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Transferring Unsupervised Adaptive Classifiers Between Users of a Spatial Auditory Brain-Computer Interface

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Abstract

The transfer of knowledge allows to rapidly set up a functioning BCI system for a novel user without user specific calibration. For spelling paradigms based on event-related potentials (ERP) of the EEG, a recent unsupervised classification method is able to train the classifier online by constantly adapting to the user on the fly. Hence, an explicit calibration phase can be avoided. However, due to the random initialization of the classifier, this method requires a warm-up time before it performs on the same level as a supervised trained classifier. This warm-up effect can be reduced by transfer learning. We present a thorough leave-one-user-out offline analysis (n=9 users) and additional preliminary online results from a spatial auditory ERP spelling study (AMUSE paradigm) on inter-subject transfer of an unsupervised adaptive classifier. For the online study, a classifier trained on data of n=8 previous users was transferred to two unseen users and further adapted online. The performance was evaluated in one online copy spelling session per user. Both, the offline simulations and the online results indicate that the transfer approach reduces the warm-up time by approx. 50 %.

1 Introduction

The auditory event-related potential (ERP) response of the electroencephalogram (EEG) is modulated by attention. This gave rise for the design of spatial auditory brain-computer interface (BCI) systems for communication [7, 1] to complement visual approaches.

Despite major improvements on paradigms and data analysis methods, one of the key limitations in BCI remains the dependency on a calibration session. Providing labeled data points, this recording is the prerequisite to train the EEG decoder with supervised machine learning methods. Unfortunately, this calibration session limits the time available to use a BCI online, which is a major problem for patients in need of such a BCI [5]. This problem arises especially for paradigms with long trial durations like motor imagery paradigms, and for those with intrinsic lower signal-to-noise ratio (SNR) like tactile or auditory ERP paradigms.

Hence, the BCI community has spent a considerable amount of effort to reduce the need for calibration data. In the field of ERP-based BCI systems, transfer learning approaches, which exploit information collected from previous users to facilitate decoding for a novel user, have been studied. The information can be transferred in the form of data [2] or as pre-trained classifiers [6]. The classifiers can be distinguished by their dependency onto labeled data from previous calibration recordings (supervised trained classifiers, e.g. [6]), or if unlabeled online data is sufficient to pre-train them (unsupervised trained classifiers, see [4]). These basic transfer learning methods lead to a reasonably accurate classifier for novel data. However, transferred models typically can not compete with user-specific models. To tackle this problem, a combination of transfer learning and online unsupervised adaptation has been proposed. While this combination has already been investigated offline [4] based on high-SNR visual ERP data, a test with more challenging data and its application in online experiments is still lacking. Hence, this work contributes with offline results on challenging auditory ERP data and, more importantly, by presenting preliminary online results with the spatial auditory AMUSE [7] paradigm.

2 Methods

2.1 Auditory ERP Paradigm AMUSE

AMUSE utilizes six auditory stimuli originating from a ring of six speakers surrounding the user. The stimuli can be identified by their direction or pitch, have a duration of 40 ms and were presented in pseudo-randomized order with a stimulus onset asynchrony (SOA) of 175 ms and in 15 iterations per trial. To spell one of 36 possible symbols, the user selects a group of six symbols in a first step by focusing attention to one of the six stimuli. Subsequently the user can select one of the six symbols from the previously selected group. Contrary to [7], a correction of wrong letters was not foreseen. Nevertheless, for all other details we closely replicated the setup detailed by Schreuder and colleagues.

2.2 Unsupervised Transfer Learning

We evaluated the unsupervised transfer learning model from [4]. This probabilistic model is applicable for multi-stimulus ERP paradigms. It assumes that only a single one of the six stimuli can result in a target ERP response, while the other stimuli must elicit a non-target response. On top of that, it assumes that EEG features can be projected into a single dimension, where the projected data is Gaussian with class-dependent mean and shared variance.

These assumptions allow for an unsupervised training of the model. Hence a calibration recording and labeled data are no longer required. The training is based on the Expectation Maximization algorithm and allows the model to learn how to decode ERP features while the user is interacting with the BCI. A known limitation is the initially unreliable classification, which is caused by a random initialization. Therefore, even though this model is an improvement over supervised systems with a calibration recording, this so-called warm-up period may limit the usability of the unsupervised system in the presence of tight time constraints.

To alleviate the warm-up phase, we have extended the model with inter-subject transfer learning [4]. The concept of transfer learning is introduced in the model by placing a shared hyper-prior on the user-specific mean of the prior on the weight vector. This corresponds to regularizing the subject-specific model towards the general shared model in place of regularizing towards a zero vector, which is a common approach to limit the model complexity. Due to space limitations, we refer the reader to [4] for the update equations and the training procedure of the transfer learning model.

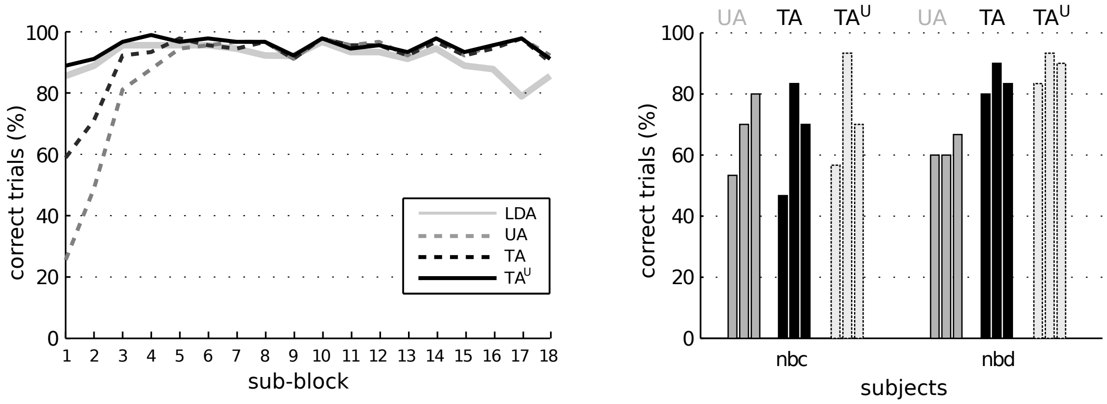

Figure 1: **Left**: Simulated grand average performance over 18 sub-blocks of ten trials each. **Right**: Online selection accuracy for two users and three blocks of 30 trials each.

2.3 Experiments and Data

An offline simulation was conducted on existing data from [3] to assess the feasibility of unsupervised adaptive transfer learning for auditory ERP data with challenging SNR. In the original study, unsupervised learning was compared to a standard supervised approach (LDA with shrinkage-regularization on the estimated covariance matrix). Each user had performed a calibration recording comprising 30 trials and six online evaluation blocks of 30 trials each. Supervised decoding was used for three blocks, and unsupervised for the remaining three blocks, resulting in 180 trials. For the simulation in the present work, this data was re-used trial-by-trial to train up a subject-specific unsupervised adaptive model per user (UA). It is compared with the fully updated unsupervised model (having seen all 180 trials) after processing the entire dataset (UA^U). Furthermore, data is combined in a leave-one-user-out transfer learning model. The simulated trial-by-trial application and updating of this transfer model to data of the left-out user is denoted TA. The final, fully updated version of this model is TA^U.

The novel online transfer experiment made use of TA. Two users of the original study were re-invited for a second session. They each performed three blocks of 30 trials of online copy-spelling spelling using the transfer learning model TA. Please note that it was reset at the beginning of each block in order to study the warm-up behavior. In addition, the fully updated model TA^U was available at the end of each block. In addition, the performance of a non-transferred, randomly initialized unsupervised classifier UA was evaluated by a post-hoc simulation. We would like to stress that the transferred models used in this work all are completely unsupervised. Label information was not used at any point in the models' training. Hence, it is sufficient to use data from free spelling sessions to build the transfer model.

3 Results and Discussion

Results from the simulated experiment on nine users are given in the left plot of Figure 1. Offline performance is estimated on sub-blocks of ten trials (corresponding to five symbols each). As a baseline, the standard supervised LDA model (trained on data from a calibration session of 30 trials in the original study) is compared to the unsupervised models UA, TA and the fully adapted model at the end of the session TA^U.

During the first two sub-blocks the subject-specific supervised LDA model performs best. Furthermore it is relatively stable over most sub-blocks, but it displays a performance drop at the end of the experiment (sub-blocks 17 and 18), while this is not observed for any of the unsupervised adapted models. The randomly initiated unsupervised model UA exhibits typical warm-up behavior during the first two experimental blocks (25 % and 47 % accuracy, with $16.\bar{6}$ % chance level). As it observes more and more data, it becomes more reliable. The transfer learning model TA was able to significantly reduce the warm-up period and achieves 60 % selection accuracy in the first block and 70 % in the second block. While it does not yet performs at the same level as the supervised LDA model, we must point out that the LDA model had already observed ten trials more data at this point (30 trials in total). Moreover, the re-evaluation of the transfer learning model TA^U can correct many of the initial mistakes committed by TA and is as reliable as the LDA model even in the first blocks. In previous work, we have shown that the revised predictions of the UA^U model are quite similar to those of TA^U. The online results given in the right plot of Figure 1 provide details on the warm-up performance for three repeated blocks of 30 trials (corresponding to 15 symbols each). They not only show the technical feasibility of the transfer approach, but are a first indication that the simulation results reported above can be replicated online. Obviously, the online results so far are limited by the fact that they comprise two users only.

However, the offline simulation in combination with these first online results of unsupervised transfer learning indicate that it is not only useful to share decoding knowledge between users, but that an additional subject-specific further online adaptation quickly leads to a very reliable model for the novel user. This study will be extended in future work and naturally, if successful, taken to patients.

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References

[1] J. Höhne, M. Schreuder, B. Blankertz, and M. Tangermann. A novel 9-class auditory ERP paradigm driving a predictive text entry system. *Front. Neuroscience*, 5:99, 2011.

[2] J. Jin, E.W. Sellers, Y. Zhang, I. Daly, X. Wang, and A. Cichocki. Whether generic model works for rapid ERP-based BCI calibration. *J. Neurosc. Meth.*, 2012.

[3] P.-J. Kindermans, M. Schreuder, B. Schrauwen, K.-R. Müller, and M. Tangermann. True zero-training brain-computer interfacing — an online study. *PLoS One*, (in press).

[4] P.-J. Kindermans, M. Tangermann, K.-R. Müller, and B. Schrauwen. Integrating dynamic stopping, transfer learning and language models in an adaptive zero-training ERP speller. *J. Neural Eng.*, 2014.

[5] K. Li, V. N. Raju, R. Sankar, Y. Arbel, and E. Donchin. Advances and challenges in signal analysis for single trial P300-BCI. In *Proc. 6th Int. Conf. Foundations of Augm. Cogn.*, FAC'11, pages 87–94, Berlin, Heidelberg, 2011. Springer-Verlag.

[6] Y. Li, C. Guan, H. Li, and Z. Chin. A self-training semi-supervised SVM algorithm and its application in an EEG-based brain computer interface speller system. *Pattern Recogn. Lett.*, 29(9):1285 – 1294, 2008.

[7] M. Schreuder, T. Rost, and M. Tangermann. Listen, you are writing! speeding up online spelling with a dynamic auditory BCI. *Front. Neuroscience*, 5, 2011.