Brain2Object: Printing Your Mind from Brain Signals with Spatial Correlation Embedding

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Abstract—Electroencephalography (EEG) signals are known to manifest differential patterns when individuals visually concentrate on different objects (e.g., a car). In this work, we present an end-to-end digital fabrication system, Brain2Object, to print the 3D object that an individual is observing by solely decoding visually-evoked EEG brain signal streams. We propose a unified training framework which combines multi-class Common Spatial Pattern and deep Convolutional Neural Networks to support the backend computation. Specially, a Dynamical Graph Representation of EEG signals is learned for accurately capturing the structured spatial correlations of EEG channels in an adaptive manner. A user friendly interface is developed as the system front end. Brain2Object presents a streamlined end-to-end workflow which can serve as a template for deeper integration of BCI technologies to assist with our routine activities.

The proposed system is evaluated extensively using offline experiments and through an online demonstrator. For the former, we use a rich widely used public dataset and a limited but locally collected dataset. The experiment results show that our approach consistently outperforms a wide range of baseline and state-of-the-art approaches. The proof-of-concept corroborates the practicality of our approach and illustrates the ease with which such a system could be deployed.

Index Terms—Adaptive spatial embedding, deep learning, 3D printer, BCI

I. INTRODUCTION

Electroencephalography (EEG) is an electrophysiological method to record the voltage fluctuations of ionic current within the neurons of brains [1]. An EEG based Brain-Computer Interface (BCI) enables people to communicate with the outside world by interpreting the EEG signals of their brains to interact with devices such as wheelchairs and intelligent robots [2]. BCI systems have been widely studied for various real-world applications ranging from the healthcare domain [3], [4] to the entertainment industry [5]. The availability of portable and affordable EEG collection devices (e.g., Emotiv and OpenBCI), has opened up new opportunities for developing BCI applications that could help us in our daily functions, e.g., personal assistants and healthcare management. Such in-situ use of this technology necessitates a shift towards a non-invasive way to collect EEG signals from the cortex surface [6] (also employed by the aforementioned portable devices) as opposed to invasive approaches which rely on inserting electrodes into the scalp [7].

However, one major challenge faced by the non-invasive collection of EEG signals is the low signal to noise ratio [8]. This can be attributed to internal and external effects. The former include the loss in the strength of the signals as the pass through the thick medium of the skull, lack of concentration from the individual, etc. The latter includes the impact of environmental noise, light stimuli and fidelity of acquisition device. It has been shown that the fidelity (measured as SNR) of non-invasive EEG signals is approximately only about 5% of that of the signals collected through sophisticated but invasive method [9].

As a result, EEG signals inherently lack sufficient spatial resolution and insight on activities of deep brain structures. To this end, several studies have focused on denoising the signals and dealing with the aforementioned artefacts by statistical feature extraction (e.g., Principal Component Analysis, Independent Component Analysis, Autoregressive model, wavelet analysis) [10]–[13] and deep learning (e.g., Recurrent Neural Networks, Autoencoder) [14]–[17]. To the best of our knowledge, the idea of exploiting multi-faceted spatial relationships of multiple EEG channels has not yet been fully explored.

Addressing the aforementioned issue, in this work, we propose a unified approach by learning the robust structured EEG feature representations for recognizing the imagery of object seen by the individual. We first design a multi-class Common Spatial Pattern (CSP) for distilling the compact EEG channel representations. CSP has proven success in extracting features using eigen decomposition based on the variance between variant classes [18]. Next, we propose Dynamical Graph Representation (DGR) of EEG signals to adaptively embed the spatial relationship among the channels (each channel represents one EEG electrode) and their neighbors by learning a dynamic adjacent matrix. Finally, a Convolutional Neural Network (CNN) is employed to aggregate higher-level spatial variations from the transformed graph representations.

Built on top of the abovementioned computational framework, we present a mind-controlled end-to-end system with integrated graphical interface, called Brain2Object. It enables an individual to print a physical replica on an object that she is observing by interpreting visually evoked EEG signals in a real-time manner. To enable the end-to-end workflow, the proposed system gathers the user’s brain activities through EEG acquisition equipment and forwards the collected EEG data to a pre-trained model which automatically recognizes the object that the user is observing. Imagine that a child observes a toy, for example Pinkie Pie (from My Little Pony) belonging to her friend and likes it very much and wishes...
that she can have one too. Brain2Object can make her wish a reality by translating her brain signals to command the 3D printer to fabricate a copy. The ability to print a replica model of any observable object could be of tremendous value to a variety of professionals including engineers, artists, construction workers, students, teachers, law enforcement, urban planners, etc. By automating the process, Brain2Object takes mystery of reading human mind out of the realm of experts and opens up the possibility of a wide range of BCI applications that can be useful for the masses.

To summarize, the paper makes the following key contributions:

- We present an end-to-end digital fabrication system, Brain2Object, atop of the precise decoding of human brain signals that allows an individual to instantly create a real-world replica (or model) of any object in her gaze. The proposed system could learn an illustration of an object seen by an individual from visually-evoked EEG signals, and print a model in real-time by automatically instructing a wireless connected 3D printer.

- We propose an effective EEG decoding model by learning a dynamical graph representation, which could adaptively embed structured EEG spatial correlations during the training process. A convolutional neural network is integrated for capturing discriminative feature representations as well as the intrinsic connections among the various EEG channels.

- The proposed approach is evaluated over a large scale benchmark dataset and a limited but locally collected dataset. Our method outperforms a wide range of baseline and state-of-the-art approaches in both instances, thus demonstrating the generalized nature of the approach. Finally, a prototype implementation demonstrates the practicality of Brain2Object.

II. THE PROPOSED SYSTEM

A. System Overview

The overall aim of Brain2Object is to automatically recognize the object that the user desires to fabricate by analyzing her visually-evoked brain signals and actuate a 3D printer accordingly. As shown in Figure [1] the system is made up of an offline and online component.

The offline component is aimed to build a robust and effective unified classification model which can recognize the specific object that the user is observing by analyzing the corresponding brain signals that are evoked during this process. For this purpose, we first record the EEG signals of individuals while they are observing a wide range of objects (the details will be introduced in Section [11]). Next, the gathered EEG data are analyzed using multi-class CSP [19] to extract the eigenvalues of various categories of objects. CSP has been widely used in EEG signal analysis (such as motor-imagery brain activity classification [20], [21]) and achieves comparable performance. Thus, in our system, we adopt CSP for discriminative preprocessing. Through CSP, the EEG signals are mapping to an optimal space where the inter-category distance is maximized. Moreover, considering the global spatial relationship among EEG channels, we propose DGR to transform the CSP processed signals to a new space since graph representation has been shown to be helpful in refining and capturing spatial information [22]. In the embedded space which encompasses the topological structure among the biological brain neurons, each channel not only represents the amplitude of the measured signals but also reflects the dependency with other channels. CNNs are widely used for processing of two dimensional data in applications such as image recognition [23], ubiquitous [24], and object searching [25], due to their salient features such as regularized structure, good spatial locality and translation invariance. Thus, we employ CNN as a classifier to distinguish the graph embedded features. After a number of training epochs, the converged classification model with stable weights is stored for online recognition.

During online operation, the user wears an EEG signal acquisition equipment, while she is concentrating on a physical object, which collects her brain signals in real time. The gathered signals are forwarded to the pre-trained model which aims to recognize the object. For example, as shown in Figure [1] the user is focusing on ‘Pinkie Pie’ instead of other ponies, the pre-trained model is empowered to automatically recognize the object and send an appropriate command to the 3D printer, which loads the 3D physical model and fabricates a copy.

B. Multi-class Common Spatial Filtering

CSP is widely used in BCI field to find spatial filters which can maximize variance between classes on which it is conditioned [26]. It has been successfully used for recognition of movement-related EEG [27]. CSP was first introduced in binary classification problems but has since been extended to multi-class scenarios [28]. In this paper, we adopt the one-vs-others strategy for multi-class CSP analysis. Assume the gathered EEG data can be denoted by $E = \{E_i, i \in \{1, 2, \cdots, N\}\}$ where $N$ denotes the number of samples and each sample $E_i \in \mathbb{R}^{M \times L}$ where $M$ denotes the number of EEG channels and $L$ denotes the number of time slices. For example, assume the EEG collection equipment contains 64 channels and has a sampling frequency of 260 Hz, then data collected for 1 second can be represented by a 2-dimension matrix $E_i \in \mathbb{R}^{64 \times 260}$ where each row denotes one channel and each column denotes one time slice. For each specific sample, we first calculate the covariance matrix as [26]

$$C_i = \frac{E_i E_i^T}{\text{trace}(E_i E_i^T)}$$

where $^T$ refers to the transpose operation and $\text{trace}()$ denotes the sum of the diagonal values in $E_i$. The covariance matrix $C_i$ presents the correlation between different columns (sampling points) in $E_i$. In other words, $C_i$ captures the temporal dependencies in the EEG samples. Suppose there are overall $K \in \mathbb{R}$ categories correspond to the total number of objects.
for which EEG data is collected. For each category, the average covariance matrix is computed as

\[
\bar{C}_k = \frac{1}{N_k} \sum_{i=1}^{N_k} C_i
\]

where \(N_k\) denotes the number of distinct samples of the \(k\)-th category. The composite covariance matrix \(\bar{C}\) is defined by the sum of each category’s covariance matrix

\[
\bar{C} = \sum_{k=1}^{K} \bar{C}_k
\]  \hspace{1cm} (1)

The eigenvalue \(\lambda\) and eigenvector \(U\) of \(\bar{C}\) can be deduced as

\[
\bar{C} = U \lambda U^T
\]  \hspace{1cm} (2)

In order to de-correlate the covariance matrix, we apply the whitening transformation on the eigenvector which is descendingly sorted by eigen values. The whitened matrix is calculated as

\[
S = PCP^T
\]

where \(S\) has unit diagonal covariance and \(P\) can be represented by

\[
P = \sqrt{\lambda^{-1}} U
\]

Based on Equation (1), we have

\[
S_i = \sum_{k=1}^{K} P \bar{C}_k P^T; \quad S = \sum_{k=1}^{K} S_i
\]

Combining with the Equation (2), we have

\[
S_i = \sum_{k=1}^{K} B \lambda_i B^T
\]

where \(B = PU\) can be regarded as the common eigen vector. Since \(S\) has unit diagonal covariance,

\[
\sum_{k=1}^{K} \lambda_i = E
\]

where \(I\) denotes the identity matrix.

The main purpose of CSP is to maximize the distance among various categories in a transformed space, in other word, to optimize the equation [29]

\[
w^* = \arg \max \frac{w S_i w^T}{\sum_{j \neq i} w S_j w^T}
\]  \hspace{1cm} (3)

where \(S_j(j \neq i)\) denotes all other classes except class \(i\) (one-vs-others). Equation (3) is in the form of Rayleigh quotient and the solution can be calculated by generalized eigenvalue

\[
S_i w = \lambda \sum_{j \neq i} S_j w
\]  \hspace{1cm} (4)

The eigenvector of the above equation is the required transformation weights. All the EEG samples share the same weights \(s\). In case of the information loss, we employ the full eigenvectors. Generally, the EEG time series has more samples than the number of channels, i.e. \(L > M\), thus the transformation weights have shape \([M, M]\) the processed sample can be described as \(\bar{E} = wE\) where \(\bar{E} \in \mathbb{R}^{M \times L}\).
The graph can be defined as \( G \) is connected to all the residual vertices in this graph. The weighted undirected graph with spatial relationship with its neighboring channels. \( M \) represents not only the specific channel amplitude but also the \( F \) separately provides the voltage amplitude of a specific electrode \( F3 \) instead of the aggregated spatial information. The signals are discrete and discontinuous in the spatial domain. Hence, traditional spatial feature representation methods such as CNN are not well suited for further processing. Instead, we invoke the knowledge of the connections of the brain neurons to map \( E \) to a new space where each element represents not only the specific channel amplitude but also the spatial relationship with its neighboring channels.

For this purpose, we regard the brain network as a complete weighted undirected graph with \( M \) vertices where each vertex denotes a channel. The term 'complete' denotes each vertex is connected to all the residual vertices in this graph. The graph can be defined as \( G = (V, E, A) \) where \( V \in \mathbb{R}^M \) denotes the set of vertex with the number of \( |V| = M \) and \( E \) denotes the set of edges connecting the vertices. Suppose \( A \in \mathbb{R}^{M \times M} \) denotes the adjacency matrix representing the connectivity within \( V \). In particular, the element in the \( i \)-th row and \( j \)-th column of the adjacency matrix measures the weight or importance of the edges between the \( i \)-th and the \( j \)-th vertices.

The graph representation is dynamic, which means that the elements of the adjacency matrix are adaptively updated with the evolution of the model during training. Hence, the name, Dynamic Graph Representation (DGR). Figure 2 illustrates an example of a complete weighted undirected graph which is composited by five vertices which are reading from Frontal (F) and Temporal (T) lobes of the human brain. The diagonal elements are zero since each vertex is not connected to itself. However, the proposed representation should also contain information representative of each individual vertex. To incorporate this information, we include an identity matrix \( I \). The resulting DGR is thus represented as \( E' = (A + I)E \).

The represented data \( E' \) with shape \([M, L]\) can dynamically learn the intrinsic relationship between different EEG channels by training a neural network and thus benefit most from discriminative EEG feature extraction.

**D. Convolutional Neural Networks**

The DGR representation of the EEG signals serves as input to a specified CNN structure for feature refining and classification. CNN could capture the distinctive dependencies among the patterns associated to different EEG categories. The designed CNN comprises of one convolutional layer followed by three fully-connected layers (as shown in Figure 1). The convolutional layer contains a set of filters to convolve the EEG data followed by the nonlinear transformation to extract the geographical features. The input \( E' \) has shape \([M, L]\) with depth as 1. We choose \( D \) convolutional filters with size \([2, 2]\) and stride size \([1, 1]\). The stride denotes the \( x \)-movements and \( y \)-movements distance of the filters. Same shape zero padding is used, which keeps the sample shape constant during the convolution calculation. In the convolutional operation, the feature maps from the input layer are convolved with the learnable filters and fed to the activation function to generate the output feature map. For a specific convolutional area \( x \) which has the same shape as the filter, the convolutional operation can be described as

\[
x' = \tanh\left( \sum_i \sum_j f_{ij} \ast x_{ij} \right)
\]

where \( x' \) denotes the filtered results while \( f_{ij} \) denotes the \( i \)-th row and the \( j \)-th column element in the trainable filter. We adopt the widely used tanh activation function for nonlinearity. The depth of EEG sample transfers to \( D \) through the convolutional layer and the sample shape is changed to \([M, L, D]\). The features learned from the filters are concatenated and flattened to \([1, M \ast L \ast D]\) and forwarded to the first fully-connected layer. Thus, the first fully connected layer has \( M \ast L \ast D \) neurons, after which, the second and the third (the output layer) fully-connected layers have \( D' \) and \( K \) neurons, respectively. The operation between the fully-connected layers can be represented by

\[
E^{h+1} = \text{softmax}(\bar{w}E^h + \bar{b})
\]

where \( h \) denotes the \( h \)-th layer and \( \bar{w}, \bar{b} \) denote the corresponding weights matrix and biases. The softmax function is used for activation. For each EEG sample, the corresponding label information is presented by one-hot label \( y \in \mathbb{R}^K \). The error between the predicted results and the ground truth is evaluated by cross-entropy

\[
\text{loss} = - \sum_{k=1}^{K} y_k \log(p_k)
\]

where \( p_k \) denotes the predicted probability of observation of an object belonging to category \( k \). The calculated error is
Since the sampling rate is 128 Hz, each subject contributes 200 seconds of EEG signals. Hence, each participant contributes 204,800 sampling points, which means the dataset has 204,800 sampling points in total.

III. DATA ACQUISITION

In this section, we aim to gather a local EEG dataset which reflects the user’s brain voltage fluctuation under visual stimulation of a number of object images. In the ideal environment, the system is expected to recognize the EEG pattern of a random image. However, as this is a first exploration of this idea, we limit our study to include images of 4 objects: a car, a boat, Pinkie Pie Pony and Mario (from the video game).

We recruit 8 healthy participants (aged 22-27 years) including 5 males and 3 females to participate this study. The data collection is conducted in a quiet room. As shown in Figure 3, the subject wears the EPOC+ Emotiv EEG headset which contains 14 channels corresponding to the 10-20 system (which is an internationally recognized method to describe and apply the location of scalp electrodes). The sampling rate is set as 128 Hz and the headset can wireless connection with the computer over Bluetooth. The participants sit in a comfortable armchair, maintain a relaxed composure and gaze at a monitor placed approximately 0.5 meters in front of them. Each subject participates in 10 sessions and each session contains 4 trials.

Each trial lasts for 15 seconds and is comprised of three phases, each lasting 5 seconds. In the first phase, the monitor shows an empty slide and the subject is asked to be relaxed. In the second phase, a random object picture is presented in the middle of the screen and the subject is instructed to focus on the projected image. The final phase is identical to the first phase. Naturally, only EEG signals collected during the second phase are used in our dataset. In the second phase, the image is chosen with equal probability from the 4 aforementioned images. To keep the balance of the dataset, the final EEG data of each specific participant is composed of 40 trials where each object appears 10 times.

For each subject, there are 40 trials where each trial lasts for 5 seconds. Hence, each participant contributes 200 seconds of EEG signals. Since the sampling rate is 128 Hz, each subject contributes 25,600 = 128 × 200 sampling points, which means the dataset has 204,800 sampling points in total.

IV. EXPERIMENTS

A. Datasets

In Section III we introduced data acquisition experiments that were conducted locally in our lab. However, this local dataset has several drawbacks: 1) the spatial and temporal resolution is limited, since the headset used only has 14 channels and a low sampling frequency of 128 Hz.; 2) the fidelity (measured by the signal to noise ratio) of the signals is low as the resolution of recording the voltage is 0.51V, which is significantly lower than more sophisticated devices such as those used for medical studies (e.g., BCI2000); 3) the limited (8) number of participants in our dataset. A dataset containing a wider population of subjects is necessary for effective evaluations. Therefore, in addition to the local dataset which is referred to as EEG-L in the rest of the paper, we utilize a rich widely used public dataset, which is named EEG-P. The EEG-P (eegmmidb) is collected by the BCI200 EEG system which records the brain signals using 64 channels with a sampling rate of 160Hz. EEG data is recorded while the subjects are provided a visual stimuli (on a monitor) of certain actions and asked to imagine performing those actions. The four actions (left hand, right hand, both hands, and both feet) are labelled from 1 to 4. In our dataset, the 560,000 samples belonging to 4 different labels and 20 subjects are selected with each subject having 28,000 samples. In EEG-L, the four objects (Mario, car, boat, and Pinkie Pie pony) are labelled as 1, 2, 3, 4, correspondingly.

Both datasets are further sub-divided into a training set and testing set. The former comprises 80% of the data, while the latter contains the remaining 20%. The training set is split into 4 equal mini-batches (i.e., each mini-batch has 20% of the data). All the features are normalized by z-score method. The normalization parameters are noted for use during the online phase. The segmentation time window is set to 64 and 16 for EEG-P and EEG-L, respectively. The rate of overlap is 50% for both datasets.

B. Overall Comparison

Next, we report the performance of Brain2Object. Recall the adopted classification method combines the multi-class CSP and the convolutional neural networks. All the experiments are run on the Titan X (Pascal) GPU and accuracy results presented are averaged over 5 runs.

First, we provide the overall comparison with several widely used baselines including KNN, Random Forest (RF), Support Vector Machine (SVM). The key parameters of the baselines are listed here: KNN with 3 nearest neighbors; SVM with RBF kernel; RF with 50 trees. The independent CNN has the identical structure of the CNN component in our system as introduced in Section II-D. The kernel and stride information have been provided above, the learning rate is set as 0.0005

https://www.physionet.org/pn4/eegmmidb/
TABLE I: Overall comparison with state-of-the-art models and metrics.

| Dataset | Method       | Accuracy | Precision | Recall | F-1   |
|---------|--------------|----------|-----------|--------|-------|
| EEG-P   | KNN          | 0.6962   | 0.7325    | 0.7552 | 0.7437|
|         | RF           | 0.7137   | 0.7536    | 0.7328 | 0.7431|
|         | SVM          | 0.6692   | 0.7122    | 0.7156 | 0.7139|
|         | CSP+KNN      | 0.9134   | 0.9273    | 0.9135 | 0.9203|
|         | CNN          | 0.8638   | 0.8619    | 0.8722 | 0.8670|
|         | Ours         | 0.9258   | 0.9325    | 0.925  | 0.9287|
| EEG-L   | KNN          | 0.5108   | 0.5212    | 0.5436 | 0.5322|
|         | RF           | 0.5826   | 0.6258    | 0.6246 | 0.6252|
|         | SVM          | 0.6538   | 0.6684    | 0.6825 | 0.6754|
|         | CSP+KNN      | 0.5833   | 0.5773    | 0.5833 | 0.5803|
|         | CNN          | 0.6863   | 0.7021    | 0.6038 | 0.6493|
|         | Ours         | 0.7523   | 0.7602    | 0.7528 | 0.7564|

and the depth of convolutional layer $D$ equals to 10. The number of hidden neurons in the second fully-connected layer is 1000 for EEG-P and 120 for EEG-L. All the parameters are determined by empirical tuning. We also compare with a range of competitive state-of-the-art models:

- Sturm et al. [30] proposes the application of Deep Neural Networks with layer-wise relevance propagation for EEG data analysis.
- Yang et al. [31] combines augmented CSP with CNNs for motor imagery performance recognition.
- Park et al. [32] introduces an augmented complex-valued CSP based on the correlation between EEG channels.
- Thomas et al. [33] study EEG classification by selecting the subject-specific spatial and spectral features.
- Zhang et al. [8] combines Recurrent Neural Networks (RNNs) with CNN in order to extract the temporal-spatial features from brain signals.

The results are depicted in Table I. Observe that our method achieves the highest accuracy (which corresponds to 0.9258 for EEG-P and 0.7523 for EEG-L) in comparison with numerous state-of-the-art approaches for both datasets. The experiments thus demonstrate the robustness, effectiveness and generality of our method. One can also readily observe that all methods achieve lower accuracy for EEG-L and as compared to EEG-P. Some of the drawbacks of EEG-L were already highlighted in Section IV-A including low fidelity, poor spatial-temporal coverage and equipment limitations. Another reason could be the fact that our participants did not have extensive experience with the usage of EEG headsets and neither were there any specialized technicians available to assist. Finally, the emotional state of the participants may have also influenced the EEG signals.

We present a range of additional metrics for our approach. This includes the confusion matrix and ROC curves with AUC scores in Figure 4 and precision, recall and F-1 score for each category in Table II.

![Confusion matrix and ROC curves with AUC score](image)

**Fig. 4:** Confusion matrix and ROC curves with AUC score. The ROC curve of EEG-P has log scaled x-axis.

**Fig. 5:** Latency comparison against the accuracy. It can be observed that our approach achieves the highest accuracy with an acceptable latency.
Fig. 6: A visualization comparing the raw data and extracted features for the two datasets. Both the raw data and the extracted feature are visualized from the corresponding testing set. This comparison demonstrates that our approach can (i) maximize the distance between the EEG data points and (ii) accurately extract the distinctive representations from the raw data.

C. Latency

In addition to accuracy, latency is also an important performance metric for a system such as Brain2Object.

Figure 5 illustrates the latency achieved by our method in comparison with a selected sub-set of baselines used in Section V-B. We can observe that our approach has competitive latency compared with other methods while achieving the highest accuracy. The overall latency is less than 0.5 second. We computed the latency incurred by the different methods that are employed in our system and observed that CNN requires about 0.35 seconds for execution, while CSP and DGR together only require about 0.12 seconds. This illustrates that the use of deep learning techniques do not have a significant effect on the overall latency.

In a fully functional system, the end-to-end latency is not only comprised of the algorithmic latency but also includes the delay incurred for signal acquisition and signal transmission. The latter will be discussed in Section V. In the following, we evaluate the signal acquisition latency. In the proposed system, the signal collection time is related to the acquisition equipment, in essential, the sampling rate. For BCI2000, a single sample/segment is composed of 64 time points, which is gathered in $0.4 = 64/160$ seconds with 160 Hz sampling frequency. On the other hand, the Epoc+ Emotiv headset only requires $0.11 = 14/128$ seconds for signal collection. We can observe that the precise equipment can achieve higher accuracy but demand larger latency. In contrast, the off-the-shelf low fidelity headset has lower accuracy but also low latency. But this statement, which is similar to ‘no free lunch’ rule, is based on the fact that the segment length equals the channel number. Could EEG-P keep the high level accuracy with the decrease of channel amount in order to implement competitive performance with low latency at the same time? This meaningful scope deserves more attention in the future.

D. Visualization

To offer a different perspective into the performance of our system, we present a visualization of the data at two levels. At the system level, as a unified classification model, we visualize the raw EEG data and the extracted distinguishable features for comparison. In Figure 6, the visualization of both EEG-P and EEG-L are presented. Through the comparison, we can demonstrate that our approach maximizes the distance among EEG signals and has the ability to automatic extract the distinctive representations from raw data.

At the component level, we present the topography of various categories in each dataset. Figure 7 provides the EEG topographies after CSP processing. The first row contains 64 channels while the second row map contains 14 channels. Through the comparison, it can be observed that the patterns belong to different categories are obviously variant, which indicates that the CSP processed features ought to be easier classified.

V. ONLINE DEMONSTRATION

In this section, we summarize our experience in developing a working prototype of Brain2Object. Figure 8 shows the working prototype in action. A video demonstration can be accessed through this site. The graphical user interface is provided in Figure 9. The top of the interface shows the port number and baud rate of the IP printer. The IP address of the server which stores the pre-trained model and makes the

https://drive.google.com/open?id=1jzZzKkWGhBkFJTaaAgVZ5zKSn4Ho5DD
object recognition decision is also shown. The main body of the interface displays object models for the four objects in our experiments, namely, Mario, car, boat and Pinkie Pie Pony.

Figure 9 illustrates the operational workflow of the Brain2Object demonstrator. While the user is focusing on a target object (e.g., the Pinkie Pie), the corresponding brain signals are collected by a properly mounted Emotiv headset and transmitted to client 1 over Bluetooth. Client 1 sends the EEG signal to the server over a TCP connection. The server loads the pre-trained EEG recognition model and classifies the EEG signal to one of the four categories. The classification result is forwarded to the interface through client 2. The interface will highlight the selected object by changing the color of the other 3 objects to gray (the selected object remains blue). Simultaneously, the selected object is dispatched to the printer driver which generates the corresponding Gcode which can be recognized by the mechanical 3D printer. Finally, the Gcode is sent to the 3D printer, which brings the object to life.

VI. DISCUSSION AND FUTURE WORK

In this section, we discuss the challenges and potential directions for future research.

First, the proposed approach is significantly influenced by the quality of the EEG data. The pre-trained recognition model requires each sample with 14 sampling point and each sampling point corresponds to a classification output. To achieve steadiness and reliability, the server will maintain a window of the last 10 classification output and a count of how many times each of the 4 objects has been recognized. The server will send the target to the client 2 only if one specific target appears more than 6 times in this window. In this situation, the classification is higher than 90% although the latency is increased to about 2 sec which includes data collection time (1.1 sec), recognition time (0.47 sec), transmission time, etc.

We used a Tonxy X1 desktop 3D with the following specifications. Printer size: 220 × 220 × 250mm, build area: 150 × 150 × 150mm, MK10 extruder diameter: 1.75mm, nozzle diameter: 0.4mm, engraving accuracy: 0.1mm, filament material: 1.75mm polylactic acid (PLA). The physical 3D model can be transmitted from a computer to the printer or directly stored in minor SD card mounted on the printer.

The sampling frequency of the Emotiv headset is 128 Hz which indicates it can collect 128 sampling point each second. The pre-trained recognition model requires each sample with 14 sampling point and each sampling point corresponds to a classification output. To achieve steadiness and reliability, the server will maintain a window of the last 10 classification output and a count of how many times each of the 4 objects has been recognized. The server will send the target to the client 2 only if one specific target appears more than 6 times in this window. In this situation, the classification is higher than 90% although the latency is increased to about 2 sec which includes data collection time (1.1 sec), recognition time (0.47 sec), transmission time, etc.

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Second, the object repository in this work is limited. An ideal instantiation of Brain2Object should recognize any object the user observed. However, in this paper, the object repository only contains four items. The limitation of the repository scale is constrained by the learning algorithm, i.e., the ability of multi-class classification algorithms to discriminate between a large number of classes. The classification accuracy dramatically reduces with the increase of category numbers. In our pre-experiment which are not presented in this paper for the space limitation, in the offline test, the proposed approach can achieve around 90% on binary classification using the Emotiv headset, however, the accuracy drops to near 80% with three categories and about 70% with 4 objects. In our future work, we attempt to propose an algorithm to increase the multi-class classification performance.

Additionally, the ideal printing system is supposed to automatically detect the object which the subject ‘thinking’ (without visual stimulation) instead of ‘observing’ (with visual stimulation). However, the EEG SNR without visual stimulation is much lower than the SNR with visual stimulation. To enhance the SNR and help the subject to concentrate on the object, we adopt visual stimuli in our experiments. Therefore, in the local dataset and the online demonstration phase, the corresponding object images are shown on the monitor to remind the participants. However, the public dataset not only contains visual stimuli but also includes motor imagery, which is one possible reason why EEG-P is classified so accurately. Most of the existing public EEG dataset with visual stimulation focus on motor imagery (like the selected EEG-P) or evoked potentials [34]. In the latter instance, the visual images are flashed at a high frequency which results in pulsed EEG data, i.e., as objects flash by, short pulses of corresponding EEG data are generated. However, the model used in this paper is based on stable EEG signal caused by steady stimuli. Hence, we select EEG-P instead of evoked potential-based dataset for the evaluation.

Furthermore, through the online demonstration experiment, we observed that the online performance is lower than the offline analysis, which could be attributed to a number of reasons: 1) the users mental state and fluctuations in emotions may affect the quality of the EEG signals. For instance, if the pre-trained model is tuned based on the EEG data which is collected when the user is relaxed, the classification performance may be affected while the user is excited in the online phase. 2) the conductive of the electrodes in headset is not exactly invariant during the offline stage and online stage, which will have impact on the data quality; 3) subtle variations (e.g., the position of each of the electrodes) in the way the EEG headset is mounted on the subjects head may also influence online decision making; 4) subjects often have difficulty in maintaining concentration during signal acquisition.

VII. RELATED WORK

The problem of accurately classifying EEG signals has been extensively researched in recent years [11]–[17], [35]–[37]. Michelmann et al. [11] use Independent Component Analysis to derive filter coefficients that reflect the statistical dependencies of the data at hand. This work quantitatively shows that ICA outperforms the bipolar referencing operation in sensitivity and importantly in specificity when revealing local time series from the superposition of neighboring channels. Liu et al. [15] propose a multi-layer RNN based model with two attention mechanisms, which achieves high accuracy and boosts the computational efficiency of EEG signal classification. Zhang et al. [13] present two combination strategies of feature extraction on EEG signals where the first strategy assembles the autoregressive coefficients and approximate entropy and the second strategy adopts wavelet packet decomposition.

Among the existing studies, the spatial feature based algorithms had been illustrated to be one of the most promising methods. In particular, CNN, as one of the most popular and powerful deep learning structures, had been widely used to cope with various EEG-based applications. Acharya et al. [35] employ a standard CNN to analyze patients’ brain signals in order to detect normal, preictal, and the seizure state. Ma et al. [36] apply CNN to automatically extract an individual’s best and most unique neural features and conduct classification, using EEG data derived from both resting states with open eyes and resting state with closed eyes, for the aim of individual identification. Lawhern et al. [37] introduce the use of depth-wise and separable convolutions to construct an EEG-specific model which encapsulates well-known EEG feature extraction concepts for BCI. Zhang et al. [8] exploit the temporal-spatial information extracted by a combined RNN and CNN, however, this work is based on single sample classification which causes the unstable performance in online stage.

VIII. CONCLUSION

In this paper, we propose an end-to-end printing system based on the combination of multi-class CSP and graph embedded CNN. The performance of the proposed model is evaluated over two datasets in offline and also demonstrated in the online environment. Brain2Object serves as a harbinger for exciting BCI applications which can help individuals with various tasks in their daily lives. The proposed system employs multi-class CSP to map the EEG data to a common space for the aim of maximizing the distance among various EEG patterns. The processed data are embedded by dynamic graph transformation and then fed into a designed convolutional neural network for automatically spatial feature learning. Extensive evaluations using a large-scale public dataset and a more relevant but limited local dataset showed that our scheme significantly outperforms a number of state-of-the-art approaches. The system latency is shown to be acceptable and a visualization of the signals is presented to offer additional perspectives into the performance. The online demonstration is presented to show the applicability of the proposed system.
