2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)
4-7 March 2018
Las Vegas, Nevada, USA

Generating Target/non-Target Images of an RSVP Experiment from Brain Signals in by Conditional Generative Adversarial Network

Yonggun Lee and Yufei Huang

Department of Electrical and Computer Engineering,
the University of Texas at San Antonio, 1 UTSA Circle, San Antonio, TX 78249, USA.

***Abstract*— Understanding human brain activities and their associations with sensory stimuli is an important area of brain research. We present in this paper 소 e reconstruction of target and nontarget images from Electroencephalography (EEG) signals collected in a Rapid serial visual presentation (RSVP) experiment. We proposed a novel model based on conditional Generative Adversarial Networks (cGAN), which includes a generator to generate target/nontarget images from input EEG epochs and discriminator to discriminate true images from the generated images. We showed the performance of image generation of the proposed cGAN model based EEG or EEG plus noise as input. We further demonstrated how we could use the trained model to examine the associations between target/nontarget images and their induced EEG patterns.**

Keywords*— *Rapid serial visual presentation (RSVP), Condtional Generatie Networks, EEG.

I. INTRODUCTION

Understanding human brain activities and their associations with different cognitive behaviors is a key focus in brain research. We have long dreamed of possessing the mind-reading ability to predict and reconstruct what we see, hear, and feel from brain signals. While considerable advancements have been made in predicting certain cognitive behaviors including visual and audio response, fatigue, and emotions from brain signals, mapping the sensory stimuli from brain signals still faces significant challenges. Because human brain does not necessarily respond to every details in the stimuli, it is virtually impossible to reconstruct the complete stimuli, whether they are pictures or sound. Another limiting factor is partial information captured by different neuroimaging modalities as they are designed to only measure specific aspects of brain activities, not to mention the device-associated limitation on signal to noise ratio (SNR).

Several recent efforts have attempted to address these issues for reconstructing visual stimuli from brain activities recorded via functional magnetic resonance imaging (fMRI). A Bayesian canonical correlation analysis (BCCA) model was proposed in [1] to model the association between stimulus images and voxel activities, whereas a deep generative multiview model was proposed in [2] to include a mechanism for estimating the visual elements missing from the brain activities.

However, such attempt from using EEG data is rare, due mostly to low spatial resolution and poor SNR of EEG. It is commonly believed that EEG signals cannot resolve the fine details of different neural responses and therefore may not be used to reconstruct visual images. However, to what degree that EEG can and cannot discern the specific image-related neural responses is largely unknown.

In this paper, we investigated the reconstruction of target and nontarget images from EEG in an image RSVP experiment. RSVP is an experiment for examining visual attention. The widely acknowledged patterns in EEG signals associated with target images are p300 signals in EEG recordings taken around the visual cortex. Instead of attempting to reconstruct images directly from EEG [3], we assume that we are given the collection of target and non-target images and our goal is to generate only the target/nontarget images from this collection based on EEG. To this end, we proposed a novel model based on conditional Generative Adversarial Networks (cGAN)[4-6]. GAN is the state-of-the-art unsupervised deep learning method for learning to generate samples from the training data distribution [4]. One of the most popular application of GAN is to generate images from noise inputs[4]. One variation of GAN is the cGAN, which provides GAN added ability to generate images of a specified category. Inspired by the cGAN, we developed a cGAN model that can generate target/nontarget images from EEG inputs directly. We investigated the performance of image generation of the proposed cGAN model based EEG or EEG plus noise as input. We further demonstrated how we could use the trained model to examine the associations between target/nontarget images and their induced EEG patterns.

II. RSVP EXPERIMENT AND DATASET

We considered the BCIT X2 Rapid Series Visual Presentation (RSVP) experiment [7, 8], where test subjects were asked to identify rare target images from a continuous burst of image clips presented at a rate of 5 Hz. X2 RSVP was designed for subject to identify complex images (512 x 662 pixels) of 5 different objects (doors, chairs, etc.). There are 10 subjects, where each subject performed 5 sessions (~1 h per session) of recording. Brain signals were measured by 256-channel BioSemi systems. Preprocessing was performed using a standardized, automated EEG preprocessing pipeline called PREP [9, 10], which included band-pass filtering from 0.1 to 55 Hz, robust signal referencing, and identifying and interpolating the bad channels (channels with a low recording SNR), and baseline removal using EEGLab [11]. All these preprocessed datasets were down-sampled to 32Hz and a subset of 32-channels associated with the visual cortex region were selected. For this paper, 440 clear, easy recognizable chair images were selected as target images and another 440 non-target images were also selected randomly, which did not include any chairs. One-second epochs of the EEG samples after each onset of a selected target or nontarget image were then extracted. Normalized epochs were also obtained, which normally standardized the EEG elements in an epoch by the epoch mean and standard deviation. Note the EEG epochs came from all subjects.

III. Proposed Model

A. Generative Adversarial Network

Generative Adversarial Network (GAN) is an unsupervised deep learning model proposed originally proposed in [4]. GAN consists of a generator (G) and a discriminator (D). The generator generates images from the noise input vectors sampled from the uniform or Gaussian distributions. The discriminator discriminates true images from the generated images. The generator and the discriminator are trained to minimize a two-player minimax game, where the generator learns to fool the discriminator and the discriminator learns to prevent itself from being fooled. The optimization can be formulated as

$$\min_G \max_D V(D,G) =$$
$$E_{x\sim P_{data}(x)}[\log D(x)] + E_{x\sim P_z(z)}[\log(1 - D(G(z)))] \quad (1)$$

where x is data, z is noise inputs, $P_{data}(x)$ is the data distribution , and $P_z(z)$ is a prior noise distribution. The training of GAN follows an iterative scheme that applies stochastic gradient descent algorithms to optimize the generators and discriminators iteratively.

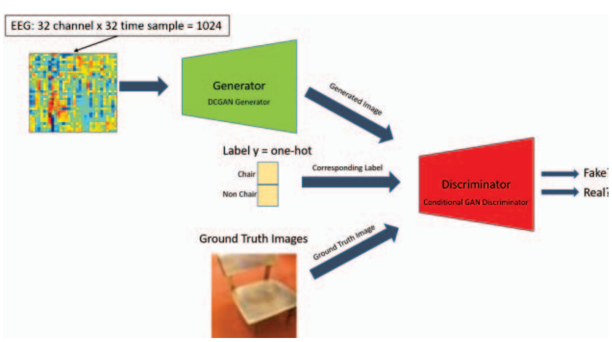

Figure 1. Proposed conditional GAN Model.

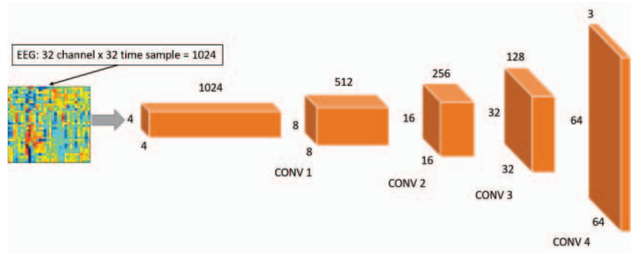

Figure 2. The proposed DCGAN generator structure. The Generator contains 4 convolutional layers with Leaky ReLU activation function and The Discriminator also has 4 convolutional layers but with ReLU and concatenated one-hot labels at last two layers.

B. Conditional GAN

Conditional GAN is a variation of GAN that is trained to generate images from specified categories [5, 6], thus conditions. In cGAN, the inputs to the generator are random noise vectors appended by condition labels and the labels are also incorporated into the discriminators. The optimization formulation of cGAN can be expressed as

$$\min_G \max_D V(D,G) =$$
$$E_{x\sim P_{data(x)}}[\log D(x,y)] + E_{z\sim P_z(z)}[\log(1 - D(G(z,y),y)] \quad (2)$$

where y is the label of the corresponding x.

C. Proposed cGAN for generating target/non-target images from EEG

Our proposed cGAN model follows the general cGAN formulation and is depicted in Fig. 1. Specifically, the generator adopts the generator architecture of the Deep Convolutional GAN (DCGAN)[12], which is a deconvolutional model and includes 4 convolutional layers. The specification of each layers is described in Fig. 2. The

Figure 3. Examples of 16 generated images by cGAN from random noise. The true conditions for the first 8 are target, i.e, chair images and the last 8 are nontarget images.

discriminator follows opposite direction of generator, but it contains conditional information at the last two convolutional layers to perform as cGAN.

IV. RESULTS

A. Performance of EEG-based event classification

We first investigated the performance of predicting target/nottarget events from EEG epochs. The goal was to examine if the EEG epochs for target and nontarget events were significantly different to be used as conditions in cGAN. To this end, we trained a convolutional neural network (CNN) proposed in[10]. Table 1 shows the accuracy and Area Under the Curve (AUC) statistics of the CNN models trained using either raw or normalized EEG data. To obtain these performances, the CNN models were trained on a subset of randomly selected 704 EEG epochs and the performance metrics were calculated using the remaining 176 epochs. As can be seen from the performance, both raw and normalized EEG epochs are not significantly different, although there were still many misclassified samples.

	Accuracy	AUC
Raw EEG	0.775000	0.821182
Normalized EEG	0.768750	0.847894

Table 1. Classification performances of CNN trained using raw or normalized EEG data.

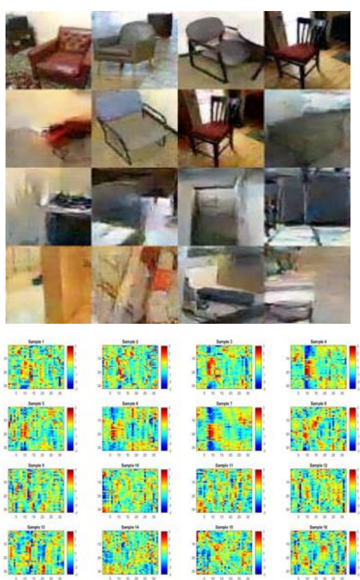

Figure 4. Examples of 16 generated images by cGAN from raw EEG inputs (top). The true conditions for the first 8 are target, i.e, chair images and the last 8 are nontarget images. The heapmaps of corresponding 16 1s EEG epochs. For each epoch, the horizontal axis represents time and vertical axis represents channels.

B. Performance of cGAN for generating target and nontarget images based on random noise

Before evaluating the performance of the proposed cGAN to generate images from EEG epochs, we first examined its ability to generate target and nontarget images when the inputs under two conditions are completely different. Particularly, we trained the cGAN model with noise inputs of the same size as an EEG epoch, where for target, the noise was generated from a uniform distribution between 0 to 1, and for nontarget, between -1 to 0. Batch training with 16 samples per batch was carried out and training took 2.1 hour to output significant images. The training Fig. 3 shows examples of the generated images, where we observed that the generated images were fairly clear and they agreed with the true target/nontarget conditions completely. As visually inspection of the conditions of all the generated images was practically infeasible, we randomly selected 48 images (Target: 22, Non-Target: 26 Images) and we found that there was a 100% agreement between the true conditions and the conditions of the generated images. The result suggests that the proposed cGAN can generate images with correct target and nontarget conditions when the inputs are completely discriminative of the two conditions.

Raw EEG	True P: 15	False P: 9
	False N: 9	True N: 15
	Accuracy: 0.625	Sensitivity: 0.625
	Specificity: 0.625	F-measure: 0.625
Raw EEG+Noise	True P: 13	False P: 8
	False N: 12	True N: 15
	Accuracy: 0.5833	Sensitivity: 0.5200
	Specificity: 0.6522	F-measure: 0.5652
Normalized EEG	True P: 15	False P: 9
	False N: 9	True N: 15
	Accuracy: 0.625	Sensitivity: 0.625
	Specificity: 0.625	F-measure: 0.625
Normalized EEG+Noise	True P: 12	False P: 11
	False N: 12	True N: 13
	Accuracy: 0.5208	Sensitivity: 0.5000
	Specificity: 0.5417	F-measure: 0.5106

Table 2. The performance of generating target/nontarget images from different types of EEG inputs.

C. Performance of cGAN for generating target and nontarget images based on EEG

Next we examined the performance of the cGAN model for target/nontarget image generation from EEG inputs that are not completely discriminative. We examined four different types of inputs, namely raw EEG, raw EEG appended with a 192 dimension random noise vector, normalized EEG, and normalized EEG appended with the noise vector. For each noise vector, the values were sampled from the uniform distribution between -1 to 1 and trained as

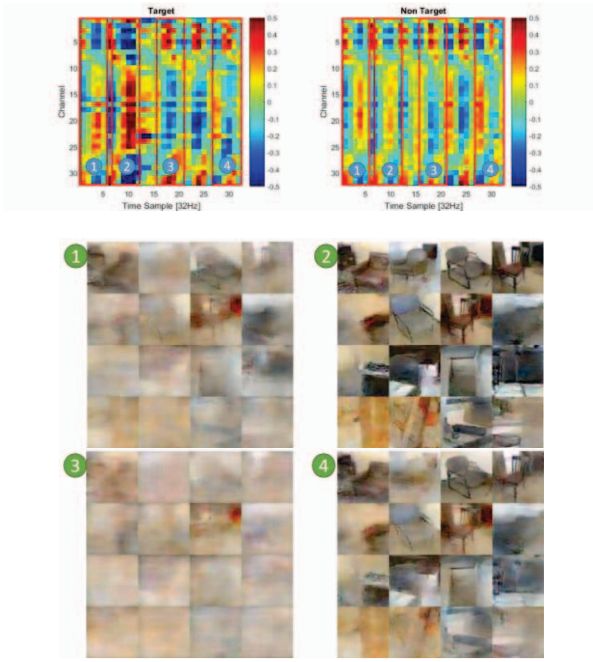

Figure 5. Top: Heatmaps of averaged target (left) and nontarget epochs (right). Four red rectangular boxes indicate four zero-masked regions. Bottom: The generated images after zero-masked each of the four regions in EEG epochs of Fig. 4.

batch training for 3 hours of training. Once again, we visually inspected 48 randomly picked samples to evaluate the agreement between the generated image conditions and the true conditions. We summarized the results in Table 2. We can see that raw EEG and normalized EEG resulted in similar performance and adding noise decreases the ability of cGAN to generate correct conditions. However, with an accuracy of 0.625, the overall performance was still low. Fig. 4 shows the examples of the generated images and corresponding raw EEG inputs. Compared with the generated images from random noise in Fig. 3, these EEG-generated images are clearer and include more varieties and details, suggesting the EEG signals contain more target/nontarget images related information.

D. Investigation of associations between EEG patterns and generated images

The trained cGAN provides a unique opportunity for us to investigate the relationship between EEG and its generated image. To this end, we zero-masked different regions of an EEG epoch and then examined its impact on the original generated images. To determine the masked regions, we examined the heatmaps of the averaged target and nontarget EEG epochs (Fig. 5) and selected 4 different masked regions. Fig. 5 also shows the resulted images after masked each of the 4 regions in EEG epochs of Fig. 4. We observed that region 1 and 3 were epoch regions that affected the generated images the most. In both cases, the generated images were completely blurred. Interestingly, these two regions are those right before and after P300 (region 2). In contrast, the regions that contain P300 did not seem to affect the generated images in any significant ways.

V. CONCLUSION

We proposed a conditional Generative Adversarial Network model for generating target and nontarget images from EEG epochs in an RSVP experiment. We demonstrated the performance of the proposed cGAN model and showed that generation with raw or normalized EEG produced better performance than that with added noise. We also showed how this model could be used for investigating the EEG and image associations.

In the current result, the generated images from EEG only has only 62.5% agreement with the true conditions. This is partially due to fact that EEG epochs are not completely discriminant. In addition, even in highly discriminant epochs, most parts of EEG signals are virtually noise. Therefore, our future work will aim to develop new approaches that can enhance the discriminate information in input EEG.

VI. ACKNOWLEDGEMENTS

This work was supported by the Army Research Laboratory Cognition and Neuroergonomics Collaborative Technology Alliance (CANCTA) under Cooperative Agreement Number W911NF-10-2-0022.

VII. REFERENCES

1. Fujiwara, Y., Y. Miyawaki, and Y. Kamitani, *Modular encoding and decoding models derived from Bayesian canonical correlation analysis.* Neural computation, 2013. **25**(4): p. 979-1005.
2. Du, C., C. Du, and H. He, *Sharing deep generative representation for perceived image reconstruction from human brain activity.* arXiv preprint arXiv:1704.07575, 2017.
3. Wang, Q., O. Sourina, and M.K. Nguyen. *Eeg-based" serious" games design for medical applications*. in *Cyberworlds (cw), 2010 international conference on*. 2010. IEEE.
4. Goodfellow, I., et al. *Generative adversarial nets*. in *Advances in neural information processing systems*. 2014.
5. Mirza, M. and S. Osindero, *Conditional generative adversarial nets.* arXiv preprint arXiv:1411.1784, 2014.
6. Gauthier, J., *Conditional generative adversarial nets for convolutional face generation.* Class Project for Stanford CS231N: Convolutional Neural Networks for Visual Recognition, Winter semester, 2014. **2014**(5): p. 2.
7. Touryan, J., et al., *Estimating endogenous changes in task performance from EEG.* Using Neurophysiological Signals that Reflect Cognitive or Affective State, 2015: p. 268.
8. Touryan, J., et al., *Common EEG features for behavioral estimation in disparate, real-world tasks.* Biological psychology, 2016. **114**: p. 93-107.
9. Bigdely-Shamlo, N., et al., *The PREP pipeline: standardized preprocessing for large-scale EEG analysis.* Frontiers in neuroinformatics, 2015. **9**.
10. Mao, Z., W.X. Yao, and Y. Huang. *Design of deep convolutional networks for prediction of image rapid serial visual presentation events*. in *Engineering in Medicine and Biology Society (EMBC), 2017 39th Annual International Conference of the IEEE*. 2017. IEEE.
11. Delorme, A. and S. Makeig, *EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis.* Journal of neuroscience methods, 2004. **134**(1): p. 9-21.
12. Radford, A., L. Metz, and S. Chintala, *Unsupervised representation learning with deep convolutional generative adversarial networks.* arXiv preprint arXiv:1511.06434, 2015.