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Light-weight Single Trial EEG Signal Processing Algorithms: Computational Profiling for Low Power Design

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Abstract— **Brain Computer Interface (BCI) systems translate brain rhythms into signals comprehensible by computers. BCI has numerous applications in the clinical domain, the computer gaming, and the military. Real-time analysis of single trial brain signals is a challenging task, due to the low SNR of the incoming signals, added noise due to muscle artifacts, and trial-to-trial variability. In this work we present a computationally lightweight classification method based on several time and frequency domain features. After preprocessing and filtering, wavelet transform and Short Time Fourier Transform (STFT) are used for feature extraction. Feature vectors which are extracted from θ and α frequency bands are classified using a Support Vector Machine (SVM) classifier. EEG data were recorded from 64 electrodes during three different Go/NoGo tasks. We achieved 91% classification accuracy for two-class discrimination. The high recognition rate and low computational complexity makes this approach a promising method for a BCI system running on wearable and mobile devices. Computational profiling shows that this method is suitable for real time signal processing implementation.**

I. Introduction

THE main objective for brain–computer interface (BCI) research is to provide communication channels to translate brain rhythms of an individual into application-specific signals for computers. BCI's allow a physically disabled person to use the mental process to communicate with external devices [1]. Therefore, it can provide an alternative means of communication to the people with neuromuscular disorders due to disease or spinal cord injury. However, the possibility of this communication channel depends on the quality and the robustness of the electroencephalography (EEG) signals and their associated signal processing methods.

There are three major steps involved with BCI systems: 1) measuring neural signals from the brain, 2) Decoding brain's state/intention from recorded signals, and 3) Mapping intentions into actions in the physical world. EEG is a non-invasive method for recording brain activity via electrodes placed on the scalp. The summed field potentials of the simultaneous firings of a large number of cortical neurons generate electrical activity. Some cognitive tasks generate characteristic EEG signals called Event Related Potential (ERP) in reaction to a stimulus. Using this method brain activity can be interpreted by decoding EEG signals.

BCI algorithms that investigate decoding neural signals are divided into two main categories: cue-paced (synchronous) BCI and self-paced (asynchronous) BCI. The majority of existing EEG-based BCI are synchronous BCI's in which the classification of brain signals is locked to a predefined time window, and the time of excitation or the arrival of the stimuli is known to the algorithm. An advantage of synchronous BCI is that the onset of mental activity is known in advance and associated with a specific stimulus. Although inferring intention based on an external stimulus is not the natural way of human-machine interaction, this knowledge is useful to boost the accuracy of the signal processing and intent detection. In modern neuroscience, researchers have been studying mental state identification based on single trial EEG signal processing. Single trial EEG signals which have very low signal-to-noise (SNR) ratio create challenges for signal processing.

In BCI systems, brain activity patterns will be identified by a classification algorithm. Some popular machine learning techniques like linear discriminant analysis (LDA) [2, 3, 4], support vector machine (SVM) [5, 6, 7], or artificial neural networks (ANNs) [8, 9] are used as classifier.

An important advantage of using EEG -for brain imaging- is that it uses light sensors to allow near-complete freedom of movement of the head and body. Neural signals are everywhere much likes mobile phones. Advances in mobile phone technology have allowed phones to become a convenient platform for real-time processing of the EEG. The cell phone-based platform propels the mobility, convenience and usability of online BCI's. There has been much effort developing accurate techniques for BCI systems [10, 11, 12]. However, in real time applications it is highly desirable to consider simpler mathematical models to reduce computational cost while maintaining adequate classification accuracy. Feature extraction is a major step in classification problems. Many algorithms such as Independent Component Analysis (ICA) [13, 14], Common Spatial Patterns (CSP) [7, 8, 14] are successful in feature extraction from EEG data. However, those techniques have large computational cost.

In this work, we implement a lightweight classification method for single trial EEG classification. Some simple and commonly used methods such as wavelet transform and STFT are used for feature extraction. First, we apply a band-pass filter to remove high frequency and very low

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frequency noise from the desired signals (>1Hz and <25 Hz). There has been prior evidence that power in theta and alpha frequency bands vary when considering inhibition tasks [15, 16, 17]. Therefore, we consider theta and alpha bands for features extraction. An SVM classifier is used for classifying features.

In this paper, the EEG data were obtained from three different inhibition Go/NoGo tasks. The Go/NoGo task is a type of continuous performance neuropsychological test that has been designed to explore complex attention function such as response inhibition. Response inhibition refers to the ability to suppress responses that are no longer required or inappropriate. Each task includes Go items presented 80% of the time and NoGo items presented 20% of the time. Those tasks each require a different level of semantic abstraction to make a correct response: 1) The "Single" task includes one image of a car (Go) and one image of a dog (NoGo). In this task, an identical image is repeated, so the perceptual properties of the item stay identical. 2) The "Multiple" task contains multiple pictures of cars (Go) and multiple pictures of dogs (NoGo). Therefore, correct responses require identification across a category that can be accomplished by focusing on common perceptual features of the items (e.g. legs, wheels, eyes, windshields) and grouping them based on semantic representation (car, dog). 3) The "Semantic" task includes a wide range of dissimilar non-animals (Go) from categories of clothing, tools, furniture, and vehicles and a wide range of animals (NoGo), containing a spider, a worm, a lobster, and a dog. Fig. 1 shows the stimulus for Go and NoGo objects.

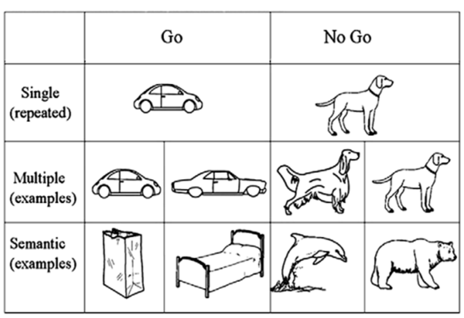

Fig. 1 Sample of stimuli used across all three inhibition tasks.

The rest of this paper proceeds as follows: we will first provide an overview of the related literature in Section II. Methods and materials are explained in Section III. In Section IV, we discuss experimental results. Section V summarizes a discussion and directions for future work.

II. PREVIOUS WORK

BCI has been gaining much attention as a solution to convert brain signals to usable control commands. BCI's can use a variety of electrophysiological sources. However, most of current BCI implementations rely on three main electrophysiological sources: motor imagery, steady-state visual evoked potential, and P300 potential. Many algorithms such as Independent Component Analysis (ICA) [9, 10] and Common Spatial Patterns (CSP) [7, 8, 9] were applied to motor imagery applications [7, 8, 9, 10]. Although the performance is suitable, the computational complexity creates challenges for real time implementation. Calculating power spectrum for different EEG frequency bands is a popular method in the literature [15, 18]. In the following, we provide an overview on the current state-of-the-art signal processing techniques.

In [15], authors analyze changes in EEG power and synchrony between pairs of channels during the Go/NoGo task. They reported that common processes such as attention, and discrimination were characterized by changing power and synchrony in different frequency bands. These changes happen in different frequency bands for different time window during Go and NoGo. This information is useful for feature extraction design.

In [12], authors propose classification of three imagery movements. They used temporal filters and CSP for classification. The effects of imagery movements on measured EEG data are different for various frequency bands. The authors used temporal filters to decompose EEG signals to various frequency bands. They obtained a weighed combination of electrodes according to their importance in classification task. Although the method they proposed has 92% accuracy, it is complex in terms of computational power. Another disadvantage is the relative sensitivity to the artifacts.

M. Naeem, et al. in [13] applied several ICA algorithms in the preprocessing phase for four motor imagery tasks. They analyzed the performance of ICA algorithms on the overall classification task. Their results demonstrate among all ICA algorithms, the best performance was obtained using Infomax. The authors also used CSP for preprocessing to compare the results with Infomax algorithm. The results illustrate that CSP can improve the classification accuracy. They reported an overall accuracy of 76% for a four-class motor imagery task.

A method for classification of wrist movement imagery was proposed in [19]. The authors extracted key features for classification by applying spatial filtering (CSP method) on EEG signals in the gamma frequency band. They used radial bias function to classify features which were extracted by the spatial patterns to classify a four movement imagery task.

Authors in [7] proposed a Combination of CSP and SVM for classification of a three movement motor imagery task. They used CSP for feature extraction and SVM for classification. Features were then sent to SVM, and classified into left hand, right hand, or foot movements. An average recognition rate of 90% was reported.

In [18], a method for classification of Bipolar Mood Disorder (BMD) and Attention Deficit Hyperactivity

Disorder (ADHD) based on EEG signals was proposed. The authors extracted several features such as band power, fractal dimension, AutoRegressive (AR) model coefficients and wavelet coefficients from EEG signals and used a group of classifiers for discrimination.

Despite the current literature demonstrate an impressive body of work that proves the useful of BCI and signal processing in several application domains, researchers have not investigated computational profiling to possibly address issues associated with real-time and low power operation of BCI signal processing algorithms.

III. METHODS AND MATERIALS

A. Experiment and Data

Continuous EEG was recorded from 64 silver/silver-chloride electrodes mounted within an elastic cap (Neuroscan Quickcap) which are placed according to the International 10–20 electrode placement standard (Compumedics, Inc.). The data was collected using a Neuroscan SynAmps2 amplifier and Scan 4.3.2 software sampling at 1 kHz with impedances typically below 10 kΩ. Blinks and eye movement were monitored via two electrodes, one mounted above the left eyebrow and one mounted below the left eye. The data were processed to remove ocular and muscle artifacts in the following way: First, poorly functioning electrodes were identified visually and removed. Second, eye blink artifacts were removed by a spatial filtering algorithm in the Neuroscan Edit software using the option to preserve the background EEG. Third, time segments containing significant muscle artifacts or eye movements were rejected. The EEG data were segmented offline into 2s epochs spanning 500ms before to 1500ms after the presentation of the visual stimuli.

B. Frequency Decomposition using Wavelet

Analyzing frequency spectrum for different frequency bands is a commonly used method for single trial EEG classification [13, 14, 20]. These sub-bands are called delta (d), theta (θ), alpha (α), beta (β) and gamma (γ) bands. There are no strict frequency ranges for these different bands. In this paper, ranges are selected as follows: delta (0.5–4), theta (4–8), alpha (8–13), beta (13–25) and gamma (25–40). Wavelet transformation is a time-scale analysis method and has the capacity of representing signal's local characteristics in the time and frequency domains. In the low frequency, it has a lower time resolution and higher frequency resolution, and in the high frequency, it has a higher time resolution and lower frequency resolution. As described earlier, the sampling frequency on our EEG data was 1 kHz. We used 7-level wavelet to decompose each trial to corresponding signals in different frequency bands. Fig. 2 shows the decomposition of each trial into signals with different frequency bands. After decomposition of signal, power spectral density for delta, theta, alpha and beta bands computed and for each band, maximum power extracted. In fact each time series converted to a 4-element vector. In [21], authors analyzed the influence of perceptual categorization on inhibitory processing by measuring N2-P3 response in Go/NoGo task. They demonstrated that N2 (a negative peak around 200ms following the visual stimuli) is found over fronto-central areas and P3 (a positive peak around 300ms following the visual stimuli) is a fronto-central component. They considered averaging across participants over frontal channels like Fz for N2 component and over central electrodes such as FCz for P3 effect. They showed that these two channels are good candidates to observe the N2-P3 responses in Go/NoGo task. Therefore, we consider the Fz, FCz, and Cz channels and use average signals of these channels for each trial in our processing.

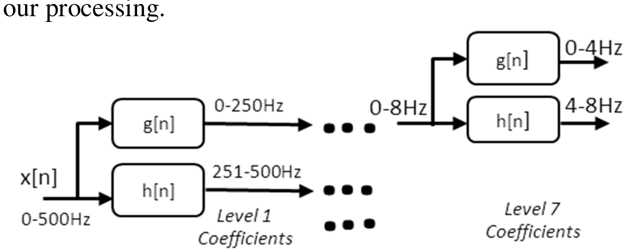

Fig. 2 Frequency decomposition of EEG trials using wavelet.

C. Short Time Fourier Transform

Short-Time Fourier Transform (STFT) is an extension of conventional Fourier analysis for non-stationary data. STFT performs Fast Fourier Transform (FFT) on consecutive segments or blocks of data that are assumed stationary, and is equivalent to a sliding window that analyzes the local frequency content of the signal. The STFT for signal $x(\tau)$ windowed by a fixed-length function $w(t - \tau)$ is defined by (1). STFT power or energy, $P_x(t, f)$ is defined in (2).

$$STFT_x(t,f) = \int_{-\infty}^{\infty} x(\tau)w(t-\tau)e^{-2j\pi f\tau}\, d\tau \qquad (1)$$

$$P_x(t,f)_{STFT} = |STFT_x(t,f)|^2 \qquad (2)$$

In our analysis, we use a 1s window and 90% overlap for the STFT. Length of each trial is 2s spanning 500ms before to 1500ms after the activation of the stimuli. The STFT was applied to average of selected channels (Fz, FCz, Cz) of each trial from 500ms to 2s by 1s windows and with 90% overlapping. The first window spans from 500ms to 1500ms and the next window is shifted 100ms covering 600ms to 1600ms. Fig. 3 illustrates the sliding window on which the STFT is applied. Neuroscientists have indentified that the effect of cognitive task appears on EEG signals often 300ms after the visual stimuli [15, 21]. Therefore, we particularly select the first four windows which cover 300ms after the stimulus. Output of STFT is the power of signal in different frequency bands and time segments. For this work, we consider the frequency band of 3-14Hz that covers theta and alpha bands.

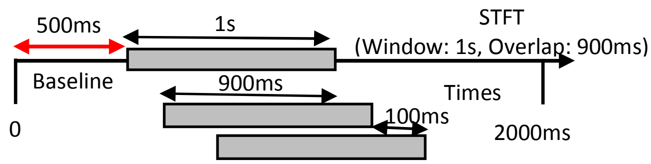

Fig. 3 Sliding windows for STFT.

D. Feature Extraction

Features that we used in this paper are a combination of band power and STFT features. Each trial represented with a feature vector containing 8 elements (4 band power and 4 STFT features). In this work, our analysis is based on single subject training and testing. For each subject, the data were divided into train and test sets, half of the data were used for training and the other half for testing.

E. Classifier

A comprehensive review of classifiers for BCI is presented in [22] with many classifiers such as Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), Neural Networks (NN), and Hidden Markov Models (HMM). In this work, we use SVM classifiers for several reasons including good generalization properties, insensitivity to overtraining, and robustness to the curse-of dimensionality. The SVM approach offers an effective classification strategy in separating input feature vectors and has been used in many different applications [23]. In SVM, the input vector $\boldsymbol{x}$ is projected into a scalar value $f(\boldsymbol{x})$ as,

$$f(x) = \sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b \tag{3}$$

where $y_i = \{-1, 1\}$, the vectors $\boldsymbol{x}_i$ are support vectors, N is the number of support vectors, α_i are adjustable weights, b is the bias term, and the function $K(x_i, x) = \emptyset(x_i)^t . \emptyset(x)$ is the kernel, where $\emptyset(.)$ is a mapping from the input space to a high dimensional space which creates nonlinear decision boundaries.

F. System Architecture

In this study, we implement a computationally light-weight classification method for single trial EEG. First, the baseline is removed, that is, the average of baseline segment (0-500ms) for each trial is subtracted from all samples of the same trial. Then the data are re-referenced to the average potential over the entire head. In the next step we apply a band-pass filter (1-25 Hz) to eliminate high frequency and very low frequency noise. Then we use wavelet transform and STFT to extract features. Based on the training data, we determine the SVM classifier model parameters and use the model for testing. Fig. 4 shows the block diagram of our classification method.

IV. Classification Results

Table I reports the classification results on data acquired from 5 subjects for Go/NoGo tasks. The first two rows show the classification results for each feature set (*i.e.* band power, and STFT) applied to the EEG signal. The third row shows the results of a combination of the two feature sets. As we generally expect, combining the two features sets will enhance the recognition accuracy.

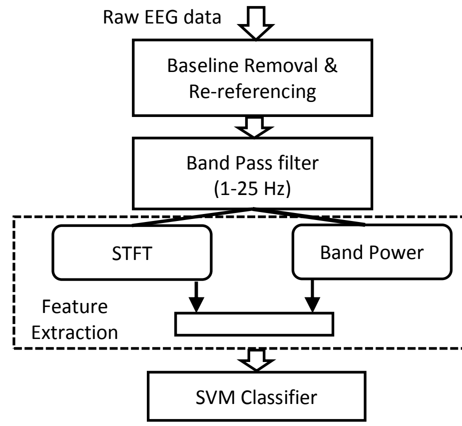

Fig. 4 Architecture for the classification system.

TABLE I
CLASSIFICATION ACCURACY FOR DIFFERENT FEATURES WITH INDIVIDUAL SUBJECTS

Subjects / Features	A1	A2	A3	A4	A5
Band Power	77.14	95	83.33	80.56	67
Short Fourier	94.29	77	75	75	72
Combination	94.29	97.5	91	86.11	83

The main advantage of our proposed signal processing is its low computational complexity in comparison to other techniques that use ICA or CSP. Computational complexity of a signal processing algorithm is a measure of power consumption. Enhancing wearability, portability, and durability are three major important objectives in design and development of wearable and power aware BCI devices. Lowering the power consumption translates to reducing the size of the battery, the form factor, and improving the wearability of the device. In order to reduce the power consumption of a real-time BCI, we need to examine the computational complexity of BCI algorithms, and if possible, techniques that will reduce the computational complexity are deployed. Therefore, it is desirable to consider the computational cost and the accuracy of BCI systems at the same time. We extracted the computational complexity of the signal processing method described in this paper, which will provide guidance for hardware implementation. Table II shows the computational complexity of this work and other widely used methods for our setup. Complexity measures are obtained in terms of FLOPS (FLoating point OPerations per Second). It is shown in Table II that our feature extraction method requires lower computational power in comparison to ICA and CSP while maintaining a promising recognition rate.

V. DISCUSSION AND FUTURE WORKS

In this work a classification method for single trial EEG was implemented by using light-weight signal processing algorithms. We used features that were extracted based on band power and STFT. In order to classify incoming EEG trials, SVM classifiers were used. Results of our investigation on Go/NoGo tasks show that a classification accuracy of 91% can be achieved using relatively low computationally intensive algorithms. In future, we will implement the proposed algorithm on a mobile device and will assess the power and accuracy trade-offs.

VI. ACKNOWLEDGMENT

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TABLE II
COMPARISON OF COMPUTATIONAL COMPLEXITY OF CURRENT WORK VERSUS ICA AND CSP METHODS

Method	Complexity	Typical value
ICA (Infomax)	$\mathrm{Min}(TP^2/2 + 4P^3/3 + NPT,\ 2TP^2) + (N^2 + N^3 + 4N + 5TN)J$	1.7 GF
CSP	$P^2T + 5P^3$	83 MF
Current work:		
Wavelet	4LK	56KF
PSD	$K\log_2^K + 2K$	28KF
STFT	$(K-W)/(W-OW) * 1.5W\log_2^W$	75KF
Total		159KF

P: Number of electrodes (64)
N: Number of sources (64)
T: Number of sample points (10 *2 * Fs = 20000)
J: Number of iterations takes for ICA to converge (250)
K: Trial length (2000)
W: Length of STFT window (1000)
OW: Overlapping window (900)
L: Number of wavelet levels (7)
GF: Giga FLOPS, MF: Mega FLOPS, KF: Kilo FLOPS

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