7F-03

Phantom Noise Caused by Deficit of Prediction Ability in Autism Spectrum Disorder

Jyh-Jong Hsieh[†‡] Yukie Nagai[‡] Minoru Asada[†]

Graduate School of Engineering, Osaka University[†] Center for Information and Neural Networks, National Institute of Information and Communications Technology[‡]

Introduction

Autism spectrum disorder (ASD) is a developmental disorder characterized by impaired social abilities and stereotyped behaviors, and the atypical perceptions might be an important cause of the social impairments [1]. Our previous studies [2][3] showed that some people with ASD percieve visual/auditory noise which does not exist in the environment, especially when the environmental stimuli (e.g. movement of objects or loudness of sound) change rapidly.

The aim of this study is to investigate the underlying neural mechanism of phantom noise in ASD. Both top-down prediction and spontaneous neural activities are assumed to play a role in perceiving sensory stimuli [4][5]. Based on this idea, we hypothesize that in case of individuals with ASD, their deficit in referring prior information [6] induces hyper spontaneous neural activities, which may become the source of phantom noise. Our current study verifies the hypothesis by building a computational model.

Model design

We propose a computational model that integrates the prediction and spontaneous neural activities into the process of perceiving sensory input (Figure 1). The model consists of four modules: The sensation module first receives an external stimulus. Then the modules of prediction and stochastic resonance, which is a type of spontaneous neural activity, modulate the signal. The resulting signal is finally perceived as a meaningful pattern by the perception module.

1. Stochastic resonance

This study adopts stochastic resonance as a mechanism of spontaneous neural activities. Stochastic resonance is a phenomenon that a subthreshold signal can be boosted and better recognized by adding a moderate level of noise [5]. The module of stochastic resonance implements a feedback-loop control to determine the optimal level of noise which could maximize the information content of output response.

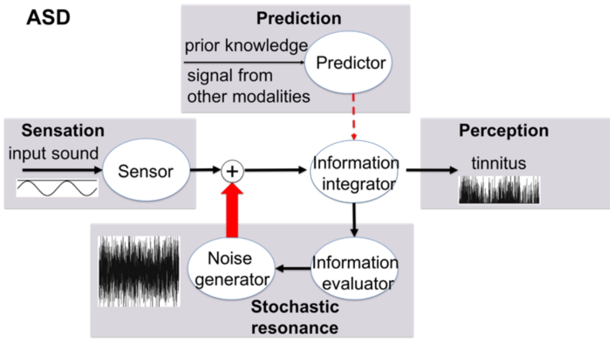

Figure 1. The architecture of the computational model.

The information evaluator calculates the information content by autocorrelation AC, wich is the correlation between a sequence of signal and another sequence of the same signal but with a lag-time τ:

$$AC(\tau) = \frac{\frac{1}{W/2-\tau}\sum_t (x(t)-\mu_x)(x(t+\tau)-\mu_x)}{\sigma_x^2}, \quad (1)$$

where W is the time window of the preceding signal, μ_x is the mean of signal intensity x, and σ_x^2 is the standard deviation of x. By averaging the results of autocorrelation with different lag-times, we finally obtain the mean autocorrelation:

$$AC = \frac{1}{W/2}\sum_{\tau=1}^{W/2} AC(\tau), \quad (2)$$

which is used to represent the information content of the output response.

2. Predictor

We designed a prototype of the predictor and tested its performance in a simplified situation, where the input signal was a sinusoid:

$$x = A \cdot \sin(vt). \quad (3)$$

The predictor follows the idea of predictive coding, which applies Baye's thereom [4]:

$$p(v|u) = \frac{p(v)p(u|v)}{p(u)}, \quad (4)$$

where u is the observation of x, to estimate the most likely v as ϕ. Figure 2 shows an example how it predicts an input signal with a perceptual threshold. The prior knowledge of ϕ was set as 1.5. The result of estimationproperly converged to the true value as 2.0.

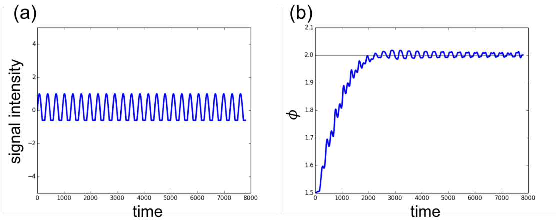

Figure 2. The performance of predictor: (a) Input signal (b) Estimation of parameter ϕ of the signal.

Preliminary experiment

We conducted a preliminary experiment to verify our hypothesis that the deficit in referring prior information may cause hyper spontaneous neural activity, which results in phantom noise. We manipulated the time window (W in Eq. 1) to examine its efffect on the level of neural noise created by the stochastic resonance module. The length of time window indicates how much prior information should be referred to in order to determine the optimal level of noise that maximizes the information content.

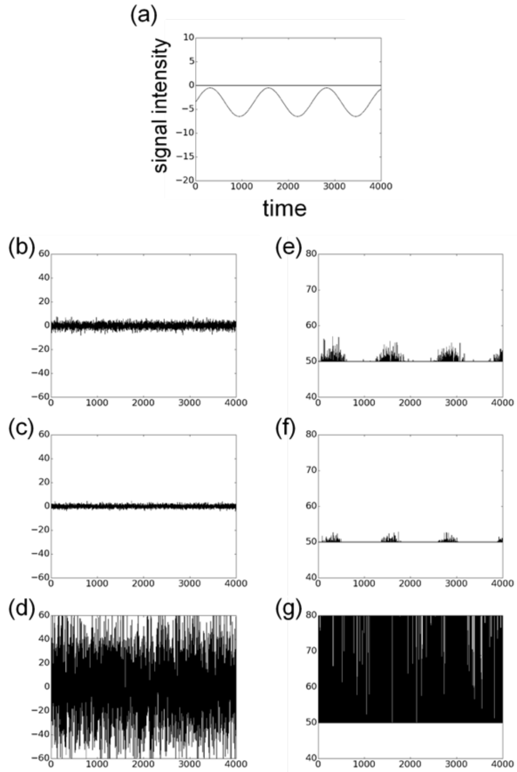

Figure 3. The results of preliminary experiment: (a) Input signal. (b)(c)(d) Added noises with time window 900, 500, and 100 respectively. (e)(f)(g) Output responses with time window 900, 500, and 100 respectively.

We used a sine wave signal with an intensity below the perceptual threshold (Figure 3a) as an input stimulus. The results show that the pattern of the input stimulus was better revealed in the output response (Figure 3e, f) with the moderate levels of noise (Figure 3b, c) when W was longer enough (W = 900 and 500, respectively). This demonstrates the advantage of stochastic resonance. In contrast, when the time window was too short (W = 100), a stronger noise (Figure 3d, g) was generated, resulting in the difficulty in recognizing the original signal.

The above results could be explained by a systematic analysis of autocorrelation shown in Figure 4. The autocorrelation should exhibit a peak with a moderate level of noise, like the curves of time window 500 and 900, but there is no a such peak in the curve of time window 100. This may be caused by the insufficient information from the preceding signal.

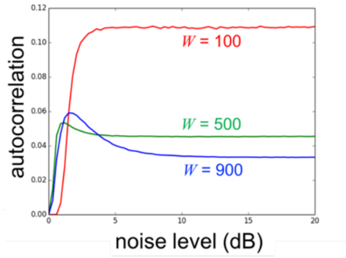

Figure 4. The autocorrelation corresponds to a variety of noise level with different time window W.

Conclusion

We proposed a computational model to account for the phantom noises observed in ASD. Stronger neural noise was generated when the time window of the preceding signal was too short, which is considered as less prior information. The results support our hypothesis that the deficit in referring prior information may be a cause of phantom noise. Future work will be carried on to further demonstrate how the atypical function of the predictor influence the intensity of neural noise.

References

[1] S. Ayaya and S. Kumagaya, "Hattatsu Shogai Tojisha Kenkyu," *Igaku-shoin*, 2008.

[2] Y. Nagai, S. Qin, S. Kumagaya, S. Ayaya, and M. Asada, "Computational Analysis of Atypical Visual Perception in Autism Spectrum Disorder: Application to Perception Simulator," *Proceedings of the 32nd Annual Meeting of the Japanese Cognitive Science Society*, pp. 32-40, Sept. 2015.

[3] J. Hsieh, Y. Nagai, S. Kumagaya, S. Ayaya, and M. Asada, "Atypical auditory perception in autism spectrum disorder: Different patterns caused by environmental stimuli," *3rd Int. Symp. Cogn. Neurosci. Robot. Towar. Constr. Dev. Sci.*, 2016.

[4] K. Friston, "A theory of cortical responses.," *Philos. Trans. R. Soc. Lond. B. Biol. Sci.*, vol. 360, no. 1456, pp. 815–36, 2005.

[5] F. Moss, L. M. Ward, and W. G. Sannita, "Stochastic resonance and sensory information processing: A tutorial and review of application," *Clin. Neurophysiol.*, vol. 115, no. 2, pp. 267–281, 2004.

[6] E. Pellicano and D. Burr, "When the world becomes 'too real': A Bayesian explanation of autistic perception," *Trends Cogn. Sci.*, vol. 16, no. 10, pp. 504–510, 2012.