A Novel Procedure for Classification of Early Human Actions from EEG Signals

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***Abstract*—We introduce a novel procedure that extends the time feasibility for classification of early human actions. Its major characteristic is to use epoch training data from a wider time duration before action onset (i.e., within the intention period) instead of data from localized sliding windows. This is the case of time-specific and selected fixed classifiers. Our approach models human actions from EEG signals and leverages on amplitudes and power frequencies to construct fifteen groups of action vectors, which were subjected to a set of classifiers. Regarding early classification our approach did it earlier than both time-specific and selected fixed classifiers. Moreover, our results reported an increase in classification performance.**

***Keywords*-EEG; Anticipation; Single-trial; classification procedure**

I. Introduction

Classification of early human actions from Electroencephalography (EEG) of brain activity has important applications in health and safety (e.g. accident prevention during car driving [1]). One usual approach to performing this task is the use of trial averaging techniques [2], which mitigates the problem of inherent noise associated with the direct decoding of EEG signals. However, trial averaging needs several examples to infer early classification, what makes it unsuited to on-line applications. On the other hand, single trial analysis of EEG activity has started to be explored [3]. This technique is promising because it favors on-line decoding.

Single trial techniques require the use of training strategies capable to handle sliding window classification. Nowadays, two training strategies are normally used [4]. The first, known as time-specific classifier strategy (TSC) - uses per-window training data for building per-window classifiers. This strategy works well for early classification, for example, good classification accuracy happens around $1000ms$ before action onset, but by construction TSC is unpractical for on-line applications. The second, known as the selected fixed classifier strategy (SFC), takes the best classifier of the TSC and uses it as a single model. Since the SFC is trained off-line, it can handle on-line classification. However, a SFC drawback is that classification of early actions happens closer to the time window from where the classifier was selected (normally $250ms$ before action onset) [5]. Another challenge for classification of early human actions is to determining the relevant frequency components that encapsulate anticipatory behaviour and improve classification performance. It has been observed experimentally that discriminant information for classifying anticipatory behaviour can be extracted from frequencies below 4Hz [4].

Our approach models human actions from EEG signals and leverages on epoch [6] training data to build a set of linear models for classification of early human actions. At a first stage of classification, EEG raw data was recorded while subjects drove a virtual car as steering actions (i.e., left and right turns) were acquired and segmented into trials. Time and time-frequency analysis were used to decode human actions at different frequency ranges and domains. Finally, we extract a set of features from EEG amplitudes and power frequencies that were used to construct fifteen groups of action vectors, which were subjected to a set of classifiers. Although, the traditional TSC and SFC techniques use just the information of the current time window for training a classifier, we used epoch data from the intention period of $1s, 2s$ and $3s$ before action onset. Our results reported an increase in classification performance. Regarding early classification our approach did it earlier than both TSC and SFC techniques.

II. Human Action Modeling

A. Action Acquisition

The experiment for data acquisition consisted in controlling a virtual car in a custom circuit where the main actions correspond to turn the car to either left or right [5]. The data is composed of two actions, namely *steering left* (class 1) and *steering right* (class 2). Steering actions were performed with an ordinary keyboard. All subjects were instructed to perform an action with their left or right hands by using their index finger to control the virtual car. To turn the car to the left subjects were instructed to use their left hand to press a predefined letter located on the left side of the keyboard (letter A in this case). When turning right a similar action was required on the right side of the keyboard by pressing letter P. The driving experiment was performed during four days and EEG data of five healthy subjects were recorded and sampled at 128Hz using an Emotiv EPOC neuroheadset with 14 channels: $\{AF3$, $F7$, $F3$, $FC5$, $T7$, $P7$, $O1$, $O2$, $P8$, $T8$, $FC6$, $F4$, $F8$, $AF4\}$, spatially arranged as shown

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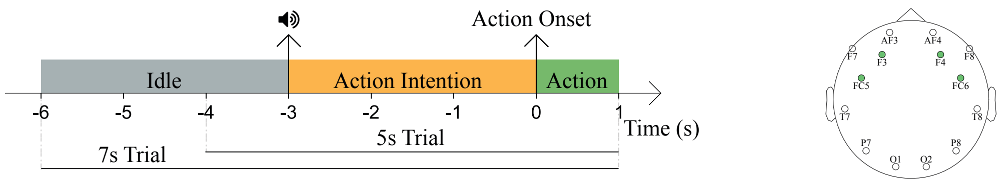


(a) Time window

(b) Emotiv Electrode Positioning

Figure 1: a) Trial timing for actions in temporal and time-frequency domains. The change from idle state to action intention is triggered by a beep sound occurring around $-3s$. Negative time means a period before the action onset. b) Emotiv EPOC electrode positions according to the international 10-20 locations. The electrodes used in this study are shown in green, which were chosen due to the relation of the locations of these channels to motor actions [7].

in Figure 1b according to the international 10-20 system. The complete frequency range available from the EEG raw data comprised $[0.2 - 45]$Hz. Four sessions per day were recorded for each subject. Each session contained 28 turns (14 for each class), yielding a total of 2240 turns (all subjects). Each steering was segmented into trials lasting $5s$ for temporal analysis (amplitude features) and $7s$ for time-frequency analysis (power features), respectively. These time intervals were used to include the idle period (no action), action intention period (preparing for action), the action onset (starting the action) and the action itself (performing the action), as shown in Figure 1a. As movement intention is related to motor actions, we used channels located in the frontal lobe $\{F3, F4\}$ and fronto-central lobe that capture activity from pre-motor and motor cortex $\{FC5, FC6\}$ [7].

B. Action Parameterization

In this section, we show how actions of subjects performing the same activity over trials can be parameterized from neural data. Brain activity using EEG are time series that can be decomposed into different frequency components, also known as brain rhythms [8]. Classically, these frequency components are divided as δ $(0.2-4$ Hz), θ $(4-8$ Hz), μ $(8-13$ Hz), β $(12-30$ Hz) and γ $(30-80$ Hz). Due to hardware limitations, we explore low γ $(30-45$ Hz). These frequencies have been related to several behavioural and cognitive states. For example, the amplitude of μ and β rhythms change when a subject performs motor actions [9], [10]. Thereby, we explore time and frequency domain (i.e., amplitude and power) to extract discriminant attributes for parameterizing human actions. An action encoded by the EEG can be represented as:

$$\mathbf{x}^c = [x_1^c, x_j^c, \ \dots \ , x_N^c]. \tag{1}$$

Where $\mathbf{x}^c \in \Re^N$ is a trial, N denotes the number of sampled time-points of channel $c = \{c_1, c_k, \ \dots \ , c_{14}\}$ where $\{c_1 = AF3, \ \dots \ , c_{14} = AF4\}$ and x_j^c is the j^{th} attribute of channel c. Then given $\mathbf{x}^c$, temporal amplitudes are obtained by applying temporal filtering techniques on $\mathbf{x}^c$. So, in order to handle border distortions [11], EEG data lasting $8s$ before and after action onset were band-pass filtered by a Butterworth zero-phase filter to obtain features within the five frequency components $f \in \{\delta, \theta, \mu, \beta, \gamma\}$:

$$\mathbf{x}_{af}^c = \mathbf{x}^c * H_f(z), \tag{2}$$

where $\mathbf{x}_{af}^c$ parameterizes an action within a frequency component f, electrode c and amplitude a, $H_f(z)$ is the band-pass Butterworth digital filter for the frequency band f, z is the filter parameters and $*$ is the convolution operator. In order to avoid the ripple side-effect of producing a higher order filter that has a steep roll-off [12], if the difference between the highest and lowest cutoff frequencies < 3, a 3$^{\text{rd}}$ order filter was used, otherwise a 4$^{\text{th}}$ order filter was applied. After the temporal filtering, trials lasting $5s$ are cut-off, as shown in Figure 1a.

In time-frequency domain, actions are modeled by a 3-cycle complex Morlet wavelet [13]:

$$\Psi_f(t) = Ae^{-t^2/2s^2}e^{i2\pi ft} \tag{3}$$

where A is a frequency band-specific scaling factor defined as $A = \frac{1}{(s\sqrt{\pi})^{1/2}}$ and s is the standard deviation of the Gaussian function. More formally, power features are computed as:

$$\mathbf{x}_{pf}^c = \frac{|\mathbf{x}^c * \Psi_f(t)|^2}{mean(\mathbf{x}_{pf}^{bc})}, \tag{4}$$

where p indicates power and $\mathbf{x}_{pf}^{bc}$ is the power of the baseline (i.e., a period with no action that is used to remove background information) computed from the idle period (see, Figure 1a) for channel c at frequency f. Finally, human actions from neural activity encapsulated by an EEG channel are then modeled as a state vector, given as:

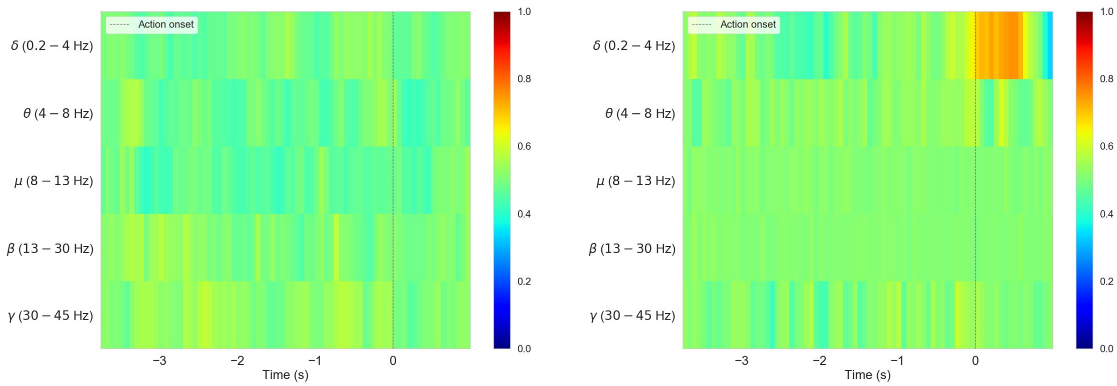
$$\mathbf{x}_{\zeta f}^c = [x_{\zeta f1}^c, x_{\zeta fj}^c, \ \dots \ , x_{\zeta fN}^c], \tag{5}$$

where, $\zeta = \{a, p\}$ as described by Equations 2 and 4.

III. A Model for Early Action Classification

A. Epoch-based Datasets

Based on TSC results [5], [14], we noticed that classification accuracy starts increasing around $-1s$, so the idea is to train classification models by using trials from the action intention period. At a first stage, error trials related to in-driving action were removed, for example, if the driver hits the wall within the action intention period,



(a) Time-frequency domain

(b) Time domain

Figure 2: Classification accuracy results using frequency bands described in III-A, action onset is shown as a grey dashed line. a) Using time-frequency features. b) Using time domain features.

this trial is removed. Then noisy trials are removed based on visual inspections of the raw EEG data. After removing noisy data, a total of 1290 trials out of 2240 were selected. The next step divides the data for training and testing. To do so, 90% of the trials were randomly selected for training a classification model and the rest for model validation, by maintaining the original class distribution using stratified split [15]. Training data were extracted from the $[-1s\ 0]$ time window, but model validation is performed over a $5\ s$ time window: $[-4s\ 1s]$.

We build two main training datasets, one for time (dataset A) and another for time-frequency (dataset B) analysis. In both cases, EEG raw data (Equation 1) is band-pass filtered into the five frequency components $\{\delta, \theta, \mu, \beta, \gamma\}$ by using Equations 2 and 4, respectively, and sampled at 128Hz. Differently from the Butterworth filter, the Wavelet function decomposes the frequency range into single frequency unities. So, in the case of dataset B, each of the five brain rhythms is linearly interpolated at ten different frequencies. For each of these frequencies, power is calculated using Equation 4 and then averaged, which gives one frequency band power per brain rhythm. Lets take the μ rhythm as an example, $n = 10$ different frequency unities are generated: $\mathbf{f} = [\mu_1, \mu_2, ..., \mu_n]$, then Equation 4 is applied generating $\mathbf{x}^c_{p_{\mu_i}}$ for each frequency in $\mathbf{f}$. Finally, $\mathbf{x}^c_{p_{\mu_i}}$ are summed and divided by n: $\mathbf{x}^c_{p_\mu} = \sum_{i=1}^{n} \frac{\mathbf{x}^c_{p_{\mu_i}}}{n}$. Overall, intra-frequency averaging is performed to reduce the dimensionality of the feature space.

The next step handles epoch extractions. Epochs are obtained by using time-based epoching technique. This technique consists in dividing a trial into smaller timing periods called epochs [6]. So, within this $1s$ time window ($[-1s\ 0]$), we extract epochs of $250ms$ overlapping every $31.25ms$, which gives 25 epochs per trial and 32 sampled time-points per channel. Datasets A and B have the same number of epochs: 29025.

B. Action Feature Vectors

In the current study, to build a set of feature vectors that represent one of the two steering actions, we leverage on the data of four selected channels $\{c_3, c_4, c_{11}, c_{12}\}$ and in one of the five selected frequency components in time or time-frequency domains. We used dataset A to build action feature vectors from the temporal amplitudes of EEG signals. For dataset B, feature vectors were constructed from the average band power. For each epoch data, these four channels are concatenated. An action feature vector is represented as:

$$\mathbf{X}_{\zeta f} = [\mathbf{x}^{c_3}_{\zeta f}, \mathbf{x}^{c_4}_{\zeta f}, \mathbf{x}^{c_{11}}_{\zeta f}, \mathbf{x}^{c_{12}}_{\zeta f}]. \tag{6}$$

As EEG data are sampled at 128Hz and each channel has 32 attributes, the vector in Equation 6 has $N = 128$ coefficients.

C. Learning a Classification Model

After building the action feature vectors, they are subjected for learning classification models. For the classifier, we used the Linear Discriminant Analysis (LDA) technique because it works well in on-line applications and have proven to be effective in EEG signal classification [4], [16]. Due to individual differences in behaviour and to increase the generalization power of the model, training data from the five subjects were used to learn LDA classifiers. To limit the amount of over-fitting and speed up learning, we used a stratified 10-fold cross-validation procedure [15], where all the epochs of the training sets A and B were used for training, and the remaining data were used to determine classification accuracy (ACC):

$$ACC = \frac{A_{crt}}{A_{tot}} \times 100\%, \tag{7}$$

where A_{crt} is the number of correct classified actions and A_{tot} is the total number of actions to be classified in the test data. After the learning procedure had been finalized, the 10 trained classifiers were applied to the test set. By doing so, we can analyze the mean and standard deviation accuracies. Regardless of time or power features, each test trial lasted $5s$ for both dataset A and B (see, Figure 1a). Then, by using a single trial classification approach [4], we classify actions from sliding windows of $250ms$ overlapping every $62.5ms$, in the period from $4s$ before the action onset to $1s$ after. In this study, the time reported always corresponds to the endpoint of the sliding window.

IV. Results

A. Overall Classification Performance of Early Actions

We evaluated the overall classification performance of early actions. To do so, we compared the results of the classification for the two steering actions studied according to Equation 6: $\{\mathbf{X}_{p\delta}, \mathbf{X}_{p\theta}, \mathbf{X}_{p\mu}, \mathbf{X}_{p\beta}, \mathbf{X}_{p\gamma}, \mathbf{X}_{a\delta}, \mathbf{X}_{a\theta}, \mathbf{X}_{a\mu}, \mathbf{X}_{a\beta}, \mathbf{X}_{a\gamma}\}$ A total of 10 action vectors were analyzed and compared. We then trained 10 classifiers with epoch data from the time interval $[-1s\ 0]$ for each action vector group. We used this interval because previous works [5], [14] reported an increase in classification performance from chance level around $-1s$. Figures 2a and 2b show the mean accuracy results from the 10 trained classifiers applied to the test set (also called evaluation data), for both power and temporal amplitude features, respectively.

Independently of the frequency range, both power and amplitude (Figure 2a) have not shown patterns to be discriminated during early human action classification. Before action onset, the classification accuracy for all frequency ranges were close to chance level. That is approximately 50% matching the random accuracy defined as: $\frac{1}{\mathrm{m}} \times 100\%$, m is the number of classes. On the other hand, we observed an increase in classification performance in δ band before action onset for amplitude vectors, $\mathbf{X}_{a\delta}$ (first line of Figure 2b). So, δ band $(0.2 - 4\ \text{Hz})$ seems to provide information that may allow earlier classification of human actions, by using our classification model (Section III), when compared to the other frequency components. This earlier action classification was previously observed for narrower bands extracted from δ component [5], [4], but as stated before, the TSC and SFC classification strategies had some drawbacks.

B. Optimum Classification Performance of Early Actions

We evaluated our model for classification of early human actions on the temporal amplitudes of action vectors extracted from very narrow frequency components. So, to optimally classify early actions, we decomposed the δ band into 10 frequency components: $\delta_1 = (0.2-1\ \text{Hz})$, $\delta_2 = (0.2-2\ \text{Hz})$, $\delta_3 = (0.5-1\ \text{Hz})$, $\delta_4 = (0.5-2\ \text{Hz})$, $\delta_5 = (1-2\ \text{Hz})$, $\delta_6 = (1-3\ \text{Hz})$, $\delta_7 = (1-4\ \text{Hz})$, $\delta_8 = (2-3\ \text{Hz})$, $\delta_9 = (2-4\ \text{Hz})$ and $\delta_{10} = (3-4\ \text{Hz})$. For comparison reasons, we maintained the same training and testing configuration described in section IV-A.

Figure 3 shows the classification performance results for the 10 bands. We observed earlier action classification for signals filtered in the δ band below 1Hz (low cut frequency). One can note a correlation, as the filtered signal increases from 1Hz to 4Hz (high cut frequency) the later action classification occurs. Moreover, optimum classification performance of early actions seems to be in the narrow frequencies: δ_1 and δ_3. Another important finding is that, we observed an interesting result regarding the δ_2 band, for this component the classification duration remained wider, almost $500ms$ after action onset. This classification behavior had been previously observed only for the TSC [5], [4]. Finally, we noticed that for filtered signals above 2Hz anticipatory patterns seems to disappear, as observed on the δ_8, δ_9 and δ_{10} bands.

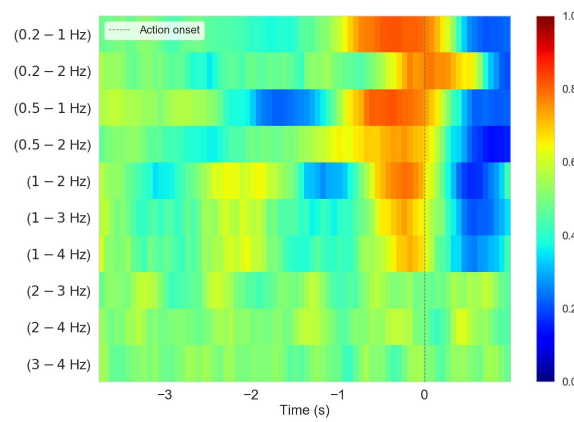


Figure 3: Classification performance results of early actions. Optimum classification performance of early actions was determined for bands δ_1 and δ_3. The dashed line represents the action onset at $t = 0$.

C. Epoch-based Datasets for Extended Durations

In order to extend the time feasibility of early action classification, we evaluated the performance of the 10 classifiers trained with epoch data from three time intervals within the intention period: $1s$, $2s$ and $3s$ prior to action onset. We used the action vectors from δ_1 and δ_3 bands, for reasons described in Section IV-B. The training data were obtained using the same approach described in Section III-A. For time window $[-2s\ 0]$, 57 epochs per trial were extracted resulting in a total of 66177 epochs, and for time window $[-3s\ 0]$, 89 epochs per trial were extracted resulting in a total of 103329 epochs. For comparison reasons the training test was the same.

The detailed view of classification accuracies of all time windows and for each frequency component is summarized in Figures 5a and 5b. As seem from Figure 5a, average accuracy and the classification curve kept almost the same value across the time intervals. For the $2s$ and $3s$ time intervals, the action classification occurred $188ms$ earlier when compared to the $1s$ time interval. From Figure 5b, we can see that for the $2s$ and $3s$ time intervals, a peak in classification accuracy occurred exactly $250ms$ earlier than 5a (δ_1). Regarding early classification, that is, the time when accuracy exceeds chance level (we considered an exceed when accuracy is $> 60\%$), for $2s$ and $3s$ classifiers, accuracy exceeded the chance level earlier than the $1s$ classifiers (around $1500ms$ vs. $1000ms$, respectively).

Overall, early classification of δ_1 and δ_3 classifiers happened at similar time for the $2s$ and $3s$ time intervals, and all classifiers achieved basically the same accuracy performance.

D. Comparison to Previous Work

To compare with the results of the time-specific and selected fixed classifiers, we trained 10 classifiers for each sliding window of $250ms$ using the epoch data of that window and used amplitude feature vectors from δ_1 band (TSC). We also used the best trained classifier before action onset (SFC). Figure 4 shows the results for the TSC and SFC. Regarding early action classification when they exceeded chance level, time-specific classifiers did it earlier than selected fixed classifiers (aroud $750ms$ vs. $350ms$, respectively). Similarly, Lew et al. [4] reported earlier classification of TSC. On the contrary, our results outperforms both TSC and SFC regarding earlier classification, as depicted in Figure 5a. In our approach, early action classification from chance level happened $1000ms$ before action onset.

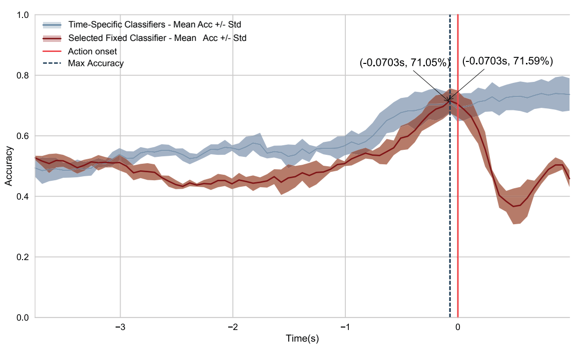


Figure 4: Comparison results of classification accuracies for time-specific classifier (TSC) and selected fixed classifier (SFC) for all subjects. Grey dashed lines shows where the best accuracies and classification time of both models occurred.

E. Evaluating the Effect of Frequency Combination

In some situations it may be of interest to encapsulate information regarding early and post activity, for example, to know if a driver will change his car direction and for how long he continued acting. In order to investigate this behaviour, we combined the feature vectors of the best bands δ_1 and δ_3 with δ_2 band, and analyzed its encapsulation capabilities in acquiring early and post action patterns together. The feature vectors were concatenated as:

$$\mathbf{X}_\zeta = [\mathbf{X}_{\zeta f_1}, \mathbf{X}_{\zeta f_2}], \tag{8}$$

where $f_1 = \{\delta_1, \delta_3\}$ and $f_2 = \delta_2$.

We can observe in Figure 5c that the classification accuracies of the concatenated vector $\delta_{1,2}$ are similar of the action vectors δ_1 (Figure 5a) for all three time intervals, but early action for peak classification happened $188ms$ later. On the other hand, for the concatenated vector $\delta_{3,2}$, early action for peak classification happened $-1007.8ms$ for the classifiers trained with epoch data from the ($[-2s\ 0]$) time interval, increasing in $187.5ms$ early action classification compared to δ_3 alone. One side effect of the concatenation was the lost of post activity classification of the δ_2 band.

V. Discussions and Future Directions

We have presented a new approach for classification of early human actions. Our approach uses epoch training data from several sliding windows within the intention period of $1s, 2s$ and $3s$ before action onset instead of fixed epochs, which is used for training time-specific and selected fixed classifiers. We demonstrated the performance of our approach by classifying early actions encapsulated into a set of fifteen feature vectors from EEG amplitudes and power frequencies and by comparing our results against the time-specific and fixed selected classifiers. Our approach provided higher classification accuracies than TSC and SFC, by using amplitude features extracted from very narrow frequency bands of $[0.2 - 1\ \text{Hz}]$ and $[0.5 - 1\ \text{Hz}]$. Moreover, regarding early classification our approach did it earlier than both TSC and SFC techniques.

Regarding the combination of narrow frequency components, one side effect was the loss of post activity classification encapsulated into the δ_2 band. However, the concatenation of $\delta_{3,2}$ bands increased the early action classification time when compared to δ_3 band alone from $-820ms$ to $-1007.8ms$.

By analyzing data in different domains, time intervals and frequency ranges, we were able to increase early action classification around $500ms$ if considering the highest accuracy shown in Figure 5a, and in about $930ms$ if considering the best anticipation interval depicted in Figure 5d. We also increased the overall classification accuracy performance in about 10.30% compared to TSC and SFC. In addition, this study shows that in case of anticipatory motor action classification, the best features to be analyzed are EEG amplitudes from the frequency ranges: $[0.2 - 1\ \text{Hz}]$, $[0.5 - 1\ \text{Hz}]$ and $[0.2 - 2\ \text{Hz}]$.

Although our approach is suitable for early action classification, it is unsuited for on-line applications, because of the filtering technique we used. Extending it to handle on-line applications is the next step of our research.

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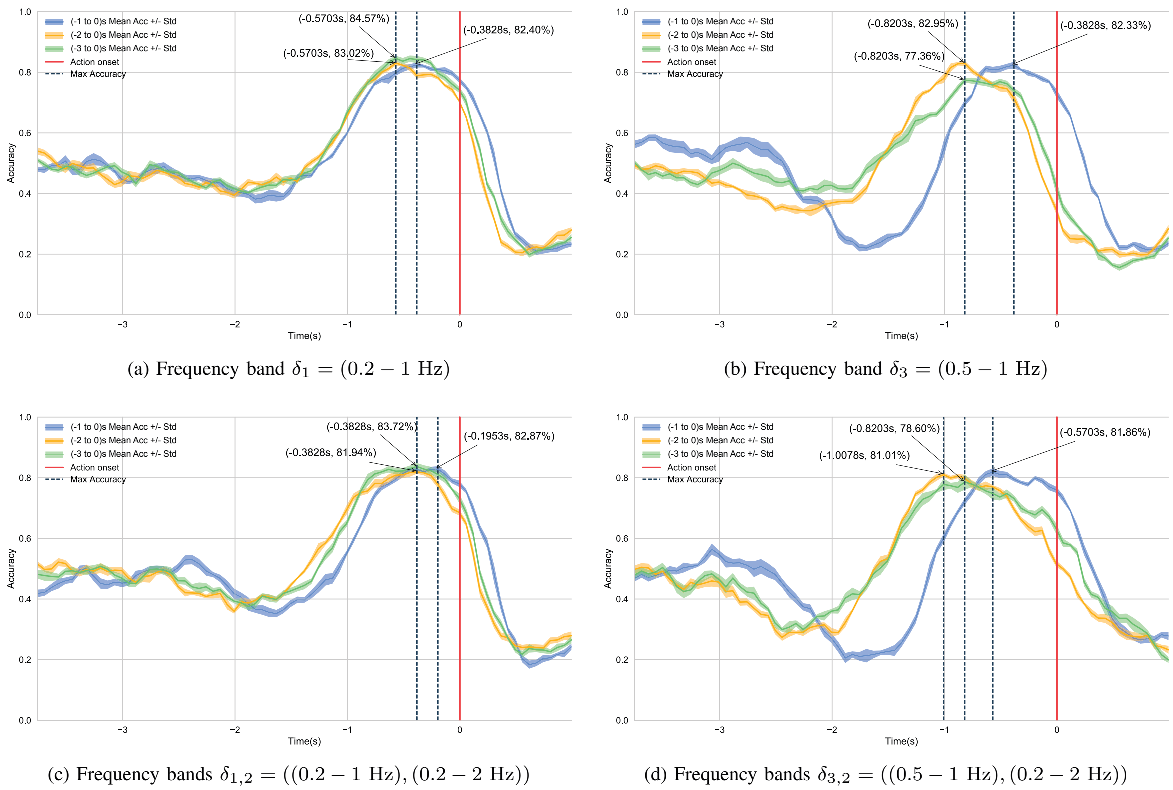

(a) Frequency band $\delta_1 = (0.2 - 1 \text{ Hz})$

(b) Frequency band $\delta_3 = (0.5 - 1 \text{ Hz})$

(c) Frequency bands $\delta_{1,2} = ((0.2 - 1 \text{ Hz}), (0.2 - 2 \text{ Hz}))$

(d) Frequency bands $\delta_{3,2} = ((0.5 - 1 \text{ Hz}), (0.2 - 2 \text{ Hz}))$

Figure 5: Comparison results of classification mean accuracy and standard deviation for training data from $1s$, $2s$ and $3s$ prior to action onset. Grey dashed lines show where the best accuracies of all 3 models occurred, the exactly time and accuracy are also annotated. a) Frequency band $(0.2 - 1 \text{ Hz})$. b) Frequency band $(0.5 - 1 \text{ Hz})$. c) Concatenated frequency bands $((0.2 - 1 \text{ Hz}), (0.2 - 2 \text{ Hz}))$. d) Using concatenated frequency bands $((0.5 - 1 \text{ Hz}), (0.2 - 2 \text{ Hz}))$.

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