Method to Detect Impulses of Various Duration Generated by Purkinje Cells of Cerebellar Cortex[1]

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Abstract—An algorithm for the detection of electric potentials characteristic of the simple spikes (SSs) and complex spikes (CSs) generated by the Purkinje cells of the cerebellar cortex is considered. The algorithm is based on the determination of the leading edge of the detected signal, construction of its feature description with allowance made for the dynamics of the potential amplitude in the successive bins, and comparison of vectors describing the reference impulse portrait and the current signal. The algorithm is tested using artificial series of impulses and measurements of neuron activity. The results prove accuracy in the detection of the impulse leading edge and point to the possibility of selective identification of SSs and CSs having similar features.

INTRODUCTION

A characteristic feature of the electric activity of Purkinje cells (PCs), which represent the main element of the cerebellar cortex structure, lies in the generation of simple spikes (SSs) and complex spikes (CSs) having different durations and corresponding to different inputs [10, 11]. The interaction mechanisms of these inputs at the PC level are one of the central problems of the physiology of the cerebellum. On the other hand, selective automatic detection of SSs and CSs in the PC activity is a complicated methodological problem [10].

There exist a few reasons for the need in the special method aimed at the SS and CS extraction from noise (Fig. 1). First, these electric signals generated by one cell have both similar (amplitude, polarity, and time parameters of the initial components) and different (impulse duration and the shape of the later components) features [8, 10]. Second, both impulses exhibit significant variations in parameters during measurements. Finally, searching for pairs of PC twins innervated with a common liana-cell afferent [3, 4] necessitates the development of a method providing for minimum error in measurements of the impulse generation instant and making it possible to detect low-amplitude potentials using averaging relative to the reference impulse [2].

Most of the known methods for the identification of neuron impulses using computer analysis [1, 6, 7, 9] aim at determining the impulse generation instants and can be tuned to various relatively stable impulse parameters. However, they are sensitive to a developed variability in the impulse parameters (this is typical of the activity of the cerebellar PCs, especially of CSs). In this case, erroneous events can be identified or the detected signal can be ignored.

In this work, we propose a method for the detection of SSs and CSs of cerebellar cortex PCs that makes it possible to solve the aforesaid problems.

METHOD FOR IDENTIFICATION OF SSs AND CSs

The generation of nerve impulses is related to a sharp variation in the permeability of the cell membrane for sodium ions. This process, with a duration of no longer than 300 μs [5], exhibits the most stable parameters (in comparison to the other characteristics of impulse). In addition, it is known from [10] that the neuron spikes cannot be generated at a repetition rate of greater than 500 Hz (for SSs).

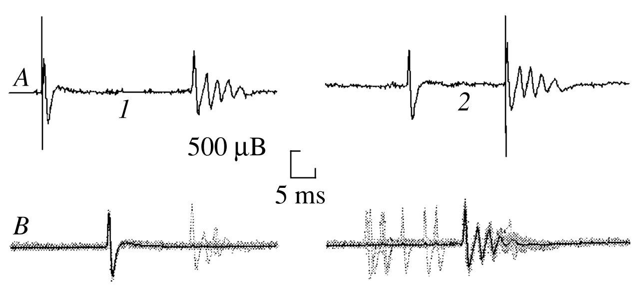

Fig. 1. Example of selective detection in (*A*) the original records of (*1*) SSs and (*2*) CSs of the cerebellar PCs and (*B*) their superposition at $n = 50$. In panel (*A*), vertical lines show the signals detected.

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Thus, the problem can be formulated in the following way: we need to identify the signal and determine the moment of generation under the condition that the signal has at least one stable characteristic (a sharp variation in the potential amplitude (leading or trailing edge)) that is regularly reproduced upon the detection of pulses generated by a single cell and that can be considered as the moment of the signal generation.

Algorithm for Signal Detection

In general, the algorithm of SS (CS) identification involves three procedures: detection of the impulse leading edge, construction of the feature description of the spike that encodes the amplitude variation in successive bins, and the comparison of the portraits of the arbitrary and reference impulses.

We assume that the original signal is represented as the vector $\vec{\mathbf{a}} = \{a_i\}$ ($i = 1, \ldots, N$), where a_i is the signal amplitude at time moment t_i (Fig. 2). We transform the signal in the following way:

$$\vec{\mathbf{a}} \longrightarrow \vec{\mathbf{\Delta}} = \{\Delta_j\} \quad j = 1\ldots N-1,$$

where

$$\Delta_j = \begin{cases} \dfrac{\Delta a_j}{\theta} & \Delta a_j > \eta \\ 0 & \Delta a_j \le \eta, \end{cases} \tag{1}$$

$\Delta a_j = a_{j+1} - a_j$, θ is the threshold, and η is the noise level.[2]

Then, the feature description of the signal $\vec{\mathbf{a}}$ can be represented as an n-dimensional vector $\vec{\mathbf{F}}$. Each component of this vector encodes a significant (above-threshold) variation in the amplitude Δa of the original signal:

$$\vec{\mathbf{a}} \longrightarrow \vec{\mathbf{\Delta}} \longrightarrow \vec{\mathbf{F}} = \{\vec{\mathbf{f}}_k\} \quad k = 1\ldots n, \tag{2}$$

where $\vec{\mathbf{f}}_k = \{\tau_k, \varsigma_k\}$, τ_k is the number of the successive components of vector $\vec{\mathbf{\Delta}}$ having the same sign and $\varsigma_k = \sum^{\tau_k} \Delta_i$.

We assume that the reference signal (portrait of the impulse characteristic of the given PC) $\vec{\mathbf{a}}$ and current signal $\vec{\mathbf{a}}'$ are identical if the dimensions n and n' and the components of the corresponding description vectors $\vec{\mathbf{F}}$ and $\vec{\mathbf{F}}'$ coincide. We also assume that the components $\vec{\mathbf{f}}_k$ and $\vec{\mathbf{f}}'_k$ of vectors $\vec{\mathbf{F}}$ and $\vec{\mathbf{F}}'$, respectively, are equal if the condition

$$\begin{cases} \operatorname{sgn}(\varsigma'_k) = \operatorname{sgn}(\varsigma_k), \\ \tau'_k - \varepsilon_k \le \tau_k \le \tau'_k + \varepsilon_k, \\ \dfrac{\min(|\varsigma'_k|, |\varsigma_k|)}{\max(|\varsigma'_k|, |\varsigma_k|)} \ge w_k, \end{cases} \tag{3}$$

where ε_k is the variability in the duration τ_k of the component $\vec{\mathbf{f}}_k$ of vector $\vec{\mathbf{F}}$, is satisfied.

[2] Based on the results of the preliminary testing of the algorithm using the measurements of the PC activity, the threshold and noise level are empirically chosen to be $\theta = 0.4\Delta a_{max}$ and $\eta = 0.1\theta$.

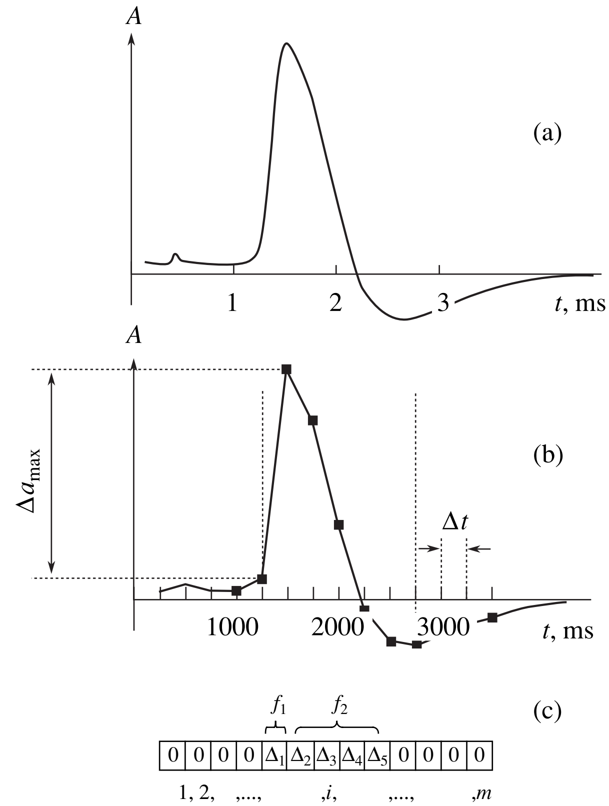

Fig. 2. Scheme for the construction of the feature description of the reference signal using an example of SS: (a) impulse detected with an amplifier of biopotentials and (b) the same impulse after analog-to-digital conversion with the bin $\Delta t = 250$ μs, and (c) vector $\mathbf{F} = \{\mathbf{f}_1, \mathbf{f}_2\}$ of the impulse feature description.

Features of the SS and CS Detection

Taking into account the known difference [10] between the SS and CS properties (see, for example Fig. 1), the above algorithm exhibits a few features upon the detection of pulses of different types. In particular, the dimension of the vector describing CSs is significantly greater than that describing SSs. In addi-

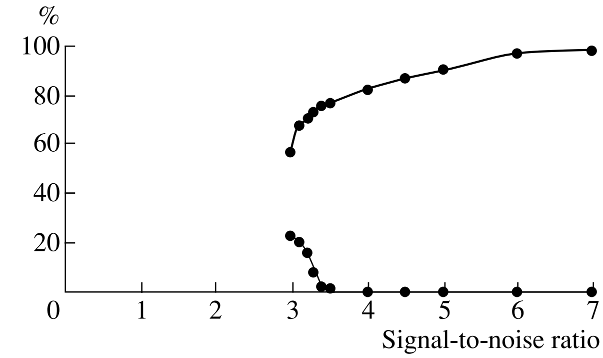

Fig. 3. Plots of the numbers of (—) correctly identified SSs and (—) erroneous events vs. signal-to-noise ratio.

tion, upon the construction of the feature description of SSs, we do not consider zero components of vector $\vec{\mathbf{\Delta}}$ in expression (2). Finally, SS detection employs an additional analysis of the refractoriness (time interval when the generation of the next impulse is prohibited). In this case, after obtaining the vector of the feature description for the next fragment of record $\vec{\mathbf{E}}' = \{\vec{\mathbf{e}}_l'\}$, we prohibit (in accordance with expressions (1) and (2)) a variation in the potential amplitude that is comparable to the threshold θ for an interval τ_R of about 2 ms. In other words, if $\tau' \le \tau_R$ and $|\varsigma'| > \theta$ for any component of vector $\vec{\mathbf{E}}'$, the signal $\vec{\mathbf{F}}$ is not classified as related to SS. Upon CS detection, we do not analyze the refractoriness owing to the presence of a few high-amplitude components.

Estimate of the Efficiency of the Signal Detection Algorithm

The software implementation of the above algorithm is tested using an artificial series of noisy signals similar to SSs of PC activity. Figure 3 demonstrates the results of this test. It is seen that, at a ratio of signal amplitude to noise greater than 6, we can identify more than 97% of the impulses, the parameters of which correspond to the predetermined reference portrait. Erroneous events (random noise spikes) are not detected.

For processing of the real electric-activity records of cerebellum PCs (Fig. 1) with the same range of the signal-to-noise ratio, the number of correctly detected SSs is slightly lower (about 90%) than that for the processing of the artificial series.[3] The detection accuracy depends on the parameters of the impulse that serves as the reference portrait, the details of the pulse shape for the given cell, and their time distribution. Note that the number of errors of the first kind (unidentified pulses) is virtually equal to the number of errors of the second kind (erroneous events). Errors of the second kind are, most often, represented by short (less than 5-ms) CSs, whereas the slow oscillations of the potentials (including the oscillations with high amplitudes) that have more smooth leading edges and the high-rate trains of impulses (e.g., stimulation artifacts) are completely ignored.

To raise the accuracy of the impulse detection, the software also employs an algorithm for correction of the feature description of the reference pulse in accordance to its dynamics during measurements. The algorithm is based on averaging of the parameters of impulses detected in the current fragment of the record and on the optimization of coefficients ε_k and w_k entering expression (3). This makes it possible to increase the number of correctly identified pulses upon a developed variability in their parameters.

The accuracy of CS detection that is less than the accuracy of SS detection also depends on a few factors: the mean accuracy of CS detection is about 60% in the absence of the correction of the algorithm initial conditions. However, if the SS duration substantially differs from the CS duration (Fig. 1), the pulses of two types of the PC under study are detected with nearly equal accuracies (up to 95%).

CONCLUSIONS

The proposed algorithm and software complex is used for the neurophysiological and model study upon the processing of the impulse activity of the cerebellar cortex and visual cortex neurons [4, 8]. This complex makes it possible to simultaneously analyze time series of impulses and the dynamics of potentials with acceptable detection accuracy and high time resolution (about two bins of the analog-to-digital conversion of the original records). In addition to the analysis of the high-amplitude impulses, this method enables one to reveal low-amplitude field potentials [4] near the reference impulse upon the summation of potentials when the low amplitudes are comparable to the noise level in the detection channel.

The proposed method also allows for a real-time quantitative analysis of the experimental data and the visualization of the results. This makes it possible to correct experiment in the course of measurements.

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