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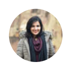
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Low SNR Neural Spike Detection Using Scaled Energy Operators for Implantable Brain Circuits

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Abstract— **Real time on-chip spike detection is the first step in decoding neural spike trains in implantable brain machine interface systems. Nonlinear Energy Operator (NEO) is a transform widely used to distinguish neural spikes from background noise. In this paper we define a general form of energy operators, of which NEO is a specific example, which gives better spike-noise separation than NEO and its derivatives. This is because of a non-linear scaling applied to the general discrete energy operator. Using two well-known publically available datasets, the performance of several operators is compared. On data sets that contain multi-unit spikes with low Signal to Noise ratio, the detection accuracy was improved by approximately 15%.**

Keywords—**Spike detection, Non-Linearly Scaled Energy Operator, Taeger Energy Operator, Higher Order Energy Operators.**

I. INTRODUCTION

With the advancement of technology, present-day multimodal intracranial recording systems offer high temporal and spatial resolution needed for brain machine interface systems such as implantable neuro-prosthetics [1]. In a general system, analog data acquired using electrodes and analog front-ends appears in the form of spikes; each spike representing a single neuron's activity. These spikes represent different neurons communicating with each other inside the brain, and thus, can be considered as a window to the cognitive processes of a being. In most of the cases, before this data can be used for any application, it needs to be processed on the basis of the neurons generating these signals, as well as the time at which these spikes were created and for this purpose, spike detection is used to extract the neuronal activity (spikes) from the noisy data. In some applications, spike sorting is required before computation of neuron firing rates. Spike sorting involves separating spike recordings from a channel into multiple spike trains, based on the specific distinguishing features. Nevertheless, spike detection is applied on the data as the first process of neural signal processing [1], making it an essential part of any neural processing application, including spike sorting, early detection of epileptic seizures, and sleep disorders. Most applications involving spike detection, such as neuro-prostheses, need data from multiple channels at high sampling rates, along with the requirement for the processing to be done in real time for precise operation. The bandwidth and communication constraints necessitate on-chip spike detection, allowing for the data to be sent only when a spike is detected, thus, reducing the amount of data to be transmitted wirelessly [1].

The accuracy of spike detection greatly influences performance of succeeding steps. The most basic technique used for spike detection is amplitude thresholding in which a spike is detected only when the amplitude crosses a pre-defined threshold. The threshold can be selected manually or on the basis of the standard deviation of the data. This technique works well at high SNR but its accuracy is greatly reduced when the data has a predominant low SNR. The Non-linear Energy (NEO) operator with an absolute threshold has also been widely used in neural spike detection. Its instantaneous nature and low computational resource demand makes it ideal for on-chip implementation [2] but NEO has a disadvantage of not being highly accurate when applied to low SNR data. [1] presents a Hybrid Neural Spike Detection algorithm that conditionally conducts NEO operator, thus, reducing power consumption but it still has the same accuracy as that of NEO.

Wavelets have also been used for neural spike detection. The use of wavelets improves the detection accuracy [3] and can give good results even at low SNR, but the use of algorithms involving wavelets is computationally demanding and may not be feasible for an on-chip system. Moreover, the accuracy of wavelets depends substantially on the choice of the mother wavelet. Similarly, many other spike detection techniques including template based detection methods also work well at low SNR, but these techniques are computationally expensive and impractical to be implemented on-chip.

In this paper we develop upon and generalize the theory of energy operators. A more general form of energy operators i.e. SEO is proposed, which delivers more flexibility and is essentially a non-linearly scaled form of common discrete energy operators. These scaled operators have a characteristic of improving contrast between noise and spikes, thus being able to detect low SNR multi-unit spikes much more effectively. We will show that DEAO, which is already being used on speech signals gives better performance than NEO when used on neural signals and that both of these can be generalized into SEO. Furthermore SEO class energy operators are shown to outperform the above mentioned operators especially in low SNR data. These algorithms were tested on two synthetic extracellular

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recordings developed by the Neuro-Engineering Lab at the University of Leicester [4, 10].

II. ENERGY OPERATORS

Energy operators basically measure the cross energy between a signal and its derivatives [5]. This makes them suitable for spike detection as spikes are the highest energy components of a neural signal. These operators are typically not computationally intensive and are therefore ideal for on-chip implementations.

The general k^{th} order discrete energy operator (DEO) [5] is defined as (1)

$$\begin{aligned}\gamma_k\,(x[n]) &= F(x[n], x[n+k-1]), \quad k = 0,1,2,3 \ldots \\ &= x[n]x[n+k-2] - x[n-1]x[n+k-1]\end{aligned} \tag{1}$$

where x[n] is the input signal, and k is the delay in samples.

A. Non-Linear Energy Operator

When k=2, the general DEO in (1) is transformed into the simple Taeger Energy Operator (TEO) given by (2). This is also known as Non-Linear Energy Operator (NEO).

$$NEO(x[n]) = x^2[n] - x[n+1]x[n-1] \tag{2}$$

The NEO has been traditionally used to separate high energy and high frequency regions in a signal, i.e. spikes, from low energy low frequency part of the signal, i.e. noise.

B. Discrete Energy Acceleration Operator

If k=4 in the general DEO of (1), the resulting operator is called the Discrete Energy Acceleration Operator (DEAO) [5] defined as (3)

$$DEAO(x[n]) = x[n]x[n+2] - x[n-1]x[n+3] \tag{3}$$

The DEAO can be used in a similar manner as the NEO. Although we could not find any reference of this operator being used for neural spike detection, we observe in section 4 that, on average, DEAO gives better results than NEO.

C. Non-Linearly Scaled Energy Operator

We propose a generalized class of k^{th} order energy operators, called non-linearly scaled energy operator (SEO), given in (4), which provide a whole spectrum of energy contrasts.

$$\begin{aligned}&SEO_{k,a,b}[n] \\ &\quad = (x[n]x[n+k-2])^a - (x[n-1]x[n+k-1])^b\end{aligned} \tag{4}$$

In the specific case when a=b, this generalized operator, SEO, can be factorized into the form of (5)

$$\begin{aligned}&SEO_k[n] \\ &\quad = J[n](x[n]x[n+k-2] - x[n-1]x[n+k-1])\end{aligned} \tag{5}$$

which is equivalent to (1), scaled with a factor J[n]. This non-linear scaling factor depends on the input data samples and the value of 'a'. J[n] suppresses the noise relative to the spikes, giving a better contrast between the two. In this paper, unless otherwise specified, all simulations assume a=b=8 and k=2. In this case, given by (6) the operator becomes a non-linearly scaled form of NEO in (2).

$$SEO_{2,8,8}[n] = J[n](x[n]^2 - x[n-1]x[n+1]) \tag{6}$$

The expression for $J_{2,8,8}$[n] comes out to be

$$\begin{aligned}J_{2,8,8}[n] = \; &(x[n]^8 + (x[n-1]x[n+1])^4) \\ &* \ldots \ldots * \; (x[n]^2 \; + x[n-1]x[n+1])\end{aligned} \tag{7}$$

Thus for SEO= $SEO_{2,8,8}$, the final form can be written as

$$SEO_{2,8,8}[n] = x^{16}[n] - (x[n+1]x[n-1])^8 \tag{8}$$

Fig. 1 shows how different operators transform an example input signal. Fig 1(a) shows a segment of a neural signal taken from simulation_1 described in [4], containing several low SNR multi-unit and single-unit spikes. Fig. 1(b) and Fig. 1(c) show the resulting waveforms when NEO ($SEO_{2,1,1}$) and DEAO ($SEO_{4,1,1}$) are applied to the input signal. It can be seen that NEO gives false alarms as well as a number of spikes are missed which reduce its performance as compared to other operators.

Fig 1(d) clearly shows the noise suppressing and spike enhancement characteristic of J[n]. This is the reason that SEO, in Fig. 1(e) is able to detect low SNR multi-unit spikes more effectively. In Fig1 (a) the red marks represent spikes. All the operators can easily detect the two large amplitude single unit spikes, but only SEO detects most of the low SNR multi-unit spikes. It enhances the contrast between noise and spikes, making it possible to detect spikes that are missed by other operators. The general algorithm is to apply this operator on the input neural signal, determine an optimal threshold using the method explained in [6] and then apply the threshold for spike detection. It is noteworthy that optimal values of 'a' and 'b' may vary in different datasets.

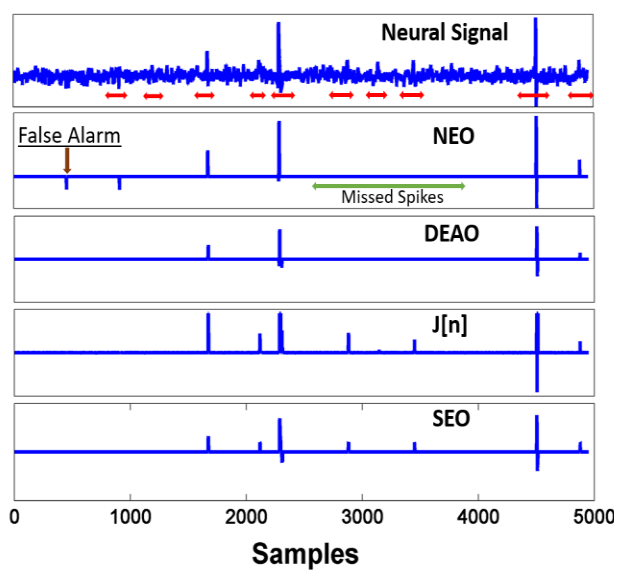

Fig. 1 (a) Segment of a Neural signal on which spike detection is applied (b) Spike Detection using NEO operator (c) Spike Detection using DEAO (d) Visual Representation of Scaling Factor J[n] (e) Spike Detection using SEO

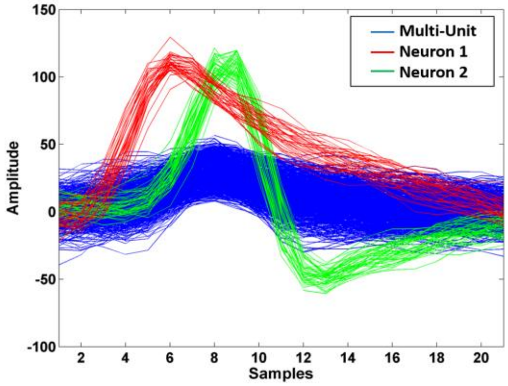

Fig. 2 Shapes and firing rates of three neurons present in a dataset

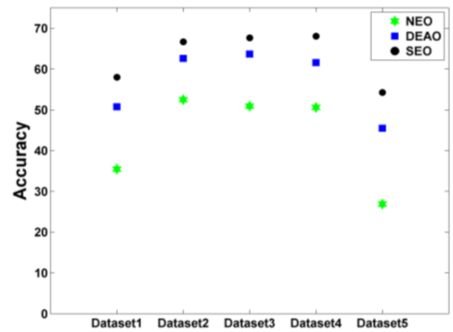

Fig. 3. A comparison of accuracies of different algorithms, when applied to the datasets explained in [4].

III. EXPERIMENTAL SETUP

A. Simulated Datasets

The algorithms were applied on two different public databases, provided by Quiroga et al. from the University of Leicester Neuro-Engineering Lab [4][7].

The algorithms were primarily applied on a realistic database, the realistic simulated extracellular recordings described in [4]. This collection has five data sets, each comprising of a very large proportion of low SNR multiunit spikes and two less frequent single unit spikes with a higher amplitude. The presence of low SNR multi-unit spikes makes detection very challenging using conventional methods but makes it easier to compare different detection techniques. Therefore, our main focus is on this collection of datasets. The data was scaled down by a factor of 30 to make its representation more visible. The three spike classes from a sample set in this collection are shown in Fig 2. (the very large number of low SNR multi-unit spikes can be observed in blue).

To select the parameter k for DEAO, accuracies across a range of k were computed. It was observed that optimal spike detection occurs at k=4. A larger value increased the number of false alarms and caused the accuracy to decrease. The parameters used for SEO were a=b=8 and k=2.

To further ensure concreteness, the algorithms were also applied on a much less complex database described in [7]. Each dataset in this database is composed of single unit neurons. It should be mentioned that all the datasets in this collection have a well-defined difference between spikes and noise, making detection very easy for all the algorithms applied, and are therefore used only to check the viability of a proposed algorithm, to ensure its correctness. Table 1 shows characteristics of different datasets defined in [4].

B. Accuracy Calculation

The accuracy of any spike detection technique can be computed using (9)

$$\text{Percentage Accuracy} = \frac{\text{TDS}}{\text{TDS} + \text{MS} + \text{FA}} \times 100 \tag{9}$$

where *TDS* is the number of truly detected spikes, *MS* is the number of missed spikes, and *FA* is the number of false alarms.

IV. RESULTS AND DISCUSSIONS

In order to verify the proposed methods, they were compared with conventional on-chip spike detection operators, with the simulations performed on the datasets described in [4].

A plot of the detection accuracies of datasets is shown in Fig.3. It can be seen that SEO gives the best performance for all data sets, followed by DEAO. Table 2 shows the results of application of all operators on simulations of realistic dataset. It is evident from the table that SEO gives the least amount of false alarms and missed spikes, for all the simulations. Therefore, it gives the highest accuracy for all the cases, followed by DEAO, which also performs better than NEO.

TABLE I: PERCENTAGE OF VARIOUS SPIKE UNITS PRESENT IN DATASET

Simulation	Percentage of Spikes		
	Multi-unit	Neuron-1	Neuron-2
simulation_1	90.23	5.217	4.55
simulation_2	67.08	16.46	16.46
simulation_3	66.86	17.20	15.93
simulation_4	67.11	15.94	16.94
simulation_5	94.93	2.66	2.41

TABLE II. PERFORMANCE OF VARIOUS OPERATORS APPLIED ON REALISTIC DATASET

Data	No. of Spikes	NEO				DEAO				SEO			
		TDS	MS	FA	Acc	TDS	MS	FA	Acc	TDS	MS	FA	Acc
Simulation_1	2415	1112	1303	328	40.53	1460	955	423	51.45	1536	879	233	58.01
Simulation_2	3214	1908	1306	278	54.63	2188	1026	232	63.49	2306	908	224	67.06
Simulation_3	3283	1969	1314	355	54.12	2318	965	343	63.92	2380	903	218	67.98
Simulation_4	3193	1921	1272	328	54.54	2218	975	299	63.52	2330	863	220	68.26
Simulation_5	2328	1002	1326	416	36.51	1337	991	409	48.85	1399	929	253	54.25

TABLE III. PERCENTAGE OF INDIVIDUAL SPIKE UNITS DETECTED FOR SIMULATION_2

Operator	Percentage of Detected Spikes				
	Multi-unit Spikes	Single Unit 1 Spikes	Single Unit 2 Spikes	False Alarms	Accuracy %
NEO	41.88	100	100	11.82	55.14
DEAO	53.43	100	100	8.4	63.7
SEO	59.42	100	100	8.6	66.96

To get a look at why these operators improve detection accuracy, we need to observe Table 3. We have applied NEO, DEAO and SEO on simulation_2 of the realistic dataset where the total number of spikes in the dataset were 3214.The table shows detection percentage of all three units individually relative to the total number of spikes of that particular unit in the entire data, along with the percentage of false alarms relative to total number of spikes in the dataset.

It can be seen that all operators can detect the single unit spikes easily, but the real challenge lies in detection of low SNR multi-unit spikes. As the detection of single unit spikes is 100% by all operators, it shows an improved performance as compared to absolute thresholding detection results shown in [4], which applied detection only on single units, terming the multi-unit spikes very challenging to detect.

Moreover, it is evident that DEAO and SEO give better detection percentage of multi-unit spikes as compared to NEO and thus, show a greater accuracy as shown in Table 3. The reason for improved performance of SEO is that in the process of reducing the number of missed spikes, it also gives a very small number of false alarms. It can be said that it delivers an appropriate balance. SEO is able to detect low SNR spikes adequately without giving a lot of false alarms, as shown in Table 3.The accuracy-threshold plots are shown in Fig.4. It is evident that SEO and DEAO show a significant improvement in accuracy as compared to NEO for optimal threshold. We can observe from Fig. 4 that the accuracies of DEAO and NEO have a sharp roll-off after their peak values. We need to be precise when selecting a threshold value for these operators. SEO on the other hand has a small gradient of decrease, so we get flexibility in the threshold values, giving rise to the possibility of using constant threshold.

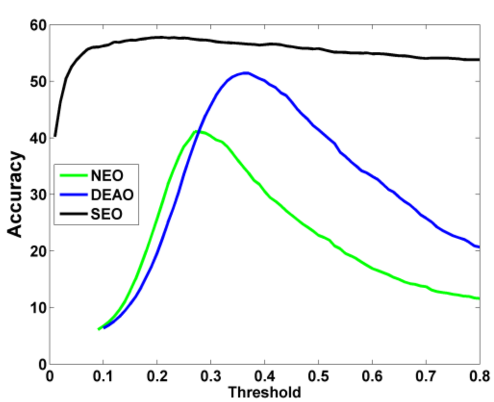

Fig. 4. Accuracy vs. Threshold plots of described operators

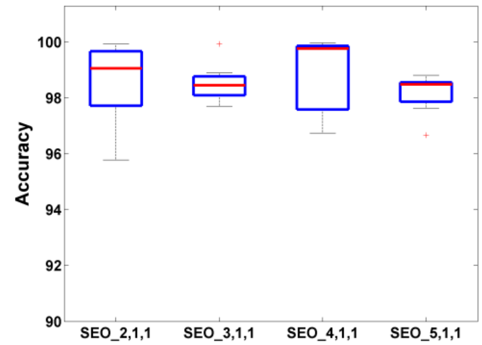

Fig. 5. A comparison of accuracies of different algorithms, when applied to the single-unit datasets explained in [7]

To ensure correctness, the algorithms were also applied on the simpler simulated datasets [7]. A box-plot of the results of simulations on 8 random sets is shown in Fig. 5. The datasets consisted of high SNR spikes which were easily detected by all the operators. It is evident from Fig. 5 that different values of ‘k’ used in (4) give an average accuracy > 96%, thus, ensuring correct functionality.

V. CONCLUSIONS

This paper generalizes common discrete energy operators into a broader and more flexible general class. The SEO operator is efficient in the detection of low SNR multi-unit spikes which elude commonly used operators such as NEO, while limiting false alarms simultaneously. It can also be implemented on-chip and gives better detection percentage but has a relatively higher number of computations. Moreover, the Discrete Energy Acceleration Operator (DEAO), when used with an optimal threshold, also gives better accuracy than NEO and has a low computational demand. On average, the detection accuracy for NEO with optimal threshold is 43.262%, for DEAO is 56.8% while SEO gives an accuracy of 62.64% on average.

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