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Design of a Parkinsonian Biomarkers Combination Optimization Method Using Rodent Model

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***Abstract*—This work seeks to determine a group of neural biomarkers that a classification algorithm could use in an adaptive deep brain stimulator using rodent animal models. To overcome the variability introduced from the small sample size, this work proposes a novel method for combining and running Genetic Feature Selection and Stepwise Feature Selection. Three separate classification algorithms, Logistic Regression (LR), *k*-Nearest Neighbor (KNN), and Random Forest (RF) are used to verify the proposed method. For LR, the method finds the set of Alpha Power, High Beta Power (20-30 Hz), and 55-95 Hz Power to have the best performance in classification. For KNN, it finds Low Beta Power (12-20 Hz), High Beta Power, All Beta Power (12-30 Hz), 55-95 Hz Power, and 95-105 Hz Power. For RF, the results are High Beta Power, All Beta Power, 55-95 Hz Power, 95-105 Hz Power, and 300-350 Hz Power.**

***Clinical Relevance*— This experiment provides a method for determining the most effective biomarkers for classifying Parkinsonian behavior for an aDBS device.**

I. INTRODUCTION

Adaptive Deep Brian Stimulation (aDBS) is a promising treatment for Parkinson's Disease (PD) to overcome the negative consequences of constant stimulation from traditional Deep Brain Stimulation [1]. aDBS triggers stimulation based on the expected values of features which it monitors in neural activities. Various individual neural biomarkers have been examined in literature targeting on the detection of PD [2, 3]. However, few works have examined how these different biomarkers work together to characterize Parkinson's disease.

II. METHODS

Approximately 310 2-minute recordings were acquired individually from 4 unilateral 6-OHDA rat models of PD and 4 control rats. Twenty-two biomarkers were extracted from each recording. Sixteen represented the average powers within different neural bands. The rest were the High Frequency Oscillations Power Ratio, the Hjorth parameters, the phase amplitude coupling (PAC) between 13-30 Hz and 60-90 Hz, and the PAC between 13-30 Hz and 80-120 Hz.

Two feature selection wrapper algorithms—Stepwise Feature Selection (SFS) and Genetic Feature Selection (GFS)—were run in conjunction with three classification algorithms—Logistic Regression (LR), *k*-Nearest Neighbor (KNN), and Random Forest (RF)—through a three-stage process (Figure 1) to determine which biomarkers fundamentally characterize PD behavior. To avoid recordings from the same rat appearing in both training and test sets, before a run, each model rat was randomly paired with a healthy rat to act as a fold for four-fold cross validation. In stage one, GFS is run 20 times. In stage two, GFS and SFS are each run 10 times on all features returned in at least half the runs from stage one. In stage three, all feature sets returned from stage two are tested across all possible rat pairings to determine which performs with the best overall accuracy.

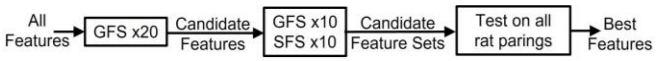

Figure 1. Feature Selection Process.

III. RESULTS

For LR, the ideal biomarker set was Alpha Power (7-12 Hz), High Beta Power, and 55-95 Hz Power. For KNN, it was Low Beta Power (12-20 Hz), High Beta Power (20-30 Hz), All Beta Power (12-30 Hz), 55-95 Hz Power, and 95-105 Hz Power. For RF, it was High Beta Power, All Beta Power, 55-95 Hz Power, 95-105 Hz Power, and 300-350 Hz Power.

TABLE I. FEATURE SET PERFORMANCES

Algorithm	Biomarkers	Accuracy	Sensitivity	Specificity
Logistic Regression	Ideal	77.65 ± 2.58%	82.83 ± 1.73%	72.28 ± 5.54%
	All	58.97 ± 2.03%	72.43 ± 3.31%	44.83 ± 4.16%
k-Nearest Neighbor	Ideal	73.37 ± 2.29%	78.66 ± 2.05%	67.73 ± 5.21%
	All	49.47 ± 1.33%	69.87 ± 1.66%	28.42 ± 3.36%
Random Forest	Ideal	71.14 ± 2.90%	72.13 ± 3.79%	70.16 ± 5.32%
	All	55.05 ± 2.64%	58.73 ± 3.82%	51.34 ± 5.41%

IV. DISCUSSION & CONCLUSION

All three algorithms returned High Beta Power and 55-95 Hz Power indicating their usefulness in characterizing PD behavior. The feature selection process greatly improved the algorithms' performances verifying its utility for future experiments with other biomarkers or other classification algorithms. Finally, if these methods were used to determine whether a recording comes from a PD patient currently experiencing symptoms, then the experiment would result in a classification algorithm that knows which biomarkers are the most important that could be implemented on an aDBS.

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