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BINARY DETECTION IN PARALLEL SENSOR NETWORKS SUBJECT TO ADDITIVE NOISE AND MULTIPLICATIVE NOISE

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Abstract. *This paper aims to investigate the stochastic resonance (SR) phenomenon of binary detection in parallel sensor networks (PSNs) with additive noise and multiplicative noise. Unlike many other kinds of networks, PSN is the special one that flows from a source common to all nodes in the sensor network. In this PSN, the background additive noise can always be regarded as Gaussian form in terms of the central limit theorem (CLT), while the external multiplicative noise exhibits a different style under different scenarios. Based on the maximum a posteriori probability (MAP) criterion, we first analyze the influence of both multiplicative and additive Gaussian noise intensities on error detection probability of the PSN. The theoretical and numerical analyses reveal that noise can improve binary signal detection performance for the simplified version of the PSN (single-sensor system), which leads to producing increased information-rich responses. Meanwhile, we find that more sensor nodes can bring higher signal transmissions and SR occurs easier with the signal in larger sensor threshold levels. Finally, we extend the multiplicative noise form to uniform case and present the corresponding SR efficacy.*
Keywords: Stochastic resonance, Parallel sensor networks, Error detection probability, Background additive noise, External multiplicative noise

1. Introduction.

Noise can sometimes enhance the responses of some nonlinear systems. This counterintuitive phenomenon is primarily known as stochastic resonance (SR), which was proposed by Benzi et al. in 1981 to explain the periodic climate change of Earth's ice and warm ages in remote antiquity [1]. In the field of artificial sensors and biological senses, noise is ubiquitous. Extensive studies have been reported on SR as an effective way to make use of the noise [2-12].

Parallel sensor networks (PSNs) are proposed to model the simplest architectures in sensor networks where the common information source is processed separately through multiple sensors and a fusion operator that combines the individual measurements of each sensor to create an overall response. Owing to the interaction between random noise and nonlinearity, SR phenomena are often observed in the PSNs. It is worth noting that PSNs can potentially imitate from biological sensory processing to engineered sensors, such as synapses, receptor cells, and noisy analog-to-digital converters. Zozor et al. [6] first came up with the conception of PSN to depict a population of sensors that a common information source is transmitted to each sensor to produce binary measurements. McDonnell [7] investigated the information transmission optimization in PSNs. It is demonstrated that the information capacity in the PSN (their nodes are quantized to finite states) can be achieved by discrete input signal. In [8], Chen et al. explored the distributed detection problem in a parallel fusion network to achieve possible global optimization performance. They compared the optimal and suboptimal rules for distributed detection, where the input constant signal is subjected to Gaussian noise.

A PSN is equipped with the three salient features. First, multiple sensor nodes receive a common input signal and make stochastic observations. The measured input signal can be various kinds of information source, such as discrete binary signal [5,9] and continuous Gaussian signal [10]. The meaning of stochastic observations is that each measurement denotes a random variable under the common input signal. This stochasticity may arise either internally in a sensor node (background additive noise) or externally (multiplicative random noise). Second, each sensor makes local processing of the noisy signal via quantization. The node's input is composed of the information source and random noise. Due to the quantization nature of each sensor node in the network, the node's output is a discrete variable with finite states. Finally, all the outputs from the PSN's individual sensors are combined by summation in the 'fusion center'. The resulting measurements are pooled to form an overall network response, which results in a single observation of the information source.

Unfortunately, most of researches on PSNs only stare at one noise source. As a matter of fact, various noise sources such as the synchronous action of both additive and multiplicative noise are bound to arise in PSNs, e.g., the background and external noise in electronic devices. In this paper, we attempt to investigate the influence of background and external noise on the binary detection of PSN. The background noise is usually induced by the complex motion of the atoms in electronic components, which can be approximately regarded as additive Gaussian noise on the basis of the central limit theorem (CLT) [2,13]. The external noise produced with signals or information channels is often signal-dependent or multiplicative, which has a variety of forms [5,12]. First, we describe a PSN model and introduce the mechanism of information transmission. Second, we explore the binary distributed detection of the PSN in the scenario with background additive Gaussian and external multiplicative Gaussian noise. Then, we extend the external disturbance to the uniform case, which represents a general class of scenario. Finally, we analyze the influence of noise, threshold and array number altogether and evaluate the detection performance of the PSN in detail.

2. **System Model.**

Consider a parallel sensor network with N noisy sensor nodes as shown in Figure 1. All sensors receive the common input s, which is a binary signal (s_1, s_2).

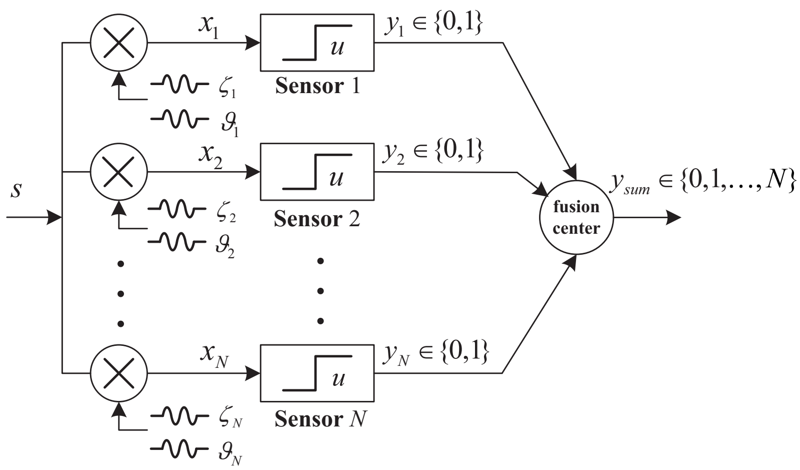

FIGURE 1. Schematic diagram of a parallel sensor network. This PSN consists of N identical binary-quantizing nodes, the input signal s is simultaneously disturbed by background additive noise ζ_i and external multiplicative noise ϑ_i and the output of each sensor node y_i is quantized to produce binary discrete results. The overall PSN's response y_{sum} processed by a fusion center is the sum of the N sensors' outputs, i.e., $y_{sum} = \sum_{i=1}^{N} y_i$.

It is well known that the background additive noise and the external multiplicative noise are widely distributed in physical systems. Due to the CLT, the background additive noise is always Gaussian noise [2,13]. In addition, the external multiplicative noise may be a variety of distribution. Here, we first assume that the i-th individual sensor node is subject to independent and identically distributed ($i.i.d.$) additive Gaussian noise ζ_i and multiplicative Gaussian noise ϑ_i, respectively. So, we have

$$\langle \zeta_i, \zeta_j \rangle = 0,\ \langle \vartheta_i, \vartheta_j \rangle = 0,\ i \neq j \quad \text{and} \quad \langle \zeta_i, \vartheta_j \rangle = 0, \quad i, j = 1, 2, \ldots, N \tag{1}$$

In order to quantitatively explore the effect of noise, we assume that the probability density of Gaussian noises ζ_i, ϑ_i, are obedient to the standard Gaussian distribution. Hence, the probability density function (PDF) and cumulative distribution function (CDF) of variables ζ_i, ϑ_i are expressed as $f(t) = 1\big/\sqrt{2\pi}\exp\left(-t^2/2\right)$ and $F(t) = 1/2 + 1/2 erf\left(t\big/\sqrt{2}\right)$ with the error function $erf(t) = 2\int_0^t \exp\left(-z^2\right)dz\Big/\sqrt{\pi}$.

In the PSN, the output of each sensor node y_i is given by the Heaviside function [10]

$$y_i = \begin{cases} 1, & x_i \geq u \\ 0, & x_i < u \end{cases} \tag{2}$$

where u is the threshold level of sensor nodes in the PSN.

The input to each sensor node x_i is disturbed by multiplicative and additive noises as

$$x_i = s + M\zeta_i s + A\vartheta_i \tag{3}$$

where M, A denote the multiplicative noise intensity and additive noise intensity, respectively.

For the given input signal s, the overall response of the PSN $y_{sum} = \sum_{i=1}^N y_i$ obeys the binomial distribution, and its values range from 0 to N (we denote this domain as $R = \{m | m = 0, 1, \ldots, N\}$). The probability of $y_{sum} = n$ ($n \in R$) can be calculated by

$$P\left\{\sum_{i=1}^N y_i = n | s\right\} = C_N^n q_s^n (1 - q_s)^{N-n} \tag{4}$$

where $C_N^n = \frac{N!}{n!(N-n)!}$, $q_s = P\{y_i = 1 | s\}$, $n = 0, 1, \ldots, N$.

3. **A Noisy Binary Detection in the PSN.** In this section, we give the analysis of the detection performance of the proposed PSN subject to both additive Gaussian noise and multiplicative Gaussian noise. The exact expression of error detection probability (EDP) is derived. In order to have a better understanding of the impact of multiplicative noise, additive noise, sensor threshold and the array number on signal detection, we analyze the EDP metrics of the PSN.

The detection problem of the PSN can be formulated as a binary hypothesis-testing problem for deciding a null hypothesis H_0 ($s = s_0 = 0$) and an alternative hypothesis H_1 ($s = s_1 = 1$), and their prior probabilities are P_0 and P_1 ($P_0 + P_1 = 1$). Based on the likelihood ratio, the binary detection of the PSN can be obtained by

$$\frac{P_0 \cdot P_r\left(y_s = n \left| H_0\right.\right)}{P_1 \cdot P_r\left(y_s = n \left| H_1\right.\right)} > 1 \tag{5}$$

to decide hypothesis H_0, or to decide hypothesis H_1 conversely.

In terms of the maximum a posteriori probability (MAP) criterion, the minimal EDP reached by this PSN can be expressed as

$$P_{er} = \frac{1}{2} - \frac{1}{2}\sum_{n \in M} \left| P_0 \cdot P_r\left(y_{sum} = n \left| H_0\right.\right) - P_1 \cdot P_r\left(y_{sum} = n \left| H_1\right.\right) \right| \tag{6}$$

where $P_r\left(y_{sun} = n \left| H_l\right.\right)$ denotes the conditional probability of obtaining y_{sum} for hypothesis H_l holds ($l = 0, 1$).

So we can also formulate the conditional probabilities as follows:

$$P_r\left(y_i = 0 \left| H_0 \right.\right) = P_r\left(s_0 + M\zeta_i s_0 + A\vartheta_i < u \left| H_0 \right.\right) = F\left(\frac{u - s_0}{\sqrt{M^2 s_0^2 + A^2}}\right) = q_0 \quad (7)$$

$$P_r\left(y_i = 1 \left| H_0 \right.\right) = 1 - q_0 \quad (8)$$

$$P_r\left(y_i = 0 \left| H_1 \right.\right) = P_r\left(s_1 + M\zeta_i s_1 + A\vartheta_i < u \left| H_1 \right.\right) = F\left(\frac{u - s_1}{\sqrt{M^2 s_1^2 + A^2}}\right) = q_1 \quad (9)$$

$$P_r\left(y_i = 1 \left| H_0 \right.\right) = 1 - q_1 \quad (10)$$

Herein, we use q_0 to denote the conditional probability $P_r\left(y_i = 0 \left| H_0 \right.\right)$, and q_1 to denote the conditional probability $P_r\left(y_i = 0 \left| H_1 \right.\right)$.

For the sake of convenience and without loss of generality, we assume the input binary signal s takes the same prior probability ($P_0 = P_1 = 0.5$). In [11], Mitaim and Kosko considered the binary signal which has bipolar form $\{-A, +A\}$. While here, we adopt a more universal unipolar shape with the unit amplitude, i.e., $s_0 = 0$, $s_1 = 1$. The overall response of the PSN y_{sum} obeys the binomial distribution, which is given as

$$\begin{cases} P_r\left(y_{sum} = n \left| H_0 \right.\right) = C_N^n (1 - q_0)^n q_0^{N-n} \\ P_r\left(y_{sum} = n \left| H_1 \right.\right) = C_N^n (1 - q_1)^n q_1^{N-n} \end{cases} \quad (11)$$

Specially, when the array number of the PSN $N = 1$, the PSN degenerates into a single-sensor system. Yet, Equation (6) can be simplified as

$$\begin{aligned} P_{er} &= \frac{1}{2} - \frac{1}{2}\left[\left|\frac{1}{2}P_r\left(y = 0 \left| H_0 \right.\right) - \frac{1}{2}P_r\left(y = 0 \left| H_1 \right.\right)\right| + \left|\frac{1}{2}P_r\left(y = 1 \left| H_0 \right.\right) - \frac{1}{2}P_r\left(y = 1 \left| H_1 \right.\right)\right|\right] \\ &= \frac{1}{2} - \frac{1}{4}\left\{ erf\left(\frac{u}{\sqrt{2}A}\right) - erf\left(\frac{u-1}{\sqrt{2\left(M^2 + A^2\right)}}\right)\right\} \end{aligned} \quad (12)$$

We first use the degraded PSN (a single-sensor system) to investigate the influence of sensor threshold u, additive noise intensity A and multiplicative noise intensity M for SR efficacy in Sections 3.1 and 3.2.

3.1. The effect of threshold u.

Theorem 3.1. *The error detection probability P_{er} increases as noise intensity A and M when $u \in (0, 1]$.*

Proof: Equation (12) can be simply denoted as $P_{er} = 1/2 - 1/4\left\{ erf\left(u/\sqrt{2}A\right) - erf\left((1-u)/\sqrt{2(M^2 + A^2)}\right)\right\}$. Due to the monotonous nature of the error function, we know that at a fixed additive noise intensity A the P_{er} increases with increasing multiplicative noise intensity M when $u \in (0, 1]$ and decreases with increasing multiplicative noise intensity M when $u \in (1, \infty]$, i.e., it shows that the multiplicative noise is always beneficial to the detection of subthreshold signal. When $u \in (1, \infty]$, u and $u - 1$ are both positive, the P_{er} increases as the noise intensity A and M, i.e., SR does not exist. When $u \in (1, \infty]$, the P_{er} alternately increases and reduces with the increasing A, i.e., SR will happen.

On the other hand, we take a derivative with respect to Equation (12), and the optimal sensor threshold is $u_{opt} = \frac{-\frac{2}{A^2+M^2} + \sqrt{\frac{4}{(A^2+M^2)^2} + 4\left(\frac{1}{A^2} - \frac{1}{A^2+M^2}\right)\left(\frac{1}{A^2+M^2} + 2\ln\frac{\sqrt{A^2+M^2}}{A}\right)}}{2\left(\frac{1}{A^2} - \frac{1}{A^2+M^2}\right)}$ which means no reduction of P_{er} via adding A and M. Otherwise, it is possible to promote information transmission with noise.

3.2. **The effect of additive noise intensity A and multiplicative noise intensity M.** For the case of single-sensor structure with different threshold level u, Figure 2 and Figure 3 show that for fixed multiplicative noise intensity M (or A), the EDP of the sensor system P_{er} versus additive noise intensity A (or M). In the following experiments, the curves are obtained by theoretical calculations and the data points marked with solid triangles are simulated by 10^5 Monte-Carlo realizations.

3.2.1. *Fixed multiplicative noise intensity M.* From Figure 2(a), as far as the suprathreshold input signal case ($u = 0.5$), the EDP of the single sensor system P_{er} is always monotone increasing with the increase of additive noise intensity A, and in other words, noises play the part of negative roles; for the case of subthreshold input signal ($u = 2, 4, 8, 16$), with the increase of A, the EDP curves first drop to trough then rise, which shows a certain amount of noise is beneficial to the signal detection. Figure 2(b) shows, when $u = 0.5, 2, 4$, additive noise restrain signal detection, when $u = 8, 16$, the variation tendency of EDP curves displays SR efficacy, and larger threshold can induce stochastic resonance happened. Compared with Figure 2(a) ($M = 1$) and Figure 2(b) ($M = 10$), Figure 2(c) ($M = 100$) demonstrates whether the signal is above threshold or not, the EDPs are invariably monotone increasing with the increase of the additive noise intensity, i.e., it does not exhibit the SR (SSR) phenomenon. This is due to the fact that too strong multiplicative noise leads the composition of the input signal before entering the threshold comparator from subthreshold to suprathreshold, so the additive noise worsens detection performance all the way.

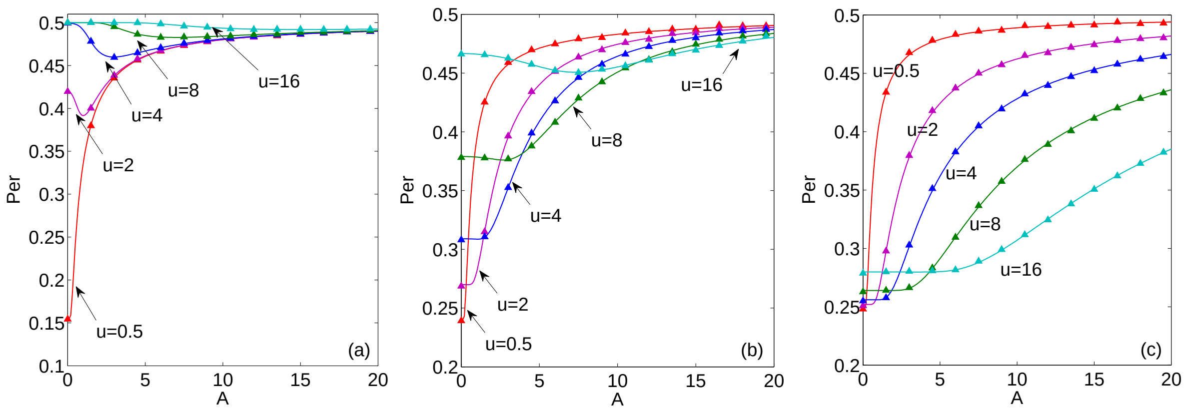

FIGURE 2. The P_{er} versus additive noise intensity A for various threshold levels ($u = 0.5, 2, 4, 8, 16$) with fixed multiplicative noise intensity M, (a) $M = 1$; (b) $M = 10$; (c) $M = 100$

3.2.2. *Fixed additive noise intensity A.* As shown in Figure 3, when the signal arises in the shape of suprathreshold ($u = 0.5$), detection performance inhibition was continuously observed by noises; when the signal locates in subthreshold ($u = 2, 4, 8, 16$), appropriate multiplicative noise can improve detectability, which is typical SR. In association with Figure 3(a) and Figure 3(b), we learn that the EDP P_{er} sharply declines at first (for the weak multiplicative noise) and eventually approaches 0.25 when the fixed additive noise intensity is small ($A = 0.001, 1$), which can be obtained by Equation (12) through the limit method, given as $\lim_{\substack{A\to 0\\ M\to+\infty}} \sum \frac{1}{2} - \frac{1}{4}\left| erf\left(\frac{u}{\sqrt{2}A}\right) - erf\left(\frac{u-1}{\sqrt{2(M^2+A^2)}}\right)\right| = \frac{1}{4},\ u \geq 1.$

It also reveals that the larger the threshold level is, the larger the added noise is needed. As a result, added multiplicative noise is more sensitive in small threshold scenarios. Figure 3(c) ($A = 10$) shows only larger multiplicative noise intensity M can gain a remarkable reduction of EDP, and the decreasing tendency of the EDP curve is significant in large

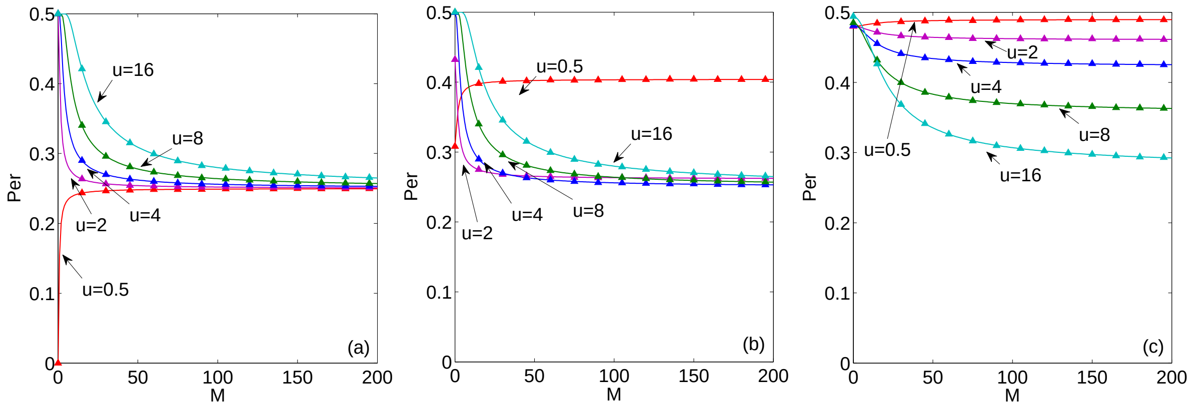

FIGURE 3. The P_{er} versus multiplicative noise intensity M for various threshold levels ($u = 0.5, 2, 4, 8, 16$) with fixed additive noise intensity A, (a) $A = 0.001$; (b) $A = 1$; (c) $A = 10$

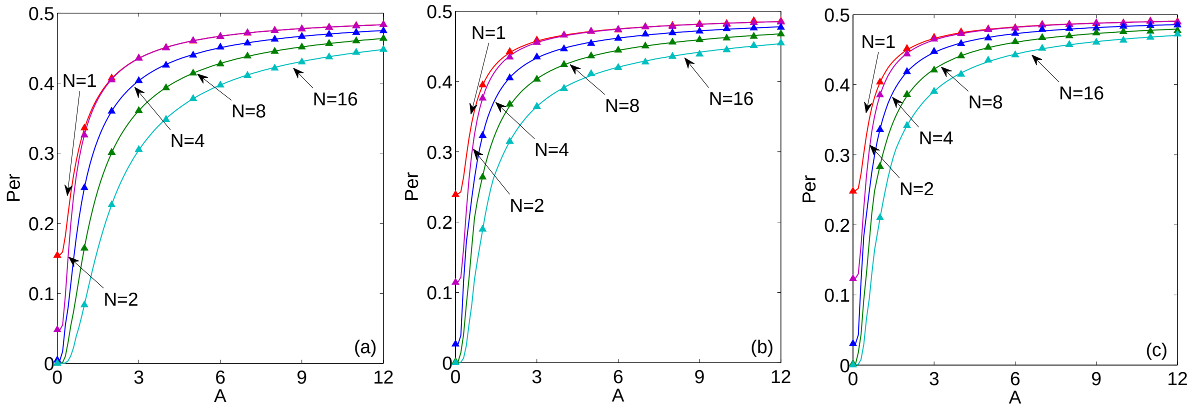

FIGURE 4. The P_{er} versus additive noise intensity A for various array numbers ($N = 1, 2, 4, 8, 16$) with suprathreshold ($u = 0.5$) and fixed multiplicative noise intensity M, (a) $M = 1$; (b) $M = 10$; (c) $M = 100$

threshold scenarios. When injecting the equivalent of multiplicative noise intensity, noise-enhanced detectability in Figure 3(c) is inferior to Figure 3(a) and Figure 3(b). It is demonstrated that additive noise intensity should not be too large in inducing SR.

3.3. **The effect of array N.** For the case of parallel sensor networks, Figures 4 to 8 illustrate that for different threshold levels u, the EDP P_{er} versus the additive noise intensity A (or multiplicative noise intensity M) when fixing multiplicative noise intensity M (or additive noise intensity A).

3.3.1. *Fixed multiplicative noise intensity M.* Figure 4 gives that when the signal is suprathreshold ($u = 0.5$), for the fixed multiplicative noise intensity ($M = 1, 10, 100$), the increase of additive noise intensity A always inhibits detection performance, i.e., SR effect is invalid at this moment. Figure 5(a) shows that when the signal is subthreshold ($u = 5$), the EDP curves exhibit a significant decline with the increase of additive noise intensity A in the small multiplicative noise case, i.e., SR appears; Figure 5(b) and Figure 5(c) illustrate when the multiplicative noise intensity M is larger, the addition of additive noise plays an inhibitory effect on detection. Consequently, the appropriate selection of threshold level, multiplicative noise intensity M and additive noise intensity A has a crucial role in triggering SR.

3.3.2. *Fixed additive noise intensity A.* Figure 6 brings out that the SR phenomenon does not take place; however, with the increase of N, the minimum value of EDP P_{er}

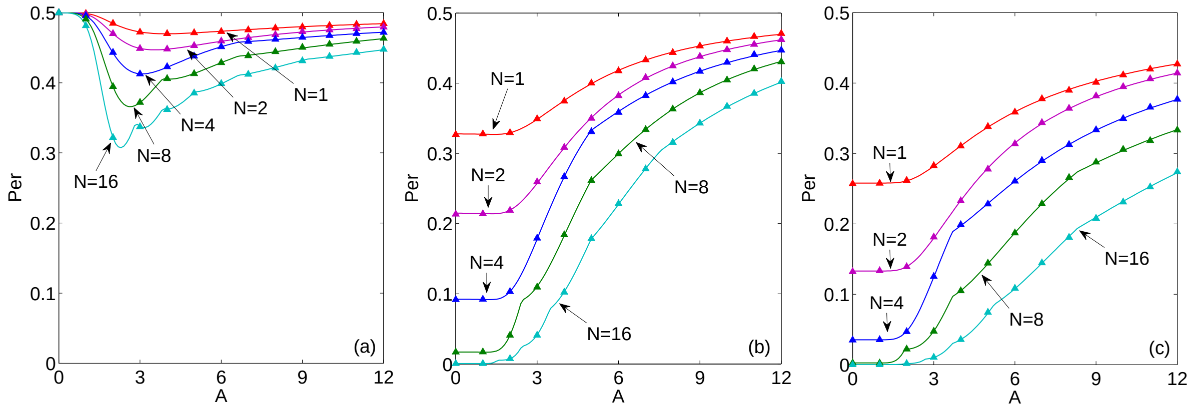

Figure 5. The P_{er} versus additive noise intensity A for various array numbers ($N = 1, 2, 4, 8, 16$) with subthreshold ($u = 5$) and fixed multiplicative noise intensity M, (a) $M = 1$; (b) $M = 10$; (c) $M = 100$

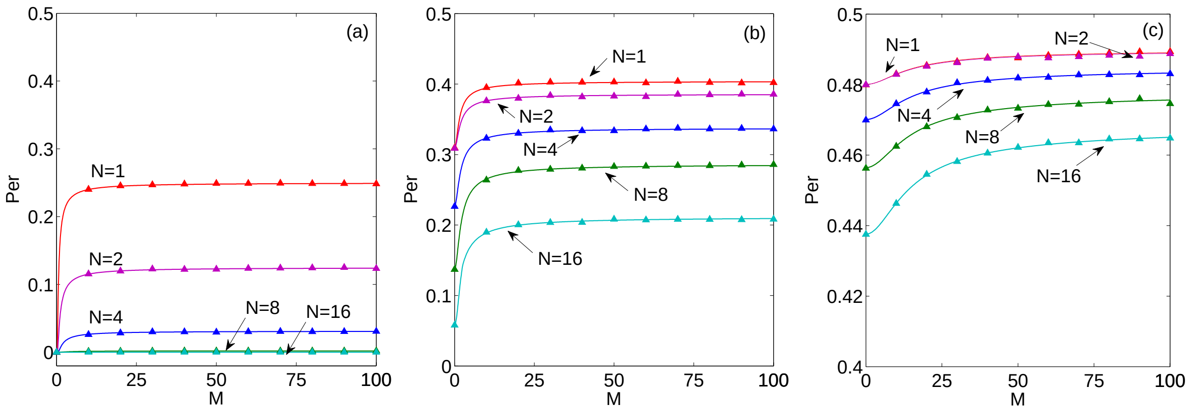

Figure 6. The P_{er} versus multiplicative noise intensity M for various array numbers ($N = 1, 2, 4, 8, 16$) with suprathreshold ($u = 0.5$) and fixed additive noise intensity A, (a) $A = 0.001$; (b) $A = 1$; (c) $A = 10$

is reducing, which results in improving detection performance. In Figure 6(c), the two curves ($N = 1$ and $N = 2$) almost overlap, and the value of P_{er} has greatly increased in comparison to Figure 6(a) and Figure 6(b). We also found that large additive noise intensity A can seriously deteriorate detectability.

Comparing between Figure 4 with Figure 6, in the case of small threshold ($u = 0.5$), when fixing an equal amount of multiplicative noise and additive noise ($M, A = 1$ and 10), we observed that under $A = 0$ the EDP value P_{er} is comparatively small in Figure 4(a) and Figure 4(b); under $M = 0$ the EDP value P_{er} is comparatively large in Figure 6(b) and Figure 6(c). It indicates when adding the equivalent strength noise the influence of additive noise on the system is greater than that of multiplicative noise. On the other hand, multiplicative noise has better robustness.

Figure 7(a) and Figure 7(b) produce better SR efficacy than Figure 7(c). For the large N, the EDP P_{er} in Figure 7(a) and Figure 7(b) tend to 0 with the increase of multiplicative noise, which shows the occurrence of SR is closely related with the additive noise intensity A and the array number of PSN N.

By comparing Figure 5 with Figure 7, in the case of large threshold ($u = 5$), when fixing equivalent multiplicative noise and additive noise ($M, A = 10$), noise always deteriorates detection performance in Figure 5(b), and the downward trends of the EDP in Figure 7(c) exhibit SR and also improve the signal detection. Therefore, multiplicative noise is more effective than additive noise in stimulating SR at present.

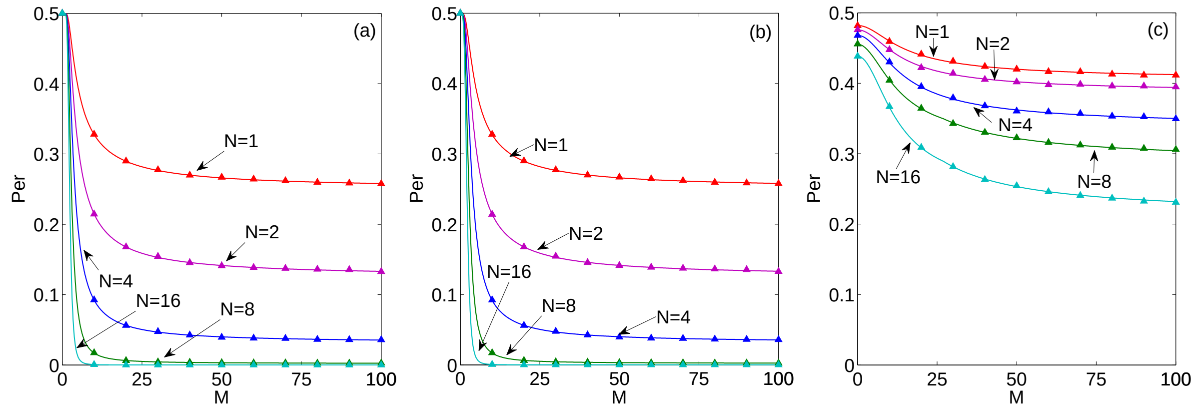

FIGURE 7. The P_{er} versus multiplicative noise intensity M for various array numbers ($N = 1, 2, 4, 8, 16$) with subthreshold ($u = 5$) and fixed additive noise intensity A, (a) $A = 0.001$; (b) $A = 1$; (c) $A = 10$

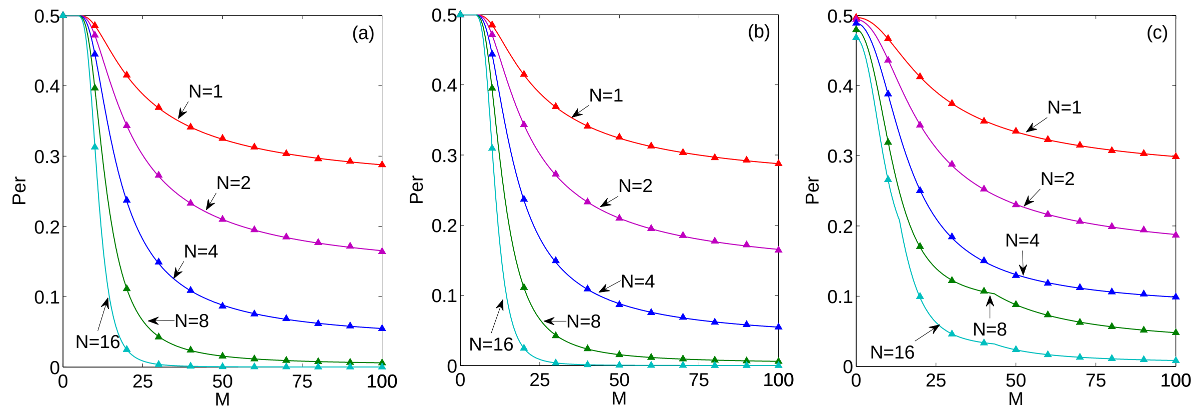

FIGURE 8. The P_{er} versus multiplicative noise intensity M for various array numbers ($N = 1, 2, 4, 8, 16$) with subthreshold ($u = 20$) and fixed additive noise intensity A, (a) $A = 0.001$; (b) $A = 1$; (c) $A = 10$

The standard SR phenomenon is shown in Figure 8, namely, the EDP P_{er} decreases with the increase of M. Contrasting Figure 7 and Figure 8, it can be seen that both of them have the similar SR efficacy in the context of small additive noise intensity ($A = 0.001, 1$); when the additive noise intensity is large ($M = 10$), in contrast with Figure 7(c), Figure 8(c) shows that the EDP curves decrease even faster and also the minimum value of EDP P_{er} is even smaller. This is because that the increasing in threshold makes the signal element locate more in subthreshold, adding noise is effective to improve signal detection performance.

4. **Extension and Discussion.** Due to the CLT, the background additive noise in the PSN can always be regarded as Gaussian form. The type of the external multiplicative noise in the PSN is various, where different noise forms are presented in many different contexts. For further exploration of multiplicative noise effect, we then consider the external noise in the PSN to a uniform case. Every sensor node is independent of each other and is subject to noisy signal with independent background additive ζ_i and external multiplicative noise ϑ_i.

Figure 9(a) shows how external multiplicative uniform noise can improve signal detection of a single-sensor system. It is found that the background additive Gaussian noise works in a certain range while the external multiplicative uniform noise is in the optimization state as the level goes to infinity. Figure 9(b) shows that for a fixed additive

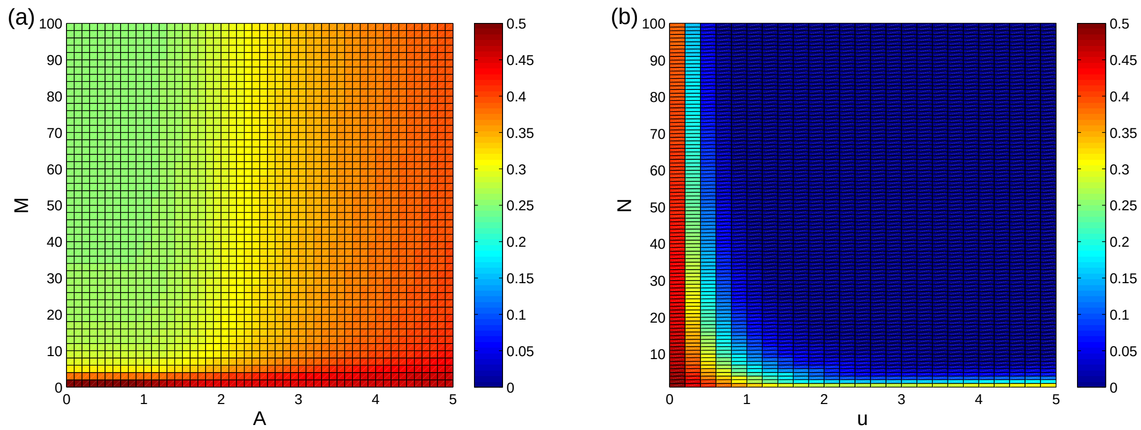

Figure 9. (a) The P_{er} versus multiplicative uniform noise intensity M and additive Gaussian noise intensity A in the single-sensor system for $u = 2.8$ (b) The P_{er} versus sensor threshold u and array of the PSN N for $A = 1$ and $M = 10$

Gaussian noise intensity A and multiplicative uniform noise intensity M, the three dimensional image of EDP P_{er} as a function of two independent variables (N and u) in the PSN. The larger the sensor threshold and the array of PSN are, the more apparent the phenomenon of SR is. The effect of uniform case overmatches those of Gaussian case, which is consistent with the description in [11]. By comparing Figure 9(b) with Figure 9(a), we can see that signal detection performance is significantly improved. So an array of sensor nodes (PSN) is superior to a single-sensor system. It is worth noting that the array number N does not need to be infinite. In addition, remarkable improvement will be obtained in the PSN.

5. **Conclusions.** We have studied the SR effect of a PSN for binary signal detection, where each sensor node is suffered from both background additive noise and external multiplicative noise. Due to the central limit theorem, the background additive noise can always be regarded as Gaussian sharp. However, the external multiplicative noise may manifest as a number of forms in different scenarios. We first explored the Gaussian multiplicative noise case using a degraded PSN (a single-sensor system) and also provided the EDP metric to characterize binary signal detection performance on PSN. It has been seen that for a comparatively small sensor threshold, the impact of noises is negative. Hence, the SR effect will vanish and no improvement of system performance will occur. Further, we extended the single-sensor system to PSN with background and external Gaussian noise. Results show that the noise-enhanced effect in the PSN significantly outperforms that of single-sensor system. Arbitrary weak signal (i.e., high sensor thresholds) can be amplified by multiplicative noise, thus introducing a robust method for signal detection in noise involved. Finally, a uniform case of external multiplicative noise was studied, which denotes a class of scenarios. To summarize, background additive noise and external multiplicative noise can promote the signal transmission in PSNs. In future work, we will examine the effect of two correlated noises on SR, thereby achieving effective control of sensor systems.

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