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Classification of frontal cortex haemodynamic responses during cognitive tasks using wavelet transforms and machine learning algorithms

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A B S T R A C T

Recent advances in neuroimaging demonstrate the potential of functional near-infrared spectroscopy (fNIRS) for use in brain–computer interfaces (BCIs). fNIRS uses light in the near-infrared range to measure brain surface haemoglobin concentrations and thus determine human neural activity. Our primary goal in this study is to analyse brain haemodynamic responses for application in a BCI. Specifically, we develop an efficient signal processing algorithm to extract important mental-task-relevant neural features and obtain the best possible classification performance. We recorded brain haemodynamic responses due to frontal cortex brain activity from nine subjects using a 19-channel fNIRS system. Our algorithm is based on continuous wavelet transforms (CWTs) for multi-scale decomposition and a soft thresholding algorithm for de-noising. We adopted three machine learning algorithms and compared their performance. Good performance can be achieved by using the de-noised wavelet coefficients as input features for the classifier. Moreover, the classifier performance varied depending on the type of mother wavelet used for wavelet decomposition. Our quantitative results showed that CWTs can be used efficiently to extract important brain haemodynamic features at multiple frequencies if an appropriate mother wavelet function is chosen. The best classification results were obtained by a specific combination of input feature type and classifier.

1. Introduction

Research on brain–computer interfaces (BCIs) is expanding in hopes of improving quality of life for people who are paralysed or severely motor impaired [1]. In BCI research, brain signals are analysed in order to decode the subject's mental state and map it onto some external action (e.g., controlling a computer cursor or a wheelchair). Over the last decade, different types of brain signal have been studied in order to derive useful information about the subject's mental state. Most BCI systems use electroencephalograms (EEGs) because they have been thoroughly studied in neural engineering [2,3]. Most notably, major success has been achieved with dependent BCI paradigms that use the modulation of the steady-state visual evoked potential, which is a brain response to external flickering lights or patterns [4].

Recent advances in neuroimaging have demonstrated a new way of accessing the brain's functional state by using functional near infrared spectroscopy (fNIRS). This emerging sensing modality is non-invasive, safe, and portable; it is used to monitor physiological changes that occur in the human brain during cognitive tasks [5]. fNIRS presents information about cortical haemodynamics and oxygenation status during functional activity through three parameters: the concentrations of oxyhaemoglobin (Oxy-Hb), deoxyhaemoglobin (deOxy-Hb), and total haemoglobin (total-Hb). The ratio of these concentrations is determined by a combination of oxygen consumption, supply of oxygenated arterial blood flow, and drainage of de-oxygenated venous blood [6]. The concentrations may provide important information regarding subjects' cognitive states that can be decoded and verified for use in a BCI [7,8].

fNIRS has already been used in several studies to investigate haemodynamics and oxygenation for a BCI. For instance, Sitaram et al. classified brain haemodynamics arising from right- and left-hand motor imagery from five subjects using support vector machines (SVMs) and hidden Markov models [9]. They also described future plans for a possible word speller interface in which the user employs left- or right-hand imagery to move the cursor to the left or right, respectively, to select a letter. Utsugi et al. demonstrated mental-task-based real-time control of a toy train, which was achieved only by performing complex mental arithmetic tasks [10]. In addition, Sassaroli et al. demonstrated that a simple k-means algorithm successfully classified the brain haemodynamics associated with five mental tasks [11]. Furthermore, Truong and Masahiro studied a neural network approach to the classification of brain fNIRS results using wavelet input features [12] and showed that their wavelet-based approach is suitable for selecting mental task relevant input features for a neural network classifier. One

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interesting research by Tai and Chau shows the feasibility of fNIRS-BCI framework as a rehabilitation system for patients with motor impairments [13].

The current status of fNIRS technology may not be optimal for real-time BCI because of the slow inherent latency of the brain haemodynamics response, which occurs over 4–8 s [14,15]. This is in contrast to EEG, which measures brain activity over a few milliseconds. A few studies focused on measuring fast haemodynamic response, which could provide nearly instantaneous measurements, but this has not been extensively explored yet [16]. We consider that fNIRS-BCI systems have potential for a neuro-rehabilitation of motor functions of post-stroke patients that involve slow operations to induce spontaneous cortical plasticity or neurofeedback paradigms for a treatment of attention deficit hyperactivity disorder. However, fNIRS-BCI may not be proper at this stage for a direct translation of mental intent to support voluntary movements or locomotion which requires fast and instantaneous feedback.

In this study, we report our preliminary experimental results in the analysis and classification of haemodynamic signals for BCI. First, we explain the procedure for fNIRS signal acquisition from nine participants who performed four mental tasks. Next, we present a wavelet-based pre-processing technique for feature estimation. We consider two aspects of neural signal quality: extraction of the true mental-task-relevant signal and elimination of interference from noise. True neural signals are detected in two steps; we first decompose the signal using four candidate wavelet functions and then perform soft thresholding on the scale of each wavelet to eliminate various types of noise in the fNIRS signals. Using the extracted wavelet coefficients, we construct important signal features for further classification. Finally, we study and compare the effects of three classifiers in order to maximize the accuracy of mental task recognition. These classifiers are a back-propagation neural network (BPNN), linear discriminant analysis (LDA), and an SVM. This procedure enables us to determine a suitable wavelet function, describe the effects of soft thresholding on the classification accuracy, and identify the optimal classifier for a particular task. Fig. 1 shows a flowchart describing the process; details on each step are presented in the following sections.

2. Materials and methods

2.1. fNIRS data acquisition

Fig. 2 illustrates the data acquisition procedure. We used a multi-channel optical brain-function imaging system for data acquisition (FOIRE-3000, Shimadzu Co. Ltd., Kyoto, Japan). The system uses different laser diodes emitting different wavelengths of 780 nm, 805 nm, and 830 nm to calculate the proportional cerebral oxygenations of the Oxy-Hb and deOxy-Hb contents of the brain surface. We used 19 channels to measure the concentration levels of Oxy-Hb, deOxy-Hb, and total-Hb in the frontal cortex of nine right-handed subjects (mean age 32.1, age range 25–37, eight males). A cap with optical fibre probes was placed on the pre-frontal cortex according to the 10–20 international electrode placement system [17]. Fig. 2(a) shows the locations of the transmitter laser diodes and receiver optodes on the brains surface. The red-circled numbers represent the transmitters, and the blue-circled numbers represent the receivers; the white squares show the locations of the 19 channels. The distance between the transmitter and receiver optodes is equal to 30 mm (see Fig. 2(a)). The acquired signals were digitized using a 16-bit A/D converter with a sampling rate of 10 Hz.

Before the measurements began, participants were asked to sit relaxed and to rest in order to stabilize the blood flow in all channels. We divided the data recording into five sessions, each of which consisted of three trials of a given mental task. Each trial lasted 35 s, which was divided into three time segments: pre-task rest, task, and post-task rest [Fig. 2(b)].

The participants performed the following four mental tasks:

Baseline task: subjects were asked to relax and think of nothing in particular. This task was used as a control and a baseline measure of the fNIRS signals.

Object rotation task: a variety of objects were presented to the participants for imaginary rotation. We also provided tasks in the form of puzzles so that their brain activity could be easily assessed.

Multiplication task: subjects were asked to multiply two random numbers, for example, 35×72, without making any physical movements. This task was designed such that it was difficult but could be accomplished within the given time segment. The subjects verified at the end of the task whether they arrived at the solution.

Letter padding task: in this task the operator shows a randomly selected letter such as *a* [ei], and the participant would have to say words starting with the same character (e.g., apple and ant) within the given time.

All tasks were presented on flash cards by the operator. We did not use a computer screen to present the mental tasks in order to avoid any light interference in the fNIRS signals.

In this study, we focused on the analysis of Oxy-Hb concentration levels because they have been found to consistently reflect neural activities. A study reported that an increase in nervous activity results in an increase in the local oxygen consumption. As a result, oxygenated haemoglobin levels decrease, and those of deoxygenated haemoglobin increase. Further, the blood vessel activity is enhanced in order to supply fresh blood. Thus, the blood flow volume increases locally. Therefore, Oxy-Hb levels increase, and deOxy-Hb levels decrease. These processes are reactions that occur within a few seconds [18]. The blood-oxygen-level dependence (BOLD) signal is an index of the blood stream change appearing in functional magnetic resonance imaging measurements. Oxy-Hb reportedly has a strong correlation with the BOLD signal [19]. To evaluate the functional brain state, we can judge brain activation using primarily the increase in Oxy-Hb. The deOxy-Hb concentration is reportedly weak and difficult to detect in real-time BCI [20].

3. Pre-processing

fNIRS transients exhibit slowly and smoothly varying waves at low frequencies. It is important to analyse both the spatial and temporal characteristics of the signal. In other words, we need to extract only true neural features from the low- and high-frequency components of the noisy signal. For this purpose, we apply continuous wavelet transforms (CWTs) and a soft thresholding rule. The ability of a CWT to localize the time-frequency characteristics of non-stationary signals enables us to capture important fNIRS signal features. Furthermore, we employ a soft thresholding rule to reduce noise interference in the signals. We present the following strategy for noise reduction and feature selection:

- Perform dyadic CWT with four different mother wavelets
- Separate a neural signal from noise at each scale by soft thresholding
- Combine decisions from all scales
- Construct signal features for classification