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Detection of Action Potentials in the Presence of Noise Using Phase-Space Techniques

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***Abstract*—**Emerging Bio-engineering fields such as Brain Computer Interfaces, neuroprothesis devices and modeling and simulation of neural networks have led to increased research activity in algorithms for the detection, isolation and classification of Action Potentials (AP) from noisy data trains. Current techniques in the field of 'unsupervised no-prior knowledge' biosignal processing include energy operators, wavelet detection and adaptive thresholding. These tend to bias towards larger AP waveforms, AP may be missed due to deviations in spike shape and frequency and correlated noise spectrums can cause false detection. Also, such algorithms tend to suffer from large computational expense.

A new signal detection technique based upon the ideas of phase-space diagrams and trajectories is proposed based upon the use of a delayed copy of the AP to highlight discontinuities relative to background noise. This idea has been used to create algorithms that are computationally inexpensive and address the above problems.

Distinct AP have been picked out and manually classified from real physiological data recorded from a cockroach. To facilitate testing of the new technique, an Auto Regressive Moving Average (ARMA) noise model has been constructed bases upon background noise of the recordings. Along with the AP classification means this model enables generation of realistic neuronal data sets at arbitrary signal to noise ratio (SNR).

***Keywords*—**Action potential detection, Low SNR, Phase space diagrams/trajectories, Unsupervised/no-prior knowledge.

I. Introduction

THE detection of bio-electricity from the human body has been an area of human interest and active research for many years. The recent rapid growth of electronics through advances in VLSI is leading to a wide range of electronics technology being integrated into electrophysiological research and medical devices.

One such area of integration is that of implantable system-on-chip (SoC) devices, equipped with analogue and digitising stages to read neuronal depolarization events from live cell cultures. Such devices have been employed to yield new insights into how the nervous system encodes, transmits and processes sensory information from its environment. Devices require many channels sampling at high data rates (e.g. ten kHz) [1], to faithfully capture the position and form of the raw AP signal, as such data rates can be high as tens or hundreds of mega samples per second. The high data rate combined with strict limitations on size and power usage of implantable devices leads to a data bottleneck when attempting to transmit the data wirelessly off chip [2]. Wireless methods are increasingly being chosen since tethered wires lead to restrictions on possible clinical applications [2]. If the processing of captured data could be performed on-chip, then instantaneous usage of the data at the neuronal culture site would help trials of neuronal activity and correlated stimulation and resulting action.

Different methods of overcoming this hardware problem have been reported recently [2-5]. In [3] a full VLSI design for processing of neuronal signals is described. The processing of data to identify the neurons signature AP message is carried out via the use of a simple comparator. The designers managed to create the system in 0.5 micron CMOS that fits a suitable neuronal amplifier and the spike detection hardware positioned beneath each electrode of a Utah Microelectrode Array, (pitch 400 micron). Whilst this is still a rather large pitch array, not on the same scale as the neurons (10-20micron), and the detection method is still quite simple (being biased towards larger action potentials and susceptible to low SNR) it does comprise a first attempt into an area that will surely see large growth in coming years.

Other hardware methods of surmounting this problem have employed the use of FPGAs [2,4,5]. One of these [2] saw a FPGA surface mount chip connected to a small circuit board. The circuit board would be intrusive for implantation but it does provide a simple digital threshold method for the detection of action potentials. Reference [4] shows a similar data reduction technique using an FPGA in between a System-on-chip device and a PC. Blind source separation of bio-signals has been implemented on an FPGA via use of the FastICA algorithm [5]. This method is commonly used in bio-signal processing and the demonstration of it in FPGA hardware is a significant step towards action potential detection hardware. Another avenue of research in hardware solutions to this problem is the method of data compression [6]. The raw neuronal data is compressed using the discrete wavelet transform technique, then transmitted wirelessly. The compression/reconstruction process affects the shape of the AP (with obvious effects on classification) but may prove adequate for detection purposes.

The problems described above relating to hardware

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restrictions have led a number of researchers to develop computationally minimised software based algorithms. These methods include novel adaptive thresholding techniques, energy operators, peak detectors and wavelet based methods.

Adaptive thresholding is a logical progression from a static level set in hardware. A review of these techniques is provided [7] and found that method chosen affects the ratio of detection to false positive. Other techniques mentioned are pre-processing techniques aimed at enhancing the action potentials from within the data in order to increase the ratio of true detection over false alarm gained by adaptive thresholding. A comprehensive review of pre-processing techniques including template based methods is given in [8]. The paper also proposes a new technique based on the increase in energy that an action potential adds to a neuronal signal. The energy in each small bin (e.g. 1ms) is compared against the energy in a much larger segment. In a another series of research [9-11] the use of the Teager energy operator that helps identify peaks in data trains is employed. These two techniques are both computationally efficient and are used as a comparison to the new technique developed here. A technique that has been adapted to suit this field is that of wavelet detection [12-14]. Wavelet detection uses a general "spiky" waveform to which segments of the neuronal data is matched. This approach is about ten times more computationally expensive making it less well suited to real time multi-channel operations and thus has not been included for comparison here.

II. Phase Space Techniques

The concepts of phase space portraits [15] and phase space trajectories [16] have been shown to be relevant for action potential classification. Reference [15] gives a good introduction to plotting of phase-space diagrams. In essence phase techniques identify changes that occur in the phase of a signal by comparing it with a time delayed version of itself.

This study combines the concepts of phase space and trajectories to develop a new technique for the detection of a wide range of action potential shapes, in the presence of noise. The approach is based on the idea that a sudden change in the phase of the signal is accompanied by a dramatic change in the trajectory on a phase space diagram.

III. Methods

A. Data Collection

Data for these experiments was collected by the authors in the form of several recordings made from the Ventral Nerve Cord of a Cockroach using a differential amplifier built from Texas Instrument op-amps. The amplified signal was then digitized by an ADC using a sample frequency of 11 kHz.

B. Simulation Data for Arbitrary SNR

The simulation of relevant data for testing bio-signal processing techniques is a research field in its own right and many different simulators are available. Two relevant data simulators [17,18] and the methods described in [11] were studied to aid the production of realistic test data.

Firstly using various action potential detection techniques and aided by manual classification, clear examples of AP from within the data sets were identified. These AP were then aligned using the first major peak within the segment to identify similar shapes and hence classify them. Every instant within a class was then summed and a class average produced. Fig. 1 shows the culmination of instances that made up the each AP class and below the averaged and normalized class means of the quickest and slowest action potential shapes.

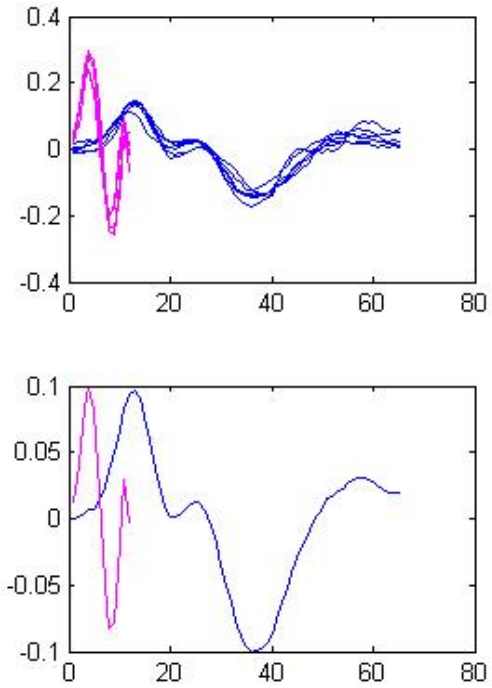

Fig. 1 Above instances that make up each class: Below averaged and normalized class means

From these, the two extrema of quickest and slowest AP shapes were chosen to provide the most difficult test to any detection technique. The two extreme cases had periods of 1.1ms and 6ms.

Relevant noise (non-Gaussian) was then required to simulate neuronal signals with known firing times. To achieve this, five noise segments were taken from separate recordings. To allow for replication of this noise at arbitrary SNRs an auto regressive moving average model of each noise segment was created.

The SNR of the simulated neuronal data is defined in equation one below.

$$SNR = \left(\frac{height\_of\_action\_potential}{RMS\_noise} \right)^2 \quad (1)$$

To convert this to decibels, the logarithm of the SNR was

multiplied by ten.

C. Review of Relevant Methods

As previously mentioned to demonstrate the effectiveness of the new technique, two methods from recent literature were chosen as a performance comparison. Reference [8] introduces the normalized cumulative energy difference (NCED) technique. This technique can best be described as looking for sudden changes in the energy of a signal compared to the overall energy within a signal and can be defined by equation two, where x(i) is the current sample and bin size is an arbitrary choice of a number of samples (in these tests ten).

$$NCED = \frac{\sum_{1}^{binsize} x(i)^2}{total\_energy} \quad (2)$$

The Teager energy operator (TEO) a non-linear energy operator is the product of instantaneous frequency and amplitude and highlights the action potential peak [9-11]. It can be defined by equation three, where x(i) is the current sample and x(i-1) and x(i+1) are the previous and next sample respectively.

$$TEO = x^2(i) - x(i-1).x(i+1) \quad (3)$$

D. Proposed Technique

The proposed technique uses the concepts of phase space diagrams and trajectories, whilst maintaining computationally efficient. The method proceeds as follows:- the instantaneous power (or energy) in a signal is summed positively over the whole period of an action potential. To compute when the power of the signal rises sharply the difference between the powers at two points is compared for both phases of the signal. This is done by adding the change in power from the time delayed signal to the start of a small segment in the current signal and comparing this value to the current value of power, as shown in equation four The technique can also be thought of as a method for linearly predicting the power in a signal and comparing the difference in the linear prediction to the actual power. If the bin size b is the same as the time delay, (as in linear prediction) then the computation required can be reduced to equation five, (using the same notation as above).

$$PP = x^2(i) - \left(x^2(i-b) + \left(x^2(i-b) - x^2(i-2b)\right)\right) \quad (4)$$

$$PP = x^2(i) - 2.x^2(i-b) + x^2(i-2b) \quad (5)$$

IV. Results

A. Simulated data results

Tests of the three techniques discussed in the methods section were run using the five different noise models and the two extrema AP shapes. The results were classified by an adaptive threshold method. The threshold was set at the signal mean plus two or three standard deviations, and the threshold was calculated in ten ms bins equating to 100 samples. The NCED technique was applied using a bin size of ten samples (0.9ms) and the phase technique used a delay of two samples (0.18ms). The results are summarised in the Tables I to III below. Table I's results are at SNR=4.9DB and Table II's are at SNR=8.1DB. In Tables I and II the first figure is the correct detection ratio and the second figure is the false positive ratio. Table III summaries these results averaged over all five noise segments noise segments as a percentage.

TABLE I
4.9DB SNR

Sigma level =3	Noise 1	Noise 2	Noise 3	Noise 4	Noise 5
TEO	0.5/0.2	0.2/0.3	0.3/0.6	0.2/0.3	0.5/0.5
NCED					
PHASE	0.4/0.1	0.4/0.2	0.5/0.5	0.5/0.1	0.1/0.1
Sigma level =2	Noise 1	Noise 2	Noise 3	Noise 4	Noise 5
TEO	0.9/0.8	0.6/1.3	0.5/0.8	0.6/0.7	0.5/1.1
NCED	0.4/0.1	0.5/0.2	0.5/0.2	0.5/0.2	0.4/0.4
PHASE	0.9/0.3	0.8/0.8	0.6/0.6	0.8/0.4	0.8/0.4

TABLE II
8.1DB SNR

Sigma level =3	Noise 1	Noise 2	Noise 3	Noise 4	Noise 5
TEO	0.6/0.4	0.2/0.3	0.6/0.3	0.6/0.4	0.7/0.4
NCED					
PHASE	0.4/0.1	0.4/0.2	0.7/0.2	0.5/0	0.5/0.3
Sigma level =2	Noise 1	Noise 2	Noise 3	Noise 4	Noise 5
TEO	0.9/0.7	0.8/0.8	0.8/0.6	0.9/0.6	0.9/0.9
NCED	0.6/0.1	0.5/0.2	0.5/0.2	0.7/0.2	0.5/0.3
PHASE	0.9/0.3	0.9/0.6	0.8/0.5	1/0.1	0.9/0.4

TABLE III
AVERAGED DETECTION/FALSE ALARM RATE

Average Results	SNR=4.9 sigma=2	SNR=4.9 sigma=3	SNR=8.1 sigma=2	SNR=8.1 sigma=3
TEO	62% / 94%	34% / 38%	86% / 72%	54% / 36%
NCED	46% / 22%		56% / 20%	
PHASE	78% / 50%	44% / 26%	90% / 38%	50% / 16%

From Table III it can be seen that the new phase technique has a higher detection rate on three out of the four different tests than the Teager energy operator. Paired with this the new technique, has a much lower false alarm rate. Compared with the NCED technique at the two sigma level, (NCED does not transform any of the data points to greater than three standard deviations from the mean) the detection rate is approximately double. NCED also has a false alarm rate that is approximately half that of the proposed technique.

B. Computational Expense

The proposed technique has similar computational demands

to the other two techniques, (tabulated below in Table IV) so can be considered as a direct comparison in terms of computationally inexpensive algorithms for large multi-channel real time processing systems.

The computational demands of each technique are considered in terms of multiplication, additions and subtractions. The TEO requires two multiplications and one subtraction, per operation, and therefore for a bin size of ten requires twenty multiplications and ten additions or subtractions. The NCED technique over a bin size of ten requires ten multiplications and nine additions to compute the energy segment and an extra division to compute the normalized energy. The total energy is calculated over a much larger bin and requires more samples to be kept in memory. In these tests a larger bin ten times the size of the small bin size was used. This means that the energy total can be calculated each time by keeping a sum of the last ten (small) bin sizes which requires one subtraction and one addition per bin size. Hence the NCED technique requires eleven multiplications and eleven addition or subtractions per bin size. The proposed new phase technique requires one multiplication to square the current sample and another one to double the last result. It further requires two addition and subtractions to subtract this doubled value and add the twice previous delay value. It is worth noting that the new phase technique could also be done as ten multiplications and thirty addition and subtractions. Table IV summaries the computational expense of each technique.

TABLE IV
COMPARISON OF COMPUTATIONAL EXPENSE

	Multiplication	Addition/subtraction
TEO	20	10
NCED	11	11
PHASE	20 / 10	20 / 30

V. CONCLUSION

The technique presented in this paper for detection of AP from noisy neuronal data has been shown to be particularly effective on the data. This data is regarded as an extreme test since the noise is in the same frequency range as the action potentials and the action potentials show a large range of periods. It has also been shown that the algorithm is of a similar computational expense as other techniques. These features render it suitable for hardware implementation within the space and power dissipation restrictions that apply to implantable system-on-chip devices.

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