary part of the Fourier transformed signals, respectively, as well as the pre-saved inverse operator **W**. The real part $\mathbf{q}_j(f_i)_{Re}$ and imaginary part $\mathbf{q}_j(f_i)_{Im}$ of the current source vector at j-th cortical vertex with respect to the frequency of interest f_i can then be evaluated by multiplying the corresponding rows (3j-2, 3j-1, and 3jth rows) in **W** with the Fourier transformed signals $\mathbf{B}(f_i)_{Re}$ and $\mathbf{B}(f_i)_{Im}$. Finally, the absolute current source power at j-th cortical vertex with respect to the frequency band of interest is calculated as

$$\boldsymbol{Q}_j = \frac{1}{2n}\sum_{i=1}^{n}(\|\mathbf{q}_j(f_i)_{Re}\|^2 + \|\mathbf{q}_j(f_i)_{Im}\|^2) \qquad (3)$$

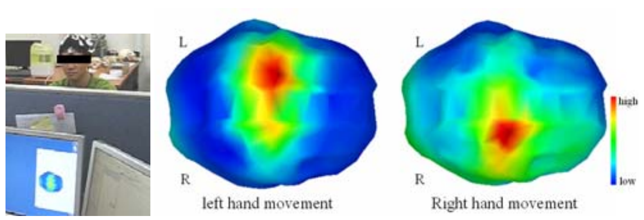
After the current source power at every cortical vertex is calculated, a 3D visualization program is executed and visualizes the resultant source distribution at a given frequency band.

In the earliest pilot system reported in [8], the cortical activation maps could be visualized with a maximal delay time of 200 ms, when 18 channel EEG data are analyzed under Pentium4 3.4GHz environment. Thanks to the rapid development of computer systems and our team's efforts, the delay time is now reduced to be less than 100 ms (90 EEG electrodes are assumed, Intel Core2-6300 1.86 GHz).

Figs. 1(a) and 1(b) show the cortical alpha (8-13 Hz) activity changes when a subject (YJ, male, age 26) opened and closed his eyes and the cortical mu (8-12 Hz) activity changes when a subject (JJ, male, age 23) raised his left and right hand, respectively (experimental conditions: 16 EEG electrodes, 256 Hz sampling rate, FFT for 128 data samples, 4 image frames per second).



(a)



(b)

Fig. 1. Examples of our preliminary experiments: (a) cortical alpha activity imaging; (b) cortical mu activity imaging (modified from [8]).

III. Applications of Real-time Neuroimaging

A. A Motor Imagery Training System for BCI

Brain activities modulated by motor imagery of either the left or right hand are regarded as good features for brain-computer interfaces (BCIs), because such activities are readily reproducible and show consistent EEG patterns on the sensorimotor cortical areas [10, 11] Moreover, thanks to the contralateral localization of the oscillatory activity, the activities evoked from left and right hand motor imagery are, comparatively, readily discriminated [12]. However, many individuals have difficulty in getting used to the feel of motor imagery, since most people do not easily recognize how they can have a concrete feeling of motor imagery and tend to imagine the images of moving their hands or legs instead [13]. Therefore, one of the challenging issues in the EEG-based BCI studies has been how one can efficiently train individuals to perform motor imagery tasks.

In our recent study [9], we proposed a neurofeedback-based motor imagery training system for EEG-based BCI, based on the real-time dynamic neuroimaging. The proposed system could help individuals get the feel of motor imagery by presenting them with real-time brain activation maps on their cortex. Ten healthy participants took part in our experiment, half of whom were trained by the suggested training system and the others did not use any training. All participants in the trained group succeeded in performing motor imagery after a series of trials to activate their motor cortex without any physical movements of their limbs. To confirm the effect of the suggested system, we recorded EEG signals for the trained group around sensorimotor cortex while they were imagining either left or right hand movements according to our experimental design, before and after the motor imagery training. For the control group, we also recorded EEG signals twice without any training sessions. The participants' intentions were then classified using a time-frequency analysis technique, and the results of the trained group showed significant differences in the sensorimotor rhythms between the signals recorded before and after training. Classification accuracy was also enhanced considerably in all participants after motor imagery training (from 58.8% to 71.4%), compared to the accuracy before training. On the other hand, the analysis results for the control EEG data set did not show consistent increment in both the number of meaningful time-frequency combinations and the classification accuracy, demonstrating that the suggested system can be used as a tool for training motor imagery tasks in BCI applications.

Fig. 2 shows the screenshots of real-time cortical mu-rhythm activity monitoring, taken while a subject (EK, male, age 23) was attempting to generate cortical activations around his sensorimotor cortex by imagining his left or right hand movement (supplementary movie is also included in the article [9], experimental conditions: 16 EEG electrodes, 256 Hz sampling rate, 4 image frames per second).

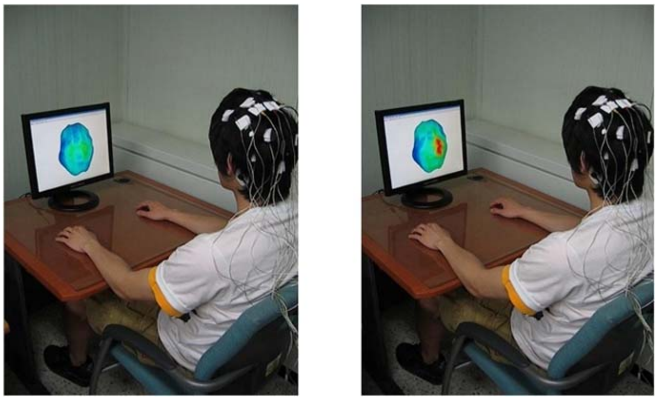


Fig. 2. Screenshots of real-time cortical mu-rhythm activity (8-12 Hz) monitoring (adapted from [9]): Cortical activation maps at rest state (left) and when the participant was performing motor imagery (right).

B. Real-time Cortical Functional Connectivity Monitoring

Based on the real-time dynamic neuroimaging system, we recently developed a real-time cortical functional connectivity monitoring system, which can monitor and trace temporal changes of cortical connectivity between different regions of interest (ROIs) on the subject's cortical surface. To verify the implemented system, we monitored the changes of cortical functional connectivity patterns while presenting three subjects with images of various human faces. We quantified the changes of the number of meaningful connections of which the phase difference between two ROIs is less than a threshold value (empirically determined in this pilot study).

Fig. 3 shows the screenshot of the experiment and the operating software. 100 facial images of famous Koreans were randomly presented to three male volunteers (ages 22, 24, and 26, experimental conditions: 32 EEG electrodes, 256 Hz sampling rate, 5 updates per second) and the number of the functional connectivity connections was counted at each time slice. 12 ROIs were manually assigned on the inflated cortical surface (see Fig. 4a) and the phase difference between each pair of ROIs was evaluated at the frequency of 30 Hz. Figs. 4(a) and 4(b) show the distribution of ROIs and the cortical connectivity patterns before and after presenting the pictures, respectively, which were captured during the online experiment. The average number of the connectivity connections during 1s after presenting the face images was 3.5, 4.5, and 4.8 times more than that of the connectivity connections during 1s before presenting the images. Since the gamma band phase synchronization between different brain areas during the processing of facial structure was significantly reduced in most schizophrenia patients, according to our previous study [14], we are expecting that this new system can possibly be used to the real-time diagnosis of schizophrenia or Alzheimer's disease, after conducting more clinical examinations.

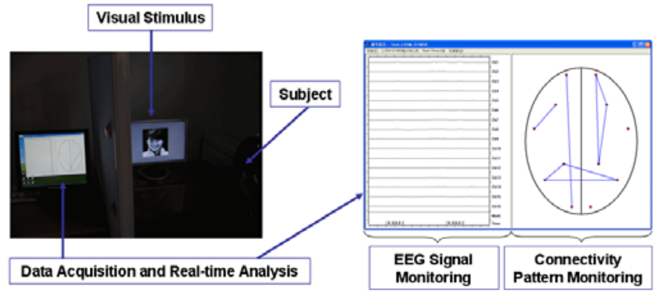
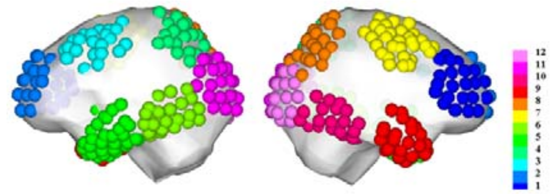
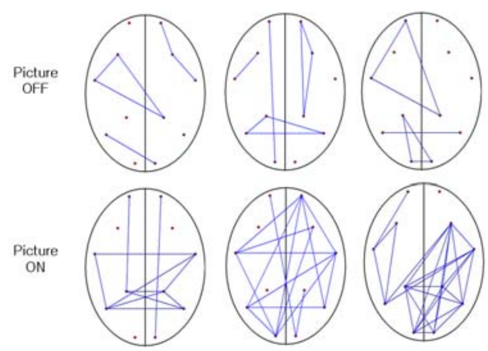


Fig. 3. A real-time cortical functional connectivity monitoring system: Experimental environment (left) and operating software (right). 100 grayscale face images were randomly presented to the volunteered subjects.



(a)



(b)

Fig. 4. An example of real-time cortical functional connectivity monitoring: (a) distribution of ROIs (sets of colored dots represent each ROI); (b) the cortical connectivity patterns before (upper three figures) and after (lower three figures) presenting the facial images.

C. Other Potential Applications

Currently, we are attempting to apply the real-time neuroimaging system to other potential applications.

The developed system can be potentially used in some neurorehabilitation applications. For example, stroke patients who need rehabilitative training for motor recovery of his paralyzed right upper limb tend to move his normal side (i.e. left upper limb) during the training processes, generally decreasing the training efficiency. Since the mu-rhythm activity on the patients' motor cortex can be monitored using our real-time system, the trainer can provide them with an appropriate instruction immediately. Fig. 5 shows an example of mu-rhythm activation changes on a subject's motor cortex (KS, male, age 23) recorded while he was moving his left and right hand by turns (experimental conditions: 32 EEG electrodes, 256 Hz sampling rate, 5 image frames per second). We are expecting that our system can also be used to quantify the degree of motor recovery after the rehabilitative training. We hope that we can present clinical results at the conference.

The real-time neuroimaging system can also be used for online monitoring of EEG experiments regarding various cognitive and functional brain studies. The experimenter can modify the experimental protocols without stopping the on-going measurement with the aid of our system. For example, the experimenter can monitor if the subject falls into a doze, simply watching the cortical alpha activation changes (e.g. see Fig. 6).

Another possible application of the real-time cortical activation monitoring system is the EEG-based brain computer interface (BCI) system. Although such a system has not been realized yet, offline simulation studies demonstrated that the use of inverse solutions can enhance the classification capability of the EEG-based BCI system [15].

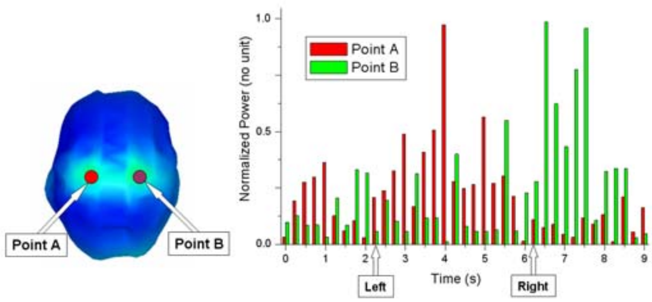


Fig. 5. Mu-rhythm activation changes on a subject's motor cortex recorded while he was moving his left and right hand by turns.

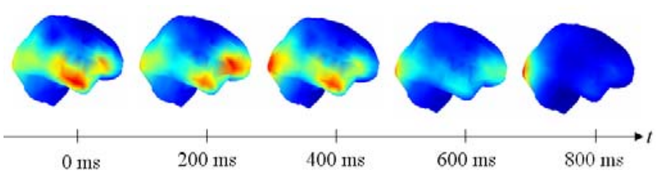


Fig. 6. An example of sequential cortical source images (5 frames per second) acquired during an EEG experiment.

IV. Conclusions

In the present article, an EEG-based real-time dynamic neuroimaging system, which can monitor spatiotemporal changes of cortical rhythmic activity on a subject's cortical surface, was introduced. The developed real-time dynamic neuroimaging system was applied to some applications such as neurofeedback based motor imagery training, cortical functional connectivity monitoring, neurorehabilitation, etc.

References

[1] S. Salenius, M. Kajola, W. L. Thompson, S. Kosslyn, and R. Hari, "Reactivity of magnetic parieto-occipital alpha rhythm during visual imagery," *Electroencephalogr. Clin. Neurophysiol.,* vol. 95, pp. 453-462, 1995.

[2] R. Salmelin, and R. Hari, "Spatiotemporal characteristics of sensorimotor neuromagnetic rhythms related to thumb movement," *Neuroscience,* vol. 60, pp. 537-550, 1994a.

[3] T. Gruber, M. M. Muller, A. Keil, and T. Elbert, "Selective visual-spatial attention alters induced gamma band responses in the human," *EEG. Clin. Neurophysiol.,* vol. 110, pp. 2074-2085, 1999.

[4] J. Kaiser, B. Ripper, N. Birbaumer, and W. Lutzenberger, "Dynamics of gamma-band activity in human magnetoencephalogram during auditory pattern working memory," *NeuroImage,* vol. 20, pp. 816-827, 2003.

[5] W. H. Miltner, C. Braun, M. Arnold, H. Witte, and E. Taub, "Coherence of gamma-band EEG activity as a basis for associative learning," *Nature*, vol. 397, pp. 434-436, 1999.

[6] J. S. Kwon, B. F. O'Donnell, G. V. Wallenstein, W. Greene, Y. Hirayasu, P. G. Nestor, M. E. Hasselmo, G. F. Potts, M. E. Shenton, and R. W. McCarley, "Gamma frequency-range abnormalities to auditory stimulation in schizophrenia," *Arch. Gen. Psychiatry,* vol. 56, pp. 1001-1005, 1999.

[7] D. Osipova, J. Ahveninen, O, Jensen, A. Ylikoski, and E. Pekkonen, "Altered generation of spontaneous oscillations in Alzheimer's disease ," *NeuroImage,* vol. 27, pp. 835-841, 2005.

[8] C. H. Im, H. J. Hwang, H. Che, and S. Lee, "An EEG-based real-time cortical rhythmic activity monitoring system," *Physiol. Meas.*, vol. 28, pp. 1101-1113, 2007.

[9] H. J. Hwang, K. W. Kwon, and C. H. Im, "Neurofeedback-Based Motor Imagery Training for Brain-Computer Interface (BCI)," *J. Neurosci. Methods,* vol. 179, no. 1, pp. 150-156, 2009.

[10] P. Hollinger, R. Beisteiner, W. Lang, G. Lindinger, A. Berthoz, "Mental representations of movements. Brain potentials associated with imagination of eye movements," Clin. Neurophysiol., vol. 110, pp. 799-805, 1999.

[11] G. Pfurtscheller, C. Neuper, "Motor imagery activates primary sensorimotor area in humans," *Neurosci. Lett.*, vol. 239, pp. 65-68, 1997.

[12] N. F. Ince, S. Arica, A. Tewfik, "Classification of single trial motor imagery EEG recordings with subject adapted non-dyadic arbitrary time-frequency tilings," *J. Neural. Eng.*, vol. 3, pp. 235-244, 2006.

[13] C. Neuper, R. Scherer, M. Reiner, G. Pfurtscheller, "Imagery of motor actions: Differential effects of kinesthetic and visual-motor mode of imagery in single-trial EEG," *Cognit. Brain Res.*, vol. 25, pp. 668-677, 2005.

[14] S. H. Lee, E. Y. Kim, S. R. Kim, Y. M. Park, H. Che, and C. H. Im, "Dysfunctional gamma activity during the processing of facial structure in schizophrenia patients, " *Eur. Neuropsychopharmacol.*, vol. 18, pp. S475-S476, 2008.

[15] B. Kamousi, A. N. Amini, and B. He, "Classification of Motor Imagery by Means of Cortical Current Density Estimation and Von Neumann Entropy for Brain-Computer Interface Applications," *J. Neural Eng.*, vol. 4, pp. 17-25, 2007.