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Asynchronous Neuro-Spike Array-Based Communication

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***Abstract*— Nano-networks employ novel nano-scale communication techniques. A new example of nano-networks is the artificial neural system where nano-machines are linked to neurons to treat the neurodegenerative diseases. Many of the nano-scale communication techniques are inspired by biological systems. Neuro-spike communication is one example of this communication paradigm which is exploited to transfer vital information through the nervous system by neurons or nano-machines. Neurons and nano-machines exploit spike rate and the temporal coding to transmit information by action potentials. However, the efficiency of these encoding methods decreases when the transmitter and receiver are asynchronous. Synchronization is beyond the capabilities of nano-machines. In this paper, first we propose a mathematical model for the jitter of the neuro-spike communication channel. Next, we propose an asynchronous neuro-spike array-based communication scheme in which the transmission order of the generated spikes by different elements of the nano-machines array is used to convey information. Thus, in this scheme, there is no need for time synchronization between the transmitter and receiver nano-machines. Finally, we evaluate our proposed scheme via numerical results. It can be observed that our scheme improves the communication rate in comparison to other schemes about 50%.**

***Index Terms*— Neuro-spike communication, array-based communication, Communication rate.**

I. Introduction

Recent developments in nano technology and communication engineering are expected to lead to a new generation of nano-scale devices implantable inside the human body [1]. These nano-scale devices are called nano-machines. They form intra-body nano-network. In spite of their individual limitations, they can perform complex tasks through interconnecting in a nano-network. The main aim of these nano-networks is to develop new medical diagnosis and treatment techniques. These intra-body nano-networks can monitor the nervous system [2] due to the dimensional similarity of them and the nervous biological cells. Another example of these nano-networks is the artificial neural system where nano-machines are linked to neurons to treat the neurodegenerative diseases [1]. In these networks, nano-machines are used to replace damaged segments of the nervous system and have to behave exactly like the biological entities. Novel nano-scale communication techniques are used in nano-networks. These communication techniques are inspired by biological systems [3]. Neuro-spike communication is one example of this communication paradigm which is exploited to transfer vital information through the nervous system by neurons or nano-machines. The information is transmitted by the configuration of spikes which propagate along the nerve fiber, i.e., the axon, since all spikes of a nervous system are analogous. In particular, neurons and nano-machines employ the spike rate and temporal coding [4] to transmit information by action potentials in the neuro-spike communication. Neural coding refers to the mapping from the stimulus to the transferred spikes. The pre-synaptic terminals are located at the end of the axon. They release the neurotransmitters to the gaps between two neurons according to the received spikes. The information is transmitted between two neurons through these junctions, namely, synapses. When the neurotransmitters corresponding to each spike arrive at the post-synaptic terminal, with a high probability another spike is generated at the connecting nerve fiber and hereby the information is transmitted from one neuron/nano-machine to another neuron/nano-machine in the nervous system.

Several works have been performed in the neuro-spike communication paradigm. A physical channel representation for the neuro-spike communication has been offered in [5] to characterize its fundamental properties. In [6], [7] the effect of axonal noise on the axonal transmission capacity has been investigated. In [8], a comprehensive error probability for the neuro-spike communication channel has been derived. All of the existing and developed neuro-spike communication channel models which have been considered between two nano-machines exploit either spike rate or timing to transmit information. However, the efficiency of these encoding methods decreases when the transmitter and receiver are asynchronous. Synchronization is beyond the capabilities of nano-machines. Hence, it is imperative for the future nano-networks to develop synchronization-free neuro-spike communication schemes.

In this paper, we propose an asynchronous neuro-spike array-based communication scheme in which the transmission order of the generated spikes by different elements of the nano-machines array is used to convey information. Thus, in this scheme, there is no need for time synchronization between transmitter nano-machine (TN) and receiver nano-machine (RN). This scheme is similar to the natural encoding of genetic information, i.e., DNA arrays. The key contributions of this paper is summarized as follows:

- First, we comprehensively investigate the channel charac-

teristics and we show that each spike sustains a random delay to transmit between two neurons or nano-machines. We propose a mathematical model for the jitter of the neuro-spike communication channel.
- Next, we propose the neuro-spike array-based communication scheme which is a timing based modulation to transfer information.
- Finally, we evaluate our proposed scheme via numerical results. It can be observed that our scheme provides a higher rate in comparison to other schemes.

This paper is organized as follows. First, we present a mathematical model for the neuro-spike communication in Section II. In Section III, we propose an asynchronous neuro-spike array-based communication scheme to transmit information. In Section IV, we present numerical results to evaluate the neuro-spike array-based communication scheme. Finally, in Section V, we conclude this paper.

II. System Model

The system model for the neuro-spike communication contains three main parts, i.e., axonal pathway, synaptic transmission and spike generation. We investigate these parts with details to be able to find a proper mathematical model for the neuro-spike communication jitter.

The time relations of the output spikes are different from the input spikes due to the refractory period of the axon. The refractory period cuts off short action potential intervals and alters the propagation velocities of the spikes. Hence, it is entirely probable that the biological information which is encoded by the time intervals of the spikes is disturbed by the jitter noise. To realize the temperament of this noise, in [9], the authors have considered an axon to measure the propagation speed of spikes. To evaluate the spikes interval distributions, autocorrelations and cross correlations of stimuli and response spikes have been processed. It has been observed that a Gaussian distribution is a suitable description for the spread of the cross correlation distribution function. In this paper, we use the results of [9] for the axonal pathway analysis. In their scenario, the mean of the cross-correlation function has been obtained $3.8\,ms$. Moreover, the spread of the conduction time in response spikes has been obtained about $1.4\,ms$. It is worth to mention this assumption is valid for input time intervals lower than $20\,ms$ according to [9].

In the synaptic transmission part, we assume when a spike arrives to the pre-synaptic terminal, one vesicle is released. We assume each vesicle contains n neurotransmitters and they diffuse to the post-synaptic terminal. We consider that the movement of neurotransmitter molecules is governed by a Brownian motion [10]. The delay experienced by any neurotransmitter to cross from the synapse to the post-synaptic terminal, i.e., t_s, at every distance obeys the following probability density function:

$$f(t_s) = \frac{\lambda}{\sqrt{4\pi {t_s}^3}} e^{-\frac{\lambda^2}{4(t_s)}}, \;\; t_s > 0, \tag{1}$$

where $\lambda = \frac{d_s}{\sqrt{D}}$, D is the diffusion coefficient of the neurotransmitter and d_s is the synaptic gap distance. We assume $d_s = 10\,nm$ and $D = 100\,\mu m^2/s$ in the following.

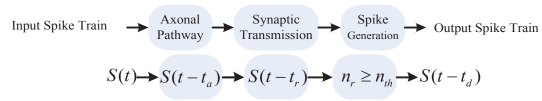

Fig. 1. System model of the neuro-spike communication channel.

We consider a simple and efficient model for generation of spikes, which is called Integrate-and-Fire (I&F) model [11]. In this model, the output neuron is considered as a capacitance, C, and a voltage threshold V_{th} is assumed to be fired. When the capacitance charge reaches to V_{th}, an output spike is generated and the velum potential is reset to zero. In I&F model, it is assumed that the input contains n excitatory neurotransmitters with equal charges, a_E. Moreover, it is assumed neurotransmitters are independent.

III. Asynchronous Array-Based Communication Scheme

In this section, we first model the jitter of the neuro-spike communication channel as an additive Gamma noise channel. Then, we propose a neuro-spike array-based communication scheme. It can be observed, our proposed scheme provides high- performance communication.

A. Modeling the Channel Jitter as the Channel Noise

Fig. 1 shows the statistical system model of the timing of propagation process in the neuro-spike communication channel. We assume the length of axon is equal to d_a and the average of velocity of propagation of spikes along the axon is $\bar{V}$. According to Section II, we consider a Gaussian stochastic variable to model the transmission time of spikes along the axon, i.e., t_a. The distribution is described as

$$f(t_a) = \frac{1}{\sqrt{2\pi{\sigma_a}^2}} e^{-\frac{(t_a-\mu_a)^2}{2{\sigma_a}^2}} \sim \mathbb{N}(\mu_a, {\sigma_a}^2), \tag{2}$$

where $\mu_a = \frac{\bar{V}}{d_a}$ is the mean of the travelling time and ${\sigma_a}^2$ is the variance of traveling time. By considering the propagation time of the neurotransmitters along the synapse based on the Section II, i.e., t_s, the conditional distribution function of the arrival time of each neurotransmitter to the post-synaptic terminal, i.e., $t_r = t_s + t_a$, when the travelling time of spikes through the axon is given by using (1), can be obtained as

$$f(t_r|t_a) = \frac{\lambda}{\sqrt{4\pi(t_r-t_a)}^3} e^{-\frac{\lambda^2}{4(t_r-t_a)}}, \quad t_r > t_a. \tag{3}$$

The joint distribution function of t_r and t_a is $f(t_r, t_a) = f(t_a)f(t_r|t_a)$. Hence, the marginal probability distribution function of t_r is obtained by

$$f(t_r) = \int_{-\infty}^{+\infty} f(t_r, t_a)dt_a = \int_{-\infty}^{+\infty} f(t_r|t_a)f(t_a)dt_a. \tag{4}$$

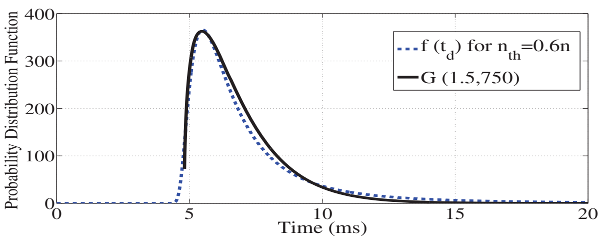

Fig. 2. The PDF $f(t_d)$ for $\rho = 0.6$ and its approximation by shifted $\mathbb{G}(1.5, 750)$ distribution.

By substituting the $f(t_r, t_a)$ into (4), we have

$$f(t_r) = \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi{\sigma_a}^2}} e^{-\frac{(t_a-\mu_a)^2}{2{\sigma_a}^2}} \frac{\lambda}{\sqrt{4\pi(t_r-t_a)^3}} e^{-\frac{\lambda^2}{4(t_r-t_a)}} dt_a. \tag{5}$$

For the spike generation part, we consider that n is the number of released neurotransmitters and $n_{th} = \frac{V_{\text{th}}}{a_E}$ is the number of neurotransmitters needed to reach the threshold. Therefore, the time t_d, for which the I&F unit generates an output spike is defined as the time that the n_{th}-th neurotransmitter arrives. We assume $n_{th} < n$. To derive the PDF of output spikes time when we assume $t_{r1} \le t_{r2} \le t_{r3} \le ... \le t_{rn_{th}} \le ... \le t_{rn}$, we exploit the PDF for the order statistics [12] of a sample of size n_{th} drawn from the distribution of $f(t_r)$, and thus, we have

$$f(t_d) = n_{th} \begin{pmatrix} n \\ n_{th} \end{pmatrix} (F(t_r))^{n_{th}-1}(1-F(t_r))^{n-n_{th}} f(t_r). \tag{6}$$

We assume $n_{th} = \rho n$ and we derive the $f(t_d)$ by numerical methods. Fig. 2 shows $f(t_d)$ for $\rho = 0.6$. Thus, as can be observed, a shifted Gamma distribution is a suitable choice to approximate the $f(t_d)$. We exploit this approximation for $f(t_d)$ later on. This approximation is valid for different values of ρ and we can use different Gamma distributions to approximate $f(t_d)$.

It is apparent that the output spikes arrival times are affected by different delays. We consider a jitter as an additive noise in the form of the random propagation delay. We assume this jitter is the only source of uncertainty in output spikes arrival times. As this additive noise has a Gamma distribution, we refer to the channel as an additive Gamma noise channel. Since the obtained Gamma distributions have shifts from the origin, we assume the delay of the channel contains two terms. The minimum propagation delay, denoted as δ, which is deterministic and a random delay which is modeled by a Gamma distribution without any shift, called as τ. Thus, the arrival time of a spike to the next neuron, i.e., $\hat{Y}$ can be modeled as $\hat{Y} = \tilde{X} + \tau + \delta$, where $\tilde{X}$ is the departure time of the input spike. For simplicity, since δ is a deterministic term, we define $\tilde{Y} = \hat{Y} - \delta$, and henceforth, we consider $\tilde{Y}$ as the arrival time of output spikes. We can consider τ as a Gamma stochastic variable by the following probability distribution function.

$$f_\tau(\tau) = \frac{\beta^\alpha}{\Gamma(\alpha)} \tau^{\alpha-1} e^{-\beta\tau} \sim \mathbb{G}(\alpha, \beta). \tag{7}$$

By substituting $\hat{Y} = \tilde{X} + \tau + \delta$, into (7) and considering the fact that $\tilde{Y} = \hat{Y} - \delta$, the probability distribution function of arrival time of the output spike $\tilde{Y} = \tilde{y}$ when the input spike is propagated at $\tilde{X} = \tilde{x}$ is obtained as

$$f_{\tilde{Y}|\tilde{X}}(\tilde{y}|\tilde{x}) = \begin{cases} \frac{\beta^\alpha}{\Gamma(\alpha)} (\tilde{y} - \tilde{x})^{\alpha-1} e^{-\beta(\tilde{y}-\tilde{x})}, & \tilde{y} > \tilde{x}, \\ 0, & \tilde{y} \le \tilde{x}. \end{cases} \tag{8}$$

B. Proposed Asynchronous Array-Based Communication Scheme

Generally, in modulations when the transmission alphabet includes l different symbols, the number of possible code words is l^k. Let us consider the binary case in which $l = 2$. We assume in the transmission systems, the alphabet contains two symbols, i.e., $\{0, 1\}$, and thus, there are 2^k different code words when the transmitted code word is a sequence of k symbols. We assume a scenario in which there are two nano-machines as the transmitter array. Moreover, there are two nano-machines as the receiver array. Transmitter array nano-machines choose different types of neurotransmitter to emit to the synapse. We assume every RN only receives the neurotransmitter of the corresponding TN, and thus, the spike of i-th TN only is received by the i-th RN. Hence, we can neglect the co-channel interference in the synaptic transmission part. It is worth mentioning that neurons can use different types of neurotransmitter such as Cyclic Adenosine Mono Phosphate (CAMP), Cyclic Guanosine Mono Phosphate (CGMP), calcium and diacylglycerol [13] as the messenger molecules.

We denote the generated spikes of first and second nano-machines by A and B, respectively. We exploit a temporal modulation to transfer information. Thus, without loss of generality, we associate the transmission order $\{A - B\}$ for spikes with input bit $x = 0$ and $\{B - A\}$ order with input bit $x = 1$. In fact, bit 0 is transmitted by first generated spike A and then B. On the other hand, bit 1 is transmitted by first generated spike B and then A. We assume the intermission time of spikes is denoted by T_o. Hence, if the spike of first nano-machine is generated at time t, the spike of the second nano-machine is generated at time $t + T_o$. Fig. 3 presents the time diagram of this scenario. We use the proposed model in (7) for the experienced delay of each spike. Hence, the delay experienced by any spike to reach the RN obeys a Gamma probability density function. In (7), $\Gamma(\alpha) = \int_0^\infty q^{\alpha-1}e^{-q}dq$, α and β are functions of V_{th}, D, d_a and d_s. The cumulative distribution function of $f_\tau(\tau)$, i.e., $F_\tau(\tau)$ can be given as $F_\tau(\tau) = \frac{\gamma(\alpha,\beta\tau)}{\Gamma(\alpha)}$, where $\gamma(\alpha, \beta\tau) = \int_0^{\beta\tau} q^{\alpha-1}e^{-q}dq$.

Next, we obtain the probability of a successful transmission for our proposed scheme, i.e., the probability that a symbol is correctly received by RN.

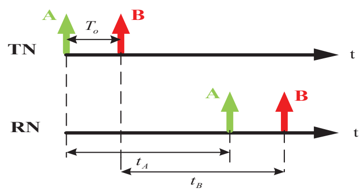

Fig. 3. The time diagram of the binary scenario. The intermission time of spikes is denoted by T_o.

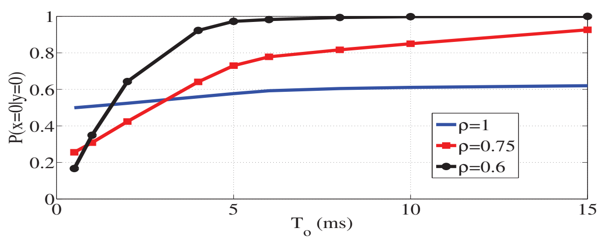

Fig. 4. The successful transmission probability versus intermission time T_0 when bit $x = 0$ is transmitted.

Theorem 1: The probability that symbol $x = 0$ is transmitted by TN and it is correctly received by RN is derived as:

$$\Pr(x=0|y=0) =$$
$$\frac{\gamma(\alpha,\beta T_o)}{\Gamma(\alpha)} + \frac{\Gamma(\alpha,\beta T_o)}{\Gamma(\alpha)} \int_{T_o}^{\infty} f_\tau(t) \frac{\Gamma(\alpha,\beta(t-T_o))}{\Gamma(\alpha)} dt. \quad (9)$$

Proof: The proof is given in Appendix I.

Fig. 4 shows the successful transmission probability when bit $x = 0$ is transmitted, i.e., $\Pr(x = 0|y = 0)$ as a function of T_o for different values of ρ. It can be observed that the probability of correct reception enhances when T_o increases. Moreover, we can conclude that a larger T_o is required to achieve a high probability of successful reception for higher values of ρ. Numerical results show for higher values of ρ, $\Pr(x = 0|y = 0)$ is almost independent of the intermission time. We can interpret the successful transmission probability as the capacity per transmission. Thus, the communication rate of our scheme is obtained as $\Pr(x = 0|y = 0)/T$(bps).

IV. Numerical Results

In this section, we present the numerical results to analyze the performance of our proposed scheme. We first investigate the communication rate of our proposed scheme for different values of the inter symbol duration. In this section, the numerical computations are carried out by using Matlab software.

Fig. 5 compares the communication rate of our proposed scheme with the On-Off Keying scheme in the binary channel and Z-channel models for different values of ρ. The communication rate of these channel models is presented in Appendix II. Since our goal is designing the most efficient communication system which maximizes the communication rate, in different schemes, we should obtain the highest communication rate and its corresponding value of T. Based on Fig. 5, we can conclude the rate of our proposed scheme reduces for higher values of T. We only analyze our scheme for values of T lower than $20\,ms$, since the proposed channel model is valid for these values of T. It can be observed, our proposed communication scheme significantly outperforms the Z-channel and binary channel models in terms of the communication rate. Besides, we can conclude our scheme requires lower inter symbol time T to provide higher communication rate.

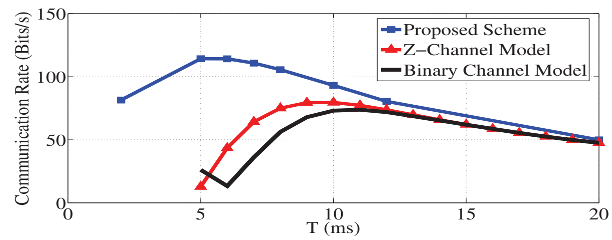

Fig. 5. The communication rate of our proposed scheme and On-Off Keying scheme in the binary channel and Z-channel models for $\rho = 0.6$.

V. Conclusion

In this paper, we have proposed a neuro-spike array-based communication scheme which exploits the transmission order of generated spikes of different nano-machines to convey information between nano-machines in the artificial neural system. Numerical results have shown that our scheme outperforms the On-Off Keying scheme in the binary channel and Z-channel models. It has been observed our scheme enhances the communication rate by over 50%.

Appendix I
Proof of Theorem 1

The probability that symbol 0 is transmitted by TN and it is correctly received by RN is derived as:

$$\Pr(x=0|y=0) = \Pr(t_B > t_A - T_o) = \begin{cases} 1, & t_A \le T_o, \\ \omega(T_o), & t_A > T_o. \end{cases} \quad \text{(I.1)}$$

We denote the random time delays of spikes A and B, by t_A and t_B, respectively. Since t_A and t_B have the same PDF given in (7), i.e., $f_\tau(t) = f_{t_A}(t) = f_{t_B}(t)$, we can conclude $\Pr(x = 0|y = 0) = \Pr(x = 1|y = 1)$. In fact, we can rewrite the expression in (I.1) in a more compact form as

$$\Pr(x=0|y=0) = 1 \times \Pr(t_A \le T_o) + \omega(T_o) \times \Pr(t_A > T_o). \quad \text{(I.2)}$$

By exploiting the PDF of t_A and t_B in (I.1), the function $\omega(T_o)$ can be derived as

$$\omega(T_o) = \int_{T_o}^{\infty} \int_{t-T_o}^{\infty} f_{t_A t_B}(t,t')dt'dt$$

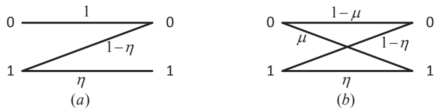

Fig. 6. (a) Z-channel model. (b) Binary channel model.

$$= \int_{T_o}^{\infty} \int_{t-T_o}^{\infty} f_{t_A}(t) f_{t_B}(t') dt' dt = \int_{T_o}^{\infty} f_{t_A}(t) \frac{\Gamma(\alpha, \beta(t-T_o))}{\Gamma(\alpha)} dt, \tag{I.3}$$

where $\Gamma(\alpha, \beta t) = \int_{\beta t}^{\infty} q^{\alpha-1} e^{-q} dq$ and $f_{t_A t_B}(t, t')$ is the joint PDF of t_A and t_B. We can write $f_{t_A t_B}(t, t') = f_{t_A}(t) f_{t_B}(t')$ since we assume these delays are independent. Moreover, the probability $\Pr(t_A \le T_o)$ which means t_A does not exceed the intermission time T_o is derived as

$$\Pr(t_A \le T_o) = \int_0^{T_o} f_{t_A}(t) dt = \frac{\gamma(\alpha, \beta T_0)}{\Gamma(\alpha)}. \tag{I.4}$$

By, inserting (I.3) and (I.4) into (I.2), $\Pr(x=0|y=0)$ can be obtained as (9). ■

Appendix II
Communication Rate of On-Off Keying scheme in the Z-Channel and Binary Channel Models

In this section, we introduce On-Off Keying scheme by considering the Z-channel and the binary channel models. In On-Off Keying scheme in the Z-channel model [14], a spike is generated by TN to show logic 1 at the beginning of the time slot. If the spike reaches RN within a time slot, i.e., T, RN can detect the bit 1 with the probability η. Otherwise, RN erroneously detects the logic bit 0 with probability $1-\eta$. Therefore, the probability η can be obtained as $\eta = \int_0^T f_\tau(t) dt = \frac{\gamma(\alpha, \beta T)}{\Gamma(\alpha)}$. In order to transmit bit 0, TN generates no spike within the time slot, and thus, the transmissions of bit 0 is assumed successful in the Z-channel model. By exploiting η, the channel transition matrix for the Z-channel is derived as $P_z(y|x) = \begin{pmatrix} 1 & 0 \\ 1-\eta & \eta \end{pmatrix}$, where x and y are the channel input and output bits, respectively. According to $P_z(y|x)$, the channel capacity of the Z-channel model, i.e., C_z is derived as $C_z = \max_{Q(x)} I(X;Y)$, where $I(X;Y)$ denotes the mutual information of the channel. Thus, we have

$$C_z = \max_{Q(x)} \sum_{x \in X} \sum_{y \in Y} Q(x) P_z(y|x) \log_2 \left(\frac{P_z(y|x)}{\sum_{x' \in X} P_z(y|x')} \right). \tag{II.1}$$

The input distribution is assumed as $Q(1) = \Pr(x=1)$ and $Q(0) = \Pr(x=0)$. Since C_z is in bits per transmission, hence, the communication rate for the Z-channel model is obtained as C_z/T(bps). In the Z-channel model, it is assumed that all transmissions of bit 0 are successful. However, since the spikes are generated in the last intervals may arrive to the RN later, it is not a realistic model. Hence, the erroneous transmissions of logic bit 0 are taken into account via the binary model which is shown in Fig. 6 as previously introduced in [15]. We assume that the current transmission of bit 0 is only affected by the bit 1 transmitted in the previous interval. Hence, the probability that a bit 0 is not detected successfully by RN, is obtained as

$$\mu = Q(1) \int_T^{2T} f_\tau(t) dt = Q(1) \frac{\gamma(\alpha, 2\beta T) - \gamma(\alpha, \beta T)}{\Gamma(\alpha)}. \tag{II.2}$$

By exploiting μ and η, the channel transition matrix for the binary channel model is derived as $P_b(y|x) = \begin{pmatrix} 1-\mu & \mu \\ 1-\eta & \eta \end{pmatrix}$. According to $P_b(y|x)$, the achievable rate of the binary channel model in bits per transmission, i.e., C_b, is obtained by solving the optimization problem which is described in (II.1) similar to the Z-channel model. Moreover, the communication rate for the binary channel model is derived as C_b/T(bps).

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