Motion and Single-trial Biosignal Analysis Platform for Monitoring of Rehabilitation

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Abstract. Three-dimensional motion analysis is a powerful tool for the assessment of human movements during different rehabilitation applications. An adaptive virtual reality rehabilitation environment which is based on modern motion and biosignal analysis techniques is described.

1 Introduction

Noninvasive brain computer interface (BCI) has in the recent years become a highly active research topic in neuroscience, engineering and signal processing. BCIs utilize neurophysiological signals to interact with external devices and computers. Despite diverse applications that BCI technologies promise, the general methodology may open new opportunities for clinical rehabilitation, for example, by training patients with movement disabilities to control abnormal activity in selected brain regions.

Stroke can affect physical, mental and social functions. Disability or paralysis is often affected only to one hemisphere, e.g. movements of one hand can be impaired while the other hand remains intact. Some stroke survivors exhibit poor control of movement smoothness [1], and movements seem to grow more smooth with recovery [2]. In monitoring of rehabilitation of stroke patients, objective evaluation methods are required. Furthermore, evaluation of the effectiveness of rehabilitation is also crucial. However, at present monitoring can only be based on qualitative measures, such as visual interpreting of movements during specific tasks.

Three-dimensional motion analysis techniques can be a powerful and objective tool for the assessment of human movements and it can be used to monitor rehabilitation progress. With an adaptive task setting customized to individual patient's needs and performances, motion analysis can give valuable quantitative information. Additionally, combining 3D motion analysis techniques with neurophysiological signals could provide feedback for adaptive rehabilitation tasks, thus further improving the effectiveness of the whole process. In this paper, a virtual, adaptive and controllable rehabilitation environment which uses modern motion and biosignal analysis techniques in parallel is described.

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2 Multimodal Platform

Human motion, and thereby, performance in a specific rehabilitation task can be tracked by using motion analysis methods. The physiological or neurophysiological status of the patient, on the other hand, can be estimated from different biosignals acquired during the rehabilitation task. By combining these modalities, a multimodal platform for monitoring of rehabilitation can be constructed.

2.1 Motion and Performance Tracking

Motion analysis methods have been widely used to measure and model human movements. Biomechanics can be considered as the base of modern motion analysis, which aims for modeling of human body as a mechanical composition of joints and rigid segments [3]. Motion analysis can be considered to consist of three components: kinematics, kinesiological electromyography (EMG) and kinetics. Kinematics examines the motion of body segments from geometric point of view without paying attention to forces producing the movements, whereas kinetics interlinks forces and movements produced by the forces [4, 5].

In human body modeling, the body is modeled as joints and bones, and in more sophisticated models, also muscles and ligaments are included in the model. The kinematic 3D human body model describes the translational motion and orientation of different body parts. By using the model various parameters such as velocities and accelerations of body segments or joint angles can be derived for further analysis.

The most advanced methods in motion analysis, which can be used for modeling of movements of the whole human body, are based on photogrammetric methods [6]. The camera technology has advanced during last years. Cameras utilizing FireWire or Ethernet interface are nowadays available at a reasonable price. Photogrammetry can be defined as measurement of three-dimensional objects geometry through two-dimensional images. In motion analysis the photogrammetric methods are utilized for determining the temporal positions and orientations of body segments with help of markers attached on the body. When the three-dimensional point of interest, e.g. a marker, is observed simultaneously with at least two calibrated cameras, the 3D-coordinates of the point can be solved.

We have developed and built a flexible mobile motion analysis laboratory which consists of multiple high speed cameras, image processing system, biosignal and inertial sensor measurement system and pressure insoles. The setup is suited for various research projects as well as development of methods applied in motion analysis. As an example, marker placements and marker trajectories for tracking of hand in rehabilitation task is shown in Fig. 1[7].

In many applications, motion tracking is performed in real time. This opens new possibilities for adaptive and interactive task settings, especially in virtual or augmented reality (VR or AR) applications.

2.2 Biosignal Analysis Platform for BCI Applications

Modeling brain's activity following environmental stimuli or in the context of dynamically changing tasks is crucial for better understanding the central nervous system

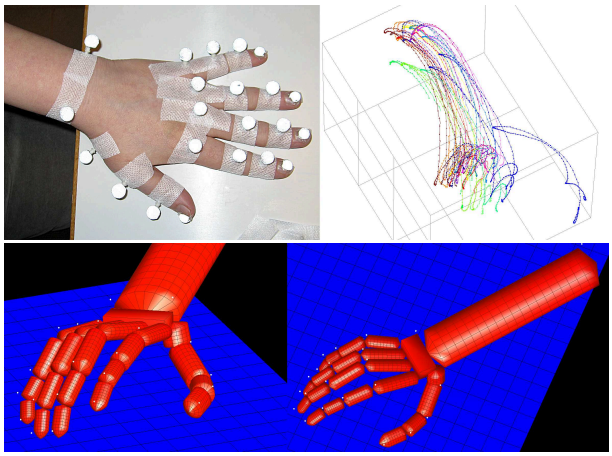

Fig. 1. The placement of retroreflective markers attached to hand and trajectories of markers reconstructed from a grabbing task. A reconstructed 3D-model of the hand [7].

(CNS). Ideally, methods for assessing brain's ability to interact with the environment should be computationally feasible, adaptive, and sensitive to cognitive changes. The ultimate goal is to make joint inference about the CNS dynamics based on complementary information from multimodal data sets [8], by conducting experiments focusing on adaptively changing cognitive tasks, such as time-varying workload and task difficulty. Furthermore, various autonomic nervous system signals such as heart rate (HR), blood pressure (BP) and galvanic skin response (GSR) are also important for phychophysiological modeling and monitoring.

Electroencephalogram (EEG) provides information about neural dynamics on a millisecond scale. EEG's ability to characterize certain cognitive states and to reveal pathological conditions is well documented. A significant advantage of single-trial EEG analysis is that cortical reactivity and function can be assessed with high-temporal resolution. However, the limited signal-to-noise ratio (SNR) of noninvasive brain signals, makes the detection of single-trial events a difficult estimation task. Traditional way of analyzing event related potentials (ERPs), or any other event-related biosignals, has been to use heavy averaging, and thereby loosing significant inter-trial variability. Recently, several methods for single-trial estimation of even related EEG have been proposed [9–13].

Functional magnetic resonance imaging (fMRI) is another noninvasive method for studying cognitive function by measuring the hemodynamic response related to neural activity in the brain. The blood oxygenation level dependent (BOLD) effect is used for determining where activity occurs in the brain. The relationship between stimulation, neural activation, and BOLD response has been studied since fMRI was introduced. However, it is still not yet thoroughly understood. It has been found that the shape of the BOLD response varies across subjects and also within subject depending on the type of the stimulus and active brain area. Recently, BCIs based on single-trial metabolic activity of the brain have been introduced, defining new opportunities in neu-

roscience research, for instance, for studying brain plasticity and functional reorganization following sustained training [14]. Furthermore, simultaneous acquisition of EEG and fMRI combined with single-trial analysis provides an additional monitoring tool for the investigation of brain state fluctuations [15].

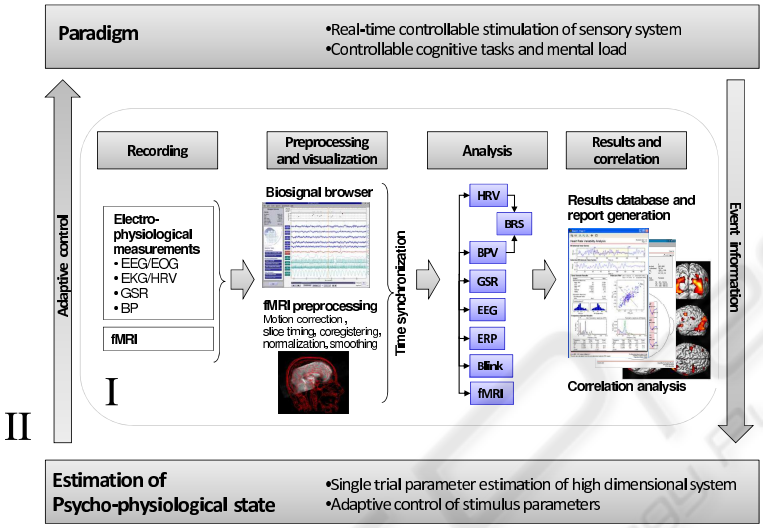

Fig. 2. A closed-loop biosignal analysis system for BCI based on adaptive stimulation.

An illustration of a biosignal acquisition and analysis system for BCI applications is given in Fig. 2. The system is operating in two phases, namely the signal acquisition and parameter estimation phase, and the feedback and adaptive control phase. During the first phase, all relevant signals are simultaneously recorded and synchronized in relation to various tasks. Individual signals are preprocessed simultaneously or separately, depending on the type of the signal and task, for accurate noise reduction. Then, features of interest are extracted for visualization, extra analysis, or classification. This procedure is performed by combining all information extracted from multimodal measurements with all available prior information in a Bayesian mathematical framework. In the second phase, event-related information is used to define and differentiate psychophysiological states of the subject and subject's performance. Finally, the extracted parameters are used as a feedback to the subject, for instance as a visual feedback providing a reward mechanism or within a virtual reality environment. Furthermore, the parameters can be directly used to adaptively change physical characteristics of the sensory stimulation, for instance, type, intensity and duration of the next stimulus, or even to control task difficulty for optimal subject's performance, thus providing an adaptive control mechanism.

Example 1: Dynamic Estimation of Event Related Potentials. An example of single-trial estimation of evoked potentials is given in Fig. 3. In this example, measurements

were obtained from an experiment with visual stimulation. A number of fixed intensity, fixed duration flash stimuli were predefined and sequentially delivered to the subject through a monitor. A decrease in amplitude of the dominant positive peak is clearly observed, suggesting possible habituation to the stereotypic stimuli. For this particular example, amplitude information can provide an indicator for the degree of habituation, and thereafter used to adaptively change the stimuli characteristics in real time with goal of forcing stable responses.

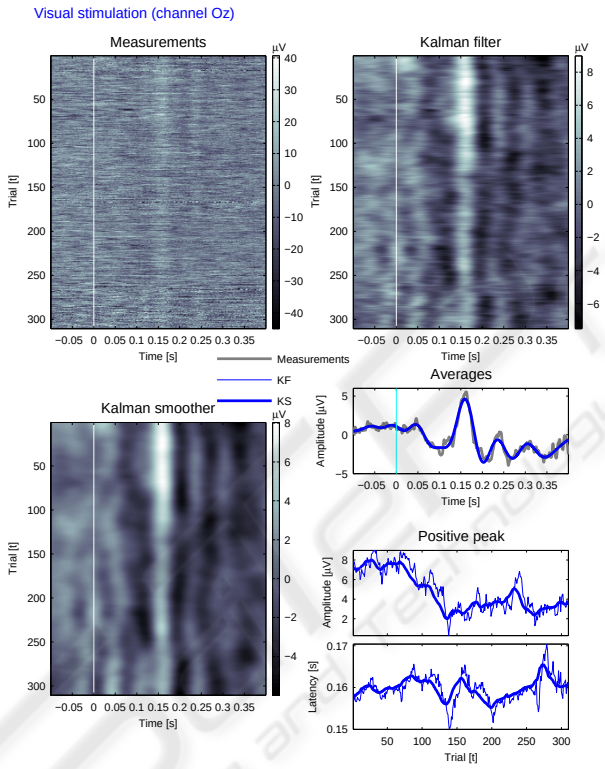

Fig. 3. Tracking single-trial characteristics (amplitude and latency) of evoked potentials during visual stimulation with a Kalman filter based approach.

Example 2: Single-trial Estimation of Multimodal Brain Responses. In simultaneous fMRI/EEG studies, the necessity of single-trial approaches is recognized. Single-trial EEG estimates are usually used as predictors for the voxel-wise activity. However, most of the approaches do not take into account variation in the latency or shape of the BOLD response. In Fig. 4, an example of single trial fMRI/EEG analysis is illustrated. A set of simultaneous fMRI and ERP measurements was acquired, and in the approach a joint model is defined and parameter estimates are obtained through subspace regularization [16].

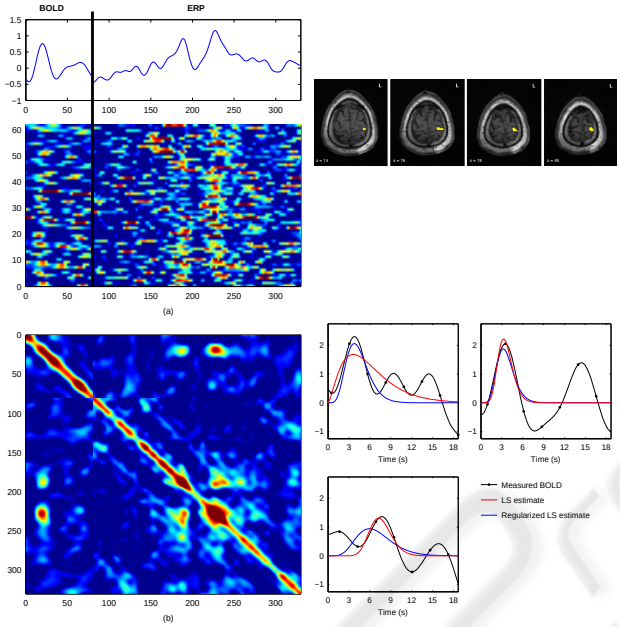

Fig. 4. Typical BOLD response estimates when reaction time locked ERP responses are used in the regularization. (a) Concatenated data of the 62 BOLD responses and ERPs from channel Cz (bottom) and mean of the data (top). The amplitudes of the data are arbitrary and x-scale is in points. (b) Correlation matrix of the concatenated data.

Example 3: Dynamic Estimation of Heart Rate Variability (HRV). HRV is a reliable quantitative marker of ANS activity. HRV is typically assessed with a group of time and frequency-domain methods. By using these methods, the activities of the sympathetic and parasympathetic branches of ANS can be evaluated, and thus, useful information of the (neuro)physiological state of the subject can be extracted. In Fig. 5, dynamic HRV analysis corresponding to a sudden change in physiology caused by an orthostatic test is shown. This example demonstrates how evident the changes in heart rate and also in HRV characteristics can be in case of a change in physiology.

3 Virtual Rehabilitation Environment

Three-dimensional motion analysis techniques can be a powerful and objective tool for the assessment of human movements and it can be used to monitor rehabilitation progress. With an adaptive task setting customized to individual patient's needs and performances, motion analysis can give valuable quantitative information. Combining 3D motion analysis techniques with neurophysiological signals could provide feedback for adaptive rehabilitation tasks, thus further improving the effectiveness of the whole process. In order to be practically applicable, such a system has to be highly automatized

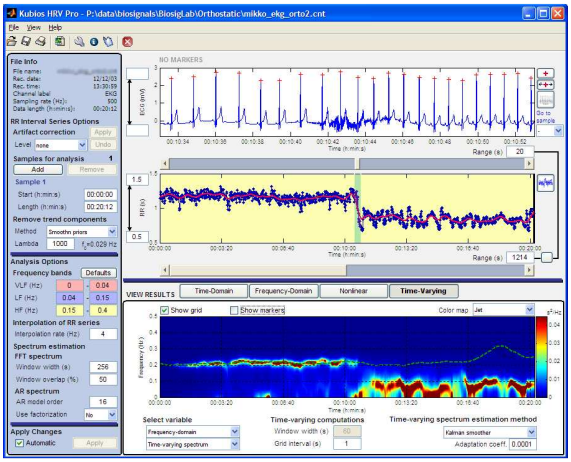

Fig. 5. Tracking changes in HRV spectrum during an orthostatic test (standup test). Screen-shot from Kubios HRV software [http://kubios.uku.fi].

and robust. Furthermore, a virtual reality environment (VRE) which can be applied to various rehabilitation tasks will extend the applicability and performance of the system.

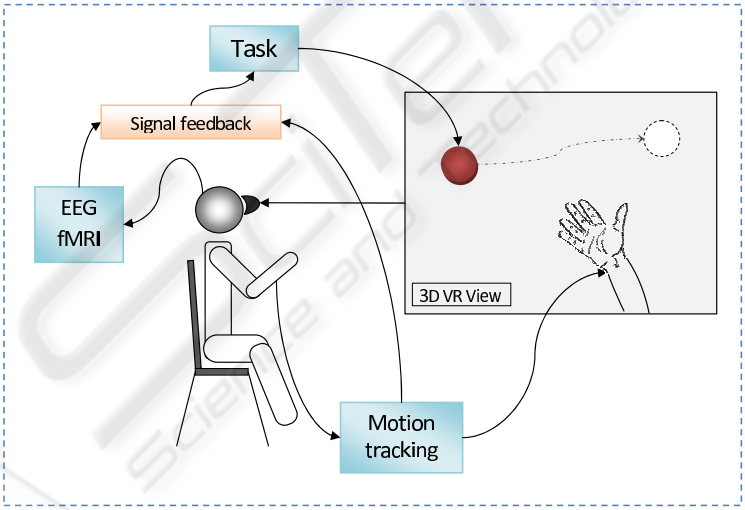

Fig. 6. Schematic diagram of virtual rehabilitation environment.

The main components of VRE are real time motion tracker, three-dimensional VR goggles and visualization engine, EEG and other biosignal measurement system and adaptive signal feedback driven task control system. An example of such a VRE is illustrated in Fig. 6. Such approaches, when utilized for rehabilitation or clinical appli-

cations, will enable more realistic and motivating tasks for patients. Finally, VR environments are easily controlled and patient safe, e.g. crosswalk simulation.

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