Real-time EEG processing based on Wavelet Transformation

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Abstract: We report on a novel data acquisition system, as part of a project to measure feedbackcoupled ERP signals, which uses wavelet transformation to decompose EEG signals in realtime in their respective energy bands. Due to constraints in DSP-based computing power, we have to settle for the less than optimal decomposition by short wavelets, but nevertheless achieve satisfactory discrimination power for clinical applications.

Keywords: Real-time wavelet transform, EEG band discrimination, digital signal processor

Introduction

Long going research into the possibilities of braincomputer-interfaces [2] for locked-in patients points currently at the utilisation of evoked potentials instead of slow brain waves to command input devices [1]. However, physiological research at our university [4], strongly suggests that the macroscopic electric (i.e. EEG) state of a subject's brain influences the responses to defined stimuli, manifested in higher amplitudes of evoked potential and thus influencing all control attempts.

In order to investigate this evidence in realtime, we built a data acquisition system able to record raw EEG signals from up to 32 scalp electrodes from standard amplifier configurations over a prolonged period of time. The design is meant to evaluate the incoming signals according to user defined criteria and in succession trigger the stimulus to evoke an ERP by either of auditory, visual or sensory stimuli [7]. Of particular interest are EEG recordings in a Virtual Reality car simulator, currently under construction, where the visual stimulus consist of the break lights of preceeding cars.



Figure 1: Sketch of low-cost experimental setup, to record EEG/ERPs while driving in a virtual environment.

Materials and Methods

In order to satisfy the need for a cost-effective system, we rely on a Windows-PC and Texas Instruments (TI, Dallas, TX, USA) digital signal processors of type C6701 to record and digitize signals, amplified by any available, analog EEG-amplifier. A single DSP is integrated by Innovative Integration, Inc. (II, Thousand Oaks, CA) onto a M67 PCI-card, which carries in turn two OMNIBUS cards (*AD 16*) with 16 analog/digital converters each, without multiplexing.

Programming is done with TI's "Code Composer Studio" and Borland's "C++ Builder". The interrupt driven, DSP-BIOS II based, raw data recording routines utilize less than 5% of the DSP's computing power at a sampling rate of 5 kSamples/sec. The A/D conversion itself may run with up to 50 kSamples/sec.

The GUI-controlled program contains the following display panels: The **command panel** contains the command and editing functions necessary for each experiment and known from a tape recorder: Run, Stop, Record, Replay, Forward, Back. It furthermore toggles the available online toolpanels and provides information on the hardware status and opportunity to take notes, which are all stored together with incoming data. A traditional multi-channel **polygraph** plot (blue-onwhite) displays scalp electrodes amplitudes and trigger channels. A **spectrogram** window may be opened and shows the Fourier transform of one arbitrary channel. An **array potential display** illustrates the ongoing activity on scalp electrodes by color-coding and logarithmically interpolating their potentials. This panel may be replaced by a 2D-current source density display [6]. Another panel shows an **average** of one channel based on a trigger signal on another channel (online ERP-display). The most important panel is the **energy decomposition** display, which utilizes an online wavelet decomposition scheme proposed by [5] and implemented with a fast lifting scheme described elsewhere [3].



Figure 2: EEG-band decomposition panel. Left for a 20Hz, right for a 5 Hz sinusoidal signal. From top to bottom are γ , $\beta \alpha$, θ , and δ components and the original signal over time displayed. The bottom most bar graph shows the energy at any given moment.

Numerical tests and simulations of algorithms were performed under Matlab (The Mathworks Inc., Natick, MA, USA) and then implemented in C on the DSP.

Results and Discussion

Despite our progress in implementing fast wavelet transform (WT) algorithms, we have to pay attention to the limited computing power and signal delays and thus cannot use high-order wavelets like Daubechie's No 8 (db8), but instead have to settle for smaller ones like Daubechie's No 3 (db3). Figure 3 illustrates the price in discriminatory power coming with this limitation:

From top to bottom are the δ , θ , α , β and γ bands sketched in rows. Each row contains (from top)

measured selectivity with a db3 and simulated selectivity with the same db3 and the db8 wavelet. Selectivity is gray scale coded as percentage of the whole signal's energy. It is clearly visible, that the use of db8 leads to a clearer discrimination of components (sharper gray bars), however at higher computing costs and signal delays.



Figure 3: Frequency discrimination achieved with WT (see text for further description)

Although our online decomposition seems to work satisfactory, a real feedback coupled ERP-experiment with triggering a VR-stimulus on reaching a predefined threshold e.g. in the γ -band, is still pending, but under construction.

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