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

Shan, H.

Author: Shan, H.
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Chapter 6

An Improved Ensemble of Convolutional Neural Networks for P300 Speller with a Small Number of Sensors

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In Chapter 4, we have presented our EoCNN which achieves higher spelling accuracy and ITR compared to other state-of-the-art methods for the P300 speller. In Chapter 5, we have presented our SLES method that can reduce the number of sensors needed to acquire EEG signals in our EoCNN-based P300 speller while keeping the character spelling accuracy and the ITR the same as the character spelling accuracy and the ITR achieved by EoCNN when an initial large set of 64 sensors is used in the P300 speller. We call the character spelling accuracy and the ITR, achieved by EoCNN for the P300 speller with a large number of sensors (i.e, 64 sensors), the state-of-the-art character spelling accuracy and ITR of the P300 speller. Table 5.7, 5.8, and 5.9 in Chapter 5 show that in most cases, in order to not lose the state-of-the-art character spelling accuracy and ITR of the P300 speller, we need to use more than 16 sensors to acquire EEG signals in the EoCNN-based P300 speller. 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. For example, BCI systems such as MUSE [MUS], EMOTIV Insight [Ins], Quick-8 [Qui], B-Alert X10 [B-A], EMOTIV EPOC+ [EMO], and OPEN BCI Mark IV [Mar] utilize only 4, 5, 8, 10, 14, and 16 sensors, respectively. Therefore, in this chapter, we present our research on how to achieve the state-of-the-art character spelling accuracy and ITR of the P300 speller with popular low-complexity and relatively cheap BCI systems that use a small number of sensors (i.e., less than or equal to 16 sensors) to acquire EEG signals. The novel contributions of this chapter are the following.

- We perform a study on EoCNN as well as the three CNNs used in EoCNN, i.e., OTLN, OSLN, and OCLNN, for the P300 speller with different number of sensors in order to find the reason why EoCNN cannot achieve the state-of-the-art character spelling accuracy and ITR for a P300 speller with a small number of sensors. This study shows that the reason for this is that EoCNN has the problem of putting equal importance on OSLN, OTLN, and OCLNN in the ensemble processing of the outputs from these three CNNs (see Section 4.1.4 as well as Equation (4.1) and (4.2)) for the P300 speller irrespective of the number of sensors used to acquire EEG signals.

- In order to solve the problem of EoCNN, mentioned in the above contribution, we propose an improved EoCNN for the P300 speller called PEoCNN. In PEoCNN, first, we parameterize the ensemble processing of the outputs from OSLN, OTLN, and OCLNN. Then, we use the Sequential Model-based Algorithm Configuration (SMAC) [HHLB11] to automatically find and set values for the parameters, used in the parameterized ensemble processing of PEoCNN, depending on the number of sensors utilized in the P300 speller. In this way, PEoCNN is able to adopt/configure the importance of using the outputs from OSLN, OTLN, and OCLNN for the P300 speller depending on the number of sensors that are utilized.

- Experiments on three benchmark datasets show that, when using our PEoCNN for the P300 speller, the state-of-the-art spelling accuracy can be achieved in a BCI system with less than or equal to 16 sensors to acquire EEG signals in most cases. In addition, the state-of-the-art max-ITR[1] of the P300 speller can be achieved in a BCI system with less than 16 sensors to acquire EEG signals.

The rest of this chapter is organized as follows. Section 6.1 presents our study on the EoCNN-based P300 speller with different number of sensors in order to analyze and find the reason why EoCNN cannot achieve the state-of-the-art spelling accuracy

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

and max-ITR for a P300 speller with a small number of sensors. Section 6.2 introduces our approach to solve the problem of EoCNN revealed by the aforementioned study. Section 6.3 describes the experimental evaluation of our approach to show that by using our approach, we are able to achieve the state-of-the-art character spelling accuracy and max-ITR of the P300 speller with less than or equal to 16 sensors to acquire EEG signals. Section 6.4 ends this chapter with conclusions.

6.1 Study on EoCNN-based P300 Speller with Different Number of Sensors

In this section, we perform a study on the EoCNN-based P300 speller with different number of sensors in order to find the reason why EoCNN cannot achieve the state-of-the-art character spelling accuracy and ITR for a P300 speller with a small number of sensors. In this study, we perform experiments to examine the character spelling accuracy and the max-ITR achieved by EoCNN as well as the three CNNs used in the EoCNN, i.e., OCLNN, OTLN, and OSLN, for the P300 speller with different number of sensors. First, we describe the experimental setup of this study in Section 6.1.1. Then, we show and analyze the experimental results of this study in Section 6.1.2.

6.1.1 Experimental Setup

In this study, we use four implementations of the P300 speller to perform the experiments: the EoCNN-based P300 speller, the OCLNN-based P300 speller, the OSLN-based P300 speller, and the OTLN-based P300 speller. In order to examine the character spelling accuracy and the max-ITR of the aforementioned four P300 speller implementations when different number of sensors are utilized to acquire EEG signals, we perform the following two steps:

Step 1. We select different appropriate sensor subsets, containing different number of sensors, from an initial large set of sensors to acquire EEG signals for a subject who uses a P300 speller. The subject in this study is the subject used to acquire the EEG signals in Dataset III-A. We call this subject Subject III-A. We apply our SLES method (proposed and presented in Chapter 5) to select different appropriate sensor subsets from an initial large set of 64 sensors for Subject III-A. Therefore, we can use the training dataset of Dataset III-A to apply our SLES sensor selection method. More specifically, for our SLES method, this training dataset is used to train the $OSLN_{(S)}$ and calculate $score_j$ in each iteration of our SLES method (see Algorithm 1 in Chapter 5). For the details of the setup for our SLES please refer to the last paragraph in Section 5.3.1.

Step 2. After using our SLES method to select different sensor subsets for Subject III-A, we calculate the spelling accuracy and the max-ITR of the aforementioned four P300 speller implementations with the selected sensor subsets using Dataset III-A. The training dataset of Dataset III-A is used to train the CNN-based classifiers used in the aforementioned P300 speller implementations with the selected sensor subsets. Then, the test dataset of Dataset III-A is used to calculate the spelling accuracy and max-ITR of the aforementioned P300 speller implementations with the selected sensor subsets. The spelling accuracy $acc^{m}_{char(k)}$ is calculated using Equation (5.3) in Section 5.3.1, where $acc^{m}_{char(k)}$ denotes the spelling accuracy achieved when using the first k epochs for each character and using the EEG signals acquired with the selected sensor subset containing m sensors. The ITR ITR^{m}_{k} is calculated using Equation (6.1) and (2.35), where ITR^{m}_{k} denotes the ITR achieved when using the first k epochs for each character and using the EEG signals acquired with the selected sensor subset containing m sensors; N_{cla} =36 because we have 36 possible characters to spell (see Figure 2.10); $acc^{m}_{char(k)}$ is calculated using Equation (5.3); and T_k is calculated using Equation (2.35). After the calculation of ITR^{m}_{k}, we calculate the max-ITR $maxITR^{m}$ using Equation (6.2), where $maxITR^{m}$ denotes the max-ITR achieved when the EEG signals are acquired with the selected sensor subset containing m sensors.

$$ITR^{m}_{k} = \frac{60(acc^{m}_{char(k)}\log_2(acc^{m}_{char(k)}) + (1-acc^{m}_{char(k)})\log_2(\frac{1-acc^{m}_{char(k)}}{N_{cla}-1}) + \log_2(N_{cla}))}{T_k} \tag{6.1}$$

$$maxITR^{m} = \max_{1\leq k\leq 15}\{ITR^{m}_{k}\} \tag{6.2}$$

6.1.2 Experimental Results

The experimental results on the spelling accuracy and the max-ITR of the EoCNN-based P300 speller, the OSLN-based P300 speller, the OTLN-based P300 speller, and the OCLNN-based P300 speller when different number of sensors m is used to acquire Subject III-A's EEG signals are shown in Figure 6.1 and Figure 6.2, respectively. Figure 6.1 shows that, in most cases (with respect to the number of sensors m), the OCLNN-based P300 speller achieves higher spelling accuracy than the OTLN-based P300 speller and the OSLN-based P300 speller. When the number of sensors used to acquire EEG signals is between 1 and 36, the OTLN-based P300 speller achieves higher spelling accuracy than the OSLN-based P300 speller. When the number of sensors used to acquire EEG signals is between 37 and 64, the OSLN-based P300 speller achieves higher spelling accuracy than the OTLN-based P300 speller. Figure 6.2

shows that, in most cases (with respect to the number of sensors m), the OCLNN-based P300 speller achieves higher max-ITR than the OTLN-based P300 speller and the OSLN-based P300 speller. When the number of sensors used to acquire EEG signals is between 1 and 30, the OTLN-based P300 speller achieves higher max-ITR than the OSLN-based P300 speller. When the number of sensors used to acquire EEG signals is between 32 and 64, the OSLN-based P300 speller achieves higher max-ITR than the OTLN-based P300 speller.

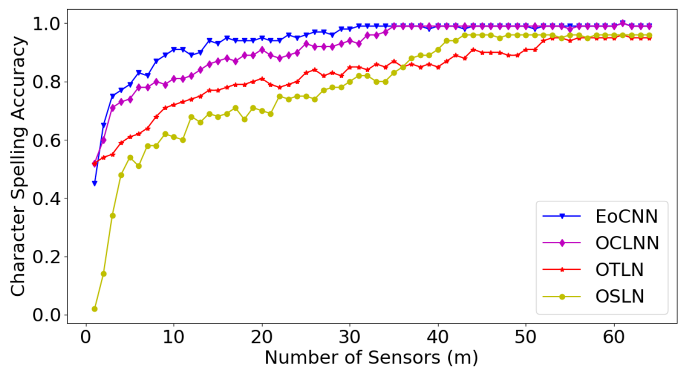

Figure 6.1: Spelling accuracy of different P300 speller implementations when different number of sensors m is used to acquire EEG signals.

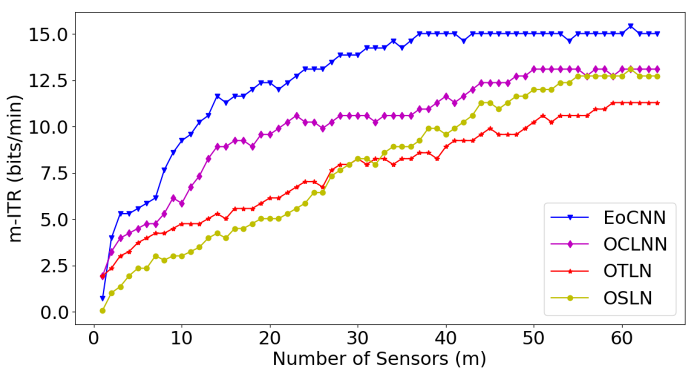

Figure 6.2: max-ITR of different P300 speller implementations when different number of sensors m is used to acquire EEG signals.

The aforementioned experimental results reveal that overall, the three CNNs, i.e., OCLNN, OSLN, and OTLN, have different importance and impact on the spelling accuracy and the max-ITR of a P300 speller depending on the number of sensors that are used to acquire EEG signals. This implies that when we use a CNN, which combines the outputs of OCLNN, OSLN, and OTLN, for a P300 speller, we should adopt/configure the importance of using the outputs from OCLNN, OSLN, and OTLN depending on the number of sensors that are used to acquire EEG signals. Unfortunately, the EoCNN (presented and proposed in Chapter 4) has the issue of putting equal importance on OSLN, OTLN, and OCLNN in the ensemble processing of the outputs from these three CNNs (see Section 4.1.4 as well as Equation (4.1) and (4.2)) for the EoCNN-based P300 speller irrespective of the number of sensors used to acquire EEG signals.

6.2 Our Solution Approach

In this section, in order to address the issue of EoCNN revealed in Section 6.1, we present our solution approach on how to make EoCNN adopt/configure the importance of using the outputs from OSLN, OTLN, and OCLNN for a P300 speller depending on the number of sensors used to acquire EEG signals. In our approach, first, we parameterize the ensemble processing of EoCNN as described in Section 6.2.1. Then, we find and set values for the parameters, that are used in the ensemble processing of EoCNN, depending on the number of sensors used to acquire EEG signals in the P300 speller as described in Section 6.2.2.

6.2.1 Parameterized Ensemble Processing

Our approach is based on EoCNN that is proposed and presented in Chapter 5. We use the architecture of EoCNN, i.e., the ensemble of OTLN, OSLN, and OCLNN, for the P300 speller (see Figure 4.1). However, the difference is in the ensemble processing of the outputs from OTLN, OSLN, and OCLNN. That is, EoCNN puts equal importance on OSLN, OTLN, and OCLNN in the ensemble processing of the outputs from OSLN, OTLN, and OCLNN (see Equation (4.1) in Section 4.1.4) irrespective of the number of sensors used to acquire EEG signals. In contrast, our approach here parameterizes the ensemble processing of the outputs from OSLN, OTLN, and OCLNN for the P300 speller in order to make this ensemble processing adaptable/configurable to the number of sensors used to acquire EEG signals.

Our parameterized ensemble processing of the outputs from OSLN, OTLN, and OCLNN is shown in Equation (6.3). We call EoCNN, with this parameterized ensemble processing, PEoCNN. In Equation (6.3), for epoch i and for intensification j, $P^1_{PEoC}(i,j)$ denotes the predicted probability by PEoCNN for class "P300"; $P^1_{OT}(i,j)$ denotes the predicted probability by OTLN for class "P300"; $P^1_{OS}(i,j)$ denotes the predicted probability by OSLN for class "P300"; $P^1_{OCL}(i,j)$ denotes the predicted probability by OCLNN for class "P300"; and p_1, p_2, and p_3 are three parameters that weight the importance of the predicted probability by OTLN, OSLN, OCLNN, respectively, for class "P300", in order to determine the output $P^1_{PEoC}(i,j)$ of PEoCNN. $p_1 \in [0,1]$, $p_2 \in [0,1]$, and $p_3 \in [0,1]$. In addition, we set the constraint p_1 + p_2 + p_3 = 1 to guarantee that $P^1_{PEoC}(i,j)$ is in the range [0, 1] because $P^1_{PEoC}(i,j)$ is the probability predicted by PEoCNN for class "P300".

$$P^1_{PEoC}(i,j) = p_1 \times P^1_{OT}(i,j) + p_2 \times P^1_{OS}(i,j) + p_3 \times P^1_{OCL}(i,j) \tag{6.3}$$

How we select appropriate values for p_1, p_2, and p_3, depending on the number of sensors used in the P300 speller for acquisition of EEG signals, is described in Section 6.2.2. After the selection of values for p_1, p_2, and p_3, we use $P^1_{PEoC}(i,j)$, i.e., the output of PEoCNN for class "P300", to calculate the position of the target character in the character matrix shown in Figure 2.10. For the detailed calculation process, please refer to Section 2.4.2, Equation (2.30), (2.31), and (2.32).

6.2.2 Parameter Configuration for Parameterized Ensemble Processing

As described in Section 6.2.1, in the parameterized ensemble processing of PEoCNN, there are three parameters, i.e., p_1, p_2, and p_3, that need to be configured (see Equation (6.3)). This section describes how we select appropriate values for these three parameters depending on the number of sensors used for the acquisition of EEG signals in the P300 speller.

For a given number of sensors m used to acquire EEG signals in the P300 speller, we select a set of appropriate values for p_1, p_2, and p_3 by looking at this selection problem as an optimization problem. We define this optimization problem as shown in Equation (6.4), where **p** is a vector of p_1, p_2, and p_3, i.e., $\mathbf{p} = [p_1, p_2, p_3]$; $Q(\mathbf{p})$ is the cost function. We define $Q(\mathbf{p})$ using Equation (6.5), where $maxITR_{ta}$ denotes the theoretically achievable maximum ITR of a P300 speller; $maxITR^m(\mathbf{p})$ denotes the max-ITR achieved by PEoCNN, configured with **p**, for the P300 speller when the EEG signals are acquired using the given m sensors. $maxITR^m(\mathbf{p})$ is calculated using Equation (6.6), where E denotes the total number of epochs used in a P300 speller. Here, E=15 because we use 15 epochs in the P300 speller (see Section 2.5). $ITR^m_k(\mathbf{p})$ denotes the ITR achieved by PEoCNN, configured with **p**, when k epochs are used for the P300 speller and the EEG signals are acquired using the given m sensors. $ITR^m_k(\mathbf{p})$ is calculated using Equation (6.7),where N_{cla} =36 because we have 36 possible characters to spell (see Figure 2.10); T_k is calculated using Equation (2.35); $acc^m_{char(k)}(\mathbf{p})$ denotes the character spelling accuracy achieved by PEoCNN, configured with **p**, when k epochs are used for the P300 speller and the EEG signals are acquired using the given m sensors. $acc^{m}_{char(k)}(\mathbf{p})$ is calculated using Equation (6.8), where $N^{m}_{tc(k)}(\mathbf{p})$ denotes the number of correctly inferred characters by PEoCNN configured with **p** when using k epochs for each character and the EEG signals are acquired using the given m sensors, and S_c denotes the number of all spelled characters.

$$\begin{aligned} &\underset{\mathbf{p}}{Minimize}\; Q(\mathbf{p}) \\ subject\; to:\;\; & p_1 + p_2 + p_3 = 1, 0 \leq p_1 \leq 1, 0 \leq p_2 \leq 1, and\; 0 \leq p_3 \leq 1 \end{aligned} \tag{6.4}$$

$$Q(\mathbf{p}) = maxITR_{ta} - maxITR^{m}(\mathbf{p}) \tag{6.5}$$

$$maxITR^{m}(\mathbf{p}) = \underset{1 \leq k \leq E}{max}\; \{ITR^{m}_{k}(\mathbf{p})\} \tag{6.6}$$

$$ITR^{m}_{k}(\mathbf{p}) = \frac{60(acc^{m}_{char(k)}(\mathbf{p}) \log_2(acc^{m}_{char(k)}(\mathbf{p})) + (1 - acc^{m}_{char(k)}(\mathbf{p})) \log_2(\frac{1-acc^{m}_{char(k)}(\mathbf{p})}{N_{cla}-1}) + \log_2(N_{cla}))}{T_k} \tag{6.7}$$

$$acc_{char(k)}(\mathbf{p}) = \frac{N_{tc(k)^m}(\mathbf{p})}{S_c} \tag{6.8}$$

Equation (6.4) shows that we define the selection of values for $\mathbf{p} = [p_1, p_2, p_3]$ as a single-objective optimization problem. In this optimization problem, we aim at finding **p** such that the cost function $Q(\mathbf{p})$ is minimized. By using this cost function, we aim at finding appropriate **p** to configure PEoCNN such that for a given m sensors used to acquire EEG signals, the max-ITR achieved by PEoCNN, i.e., $maxITR^{m}(\mathbf{p})$, is the closest possible to the theoretically achievable maximum ITR $maxITR_{ta}$. Typically, the ultimate goal of designing methods for the P300 speller is to increase the max-ITR in order to bring it closer to the theoretically achievable maximum ITR (for detailed discussion please see Section 3.3.5 and Section 4.2.4.). Thus, we define the cost function, shown in Equation (6.5), to find appropriate **p** to configure PEoCNN.

We use the Sequential Model-based Algorithm Configuration (SMAC) [HHLB11] as an optimization algorithm to solve the aforementioned single-objective optimization problem defined by Equation (6.4) because SMAC is currently one of the best-performing and versatile optimization algorithms for parameter configuration. For more details on SMAC please refer to [HHLB11]. In the optimization process of SMAC, the cost function $Q(\mathbf{p})$ is calculated as follows. We use a dataset to train PEoCNN configured by $\mathbf{p}$ selected by SMAC. The training process of PEoCNN is the same as the training process of EoCNN described in Section 4.1.3. Then, we run this trained PEoCNN on another dataset to calculate $Q(\mathbf{p})$ using Equation (6.5), (6.6), (6.7), and (6.8).

6.3 Experimental Evaluation

In this section, we present the experiments, we have performed, to determine and evaluate the minimal number of sensors needed to acquire EEG signals in the PEoCNN-based P300 speller and in the EoCNN-based P300 speller without losing the state-of-the-art character spelling accuracy and max-ITR. The goal is to demonstrate that: 1) by using our PEoCNN, we are able to achieve the state-of-the-art character spelling accuracy and max-ITR of the P300 speller when using less than or equal to 16 sensors to acquire EEG signals; 2) our solution approach, described in Section 6.2, is effective, i.e., the PEoCNN-based P300 speller needs less number of sensors to acquire EEG signals than the EoCNN-based P300 speller without losing the state-of-the-art spelling accuracy and max-ITR. First, we describe the experimental setup in Section 6.3.1. Then, in Section 6.3.2, we show and analyze the obtained experimental results for the minimal number of sensors needed to acquire EEG signals in the PEoCNN-based P300 speller and in the EoCNN-based P300 speller.

6.3.1 Experimental Setup

We perform the following three steps in order to compare the minimal number of sensors needed to acquire EEG signals in the PEoCNN-based P300 speller and in the EoCNN-based P300 speller without losing the state-of-the-art character spelling accuracy and max-ITR.

Step 1. We select different appropriate sensor subsets, containing different number of sensors m, from an initial large set of sensors to acquire EEG signals for a subject who uses a P300 speller. The subjects in our experiments is the subjects used to acquire the EEG signals in Dataset II, III-A, and III-B. We call the subjects in Dataset II, III-A, and III-B, Subject II, Subject III-A, and Subject III-B, respectively. We apply our SLES method (proposed and presented in Chapter 5) to select different appropriate sensor subsets from an initial large set of 64 sensors for Subject II, Subject III-A, and Subject III-B. Therefore, we can use the training dataset of Dataset II, III-A, and III-B to apply our SLES sensor selection method. More specifically, for our SLES method, these training datasets are used to train the $OSLN_{(S)}$ and calculate

$score_j$ in each iteration of our SLES method (see Algorithm 1 in Chapter 5). For the details of the setup for our SLES please refer to the last paragraph in Section 5.3.1.

Step 2. We build two P300 speller implementations, namely the PEoCNN-based P300 speller and the EoCNN-based P300 speller. For the PEoCNN-based P300 speller, depending on given subset of m sensors selected to acquire EEG signals in **Step 1**, we select values for p_1, p_2, and p_3, which are used to configure PEoCNN. As described in Section 6.2.2, we use SMAC to select appropriate values for p_1, p_2, and p_3. When using SMAC, we need to calculate $Q(\mathbf{p})$ which is the cost function minimized by SMAC (see our defined optimization problem in Equation (6.4)). We use the training dataset in Dataset II, III-A, and III-B to calculate $Q(\mathbf{p})$. We divide each training dataset in Dataset II, III-A, and III-B into two parts: the first sub-dataset containing 60% of a given training dataset and the second sub-dataset containing the left 40% of the given training dataset (for the reason of using 60% and 40% to split a dataset please refer to Section 5.4.1.). The first sub-dataset is used to train PEoCNN configured with $\mathbf{p} = [p_1, p_2, p_3]$, selected by SMAC, in the PEoCNN-based P300 speller with the selected m sensors to acquire EEG signals. We run the trained PEoCNN on the second sub-dataset to calculate $Q(\mathbf{p})$ using Equation (6.5), (6.6), (6.7), and (6.8).

Step 3. After selecting $\mathbf{p}$ and configuring PEoCNN, we calculate the minimal number of sensors needed to acquire EEG signals in the PEoCNN-based P300 speller and in the EoCNN-based P300 speller without losing the state-of-the-art character spelling accuracy and max-ITR. Firstly, we calculate the spelling accuracy and the max-ITR of the PEoCNN-based P300 speller and EoCNN-based P300 speller with the different selected sensor subsets from **Step 1** using Dataset II, III-A, and III-B. The spelling accuracy $acc^m_{char(k)}$ is calculated using Equation (5.3) in Section 5.3.1, where $acc^m_{char(k)}$ denotes the spelling accuracy achieved when using the first k epochs for each character and using the EEG signals acquired with the selected sensor subset containing m sensors. The ITR ITR^m_k is calculated using Equation (6.1) and (2.35), where ITR^m_k denotes the ITR achieved when using the first k epochs for each character and using the EEG signals acquired with the selected sensor subset containing m sensors. After the calculation of ITR^m_k, we calculated the max-ITR $maxITR^m$ using Equation (6.2), where $maxITR^m$ denotes the max-ITR achieved when using the EEG signals acquired with the selected sensor subset containing m sensors. Secondly, after the calculation of $acc^m_{char(k)}$ and $maxITR^m$, we calculate the minimal number of sensors needed to acquire EEG signals without losing the state-of-the-art spelling accuracy and max-ITR of the P300 speller. We use m^{acc}_{min} to denote the minimal number of sensors needed to acquire EEG signals without losing the state-of-the-art spelling accuracy. m^{acc}_{min} is calculated as the minimal $m \in [1, 64]$ which makes $acc^m_{char(k)} >= acc^{soa}_{char(k)}$. Here, $acc^{soa}_{char(k)}$ denotes the state-of-the-art spelling accuracy of the P300 speller when using k epochs, i.e., the spelling accuracy achieved by EoCNN using k epochs when 64 sensors are used to acquire EEG signals in the P300 speller. We use m_{min}^{itr} to denote the minimal number of sensors needed to acquire EEG signals without losing the max-ITR of the P300 speller. m_{min}^{itr} is calculated as the minimal $m \in [1, 64]$ which makes $maxITR^{m} >= maxITR^{soa}$. Here, $maxITR^{soa}$ denotes the state-of-the-art max-ITR of the P300 speller, i.e., the max-ITR achieved by EoCNN when 64 sensors are used to acquire EEG signals in the P300 speller.

6.3.2 Experimental Results

In this section, we present the experimental results, we have obtained, for the minimal number of sensors needed to acquire EEG signals in the PEoCNN-based P300 speller and in the EoCNN-based P300 speller without losing the state-of-the-art spelling accuracy (see Section 6.3.2.1) as well as the minimal number of sensors needed to acquire EEG signals in the PEoCNN-based P300 speller and in the EoCNN-based P300 speller without losing the state-of-the-art max-ITR (see Section 6.3.2.2).

6.3.2.1 Minimal Number of Sensors Without Losing State-of-the-art Spelling Accuracy

Table 6.1, 6.2 and 6.3 show the minimal number of sensors needed to acquire EEG signals in the PEoCNN-based P300 speller and in the EoCNN-based P300 speller without losing the state-of-the-art spelling accuracy for epoch $k \in [1, 15]$. The first column in the tables lists the different CNNs used in a P300 speller for the inference of the characters. Each row provides the minimal number of sensors needed to acquire EEG signals used to acquire EEG signals in a P300 speller for different epoch numbers $k \in [1, 15]$. A number in bold indicates that the minimal number of sensors needed to acquire EEG signals in the P300 speller based on the corresponding CNN is lower than or equal to the minimal number of sensors needed to acquire EEG signals in the P300 speller based on the other CNN.

Table 6.1: Minimal number of sensors needed to acquire EEG signals in the P300 speller based on different CNNs without losing the state-of-the-art spelling accuracy of the P300 speller on Dataset II.

	Epochs														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
PEoCNN	**10**	**13**	**20**	**15**	**17**	**8**	**8**	**3**	**3**	**3**	**3**	**4**	**3**	**3**	**3**
EoCNN	**10**	16	28	19	22	9	**8**	**3**	**3**	**3**	**3**	**4**	**3**	**3**	**3**

Table 6.2: Minimal number of sensors needed to acquire EEG signals in the P300 speller based on different CNNs without losing the state-of-the-art spelling accuracy of the P300 speller on Dataset III-A.

	Epochs														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
PEoCNN	**12**	**14**	**14**	**12**	**19**	**17**	**11**	**24**	**29**	**16**	**30**	**13**	**13**	**15**	**18**
EoCNN	18	39	37	21	41	38	20	39	44	23	46	33	21	16	31

Table 6.3: Minimal number of sensors needed to acquire EEG signals in the P300 speller based on different CNNs without losing the state-of-the-art spelling accuracy of the P300 speller on Dataset III-B.

	Epochs														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
PEoCNN	**14**	**13**	**15**	**23**	**12**	**10**	**13**	**19**	**22**	**21**	**24**	**15**	**18**	**16**	**11**
EoCNN	25	26	28	27	23	14	16	25	30	29	33	22	30	29	23

Table 6.1, 6.2, and 6.3 show that in all 45 cases (i.e., all epoch columns in the three tables), the minimal number of sensors needed to acquire EEG signals in the PEoCNN-based P300 speller is lower than or equal to the minimal number of sensors needed to acquire EEG signals in the EoCNN-based P300 speller without losing the state-of-the-art spelling accuracy. This demonstrates that our solution approach, described in Section 6.2, is effective, i.e., the PEoCNN-based P300 speller needs less number of sensors to acquire EEG signals than the EoCNN-based P300 speller without losing the state-of-the-art spelling accuracy.

In addition, Table 6.1, 6.2 and 6.3 show that for 31 different epoch numbers out of all 45 epoch numbers, the PEoCNN-based P300 speller can achieve the state-of-the-art spelling accuracy with less than or equal to 16 sensors to acquire EEG signals. In contrast, only for 15 different epoch numbers out of 45 epoch numbers, the EoCNN-based P300 speller can achieve the state-of-the-art spelling accuracy with less than or equal to 16 sensors to acquire EEG signals. When a P300 speller is configured with different epoch numbers, the P300 speller has different spelling accuracy and communication speed: typically, a P300 speller, configured with a large epoch number, has a high spelling accuracy but a low communication speed while a P300 speller, configured with a small epoch number, has a low spelling accuracy but a high communication speed. The PEoCNN-based P300 speller has more configurations, in terms of the epoch numbers, than the EoCNN-based P300 speller when used in a low-complexity BCI systems with less than or equal to 16 sensors to acquire EEG signals. Thus, the PEoCNN-based P300 speller has more options to trade off the spelling accuracy for the communication speed and vice versa than the EoCNN-based P300 speller when used in such low-complexity BCI systems.

6.3.2.2 Minimal Number of Sensors Without Losing State-of-the-art max-ITR

Table 6.4 shows the minimal number of sensors needed to acquire EEG signals in the PEoCNN-based P300 speller and in the EoCNN-based P300 speller without losing the state-of-the-art max-ITR for Dataset II, III-A, and III-B. In this table, the first column lists the different CNNs used in a P300 speller for the inference of the characters. Each row provides the minimal number of sensors needed to acquire EEG signals in a P300 speller without losing the state-of-the-art max-ITR for the different datasets. A number in bold indicates that the minimal number of sensors needed to acquire EEG signals in the P300 speller based on the corresponding CNN is lower than or equal to the minimal number of sensors needed to acquire EEG signals in the P300 speller based on the other CNN.

Table 6.4: Minimal number of sensors needed to acquire EEG signals in the P300 speller based on different CNNs without losing the state-of-the-art max-ITR on Dataset II, III-A, and III-B.

	Dataset II	Dataset III-A	Dataset III-B
PEoCNN	**10**	**14**	**13**
EoCNN	**10**	37	26

Table 6.4 shows that for all three datasets, the minimal number of sensors needed to acquire EEG signals in the PEoCNN-based P300 speller is less than the minimal number of sensors needed to acquire EEG signals in the EoCNN-based P300 speller without losing the state-of-the-art max-ITR. This demonstrates again that our solution approach, described in Section 6.2, is effective, i.e., the PEoCNN-based P300 speller needs less number of sensors to acquire EEG signals than the EoCNN-based P300 speller without losing the state-of-the-art max-ITR.

Moreover, Table 6.4 shows that for all three datasets, the PEoCNN-based P300 speller achieves the state-of-the-art max-ITR when using less than 16 sensors to acquire EEG signals. In contrast, for only one dataset, the EoCNN-based P300 speller achieves the state-of-the-art max-ITR when using less than 16 sensors to acquire EEG signals. This demonstrates that by using our solution approach, described in Section 6.2, we enhance the usability of a P300 speller, having the state-of-the-art max-ITR, on low-complexity BCI systems across different subjects.

6.4 Conclusions

In this chapter, we present our research on how to achieve the state-of-the-art character spelling accuracy and max-ITR of the P300 speller with popular low-complexity and relatively cheap BCI systems that use less than or equal to 16 sensors to acquire EEG signals. We perform a study on the EoCNN-based P300 speller with different number of sensors to show that EoCNN has the problem of putting equal importance on using OSLN, OTLN, and OCLNN for the P300 speller irrespective of the number of sensors used to acquire EEG signals. In order to solve this problem, we propose an improved EoCNN called PEoCNN. In PEoCNN, we parameterize the ensemble processing of the outputs from OSLN, OTLN, and OCLNN. Then, we use SMAC to select appropriate values for the parameters depending on the number of sensors utilized in the P300 speller. Experimental results on three benchmark datasets show that by using our PEoCNN, we are able to achieve the state-of-the-art performance, in terms of the character spelling accuracy and the max-ITR, of the P300 speller when using less than or equal to 16 sensors to acquire EEG signals. Moreover, our proposed PEoCNN enhances the usability of a P300 speller, having the state-of-the-art performance, on low-complexity BCI systems across different subjects.