Towards Biometric Person Identification using fNIRS

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Abstract. We investigate the potential of using fNIRS signals for biometric person identification. Independent sessions for training and testing have been recorded using 8 channels of frontal fNIRS. We extract logarithmic power spectral densities as features to train and test a Naïve Bayes Classifier. We evaluate different frequency bands and report classification results for different trial lengths.

Keywords: fNIRS; near infrared spectroscopy; person identification; biometrics; power spectral densities

1 Introduction

Person identification, i.e. the recognition of an individual within a closed group of people (1 to N matching), using biometric signals, such as iris scans, finger prints, and speech, is widely used for security applications and intelligent user interfaces. Brain activity is known to contain strongly subject-specific signal patterns that are hard to forge and can only be assessed if the user is present and alive. Furthermore, they allow a continuous recognition and can be combined with other techniques in multimodal setups. Up to now, EEG has primarily been used for brain biometric person identification and authentication systems (e.g. [Poulos et al., 1999; Marcel and Millán, 2007]). Functional Near Infrared Spectroscopy (fNIRS) is an promising measurement technique for Brain Computer Interfaces (BCIs) [Coyle et al., 2004]. It is non-invasive, portable, cost-effective, and comes with the benefits of using optical signals, i.e. no electrode gel is required and the signals are not susceptible to electrical artifacts. In this paper we evaluate frontal fNIRS signals for person identification. To the best of our knowledge, fNIRS has not been investigated for biometric applications before.

2 Material and Methods

2.1 Data Corpus

We used an Oxymon Mk III system by Artinis Medical Systems for the data collection. Four optodes (two transmitters and two detectors) were attached to the left and the right side of the subjects' forehead. Using this setup, we measured concentration changes in oxygenated (HbO) and deoxygenated (HbR) hemoglobin at 8 source-detector pairs at a distance of 3.5 cm using a sampling rate of 10 Hz.

fNIRS signals from $N = 5$ healthy volunteers have been used for the evaluation. The recordings contain 10 seconds long trials of different mental tasks (mental calculation, mental rotation, text reading), as well as relax phases of variable length following each trial (15-25 seconds). Only mental calculation trials and the adjoined relax phases have been used for the evaluations presented here (10 trials per session). Within these trials the subjects consecutively subtracted a given number between 7 and 19 starting at a number between 500 and 1000 displayed on the screen. As mental states can change over time (e.g. due to fatigue) and because repositioning of the optodes can strongly influence the characteristics of the recorded signals, we recorded two sessions from each subject at two different days. The data of one day was used for training and the other day was used for evaluation of the system.

2.2 Signal Processing and Classification

External and physiological artifacts influence the raw HbO and HbR signals (see e.g. [Matthews et al., 2008; Cooper et al., 2012]). Therefore, we applied linear detrending to remove signal drifts from each trial. Then, we smoothed out influences of heart beat and high frequency disturbances using a moving average filter (sliding window 1.5 seconds before and after each sample). Logarithmic power spectral densities were calculated using Welch's method and spectral coefficients outside the desired frequency band were discarded. To reduce the dimensionality of the feature space, we combined each five adjacent frequency bins by averaging. The final feature vector consisted of the concatenated values of all channels.

We trained a Naïve Bayes Classifier based on kernel density estimation on the features extracted from the first recording sessions of the five subjects and recognized the subjects' identities from the trials of the other day's sessions.

3 Results

To assess the performance of our fNIRS based person identification system, we evaluated the power spectral density based approach for different trial lengths and frequency bands. Figure 1 shows the recognition accuracies averaged over the test trials using power spectral density features in the frequency band 0-1 Hz and trial lengths from 1.5 to 25 seconds. Error bars indicate the standard deviations across subjects. Longer windows tended to produce higher recognition rates than shorter ones. Higher frequency bands appeared to produce significantly lower recognition performance using our approach, which can be explained by the slow dynamics of hemodynamic responses. The best average recognition accuracy (above 80 %) could be reached using power spectral density features in the low frequency band 0-1 Hz calculated from a 25 seconds long window.

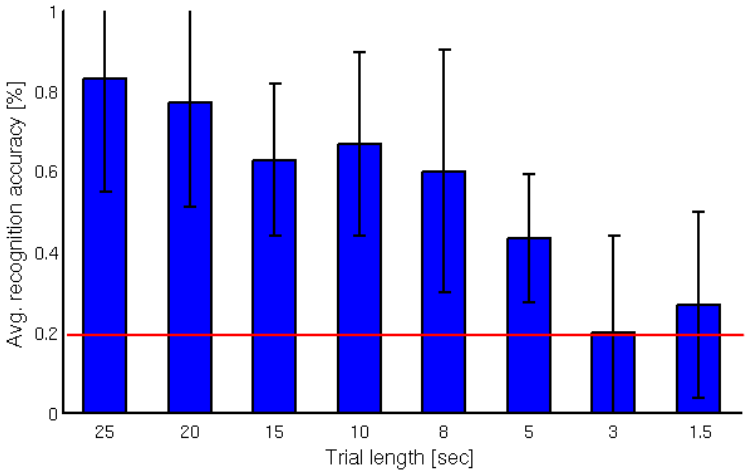

Figure 1: *Recognition accuracies for different trial lengths using power spectral density features in the frequency band 0-1 Hz. Error bars indicate standard deviations across the subjects. The horizontal red line shows the chance level of 20 %.*

4 Discussion

The results of our first study on person identification based on fNIRS data are encouraging. fNIRS signals appeared to contain subject-specific information that enable recognition rates of more than 80 % using logarithmic power spectral density features. We found that predominantly slow frequency components convey relevant information for fNIRS person identification. However, the amount of data that has been used for the evaluations was very limited. To analyze the validity and robustness of fNIRS based person identification, more subjects and multiple sessions per subject over a longer period of time should be assessed in future work. Further analyzes should also investigate the spectral signal properties in more detail, such as slow wave influences by cardiovascular and respiratory activity (e.g. Mayer waves [Julien, 2006; Pfurtscheller et al., 2011]).

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