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An SSVEP Regression Network for Cross-stimulus Transfer in SSVEP-BCIs

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Introduction: SSVEP-based BCIs achieve high information transfer rates (ITR) over 300 bits/min but require prolonged calibration time. Cross-stimulus transfer addresses this by enabling models trained on a subset of classes (seen classes) to decode both seen and unseen classes. Existing approaches obtain templates of unseen classes for decoding using common components from seen class templates [1]; however, these templates suffer from class-relevant activities, leading to degraded performance. This study proposes a neural network to directly map visual stimuli (sine-cosine reference signals) to SSVEP responses (SSVEP templates). Moreover, a novel framework is introduced by combining the proposed regression network and spatial filtering to identify targets from both seen and unseen classes.

Materials and Methods: A public SSVEP dataset comprising 35 participants was utilized [2]. Each participant completed six blocks, each containing 40 trials representing 40 classes/visual stimuli. A k-fold cross-validation scheme was implemented, with one block as the test set and the remaining as the training blocks. In the training blocks, 32, 20, and 8 classes were chosen as the training set, i.e., the seen set, with the remaining classes as the unseen set. The network employs three modules: (i) an Embedding block, embedding sine-cosine reference signals into high-dimensional features; (ii) a Spatial-temporal Extraction block, using 1D convolutional layers and residual connections to extract spatial and temporal features; and (iii) a Bi-direction block, using recurrent layers to further extract temporal features. As shown in Figure 1(A), with obtained SSVEP templates of all classes, spatial filters mapped multi-channel data into 1D vectors, followed by correlation analysis for target prediction.

Results and Discussions: Figure 1(B) shows that the regressed SSVEP templates closely align with the true templates, indicating that the proposed network captures frequency and phase information. Moreover, Figure 1(C) shows that the framework outperforms existing approaches by a 10% improvement.

Significance: The proposed network can regress SSVEP responses of any class without collecting corresponding training samples. Integrated with the spatial filtering technique, the proposed framework enhances decoding performance and facilitates practical applications of SSVEP-based BCIs.

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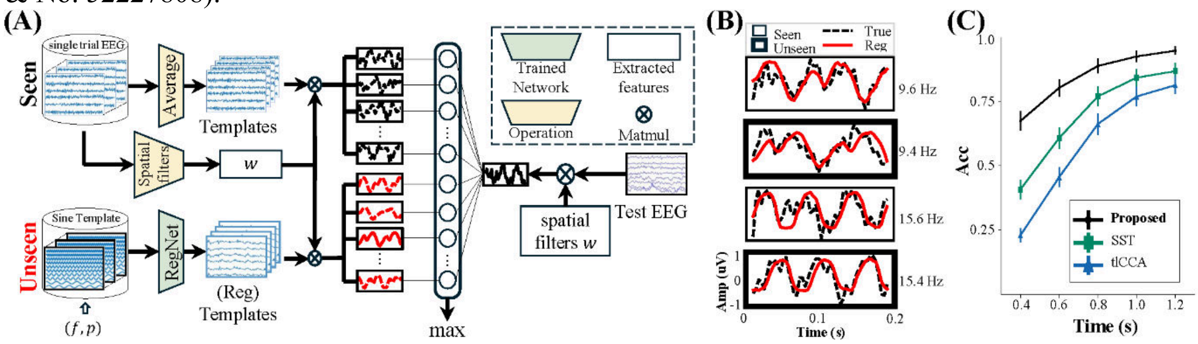

Figure 1. **(A)** *Overall scheme of the proposed framework. SSVEP templates of seen classes, spatial filters* w*, and RegNet are derived from the training set. SSVEP templates of unseen classes are regressed by the RegNet using sine-cosine reference signals as input.* ***(B)*** *Comparison between true SSVEP templates and regressed SSVEP templates.* ***(C)*** *Accuracies of different approaches under eight unseen classes.*

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