Classifying User Actions in a Brain-Computer Interface with Non-Temporal Models

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ABSTRACT

We attempt to predict a test subject's actions based on pre-computed EEG-signal features. The features contain power spectral density data over a frequency range of 8-30 Hz in 2 Hz intervals over the 8 centro-parietal channels. We will model this activity with a Naive Bayes model and a Support Vector Machine model. Our assumption with these models is that brain activity is not a time series. Our hypothesis for this project is that brain activity at a specific timestamp is independent of activity at a previous timestamp, i.e. it is not a time series. We test our hypothesis by comparing the classification accuracy attained with the Naive Bayes and SVM models to results attained with temporal models, such as HMMs, in previous research.

1 INTRODUCTION

Brain-computer interfaces are at the forefront of modern control systems, as direct access to the brain would eliminate abstraction layers between a machine and its operator. They could also allow humans gain use of artificial limbs that are controlled by thoughts. This would greatly increase the usability and accuracy of prosthetic limbs or mechanical manipulators such as microsurgery devices. This is why BCI is an interesting research subject.

A major challenge in interpreting user actions is the continuous nature of the human brain, which always has some activity even when the operator is physically at rest. Developing accurate models of brain activity and classifying user actions has been the focus of many research groups in this field.

We will be using a data set in which an operator is told to think of two separate motoric actions and of words beginning with the same letter to train a classifier that can predict the action based on EEG readings. The data set has been used previously in the BCI Competition III, held in 2004. [1]

When an operator thinks about an action, the associated brain activation can be detected with brain imaging methods such as an EEG or fMRI. The detected activation pattern is the product of neurons in the brain firing electrochemical signals along neural pathways. Neurons in the brain are activated only when an adequate level of stimulus is provided, which gives rise to very distinct patterns between actions. This means that similar actions are likely to activate the same area of the brain, while retaining a distinct pattern between them.

When the operator no longer thinks about an action, the corresponding stimulation of neurons is stopped. This leads to a cascade effect, whereby the receptors at each neuron are released in turn and the neuron stops transmitting a signal. Eventually the entire chain of neurons is inactive in terms of the original action.

As this signal cascade takes place when the operator starts and stops thinking about an action, an activation pattern can be thought to have a dependency on the pattern at a previous sampling moment. However, taking the previous samples in to account requires knowledge about the time it takes for the cascade to develop, as we must know how far any specific activation will affect future patterns. This will complicate the model considerably and increase online computation time.

We attempt to model the brain with the assumption, that the transition from one pattern to another is quick enough to be analogous with a discrete system and that the current activation pattern is only dependent on the current action. This should be a simpler model both to formalize and to compute in real time. Our hypothesis is that it is possible to model brain activity and classify actions using a non-temporal model. We will test this hypothesis by implementing two non-temporal models and use them to classify actions in our data set. Our hypothesis holds if the non-temporal models achieve higher prediction accuracy than temporal models implemented in previous research [2][3].

2 DATA SET AND METHODS

I this section we elaborate on our data set and the classifiers we will use to predict user actions. We are using EEG measurements from three test subjects who participated in four consecutive recording sessions. We use this external data to develop and test our action classifiers. The data is provided to us by the IDIAP Research Institution and the organizers of the BCI Competition. [1]

2.1 BCI Data Set

The data set we are using for our project was obtained from three separate test subjects over four sessions. The subjects were given instructions to think of three activities while wearing a cap equipped with electrodes that were used to perform EEG measurements. The sampling rate for the measurements was 512 *Hz* and no artifact rejection or correction was applied. The raw data was then filtered with a surface Laplacian. The filtered data was then computed at 16 *Hz* for a power spectral density over the previous second of measurements. This produced 96 dimensional samples in 8 centro-parietal channels, each with 12 frequency components. The frequency components were in the 8 – 30 *Hz* band at a resolution of 2 *Hz*. [1]

The recording sessions were performed in one day with 10-15 minute breaks between sessions. During the sessions the subjects sat in a chair with their arms relaxed. The activities they were instructed to perform were: Thinking of moving the left hand or moving the right hand in a repeated motion and thinking about words that begin with the same, predefined letter. Each action was thought of for 15 seconds at a time, after which another action was selected at random [1]. As only the first three recording sessions are provided with action labels, we will use data of one session for training our classifiers and the others for testing the classifiers.

We believe that this setup provides consistent data for each subject over all the sessions with minimal variance between responses to the described actions. Whether this assumption is correct can be determined by testing the prediction accuracy over all sessions of a subject. It is unlikely that EEG patterns correlate between individuals, so we suspect that none of our classifiers will accurately predict a person's actions unless it is trained for that person.

2.2 Naïve Bayes model

We want to predict a certain mental action given a set of 96 power spectral densities (PSD) in the brain at a certain timestamp. These PSDs represents 12 frequency components for 8 centro-parietal channels. As we assume that brains signals can be measured without a temporal conditionality, it is feasible to model this problem as a Naïve Bayesian network.

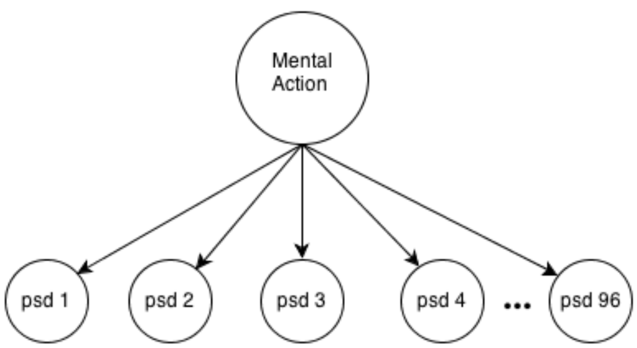

Figure 2: Naïve Bayesian model for predicting mental action

Our Bayesian model has 97 variables, which correspond to the current mental action and the power spectral densities at that measurement. The PSDs are modeled as the effect variables and our mental action is the cause variable. This model is particularly sensitive to our conditional independence assumption, since we are assuming that the PSDs are conditionally independent given the mental action.

The EEG used to measure brain signals produces continuous signals, so our effect variables will also be continuous. Therefore we must have an approximation for the signal distribution in order to effectively use our Naïve Bayes model. Figure 2 illustrates how the PSD values are distributed in a single frequency component during each action. The same approximate distribution is observed across the entire frequency component space. The argument can be made that our PSDs are distributed according to a distribution that shares similarities with a Gaussian. However, the PSD distributions in figure 2 do show a bias towards the lower end of the power range, which can affect our classifiers. We assume that this difference should be minimal. Therefore we will train and evaluate our model using the PSD distributions in their original form.

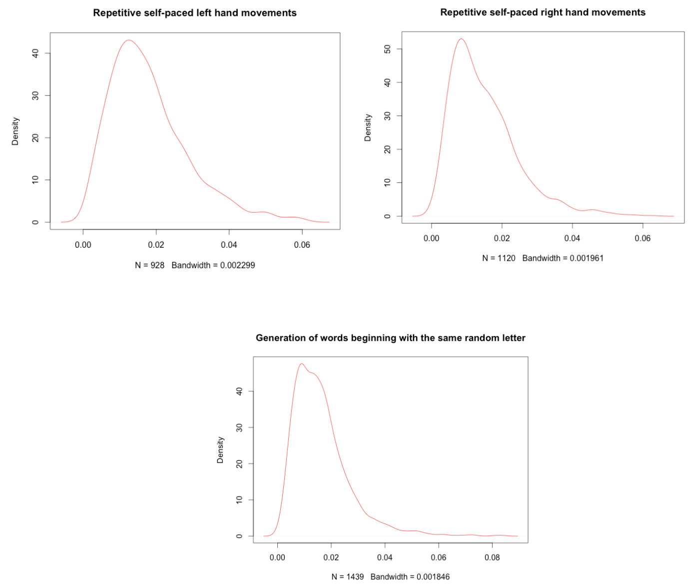

Figure 1: Distribution curves for PSD values during each action

2.2.1 Naïve Bayes Algorithm

Modeling this problem as a Naïve Bayes network as opposed to other Bayesian networks simplifies our learning function significantly. Our model is dependent only on the mean and variance of each PSD feature vector for a given mental action, which allows us to ignore the full joint probability of our PSD variables. The Naïve Bayes model is trained by learning the conditional probabilities of a PSD having a certain value during a given mental action.

The probability of observing any mental action is obtained by applying Bayes' Theorem to the conditional probability tables of all PSDs at that timestamp:

$$P(m \mid f_1, ..., f_{96}) = \alpha P(m)*P(f_1|m)*...*P(f_{96}|m) \qquad (1)$$

Where m is some mental action, f_n is the nth PSD and α is the normalization constant.

2.3 Support Vector Machine (SVM)

When temporal dependency is removed, we can model EEG data with a SVM, which considers each measurement and feature set as a point in feature space. In our data each measurement represents a brain state and each brain state consists of 96 PSD elements. In the SVM each of these elements represents a dimension in feature space and the SVM algorithm finds the optimal hyperplanes in feature space that separates actions.

An SVM can also be defined with other separation methods, such as a radial limiter. These kernel techniques can be very useful when dealing with high dimensional data. With these methods the separation can be done with radial parameters or polynomial functions.

2.3.1 Applying the SVM algorithm

For our evaluation of the SVM classifier we will be using *libsvm*, a very flexible library for using Support Vector Machines in machine learning. In a multiple class problem such as ours, the SVM tests for the correct class by testing all classes against each other and selecting the correct class by a voting mechanism [4].

The SVM algorithm solves a constraint satisfaction problem that is formed by the spread of data points in feature space. As we are attempting to separate our previously specified actions, the SVM will try to find constants that satisfy the optimal decision function for action classification.

Maximizing the margin between actions becomes harder as the feature space increases in dimensions. To allow for errors in data separation, the algorithm uses a soft margin, which allows single points in data to differ from the majority but places a cost for incorrect positioning.

3 Results and Evaluation

We evaluated our models by training both classifiers with one data set and then testing their prediction accuracy against the remaining data sets. Training and testing was validated across all data sets and performed for all subjects to provide a more accurate evaluation of performance.

Prediction accuracy was computed by comparing the action labels in the data set with the predictions of our classifiers. Our reference point for a model's functionality is the expected prediction accuracy when guessing actions randomly. As we have 3 actions, the reference prediction accuracy was 33 %.

Prediction accuracy for our classifiers is gathered to table 1. Initially we saw quite promising results with the first test subject, as we achieved a maximum accuracy of over 70 % and an average of 62,3 % with both the Naive Bayes and the SVM classifier. However, these results did not correlate with the other test subjects. With subjects 2 and 3 our models achieved significantly lower prediction accuracy, at worst only 42,4 %. While this is higher than choosing at random, it does demonstrate that our hypothesis may be faulty.

We suspect that the variance between test subjects may be related to the subject's capability of concentrating on a specific task. Our results may be influenced by the fact that we did not account for the skewedness of the PSD distribution. It is also possible that the measurements for subjects 2 and 3 contained more noise than the measurement acquired from subject 1. Noise can affect a non-temporal model significantly, as it is not possible to use temporal features to correct for the noise.

Table 1: Results of our classifiers for each subject

Accuracy		
Subject	**Naïve Bayes**	**SVM**
1	62.25 %	65.79 %
2	50.29 %	49.77 %
3	42.42 %	43.30%

Our hypothesis was that it would be possible to model the brain with a non-temporal model. This could be verified if a non-temporal model could outperform a temporal model as a training algorithm for an action classifier.

Given that our results were not consistent for all subjects, we are inclined to reject our hypothesis. This is also supported by the fact that previous research has shown that temporal models can outperform both of our models in prediction accuracy: Lee and Choi [2] achieved a prediction accuracy of 78.15 % by using principal component analysis and a hidden Markov model to learn the conditional probabilities in state transitions and observations. Park et al. achieved even higher accuracy by implementing independent and oriented principal component analysis with a hidden Markov model.

Our approach was implemented as a way of testing whether it is possible to use very simple modeling in a complex system, such as the brain.

4 Conclusion

Our findings suggest that non-temporal models are not very good for training classifiers that are used for predicting mental actions. However, it would be useful to study the application of non-temporal models for this use further, as non-temporal models are simpler to implement than temporal models.

Our models could be refined further by studying the effects of the PSD skewedness on prediction accuracy and by accounting for noise in the measurement signal. A larger training set could also be used.

Alternative non-temporal models could incorporate K-means clustering or logistic regression to further refine our predictions. Especially logistic regression could be used to weight down features that are not independent when given a mental action.

Research in this field has been mostly done with temporal models and with promising results, it would be most beneficial for us include the temporal element to our models in future research. As the brain is an extremely complex and multivariate system, accurate and efficient modeling is the key to understanding its internal dynamics.

5 ACKNOWLEDGMENTS

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6 REFERENCES

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