Towards high performance and efficient brain computer interface character speller : convolutional neural network based methods

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Chapter 7

Summary and Conclusions

A P300-based Brain Computer Interface (BCI) character speller, also known as P300 speller, has been an important communication pathway, under extensive research, for people who lose motor ability, such as patients with Amyotrophic Lateral Sclerosis (ALS) or spinal-cord injury because a P300 speller allows human-beings to directly spell characters using eye-gazes, thereby building communication between the human brain and a computer. Unfortunately, P300 spellers are still not used in human's daily life and remain in an experimental stage at research labs. The reason for this situation is that the performance and the efficiency of current P300 spellers are unacceptably low for BCI users in their daily life. Therefore, in this thesis, we have focused our attention on developing high performance and efficient P300 spellers in order to bring P300 spellers into practical use. More specifically, in order to increase the performance of a P300 speller, we have developed methods to increase the character spelling accuracy and the Information Transfer Rate (ITR). In order to improve the efficiency of a P300 speller, we have developed methods to reduce the number of sensors needed to acquire EEG signals as well as to reduce the complexity of the classifier used in a P300 speller without losing the performance.

We summarize the contributions of each chapter of this thesis in Figure 7.1 in order to show how the proposed methods in each chapter improve the performance and/or the efficiency of a P300 speller. In this figure, BA denotes our baseline, i.e., the CNN, called BN3 [LWG$^+$18], used for a P300 speller. We select this baseline because BN3 achieves better spelling accuracy and ITR than other state-of-the-art methods (excluding our proposed methods) for the P300 speller. CH3, CH4, CH5, and CH6 denote our proposed methods in Chapter 3, Chapter 4, Chapter 5, and Chapter 6, respectively. The "Performance" axis in Figure 7.1 shows the max-ITR[1] of a P300

[1]The notion of max-ITR is introduced in Section 3.3.5

speller. In this axis, TA shows the theoretically achievable maximum ITR[2] of a P300 speller. The "Cost" axis shows the number of sensors used to acquire EEG signals in a P300 speller. The "Complexity" axis shows the number of parameters (i.e., weights and biases) of a CNN used as the classifier in a P300 speller. Based on Figure 7.1, we summarize and draw the following conclusions for each chater's contributions:

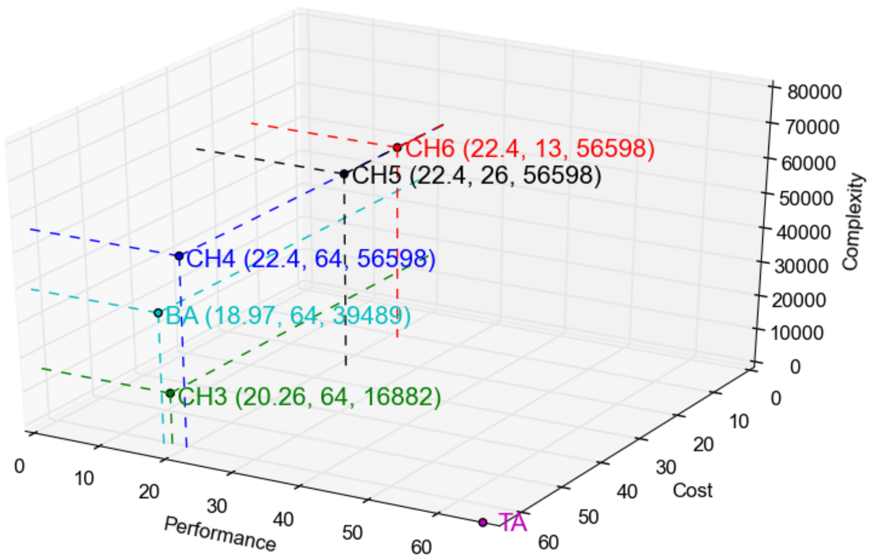

Figure 7.1: Overview of how each chapter's contributions improve the performance and/or the efficiency of a P300 speller.

• **Chapter 3 (CH3):** In order to improve the performance and the efficiency (i.e., to reduce the complexity) of a P300 speller with respect to BA, in Chapter 3, we have proposed a simple, yet effective CNN architecture, called One Convolution Layer Neural Network (OCLNN), for the P300 speller. This CNN has only one convolution layer which is the first layer of the network. This layer performs both a spatial convolution and a temporal convolution at the same time, thereby learning very useful P300-related features from both raw temporal information and raw spatial information. Our OCLNN exhibits very low network complexity because it uses only one

[2]The theoretically achievable maximum ITR is discussed in Section 2.4.3

convolution layer and does not use fully-connected layers before the output layer. Figure 7.1 shows that, compared to the baseline BA, by using our OCLNN (see CH3 in Figure 7.1), we have improved the performance, in terms of the spelling accuracy and the ITR, of the P300 speller, as well as we have improved significantly the efficiency, i.e., the complexity of the CNN used in the P300 speller is reduced.

• **Chapter 4 (CH4):** The ITR achieved by our OCLNN (see CH3 in Figure 7.1) still cannot reach the theoretically achievable maximum ITR (see TA in Figure 7.1). Therefore, to increase the ITR of a P300 speller in order to bring it closer to the theoretically achievable maximum ITR, in Chapter 4, we have proposed an ensemble of CNNs for the P300 speller. Our proposed ensemble of CNNs is called Ensemble of Convolutional Neural Networks (EoCNN). EoCNN uses two novel CNNs, we have devised, called One Spatial Layer Network (OSLN) and One Temporal Layer Network (OTLN), respectively. OSLN and OTLN both have only one convolution layer. OTLN performs a temporal convolution in the first layer to learn P300-related separate temporal features. OSLN performs a spatial convolution in the first layer to learn P300-related separate spatial features. Our EoCNN uses the ensemble of OSLN and OTLN together with OCLNN (proposed in Chapter 3), thereby extracting more useful P300-related features than OCLNN alone. As a result, see CH4 in Figure 7.1, our EoCNN achieves higher character spelling accuracy and ITR than OCLNN (see CH3 in Figure 7.1) and other state-of-art methods (see BA in Figure 7.1) for the P300 speller. However, the complexity of our EoCNN is higher than the complexity of OCLNN. Thus, compared to OCLNN, by using our EoCNN, we have improved the performance, in terms of the spelling accuracy and the ITR, of the P300 speller but we have impaired the efficiency, i.e., the complexity of the CNN used in our EoCNN-based P300 speller has been increased.

• **Chapter 5 (CH5):** In order to improve the efficiency of our EoCNN-based P300 speller, in Chapter 5, we have proposed a sensor reduction method, called Spatial Learning based Elimination Selection (SLES), to reduce the number of sensors used to acquire EEG signals in the EoCNN-based P300 speller without losing the state-of-the-art spelling accuracy and ITR. Here, the state-of-the-art spelling accuracy and ITR denote the accuracy and ITR achieved by EoCNN when a large number of sensors (e.g., 64 sensors) is used to acquire EEG signals (see CH4 in Figure 7.1). Our SLES uses a novel parametrized CNN, we have devised, to evaluate and rank the sensors during the sensor selection process. This method features an iterative, parametrized, backward elimination algorithm to eliminate and select sensors. The parameter configured in this algorithm controls the training frequency of the CNN and the number of sensors to eliminate in every iteration. Our SLES method significantly reduces the number of sensors used in the EoCNN-based P300 speller without losing the state-of-the-art spelling accuracy and ITR (see CH5 in Figure 7.1). Thus, by using our SLES method, we have improved the efficiency, i.e., we have reduced significantly the number of sensors needed to acquire EEG signals in the EoCNN-based P300 speller without losing the state-of-the-art performance in terms of the spelling accuracy and ITR.

• **Chapter 6 (CH6):** Although the number of sensors needed to acquire EEG signals in the EoCNN-based P300 speller is significantly reduced by our SLES method (see CH5 in Figure 7.1), we still need to use more than 16 sensors to acquire EEG signals in the EoCNN-based P300 speller in most cases in order to preserve the state-of-the-art spelling accuracy and ITR. Unfortunately, popular low-complexity and relatively cheap (affordable) BCI systems utilize a small number of sensors for the acquisition of EEG signals. Typically, such small number of sensors is less than or equal to 16 sensors. Therefore, in Chapter 6, we have performed research on how to achieve the state-of-the-art spelling accuracy and ITR of the P300 speller with less than or equal to 16 sensors to acquire EEG signals. We have performed a study on the EoCNN-based P300 speller with different number of sensors, which reveals that EoCNN has the problem of putting equal importance on OSLN, OTLN, and OCLNN when combining the outputs from OSLN, OTLN, and OCLNN irrespective of the number of sensors used to acquire EEG signals. To solve this problem, we have proposed an improved EoCNN for the P300 speller called PEoCNN. In PEoCNN, first, we parameterize the process of combining the outputs from OSLN, OTLN, and OCLNN. Then, we use the Sequential Model-based Algorithm Configuration (SMAC) to automatically find and set values for the parameters depending on the number of sensors used in the P300 speller. In this way, PEoCNN adapts/configures the importance of using the outputs from OSLN, OTLN, and OCLNN for the P300 speller depending on the number of sensors used to acquire EEG signals. As a result, see CH6 in Figure 7.1, the PEoCNN-based P300 speller can be used in popular low-complexity BCI systems with less than 16 sensors to acquire EEG signals without losing the state-of-the-art spelling accuracy and ITR. Thus, compared to EoCNN (see CH5 in Figure 7.1), by using our PEoCNN, we have improved the efficiency, i.e., we have further reduced the number of sensors needed to acquire EEG signals in the P300 speller without losing the state-of-the-art performance in terms of the spelling accuracy and the ITR.