Template-based classifiers for ERP-based BCIs

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This talk aim to present pattern recognition techniques of graphic elements (e.g. event-related potential, auditory evoked potential, k-complex, sleep spindles, vertex waves) included in electro-encephalographic signals. More specifically, template-based classifiers will be introduced to robustly detect evoked potentials in a single trial from noisy and multi-sources electro-encephalographic signals.

Brain-computer interface (BCI) system is a potentially powerful new communication and control option for those with severe motor disabilities [Wolpaw et al., 2002]. A BCI system translates brain activity into commands for a computer or other devices (e.g. wheelchair, robotic arm). In other words, a BCI allows users to act on their real or virtual environment by using only brain activity. One of the well-known and powerful BCI system is the P300 speller based on the non-invasive Electroencephalography (EEG) measuring from the subject's scalp [Farwell & Donchin, 1988]. This BCI system uses an oddball paradigm. Oddball paradigms are used in asynchronous BCIs to induce event-related potentials (ERPs) through visual or auditory stimulus. Subject pays attestation to specific stimuli that will induce ERPs when presented; others are regarded as the background neural activities. One well-defined component of ERPs is the P300 component that is a positive deflection waveform observed around 300ms after the onset of the stimulus. Brain-Computer interfaces based on evoked potentials allow more commands than the ones based on mental tasks and do not need long human training. Almost everybody reacts on them and there are used by patients. Thus, the task of the P300 speller system is to recognize the ERP components from the noisy EEG background signal. It is found difficult to accomplish this target on the base of a single trial because the magnitude of the EEG background activities is usually one-order larger than the one of the ERP components, that means the ERP components in single-trial recordings are almost covered by the background neural activities. Moreover, non-invasive electrodes produce a noisy signal because the skull dampens signals. Thus, ERP detection usually needs to average responses of repeated stimulations. Due to the averaging operation, the background EEG activities are reduced and the ERP components are enhanced and evident. From a practical point of view, an important issue is to reduce the number of repetitions, in order to obtain high communication bitrates. The methodology has been improved but a gap still exists to enable single-trial recognition.

Template-based methods with alignment techniques look potentially interesting to obtain a robust detection. ERPs are short-time events with characteristic peaks at specific times. So it is useful to be able to extract features in time domain. Template-based classifiers first estimate ERP templates by averaging in the time domain ERP responses, and then use the shorter distance between the current response and the ERP templates as the discriminant criterion. We will focus our attention in particular on several averaging techniques and distance measures such as the point-to-point averaging, the cross-correlation distance [Wastell, 1977] and the dynamic time warping [Kang et al., 2001].
One of these methods, which evokes our attention to solve this problem, is the learning vector

quantization algorithm (LVQ) [Kohonen, 1990]. LVQ is able to automatically extract morphology-specific templates. It performs a supervised learning for a classification task. Its principle is first to cluster input data using a competitive learning without any spatial relationship between codebook vectors (i.e., templates). Each cluster is pre-assigned to a specific class. Thus, when a new pattern should be classified, the method determines in which cluster the pattern belongs to and then assigns it to the corresponding class label. This machine learning technique is well known for its robustness and interpretability. However, for large-scale complex problems, its performance can be further improved by optimizing the way to combine the templates in its assignment stage instead of selecting one of the templates as the final decision. More precisely, it could be interesting to overcome the simple identity function to determine classes from clusters. Thus, a non-identity LVQ will be described. This improvement will be accomplished using the same scheme found in the extreme learning machine algorithm (ELM) [Huang et al, 2004]. The experimental results show that the proposed algorithm improves the accuracy with less computational units compared to original LVQ and ELM.

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