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Reducing BCI calibration time with transfer learning: a shrinkage approach

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Introduction: A brain-computer interface system (BCI) allows subjects to make use of neural control signals to drive a computer application. Therefor a BCI is generally equipped with a decoder to differentiate between types of responses recorded in the brain. For example, an application giving feedback to the user can benefit from recognizing the presence or absence of a so-called error potential (Errp), elicited in the brain of the user when this feedback is perceived as being 'wrong', a mistake of the system. Due to the high inter- and intra- subject variability in these response signals, calibration data needs to be recorded to train the decoder. This calibration session is exhausting and demotivating for the subject. Transfer Learning is a general name for techniques in which data from previous subjects is used as additional information to train a decoder for a new subject, thereby reducing the amount of subject specific data that needs to be recorded during calibration. In this work we apply transfer learning to an Errp detection task by applying single-target shrinkage to Linear Discriminant Analysis (LDA), a method originally proposed by Höhne et. al. to improve accuracy by compensating for inter-stimuli differences in an ERP-speller [1].

Material, Methods and Results: For our study we used the error potential dataset recorded by Perrin et al. in [2]. For 26 subjects each, 340 Errp/nonErrp responses were recorded with a #Errp to #nonErrp ratio of 0.41 to 0.94. 272 responses were available for training the decoder and the remaining 68 responses were left out for testing. For every subject separately we built three different decoders. First, a subject specific LDA decoder was built solely making use of the subject's own train data. Second, we added the train data of the other 25 subjects to train a global LDA decoder, naively ignoring the difference between subjects. Finally, the single-target-shrinkage method (STS) [1] is used to regularize the parameters of the subject specific decoder towards those of the global decoder. Making use of cross validation this method assigns an optimal weight to the subject specific data and data from previous subjects to be used for training. Figure 1 shows the performance of the three decoders on the test data in terms of AUC as a function of the amount of subject specific calibration data used.

Discussion. The subject specific decoder in Figure 1 shows how sensitive the decoding performance is to the amount of calibration data provided. Using data from previously recorded subjects the amount of calibration data, and as such the calibration time, can be reduced as shown by the global decoder. A certain amount of quality is however sacrificed. Making an optimal compromise between the subject specific and global decoder, the single-target-shrinkage decoder allows the calibration time to be reduced by 20% without any change in decoder quality (confirmed by a paired sample t-test giving p=0.72).

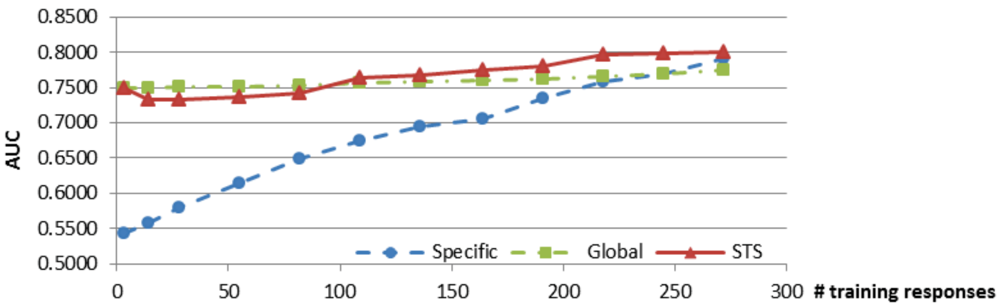

Figure 1. *Decoding performance in terms of AUC (averaged over 26 subjects) as a function of the amount of subject specific calibration data. Decoders are trained with three different methods: solely using subject specific data (specific), adding data from previously recorded subjects (global) and a compromise between these two methods using shrinkage LDA (STS).*

Significance This work serves as a first proof of concept in the use of shrinkage LDA as a transfer learning method. More specific, the error potential decoder built with reduced calibration time boosts the opportunity for error correcting methods in BCI.

References

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