31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Human Performance Evaluation based on EEG Signal Analysis: A Prospective Review

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Abstract—**Electroencephalogram (EEG) signal, the signature of brain activity, can be used to quantify for human performance evaluation. There are ongoing efforts by scientists and researchers in this area. Different traditional and novel signal processing and analysis methods have been applied to evaluate performance, mental workload, and task engagement based on EEG signals. Linear change in the indices with the increase in task difficulty was reported. In addition, EEG index has been used as parameter for performance optimization. In this review article, we will discuss briefly the literature on human performance estimation based on some physiological parameters, EEG in particular. In this paper, the current state of the research field is presented and possible future research options are discussed.**

I. Introduction

Traditionally, human cognitive performances have been analyzed using questionnaires, i.e., by means of a qualitative approach. Early approaches of studies on human performance evaluation were mostly subjective and qualitative to measure workload [1]-[4]. However, recent studies mostly employed methods using some physiological parameters for objective and quantitative performance measurement [5]. The physiological parameters those are widely used are ECG (Electrocardiogram), EOG (Electrooculogram), Heart Rate, Eye blinking, and Heart Rate Variability (HRV). A more acceptable and accurate approach is quantitative analysis using Electroencephalogram (EEG, the brain electrical activity) signals by extracting indices and features from EEG signals. The later approach is more objective and provides quantitative measurement of human performance using EEG index. In this paper, we summarize these efforts and infer methods of analysis for future research.

Manuscript received April 23, 2009. This work was supported in part by the North Dakota NASA EPSCoR and the North Dakota Space Grant Consortium.

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EEG indices were reported higher in air traffic controllers which indicates workload impose to maintain high vigilance [6]-[8]. Valid estimates of cognitive responses are important to test new equipments and procedures in complex tasks, especially in aviation tasks as such air traffic control and flight control.

II. EEG Signal Acquisition and Preprocessing

A. Acquisition

EEG signal acquisitions are performed by traditional wired EEG acquisition system, as well as, wireless EEG headset. Electrode placements are mostly based on standard 10-20 system [8][11].

B. Preprocessing

Recorded raw EEG signals have amplitudes of the order of microvolts and contain frequency components up to 100 Hz. Hence, preprocessing is required which includes filtering, and artifact removals. Notch filter with 60 Hz cutoff frequency has been used to remove line noise. Different types of noise can affect EEG signals such as breathing frequencies, dc drift, and high frequency noise. Therefore, band pass filtering of 0.5 Hz – 70 Hz is usually performed to remove very low frequency components and high frequency noise. Quantization levels are usually 16 bits and sampling frequency of 500 Hz. Signal often undergo re-sampling of 250 Hz for data processing simplicity.

III. Feature Extraction and Classification

In traditional analysis, Fast Fourier Transform (FFT) and spectral analysis is widely used for feature extraction. Conventional methods involves computation of power spectral densities (PSD) of the EEG spectra in the theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-45 Hz) bands to analyze the changes in frequency characteristics [12]-[19]. This approach allows examining the changes in the ratio of specific frequency band such as alpha band changes with mental workload, stress and fatigue [12]. Cognitive changes with variation in task load are identified simply by investigating power of specific frequency band of recorded EEG signals. The analysis is usually performed epoch by epoch. However, in some cognitive assessment models, the amplitudes of the P300

978-1-4244-3296-7/09/$25.00 ©2009 IEEE

component of the event-related potential (ERP) have been used as an effective measure. Although the P300 component of ERP has been used, it has some limitations including need for stimulation into real-world tasks, and averaging of single trials over time across scalp sites [12]. Moreover, it takes long time to obtain an ERP waveform [19].

EEG signal change abruptly in a short period of time. Therefore, because of the nonstationarity nature of EEG signals, extracting features is not easy. It is unlikely to know how the frequency characteristics change for different epochs. Therefore, Short Time Fourier Transform (STFT) and/or wavelet transform methods are considered to be more efficient as these methods can analyze the signal in time-frequency domain whereas the standard Fourier transform can only localize in frequency [12]-[19]. In addition, wavelet analysis often provides better presentation of signals using multi-resolution analysis. For feature selection, the most widely used methods are Principal Component Analysis (PCA), Independent Component Analysis (ICA) and Mutual Information (MI).

In feature classification stage, the EEG PSD bands or ERP component measures are then used as inputs to classifier models to allow identification and classification of cognitive states such as attention, alertness, mental workload, fatigue, stress, task engagement, executive function, and verbal or spatial memory [10][17][19][21]. The linear and nonlinear classifier models have been also utilized such as artificial neural networks (ANN), Gaussian Mixture Model (GMM), linear, quadratic, and logistic Discriminant Function Analysis (DFA), and Support Vector Machines (SVM) [10]-[19].

IV. EARLY APPROACHES

In early days, performance parameters such as, workload, task engagement and stress, were measured based on some questionnaire and/or measurement scale. These methods are merely qualitative in nature and subject dependent which include statement of users' behavior in analysis performing certain tasks. One of the more popular method is NASA TLX (NASA Task Load Index) which is a multi-dimensional scale designed to measure workload estimate from participants performing a task [1][17]. The task load index consists of six subscales, mental demand, physical demand, temporal demand, performance, effort, and frustration [17][18]. Task experiences are rated by subjects from 0 (low) to 100 (high). A measure of 0 represents low and 100 represents high and the scale is continuous in this range [18]. However, quantitative analysis can be performed after obtaining this subjective data.

V. QUANTITATIVE APPROACHES

Quantitative approaches incorporate numerical estimation of performance. Cognitive or mental workload can be defined as the result of reaction to task demand; it is the proportion of the capacity that is allocated for task performance [1]. Hence, mental workload can be quantified as low, medium and high [1]-[3].

In addition, with the advancement in digital signal processing techniques and algorithms, more researchers are using EEG signals for estimating alertness, cognitive workload, stress, fatigue, for performance optimization and stress management.

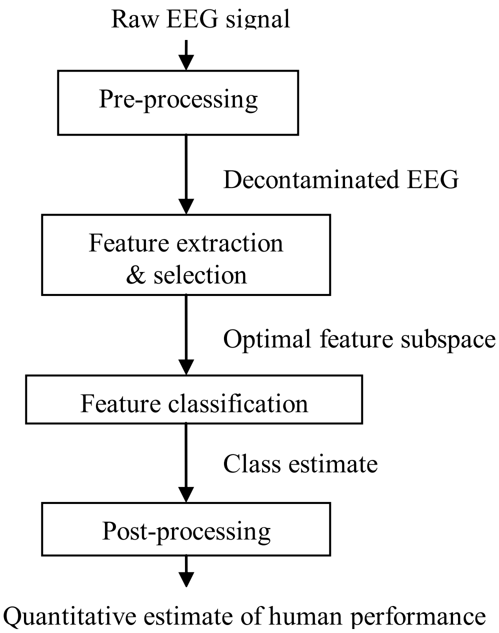

Fig. 1. Simple schematic diagram of quantitative human performance measure based on EEG signals

Many studies reported human performance estimation by using EEG signal analysis. Typical steps in a human performance estimation method by using EEG signals are shown in Fig. 1 [22]. It includes a preprocessing stage (to remove noise), feature extraction and selection (to extract signatures of EEG signal), feature classification (to group the features into different categories), and finally a post-processing stage to quantitatively estimate the human performance.

EEG indices have been developed for quantification of performance using some specific tasks performed by the subjects. Obtained EEG data is then analyzed using signal processing and statistical analysis techniques. Table 1 shows a summary of these methods. In this table, the publication year, authors name(s), number of subjects, feature extraction and classification methods, type of experiments, type of methods, and the parameter(s) that they have measured are shown in different columns. The feature extraction and selection methods are FFT, estimate of PSD, discrete wavelet transform (DWT), PCA, ICA, and correlation analysis. The performance parameters measured are accuracy, alertness, confidence, cognitive or mental workload, distraction or drowsiness, reaction time, task engagement and vigilance.

TABLE I
STUDIES ON HUMAN PERFORMANCE BASED ON EEG SIGNALS

Authors	Year	Subjects	Feature extraction & classification	Type of analysis	Experiments	Methods	Parameters
Sterman and Mann [7]	1994	15	FFT	Algorithmic	Flight simulator	Quantitative	Workload
Brookings et al. [8]	1996	8	FFT	Statistical	ATC simulator	Qualitative	Workload
Fourniera et al. [4]	1999	10	FFT	Algorithmic	MATB	Qualitative	Workload
Trejo and Shensa [9]	1999	8	DWT ANN	Algorithmic	Task simulator	Quantitative	Accuracy, Confidence, Reaction time
Levendowski et al. [5]	2000	15	DFA	Algorithmic	MPT	Quantitative	Drowsiness
Ling et al. [10]	2001	12	FFT ANN	Algorithmic	Flight simulator	Quantitative	Workload
Murata et al. [11]	2001	8	Wavelet transform	Algorithmic	CMT	Quantitative	Workload
Smith et al. [13]	2001	16	PSD	Statistical	MATB	Qualitative	Task load
Wilson [14]	2002	10	PSD	Statistical	Actual flight	Qualitative	Workload
Berka et al. [15]	2004	45	PSD	n.s.	Simulator WCT	Quantitative	Workload, Distraction, Engagement
Dussault et al. [16]	2005	12	FFT PSD	Statistical	Flight Simulator	Qualitative	Workload, Vigilance
Lin et al. [17]	2005	10	Spectral analysis Correlation analysis PCA	n.s.	Driving simulator	Quantitative	Alertness
Berka et al. [19]	2007	80	PSD DFA	n.s.	AMP	Quantitative	Workload, Engagement
Stevens et al. [20]	2007	12	PSD	Statistical	Simulation software IMMEX	Quantitative	Distraction, Engagement, Workload
Pal et al. [21]	2008	13	Spectral analysis Correlation analysis	Algorithmic	Driving simulator	Quantitative	Alertness

ATC: air traffic control; AMP: alertness and memory profiler; CMT: continuous matching tasks; DWT: Discrete Wavelet Transform; n.s.: not specified (includes both algorithmic and statistical approaches); MATB: multi-attribute task battery; MPT: mental performance tasks; WCT: warship commander task.

Several hardware and software packages have been developed by different groups for this purpose such as Alertness and Memory Profiler (AMP) and B-Alert (wireless EEG and AMP) is such an EEG technology developed by Advanced Brain Monitoring Inc. [15].

VI. STATISTICAL ANALYSIS AND VALIDATION

Descriptive and inferential statistics have been employed by most of the studies. In repeated measure scenario experiments, repeated measures ANOVA were employed to reveal the significant difference and interactions. Most of the methods involved computation of deviation from mean and average variance and develop some kind of scale providing measure for human performance estimation. For example, mental workload, distraction, alertness are measured as low, medium and high depending on the performance of subjects undertaking some specific tasks [14]-[20].

However, since the analysis mainly deal with non-stationary EEG signals, future development in this research area, should consider more rigorous statistical analysis and validation of the methods or tests performed. These may include sensitivity and specificity of the tests.

VII. CONCLUSIONS AND FUTURE DIRECTIONS

Although there have been significant advances in this area, still several challenges need to be addressed for future developments. First of all, it is required to well define a set of paradigms that can consistently extract measure of targeted cognitive state [19]. Proper validation of the measure of cognitive tasks is also necessary and these validations can be performed statistically. The obtained measure also needs to be validated across participants and correction or adjustment is required for variation due to individual differences and task nature [20].

EEG based performance estimation and/or cognitive workload assessment is particularly important in variety of applications such as, in aviation for pilots' performance estimation and enhancement, for training optimization in aviation pilots and in air traffic controls, in transportation to detect drivers' drowsiness or distraction [7][8][14]-[21]. Moreover, alertness, attention and even verbal and spatial memory can be quantified. The idea behind these developments is that the EEG spectra in alpha and theta band are highly correlated with the changes in subjects' cognitive state [19]-[22].

Most of the physiological factors, for example, heart rate variability (HRV) co-vary with drowsiness levels [7][9]. Therefore, additional physiological measure as like heart rate can be included in analysis to extend the capabilities of quantification of cognitive states [10]-[12][19]. However, EEG has some benefits as well as limitations over other physiological parameters as such ECG, and fMRI (functional magnetic resonance imaging), another method to study brain functions. EEG sensors are easily deployed for recording non-invasive EEG signals from subjects' scalp enabling high temporal resolution on the order of milliseconds. EEG is relatively tolerant of subjects' movement. With the advancements in wireless technology, wireless EEG acquisition systems are widely available these days which allow subjects to move during EEG acquisition. Moreover, EEG signals can be used in subjects who are not capable of making motor response. On the other hand, EEG provide significantly less spatial resolution comparing to fMRI and the sensor electrodes need to be applied on scalp which may introduce added stress to subjects' overall performance.

In recent years, nonlinear-dynamics, nonlinear time series based analysis and characteristic measures are attracting more researchers in analyzing brain functions and malfunctions since human brain is considered as nonlinear dynamical system. The techniques discussed in this article for feature selection from EEG signals to evaluate human performance are mostly based on linear system theory. However, EEG signals are random and aperiodic in nature. Therefore, it is more appropriate to incorporate nonlinear analysis in human performance evaluation studies.

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