

Dynamic Stopping in a Calibration-less P300 Speller

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Abstract. Even though the P300 based speller has proved to be usable by real patients, it is not a user-friendly system. The necessary calibration session and slow spelling make the system tedious. We present a machine learning approach to P300 spelling that enables us to remove the calibration session. We achieve this by a combination of unsupervised training, transfer learning across subjects and language models. On top of that, we can increase the spelling speed by incorporating a dynamic stopping approach. This yields a P300 speller that works instantly and with high accuracy and spelling speed, even for unseen subjects.

Keywords: Machine Learning, P300, Unsupervised Training, Transfer Learning, Language Model, Probabilistic Model

1. Introduction

The P300 speller was introduced in 1988 [Farwell et al., 1988] to allow locked in patients to communicate. A lot of effort has been put into reducing the calibration time and increasing the accuracy. Our approach goes one step further, we remove the calibration session altogether without accuracy penalty. We have shown that a P300 specific unsupervised algorithm [Kindermans et al., 2012a] can compete with state of the art supervised methods in off-line evaluation. But during on-line usage this method exhibits a warm-up period. The classifier is initialized randomly and therefore it makes mistakes during the initial learning phase. Enriching the classifier with transfer learning and language models suppresses this warm-up period completely [Kindermans et al., 2012b]. Transfer learning allows us to combine subject specific models into a general model, which will be adapted to the new user during on-line spelling. Language models improve the accuracy by exploiting prior knowledge about text.

In this work, we enhance the model with dynamic stopping. When the classifier is confident of its prediction, a dynamic stopping strategy stops the stimuli and outputs the symbol. This results in a drastic increase in spelling speed. We have shown that our approach is very effective in a supervised setting [Verschore et al., 2012]. But the usage of dynamic stopping in an unsupervised BCI speller is unprecedented.

2. Material and Methods

2.1. Unified Probabilistic Model with Dynamic Stopping

The basic model uses the following assumptions [Kindermans et al., 2012a]. Only the intensifications of the desired symbol will result in a P300 response. Furthermore, it assumes that the EEG can be projected into one dimension, where it is Gaussian with a class dependent mean (-1 or 1) and shared variance. This assumption is more general than the one made by LDA. The transfer learning part [Kindermans et al., 2012b] assumes that the vector used to project the EEG into a single dimension is similar across subjects. Therefore we encode that the weight vector for the new subject should be close to those of the other subjects. One should think of this as a special form of regularization. Finally, we add trigram letter models to improve spelling accuracy by using language statistics [Kindermans et al., 2012b]. The whole model is probabilistic and it uses Expectation Maximization style training, where the desired symbols are treated as latent and unknown variables.

This model is reliable from the start, even for unseen subjects. The drawback is that the spelling speed is limited by using a fixed number of epochs per symbol. We can mitigate this by exploiting the probabilistic nature of our classifier in a dynamic stopping strategy. We use the dynamic stopping approach from [Verschore et al., 2012]. When the confidence level of the classifier exceeds 0.99 then we predict the symbol and move onto the next one. We would like to stress that the combination of the unsupervised learning, transfer learning and language models allows us to combine dynamic stopping with the unsupervised speller. This is because spelling has to be reliable from the beginning for dynamic stopping to work.

2.3. Experimental Setup

All our experiments are performed on the Akimpech Dataset (akimpech.izt.uam.mx/p300db/). We used 10 channel EEG data from 22 different subjects with 15 epochs per symbol in the classic 6x6 speller with following parameters: 125 ms stimulus duration, 62.5 ms inter stimulus interval and 4 s pause between symbols.

We re-used the experimental setup from [Kindermans et al., 2012b]. We start by unsupervised training of 21 subject specific models. These are combined into a general model, which is used to initialize the subject specific model for the 22nd subject. Then for each symbol, we feed the classifier the EEG one epoch at a time. After each epoch, we make a prediction. We stop the stimuli and spell the symbol when the confidence level exceeds 0.99 or the maximum number of epochs is reached. We execute 3 EM iterations to adapt the classifier between symbols. This update takes no more than 1.1 s, thus it can be completed during the 4 s pause between symbols. Then we repeat this for the next character.

Table 1. Results for the model with a fixed number of epochs and dynamic stopping. The model uses subject transfer, trigram letter models and unsupervised learning. *DS* indicates dynamic stopping, the numbers indicate the epochs per symbol.

Error Measure	TA-5	TA-10	TA-15	TA-DS
Accuracy [%]	87.0	95.0	97.9	95.3
Symbols Per Minute	2.9	2.0	1.5	4.1

3. Results and Discussion

In Table 1, we have given the results of the setup with transfer learning, a trigram language model for both with and without dynamic stopping. Results are averaged over 22 subjects. We have used the accuracy and the number of symbols per minute [Schreuder et al., 2011] as error measures. It is clear that with an average accuracy of 95.3% across 22 subjects the combination of dynamic stopping and unsupervised learning is very reliable. The average number of epochs is 4.77 and this results in 4.09 SPM. This is a more than 33% increase over the result obtained with 5 epochs. For comparison, a supervised version of this model with a trigram achieves 94.6% accuracy and 3.6 SPM with 5 epochs. On top of that, one should keep in mind that supervised training required 10 minutes of training data. In other words, supervised training wastes as much time in calibration as we need to spell over 40 symbols.

We have discussed the merits of this model in the standard speller, but we feel that it is much more than that. This model can form the basis of extensive research with respect to unsupervised P300 speller. We plan an on-line evaluation of this method. Additionally we will verify the compatibility of this method with other P300 paradigms (e.g. AMUSE [Schreuder et al., 2010]).

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