Machine Learning in Detecting Frequency-Following Responses in American Neonates

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INTRODUCTION

- The Frequency Following Response (FFR) is a subcortical electrophysiological response of brain activity that can be obtained by placing recording pads on the participants head (Skoe & Kraus, 2010). Unlike cortical responses which are highly variable and affected by patient factors, the FFR is an extremely reliable measure unaffected by such dilemmas (Song et al., 2011).
- Utilization of FFR recordings can be implemented as a key evaluator in hearing testing among individuals who cannot provide accurate behavioral responses.
- Issues with FFR testing stems from the nature of the test response. Since it is a small potential numerous recording repetitions are required to show the response from traditional noise.
- This need for a large amount of recording repetitions constricts the time window for recordings on infants. Leading researchers to evaluate alternative methods to aid in testing timeframes.
- 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 starting point for program development, then continuously feed more data into the model as the detection accuracy increases.
- No particular algorithm has the capabilities to work efficiently in every testing experiment. In order to implement an efficient system, multiple machine learning algorithms should be evaluated. The purpose of this study was to evaluate various machine learning algorithms, with an aim to determine the feasibilities and efficiencies of machine learning in infant FFR detection.
- Therefore based on the findings of Hart and Jeng (2018), it was hypothesized that machine learning algorithms would be efficient in detecting the presence or absence of an FFR in neonates.

METHODS

Data collection

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

Participants
- 43 American neonates (~1-3 days old)
- All had normal hearing

Stimulus
- /i2/, rising pitch contour, 150 ms, human speech

Brain Wave Recording Procedure
- 3 Ambu Neuroline snap on electrodes (high forehead, right mastoid, left mastoid)
- Participant resting or fast asleep prior to recording
- Stimulus intensity: 70 dB SPL in the presentation 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.
- 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

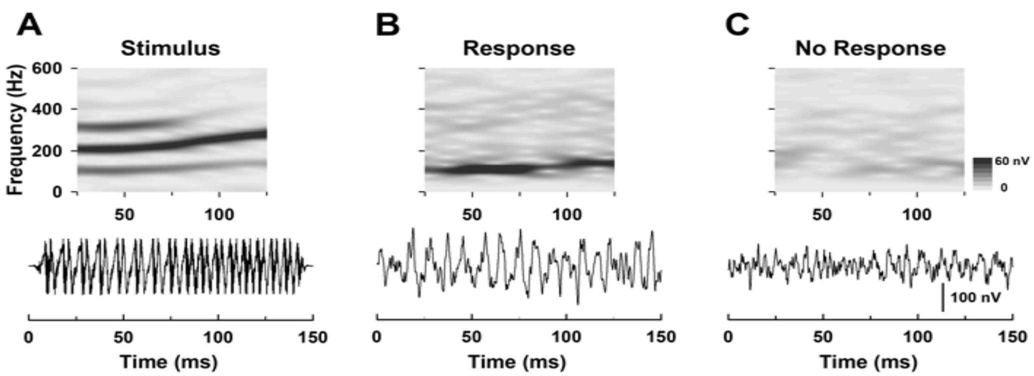

Figure 1. Seen here are spectrograms and time waveforms of the stimulus (A), a response recording (B), and a no response recording (C). The response spectrogram and time waveform (B) were obtained from one neonate. The no response spectrogram and time waveform (C) were obtained from another neonate.

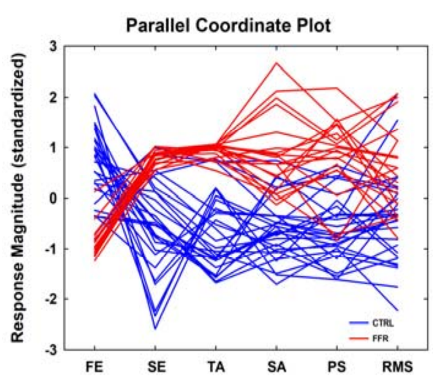

Figure 2. Displays Distributions of six key features that were extracted from the response (red) and no response (blue) recordings. Frequency error (FE). Slope Error (SE) depicts the brainstem's ability to preserve the overall shape of the pitch contour of the stimulus signal. Tracking Accuracy (TA) 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).

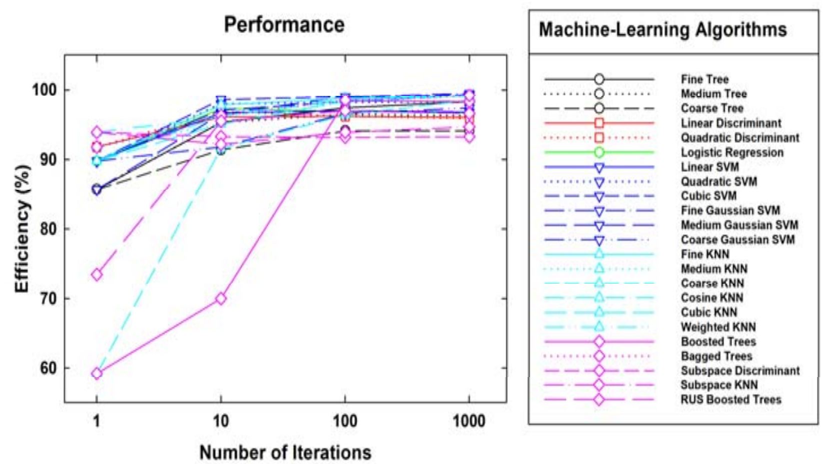

Figure 3. Shows the performance efficiencies of the 23 machine learning algorithms for 1, 10, 100, and 1000 iterations.

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

Figure 4. Operating characteristics of a test.

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 $= \frac{d}{c+d}\%$

DISCUSSION

- Results indicate that all 23 machine learning algorithms provide a feasible method in the detection of neonatal FFRs.
- A noteworthy result shows that with 100 iterations the mean of all algorithm efficiencies is as high as 97.2%.
- Clinical implications of this study are twofold. In normal developing individuals, machine learning algorithms can be utilized for the assessment of pitch processing at the brainstem level.
- For individuals with disorders associated with decreased pitch processing these methods can be implemented for screening and intervention purposes.

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