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Title: FENet: Feature Extraction Neural Network for Brain Machine Interfaces

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Abstract: Clinical neural prosthetic systems decode brain signals recorded from implanted electrode arrays to enable paralyzed human participants to control external devices. This process occurs in two basic steps. First, electrical signals that convey information about the activity of neurons around the electrode tip are transformed into "neural features". Second, the relationship between neural features and the participant's intent is learned, and subsequently decoded to control external devices. Here, we present FENet, a compact (F)eature (E)xtraction (Net)work that learns an optimized mapping between electrical signals and neural features, which significantly improves decoding performance compared to the classic feature construction methods. FENet is parameterized using a novel architecture that jointly optimizes the feature extraction and feature decoding stages of the neural decoding process, while constraining the feature extraction algorithm to use the same parameterization for all the electrodes used in our training set. This approach is based on the understanding that while the activity of different neurons will contribute to the decoding of the participants' intentions in different ways, the underlying process by which neural activity is translated into electrical fluctuations detected by an electrode is conserved across different electrodes, recording times, and brain regions.

In this work, we validate the FENet architecture by predicting the kinematics of a computer cursor movements using neural data recorded from electrode arrays implanted in human cortex. We compared performance of neural features computed from FENet against two current gold standards: 1) the rate of neural spike events computed by counting threshold crossings of the broadband neural signal; and 2) a wavelet decomposition of the broad band neural data. We found that FENet based features outperformed these two methods by 50 and 47 percent decrease in mean square error, and 51 and 28 percent increase in R2, respectively. We further present an evaluation of the effect of hyperparameter choice on FENet performance, including the amount and quality of training data as well as the choice of parameter initialization. Our results demonstrate that the trained FENet can be used for novel datasets, without modification, and leads to improved performance, generalization, and efficiency of training. Moreover, our approach demonstrates how machine learning techniques constrained by domain specific knowledge can significantly improve generalization performance.