**Semi-Supervised Contrastive Learning for Generalizable Motor Imagery EEG Classification**

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**Introduction**

Motor Imagery (MI) based EEG systems

Allow users to control external devices by mental execution by non-invasive EEG recordings.

Widely used for rehabilitation engineering.

**Challenges**
- The evoked potential of the brain activities is weak and noisy
- Expensive and difficult to label data accurately.
- High inter-session variation and inter-subject variation.

**Objective**
- To develop a semi-supervised framework with a combination of self-supervised contrastive learning and adversarial training.
- Learn transformation invariant features without any labels and diminish the feature distribution of different subjects/sessions.
- Supervised learning on the partial labelled data to force the model to learn task-relevant features.

**Experiment Settings**
- Dataset: BCI IV2A 2 MI-EEG, binary classification (left hand and right hand)
- Encoder backbones: EEGNet-8, DeepConvNet
- Validation method: Leave-One-Session-Out (LOSO) + 10-fold cross-validation

**Quantitative Results**

<table>
<thead>
<tr>
<th>Models</th>
<th>10%</th>
<th>20%</th>
<th>50%</th>
<th>100%</th>
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</thead>
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<td>FBCSP</td>
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<td>58.8</td>
<td>62.3</td>
<td>64.8</td>
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<td>EEGNet</td>
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<td>68.0</td>
<td>71.4</td>
<td>75.8</td>
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<td>65.4</td>
<td>76.5</td>
<td>80.9</td>
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<td>Semi-EEGNet</td>
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<td>71.5</td>
<td>75.3</td>
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<tr>
<td>Semi-DeepConvNet</td>
<td>67.6</td>
<td>74.3</td>
<td>77.4</td>
<td>79.4</td>
</tr>
</tbody>
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**Table 1 - Classification accuracy of different methods with different ratios of labels in the training.**

**Ablation study**
evaluate the effectiveness of augmentation, contrastive learning and adversarial training

**Method**

The framework consists of: data augmentation, an encoder, a task classifier, a domain discriminator, and a projector.

**Data augmentation**

Apply two sets of augmentations to the input EEG signals \(x\) yielding \(T_1(x_i)\) and \(T_2(x_i)\)

**Contrastive Learning**

The Encoder \(E\) produces latent representations \(h_i = E(T_1(x_i))\) and \(h_j = E(T_2(x_j))\)

The Projector \(P\) projects latent representation \(h_i\) and \(h_j\) to a lower dimension \(z_i = P(h_i)\) and \(z_j = P(h_j)\). \(E\) and \(P\) minimise the contrastive loss \(L_{\text{contrast}}(z_i, z_j)\).

**Supervised Learning**

The latent representation of labelled data, \(h_{ij} \in \mathcal{L}\) are used to train the supervised classifier \(C\) and calculate a cross-entropy loss \(L_{\text{ce}}(h_{ij}, y_j)\).

**Adversarial Training**

The domain discriminator \(D\) is trained to predict the identities of the domains based on latent vectors \(h\) by minimising the loss \(L_{\text{adv}}\).

The encoder \(E\) is encouraged to confuse the discriminator \(D\) by minimising \(L_{\text{unsup}}\).

**Discussion**

- Developed domain independent, end-to-end semi-supervised learning framework for classifying MI EEG signals with limited labels.
- Our method outperforms the baseline methods when there are limited labels.
- Our work opened new possibilities for using deep neural networks for real-world applications without the need for tedious calibration processes.

**Future Plan**

Develop a Generative model capable of generating new meaningful data to facilitate training whilst force the Encoder to learn domain invariant MI features through the training process of the Generative model.

**References**


This work has been accepted by the IEEE International Conference on Wearable and Implantable Body Sensor Networks (BSN’21)