Simulating Brain Signals: Creating Synthetic EEG Data via Neural-Based Generative Models for Improved SSVEP Classification

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Low reliability and usability of BCI caused by limitations such as difficulty of collecting high quality EEG data, requirement for per-

Issue: subject and per-session calibration and highly subject and session variant.

Approach:

Generation of new synthetic dry-EEG data using a selection of neural-based generative models.

Deep Convolutional Generative Adversarial Network



Generative Adversarial Network

- Improved Wasserstein Generative Adversarial Network
- c. Variational Autoencoder



Variational Autoencoder

Empirical SSVEP Dry-EEG Datasets (collected and detailed in [1]) :



Video-Stimuli Dataset: train the generative model



NAO Dataset: experimental evaluation









Method

Baseline

DCGAN WGAN





generalisation The real data The DCGAN data



Comparing real and synthetic data from the generative models for SSVEP signal at 10Hz, 12Hz and 15Hz. Synthetic data clearly displays the characteristic SSVEP frequency peaks at the same frequencies as those observed in the real data.

generation of synthetic dry-EEG data containing SSVEP signals using DCGAN, WGAN and VAE

Conclusion: improvement of performance in term of classification for pre-training and dataset

augmentation and convergence rate of classification models.

[1] N. K. N. Aznan, J. D. Connolly, N. A. Moubayed, and T. P. Breckon, "Using variable natural environment brain-computer interface stimuli for real-time humanoid robot navigation," in IEEE International Conference on Robotics and Automation. IEEE, 2019.



(1) Classification of synthetic and real data as a single training set [Baseline - the classification of only real data] :

Method	S01	S02	S03	Across Subjects
Baseline	0.91 ± 0.04	0.87 ± 0.10	0.84 ± 0.03	$\begin{array}{r} 0.69 \pm 0.03 \\ \textbf{0.72} \pm \textbf{0.03} \\ 0.71 \pm 0.04 \\ 0.67 \pm 0.02 \end{array}$
DCGAN	0.86 ± 0.01	0.80 ± 0.04	0.89 ± 0.03	
WGAN	0.93 ± 0.04	0.90 ± 0.04	0.87 ± 0.02	
VAE	0.92 ± 0.03	0.90 ± 0.03	0.79 ± 0.03	

(2) Pre-training classification:

Method	S01	S02	S03	Across Subjects
Baseline	0.91 ± 0.04	0.87 ± 0.10	0.84 ± 0.03	0.69 ± 0.03
DCGAN	0.97 ± 0.03	0.93 ± 0.03	0.87 ± 0.01	0.70 ± 0.02
WGAN	0.93 ± 0.03	0.90 ± 0.04	0.87 ± 0.03	0.72 ± 0.03
VAE	0.93 ± 0.03	0.92 ± 0.06	0.87 ± 0.05	0.73 ± 0.03





WG

 $X = \{1, 2, 3\}$ $Y = \{2, 3, 1\}$

Test accuracy when varying the volume of synthetic data used for pre-training.



Convergence of the Cross-Entropy value

plotted over training epochs.

(3) Cross-subject generalisation:

S01	S02	S03	Mean	N Off S
0.35	0.54	0.42	0.45 ± 0.08 0.57 + 0.12	N: On
0.40	0.60	0.50	0.57 = 0.12 0.56 + 0.13	S

Cross-subject

Nao Offline S0X

Generative Mode

Generated Data

Pre-training CNN

