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Sotirios Papadopoulos, Ludovic Darnet, Maciej J Szul, Marco Congedo, James J Bonaiuto, et al.. Fast and reliable hand motor imagery decoding based on beta burst rate modulations. Neural Traces 2024, Brain and Data Science Group at Charité-Universitätsmedizin Berlin; Machine Learning and Inverse Modeling Group at Physikalisch-Technische Bundesanstalt, Berlin; Uncertainty, Inverse Modeling and Machine Learning (UNIML) Group at Technische Universität Berlin, Apr 2024, Berlin, Germany. hal-04550531

HAL Id: hal-04550531

<https://hal.science/hal-04550531>

Submitted on 17 Apr 2024

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Fast and reliable hand motor imagery decoding based on beta burst rate modulations

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Background: Since the characterization of the event-related desynchronization (ERD) and synchronization (ERS) phenomena in the mu and beta frequency bands [1], the Brain-Computer Interface (BCI) community has heavily relied on band-limited power changes as the classification feature of interest. However, recent findings in neuroscience have challenged the idea that signal power best describes the movement-related modulation of brain activity, especially in the beta frequency band. Beta band activity has been shown to occur in short, transient events termed “bursts” rather than sustained oscillations on a single-trial level [2]. In a recent study we showed that the analysis of beta bursts during hand motor imagery (MI) can be advantageous to beta power in terms of classification [3], confirming the hypothesis that on the single-trial level beta burst rate modulations are more behaviorally relevant than beta band power changes.

Approach: In this work we extend our approach by simplifying the algorithm to transform brain signals such that we gain access to measures of waveform-resolved burst rate. We propose a simple algorithm that can take advantage of an arbitrary number of recorded signals while being computationally efficient, thus constructing decoding features that are comparable to state-of-the-art in BCI. We analyze the activity during “left” and “right” hand MI from multiple open EEG datasets [4-7]. Using a new burst detection and waveform analysis algorithm [8], we select specific beta burst waveforms whose rate is expected to be maximally modulated during the task. Then, we use these waveforms as kernels and convolve the raw signals with each waveform. The resultant signals which comprise a proxy of specific burst rates corresponding to each of the kernels are fed to the common spatial patterns algorithm (CSP) [9] and its output is used in order to assess the decoding score using linear discriminant analysis (LDA) [10]. We compare these classification features that describe the modulation of burst rate for bursts with distinct waveforms with signal power based on a classic CSP approach in the beta and mu frequency bands [11] in a pseudo-online fashion. To do so we use two approaches: an incremental increase in the window used for decoding and a sliding window approach (figure 1). Also, we assess whether the number of band-passed features provided as input to the CSP algorithm can significantly affect the decoding score by using both a single filter and a filter bank approach [12] (figure 1).

Preliminary Results: The waveform-resolved burst rate is on average superior to beta band (15-30 Hz) power throughout the duration of the MI tasks irrespective of the number of power features provided to the CSP algorithm and the window technique (incremental or sliding) used. It is also usually superior to band power following filtering in the mu and beta bands (6-30 Hz) early in the trial period, but conversely inferior later in the trial especially when using the incremental windowing approach.

Significance: This work demonstrates that BCI applications could benefit from utilizing beta burst activity by providing reliable decoding performance often needing only a short amount of data. This analysis paves the way for a real-time adaptation of the proposed methodology.

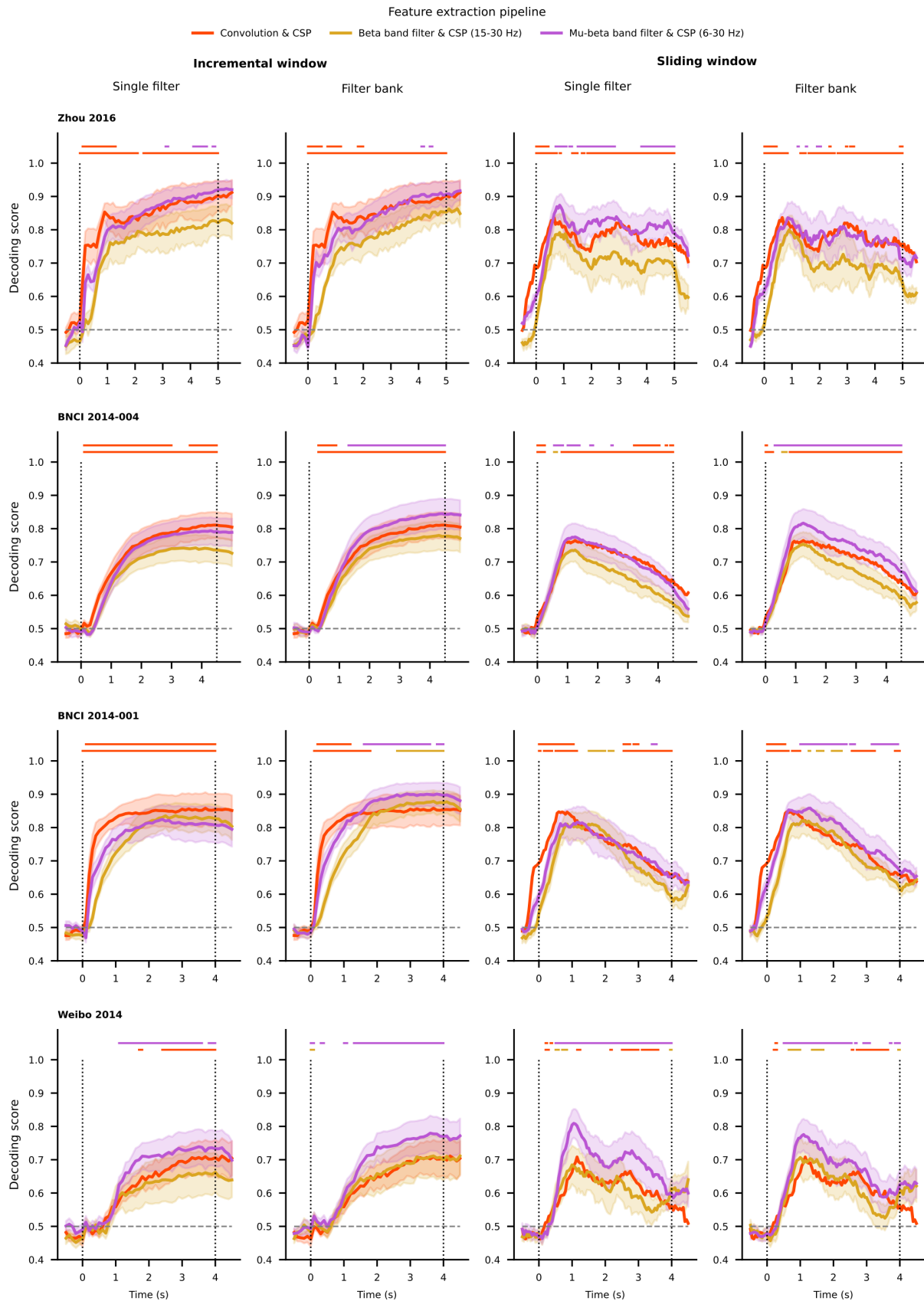


Figure 1. Time-resolved pseudo-online decoding results in “left” versus “right” hand motor imagery classification. Three feature creation techniques are assessed: convolution of raw signals with a selection of burst waveforms, beta band and mu-beta band filtering. Each row corresponds to across-subjects average decoding accuracies of a different EEG dataset. The first two columns correspond to a paradigm based on the incremental window approach. Using steps of 100ms duration, a classifier is trained on all available data up to each time point. The last two columns correspond to a paradigm based on the sliding window approach. Using

overlapping 1s-long windows (50ms step) a classifier is trained on all data of each window. For either approach, both a single filter and a filter bank are compared to the convolution technique. Above each subplot, colored lines depict permutation test results that indicate the feature extraction technique that yields superior decoding results.

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