確率共鳴に起因しうる自閉スペクトラム症のノイズ幻覚

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あらまし 我らの先行研究で，自閉スペクトラム症当事者が外界には存在しないノイズ幻覚を知覚することが明らかになった．我らは確率共鳴理論に基づいて計算モデル設計し，モデルを用いてノイズ幻覚の神経メカニズムを検証する．正常の状況に確率共鳴は入力信号の構造を強調して検知できるようにする機能があるが，調整の異常で不快なノイズを起こす可能性もある．本研究では，その計算モデルの各パラメータが聴覚の過度な神経反応にどのように影響することを検討する．

キーワード 自閉スペクトラム症，確率共鳴，ノイズ幻覚，耳鳴り，計算モデル

Stochastic Resonance as a Potential Cause for Phantom Noise in Autism Spectrum Disorder

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Abstract Our previous experiments found that some people with ASD suffer from phantom noise in both visual and auditory perception. We built a computational model based on stochastic resonance to investigate the underlying neural mechanism of phantom noise. Stochastic resonance normally helps people recognize input signals by emphasizing their structure but may induce unpleasant noise with atypical modulation. Our current study demonstrates how different parameters of the model affect hyper neural responses in auditory perception.

Keywords Autism spectrum disorder, Stochastic resonance, Phantom noise, Tinnitus, Computational model

1. Introduction

Autism spectrum disorder (ASD) is a developmental disorder characterized by impaired social abilities and stereotyped behaviors, but there are also some reports suggested that the atypical perceptions might be an important cause of the social impairments [1]. Our previous studies [2][3] found some people with ASD have noise perception in visual modality (visual snow) [2] or auditory modality (tinnitus) [3], especially when the environmental stimuli (e.g. movement of objects or loudness of sound) changes rapidly. This noise perception occurs even while there is no similar noise existing in the environment, thus we named it as phantom noise.

In addition to our studies, there are also some other reports indicating many autistic people suffer from phantom noise. For example, tinnitus was found to be more prevalent in population with Asperger's syndrome than general public [4]. Furthermore, although it's not from a formal scientific report, there are some videos made by autistic people to share their sensory experience in the internet. Perception similar to visual snow has also been mentioned many times in these videos. However, our understanding of phantom noise in ASD is still insufficient, and the studies trying to investigate the underlying mechanism are very rare. On the other hand, tinnitus is a symptom that many people have experienced , no matter they have ASD or not. Thus many studies about the potential mechanism of tinnitus in general population already exist [5][6][7], including some studies using computational model to verify the hypotheses [8][9]. Even though the cause of phantom noise may be different between ASD and general population, we still can get insights from these studies to make a hypothesis of mechanism of phantom noise in ASD.

The goal of this study is to investigate the underlying neural mechanism of phantom noise in ASD. Previous studies have shown that insufficient information of signal caused by hearing loss might induce tinnitus by stochastic resonance [8], and people with ASD have deficit in predicting abilities [13][14]. In this study we suggest a new hypothesis that the impaired information from prediction may cause the phantom noise in ASD, and we created a computational model based on stochastic resonance to verify our hypothesis. The details of our hypothesis are introduced in the following sections.

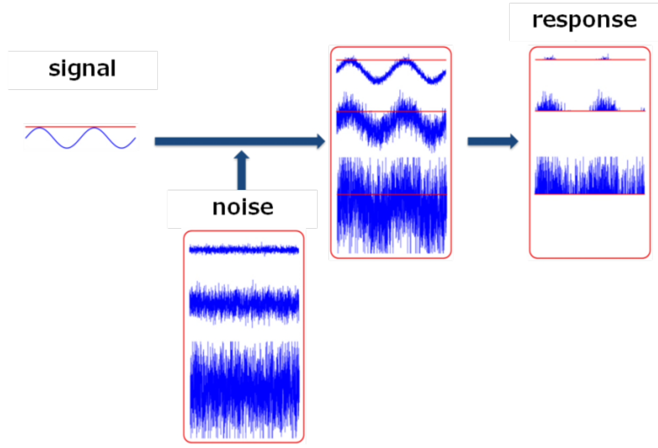

Figure 1: The enhanced detection of weak signal by stochastic resonance.

2. Key ideas

2.1. Phantom noise caused by stochastic resonance

A computational model based on stochastic resonance (SR) has been used to investigate the mechanism of tinnitus caused by hearing loss [8]. The benefit of adopting this theory to investigate phantom noise is that stochastic resonance is not restricted to auditory perception but involves in other modalities [10], whereas some models are designed only for tinnitus [9]. Stochastic resonance is a phenomenon whereby the detection of weak stimuli can be improved by adding a moderate level of noise [10] (Figure 1). The stochastic resonance works when the relationship between the input signal and output response is nonlinear. A weak signal itself cannot be detected if the intensity is below the threshold, but it may exceed the threshold after a noise was added. Only an optimal amount of added noise results in the maximization of information transmitted from signal to response. Too weak noise is unable to make the signal cross over the threshold, while too strong noise will mask the information content of signal.

2.2. Atypical prediction ability in ASD

In the previous study [8], Krauss et al. suggested hearing loss will diminish the threshold and further reduce the amount of information able to pass the threshold. To compensate the lost information of signal, a stronger noise will be produced and might become the cause of tinnitus. In conclusion, they supposed tinnitus is a side-effect of stochastic resonance while the original purpose is to assist signal detection. Although the hearing loss is considered as a common cause of tinnitus [11][12], the prevalence of hearing loss among autistic people is not higher than general population [4], which implies another cause of phantom noise might exist in ASD. Our previous studies of ASD perception exhibit the high correlation between phantom noise and the changing of stimuli [2][3], which implies the phantom noise may occur when the environment is unpredictable. Other studies also show the atypical characteristic of predicting behaviors in ASD [13][14]. Based on these evidence, we hypothesize that the hyper-prior [13][15][16] is the cause of phantom noise in ASD. Hypo-prior theory assumes people with ASD has broader prior, therefore the prediction according to prior knowledge become less effectual. As a result, the information provided by prediction in ASD is not as much as the available information in typical development (TD). Similar to the mechanism in the case of hearing loss, phantom noise might be induced when the stochastic resonance tries to compensate the information loss by adding stronger noise (Figure 2B).

3. Model design: A computational model based on stochastic resonance

We adapt a computational model based on stochastic resonance from the study of tinnitus caused by hearing loss [8] to create our model. The model originally consists of three functional units: sensor, information detector, and noise generator, to perform a feedback control of the added noise. We assume the information from prediction should be also involved to help the recognition of input stimuli, so a predictor would be included to deal with the prediction function (Figure 2). The sensor receives the

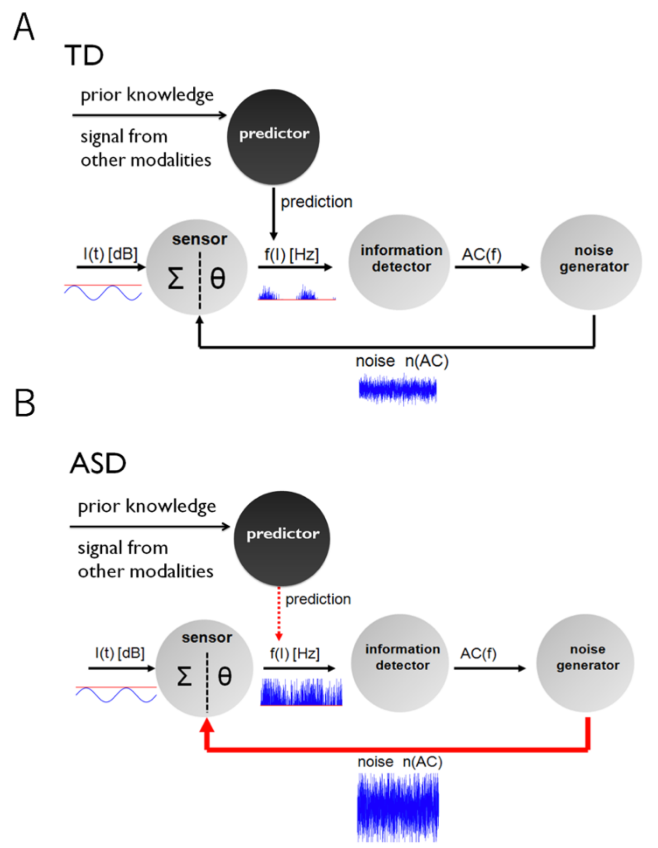

Figure 2: The architecture of the computational model based on stochastic resonance.

input signal and outputs the neural response, then the response would be checked by the information detector in order to evaluate the information content. The noise generator is controlled by the information detector and can inject a noise back to the sensor. The noise would be summed with the input signal and induce a different response. Through a feedback control, this system would choose an optimal noise which could maximize the information content in the response, where the pattern of the signal could be better recognized.

3.1. Sensor

In the current study we assume the input signal is auditory stimuli and adopt the model of auditory nerve (AN) firing rate [9] as the responses function of the sensor. However, we suppose this model could also be applied to other sensory modalities once we modify the response function for the target modality. The threshold of sensor I_θ is set as 0 dB SPL. When the intensity of input stimuli I is below the threshold the response remains on the spontaneous firing rate f_{sp} = 50 Hz. For $I > I_\theta$, The response function $f(I)$ is proportional to the normalized cumulative distribution function $\int_{I_\theta}^{I} p_I(I')dI'$ of the sound intensities according to the infomax principle [17]:

$$f(I) = \begin{cases} f_{sp} & \text{for } I < I_\theta \\ f_{sp} + (f_{max} - f_{sp}) \dfrac{\int_{I_\theta}^{I} p_I(I')dI'}{1 - P_{sp}} & \text{for } I \geq I_\theta \end{cases}, \quad (1)$$

where $P_{sp} = \int_{I_{-\infty}}^{I_\theta} p_I(I)dI$ is the probability of occurrence of spontaneous firing rate, and f_{max} is 250 Hz.

3.2. Information detector

In order to determine the optimal noise which can maximize the information content, a method to quantify the information transduction from the input signal to the output response is required. Traditional measures like mutual information [10][18] or signal-to-noise ratio (SNR) [10][19] are frequently used in theoretical approaches to investigate the performance of stochastic resonance, but these measures demand the knowledge of the input signal, which is sometimes unknown for the system. We use autocorrelation of the sensor response instead, because its calculation doesn't need the information of input signal [8][20]. Autocorrelation is the correlation between a sequence of signal and another sequence of the same signal with a lag-time. In our model, the information detector takes a time window W of the preceding signal to calculate the autocorrelation. The autocorrelation function of a particular lag-time τ is defined as:

$$AC(\tau) = \frac{\frac{1}{W/2 - \tau} \sum_t (f(t) - \mu_f)(f(t+\tau) - \mu_f)}{\sigma_f^2}, \quad (2)$$

where μ_f is the mean of AN firing rate f, and σ_f^2 is the standard deviation of f. By averaging the autocorrelation function over all estimated lag-times finally we get the mean autocorrelation:

$$AC = \frac{1}{W/2} \sum_{\tau=1}^{W/2} AC(\tau), \quad (3)$$

which would be used to represent the information content of the output response.

3.3. Noise generator

The noise from noise generator is a white noise with constant mean fixed on 0 dB, but the variance could be changed to produce a variety levels of noise. The term “noise level” in this study actually indicates the variance of the noise. This model introduces a feedback-loop to control the level of noise. The noise is summed with the signal to become the input of sensor. Still only the intensity of the input beyond can pass the threshold and be detected, so equation (1) can be modified to:

$$f\big(I + n(AC)\big) = \begin{cases} \mathrm{f_{sp}} & \text{for } \mathrm{I + n(AC) < I_\theta} \\ \mathrm{f_{sp}} + \left(\mathrm{f_{max} - f_{sp}}\right)\dfrac{\int_{\mathrm{I_\theta}}^{\mathrm{I+n(AC)}} p_{\mathrm{I}}(\mathrm{I'})\mathrm{dI'}}{1 - \mathrm{P_{sp}}} & \text{for } \mathrm{I + n(AC) \geq I_\theta} \end{cases}, \quad (4)$$

The noise with the level which can maximizes the mean autocorrelation of the response would be chosen by this system.

3.4. Predictor

The predictor is designed to provide the prediction according to prior knowledge and the stimuli of different modalities. We presume the prediction could refine the output response into a more informative state by Bayesian inference. The prediction plays the role as a prior $p(R)$, and the AN response before Bayesian inference is the observation $p(f)$. The posterior, here is the evaluated response after Bayesian inference $p(R|f)$, could be obtained by the calculation based on Bayes’ rule:

$$p(R|f) = \frac{p(f|R)p(R)}{p(f)}, \quad (5)$$

When the intensity of input is weaker than threshold, the information of the signal could not be revealed in the AN response. The inference from the prediction should be able to refill the lost information. In the case of ASD, hypo-prior make the prediction become more uncertain and unable to contribute enough information to the posterior. There are two kinds of sources for the predictor to refer to. We plan to first implement the prediction from prior knowledge. To simplify the calculation, the prior knowledge would be directly provided to the system. The pattern of the prior would be set to be close to the signal, so it should contain useful information for recognition of the signal. At the next step, we would like to further apply the idea of multimodal prediction [21][22] into this model.

4. Preliminary experiments:

We executed two preliminary experiments before formal examination of our hypothesis. The original purpose is to check whether our model could exhibit the basic performance of stochastic resonance, and to clarify the effects of different parameters of the model. However, we found some interesting results that may be able to better explain the occurrence of phantom noise than previous studs.

4.1. Effect of noise level

The elementary idea of stochastic resonance is that the recognition of a weak signal could be improved by adding a moderate level of noise, not too strong or too weak. To demonstrate this basic performance of our model, we manipulated the range of noise level to be searched by the noise generator. If our model works properly, once the range covers the optimal noise level, we should always get similar results. We simply changed the upper limit of the range between 5, 10, and 30 dB and checked the results. The input stimulus is a sequence of sine wave signal (Figure 3A) while half of it is under the threshold. The time window for autocorrelation calculation was set as 30 time steps.

Unfortunately, the results violate our prediction (Figure 3C, D). Although the pattern of the signal could be somehow revealed, especially when the upper limit of noise is 10, the noise level grows as the upper limit increases. We cannot get the moderate level of noise when the upper limit is 30, even though the optimal noise level should be already covered in this range. The good thing is that the reason to cause this failed performance was found in the next experiment. Actually it is because of the setting of time window. Another point which should be noticed is that the abnormal strong noise (Figure 3C) may be related to phantom noise. The details would be explained in the next section.

4.2. Effect of time window

Before directly using the predictor to verify our hypothesis, here we introduce a simpler way to estimate the effect of information content from prior experience. For each time point, the information detector takes a length (time window) of preceding signal to calculate the

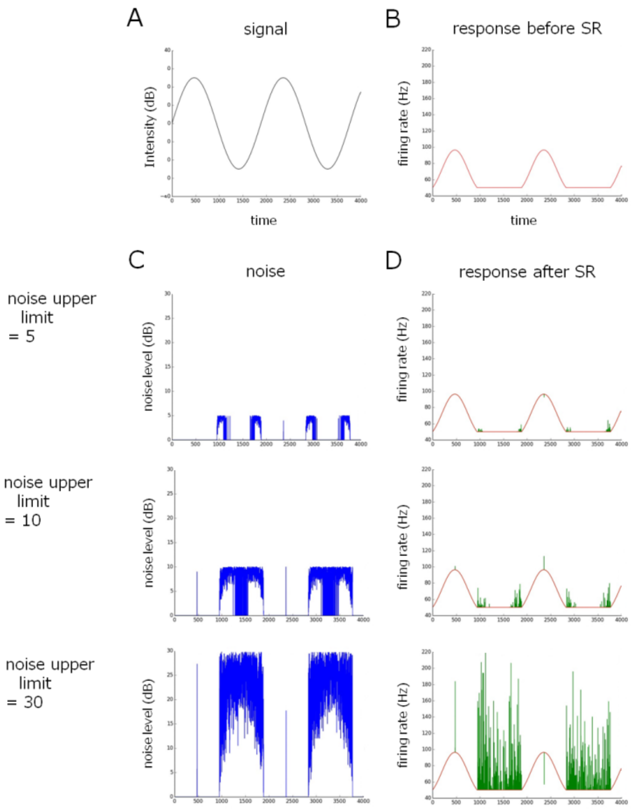

Figure 3: The results of preliminary experiment of modification on noise range. (A) The input signal. (B) The AN response without SR. The signal cannot be detected when the intensity is lower than the threshold 0 dB. (C) The noise induced by SR. (D) The AN response after adding the noise.

autocorrelation. We can consider this process as that the information detector refers to the recent states of the stimuli to predict the current state. A longer time window means the system take more information from the preceding history into account. In this experiment, we manipulated the time window between 100, 200, … , and 800 time steps and examined the effect. The input stimulus is a sine wave signal with the intensity below the threshold (Figure 4A). We also want to verify why a moderate noise could not be picked out in the previous experiment, so we recorded the mean autocorrelation of the response corresponding to different levels of noise (Figure 5). For each time window we conducted 1000 trials and averaged the results to plot Figure 5.

Figure 4C shows the result that the pattern of signal could be well revealed when the time window W is longer enough, but the abnormal strong noise appears again when the time window is too short. The reason of

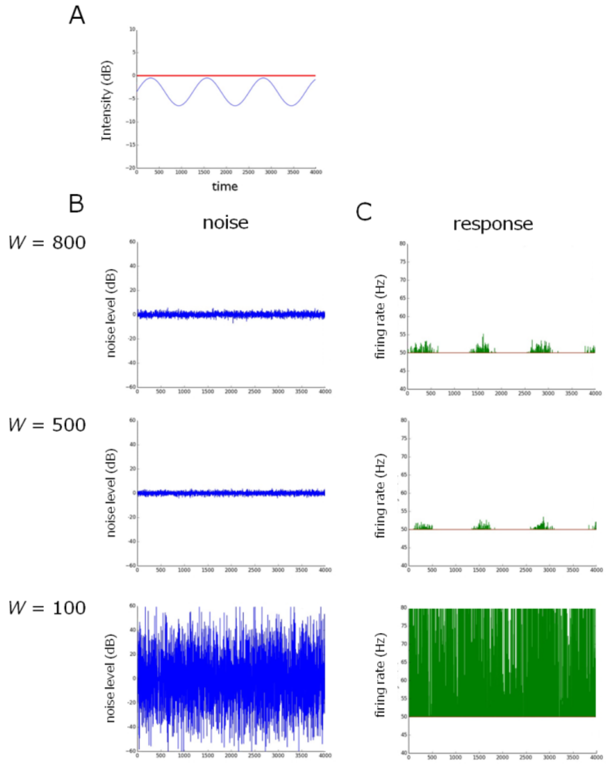

Figure 4: The results of preliminary experiment of modification on time window. (A) The input signal and the threshold. (B) The noise induced by SR. (C) The AN response after adding the noise.

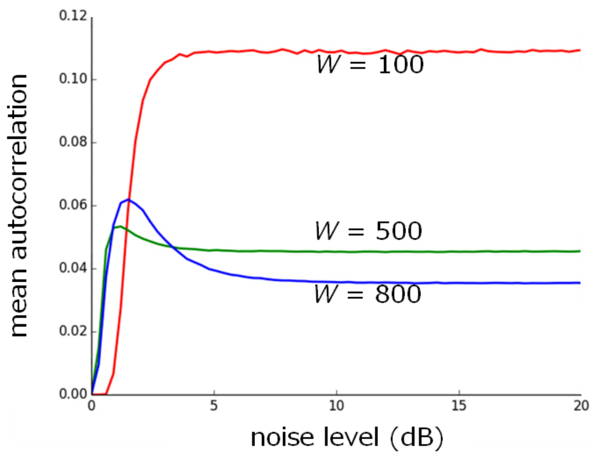

Figure 5: The autocorrelation corresponds to a variety of noise level with different time window W.

this result could be found in Figure 5. The results of the case while W = 800 or 500 shows the typical curve of stochastic resonance. There is a peak of autocorrelation locating at a moderate noise level, which is also the optimal

noise level resulting in the better recognition of signal. In contrast, when time window is only 100, the autocorrelation curve exhibits a plateau shape. An optimal noise level could not be determined. In this condition, all noise levels larger than the start point of the plateau region are possible to be chosen by the model. An abnormal strong noise like the case in lower panel of Figure 4C may probably be triggered. It can also be used to explain the unexpected results in preliminary experiment 1, since the time window is also too short, which is only 30. Following the same idea, increasing the upper limit of the noise range only extends the plateau region so that the noise cannot stay at a moderate level but is enhanced as the upper limit increases. This experiment successfully replicated the essential function of stochastic resonance and resolved the problem occurred in the previous experiment. The results also support the idea that
the abnormal strong noise, which may be the cause of phantom noise, would occur when the information from the prior event is impaired. The possible explanation is that the information from the input signal is too less and may be easily masked by the information from the noise.

5. Discussion

This study confirmed the performance of our model on stochastic resonance and demonstrated that the phantom noise may occur when the information from prior events is insufficient. In the study of tinnitus caused by hearing loss [8], Krauss et al. claimed the added noise to compensate the lost information may induce tinnitus as a side-effect, but they didn't explain the possible mechanism of how would the noise be perceived as tinnitus. The intensity of added noise in their study is similar to the one we found when time window is longer enough (Figure 4C, upper and middle panels). If the stochastic resonance works well, the added noise (partially) represents the pattern of signal and should be perceived as part of the signal. It is hard to imagine the moderate noise would result in an annoying perception as tinnitus. In contrast, the abnormal strong noise we found in the current study (Figure 4C, lower panel) is highly plausible to be the origin of the phantom noise. This result provides a new insight of how the noise created by stochastic resonance become annoying phantom noise. In this case, the phantom noise is not a side-effect of stochastic resonance, but it is a consequence when the stochastic resonance fails to perform its function.

The results of preliminary experiments stand with the side of our hypothesis that the information deprivation from prior experience may cause phantom noise. However, there is a big gap between the preliminary experiment and our hypothesis since the prediction function was not directly accessed in the preliminary experiments. Currently we are working on the implement of the prediction function into our model and plan to execute the experiment directly manipulates the prediction function. We propose to introduce the prediction from not only the previous knowledge but also the stimuli of other modalities. It is possible to create a network by connecting sensory modalities through the reference of prediction. The interaction between the phantom noise from different modalities might be able to explain phenomena like the coincidence of visual snow and tinnitus in migraine [23] might be able to be explained by this network.

Our hypothesis includes an assumption that people with ASD has the difficulty to employ the information from prediction. Even if the information loss from prediction could be proved to be a cause of phantom noise, we need more concrete evidences to support the argument that phantom noise in ASD shares the same cause with our model. A potential way to address this issue is to verify whether the characteristics (e.g. the frequency of tinnitus) of phantom noise in ASD could be replicated in our model. The present model adopts a simplified one-channel signal, which could be regarded as an auditory signal with one frequency channel. A model compatible with a complex, realistic, and multi-channel signal input is necessary for replicating the phantom noise in ASD. On the other hand, the knowledge about the characteristics of phantom noise in ASD is still poor. We are also working on an experiment to investigate the pattern and environmental cause of atypical perception in ASD. We expect the results can unveil the characteristics of phantom noise like frequency of tinnitus and might further help to verify the hypothesis in this study.

6. Conclusion

We proposed a new hypothesis that the impaired information from prediction may cause the phantom noise in ASD, and we design a computational model based on stochastic resonance to verify the hypothesis. Currently the prediction function of our model is under working, but by the preliminary experiment we still found that insufficient information from prior experience might induce phantom noise, which indirectly supports our hypothesis. We also found an abnormal strong noise produced by the model. This kind of noise has not been reported in the previous study and fit the feature of phantom noise better. Future work will be carried on to further demonstrate the effect of prediction on phantom noise.

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