CDM Based on Izhikevich Neuron Model

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Abstract. Transmission of information from within the body to the external environment has become a popular issue in making the Internet of Nanothings (IoNTs) a reality. Neural communication has been proposed as a promising solution, utilizing action potentials (APs) as the fundamental units for information transmission. Most of the existing research simplifies the membrane potential into two states: an excited state that generates an AP upon stimulation and a resting state absent of stimulation. This assumption neglects both the intrinsic oscillation of membrane potential and the uncertainty it introduces into information transmission. Therefore, neural communication requires further investigation into the biological similarity of channel models and the reliability of transmission. In this paper, we employ the Izhikevich model as the channel model to characterize membrane potential oscillations. Additionally, we devise an enhanced code division multiplexing (CDM) scheme based on this model, enabling multiple signals to share a single neuron channel. In contrast to previous CDM methods, this scheme employs further encoding of superimposed signals. The performance is evaluated in terms of bit error rate (BER), and the results indicate a significant improvement in interference resistance. This research improves the communication efficiency of engineered neural systems and achieves more precise and reliable communication.

Keywords: Internet of Nanothings · neural communication · Izhikevich model · CDM

1 Introduction

In recent years, advances in nanotechnology and biology have made the Internet of Nanothings (IoNTs) a promising research, which enables sharing of information within the body and offers various potential in-vivo applications in the biomedical field [1]. However, implementing an interface to transfer information from implanted IoNT devices to external devices poses significant challenges.

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As a promising solution, neural communication technology, utilizing nervous system as a data transmission interface has emerged [2,3]. Communication is achieved through action potentials (APs) between neurons, referring to momentary reversal of electric polarization in the membrane, which can propagate actively along the nerve fiber. In recent years, scientific research on neural communication has gradually attracted the attention of scholars, but research is still scarce. In 2013, a physical channel model for nanoscale neuro-spike communications between neurons was presented [4]. In 2017, information transmission on axons was modeled and studied [5]. In 2020, idea that one can use the modified neural system as a data transmission interface to transmit signals between internal IoNTs and external devices was proposed for the first time [6].

It is observed that the majority of studies mainly focused on end-to-end communication between neurons and established the neuro-spike communication model. They considered the membrane potential of neurons to be in a binary state: excited as "1" and unexcited as "0", based on the "all-or-none" principle [7]. However, in reality, when the membrane potential fails to reach the threshold, a significant portion exhibits a phenomenon known as damped oscillation, which can impact information transmission. In [8], the author established a communication system based on the Izhikevich model, which characterizes this oscillatory behavior prevalent in neuroscience, thus making the neural communication model more biologically relevant. In such a communication system, enhancing the robustness of neural signal transmission against interference and improving the information transmission rate are crucial.

Channel multiplexing stands as a significant method. Applying schemes such as frequency division multiplexing (FDM) and code division multiplexing (CDM) to neural spike communication has been demonstrated to enhance the efficiency of information transmission [9,10]. These studies do not take into account the oscillation of membrane potential, leading to increased uncertainty in information transmission. At the same time, the current CDM method suffers from significant information loss. In this paper, we employ the Izhikevich model as the channel model, and propose an improved CDM scheme. We use bit error rate (BER) to evaluate the system, demonstrating that our model shows improved interference resistance. The main contributions of this paper are:

– This paper incorporates the oscillations of membrane potential, as characterized by the Izhikevich model, into the channel model and develops a CDM scheme. This enhances the biological resemblance and enables more accurate simulation of multiplexing in engineered nervous systems.
– Building upon the novel channel model, we propose an enhanced CDM scheme by incorporating additional encoding of superimposed signals. Simulation results demonstrate that the scheme achieves multiplexing of several signals over a shared channel and surpasses traditional modulation and coding schemes in terms of reliability.

The rest of this paper is organized as follows. Section 2 gives the system framework of neural communication. Section 3 demonstrates the improved CDM schemes in the communication system based on the Izhikevich model. In Sect. 4, the simulation results on the performance of the proposed schemes are presented. Finally, Sect. 5 summarizes the paper.

2 System Framework

In the proposed scenario, the framework of the system consists of three main components: a transmitter, a neuron channel, and a receiver, as illustrated in Fig. 1. The transmitter, typically composed of nanomachines, conveys information by stimulating neurons to generate APs. These APs propagate actively along the neuron channel, which will be detected and recovered to the transmitted information at the receiver.

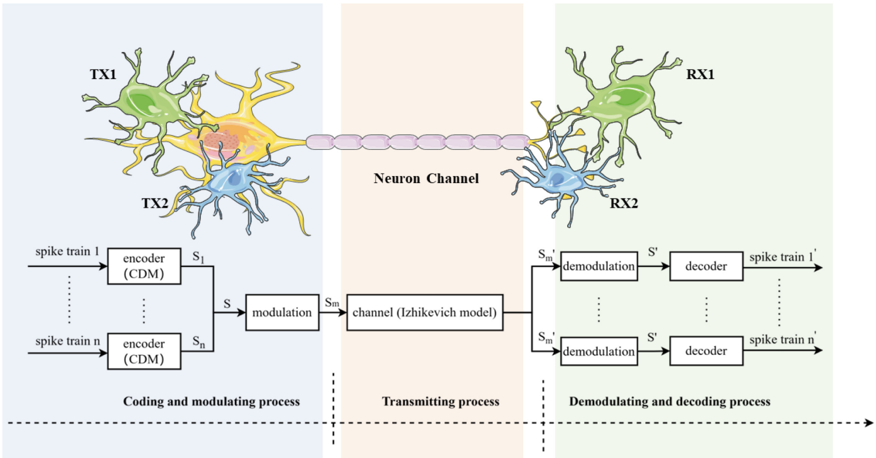

Fig. 1. System framework. The neuron communication process consists of three main components: transmitters (TX1 and TX2), a neuron channel, and receiver (RX1 and RX2). The transmitters emit stimulate nerves to generate APs. These APs propagate actively along the neuron channel. Subsequently, the receivers detect the APs and recover the transmitted information.

2.1 Transmitter

In IoNTs, there exist multiple nodes. Limited by the available biological neural pathways, each node cannot independently possess a dedicated neuron channel, posing a significant challenge. Therefore, we design channel multiplexing schemes, enabling multiple signals to share a channel. Multiplexing schemes in telecommunication systems include FDM, CDM, etc. Previous models based on FDM achieved multiplexing of two channels, while they inevitably led to severe low-frequency interference, thus limiting the multiplexing of more channels. In our work, we propose a CDM scheme, utilizing different bit sequences to encode the original signal for multiplexing. The elements in encoded matrix may be greater than 1. Due to the existence of the "all or none" principle, values other than "1" or "0" cannot be represented during modulation. Thus, we devise the second encoding step to ensure that all elements in the matrix consist solely of "0"s and "1"s.

For modulation, our neural communication system utilizes On-Off Keying (OOK) modulation to load encoded information onto neuron channels. This method commonly employs two states: stimulating the neuron to generate APs and not stimulating the neuron, representing binary bits. Specifically, a stimulus presence corresponds to bit "1", while its absence corresponds to bit "0".

2.2 Channel and Noise Model

For the noise model, neurons may generate APs spontaneously, considered as the noise in the neuron channel. In the field of neuroscience, researchers frequently employ a Poisson distribution to simulate the firing patterns of neurons, as demonstrated in [11]. Here, the noise $n(t)$ can be expressed as

$$n(t) = \text{Poiss}(\lambda), \tag{1}$$

where λ is the intensity parameter.

Researchers considered the membrane potential of neurons as binary, following the "all-or-none" principle [7]. In reality, when the membrane potential of neurons does not reach the threshold, they exhibit damped oscillation, which impacts the generation of APs. This phenomenon can be described using the Izhikevich model in the field of neuroscience. In this paper, we utilize this model as the channel model and the response to modulated stimuli can be represented as

$$r(t) = h(t) * (s(t) + n(t)), \tag{2}$$

where $h(t)$ represents the system function based on the Izhikevich model. $s(t)$ and $n(t)$ denote the source signal and noise signal, respectively. The explicit expression will be given in the next section.

2.3 Receiver

The demodulation and decoding process in our neural communication system involves recovering the original information from the received membrane potential $r(t)$. Demodulation begins by evaluating the response over specific time intervals. Based on comparisons with a decision threshold V_{th}, the estimated binary information is determined. Correspondingly, decoding schemes are designed based on the two encoding schemes to retrieve the received information.

This demodulation and decoding process allows us to recover the original information encoded and modulated at the transmitting end, enabling effective communication within the neural network.

3 Proposed Framework and Modeling

In this section, we analyze the Izhikevich neuron model from the perspective of communication theory and present multiplexing schemes aimed at improving communication efficiency (Fig. 2).

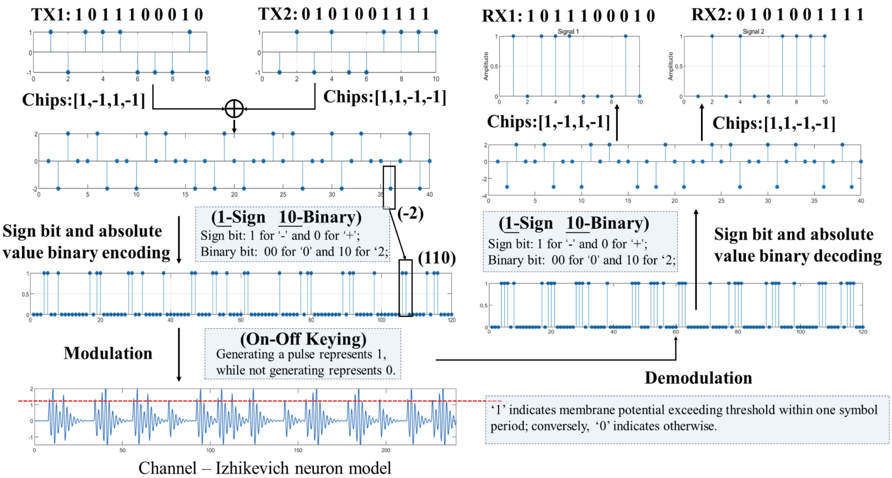

Fig. 2. An example of multiplexing. The two signal sequences, Sequence A [1011100010] and Sequence B [0101001111], achieve information transmission through an improved CDM method based on Izhikevich neuron model.

3.1 The Coding and Modulating Schemes

Code Division Multiplexing (CDM) is a technique used in communication systems to simultaneously transmit multiple signals by multiplying each signal with a unique encoding sequence. At the receiving end, the desired signals are separated from the mixed signals using corresponding decoding sequences.

The Walsh matrix, used as the encoding matrix in CDM, is a special kind of binary matrix with key properties like orthogonality and low autocorrelation. These properties make it extremely valuable in multi-user communication systems. The Walsh matrix is composed of two-level Walsh sequences, which are binary sequences made up of “+1” and “−1”. By combining different Walsh sequences, Walsh matrices can be constructed. Assuming there are two input sequences, each input sequence will be assigned a different Walsh sequence for encoding and decoding. The orthogonal matrix chosen for this model is expressed as

$$W = \begin{bmatrix} 1 & -1 & 1 & -1 \\ 1 & 1 & -1 & -1 \end{bmatrix}. \tag{3}$$

Each row represents an independent Walsh sequence, and the inner product between any two rows of the matrix equals 0. This property ensures their excellent mutual orthogonality in CDM systems. By multiplying the two spike trains with the first and second rows of the matrix individually, the two input spike trains are encoded into new sequences. The encoding of the source information can be represented as:

$$C = W^T \times S, \tag{4}$$

where the source matrix S has dimensions $m \times n$. m represents the number of signals and n represents the number of bits per signal. W^T represents the transpose of the encoding matrix W. The dimensions of W are $m \times l$, where l represents the length of the code chip. The dimension of the encoded matrix C is also $l \times n$, with each row representing the encoding result of a signal.

The elements in matrix C may exceed 1. Due to the "all or none" principle, values other than "1" or "0" cannot be represented during modulation. Therefore, coding rules for mixed sequences are developed. Each element of this sequence is divided into two parts: the sign part and the value part, which are coded separately. For the sign part, we use bit "1" for "-" and bit "0" for "+". For the value part, the element's value is converted to binary: "00" for "0", "01" for "1", and "10" for "2", etc. The corresponding encoding methods, simplified as:

$$M = E_{sym} \times C, \tag{5}$$

where E_{sym} represents the encoding matrix with dimensions of $3l \times l$. The encoded matrix M has dimensions of $3l \times n$ and consists solely of "0"s and "1"s.

In order to load the encode information onto neuron channel, our neural communication system employs OOK modulation. The mathematical expression $s(t)$ is presented as follows:

$$s(t) = A_m \textstyle\sum_{i=1}^{3l} \sum_{j=1}^{n} M_{ij}\delta(t - (i-1)T - (j-1)lT), \tag{6}$$

where A_m is the carrier amplitude, M_{ij} is the j-th symbol in the bit sequence of ith encoded bit. $\delta(t)$ is the pulse function and T is the transmission period.

3.2 Analysis of Izhikevich Neuron Model

In our proposed system, oscillation of membrane potential is characterized by Izhikevich neuron model. It is rewritten and utilized as a channel model, organized as:

$$\dot{h}(t) - (b + jw_0)h(t) = \sum_{i=1}^{L} c\delta\left(t - t_i^*\right) \equiv s(t), \tag{7}$$

where $h(t)$ and $s(t)$ describe the state and input of the neuron at time instant t, respectively. The internal parameter $b + jw_0 \in \mathbb{C}$ characterizes the system, where $b < 0$ represents the rate of attenuation and $w_0 > 0$ denotes the frequency of oscillations. Each c is a coefficient reflecting the effect of input stimuli, $\delta(t)$ is the Dirac function, and t_i^* is the nearest time instant of firing of the i-th neuron. L represents the number of pulses.

By applying Laplace transform, the equation is described as

$$sh(s) - h\left(0_-\right) - (b + jw_0)h(s) = \sum_{i=1}^{L} ce^{-t_i^* s}, \tag{8}$$

where $s = \sigma + j\omega$ is introduced to transform the differential equation into an algebraic equation. The input signal $e(t)$ is transformed into $\sum_{i=1}^{L} c_i e^{-t_i^*}$. $h\left(0_-\right)$ represents the membrane potential at the initial moment.

Thus, the response of the s-domain can be expressed as

$$h(s) = \frac{\sum_{i=1}^{L} ce^{-t_i^* s} + h\left(0_-\right)}{s - (b + jw_0)}. \tag{9}$$

The inverse Laplace transform of the above equations gives the response of the system in the time domain as

$$h(t) = \mathcal{L}^{-1}\left\{\frac{\sum_{i=1}^{L} ce^{-t_i^* s} + h\left(0_-\right)}{s - (b + jw_0)}\right\}, \tag{10}$$

which denotes the variation in membrane potential. Once the value of y, defined as $\mathrm{Im}\{h(t)\}$, surpasses the threshold, the neuron initiates an AP.

Equation (13) describes the oscillatory characteristics of membrane potential. This oscillation will affect the response to the next pulse. Taking two consecutive pulse inputs as an example, we explore this impact on information transmission, as shown in Fig. 3. Whether a subsequent pulse can surpass the threshold depends on how well it aligns with the oscillation phase in time. APs are generated when the inter-spike interval aligns closely with, or is a multiple of the oscillatory period T_o, as shown in Fig. 3(b). Such neurons prefer a certain frequency of the input that is nearly equal to the oscillation frequency. Therefore, we set the stimulation period T of the CDM method equal to the oscillation period.

3.3 Demodulating and Decoding Process

At the receiving end, the information is recovered by evaluating the value of the membrane potential $r(t)$, which is shown as follows:

$$\hat{r}_j = \begin{cases} \text{“}1\text{''}, & \max\limits_{t\in[(j-1)T,jT]} r(t) \geq V \\ \text{“}0\text{''}, & \max\limits_{t\in[(j-1)T,jT]} r(t) < -V \\ \textit{no signal}, & \max\limits_{t\in[(j-1)T,jT]} -V \leq r(t) < V \end{cases}, \tag{11}$$

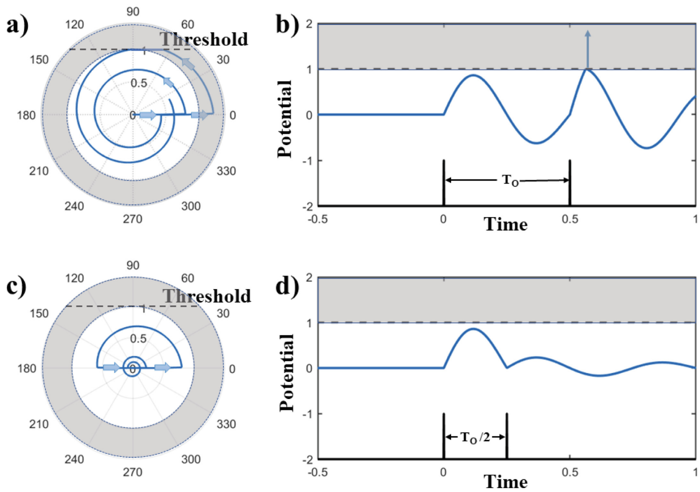

Fig. 3. The change in membrane potential when stimulated by a doublet.

where $\hat{r}_j$ is the estimated binary information bit and V_{th} represents the decision threshold of the receiver. Therefore, the demodulated vector is obtained as $\mathbf{r} = [\hat{r}^1, \hat{r}^2, \ldots, \hat{r}^n]$.

For ease of decoding, $\mathbf{r}$ can organized into the matrix $\hat{M}$ with dimensions of $3l \times n$, corresponding to the construction of matrix M at the transmitting end. Furthermore, the decoding method is as follows:

$$\hat{C} = E'_{sym} \times \hat{M}, \tag{12}$$

where E'_{sym} is the inverse matrix of E_{sym}, with dimensions of $l \times 3l$. The decoding method for CDM can be represented as:

$$\hat{S} = W \times \hat{C}, \tag{13}$$

where $\hat{S}$ denotes the received information, and $\hat{C}$ is the vector obtained from the previous decoding step. The matrix W serves as the further decoding matrix, and it is crucial to note that it is the inverse of the encoding matrix W^T. This relationship is highlighted by the property of Walsh functions, $(W^T)' = W$, indicating that W is the inverse matrix of W^T, ensuring the proper decoding of the transmitted information.

4 Simulation Results

In this section, the multiplexing schemes based on Izhikevich neuron model are simulated and evaluated by MATLAB.

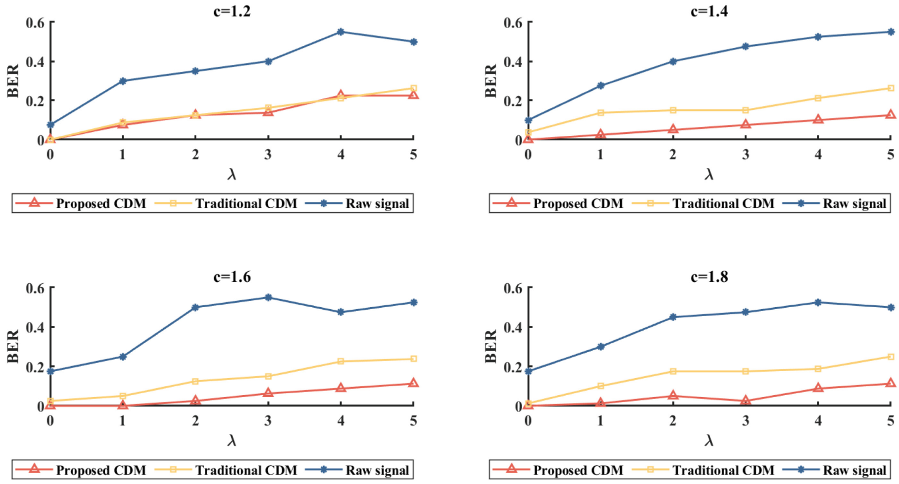

Fig. 4. Comparison of BER for the proposed CDM scheme, traditional CDM scheme, and raw signal transmission under different stimulus parameters.

As previously stated, the neural communication model consists of three processes: encoding and modulation, neuron channel transmission, and demodulation and decoding. Bits "1" and "0" are transmitted with equal probability of 0.5 and each data point represents transmission of 400 bits. In the encoding and modulation process, encoding matrix W and vector E_{sym} are constant for a specific length of source sequence. The oscillation period is set to $T = 2\,\text{ms}$. In the channel transmission stage, the Poisson noise parameter λ represents the number of pulses within a given time window and the time window is set to be $3l\dot{T}$. Additionally, the variables adjusted in the simulation results include the Poisson noise parameter λ and the amplitude parameter c. In the signal detection and decision stage, we set the decision threshold to 1 based on the range of values reported in similar studies [12] and make judgments based on the membrane potential at the receiver.

In the description of the channel model, shown in Sect. 3.2, c represents the strength of stimulation to the neurons within the body. As we increase the stimulation strength parameter, it does not alter the amplitude or shape of the AP itself. It may affect the magnitude of oscillations, thereby influencing information transmission. Therefore, we examine the transmission reliability of raw signal, traditional CDM method, and our method under varying stimulation parameters. Bit error rate (BER) is applied to evaluate the accuracy of data transmission, as shown in Fig. 4.

It can be observed that under different stimulation parameter environments, as the noise intensity λ increases, BER also increases. When the stimulation parameter c is 1.2, the stimulation is relatively weak, making it more susceptible to noise interference. Based on the above observations, it can be concluded that transmitting unencoded information directly results in lower information transmission efficiency and is more vulnerable to channel noise interference. In comparison with traditional CDM methods, our proposed approach demonstrates superior resistance to interference.

Furthermore, we choose an applicable stimulation parameter of 1.6 to compare the advantages of our CDM method over traditional CDM methods, as shown in Fig. 5. Taking the example of transmitting two signals, we set the noise parameter to vary from 1 to 10 to change the channel environment. As the noise intensity λ increases, the average BER also increases. The BER of our proposed model is significantly improved, primarily because our approach incorporates further channel encoding compared to previous CDM schemes, thus compensating for the information loss inherent in the original CDM approach.

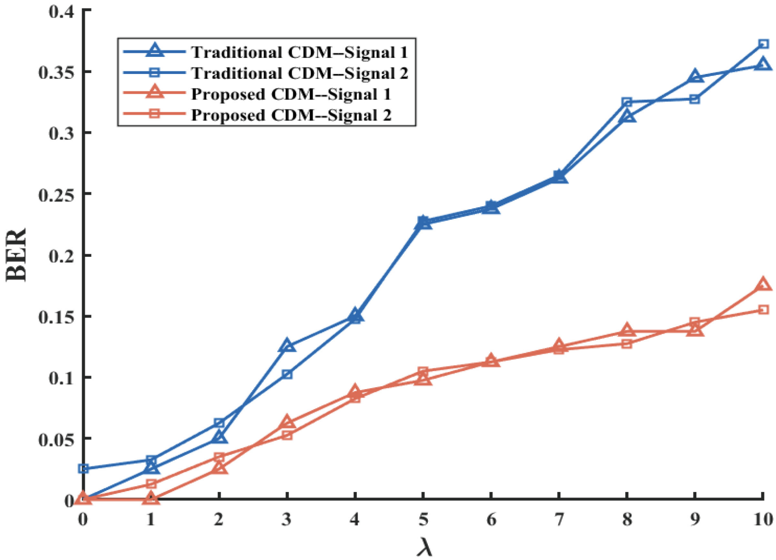

Fig. 5. Comparison of BER for the proposed CDM scheme and traditional CDM scheme as noise increases

5 Conclusion

In this paper, we have taken into account the oscillations of membrane potential, characterized by the Izhikevich model in the neural communication channel. We then devise an enhanced CDM scheme based on this model, enabling multiple signals to share a single neuron channel. In contrast to previous CDM methods, this scheme employs further encoding of superimposed signals. Not only can it transmit information correctly, the proposed system can also tell if signals is being transmitted by a certain user. The performance of the proposed strategy is evaluated in terms of BER. The results demonstrate the scheme's effectiveness in achieving low BER and a notable enhancement in interference resistance. This research enhances the communication efficiency of engineered neural systems and achieves more precise and reliable communication.

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