An Associative Memory Readout in ESN for Neural Action Potential Detection

Nicolas J. Dedual, Mustafa C. Ozturk, Justin C. Sanchez and José C. Principe

Abstract **— This paper describes how Echo State Networks (ESN) can be used in conjunction with Minimum Average Correlation Energy (MACE) filters in order to create a system that can identify spikes in neural recordings. Various experiments using real-world data were used to compare the performance of the ESN-MACE against threshold and matched filter detectors to ascertain the capabilities of such a system in detecting neural action potentials. The experiments demonstrate that the ESN-MACE can correctly detect spikes with lower false alarm rates than established detection techniques since it captures the inherent variability and the covariance information in spike shapes by training.**

I. Introduction

ECHO State Networks (ESN) have been successfully applied to problems such as system identification, control of dynamical systems and time-series prediction [7, 8, 12]. However, the use of ESNs to recognize patterns in time such as neural action potentials (spikes) has not been addressed in the literature. In this paper, we propose to use a linear associative memory (LAM) as a novel readout for ESNs to be utilized in detecting neural action potentials.

Detection of action potentials is a very challenging task due to the great variability in the spike shapes due to the difference in spike morphology, as well as the intrinsic noise collected in neural recordings. The sorting of spikes from single neurons is classically defined as a two-step process. First, the spikes must be detected using either a threshold detector or through power analysis [18]. Once the spikes are detected, a variety of algorithms such as template matching with linear matched filter, or Principal Components Analysis (PCA) can be used to isolate the waveforms of individual distinct neurons [9, 13, 15, 18]. However, the performance of this serial process is greatly dependent upon the accuracy of the first step. In threshold detection, the background noise, which can be instantaneously at a high value, can be confused with spikes, resulting in a false alarm. In addition, spikes with low power are hard to detect because they are buried in the noise floor [9, 17]. The main difficulty with the matched filtering method is the absence of a well-defined template signal, which can represent the spike class, due to great variability in signal shapes.. Furthermore, noise statistics in neural recordings is non-Gaussian and nonstationary, impairing the optimality of matched filter.

The proposed combination of ESN with LAM aims at addressing the difficulties posed by the spike detection problem by utilizing the high dimensional states of a nonlinear dynamical system to train an associative memory that can represent a class under noise and distortions with a single filter. ESNs are usually trained with a simple linear combiner with a desired target signal [9, 12]. The advantage of the LAM over the conventional linear readout is that it explicitly utilizes the covariance information of the input training set, unlike linear readouts [13]. It also simplifies the training of the ESN read out since LAM's, there is no need to train for a desired response. The proposed readout, called the minimum average correlation energy (MACE) filter, is adopted from optical pattern recognition literature, where it is used for recognition of a given object in 2-D images in the presence of noise, geometric distortions and pose changes [11]. It has been demonstrated in [13] that ESN-MACE is particularly powerful when the problem requires modeling a class of functions since ESN-MACE filter is able to build a single template containing covariance information about the full training set. Such a system will improve the ability to correctly identify neural action potentials because it is able to explicitly utilize the variability seen during the training phase.

Various experiments using *in vivo* neural recordings were used to compare the performance of the ESN-MACE with thresholds and a matched filter detector. The performance metric is the receiver operating characteristics curve (ROC), which is a standard measure for evaluating the performance of a detector by demonstrating the trade-off between probability of detection and probability of false alarms [4,15]. The ROC curve for each filter is obtained by varying the threshold value and calculating the detection rate and false alarm rate for each value of the threshold. We demonstrate that the ESN-MACE is able to detect action

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potentials with lower false alarm rates compared to established methods of spike detection.

II. Problems in Spike identification

A neural recording cannot be characterized as a deterministic signal, not only due to the intrinsic noise present in the recording instruments, but also because of the many sources of uncertainty that make a neuron fire in an vivo experimental condition [17]. The extracellular spikes, recorded from a microelectrode array, have amplitudes ranging from a few microvolts up to a few hundred microvolts. The amplitudes of the spikes, as well their varying shapes, make the process of distinguishing the spikes from instrumentation noise difficult. As such, accurate identification of spikes has been problematic [9, 17]. However, the wave shape that is registered in a conventional extracellular neural recording is basically determined by the relative distance and position of the cell body with respect to the microelectrode. We will briefly review below several spike detection algorithms.

A. Threshold Detection

One of the most commonly used techniques to detect the presence of spike activity is through the use of a threshold. This system generates a pulse whenever the amplitude of a spike exceeds a predetermined threshold [9]. This system is advantageous because it provides a quick and inexpensive way to identify and discern neural activity.

However, threshold detection is ideally suited only for spikes which are easily discernible from the background noise [9]. Threshold detection is also prone to missing spikes (false negatives) that are present in a dataset, but do not exceed the established threshold. While it is possible to lower the threshold in order to capture all spikes present, doing so increases the probability of falsely misidentifying noise for an action potential (false positives), thus reducing the overall accuracy of the system.

B. Matched Filter

Another approach to spike detection is through the use of filters, in particular by using a matched filter (MF) [13, 16, 9]. By using a set of filters designed to maximize the signal-to-noise ratio of a particular class of neural action potentials, the system is able to identify and sort different spikes based upon their response to a particular filter.

However, this approach assumes that the noise power spectrum and the shape of the action potentials are easily characterized [9]. In instances where these conditions are not met, such as whenever we have overlapping spikes present, or when the noise is characterized as nonlinear in nature, a matched filter fails to properly identify spikes [13, 9].

The fundamental problem with the matched filter is that it assumes that there is a template that represents the spike class. Matched filters were originally developed for radar and communication applications, where the signals of interest were designed by humans, and the difficulty was simply one of discovering them in high noise backgrounds. In fact in these applications the template is known a priori and so it is trivial to design the matched filter. Moreover, it is known that the MF is optimum under very restrictive conditions of white noise backgrounds, uncorrelated with the signal and where the noise can be well characterized by Gaussian statistics [16].

In neural spike detection, the use of a matched filter is very different, due to the fact that the spikes are embedded in non stationary noise, and its statistics are most likely not Gaussian. But the determining shortcoming is really the variability present due to the differences in spike morphology. Figure 1 shows a very regular spike recording from a single neuron produced a large signal-to-noise-ratio (SNR) and little intrinsic template variance. Figure 2 shows a more normal recording of activity collected by a single electrode in the rat motor cortex where several neurons are being recorded. The waveforms are aligned by their maximum slope, and show the normal variability of neural recordings.

The first step in the design of a matched filter for spike detection is the design of the spike template. Each dataset was initially spike sorted using a program designed by Cambridge Electronic Design called Spike 2 (version 5) in order to generate markers for the instance of time when the spike is first detected, commonly known as “spike times”, as well as eliminate a number of false positives present in the dataset. Using these spike times, each spike was then extracted from its dataset and sorted according to its variance from the original dataset.

Sorting each spike by its variance allowed us to determine how much variability was present within all spikes, and as such selected a number of spikes that encompassed the variability present in the dataset. Numerous experiments with different datasets showed that we were able to accurately describe the variability of all spikes present by randomly selecting a minimum of 50 spikes. This will be the training set for all the experiments presented in this paper. Once the necessary number of spikes has been extracted, an average of all spikes present is generated. In order to ensure uniformity within the template, all spikes were aligned according to their initialization time, as recorded in the dataset’s spike times. By doing this, a template is generated that characterizes the spike waveform that is most predominant in the dataset.

This approach is best when the neural spikes detected are easily discernable from the background noise and each spike varies insignificantly from each other. However, when the dataset possesses spikes with high variability,, the average proves to be inaccurate, reducing the overall accuracy of the system.

III. DESIGN OF THE ESN-MACE

A. Echo State Network

Recently, a new utilization of recurrent network topologies has been introduced by Jaeger under the name of echo state networks [6]. ESNs have a recurrent topology of nonlinear processing elements (PEs) the state of which is called *echo states*. The echo states constitute a "reservoir of rich dynamics" [6] and contain information about the history of input patterns. The parameters of the recurrent topology is never trained but *fixed* a priori. In system identification problems, the echo states are fed to a *memoryless* adaptive readout network that generates the system output. The readout network is usually a simple linear combiner, which allows the use of simple linear regression to train the readout weights. According to the framework provided by [12], the reservoir implements a representation space that is constructed dynamically by the input signal and the readout finds the best projection of the desired signal onto the representation space.

The activation of the internal PEs (echo states) is updated according to

$$\mathbf{x}(n+1) = \mathbf{f}(\mathbf{W}^{\mathbf{in}}\mathbf{u}(n+1) + \mathbf{W}\mathbf{x}(n)) \qquad (1)$$

where $\mathbf{x}(n)$ is the echo state vector, $\mathbf{W}$ is the recurrent connection weights, $\mathbf{u}(n)$ is the input signal, $\mathbf{W}^{\mathbf{in}}$ are the weights between the input and the internal PEs. Here, $\mathbf{f}$ represents the activation function of the internal units, which is usually a hyperbolic tangent function. For details of ESNs, please see [13]. The echo state condition restricts the spectral radius (the largest among the absolute values of the eigenvalues of a matrix) of the reservoir's weight matrix, $\mathbf{W}$, to be less than 1. This condition states that the dynamics of the ESN is uniquely controlled by the input and the effect of initial states vanishes..

ESNs have been very successful in applications such as system identification, controls, and time series-prediction [8, 10, 13]. In these applications, a desired training signal, $\mathbf{d}(n)$ is available which is used to compute the weights of the readout network using the Wiener solution.

B. MACE Filter

In [11], it has been argued that ESNs are particularly well-suited for dynamical pattern recognition with the use of a linear associative memory readout. The proposed readout, called Minimum Average Correlation Energy (MACE) filter, is adopted from the optical pattern recognition literature, where it is used for recognition of a given object in 2-D images in the presence of noise, geometric distortions and pose changes [11]. A single MACE filter, which represents an object class, can be computed from a number of training data using

$$\underline{\mathbf{H}} = \underline{\mathbf{D}}^{-1}\, \underline{\mathbf{X}}(\underline{\mathbf{X}}^{\mathbf{T}}\, \underline{\mathbf{D}}^{-1}\underline{\mathbf{X}})^{-1} * \mathbf{c} \qquad (2)$$

where $\underline{\mathbf{H}}$ corresponds to the Fourier transform of the MACE filter, $\underline{\mathbf{X}}$ to the Fourier transform of our training set, $\underline{\mathbf{D}}^{-1}$ as the inverse of the summation of diagonal matrices whose elements are the magnitude squares of the associated elements of $\underline{\mathbf{X}}$; and $\underline{\mathbf{c}}$ are some predetermined values at the center of the correlation plane. The interesting property of the MACE filter is that it can represent a class of signals with a single filter since it includes the covariance information of the class. For details of MACE filter computation, see [1, 11, 13].

C. ESN-MACE Filter

The recognition of a time pattern in a single time series is achieved by feeding the time series to an ESN/LSM, and utilizing a time window of states which can be interpreted as a 2-D image, one dimension being time and the other processing element number (space). Using the 2-d state image, several MACEs can be trained, one for each class.

Assume that we have P different classes of temporal patterns. The goal is to compute one MACE filter, $\underline{h}^{p}$ for each class. Assume also that for each class, the training set consists of K input patterns each with a particular temporal shape of length T. The procedure to compute each $\underline{\mathbf{h}}^{p}$ for p=1,…,P is as follows [13].

1. The i^{th} training input pattern for the p^{th} class $\mathbf{u}_i = [\mathbf{u}_i(1), \mathbf{u}_i(2), ..., \mathbf{u}_i(T)]$ of dimension MxT is used to calculate the echo states using equation 1.
2. The resulting NxT matrix of echo states forms the equivalent of a 2-D image used as an input to the MACE. The echo states are then lexicographically ordered by the columns to get the 1-D column vector $\underline{\mathbf{x}}_i = [\mathbf{x}_i(1)^T, \mathbf{x}_i(2)^T, ...\mathbf{x}_i(T)^T]^T$ with NxT elements. Here each $\mathbf{x}_i(n)$ is an Nx1 vector with the value of the echo state at time n for the i^{th} training sequence.
3. The discrete Fourier transform of $\underline{\mathbf{x}}_i$ is denoted by $\underline{\mathbf{X}}_i$. Define the overall dxK training matrix in the frequency domain by $\underline{\mathbf{X}} = [\underline{\mathbf{X}}_1, \underline{\mathbf{X}}_2, ..., \underline{\mathbf{X}}_K]$.
4. The optimal coefficients of the LAM for the class are computed using equation 2 in the frequency domain and the corresponding MACE filter weights $\underline{\mathbf{h}}^{p}$ are obtained by inverse discrete Fourier transform. The output of the MACE for the i^{th} training input pattern for the p^{th} class can be obtained by $\mathbf{x}_i^T \underline{\mathbf{h}}^{p}$.

The same procedure is repeated for the training sequences of other classes to obtain an optimal filter for each class.

The design of internal connection matrix, **W,** of the ESN is based on the metric proposed by [12] called average state entropy (ASE). ASE, when maximized, allows for the echo states to be "evenly distributed along the dynamic range" by uniformly distributing the poles of the linearization of the ESN around the origin [12].

IV. SPIKE DETECTION WITH ESN-MACE

In [13], it has been argued that the high dimensional internal states of ESN architecture coupled with the MACE filter creates an excellent medium for dynamical pattern recognition. It has been demonstrated that ESN-MACE is particularly powerful when the problem requires modeling a class of functions since ESN-MACE filter is able to build a single template containing covariance information about the full training set. In this paper, we propose to use the ESN-MACE for spike detection problem where the spikes can be considered as a family of signals due to great variability in spike amplitude and width (see figure 2).

An ESN with 28 internal units and a single input unit is used for the simulations in this paper. $\mathbf{W}$ matrix is designed according to the ASE metric presented in [12] and scaled so that its spectral radius is set to 0.9. The entries for $\mathbf{W}^{in}$ are set to -1or 1 with equal probability.

Two distinct neural recordings were used in the experiments. The first one was acquired from a single neuron with high SNR. The second dataset was collected from a rat while the animal performed a lever pressing task in order to achieve a water reward. Both datasets were sampled at 24414.1Hz and were pre-filtered between 300 – 7000Hz. Both datasets were normalized, and spike sorted in order to generate their respective spike-times files.

Fifty representative spike signals were selected as the training data for each one of the neural recordings. Figure 1 depicts the selected spike signals for the high SNR neural recording. It is evident from the figure that the spike shapes has a limited variability since they all are generated from a single neuron. On the other hand, the differences in amplitude and width of the depolarization/repolarization phases in the spike shapes in figure 2 clearly shows that the rat dataset has more than one type of neuron present in the dataset.

For each data set, the algorithm described in *section III.C* is used to train the ESN-MACE filter. Fifty representative spike signals (each with length 21) are fed to the ESN and the echo states are calculated using equation 1 with zero initial conditions. This creates an image of dimension 28x21, where 28 is the number of PEs and 21 is the signal length. Output correlation peak amplitudes are assigned to be 1.0 for the training data. The MACE filter is synthesized in the frequency domain using (2) and the corresponding image plane filters are obtained by inverse discrete Fourier transform. For a given test signal, MACE filter output is calculated by correlating the echo states of dimension 28x21 with the filter coefficients at zero lag. MACE filter output is then compared to a threshold to decide the absence or presence of a spike. Different threshold values are used to obtain the ROC figure. Figure 3 shows a section of the rat dataset where we used the ESN-MACE filter to identify several spikes. As the ESN-MACE filter is designed to provide a maximum response after a spike has been convolved with the filter, we shifted our system response by

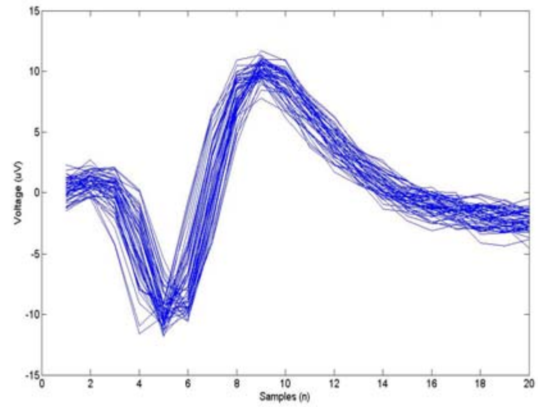

Fig. 1 : Oscilloscope trace of neuron recorded with high SNR.

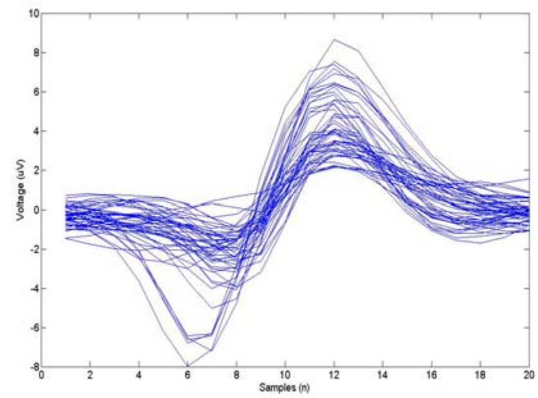

Fig. 2: Oscilloscope trace of rat dataset. Numerous distinct spike waveforms are present in this dataset.

the width of our filter, in order to use the spike times as a means of identifying whether a spike was properly detected, as seen in figure 3.

The results obtained with ESN-MACE are compared to thresholds and matched filter detectors. The matched filter is obtained from the same data set of fifty spike signals according to the method explained in *section II.B.*

In the first dataset trained, the ESN-MACE filter, the threshold detector and the matched filter correctly identify 300 spikes present in a 100,000 samples with no missed identifications, demonstrating that the ESN-MACE filter performs as well as both the matched filter system the threshold detector. [8] and [13] corroborate this fact, as the class of spikes present in this dataset are easily discernible from the background noise and come from a single class of spikes.

On the other hand, the results for the more interesting and more challenging rat data set are not as perfect since the variability in the spike signals are tremendous. Figure 4 depicts the ROC curves for the ESN-MACE, threshold detector and the matched filter. As observed from the figure, ESN-MACE gives the best results out of the three methods presented. ESN-MACE filter identifies 273 spikes within 100,000 data samples of the rat dataset, corresponding to approximately 4 seconds of recorded data. In order to

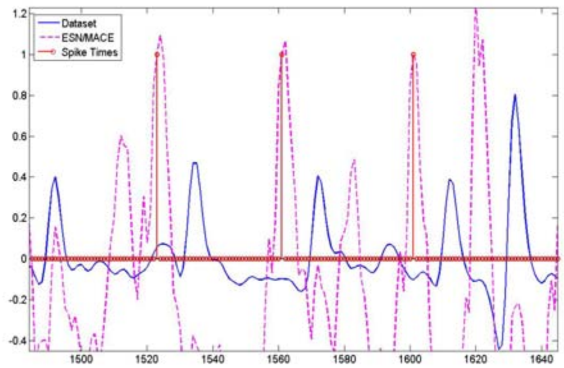

Fig. 3: Segment of rat dataset (solid line) with 4 spikes shown. Note how our spike times (line with circle) is only able to identify 3 spikes in this segment, whereas the ESN-MACE filter (dotted line) is able to identify all 4 spikes.

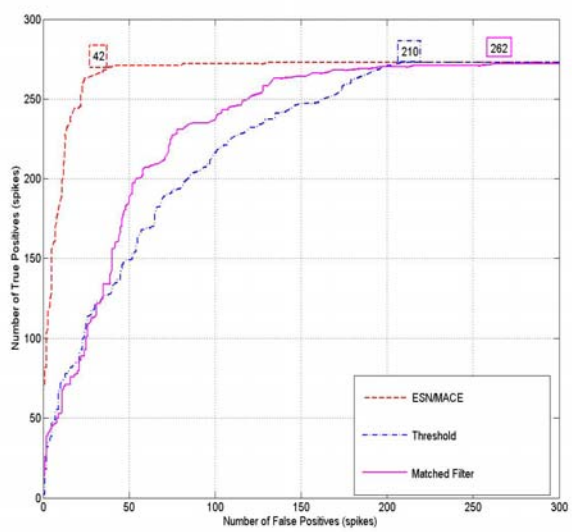

Fig. 4: Rate of identification of falsely identified spikes versus true spikes from the rat dataset. Each grid division corresponds to a division of 50 spikes. The leftmost dotted curve corresponds to our ESN-MACE filter system, whereas the solid like corresponds to a matched filter system and the dashed curve corresponds to a threshold detector system.

correctly identify all 273 spikes, the ESN-MACE filter has a cost of 42 falsely identified spikes; whereas the matched filter and the threshold detector have a cost 262 and 210 falsely identified spikes, respectively, in order to achieve this level of identification. Obviously, the variability in the rat dataset makes detection much more challenging compared to the first dataset. The ESN-MACE filter handles the variability in the spike shapes better compared to the simple threshold detector and the matched filter detector.

V. CONCLUSION

Spike detection is a challenging task due to the variability in the neural recordings and nonstationary, non-Gaussian noise embedded in the signal. The conventional techniques such as threshold detector or matched filter fail especially when the neural signal comprises recordings from multiple neurons spaced at different distances relative to the microelectrode. This paper proposed a nonlinear dynamical system coupled with a linear associative memory, namely the MACE filter, to tackle the variability in the spike detection problem. We have shown in a challenging neural data recorded from a rat's brain that ESN-MACE combination results in lower false alarm rates for perfect detection. The better results of the ESN-MACE is attributed to the fact that MACE filter can model a class of signals by incorporating the covariance information of the class whereas ESN provides a rich representation space as the input to the MACE. Moreover, it has been shown in [13] that ESN-MACE can be considered as a nonlinear matched filter with robust performance under different noise distributions.

REFERENCES

[1] Casasent, D. and Ravichandran, G.(1992) "Advanced distortion-invariant minimum average correlation energy (MACE) filters. *Applied Optics*, 31 (8):1109-1116

[2] Haykin, S. (1998) *Neural Networks: A Comprehensive Foundation*, Prentice Hall, NJ, Second Edition

[3] Haykin, S. (2001) *Adaptive Filter Theory*, Prentice Hall, NJ

[4] Helstrom, C.W (1995) *Elements of Signal Detection and Estimation*, Prentice Hall, New Jersey

[5] Hinton, G.E, and Anderson, J. A. Ed. (1981), *Parallel Models of Associative Memory*, Lawrence Erlbaum Associates, New Jersey

[6] Jaeger, H.(2001) "The echo state approach to analyzing and training recurrent neural networks" *Technical Report GMD Report 148*, German National Research Center for Information Technology.

[7] Jaeger, H. (2002), "Short term memory in echo state networks" *Technical Report GMD Report 152*, German National Research Center for Information Technology

[8] Jaeger, H. and Haas, H. (2004), "Harnessing nonlinearity: predicting chaotic systems and saving energy in wireless communication, *Science*, 304(5667):78-80

[9] Lewicki, M.S., (1998) "A review of methods for spike sorting: the detection and classification of neural action potentials", *Comput. Neural Syst*,R53-R58, IOP Publishing Ltd., UK

[10] Maas. W., Natschläger, T. and Markam, H. (2002). "Real-time computing with stable states: A new framework for neural computation based on perturbations", *Neural Computation*, 14(11):2531-2560.

[11] Mahalanobis, A., Vijaya Kumar, B.V.K., and Casasent, D. (1987), "Minimum average correlation energy filters", *Applied Optics*, 26(17):3633-3640

[12] Ozturk, M. C., Xu, D., and Principe, J.C.,(2006) "Analysis and design of echo state networks", *Neural Computation*, accepted for publication.

[13] Ozturk, M. C., and Principe, J.C. (2006) "An Associative Memory Readout for ESN and LSM for Dynamical Pattern Recognition"

[14] Pfurtscheller, G., Floritzer, D., and Kalcher, J., (1993) "Brain-computer interface – A new communication device for handicapped persons," *J. Microcomput. Appl.*, vol. 16, pp. 293-299

[15] Principe, J.C., Euliano, N.R., and Lefebvre, W.C. (2000) *Neural and Adaptive Systems: Fundamentals through Simulations*, John Wiley and Sons.

[16] Proakis, J.G (2001), *Digital Communications*, McGraw-Hill, New York, fourth edition

[17] Sörnmo, L., Laguna, P., *Bioelectrical Signal Processing in Cardiac and Neurological Applications*, Elsevier Academic Press, London, 2005.

[18] Obeid I. and Wolf, P. (2004) "Evaluation of Spike-Detection Algorithms for a Brain-Machine Interface Application" *IEEE Trans. On Biomed. Eng.* 2004 Jun;51 (6): 905-11