Towards EEG Generation Using GANs for BCI Applications

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Abstract—**Brain-computer interface has been always facing serious data-related problems such as lack of the sufficient data and data corruption. Artificial data generation is a potential solution to address these issues. Among generative techniques, the method of generative adversarial networks (GANs) with the successful applications in image processing has gained a lot of attention. The application of GANs for time-series data generation is a recent growing topic that first of all its feasibility needs to be assessed. In the present study, we investigate the performance of GANs in generating artificial electroencephalogram (EEG) signals. The results suggest that the generated EEG signals by GANs resemble the temporal, spectral, and spatial characteristics of real EEG. It thus opens new perspectives for further research in this area.**

Keywords—biomedical signal processing, artificial signal generation, EEG, GANs, brain-computer interface

I. INTRODUCTION

Brain-computer interface (BCI) systems are designed to build a direct path from brain to the external machine for a wide range of usages including medical and cognitive applications [1]. The most common modality for brain data acquisition in BCI is electroencephalography with several advantages such as being non-invasive, portable, and relatively cheap [2]. To efficiently train a BCI system, high amount of electroencephalogram (EEG) signal is needed. But, it is not convenient for subjects, especially patients, to undergo the long calibration sessions. Moreover, some parts of the collected data might be corrupted due to the several experimental factors. Beside the data corruption and insufficiency, the non-stationary nature of EEG signals is another problem. That is to say EEG signals vary from subject to subject or even within subject from session to session [3]. It is not applicative to collect the data for all the possible scenarios. The generative methods are a potential solution to address these limitations.

A newly proposed generative technique is generative adversarial networks (GANs) introduced by Goodfellow and his colleagues [4]. It is well-reputed for image processing applications [5, 6] and has been recently taken into consideration for the signal applications as well. After the introduction of GANs, there have been some contributions to overcome the limitations of the initial version such as training instability [7].

To the best of our knowledge, there are a few recent attempts on the use of GANs for EEG signals. In [8], EEG was recorded while the person was looking at some images, then this EEG data were sent to GANs to regenerate the shown image. They report that the GANs outperform the variational auto-encoders (VAE) but still the generated images are of low quality [8]. In another study [9], the researchers applied GANs in order to up-sample the spatial resolution of EEG signals. Their method compared to the bicubic interpolation as baseline showed more promising results. In [10], GANs are used to interpret the resemblance between the manifold of the original EEG and the EEG patterns that deep convolutional neural network has learned. Although the use of GAN for EEG is a new emerging topic, the few existing studies suggest that it is a promising approach to address several concerns related to EEG processing.

In this work, we investigated the feasibility of GANs in naturalistic EEG generation. We trained GANs on existing EEG data and used the trained generator network to produce artificial EEG from random input. Then, we analyzed the resemblance between the generated and the real EEG in time and frequency domains. The observations suggest that GANs are capable to efficiently generate the artificial EEG. Then, these generated real-looking samples can be used for a variety of applications such as data augmentation or restoration of corrupted data.

This paper is outlined as follow. The dataset description and the methodology are explained in section II. The results are

presented and then discussed in sections III and IV respectively. Lastly, a conclusion of the study is given in section V.

II. MATERIALS AND METHODS

A. Dataset Description

A public dataset collected by authors of [11] has been used in this study. It contains EEG data of 8 healthy participants who were asked to do a cue-based visual attention task. EEG data were recorded using 64 electrodes placed based on the international 10-10 system on an actiCAP from Brain Products with a sampling frequency of 1000Hz. Later, the data were down-sampled to 200Hz (the public version is available only at 200Hz). Sixty channels out of 64 electrodes were used for EEG collection, the rest were assigned as EOG and reference channels.

B. Input Preparation

The data were pre-processed using BBCI toolbox in Matlab [11]. We segmented the EEG data recorded during attentional task into 1-second segments (due to the experiment design) with reference to the cue onset. In total, there were 600 samples for each person. Thus, the data of each participant were stored in a matrix of size 600×200×60 to be used for GANs training. Note that 600 is the number of trials, 200 is the number of time points (1-second EEG data digitalized at 200Hz), and 60 is the number of EEG electrodes.

C. Generative Adversarial Networks

Recent advances in convolutional neural networks (CNN) with their successful implementations for EEG applications [10, 12-14] encouraged us to choose CNN over commonly used autoregressive models for time-series data generation. CNN-based GANs have two neural networks; the generator (G) and the discriminator (D). The overall idea is somehow inspired by the game theory where two players compete to beat each other. In GANs, G's task is to generate the artificial samples and D's task is to identify which sample is real and which is generated. The training target for G is to eventually deceive the discriminator so that the discriminator is no longer able to accurately distinguish between the real and the generated samples. In other words, the generated samples highly resemble the real samples.

To formulize this adversarial training procedure, consider a minimax problem as stated below:

$$\min_{\theta_g} \max_{\theta_d} V(G, D) = E_{x_r \sim p_r}[\log(D(x_r))]$$
$$+E_{x_g \sim p_g}[\log(1 - D(x_g))] \quad (1)$$

Where θ_g, θ_d, x_r, and x_g are G parameters, D parameters, real sample, and generated sample respectively. $D(x)$ returns the probability of x belonging to the real or the generated data distributions (p_r or p_g respectively). Please note that the generated sample x_g is produced by G network from a random noise input z:

$$x_g = G(z) \quad (2)$$

What is happening in the adversarial training procedure is actually training the two opposing networks D and G to simultaneously maximize $log(D(x))$, the performance of D in assigning the true labels to both real and generated samples, and minimize $log(1- D(x_g))$.

The G network of the proposed GANs has 1 up-sampling and 2 convolution layers with kernel size 5 and the D network is consisted of 2 convolution layers with kernel size 5. Each Conv layer in D is followed by a Max-pooling layer of size 2. After second Max-pooling layer, there is a flattening layer followed by a fully-connected layer and finally the last layer is a fully-connected layer with activation sigmoid for classification. The methods of tanh and Adam [15] have been used respectively for the activation and optimization purposes. For Adam, we set the learning rate and beta1 at 1e-4 and 0.2 respectively.

The D and G networks are trained on the real EEG samples (600 samples for each individual) with a batch size of 50 over 1000 repetitions. Then, a random noise is imported to the trained G network as input. As a result, G network generates the artificial EEG from random input. Now, it is crucial to evaluate the performance of GANs by extracting and analyzing the characteristics of the generated EEG. To accomplish so, the real and generated EEG of each channel has been plotted over time. Also, the topographic maps of the real and generated EEG have been calculated using fast furrier transform (FFT) to give a better visualization of the results. An overlook of the proposed methodology is given in Fig. 1.
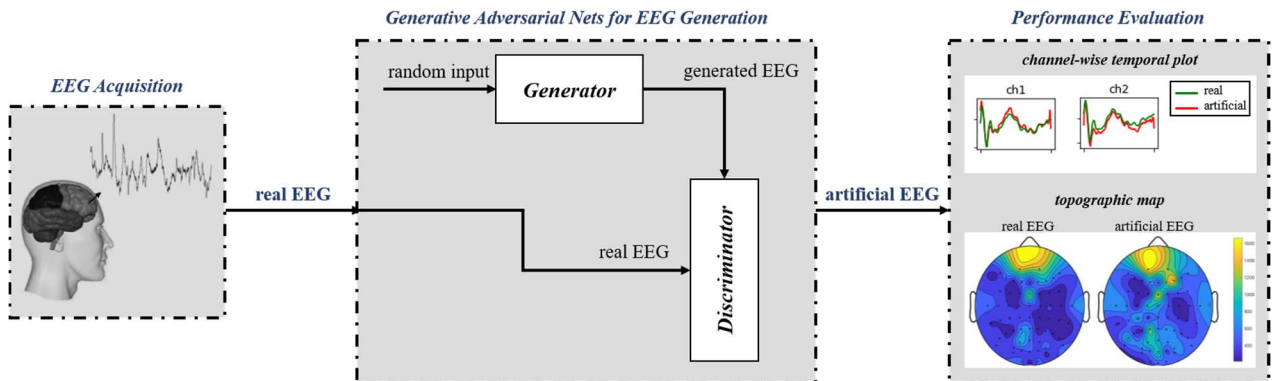

Fig. 1. The overall framework of EEG generation using generative adversarial nets (GANs). The real EEG data recorded from human brain are used to train GANs for artificial EEG generation. Then, the generated samples are compared to the real EEG samples to evaluate how naturalistic they are.

III. Results

In this section, the results including the generator and the discriminator losses over training, channel-wise temporal patterns and the topographic maps of the generated and the real EEG are presented.

A. Networks' losses over training

Fig. 2 shows the generator and the discriminator losses over 1000 iterations for one participant. As it can be seen, the generator loss (blue) gradually decreases until it becomes lower than the discriminator loss (red). After approximately 500 iterations, it seems that both networks' losses are converging to some constant values and the training becomes stable. The results of the training on other subjects' data have the same trend.

B. Generated EEG versus Real EEG

The data were recorded using 60 EEG electrodes, namely AF3, 4, Fz, F1-8, FCz, FC1-6, T7, 8, Cz, C1-6, TP7, 8, CPz, CP1-6, Pz, P1-10, POz, PO3, 4, 7-10, Oz, 1, 2 and Iz, 1, 2, placed based on the international 10-10 system [11]. After EEG generation, it is crucial to evaluate the resemblance between the artificial and the real samples over each channel to make sure that the generated EEG data encompass the temporal, spectral, and spatial features of the real data when it comes to the analysis of coherence, functional connectivity, source localization, and etc.

Fig. 3 plots the average of the generated and the real samples of each individual channel over time (1-second; 200 time points) for one subject. The green and the red colors are associated with the real and the artificial data respectively. It can be observed that there is a high match between them over all channels.

For a better illustration, the topographic maps of the real and the artificial data over scalp have been presented in Fig. 4. To compute this map, the power of each sample over each channel has been calculated using FFT and then averaged over all 600 trials (grand average). We used the electrodes' positions to plot the map. Please note that due to the paper length limitation, it was not possible to include the results of all 8 subjects, but we should mention that other results are fairly similar to the ones represented in this paper.

IV. Disscussion

The topic of the study in this paper was to generate artificial EEG to be used in a variety of use cases for EEG processing. We used the method of convolutional GANs for this task. Fig. 2 shows how the networks' losses converge over training. The descending trend of the generator loss accompanied by the ascending trend of the discriminator loss tells that the generated signals are gradually getting more similar to the real data. The analysis results show a high resemblance between the artificial and the real EEG samples. Based on Fig. 3, the generated samples lie on the pattern of the real samples. Fig. 4 better visualizes this resemblance by plotting the topographic maps.

Although, our findings highlight that the GANs are capable to output naturalistic EEG samples, the performance of these samples in the enhancement of EEG-based BCI systems is not evaluated in this study. To exemplify, consider the classification

tasks. It should be investigated whether including the artificial samples in the training set improves the detection accuracy. We will work on this and the other use cases of the generated EEG as a follow-up study to this work.

The GANs training and the results analysis in this study are done in a subject-specific manner. It is worth to investigate the inter-subject way which has potential applications in transfer learning. Moreover, depend on the task, an optimal channel selection can be done in order to avoid the high computational load and the generation of the redundant data.

Overall, this study suggests that the convolutional GANs can be successfully applied for EEG generation. To further mature this new field, it puts forward some new research questions to be investigated.
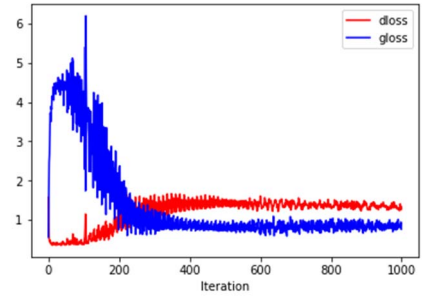

Fig. 2. The generator and the discriminator losses over training for one subject. 'dloss' is the discriminator loss and 'gloss' is the generator loss. Both eventually converge to some fixed values.
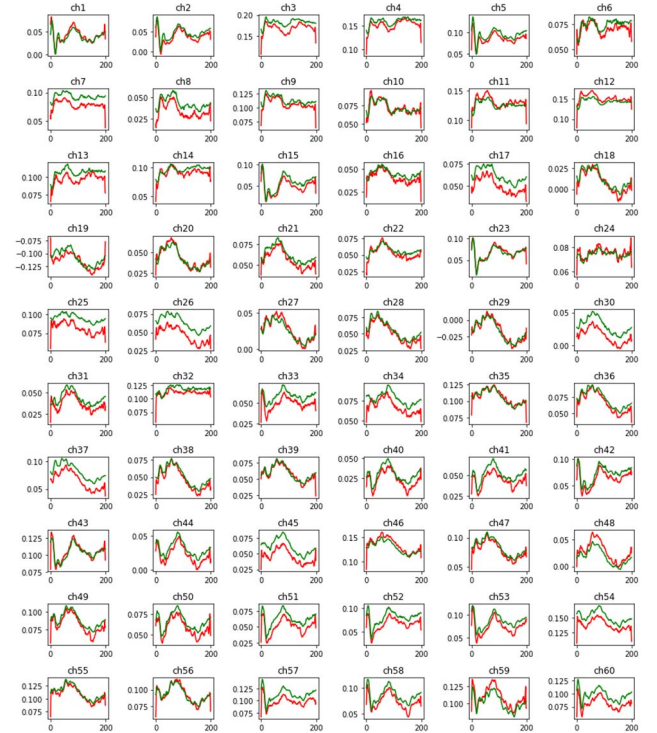

Fig. 3. The grand average of the real and the generated samples of each channel over time. The green plots are the real data and the red ones are the generated data. As can be seen, the generated EEG data have the same pattern as the real EEG over most of the channels.
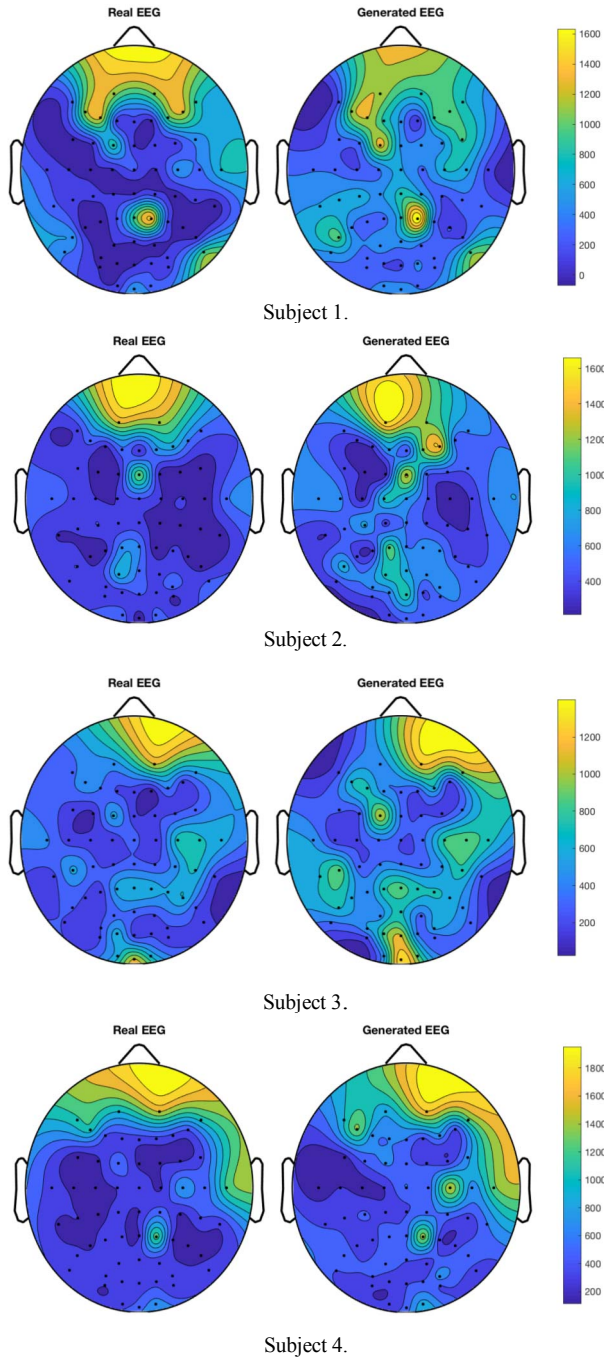
Fig. 4. The topographic maps of the real and the generated EEG samples by GANs. The bars at the right side show the energy values. The results of 4 random subjects out of 8 are presented. As can be observed, there are high resemblnace between the real and the generated EEG with regard to the activation of different brain areas.

V. CONCLUSION

This paper studied the application of the GANs in the artificial EEG generation with the variety of future usages in BCI systems, for instance restoration of the corrupted data and data augmentation. We used convolutional GANs for this purpose. Based on the observations obtained from the have the

similar temporal, spectral, and spatial characteristics to the real EEG samples. This study should be further continued to evaluate how artificial EEG data generated by this work affect the performance of the BCI system for specific tasks such as classifications.

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