Machine Learning in Detecting Frequency-Following Responses

OHIO UNIVERSITY

Breanna N. Hart and Fuh-Cherng Jeng

Communication Sciences and Disorders, Ohio University, Athens, Ohio

INTRODUCTION

- The Frequency Following Response (FFR) is a subcortical electrophysiological response of brain activity that can be recorded by placing recording pads on the participants head (Skoe & Kraus, 2010). Unlike other cortical responses which are highly variable and affected by sleep (Song et al., 2011), the FFR is an extremely reliable measure which is unaffected by these dilemmas.
- Utilization of FFR recordings can be a key evaluator in hearing testing among individuals who cannot provide accurate behavioral responses. By generating a pass/fail system based on an algorithm one can not only save testing time but also preserve efficiency and create a new gold standard.
- The purpose of this study was to evaluate multiple machine-learning algorithms in order to explore the possibilities of machine learning in FFR detection.
- Machine learning is a type of artificial intelligence that provides computer systems with the capabilities to train and learn how to analyze data without the need for human judgement or monitoring.
- This method is best achieved through an algorithm where data can be trained as a baseline to develop the program, from there one can then continuously feed more data into the model as the detection accuracy increases.
- By retrieving existing data from our lab, this study was designed to determine the feasibility of using machine-learning algorithms to detect the presence or absence of an FFR, and given that, to compare the performance (e.g., sensitivity, specificity, false positive, and false negative rates) across several machine-learning algorithms that were included in this study.
- The ultimate goal of this line of research is to eliminate the need for human judgement, therefore establishing a protocol for more of an automated system which will be able to determine the presence or absence of an FFR.

METHODS

Data collection

Data
- Data were retrieved from existing data in our lab.

Participants
- 25 native Chinese adults
- All had normal hearing

Stimulus
- /i2/, rising pitch contour, 250 ms, human speech

Brain Wave Recording Procedure
- 3 gold-plated electrodes (high forehead, low forehead, right mastoid)
- Participant resting or fast asleep prior to recording
- Stimulus intensity: 70 dB SPL in the right ear
- 8000 accepted sweeps

Machine-Learning Algorithms

FFR Features
- Six FFR features (Frequency Error, Slope Error, Tracking Accuracy, Spectral Amplitude, Pitch Strength, and Root Mean Square Ratio) were extracted from each recording and served as the key predictors in the identification of a response.
- Brain waves accumulated (from the first sweep) up to the first 500 sweeps were considered FFR absent; brain waves accumulated (from the first sweep) up to the last 1000 sweeps (i.e., from 7001 – 8000 sweeps) were considered FFR present.
- These 6 FFR features, along with the supervised responses, were used to train the algorithms.

Classification Learner App
- A 10-fold cross-validation procedure was employed by using a Classification Learner App in MATLAB.
- 23 machine-learning algorithms were tested.

RESULTS

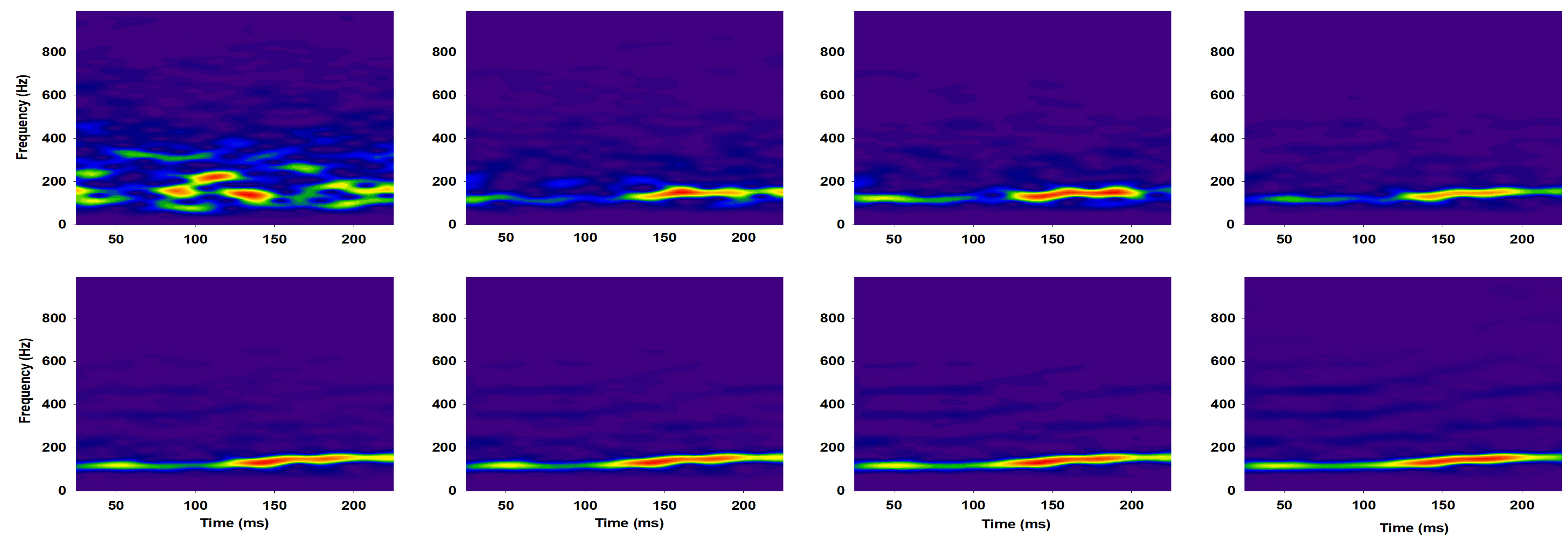

Figure 1 Seen here are spectrograms ranging from 10, 250, 500, 1000, 2000, 3000, 5000, and 8000 sweeps. Depicted here in this figure is the progression of the spectrogram. With accumulating sweeps one can visualize it showing no response to showing a response at as early as 2000 sweeps.

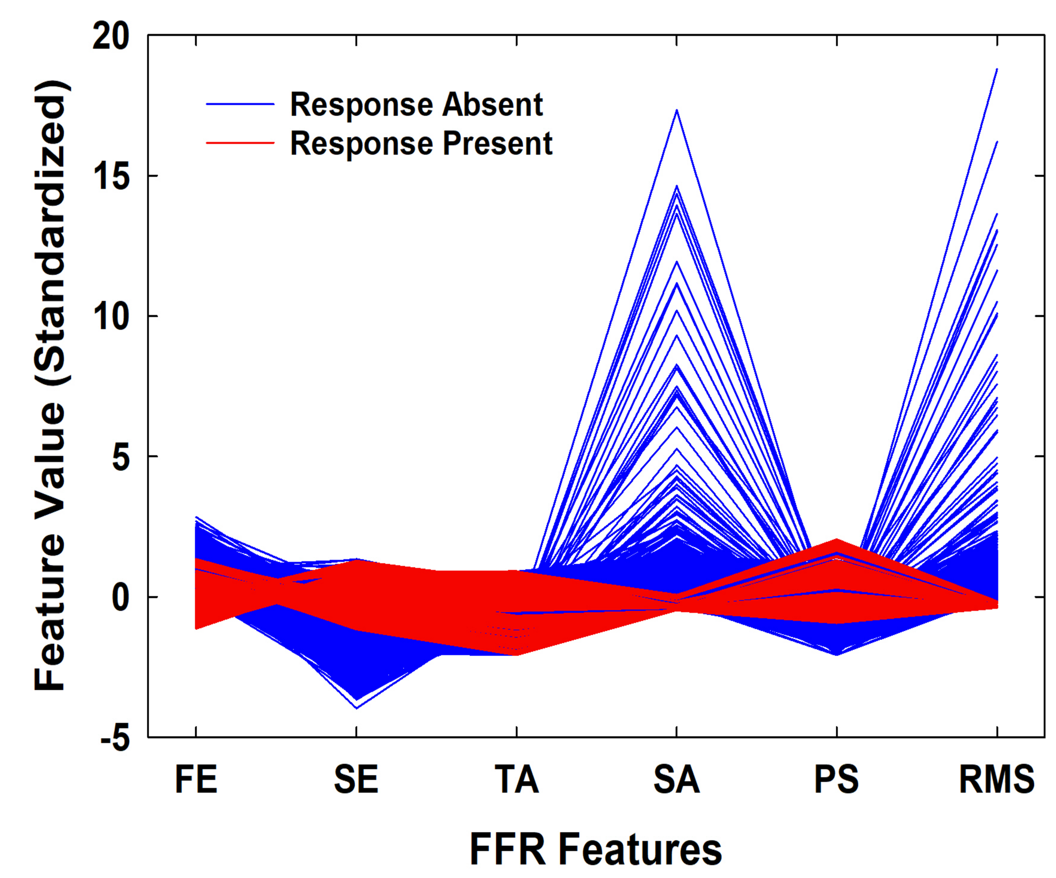

Figure 2 Depicted here is a parallel coordinate plot showing the distribution of the feature values across all predictors. Frequency error (FE) is a measure of the accuracy of pitch-encoding during stimulus presentation. Slope Error (SE) depicts the brainstem's ability to preserve the overall shape of the pitch contour of the stimulus signal. Tracking Accuracy (TA) reflects the overall faithfulness of pitch tracking between the stimulus and response *f0* contours. Spectral Amplitude (SA) measures the frequency amplitude of a recording along the F0 contour of the stimulus. Pitch Strength (PS) denotes the robustness of the phase-locking phenomenon in the human brainstem. Root-mean-square (RMS) amplitude measures the overall amplitude of a recording (See Jeng et al., 2011 for details of these FFR features).

		Human Judgement	
		Present	Absent
Test Result	Positive	True Positive (a)	False Positive (b)
	Negative	False Negative (c)	True Negative (d)

Operating Characteristics:

Sensitivity(Power) = $\frac{a}{a+c}$%

False-Negative Rate = $\frac{c}{a+c}$%

Positive-Predictive Value = $\frac{a}{a+b}$%

Efficiency = $\frac{a+d}{a+b+c+d}$%

specificity = $\frac{d}{b+d}$%

False-Positive Rate = $\frac{b}{b+d}$%

Negative-Predictive Value = $\frac{d}{c+d}$%

Type I (alpha) error = False-Positive rate = (100 – specificity) %

Type II (beta) Error = False-Negative rate = (100 – sensitivity) %

Figure 3 Operating characteristics of a test.

Machine-Learning Algorithm	True Positive	False Positive	False Negative	True Negative	Model Accuracy
Complex Tree	1854	2	3	1170	99.8%
Medium Tree	1854	2	3	1170	99.8%
Simple Tree	1853	22	4	1170	99.1%
Linear Discriminant	1636	121	221	1051	88.7%
Quadratic Discriminant	1797	1	60	1171	97.9%
Logistic Regression	1857	0	0	1172	100%
Linear SVM	1857	1	0	1171	99.9%
Quadratic SVM	1857	3	0	1169	99.9%
Cubic SVM	1857	2	0	1170	99.9%
Fine Gaussian SVM	1857	2	0	1170	99.9%
Medium Gaussian SVM	1857	9	0	1163	99.7%
Coarse Gaussian SVM	1857	36	0	1136	98.8%
Fine KNN	1857	2	0	1170	99.9%
Medium KNN	1857	7	0	1165	99.7%
Coarse KNN	1844	81	13	1091	96.8%
Cosine KNN	1857	14	0	1153	99.5%
Cubic KNN	1857	6	0	1166	99.8%
Weighted KNN	1857	4	0	1168	99.8%
Boosted Trees	1857	1172	0	0	61.3%
Bagged Tree	1857	0	0	1172	100%
Subspace Discriminant	1648	198	209	974	86.5%
Subspace KNN	1857	9	0	1163	99.7%
RUS Boosted Trees	1854	354	3	818	88.2%

1857 (61.3%)	0 (0%)
0 (0%)	1172 (38.7%)

1844 (60.9%)	81 (2.7%)
13 (0.4%)	1091 (36%)

1857 (61.3%)	1172 (38.7%)
0 (0%)	0 (0%)

Figure 4 Examples of a good-performance algorithm (left panel, Logistic Regression algorithm), a moderate-performance algorithm (middle panel , Coarse KNN algorithm), and a poor-performance algorithm (right panel , Boosted Trees algorithm).

DISCUSSION

- Results indicate that the utilization of the machine-learning algorithms can provide accurate predictions in whether or not an FFR was present in a recording.
- In this study, a fixed approach was utilized by using the top 1000 and bottom 500 sweeps as the determinant of a response. Future directions of this study will be to manipulate the cutoff sweeps to reveal the lowest sweep count to where a response can be accurately detected.
- When the lowest number of sweeps was determined by using one of the more efficient algorithms to detect the presence of a response, one can then obtain an FFR by using the least amount of time possible, and thus to the patient's time.

ACKNOWLEDGMENTS

The authors would like to thank the participants who volunteered in this study. This study was partially supported by the Deans Student Travel Grant from the College of Health Science Professions and the Graduate Student Research and Travel Award from the Department of Communication Sciences and Disorders at Ohio University.

REFERENCES

- E. Skoe and N. Kraus, "Auditory brain stem response to complex sounds: A tutorial," Ear Hear. *31*, 302–324 (2010).
- J. H. Song, T. Nicol, and N. Kraus, "Test–retest reliability of the speech-evoked auditory brainstem response," Clin. Neurophysiol. *122*, 346–355 (2011).
- Jeng, F.-C., Chung, H.-K., Lin, C.-D., Dickman, B. M., and Hu, J. (2011). Exponential modeling of human frequency-following responses to voice pitch. *Int J Audiol*, *50*, 582-593.

Corresponding author: Breanna N. Hart bh130015@ohio.edu