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DOI
10.1109/ICONS62911.2024.00010

Publication date
2024

Document Version
Final published version

Published in
Proceedings - 2024 International Conference on Neuromorphic Systems, ICONS 2024

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2024 International Conference on Neuromorphic Systems (ICONS) | 979-8-3503-6865-9/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICONS62911.2024.00010

***Abstract*—The investigation of neural activity in the murine brain through electrophysiological recordings stands as a fundamental pursuit within the domain of neuroscience. A specific area of keen interest within this field pertains to the scrutiny of Purkinje cells, nestled within the cerebellum, in order to gain insights into the mechanisms underlying brain injuries and the impairment of motor functions. Notably, Purkinje cells manifest two distinct types of spikes – complex and simple – a pivotal aspect for subsequent classification purposes. However, a critical challenge has persisted in the experimental paradigm: the prevailing setups necessitate the use of wired connections linking the mouse's head stage to data acquisition systems. This constraint substantially curtails the mouse's natural behavior during the course of experimentation, limiting the ability to study essential neural processes and motor function aspects over extended periods. In this paper, we propose a new architectural framework for the detection and classification of neuronal spikes originating from Purkinje cells. This system is engineered to exploit the distinct attributes of these neural entities, effectively winnowing out extraneous data while retaining the pertinent information. The resultant output is a refined dataset, amenable to convenient storage within the mouse's head stage, obviating the need for unwieldy wiring configurations. Our proposed implementation attains a classification accuracy of up to 98% on an in-vivo dataset. Furthermore, its compact form factor ensures unhindered mobility for the experimental mouse, fostering naturalistic behaviors during the course of scientific inquiry.**

***Index Terms*—Electrophysiological recordings, Purkinje cells, Spike detection, Spike classification, Spiking Neural Network (SNN).**

I. Introduction

Brain injuries resulting in motor function loss pose a significant healthcare challenge, impacting the quality of life for many individuals annually [1]. This pressing issue underscores the importance of comprehending and treating these disorders. In this context, the cerebellum emerges as a critical brain structure, central to motor control and hand-eye coordination [2]. Neuroscientists have long been captivated by its intricate operations, seeking to elucidate the mechanisms governing its function [2], [3].

Previous research in this area has predominantly relied on invasive experiments involving animal subjects, notably mice, due to the necessity of replicating complex neural processes [4]. However, current experimental setups, involving wired connections, limit the freedom of movement in these subjects (Fig. 1) necessitating a transition towards wire-free neuroscientific investigations [5]. While some wireless head stages have been proposed, they fall short of the requisite criteria, either being too heavy or unable to sustain long-term recordings, essential for studying various aspects of brain function [6].

This paper addresses these challenges by presenting a novel approach for detecting and classifying neuronal spikes in Purkinje cells' neural data, significantly reducing data dimensionality for efficient storage. Our proposed system architecture comprises a controller orchestrating data flow from spike detection to classification and storage in non-volatile memory. Furthermore, we introduce an SNN architecture optimized for low-power, extended operation within the size constraints of a head stage [7]. Additionally, a training algorithm ensures high classification accuracy [8], [9], enabling long-duration experiments with freely moving mice. This work represents a vital step towards facilitating comprehensive, wire-free neuroscientific investigations and extends the scope of research in understanding and treating brain injuries affecting motor function. The implementation we have put forth in this study has demonstrated an impressive classification accuracy, reaching as high as 98%. This notable level of accuracy underscores the effectiveness and reliability of our proposed approach

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in accurately classifying the recorded data. Furthermore, our system's efficiency is reinforced through the incorporation of an SNN-based architecture. This deliberate design choice empowers the head stage to maintain seamless operation over an extended duration, all while conserving energy from a compact battery source [10]. This results in prolonged and consistent performance, eliminating the necessity for frequent battery replacements.

The rest of the paper is organized as follows. A background on neuroscientific cerebellar recordings and SNN is discussed in Section II. Section III presents proposed ideas, including detection and classification architecture. Section IV describes the results to verify the proposed system-level SNN architecture. The last section concludes the paper.

II. Brain Activity Monitoring with Brain Inspired Architecture

Purkinje cells and their associated complex and simple spikes have been a subject of interest in neuroscience, particularly in understanding their role in sensory-motor and cognitive functions [11] (Fig. 2). Neuroscientists have employed electrophysiological recordings to investigate the electrical activity of these cells in the cerebellum, aiming to unravel the brain's mysteries and potentially address brain injuries and motor function losses [11]. However, experimental constraints, such as head-fixed setups for animal recordings, have limited the understanding of how neuronal signals correlate with natural body movements. Recent years have seen significant efforts in developing technologies for freely moving animal recordings, particularly for small animals like mice, known for their suitability in genetic manipulations. To achieve this, the challenge lies in creating small, lightweight, low-power, and wireless technologies to ensure the natural state of animals during experiments [12]–[15].

Brain-inspired architecture systems play a vital role in understanding neural processes and developing artificial networks [16]. To effectively design SNNs (Fig. 3), one must grasp the fundamentals of spike encoding schemes, neuron models, training algorithms, and SNN architectures [17]. Spike encoding can be approached through rate coding, temporal

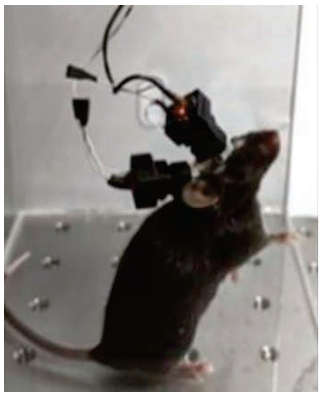


Fig. 1. Current wired setup for recording mice brain activity that disabling free movement.

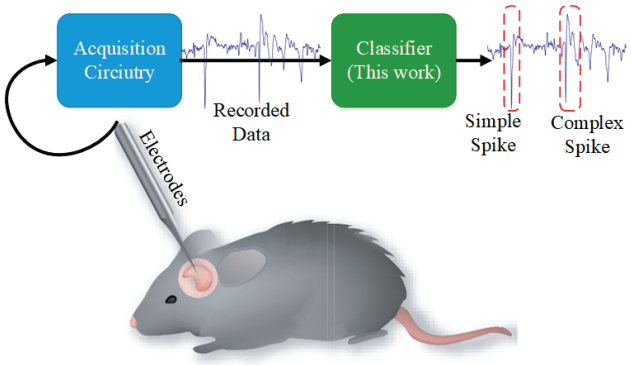


Fig. 2. Electrode-Recorded Mice Brain Activity Converted to Digital Signals and Classified into Simple Spikes and Complex Spikes

coding, or level-crossing-based coding, each requiring careful consideration of synchronization windows and digital input frequencies [18]. Notably, level-crossing-based coding offers the advantage of triggering spikes when data crosses predefined thresholds [19]. In the context of SNN systems, it is not always necessary to replicate complex neuron models used in experimental neuroscience. Simpler neuron models can be more practical and effective for designing artificial networks [20]. Training algorithms in SNNs come in three main types: unsupervised, indirectly supervised, and supervised. Unsupervised training focuses on local information but may sacrifice accuracy. Indirectly supervised training relies on spatial domain information similar to Convolutional Neural Networks (CNNs) or Artificial Neural Networks (ANNs) [21]. For achieving high accuracy, the supervised training approach is employed, where labeled data provided by neuroscientists ensures correctness throughout the training process [22].

III. Brain Inspired System

A. Overview

In the process of designing the Brain Inspired system, the initial step involves encoding input data into spike representations while also taking into account the specific neuronal model under consideration. This is followed by the integration of specialized training algorithms, ultimately resulting in the structuring of the SNN architecture (Fig. 4). The subsequent section of this paper provides an in-depth exploration of the SNN design architecture.

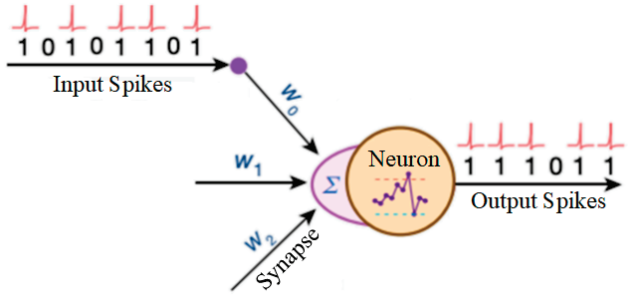


Fig. 3. A general spiking neuron model: It receives input spikes through synapses with varying weights. Upon reaching a predefined threshold, it generates an output spike.

B. Input Spike Encoding

When employing temporal or rate coding, and given an ADC frequency of 24 KHz, a digital processing frequency of 24 MHz becomes necessary. However, to reduce the computational frequency requirements, level-crossing-based encoding is adopted. In this approach, a single input channel is transformed into two channels: one for positive slope crossings (excitatory channel) and the other for negative slope crossings (inhibitory channel). A critical consideration is that each recorded data sample should not deviate by more than one level from its adjacent samples. This constraint ensures the accurate reconstruction of the encoded data. By selecting an appropriate threshold value and employing interpolation within the data, it is feasible to achieve complete data encoding while maintaining the ability to reconstruct it.

The mechanism underlying our encoding approach operates in the following manner: hypothetical levels with an appropriate level difference are first identified. The current sample and the previous sample are then considered. When the current sample is lower in level than the previous sample, a spike signal is produced in the inhibitory channel. Conversely, when the current sample is higher in level than the previous sample, a signal is generated in the excitatory channel. If the current sample falls within the same level range as the previous sample, no event or digital spike is generated.

One limitation of this encoding model is that when the current sample passes through multiple levels, only a single spike is generated instead of the expected number of spikes corresponding to the number of levels passed. This can result in an under-representation of the actual neural activity and limit the resolution of the encoded data. The issue of multiple levels being passed by the current sample is prevalent in the recorded signal due to the rapid decay of neuronal activity. As a result, this problem can significantly impact the reconstruction of the input signal from the spikes, and identifying the correct pattern of neural activity necessitates the accurate determination of the number of spikes. Therefore, it is critical to address this limitation of our encoding model to ensure a more accurate representation of the recorded neuronal activity.

To address the issue of multiple levels being passed by the current sample, we propose a solution involving interpolation to an appropriate value. This interpolation is performed in such a way that neighboring samples differ by only one level, ensuring that a spike is created from this level. For that, we first interpolate the input signal with a suitable factor and then encode the interpolated signal into spikes. To evaluate the accuracy of the encoding, the coded signal can be reconstructed and downsampled using the same factor, and then compared with the original signal. This approach helps to get an accurate representation of the recorded neuronal activity by reducing the impact of the limitation associated with multiple levels being passed by the current sample.

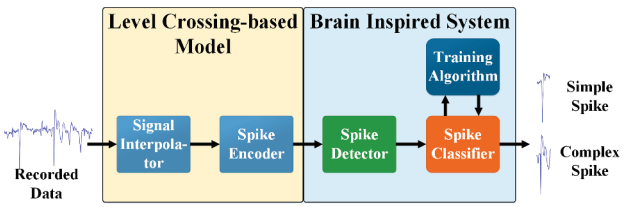


Fig. 4. Proposed top-level system architecture: The first phase involves encoding input data into spikes, followed by the second phase which is detection and then classification by trained SNN.

By implementing the proposed interpolation-based approach, we are able to preserve the time, shape, and amplitude of the signal with high accuracy during the encoding and reconstruction process. This allows for a more faithful representation of the original neuronal activity, which can be crucial for accurate analysis and interpretation of the data. Overall, the proposed approach offers a promising solution to the limitations of the original encoding model, providing a more precise and reliable method for encoding and decoding single-channel neuronal activity.

The encoding process generates two channels from the interpolated signal: the excitatory channel and the inhibitory channel. These channels represent different aspects of the neuronal activity and are used as input to the designed spiking neural network (SNN). The excitatory channel corresponds to the periods of increased neural activity, while the inhibitory channel represents the periods of decreased neural activity. Together, these channels provide a comprehensive representation of the neuronal activity captured in the original signal. This allows the SNN to capture the patterns and dynamics of the underlying neural activity more accurately.

The recorded signal is shown in Fig. 5 after applying 20 uV level crossing and 5 interpolation factors, finding empirically. The signal is a short segment of the neuronal activity recorded from a single channel, and it exhibits characteristic spikes of varying amplitudes and shapes. This level crossing and the interpolation factor of 5 has been applied to the signal as part of the encoding process, resulting in the generation of the excitatory and inhibitory channels with an input frequency of 120 kHz (Fig. 6.a).

C. Neuron Model

In this project, two distinct neuron models are employed: the Leaky Integrate-and-Fire (LIF) neuron model is utilized for the purpose of detection, while the Integrate-and-Fire (IF) neuron model is employed for classification tasks.

LIF neuron model: The rationale behind selecting these neuron models lies in their suitability for handling the input of encoded spikes, especially considering their temporal relationships and the formation of neuron spikes from a collection of encoded spikes. Leveraging neuron models in this context allows for the recognition of contributions in the time domain, which aligns with one of the primary features of SNNs – the utilization of temporal data features. Furthermore, given the sparse nature of these neuron spikes, the presence of a leaky term in these models aids in the detection of sparse neuron spikes, enhancing the robustness and accuracy of the network's

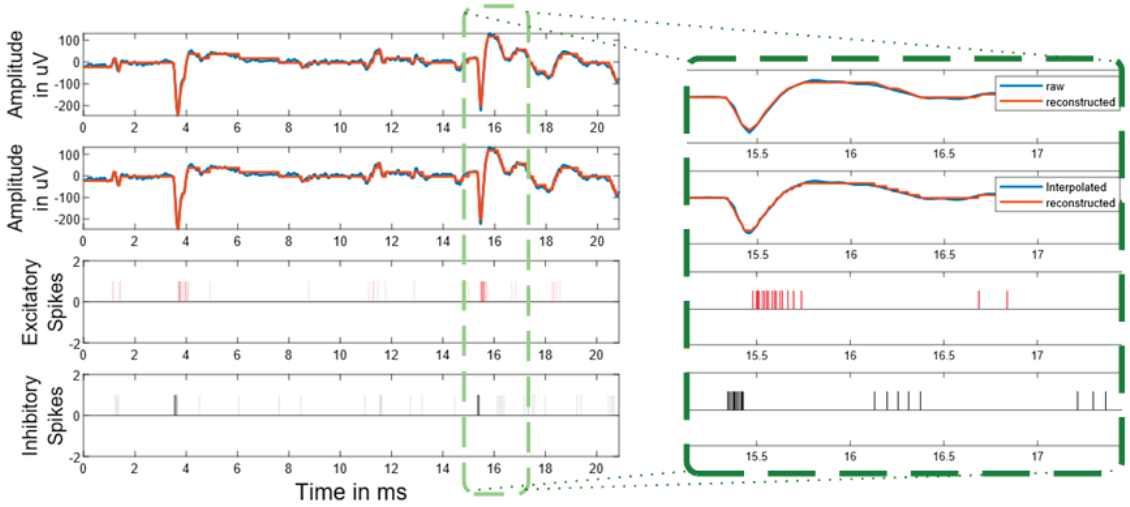
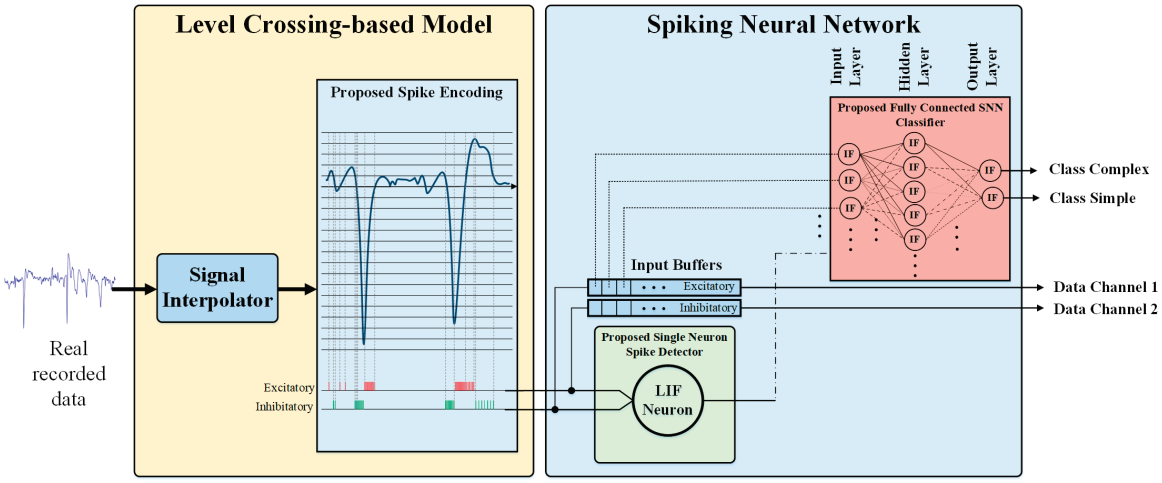


Fig. 5. Illustration of the signal encoding with a threshold level of 20uV and interpolation factor of 5: Raw signal and down-sampled reconstructed signal in the top, interpolated and reconstructed signal in the second top, excitatory digital spike channel in the third top and inhibitory digital spike channel in bottom.



(a) (b)

Fig. 6. Proposed system: (a) Input data encoding model (b) System architecture

spike-based processing. This model adheres to the following mathematical formula (Fig. 7):

$$u_t^L = u_t^L.f(O_{t-1}^L) + W.O_t^{L-1} \quad (1)$$

$$O_t^L = g(u_t^L) \quad (2)$$

Where u_t^L represents the membrane potential of neuron in layer L at time step t, $f(x) = \tau.\exp^{-x/\tau}$ is the leaky term, which depends on the previous membrane potential, W represents the synaptic weight, and $g(x)$ is the step function used to generate the output spike.

IF neuron model: The rationale for selecting this simple neuron model is grounded in the absence of correlation between successive neuron spikes, obviating the need to maintain temporal states. This model is specifically chosen for classification purposes. Here's the workflow: The input data is initially stored in a buffer. Following detection by the LIF neuron, these data are simultaneously fed into the SNN Classifier. This process enables the determination of the data class associated with the input neuron spike in a parallel fashion, facilitating efficient classification. Since there is no leaky term in this model, the corresponding part has been removed from the formula. The model of this neuron is defined by the following formula:

$$u_t^L = W.O_t^{L-1} \quad (3)$$

D. Training Algorithm

For supervised training, the backpropagation algorithm is employed. This algorithm relies on a two-step process: forward propagation through the neuron equations to compute the

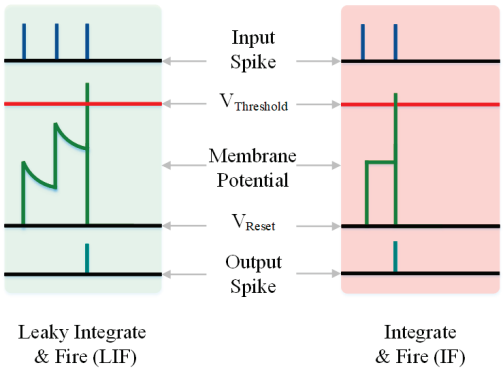


Fig. 7. Comparison of Simplified LIF Neuron Model Behavior (Left) and IF Neuron Model Behavior (Right)

output, followed by a comparison of the final output with the intended label. Subsequently, the error signal is quantified by computing the loss using a predefined formula. Finally, the synaptic weights are adjusted according to the equation 4, guided by the derivatives of both the neuron equations and the loss formula.

$$\Delta W = -\eta . \frac{\partial Ls}{\partial W} \tag{4}$$

Where η represents the learning rate, ΔW represents the synaptic weight modification, and $\frac{\partial Ls}{\partial W}$ represents error signal. The objective is to minimize the error and optimize the network's performance through these weight adjustments.

$$Ls = \frac{1}{2S} . \left\| Y_t - O_t^L \right\|_2^2 \tag{5}$$

Where Ls represents the loss, S denotes the number of samples, and Y represents the label and L is the last layer neuron output.

For the detection part, which comprises only one LIF neuron with two synapses, the appropriate values for the synapses can be determined manually due to its simplicity. However, for the IF neuron, the derivatives required for the backward propagation step are computed as follows:

$$\frac{\partial Ls}{\partial W} = \frac{\partial Ls}{\partial O_t^L} . \frac{\partial O_t^L}{\partial u_t^L} . \frac{\partial u_t^L}{\partial W} \tag{6}$$

Where

$$\frac{\partial Ls}{\partial O_t^L} = -\frac{1}{s} . (Y_t - O_t^L) \tag{7}$$

To address the issue of the step function having an infinite derivative, an approximation is employed using a surrogate gradient function, defined as follows:

$$\frac{\partial O_t^L}{\partial u_t^L} = \frac{1}{\alpha} . \frac{\exp^{v_{thr} - u_t^L}}{(1 + \exp^{\frac{v_{thr} - u_t^L}{\alpha}})^2} \tag{8}$$

Where α represents the approximation factor and v_{thr} the voltage threshold to fire a spike by the IF neuron.

Finally, this process is repeated for $N = 100$ to determine the precise value of synapses.

E. SNN architecture

As previously mentioned, for the detection phase, a LIF neuron with two synapses is employed, with each synapse connected to an input channel. Simultaneously, data is stored in shift registers. If a neuron spike is detected, the associated data is then entered into the classifier. The number of samples stored in the buffer forms the input for the neurons in the classifier.

In this designed system, the sampling frequency is set at 24 kHz, with each neuron spike having a duration of approximately 2 ms. This means that for an interpolation factor of 5, 40 samples from the input are interpolated to 200 samples. Consequently, the input for the IF neurons in the classifier consists of 200 neurons.

Moreover, the number of output IF neurons in the classifier is configured to be 2, corresponding to the number of classes (simple and complex). The architecture also includes intermediate layers, and for this specific design, a neuron layer comprising 240 IF neurons is utilized. Thus, the final architecture is structured as follows: 200-240-2.

IV. Result

A. System Setup

In this study, we utilized the MATLAB software framework to expedite the conceptualization and simulation of the system under scrutiny. The dataset used in this investigation comprises authentic data collected from mice within a medical research facility. These data were meticulously annotated by neuroscientists to ensure their accuracy and relevance. Subsequently, the meticulously curated dataset was imported into MATLAB to facilitate the design and evaluation of the system.

B. Level Crossing-Based Encoding Result

In the initial phase, input data underwent transformation via level-crossing-based encoding techniques. Subsequently, a rigorous validation process ensued, encompassing the decoding of the encoded data and the subsequent reconstruction of the signal. It is noteworthy that the threshold crossing was set at a precise value of 20uV, while the average peak-to-peak amplitude associated with neural spikes was consistently maintained at 400uV. Consequently, the system exhibited a maximum error margin of 10%.

C. Spike Detection Result

Following the encoding phase, a LIF neuron model was meticulously formulated and subsequently subjected to manual training procedures. The outcomes of these efforts were assessed through meticulous observation, with a single neuron serving as the focal point for detection (Fig. 9). This detection process was further augmented by a comprehensive comparison with labeled data within a temporal window of 40ms. This not only ensured successful detection (Table I), but also facilitated the assignment of labels for subsequent stages.

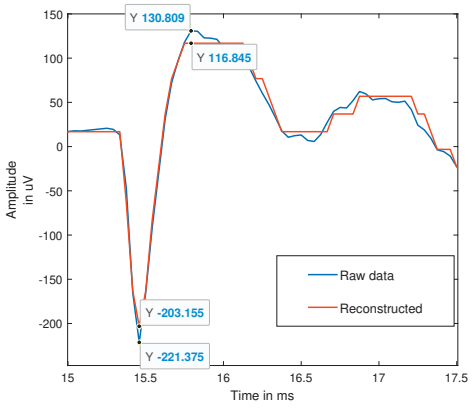


Fig. 8. Illustrated Encoding Error: The Disparity in Amplitude Range between Raw and Reconstructed Data Is Within 10% of the Original Recorded Data.

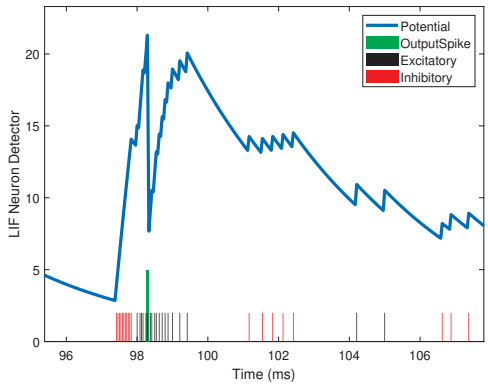


Fig. 9. Response of a Single LIF Neuron to Input Spikes Used for Detection

D. Fully Connected IF Neurons Classifier Results

The subsequent phase of the study involved the allocation of 50% of the dataset for training the classifier, while the remaining 50% was reserved for testing purposes. The results obtained from the final system are comprehensively documented in Table II for reference and analysis.

The results demonstrate an overall accuracy rate exceeding 98%, calculated as the total number of correctly detected and classified complex spikes and simple spikes over the total number of spikes, whether correctly classified or not.

V. Conclusion

In this study, we have presented a novel and innovative approach to address the limitations of traditional wired electrophysiological recording setups, particularly in the context of monitoring cerebellar Purkinje cells. Our proposed system leverages level-crossing-based spike encoding, tailored neuron models, and an SNN architecture to achieve real-time spike detection and classification with remarkable accuracy. The results obtained from our system demonstrate its effectiveness, with an overall classification accuracy exceeding 98%. Moreover, our system's compact form factor and low-power design enable unhindered mobility for experimental subjects, fostering more naturalistic behaviors during scientific inquiry. This work

TABLE I
Results of LIF Neuron Detection on Dataset: Detected, Not Detected, and Overall Accuracy

	in Dataset	Detected	Not Detected	Accuracy
CS[1]	203	203	0	100%
SS[2]	17311	17300	11	99.93%
CS+SS	17514	17503	11	99.93%

[1] Complex Spike [2] Simple Spike

TABLE II
Classifier Results for Simple and Complex Spike Classification: Total Classified, False Classified, Correct Classified, and Overall Accuracy

	Total Classified	False Classified	Correct Classified	Accuracy (CC/TC)
CS[1]	93	12	81	87.09%
SS[2]	8956	82	8874	98.97%
CS+SS	9049	94	8955	98.85%

[1] Complex Spike [2] Simple Spike

represents a significant step forward in enabling wire-free neuroscientific investigations and expanding our understanding of brain injuries affecting motor function. As we continue to refine and enhance this technology, it holds promise for advancing the field of neuroscience and contributing to the development of treatments for motor function disorders.

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