Robust Learning Algorithms for Brain Machine Interfaces

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***Abstract*— This study implements robust direction classification and magnitude regression algorithms for brain machine interfaces (BMIs). The goal is to achieve a reasonable trade-off between performance, robustness, and hardware cost. We extracted the firing rates of subpopulations of neurons as the input features and used polar representation of kinematics. A gradient boosted ensemble of decision trees (XGBoost) achieved 92.74% accuracy for direction classification and a dynamic recurrent neural network (DRNN) achieved root mean square errors (RMSE) of 0.06 and 0.07, and correlation coefficients (CC) of 0.97 and 0.92 for position and velocity magnitudes regression respectively. Therefore, these decoding algorithms are effective and reliable decoders for BMIs.**

I. Introduction

A brain-machine interface (BMI) decodes neural activity into useful control signals for guiding robotic limbs, computer cursors, or other assistive devices [1]. In its most basic form, such a system involves mapping neural signals to kinematics, then closing the loop to enable direct neural control of kinematics. Such systems have shown promise; however, improving performance and robustness remain challenges. Even for simple movements, as in the ubiquitous center-out task, decoding performance can be highly variable between users and over time.

A major problem for clinical translation of BMIs is that decoders cannot adapt to changing neural recording conditions. Moreover, almost all existing decoders run on PCs. ASIC designs are challenging because most decoding algorithms and adaptation paradigms have high computational and power costs. By choosing efficient algorithms that map well to CMOS technologies, ASIC implementations could offer substantial power and mobility benefits.

Machine learning algorithms have shown promise in attaining high performance and robustness in various medical applications. We used learning-based algorithms on polar-space kinematics to examine high-performance classification [2] and regression algorithms [3] and study BMI robustness.

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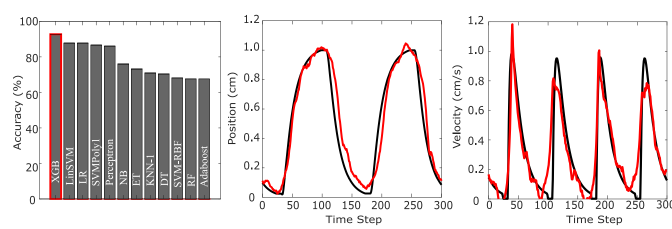
II. Methods

A tetraplegic human learned to acquire targets with a cursor controlled by neural activity. The subject made point-to-point movements of a cursor on a computer screen in a 2D center-out task with 8 targets located around the unit circle. Neural activity from supramarginal gyrus (SMG), ventral premotor cortex (PMV), and primary somatosensory cortex (S1) were recorded during three minutes of open-loop training per day, with a sampling rate of 30 kHz, using three NeuroPort arrays (Blackrock Microsystems, Salt Lake City, UT, US). The recording sessions each contain 50 trials. We used neuronal firing rates as features.

We tested 12 classification algorithms on movement direction: gradient-boosted ensemble of decision trees (XGBoost), linear SVM, Logistic Regression (LR), degree 1 polynomial SVM, Perceptron, Naïve Bayes (NB), Extra-tree classifier (ET), *k*-nearest neighbors (KNNs), Decision Tree (DT), SVM RBF, Random Forest (RF), and Adaboost. We found the best performance with XGBoost (Fig. 1a).

For magnitude regression, we use dynamic recurrent neural networks (DRNN). RNNs are capable of learning long-term dependencies. Fig.1 (b) and (c) show that this method is capable of generalizing to unseen data.



(a) (b) (c)

Figure 1. (a) Classificarion accuracy. (b) Position magnitude regression and (c) Velocity magnitude regression on test data from the same session: true target motion (black) and reconstruction using DRNN (red).

III. Conclusion

These results indicate that XGBoost and DRNN are powerful candidates for robust BMI operation.

References

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