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Cross-Task Transfer Learning in Emotion Estimating BCI

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Introduction: In the machine-learning literature, "transfer learning" often refers to cross-subject learning. In this type of transfer learning, data from other participants is used to build a classifier or model new participants. Cross-subject transfer learning has been applied for emotion estimation in the field of Brain-Computer Interface (BCI). However, cross-subject transfer learning requires a large dataset. To overcome this limitation, we implemented cross-task transfer learning, which, to our knowledge, has not been used yet in affective BCI. Here, we used a unique data-set with three different types of emotion elicitation stimuli to test this cross-task transfer learning.

Material, Methods and Results: The dataset consists of three different types of stimuli: pictures (International Affective Picture System), facial images (Pictures of Facial Affects), and music. Each stimulus was active for 15 seconds. Participants rated each stimulus on three emotional dimensions (valence, arousal, and dominance) using a 5-point Self-Assessment Manikin [1]. Twenty participants performed this study and each experienced a total of 240 stimuli. EEG data were recorded using a 64-channel Cognionics system with a sampling rate of 500 Hz.

We calculated the magnitude-squared coherence estimate (MSCE) between all 64 channels as input features and performed t-tests as a feature selection method. A binary classification was performed with a threshold of 3 in each emotional axis, using a simple tri-layer neural network (5-fold cross-validation). Here, we tested two different approaches: - in-task classification and cross-task classification. We computed balanced accuracy and its credible intervals to evaluate the performance against chance [2]. Bonferroni correction was applied to set the significance level at $\alpha/2$ for in-task classification (2 emotional axes per dataset) and $\alpha/18$ for cross-task classification (18 total comparison), where $\alpha=0.05$. Also, we performed a statistical comparison between the balanced accuracies of cross-task and their corresponding test set's in-task accuracy for both valence and arousal axis after Bonferroni correction (at the significance level of $\alpha/12$).

In Table 1, the diagonal elements represent the average balanced accuracy of in-task classification and the off-diagonal values indicate the average balanced accuracy of cross-task classification for each axis. The average in-task balanced accuracies are higher than the cross-task balanced accuracies except in three cases. For the valence axis, no significant differences were observed between in-task and cross-task performance. For arousal, none of the differences survived Bonferroni correction ($p < 0.0042$), and only the reduction in performance on POFA by training on Audio would have been significant without the correction ($p = 0.035$).

Table 1: Mean balanced accuracies for all participants of both in-task and cross-task classification

Valence					Arousal			
Train \ Test	IAPS	POFA	Audio		Train \ Test	IAPS	POFA	Audio
IAPS	**53.92***	56.25*	52.24		IAPS	**60.88***	62.04*	59.424*
POFA	52.18	**57.04***	53.33		POFA	63.06*	**69.69***	61.31*
Audio	51.85	53.2	**52.19**		Audio	59.23*	60.05*	**63.33***

*The lower bound of the credible interval is above chance.

Discussion & Significance: This study preliminary exhibits the effectiveness of cross-task transfer learning in BCI emotion detection. Cross-task transfer learning is performing well for the arousal axis since the lower credible boundary is always above chance for all cases. However, the performance of cross-task transfer learning is not satisfactory for the valence axis.

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