Commonalities of Motor Performance Metrics are Revealed by Predictive Oscillatory EEG Components

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Keywords: EEG, Oscillatory Components, Single-Trial Analysis, Performance Prediction, Machine Learning, Spatial Filters, Subspace Decomposition, Hand Motor Task, Isometric Force, Performance Metrics, Reaction Time, Jerk, Motor Rehabilitation.

Abstract: The power of oscillatory components of the electroencephalogram (EEG) can be predictive for the single-trial performance score of an upcoming task. State-of-the-art machine learning methods allow to extract such predictive subspace components even from noisy multichannel EEG recordings. In the context of an isometric hand motor rehabilitation task, we analyse EEG data of n=20 normally aged subjects. Predictive oscillatory EEG subspaces were derived with a spatial filtering method (source power comodulation, SPoC), and the transfer of these subspaces between five performance metrics but within data of single subjects was investigated. Findings suggest, that on the grand average of 20 subjects, informative SPoC subspace components were extracted, which could be shared between a set of three metrics describing the duration of subtasks and jerk characteristics of the force trajectories. Transfer to any other of the remaining four metrics was not possible above chance level for a metric describing the reaction time and a metric assessing the length of the force trajectory. Furthermore we show, that these transfer results are in line with the structure of cross-correlations between the performance metrics.

1 INTRODUCTION

Motor tasks are performed in rehabilitation scenarios or in basic research of the human motor system. The execution quality of repeated trials of the same task varies and can be assessed on a trial-by-trial basis by a large number of performance metrics. Examples are the reaction time, the smoothness of the trajectory produced, its length, or the duration of trial/repetition. Each of these metrics focus on different aspects of the motor task.

Trial-to-trial variations of the motor performance can have many different causes ranging from an unstable experimental setup over varying starting positions of the user or fluctuating muscle tone to alterations of the mental state of the user. The latter can be expressed e.g. by varying attention levels during the presentation of cues or the predisposition of brain regions involved in the motor execution, and is of interest especially in the context of motor rehabilitation after stroke. Analysing electroencephalogram (EEG) data recorded immediately before the execution of each single motor execution trial with machine learning methods (Müller et al., 2008; Parra et al., 2005; Delorme et al., 2011) can reveal oscillatory activity of the EEG, which is informative about the performance metric of the upcoming trial and may be the basis for brain-state dependent training paradigms. For the SVIPT hand motor task used in stroke rehabilitation (Meinel et al., 2015; Castaño-Candamil et al., 2015b) it was proposed to use the supervised spatial filtering method source power comodulation (SPoC, (Dähne et al., 2014)). SPoC finds spatial filters, which extract oscillatory subspace components of the EEG within a narrow frequency band. The algorithm optimizes these filters in such a way, that the resulting subspace components comodulate in power to a variable which is accessible for every trial. In the case of SVIPT training, the values of a trial-wise performance metric can be used as labels to guide the SPoC algorithm. For the SVIPT task five different trial-wise performance metrics have been extracted to describe the quality of the force control.

Concerning the search for comodulating oscilla-

Tangermann, M., Reis, J. and Meinel, A..
Commonalities of Motor Performance Metrics are Revealed by Predictive Oscillatory EEG Components.
In *Proceedings of the 3rd International Congress on Neurotechnology, Electronics and Informatics (NEUROTECHNIX 2015)*, pages 32-38
ISBN: 978-989-758-161-8

tory components of the EEG, it must be expected that the exact type of performance metric used (the labels for SPoC) will influence both, the optimal frequency band for the extraction of SPoC components, and the actual spatial filters/components revealed by SPoC. While the cross-correlations between the five metrics can easily be computed, it is an open question, if informative oscillatory subspace components can be transferred successfully between metrics.

2 METHODS

2.1 Hand Motor Task

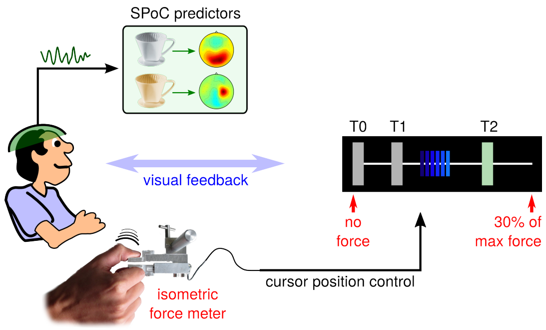

Figure 1: EEG-tracked SVIPT scheme. By force modulation, the horizontal cursor position can be controlled.

The sequential visual isometric pinch task (SVIPT) (Reis et al., 2009) requires isometric force control of the thumb and the index finger. Since SVIPT training improves motor performance upon a range of hand-motor tasks, the paradigm is applied in motor rehabilitation after stroke. During a single trial, the subject is required to control a horizontally moving cursor by generating an isometric force between thumb and index finger. All fields (T0, T1, and T3) are visible during the full duration of a trial. Field T0 corresponds to zero force and is used as the starting point of the cursor. Reaching the field T2 requires the highest force application (see Fig. 2).

Each trial comprised the following stages: the visual presentation of a light blue (still inactive) cursor indicated the *get-ready* phase. This interval randomly varied between 2 s and 3 s of duration and was terminated by the *go-cue*. At this time point, the cursor turned dark blue and its horizontal position could be controlled by the subject. During this *running* stage of the trial, the subject was asked to manoeuvre the cursor through a sequence of the three narrow target fields as quickly and as accurately as possible. The two sequence types requested to produce were either T0-T1-T0-T2-T0 (see the example force profile in Fig. 2) or T0-T2-T0-T1-T0. During a sequence, the next target field to be hit was visually highlighted in slight green color. In order to hit a target field, a dwell time of 200 ms had to be fulfilled. Skipping a target field and moving on the the next element of the sequence was not accepted.

Trials with high level of motor control are characterized by a rapid initial force ramp-up and the avoidance of overshoots beyond target fields. As introduced in (Meinel et al., 2015), we modified the original SVIPT setup by the additional recording of EEG activity throughout all stages of the experiment. To design improved rehabilitation training scenarios, it would be of interest to identify EEG correlates within an interval prior to the *go-cue*, which are predictive wrt. the trial-wise performance metric.

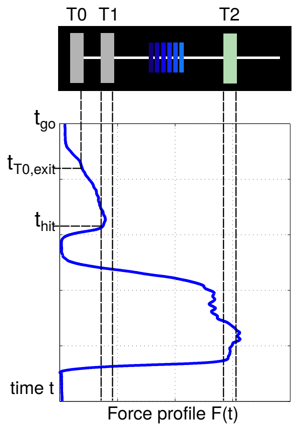

Figure 2: Force profile F(t) for single SVIPT trial. The trial start at time point t_{go} is followed by leaving the target field T0 with the blue cursor at time point $t_{TO,exit}$. The successful hit of the first target field is marked at time point t_{hit}.

2.2 Subjects, Data Acquisition and Preprocessing

In total, 20 single sessions from the same number of right-handed subjects with an average age of 53 years (std: 6 years) were recorded. Each subject controlled the cursor with the left hand during 400 trials. During the SVIPT task, EEG signals from 64 passive Ag/AgCl EasyCap electrodes placed according to the extended 10–20 system and referenced against the nose were registered by BrainAmp DC amplifiers. The data was sampled at 1 kHz. During offline preprocessing, signals were band-filtered between 0.7 Hz and 25 Hz and subsampled to 500 Hz. An amplitude and variance rejection criterion was applied per epoch and per channel in order to diminish the impact of noise, eye movements or muscular artifacts. Rejected epochs were not compensated for, and rejected channels were not replaced.

2.3 SVIPT Performance Metrics

Since there is no unique measure to validate the quality of a single repetition of the SVIPT task, we define a subset of performance metrics and contrast them among each other. In the following, five trial-wise performance scores[1] are motivated. Each of them is derived from the force profile $F_(t)$ as described in Fig. 2:

- **Reaction Time / RT:** A quick reaction upon the *go-cue* is the basis for a successful trial. Reaction time is defined as the interval between the *go-cue* at time t_{go} and the time point $t_{T0,exit}$ which indicates the cursor leaving the starting field T0.
- **Duration / DUR:** In a similar manner as RT, the duration from the *go-cue* at time t_{go} until the hit of the first target field at time point t_{hit} needs to be short for a successful trial:

$$DUR \equiv t_{hit} - t_{go} \tag{1}$$

- **Cursor Path Length / CPL:** The total path length the cursor is moved from the *go-cue* to the hit of the first target field can be described by:

$$CPL \equiv \int_{t_{go}}^{t_{hit}} |\dot{F}(t)|\, dt' \tag{2}$$

- **Integrated Squared Jerk / ISJ:** Changes in smoothness of the force profile characterize the level of fine-granular motor control. Therefore, the jerk - defined as the third derivative of the force profile - is contained in the ISJ, which is defined as:

$$ISJ \equiv \int_{t_{go}}^{t_{hit}} |\frac{d^3F(t)}{dt^3}|^2\, dt' \tag{3}$$

- **Normalized Jerk / NJ:** Related to ISJ, the NJ is a unit-free and proportional measure of the jerk:

$$NJ \equiv \sqrt{\frac{ISJ \cdot DUR^5}{2 \cdot CPL^2}} \tag{4}$$

However, the introduced scores CPL, DUR, ISJ and NJ strongly depend on the selection of an upper time limit. A good choice of this parameter requires a trade-off between staying close to the *go-cue* and the analysis window (which ends just before the *go-cue*) on the one hand, and processing the richer information of a full target sequence on the other hand. As a compromise between both requirements, we decided to extract these four metrics up to the hit of the first target field.

[1] Except for metric RT, a standardization of the distribution of performance scores had to be performed before the measurements of the two sequence types (either T0-T1-... or T0-T2-...) could be joined.

2.4 Source Power Comodulation

The trial-wise SVIPT performance metric can be used as label information to guide a data-driven machine learning approach to determine EEG subspaces which comodulate in band power with a given continuous performance metric. Source power comodulation (SPoC) (Dähne et al., 2014) is a linear spatial filtering method, which maximizes the correlation of an epoch-wise defined bandpower $\Phi_x(e) = \mathrm{Var}[\hat{s}](e)$ of the subspace signal $\hat{s} = \mathbf{w}^\top \mathbf{x}(t)$ with a given epoch-wise metric $z(e)$. The spatial filter $\mathbf{w}$ is calculated by solving $\mathrm{argmax}_\mathbf{w}\{\mathrm{corr}[\Phi_\mathrm{x}, \mathrm{z}]^2\}$. The multivariate variable $\mathbf{x}(t) \in \mathbb{R}^{N_c}$ describes the EEG signal with N_c sensors.

As the alpha band activity of the EEG has been correlated with visual attention processes (Thut et al., 2006; Romei et al., 2008) as well as with the state of the motor system (Pfurtscheller et al., 1996; Pfurtscheller and Da Silva, 1999), we chose to focus the analysis to the frequency band of 8 Hz to 13 Hz. Extracting EEG from a prediction window located within the *get-ready* phase and prior to the *go-cue* and utilizing performance metrics as described in 2.3, one can use the resulting spatial filters as predictors for estimating the motor performance of the upcoming trial. As the EEG signals need to be band-filtered before entering the approach, the frequency band of interest and the exact time interval of the prediction window are hyperparameters which influence the resulting SPoC performance. To optimize these, we performed a grid search upon different SPoC parameter configurations. The frequency bands $[f_0, f_0 + \Delta f]$ were linearly increased within the alpha band range from $f_0 = 8 - 13Hz$ with a step size of 0.5 Hz. The band width was kept fixed at $\Delta f = 1Hz$. Three different time intervals $[-\Delta t, -50ms]$ relative to the *go-cue* with $\Delta t = \{600, 800, 1000\}ms$ were investigated for the prediction window.

The parameter sweep was calculated for each of the subjects and for all five performance metrics. For further analysis, the best configuration per subject and performance metric was chosen according to their correlation values and pattern similarities. A detailed methodology to extract informative components can be found in (Castaño-Candamil et al., 2015b), and (Haufe et al., 2014) motivates the interpretation of subspace components via the resulting patterns.

2.5 SPoC Component Transfer Across Performance Metrics

The eigenvalues of SPoC filters correspond to correlations of these components with the underlying performance metric. In Fig. 3 the averaged spectrum across all 20 subjects and all five performance metrics is shown. As the correlation values drop rapidly from component to component, the first e.g. five SPoC components typically are sufficient to provide an informative subspace.

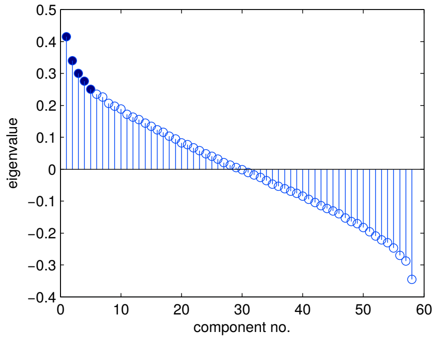

Figure 3: Eigenvalue spectrum of SPoC components averaged over 20 subjects and five performance metrics.

In order to investigate common characteristics of motor performance metrics within subjects, we now transfer SPoC filters and calculate their correlation with another performance metric, which had not been utilized for calculating the spatial filter. For a given metric i, the epoch-wise band power feature $\Phi_{x,i}$ using only the first component is extracted. In a second step, we report on the correlations of this feature with all other performance metrics j in a transfer matrix $T_k(i,j) = \mathrm{corr}[\Phi_{x,i} z_j]$ for each subject k. Since the EEG preprocessing delivers different numbers of remaining trials across subjects, we randomly select a subset of 200 epochs, which ensures the comparability of correlation values across subjects. As each matrix T_k is computed on the basis of a single subject, the grand-average transfer matrix $T_{ga} = 1/N_s \sum T_k(i,j)$ across $N_s = 20$ subjects must be derived by averaging. To evaluate the significance level of correlation values, we computed SPoC repeatedly based on 1000 randomly shuffled label values. As reported in Fig. 4, the exemplary shuffling of the ISJ labels evokes the 95 % threshold at a correlation value of 0.22. Thus, the entries of the transfer matrix $T(i,j)$ need to exceed this threshold in order to report a successful component transfer.

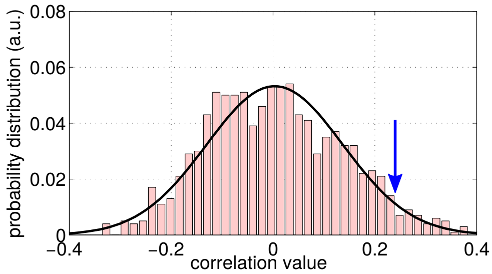

Figure 4: Bootstrapping result for metric ISJ. The 95% threshold at a correlation value of 0.22 is indicated by a blue arrow.

3 RESULTS

3.1 Correlations Across Performance Metrics

The performance metrics described in Sec. 2.3 were computed across all 20 subjects on each of the 400 trials. Their scatter plots in Fig. 5 depict the grand average correlations between five motor performance metrics. For visualization purposes, all values were z-scored, and values exceeding four standard deviations were omitted from the scatter plots. The strongest correlation is obtained between the metrics ISJ and DUR, non-linear interactions are observed between DUR and NJ. Metric RT is rather uncorrelated to the four other metrics, which is (to a lesser extend) also observed for the metric CPL. The histograms of the individual metrics reveal that there are symmetric distributions contained (DUR) as well as asymmetric ones (NJ, CPL).

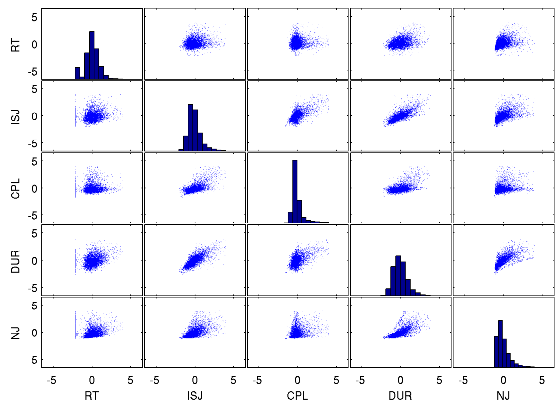

Figure 5: Scatter plots visualize the grand average correlations between five motor performance metrics for 8000 SVIPT trials, derived from 20 subjects and 400 trials per subject.

Table 1: For each performance metric, the table lists the optimal SPoC parameters derived: the frequency band specified in Hz, the time interval relative to the *go-cue*, the number of first-ranked components contributing to a maximal correlation value and the correlation value itself.

Metric	FQ band	Ival [ms]	# cp	corr
RT	9.0-10.0	-1000,-50	2	0.508
ISJ	11.5-12.5	-1000,-50	1	0.242
CPL	11.5-12.5	-1000,-50	1	0.344
DUR	9.5-10.5	-800,-50	1	0.178
NJ	8.0-9.0	-1000,-50	1	0.214

3.2 SPoC Component Transfer Across Performance Metrics

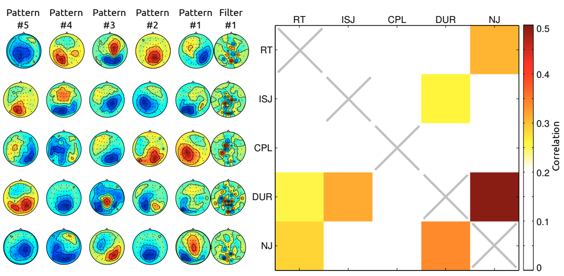

Figure 6: (Best single subject) *Left:* First five SPoC activity patterns for each performance metric according to the best parameter set are plotted. The corresponding first SPoC filter is shown in addition. *Right:* Transfer matrix $T(i, j)$. (Please see Sec. 3.2 for details).

The SPoC parameters (frequency band and interval interval) have been optimized separately for each metric, and Table 1 shows the values for the example of the best single subject. Please observe, that the derived best frequency bands vary between the performance metrics even within data of this single subject.

The transfer approach is illustrated on data of the same subject in Fig. 6. The 25 scalp maps on the left depict the patterns of the first five SPoC components of this subject (organized in columns), as derived for the five performance metrics (rows). For the first-ranked component, the corresponding spatial filter weights are depicted in an additional scalp map. Please remind, that only the first-ranked component has been used to evaluate the correlation for the component transfer across metrics. However, as the components of the ”receiving” metric may show similar patterns even in lower ranks, the full five first-ranked scalp patterns are provided.

The matrix on the right half of Fig. 6 visualizes the transfer matrix $T(i, j)$ as described in Section 2.5. It was derived for the same subject. Entry $T(i, j)$ color-codes the correlation gained by transferring the first-ranked component of the metric in row i to the metric of column j. Correlation values, which have not passed the bootstrapping test, have been marked by white entries. The entries $T(4,5)$ and $T(5,4)$ show the highest correlation values. It can be observed, that the involved metrics DUR and NJ share very similar patterns among their first-ranked components.

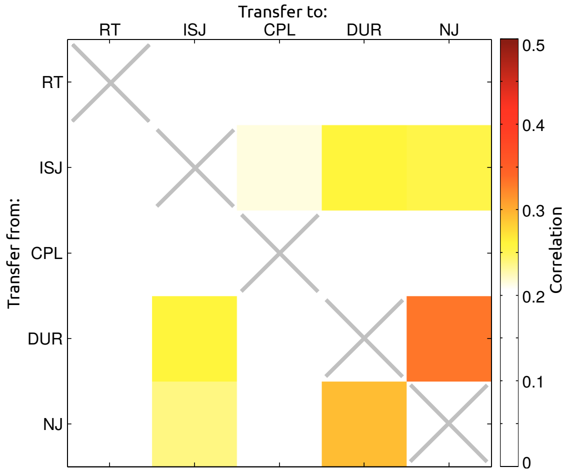

Figure 7: Grand average transfer matrix T_{ga} across all 20 subjects. Each entry (i,j) color-codes the correlation gained by applying the filter of the first ranked SPoC component of the metric in row i to the EEG data and correlating the power of the resulting oscillatory signal to the metric of column j.

The corresponding grand average results over all 20 subjects are depicted in Fig. 7. The matrix is close to symmetric, and the transfer of first-ranked components seems to work reasonably well within a set of three metrics (ISJ, DUR and NJ), while the metrics RT and CPL produce subspace components, which are not sufficiently informative for other metrics.

4 DISCUSSION AND CONCLUSIONS

Comparable to experiments close to the visual perception threshold (Schubert et al., 2009; van Dijk et al., 2008), where characteristics of occipital alpha oscillations of the EEG have been found informative about the probability to perceive a stimulus, oscillatory components can also contain information about the performance quality of a motor task, and influencing relevant oscillatory activity by user training can improve reaction time (Boulay et al., 2011). Spatial filtering with SPoC offers one possibility to access such components of the EEG.

In the scatter plots of five motor performance metrics, it was observed that the metric ISJ is correlated with the metric DUR, and DUR with NJ, while the metric RT is rather uncorrelated to the other metrics. At first glance, this is surprising, as for example the metrics RT and DUR both are temporal metrics and nevertheless are only weakly correlated. A possible explanation is that RT reflects a very early phase of the trial, while DUR includes information also from a slightly later trial stage.

Analyses based on SPoC showed, that the overall structure of those cross-correlations between the five metrics can be reproduced well by an transfer approach: first, the best oscillatory EEG component on one metric was estimated, and subsequently its informative content (in terms of power comodulation) was tested against other metrics. The metric RT, for example, does not show high correlations with the four other metrics — correspondingly, the power of the SPoC component derived by RT also does not correlate well with the four other metrics. The opposite can be observed for the metrics ISJ, DUR and NJ.

These results are astonishing, as the subspace transfer approach bears a number of potential pitfalls — the optimal frequency parameters vary between the five metrics, and the eigenvalue ranking of SPoC components reveals permutations already due to small changes of the data set, e.g. caused by label noise or overly small training data sets (Castaño-Candamil et al., 2015a). Nevertheless on the grand average, the transfer results reproduce the cross-correlation structure of the metrics.

The transfer results may have practical implications for the prediction of trial outcomes in a rehabilitation training: in cases, where no informative subspace can be derived for one metric, a transfer of a subspace derived from another metric may contain information if cross-applied. In case of patients, where lower SNR and a small number of available calibration trials are common problems, the transfer approach may be key to success. But even under higher SNR conditions, the trial outcome may be predicted with an increased reliability, if informative subspaces can be combined, which have been derived from different metrics.

ACKNOWLEDGEMENTS

The authors appreciate support by the German Research Foundation (DFG, grant EXC1086) for the cluster of excellence BrainLinks-BrainTools. Part of this work was performed on the computational resource bwUniCluster funded by the Ministry of Science, Research and the Arts Baden-Württemberg and the Universities of the State of Baden-Württemberg, Germany, within the framework program bwHPC.

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