

Unsupervised learning with signal alignment for Calibration-less P300 BCI

뇌-컴퓨터 인터페이스 데이터 간 전이학습을 위한 신호 정렬 기법

Eunjin Hwang¹, Minchul Kim², and Minkyu Ahn^{2,*}
School of Computer science and Electrical Engineering, Handong Global University
*minkyuahn@handong.edu



INTRODUCTION

Acquiring data for training a model is a crucial step for achieving a high-performance Brain-Computer Interface (BCI). To reduce or remove this time-consuming phase, re-using the previously acquired data is suggested [1]. However, problems may still exist due to different UX of applications, devices or control paradigms.

In this study, we propose an approach to minimize signal differences caused by different system environments, which possibly benefits for better BCI performance. Particularly, we focus on P300 BCI but with different environment (PC based P300 speller [1] and VR based Drone control application [2]).

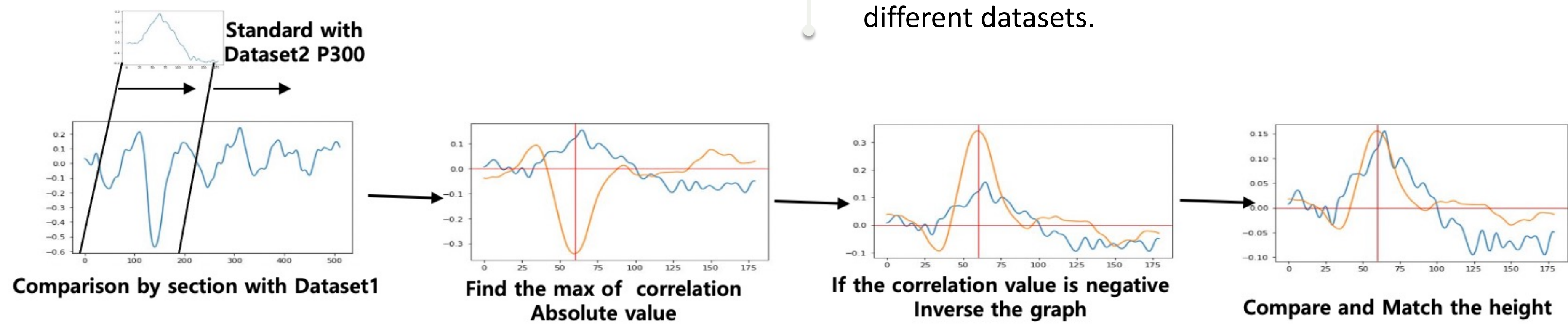
METHOD

Temporal characteristics of event related potential (ERP) may vary across UX of applications, acquisition devices or even subjects [3]. Therefore, ERP in one dataset should be transformed to the standard ERP pattern in another dataset.

To achieve this, we designed a correlation-based signal alignment (CSA) which transforms one ERP to a new pattern showing the highest correlation coefficient with target ERP in different dataset (Figure 1).

- **Two datasets** : [1] from P300 speller and [2] from VR based Drone control application
- **Evaluation method**: Comparison with this method (TL_CSA: Transfer Learning with Correlation based Signal Alignment)
 - SON: when using subject's own data
 - TL: contracting model without signal alignment
 - live training [1]: real-time unsupervised learning (Live_LDA) with pseudo labels from TL_CSA.

FIGURE 1. Signal alignment techniques



RESULT

The results are summarized in the Table 1. SOD which is a classical approach, shows obviously the highest performance since subject's training data was used to a classifier generation. TL, TL_CSA and Live_LDA show 20.8%, 58.7% and 62.0% on average. Statistical test revealed that there are significant differences among TL, TL_CSA with threshold ($p < 0.05$).

Subjects	SOD	TL	TL_CSA	Live_LDA
S01	75%	20%	67%	70%
S02	73%	20%	60%	46%
S03	90%	22%	42%	45%
S04	76%	10%	60%	70%
S05	73%	36%	40%	40%
S06	100%	36%	70%	66%
S08	100%	20%	96%	93%
S09	80%	23%	53%	53%
S10	83%	20%	60%	50%
S11	96%	20%	43%	70%
S12	70%	16%	30%	33%
S14	86%	23%	33%	46%
S15	100%	20%	46%	60%
S16	96%	13%	60%	50%
S17	100%	10%	56%	90%
S18	96%	30%	63%	50%
S19	96%	20%	96%	96%
S20	100%	16%	76%	86%
Average	89%±11%	20.8%±7%	58.7%±18%	62%±19%

TABLE 1. Individual and average accuracy of subject. SOD(Subject Own Data), TL(Transfer Learning), TL_CSA(TL with Correlation based Signal Alignment), Live_LDA(Make LDA with TL_CSA model)

CONCLUSION

In this study, we proposed a signal alignment technique. As a results, our proposed methods (TL_CSA and Live_LDA) show the reasonable performance. This implicates that signal transformation is important in transfer learning across different datasets.

Acknowledgements This work was supported by National Research Foundation of Korea (2019R1F1A1058844, 2021R1I1A3060828), National Program for Excellence in Software at Handong Global University (2017-0-00130).

Reference
[1] Lee et al., IEEE Access 8, 74385-74400, 2020. [2] Kim et al., Sensors 21(17), 5765, 2021.
[3] Won et al., Front. Hum. Neurosci. 13:261, 2019.