

A Robust and Efficient Spatio-Temporal Feature Selection for Interpretation of EEG Single Trials

Yehudit Meir-Hasson¹, Andrey Zhdanov¹,
Talma Hendler², and Nathan Intrator¹

¹ Balvatnik School of Computer Science, Tel-Aviv University, Tel-Aviv, Israel
yehudit.hasson@gmail.com

² The Functional Brain Imaging Unit, Wohl Institute for Advanced Imaging
Tel Aviv Sourasky Medical Center, Tel-Aviv, Israel

Abstract. Interpretation of brain states from EEG single trials, multiple electrodes and time points, is addressed. A computationally efficient and robust framework for spatio-temporal feature selection is introduced. The framework is generic and can be applied to different classification tasks. Here, it is applied to a visual task of distinguishing between faces and houses. The framework includes training of regularized logistic regression classifier with cross-validation and the usage of a wrapper approach to find the optimal model. It was compared with two other methods for selection of time points. The spatial-temporal information of brain activity obtained using this framework, can give an indication to correlated activity of regions in the brain (spatial) as well as temporal activity correlations between and within EEG electrodes. This spatial-temporal analysis can render a far more holistic interpretability for visual perception mechanism without any a priori bias on certain time periods or scalp locations.

Keywords: EEG, BCI, Regularization, Spatio-temporal analysis.

1 Introduction

A major challenge in neuroscience is inferring how momentary mental states are mapped into a particular pattern of brain activity. Inference, which is based on EEG single-trial (i.e. short segment of the EEG) has practical implementations for brain computer interface (BCI) applications. BCI applications are designated for people suffering from physical disabilities, helping them to communicate with an electronic device through real time interpretation of their brain signals ([1]-[4]).

A common way to analyze EEG single-trials is through classification (for review, see [5]). One of the main challenges is the amount of data needed to properly describe the different states; It increases exponentially with the dimensionality of the data and is termed the *curse of dimensionality* [6].

To reduce the dimension of the data, many feature selection methods have been developed for identifying and choosing an optimal subset of features from the data. Often, researchers focus on few electrodes based on algorithms for channel selection that pick the most promising channels for classification. Muller et al. [7] utilized Spatial Pattern Analysis and PCA for channel selection and compared it to a set of four electrodes

chosen based on prior knowledge. Palaniappan et al. [8] and Schroder et al. [9] found appropriate channels via a Genetic Algorithm; Lal et al. [10] used Recursive Feature Elimination and Zero-Norm Optimization to reduce the number of electrodes from 39 to 12. Tomika and Muller [11] reduced the dimension of the data by down-sampling the signals. Another way to alleviate the curse of dimensionality is via regularization methods, which stabilize the solutions by introducing prior knowledge or by restricting the solution ([12]–[13]). Cross-validation can be used to find the optimized model and its regularization parameter ([11], [14]–[16]).

As data is becoming more readily available, it is more desirable to let the data guide the choice of an optimal model (determine relevant electrodes and time points) while minimizing a-priori assumptions. For this, a two-dimensional representation of the spatio-temporal predictive information of the brain activity is highly desirable, especially for development of new paradigms, for which the neural correlates may not be known in advance [17].

Modern data-driven analyses, such as microstate segmentation ([18]–[19]), have been developed and used to study the spatio-temporal activity in the brain. Microstate segmentation uses the spatial distribution of the ERP which involves averaging over multiple trials of similar brain activity (for review, see [17]). Such a predictive map lacks the correlated activity between electrodes, which is lost in the traditional ERP approach. Moreover, the ability to assess the trial-to-trial variability in event-related potential experiments can provide new insights into brain functioning which may be ignored during ERP averaging.

Tomika and Muller [11] suggested an EEG single trials spatio-temporal interpretation that was based on three different regularizers. The regularizers were used to reveal different and complementary aspects of the localization of the discriminative information. (The channel selection regularizer was used for spatially localizing the discriminative information, the temporal-basis selection regularizer localized the discriminative information in the temporal domain and the DS regularizer provided a small number of pairs of spatial and temporal filters that showed both spatial and temporal localization of the discriminative information in a compact manner). The regularizers were applied on a block diagonal data matrix which was composed of first order changes (short segment of filtered EEG signal with C channels and T sampled time-points) and second order changes (the covariance matrix of a short segment of band-pass filtered EEG). Their method requires an estimation of a large-parameter model, which may be prone to overfitting. Furthermore, reducing the sampling rate may ignore important properties of the signal, which are visible in the EEG high temporal resolution. The use of different regularizers [11] may be problematic as it may produce contrasting interpretations with no clear ability to determine which of them is more accurate.

In this work, we follow the framework introduced by [16] and present an efficient and robust computational model for brain state interpretation from EEG single trials. Our approach is based on the use of regularization techniques to optimize classifier coefficients. We further demonstrate how to identify the most relevant time points and electrodes that might be most pertinent in contributing to differentiation between the mental states investigated.

Our approach employs a two-step classification scheme; First, potential time points are selected (i.e. the electrode activity in these time points is found to best separate between the two mental states). Second, the selected time points are fused to obtain a holistic network related to the paradigm. This paper extends previous work [20] and includes a comparison to time-points-selection via ERP method and to the sequential fusion of time points method. This two-step framework leads to an effective feature selection using a small number of parameters, dozens compared with thousands in [11], while maintaining a high temporal resolution.

The proposed framework is generic and can be applied to different brain imaging modalities and classification tasks. In this study we applied it to a visual task of distinction between faces and houses.

2 Materials and Methods

2.1 Experiment Setup

Four subjects (SUBJ1-SUBJ4, 4 females, two left handed, aged 23-28), participated in this experiment. All subjects gave informed consent to participate in the study, which was approved by the ethics committee of the Tel Aviv Sourasky Medical Center. Subjects were presented with images from two different categories-faces and houses. The images of faces were taken from the [21] and [22] databases and include fearful or neutral facial expression. The experiment included 4 sessions, each of 138 epochs 2-seconds-long. During each epoch, the subject was presented with one image of a fearful face, neutral face, house or blank (32, 32, 64 and 10 epochs respectively). To achieve visual field segregation, participants were explicitly instructed to ignore the pictures and to concentrate on a fixation dot at the center of the screen. Throughout the experiment, participants were asked to report the color change of the central fixation dot.

2.2 EEG Data Acquisition

Continuous EEG data was recorded simultaneously with fMRI acquisition. In this study, we are focusing on the EEG data and have set aside the combined fMRI data for further research. Good signal-to-noise ratio of the EEG data in the combined approach was previously shown at our lab ([23]-[24]).

We used a 32-channel BrainCap electrode cap with sintered Ag/AgCl ring electrodes (30 EEG channels, 1 ECG channel and 1 EOG channel, Falk Minow Services, Herrsching-Breitbrunn, Germany) and a MR-compatible, 32-channel, battery-operated amplifier (Brain Products, GmbH, Germany). The electrodes were positioned according to the 10/20 system. The reference electrode was between Fz and Cz [25]. The signal was amplified, and sampled at 5000 Hz using the Brain Vision Recorder software (Brain Products). The EEG data was transmitted from the scanner room via an optical fiber to a PC in the control room. The exact timing of stimulus onset and MRI scanner gradient switching was transmitted to the EEG amplifier and recorded together with the EEG signal.

2.3 EEG Analysis

EEG data analysis was performed with EEGLAB 6.01 software package (Schwartz Center for Computational Neuroscience, University of California, San Diego), MATLAB software and FMRIB plug-in for EEGLAB, provided by the University of Oxford Centre for Functional MRI of the Brain (FMRIB). Pre-processing of the EEG data included the following steps: MR gradient artifacts removal and Cardio-ballistic artifacts removal using a FASTER algorithm implemented in FMRIB plug-in for EEGLAB ([23]–[24]). For computational efficiency, the EEG signals were down-sampled to 250 Hz and eye blinking artifacts were removed using ICA [26]. The data was then filtered with a 0.5–45 Hz band-pass filter and segmented into epochs starting 100 ms before the stimulus onset and ending 600 after the stimulus onset. Baseline correction was performed using the 100ms of pre-stimulus activity. In this manner for each subject, we obtained several dozens of epochs, each containing 32 (number of channels) \times 175 (number of time sampling points in the segmented interval) values. Each epoch was associated with a class label *face* or *house* according to the stimulus which was presented.

3 Brain State Modeling

This section introduces the proposed brain state modeling approach for EEG single trials spatio-temporal analysis. Figure 1 demonstrates the flowchart of the ensemble method.

The essence of the modeling approach is creating a parametric family of classifiers and seeking an optimal member of this family by model selection techniques. The parameter that forms the collection of classifiers controls the bias/variance tradeoff (i.e. regularization parameter), thus a classifier with optimal bias/variance is chosen [27]. Each member of the family attempts to predict the mental states of the brain by finding the coefficients of the model which mostly differentiate the EEG data into two mental states. The selection of the optimal member is done based on classifier mental states prediction.

3.1 Model Estimation

Cross-validation is used for choosing the best model and estimating its predictive accuracy. This method is computationally expensive but is especially important when the number of samples is small. Cross-validation is applied twice: first for dividing the original data into train and test sets. We search for the optimal model on the train sets and record its accuracy on the test sets. For this we used m - k -fold cross validation, where k is the number of unique test sets, and m is the number of times, this process is repeated. Second, an additional inner n -fold cross-validation procedure is applied for selecting the optimal model on the training sets, where n is the number of averaged cross-validation iterations.

In the first cross validation procedure, the original data is partitioned into k disjoint sets. A single dataset is retained as the test data for testing the model, and the remaining $k - 1$ disjoint datasets are used as training data. The cross-validation process is then

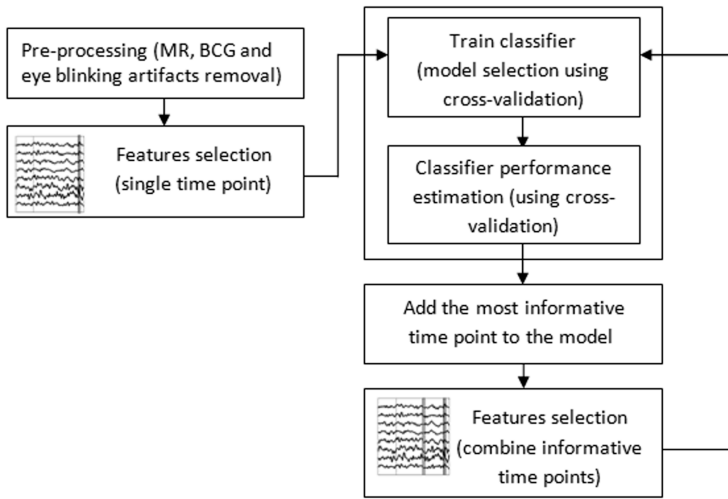


Fig. 1. Brain state modelling flow chart

repeated k times, with each of the k sets used exactly once as the test data. We repeat this process m times. The training sets are used for choosing the best model and the test sets are used to check its predictive accuracy. The predictive accuracy of the model is defined as the number of wrongly predicted samples divided by the overall number of samples.

The second cross-validation operation is used for choosing the optimal model. The training dataset is randomly splitted, n times, into 80-20% training and validation sets respectively. The classifier runs on the training set with different values of the regularization parameter (within the range of interest) and selects the one that yields the best results (i.e. bring mean square error, MSE, to minimum) (see Fig. 2).

The range of regularization values of interest is determined using the singular values, which are obtained from SVD decomposition of the processed data matrix (used for training and testing). The range is bounded between the minimal and the maximal singular values. For computational efficiency, the actual regularization values in that range are distributed uniformly on the logarithmic scale (i.e. the ratio of the two successive samples is constant).

3.2 Regularized Logistic Regression

The proposed regularized brain state interpretation can be used with a variety of linear and nonlinear classifiers. The, logistic regression model is the appropriate one for a binary classification task. It is also optimal in terms of simplicity, interpretability of its coefficients and speed ([28]-[29]).

A useful variable is the odds ratio, which is defined as the ratio of the probability that an event occurs to the probability that it fails. The logit (log odds) of the logistic regression model is given by the following equations, where w_i are the model's coefficients:

$$g(x) = w_0 + w_1x_1 + w_2x_2 + \dots + w_nx_n \quad (1)$$

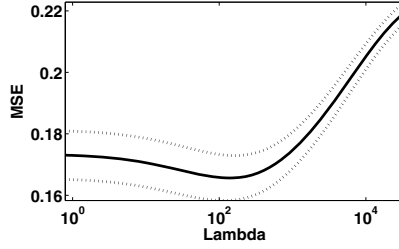


Fig. 2. MSE received on the validation set at the best time point versus the log of the regularization parameter. The lambda that minimizes the average error across iterations is chosen to be the optimal regularization parameter for the model.

$$P(Y = 1|x) = \pi(x) = \frac{e^{g(x)}}{1 + e^{g(x)}} \quad (2)$$

$$\text{logodds} = \log \left(\frac{\pi(x)}{1 - \pi(x)} \right) \quad (3)$$

The coefficients are often estimated via the Maximum Likelihood Estimation (MLE) method, which seeks to maximize the log likelihood over the entire observed data:

$$l(w) = \sum_{i=1}^n \log P(Y = y_i | x_i) \quad (4)$$

The log likelihood value represents how likely the dependent variable can be predicted from the observed values of the independent variables. Maximization of the above expression can be done in various ways, most popular being the Newton-Raphson (NR) algorithm.

The regularized version of the logistic regression algorithm seeks to find the weights (w) which maximizes the equation:

$$l^\lambda(w) = l(w) - \frac{\lambda}{2} w^T w \quad (5)$$

We use the Matlab-based MVPA toolbox [30], which implements regularized logistic regression following notes from [31].

3.3 Feature Selection

As mentioned before, one of the main challenges while working with EEG signals is the high data dimensionality. In this case, feature selection is important for reducing the dimensionality of the input signal, removing noise, improving learning performance, speeding up the learning process and improving predictive accuracy. Feature selection has been extensively researched by the machine learning/pattern recognition community over the years (for review in the context of BCI, see [5]).

A two step feature selection algorithm is implemented. First, potential time points are selected, which are found to best separate between the two mental states. Second, the selected time points are fused to obtain a holistic network related to the paradigm. In the first step of the algorithm, the selection of the time points is done in two different ways: using the ERP approach and using a predictive approach based on a single trial performance evaluation. In the ERP approach the averaged EEG signal over trials are constructed (separately for each condition). Significant time points, that have the highest difference between the average signals are chosen. In the predictive approach, 32 electrodes are selected from a single time point as an input for the classifier in the same manner as in [16]; A set of T trials labeled data samples is obtained, each represented by $N \times M$ signal matrix, where N is the number of channels and M is the number of time sampling points in the segmented interval. For each time point (from M), a feature vector that contains the EEG data of the entire electrodes in this time point, is created. (This reduces the dimension of the data from 32×175 to 32). Then, a family of classifiers is constructed with different regularization parameters and applied on the different time points. The model that achieved the minimum MSE on the validation set, over the entire time points, is chosen.

After selecting the model, the predictive accuracy of each time point is evaluated using the test sets, by applying the best model on each time point and averaging the results. The outcome of this stage is a ranking of the entire time points according to the performance of the model (Fig. 3). The coefficients of the regression equation at the time point where minimal prediction error is achieved indicate the contribution of activity in different electrodes in this time point towards the prediction. This can be interpreted as the strength of activity in electrodes, which best contribute to the mental states separation.

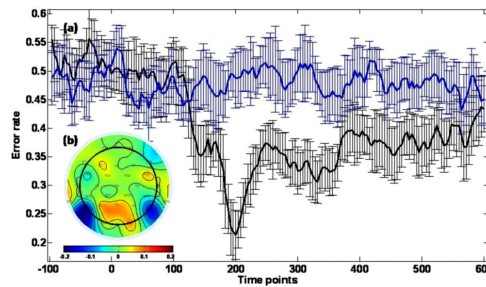


Fig. 3. (a) Predictive accuracy of each time point, on the testing set. The black line depicts the average error rate over the cross-validation iterations and the blue line represents control results obtained using the same algorithm on data with randomly scrambled target labels. It can be seen that the best prediction is achieved around 200ms after the stimulus onset (N170). (b) The coefficients of the regression equation in the best time point. The coefficients indicate the most contributing electrodes in this time point; Blue color indicates strong negative effect of faces compared to houses.

The formulation presented so far indicates the most predictive time point and the configuration of electrodes at that time point. This spatial coding, where the prediction depends on a configuration of electrodes activity at a single time point, may not be the optimal code used by the brain in interpreting the stimuli. Therefore it is possible that a temporal or spatio/temporal coding is more appropriate. The presented model can address this question, although the computational problem involved becomes too big for a single computer to handle, but using a computer grid of several hundred personal computers, the model can be extended in this direction [32].

We sort the local minima in the prediction graph to find different distinct temporal locations with prediction error minimum. The sorting is done in an increasing order (starting from the most predictable time point to the least predictable time point). Then a collection of models is applied, each using an increasing amount of information, where new time points (electrode information) are added into the model. In each such input data configuration we perform the full cross-validation estimation to estimate optimal regularization and prediction error.

The selection of the ensemble time points is done in two different ways; Primary selection using sequential assembling (i.e. the sorted time points are added to the model one after the other without additional search) and secondary selection using a wrapper algorithm [33], which is a technique for selecting an optimal subset of features from a large search space. In the wrapper algorithm, the features are assessed by their predictive power and are added to the subset one by one according to their contribution to the overall prediction. In both methods the ten most predictable time points were included in the process.

The outcome of the classifier for a different number of time points is compared and the ideal number of time points which had significantly lower error prediction is chosen (Fig. 4). Increasing the input vector adds electrode activity data, but also adds free parameters to the model leading to higher chance of overfitting the training data. We thus search for the ideal number of time points which balances between the two effects. Figure 5 depicts the best time points found for one subject and the electrodes activity in these time points contributing towards mental state discrimination.

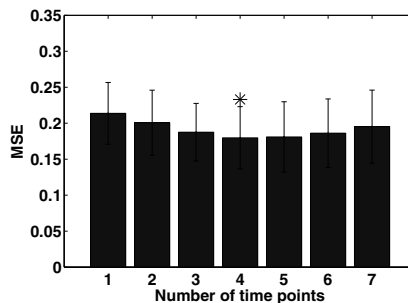


Fig. 4. Prediction error vs. number of time points. For this subject the optimal is 4, namely there was a significant prediction improvement up to that point ($*p < 0.05$).

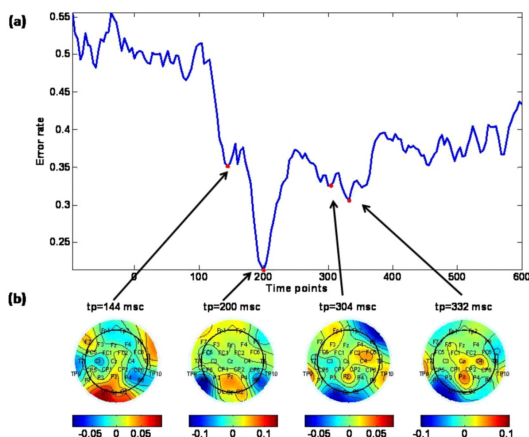


Fig. 5. (a) The ideal number of time points chosen as input for the classifier. (b) The regression coefficients received in those time points.

4 Results

4.1 Spatio-Temporal Analysis

Many studies have shown that pictures of faces elicit a much larger ERP of negative polarity than other object categories. This component peaks at occipital-temporal electrode sites at about 170 ms following stimulus onset [34]. The larger response of the N170 complex to faces is an undisputed observation among researchers in the field of face processing (Fig. 6).

We reinforce this result using EEG single trial classification (Fig. 7). For all subjects the best prediction achieved around 200 ms after the stimulus onset and the electrodes that contribute to the maximum separation between the mental states investigated are located in the occipital area. The coefficients obtained on single trial training correlated to the ERP of the corresponding electrodes. Negative coefficients indicate the ERP for faces is lower than the ERP for houses. In addition, both occipital electrodes (P7 and P8) are correlated in that time point.

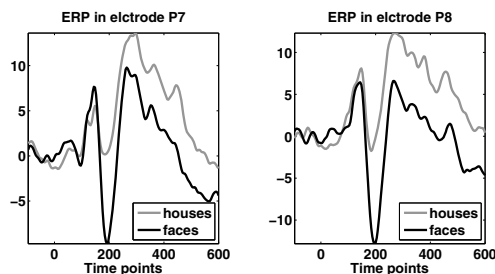


Fig. 6. ERP in electrodes P7 and P8

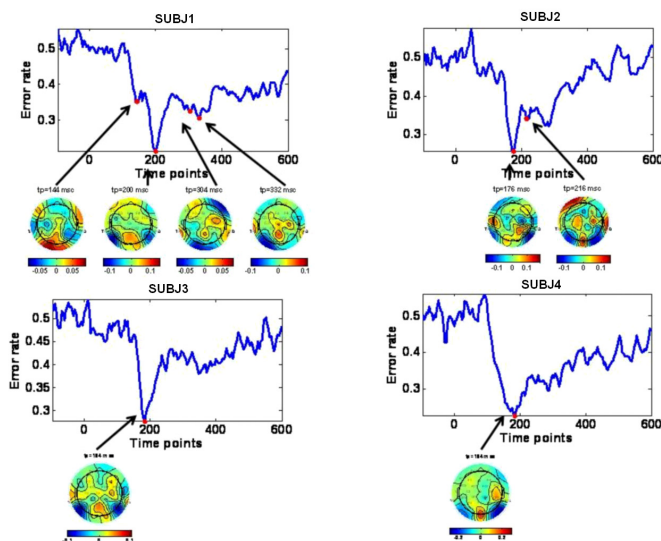


Fig. 7. Best time points found and the coefficients in these time points for different subjects in the houses and faces experiment. As expected, for the entire subjects the best prediction is achieved around 200ms after the stimulus onset and the most activated electrodes are in the occipital-temporal area.

The resulting spatial-temporal weight matrix provides a summary representation which is easily interpretable. A result of the dimensionality reduction, which is performed during the pre-processing stage, where relevant time points and electrodes are chosen, leads to simpler computational model training. This is in contrast to reducing the dimensionality via reducing the sampling rate [11]. The lowest error rates achieved for each subject using a single time point are summarized in Fig. 8 (the prediction error with the optimal number of time points is lower). The results were compared to the control experimental results, which were obtained using the same algorithm on randomly scrambled labels. The difference between the mean error estimates is significant for all subjects ($P < 0.05$).

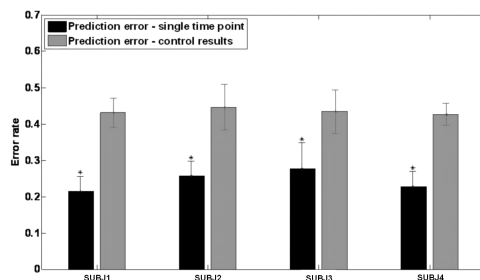


Fig. 8. Classification error rate for all 4 subjects. The classification error is compared to control results obtained using the same algorithm on randomly scrambled labels. The difference between the mean error estimates is significant for all subjects ($P < 0.05$).

4.2 Comparison with Existing Methods

As described in 3.3, our algorithm employed a two-step classification. The first step included selection of time points that were used to predict the two mental states. The time points were selected using two criteria: the ERP approach, which is based on the EEG signal average over trials and a predictive approach based on a single trial prediction performance. Table 1 demonstrates the first 10 time points selected by each method, ordered by their corresponding selection criteria. Following the time-points selection, the wrapper algorithm, which was described in 3.3 was employed to select the ensemble of time points with the highest prediction power. The time points selected by the wrapper, are marked in gray. The results indicate that the optimal time points found by the wrapper were found earlier in the prediction approach than in the ERP approach. However, the performance is similar since points which are not useful are later eliminated due to a comprehensive search of the wrapper.

Two methods for selection of the ensemble time points were compared: sequential selection and a wrapper algorithm. Figure 9 depicts the prediction error for increasing number of time points using the different approaches for time points selection and time point assembling; The results suggest that the contribution of the wrapper to eliminate time-points, which do not contribute to ensemble performance, is significant ($P < 0.05$).

Table 1. The first 10 time points found by the ERP and the predictive approaches. The time points which were selected by the wrapper are marked in gray.

ERP points (ms)	Prediction points(ms)
200	200
380	332
456	352
236	304
328	144
308	456
524	160
140	496
184	568
500	636

4.3 The Impact of Regularization

The amount of data needed to properly describe the different mental states increases exponentially with the dimensionality of the feature vectors. As the amount of training data is small compared to the size of the feature vectors, the classifier is likely to overfit to the training data and thus producing a model which does not uncover the true brain state discrimination. The only way to avoid this and still get a reliable brain state interpretation is a robust training with a regularizer which has to be carefully picked. To demonstrate the effect of non optimal regularization selection, we applied the same algorithm, with and without a regularization parameter on feature vector of size 96 (three best time points). As it can be seen in Fig. 10, the classification error with regularization is significantly lower ($P < 0.05$).

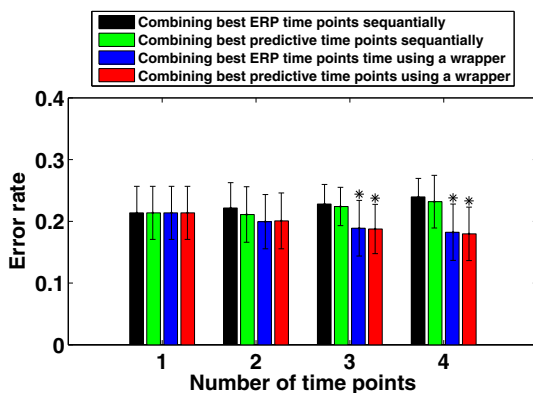


Fig. 9. Classification error rate vs. number of time points for different time-points selection and time-point assembling. It is evident that the contribution of the wrapper is significant ($P < 0.05$).

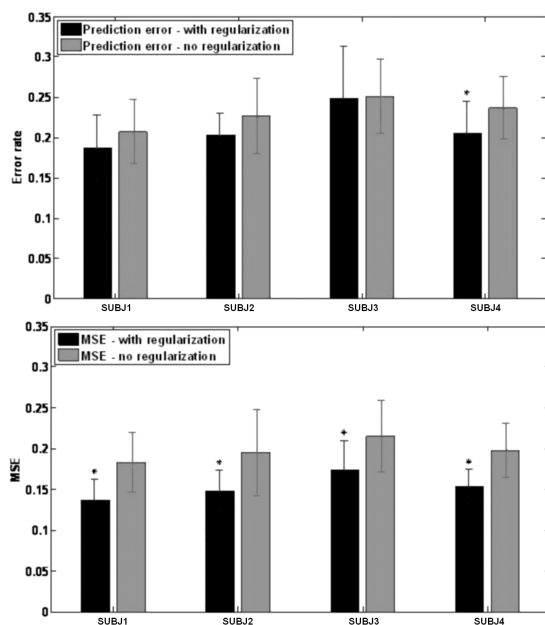


Fig. 10. Prediction error (Error rate and MSE) received for 3 best time points chosen, with and without regularization. These figures show that results with regularization are significantly better ($*P < 0.05$).

5 Conclusions

This paper proposed a robust and efficient framework for brain state interpretation using EEG single trials. This framework is based on extensive feature selection using a regularized logistic regression classifier and can be used for spatial-temporal analysis of the

EEG data as well as other 2 or 3 dimensional brain imaging modalities. The proposed framework was compared to time-points selection via ERP method and to the sequential fusion of time-points. The results indicate that the wrapper approach offers a significant improvement over sequential selection. This spatial-temporal analysis can render a far more holistic interpretability without any a priori information on certain optimal time points or electrode locations. It can thus indicate whether the coding related to the brain state discrimination task is spatial, temporal or joint, and can indicate the network of information propagation (at high temporal resolution) following the stimuli. This method, which can also be applied to a Time/Frequency representation of the signal, can reveal the different frequency bands at which brain state discrimination is optimal.

Acknowledgements. This research was supported by the Israel Science Foundation Converging Technologies Program.

References

1. Wolpaw, J., Birbaumer, N., McFarland, D., Pfurtscheller, G., Vaughan, T.: Brain-Computer Interfaces for Communication and Control. *Clin. Neurophys.* 113, 767–791 (2002)
2. Allison, B., Wolpaw, E., Wolpaw, J.: Brain Computer Interface Systems: Progress and Prospects. *Expert Review of Medical Devices* 4, 463–474 (2007)
3. Dornhege, G., del R. Millan, J., Hinterberger, T., McFarland, D., Muller, K.R.: Towards Brain-Computer Interfacing. MIT Press (2007)
4. Blankertz, B., Dornhege, G., Krauledat, M., Muller, K.R., Curio, G.: The noninvasive Berlin brain-computer interface: fast acquisition of effective performance in untrained subjects. *NeuroImage* 37, 539–550 (2007)
5. Lotte, F., Congedo, M., Lecuyer, A., Lamarche, F., Arnaldi, B.: A Review of Classification Algorithms for Eeg-Based Brain-Computer Interfaces. *J. Neural Eng.* 4, R1–R13 (2007)
6. Bellman, R.: Adaptive Control Processes. Princeton University Press, Princeton (1961)
7. Muller, T., Ball, T., Kristeva-Feige, R., Mergner, T., Timmer, J.: Selecting Relevant Electrode Positions for Classification Tasks Based on the Electro-Encephalogram. *Med. Biol. Eng. Comput.* 38, 62–67 (2000)
8. Palaniappan, R., Raveendran, P., Omatu, S.: VEP Optimal Channel Selection Using Genetic Algorithm for Neural Network Classification of Alcoholics. *IEEE Trans. Neural Netw.* 13, 486–491 (2002)
9. Schroder, M., Bogdan, M., Rosenstiel, W., Hinterberger, T., Birbaumer, N.: Automated EEG Feature Selection for Brain Computer Interfaces. In: *Proc. 1st Intern. IEEE-EMBS Conf. on Neural Eng.*, Capri Island, Italy (2003)
10. Lal, T., Schroder, M., Hinterberger, T., Weston, J., Bogdan, M., Birbaumer, N., Scholkopf, B.: Support Vector Channel Selection in BCI. *IEEE Trans. Biomed. Eng.* 51, 1003–1010 (2004)
11. Tomioka, R., Muller, K.R.: A regularized discriminative framework for EEG analysis with application to brain-computer interface. *Neuroimage* 49, 415–432 (2010)
12. Jain, A.K., Duin, R.P.W., Mao, J.: Statistical pattern recognition: a review. *IEEE Trans. Pattern Anal. Mach. Intell.* 22, 4–37 (2000)
13. Duda, R.O., Hart, P.E., Stork, D.G.: *Pattern Recognition*, 2nd edn. Wiley-Interscience, New York (2001)
14. Christoforou, C., Sajda, P., Parra, L.C.: Second order bilinear discriminant analysis for single trial EEG analysis. *Advances in Neural Info. Proc. Sys.* 20, 313–320 (2008)

15. Tomioka, R., Aihara, K., Muller, K.R.: Logistic regression for single trial eeg classification. In: Scholkopf, B., Platt, J., Hoffman, T. (eds.) *Advances in Neural Information Processing Systems*, vol. 19, pp. 1377–1384 (2007)
16. Zhdanov, A., Hendler, T., Ungerleider, L., Intrator, N.: Inferring Functional Brain States Using Temporal Evolution of Regularized Classifiers. *Comput. Intell. Neurosci.*, Article ID. 52609 (2007)
17. Murray, M., Brunet, M., Brunet, D., Michel, C.: Topographic ERP analyses: step-by-step tutorial review. *Brain Topography* 20, 249–269 (2008)
18. Lehmann, D., Skrandies, W.: Reference-free identification of components of checkerboard-evoked multichannel potential fields. *Electroenceph. Clin. Neurophysiol.* 48, 609–621 (1980)
19. Lehmann, D., Ozaki, H., Pal, I.: EEG alpha map series: brain microstates by space-oriented adaptive segmentation. *Electroenceph. Clin. Neurophysiol.* 67, 271–288 (1987)
20. Hasson-Meir, Y., Zhdanov, A., Hendler, T., Intrator, N.: Inference of Brain Mental States from Spatio-Temporal Analysis of EEG Single Trials. In: *Proc. of Biosignals* (2011)
21. Ekman, P., Friesen, W.: *Pictures of Facial Affect*. Consulting Psychologists Press, Palo Alto (1976)
22. Lundqvist, D., Flykt, A., Ohman, A.: *The Karolinska Directed Emotional Faces (KDEF)*. Dept. of Neurosci., Karolinska Hospital, Stockholm, UK (1998)
23. Sadeh, B., Zhdanov, A., Podlipsky, I., Hendler, T., Yovel, G.: The Validity of the Face-Selective ERP N170 Component During Simultaneous Recording with Functional MRI. *Neuroimage* 42, 778–786 (2008)
24. Ben-Simon, E., Podlipsky, I., Arieli, A., Zhdanov, A., Hendler, T.: Never Resting Brain: Simultaneous Representation of Two Alpha Related Processes in Humans. *PloS ONE* 3, e3984 (2008)
25. Laufs, H., Krakow, K., Sterzer, P., Eger, E., Beyerle, A.: Electroencephalographic signatures of attentional and cognitive default modes in spontaneous brain activity fluctuations at rest. *Proc. of the National Academy of Sciences, U.S.A.* 100, 11053–11058 (2003)
26. Delorme, A., Makeig, S., Sejnowski, T.: Automatic Artifact Rejection for EEG Data Using High-Order Statistics and Independent Component Analysis. In: *Proc. of the 3th Intern. ICA Conf.* (2001)
27. Geman, S., Bienenstock, E.: Neural Networks and The Bias / Variance Dilemma. *Neural Computation* 4, 1–58 (1992)
28. Hosmer, D., Lemeshow, S.: *Applied Logistic Regression*, pp. 118–124. John Wiley, New York (1989)
29. Friedman, J., Hastie, T., Tibshirani, R.: *The Elements of Statistical Learning*. Springer Series in Statistics (2001)
30. Detre, G., Polyn, S., Moore, C., Natu, V., Singer, B., Cohen, J., Haxby, J., Norman, K.: The Multi-Voxel Pattern Analysis (MVPA) Toolbox. In: *The Annual Meeting of the Organization for Human Brain Mapping*, Florence, Italy (2006), <http://www.csmbmb.princeton.edu/mvpa>
31. Minka, T.: A Comparison of Numerical Optimizers for Logistic Regression. technical report, Dept. of Statistics, Carnegie Mellon Univ. (2003)
32. <http://www.cs.wisc.edu/condor/manual/v7.0.1>
33. Kohavi, R., John, G.: Wrappers for Feature Subset Selection. *Artificial Intelligence* 97, 273–324 (1997)
34. Bentin, S., Allison, T., Puce, A., Perez, E., McCarthy, G.: Electrophysiological Studies of Faces Perception in Humans. *J. Cognitive Neurosci.* 8, 551–565 (1996)