

## Can audio features serve as marker of autism spectrum disorders?

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Identifying neurophysiological markers of autism spectrum disorders (ASD) in young children is an imperative, albeit difficult, problem. ASD is characterized, among other things, by language difficulties. It has been hypothesized that this difficulty may be due to a subtle sensory shortcoming of ASD children in making fine auditory discriminations (e.g., Roberts et al., 2010). To test this hypothesis, we present typically developing (TD) and ASD children with similar speech sound pairs, where the members of each pair differ in the voice onset time of the initial consonant and the pairs differ in place of articulation of the initial consonant (e.g., /ga-/ka/, /da-/ta/). We record the evoked magnetic fields to these speech sounds and analyze them with the purpose of determining if the same distinctive features expected to differentiate these stimuli are also found in ASD children. Absence of distinctive features differentiating speech sounds can then serve as a neurophysiological marker of ASD.

Researchers have developed computational models capable of decoding mental content from brain activity (e.g., Kay et al., 2008; Nishimoto et al., 2011). The dictionary of features, i.e. the battery of Gabor filters, used in these models is handcrafted while the weights for those features are learned using regression methods. In order to detect the absence or distortion of distinctive features, a model is required to learn the dictionary of features as well as their weights. Thus, while the above models work well for identifying stimuli from brain activity, they are insufficient for detecting absence or distortion of features in ASD children. We present a neural model that learns the features and corresponding weights for each subject for the same set of audio stimuli. The model is generative in that it takes an audio stimulus as the input and produces the corresponding brain response of a subject as the output. It consists of two layers of neurons with exhaustive feedforward, feedback and lateral (only in second layer) connectivity. The first layer operates as an input layer while each neuron in the second layer gets tuned to a unique feature encoded in the feedforward weights. Our features resemble those learned by the model proposed by Smith and Lewicki (2006). Comparisons will be drawn between the features learned by our model for TD and ASD children to judge their suitability as neurophysiological marker of ASD.

### References:

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