DETECTION OF AUDITORY STIMULUS ONSET IN THE PONTINE NUCLEUS USING A MULTICHANNEL MULTI-UNIT ACTIVITY ELECTRODE

Majd Zreik¹, Ytai Ben-Tsvi², Aryeh Taub³, Rakefet Ofek Almog², Hagit Messer²

Tel-Aviv University Department of Biomedical Engineering¹
Tel-Aviv University School of Electrical Engineering²
Tel-Aviv University Department of Psychology³

ABSTRACT

This paper discusses a real time stimulus timing detection for a Brain-Machine-Interface (BMI). We present a low complexity detector for detecting the stimulus onset time from real multichannel, multi-unit electro-physiological data, recorded from a brainstem area called Pontine Nucleus (PN). The detector contains a novel pre-processing block, which takes advantage of the high coherence between different channels during response, in order to enhance the Signal-to-Noise Ratio (SNR), as well as to achieve higher detection rates. An intuitive effective method for fusion and combination of different channels based on spike counts is used. A full detailed description of the algorithm blocks is presented, along with its optimized parameters according to real data performance evaluation.

Index Terms— Multi Unit, Multichannel, Detection, BMI, Pontine Nucleus

1. INTRODUCTION

All Brain-Machine-Interfaces (BMI) require reliable, simple and adaptive detection algorithms to reveal the neural response, enabling fast communication and interaction between the brain tissue and the machine. There has been much progress in the field of BMI in the last decade [1], mainly serving two periphery nervous system applications: sensory rehabilitation (e.g. bionic eye research), and motor control rehabilitation (e.g. limb prosthesis ). Our research aims towards rehabilitation of a learning function in the central nervous system [2] [3].

In this paper we present a simple, yet effective, detector for estimating the onset time of a stimulus from in-vivo recorded multichannel multi-unit electro-physiological data. We particularly focus on the detector’s employment of the multichannel nature of the electrode and the usage of the "hidden" information between different data channels, to boost the performance relatively to a single channel recording. Two novel blocks were used; One - the "correlation enhancement" block - enhances the data while employing the increasing coherence between channels during neural response. And the other is an intuitive effective method for channel fusion and combination based on spike counts.

In section 2 we present the data acquisition setup and the dataset. In section 3 we present the used detection criterion, while in section 4 we describe the algorithm. Section 5 describes the results of the empirical detection performance in real data. In section 6, we summarize and discuss the results of the above.

2. DATA ACQUISITION AND DATASET

The results of the presented study use real neural data collected as part of comprehensive ambitious projects [3] aimed at interfacing a biomimetic chip with a senescent cerebellum, for the sake of rehabilitating a discrete sensory-motor learning function. Specifically, the study focuses on eye-blink conditioning to an auditory tone in rats . Data is collected using a novel Titanium Nitride (TiN) multichannel multiunit electrode, which contains eight channels with 20x20 micron tip, each of an impedance of 0.5-0.75 Mohm. The rats under experiment received 60-120 Conditioned Stimulus (CS) trials, with an inter-trial interval (ITI) of 4-12 seconds. The CS was a white-noise auditory tone (470 msec in duration, 10 msec rising/falling phase and intensity of 67 dB) delivered to the right ear through a hollow ear-bar of the stereotaxic head holder. Neuronal activity was amplified using an MCP amplifier (Multi Channel Processor, Alpha-Omega, Israel), and digitized by CED 1401mk II acquisition system (Cambridge Electronic Devices, England)) with a sampling rate of 15 kHz. All samples were bandpass filtered online (0.3-10.0 kHz) using the MCP system. The dataset contains seventeen samples (17) recorded from five different anaesthetized rats ( N=5).

3. DETECTION CRITERION

This paper focuses on online detection of the auditory stimulus onset in the PN, with the Neyman-Pearson criterion as a

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detection quality indicator. This criterion is based on the principle of selecting the algorithm that has the best probability of true detection for a given probability of false alarm. We consider the detection successful if the algorithm has indicated a stimulus onset within a defined time window. Therefore, immediately after every onset, a window of [20-110] msec is opened, and every "detection" that falls outside this window is considered as a false-alarm detection. The first event detected inside the window is considered a true detection and all others (if there are any) are considered false-alarms. The true detection rate (TDR) is expressed in percentage and the false alarm rate (FAR) is expressed in Hz.

4. ALGORITHM MOTIVATION AND FLOW

Real time detection of neural responses in the brain concerns many research groups, particularly in the fields of Brain-Machine-Interface (BMI), Brain-Computer-Interface (BCI), Direct-Brain-Interface (DBI) and many clinical applications. A vast variety of signal processing algorithms is used in these fields; Cross-correlation between a trigger-averaged event-related potential (ERP) template and continuous electrocorticogram (ECoG) was used to detect movement-related ERPs [4]. A detection based on a pulse amplitude modulation (PAM) model is used in epileptic seizure identification [5]. A method using wavelet-packet features was proposed to simultaneously detect ERP [6]. Spike trains from single or small groups of cells are another option for input in direct brain-computer communication, and it has shown promising results [7].

Our algorithm is based on the "spike rate" or "fire rate" feature, which refers to the increased neural activity in the presence of a stimulus. A Peri Stimulus Time Histogram (PSTH) and a raster plot of a typical PN response is shown in Figure 1.

![Fig. 1. Typical PN PSTH. Phasic and sustained responses are combined due to using a MU electrode. Top: Raster plot. Bottom: PSTH](image)

The detector receives an input in the form of a noisy, multi-channel recording of the PN multi-unit electrical activity, and it outputs an indicator that signals ‘1’ whenever a stimulus’ onset was detected. Post the preprocessing block and within the observation window, spikes were first located using adaptive threshold based methods that adopt to the time-wear changes in the recorded signal [8], then converted to a "fire rate" or "spike rate", acting as the basis of the onset detection. A detection is declared only when the "fire rate" pattern matches a known pattern which was obtained offline in a training phase of the algorithm (similar to what was done in [4]). Figure 2 shows a general block diagram of the suggested algorithm.

![Fig. 2. General Block diagram of the suggested algorithm.](image)

4.1. "Correlation enhancement" Preprocessing Block

For the purpose of improving the detection performance, affected by the low SNR which characterizes PN recordings, this original "preprocessing block" was built. The method takes into consideration the increase in the spikes train correlation with firing rate, and the high coherence between different channels of the electrode during the response period [9], and employs it leading to a better signal-to-noise ratio. As shown in Figure 3, the preprocessing procedure contains the following steps:

1. A short time window is opened (20 msec of data is buffered);
2. The average of the correlation coefficients between different channels is calculated and rectified;
3. The average is multiplied with the same raw data window;
4. The enhanced data is preceded with to the spikes detector block;
5. Return to step 1 with a new segment of raw data;

Following to this procedure, the data window "containing" real neural response with higher coherence between different channels, will be multiplied with a higher factor (higher
correlation coefficient) relatively to the background unsynchronized responses (or noise), thus, improving the SNR.

4.2. Spikes Detection

In order to be specific to the spike shape, a Double Threshold based spike detector is suggested. This spike detection algorithm is based on the simultaneous detection of the peak and trough of the spike with specific rates and timing [8].

The threshold value is determined adaptively as:

\[
Thr = Mean(\gamma) + \alpha STD(\gamma)
\]  

(1)

Where the Mean(\gamma) and STD(\gamma) are the adaptive mean value of the signal and the standard deviation, respectively. These two values are calculated using 1st order IIR filter (exponential window).

The values of \(\alpha\) and \(\gamma\) are set to 2.5 and 0.002, respectively.

4.3. Channels Fusion

After binarizing the waveforms in the Spikes Detection block, several multi binary channels are received, later to be fused. Two fusion methods were tested:

**Unification:** Summing up all spike counts in the separated channels to form a single channel signal that contains all spikes from all channels. The motivation behind this method is to emphasize spikes found in more than one channel, which are more likely to be real spikes, as well as to weaken spikes which exist in fewer channels, and probably refer to noise.

**Voting:** Only the presence of a minimum number of spikes in the separated channels will be taken into consideration in the unified channel. Lowering the minimum requirement will lead more spikes to pass to the unified signal, and vice versa. Contrary to the previous fusion method, a presence of a spike in the joined signal is represented by ‘1’ and not by the original count of the separated spikes.

4.4. Moving Average and Matched filter

As claimed before, the basis of the detection algorithm is to identify the specific pattern of firing spikes of many neurons "caught" by the electrode. To do so, a moving average filter is suggested, converting the Boolean signal (previous block) to a local “fire rate”. Practically, the binary signal is convolved by a \(T_{MA}\) seconds length rectangular window and a step length of \(T_{step}\), which defines the overlapping between sequential windows. Both parameters were set to 20 msec. The kernel of the matched filter (the pre-known signal) is revealed in the training block by averaging the first 150 msec after each onset within the training session.

5. RESULTS

For the purpose of evaluating the performance of the algorithm, unified comparisons were applied. For each test, the averaged Receiver Operating Characteristic (ROC) over all samples is calculated, as well as the averaged Area Under Curve (AUC) and the averaged TDR at the maximum allowed FAR, which was set to one Hz. To visualize the variation between samples, the error bar was shown for both measures (AUC and TDR).

5.1. "Correlation Enhancement" Effect

This test performs an evaluation of the "correlation enhancement" preprocessing block using different BPFs. The test was performed twice, with and without the correlation enhancement block. The results are shown in Figure 4 and in Figure 5.

**Fig. 4.** ROCs for different BPFs with and without the "Correlation Enhancement" block . (a) [0.3-5] KHz BPF. (b) [0.3-7] KHz BPF.

**Fig. 5.** Top: Average AUC. Bottom: Average TDR at the maximum allowed FAR. With and without enabling the Correlation Enhancement preprocessing block.

An evident increase of performance is shown in Figure 5 for all BPFs. The largest relative gain was obtained while using this preprocessing block along with the [0.3-5] KHz BPF.
(Figure 4.a). However, using the [0.3-7] KHz BPF (Figure 4.b) along with the "correlation enhancement" block reveals a superior detection method with the highest absolute performance gain, making this configuration the preferred one.

5.2. Channels Fusion Effect

The TiN electrode has 8 channels. Therefore, nine combinations were evaluated: unification and voting for 1-8 spikes. It is clear from Figure 6 that voting for two spikes in the separated channels obtains the higher performance. Yet, voting for more spikes, i.e. being more specific and strict, decreases the performance of the detection.

Fig. 6. Top: Average AUC for different fusion methods. Bottom: Average TDR at the maximum allowed FAR for different fusion methods.

6. DISCUSSIONS AND SUMMARY

An algorithm for detection CS onset from multichannel multiunit PN recordings is suggested. A technical detailed review of the algorithm blocks is described, along with its motivation. A performance evaluation for some of the blocks is performed using a 17 PN neural recordings dataset. The usage of the novel “correlation enhancement” preprocessing block proves its efficiency in enhancing the SNR, therefore, boosting the performance. This preprocessing block casts the increase of the correlation between spikes train in the different channels on the data by multiplying it by a high factor, higher than the one multiplied by the data lacking neural response. The highest performance was obtained while pairing the correlation enhancement block with the [0.3-7] KHz BPF, proving that there are more neural information beyond the typical "spike band". In addition to the above, the minimal spike counts in the separated channels is determined. After evaluation of the fusion methods, voting for two spikes out of the eight possible channels, achieved the highest performance.

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8. REFERENCES


