

# Leveraging synthetic subject invariant EEG signals for zero calibration BCI

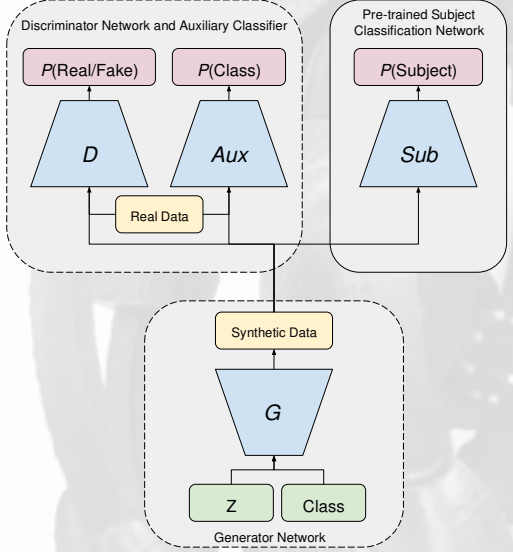
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**Issue:** The requirement of calibration stage especially for cross-subject EEG signals for SSVEP-based BCI application.

**Approach:**

Generate **realistic synthetic EEG** signals that **eliminate subject-specific features** to boost **SSVEP classification performance for unseen subject** via **Subject Invariant SSVEP GAN (SIS-GAN)**.



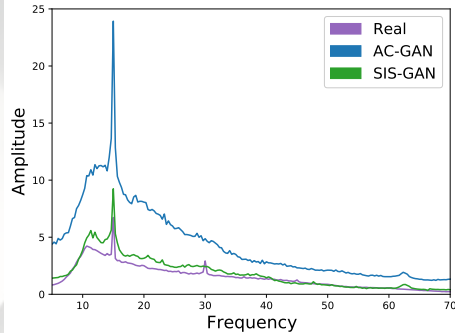
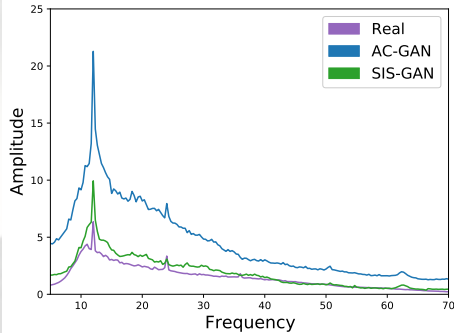
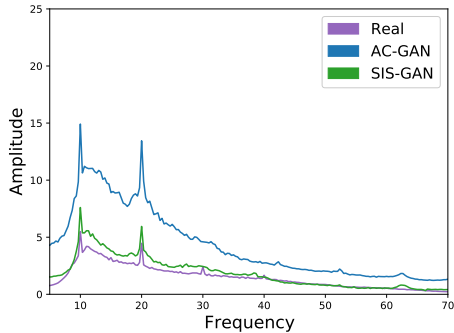
Our Subject Invariant SSVEP Generative Adversarial Network. The Generator (G) produces data with subject-specific information removed (Sub) that can fool the Discriminator (D) and is classified as a certain frequency (Aux).

The subject invariant loss component:

$$L_S = \arg \max_{\hat{y}} S(\hat{y}|x),$$

The overall training objective:

$$L = L_D + \lambda_a L_A + \lambda_s L_S$$



(a) SSVEP Signal at 10Hz. (b) SSVEP Signal at 12Hz. (c) SSVEP Signal at 15Hz. Comparing Fast-Fourier Transforms (FFT) of real and synthetic data from all the generative models.

**Contribution:**

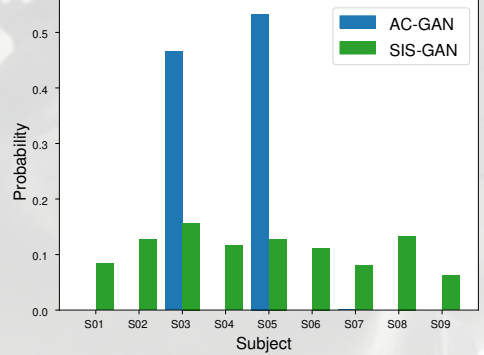
Generating subject-invariant synthetic data which can be used for training to enhance unseen subject classification.

Unseen Subject	Real data	Augmented Training Data		Synthetic Training Data	
		AC-GAN	SIS-GAN	AC-GAN	SIS-GAN
01	0.576 ± 0.055	0.534 ± 0.042	0.550 ± 0.028	0.617 ± 0.023	<b>0.665 ± 0.017</b>
02	0.705 ± 0.009	0.711 ± 0.023	0.709 ± 0.032	0.619 ± 0.053	<b>0.714 ± 0.009</b>
03	0.687 ± 0.016	0.688 ± 0.032	<b>0.732 ± 0.021</b>	0.604 ± 0.025	0.717 ± 0.006
04	0.656 ± 0.010	0.581 ± 0.023	0.600 ± 0.028	0.627 ± 0.162	<b>0.667 ± 0.012</b>
05	0.682 ± 0.027	0.694 ± 0.024	0.711 ± 0.026	0.380 ± 0.029	<b>0.768 ± 0.080</b>
06	0.757 ± 0.045	0.710 ± 0.068	0.727 ± 0.032	0.627 ± 0.162	<b>0.815 ± 0.029</b>
07	0.905 ± 0.005	0.940 ± 0.009	<b>0.943 ± 0.014</b>	0.588 ± 0.155	0.911 ± 0.025
08	0.447 ± 0.046	0.426 ± 0.038	0.378 ± 0.046	0.343 ± 0.030	<b>0.485 ± 0.018</b>
09	0.778 ± 0.012	0.807 ± 0.018	<b>0.814 ± 0.023</b>	0.710 ± 0.048	0.780 ± 0.009
<b>Mean</b>	<b>0.688 ± 0.125</b>	<b>0.677 ± 0.146</b>	<b>0.685 ± 0.155</b>	<b>0.543 ± 0.150</b>	<b>0.725 ± 0.113</b>

Mean accuracy with standard deviation when classifying SSVEP for unseen subject on offline dataset.

Subject	Realdata	Augmented Training Data		Synthetic Training Data	
		AC-GAN	SIS-GAN	AC-GAN	SIS-GAN
T01	0.736± 0.066	0.742± 0.071	0.756± 0.103	0.695± 0.100	<b>0.845± 0.019</b>
T02	0.508± 0.072	0.542± 0.062	0.592± 0.052	0.488± 0.083	<b>0.675± 0.016</b>
T03	0.240± 0.039	0.277± 0.067	0.303± 0.057	0.310± 0.060	<b>0.453± 0.017</b>
<b>Mean</b>	<b>0.495± 0.211</b>	<b>0.520± 0.202</b>	<b>0.550± 0.201</b>	<b>0.498± 0.177</b>	<b>0.660± 0.161</b>

Mean accuracy with standard deviation for cross-task when classifying SSVEP on online subject dataset.



Softmax probability values taken from the pre-trained subject-biometric classification network for the generated data. A low consistent value distributed across all subjects is best as it indicates the subject-biometric classification network is unable to find discriminative features.

**Conclusion:**

- successfully generate new synthetic SSVEP-based dry-EEG signals via **SIS-GAN**
- creation of **subject-invariant data removing subject-specific features** whilst **preserving the SSVEP frequencies**
- improvement of **unseen subjects generalisation** when performing **zero-calibration classification** by training only on synthetic signals.

