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RESEARCH ARTICLE

Validation of Artificial Neural Network Method for Action Potential Detection and Classification Based on Velocity Selective Recording

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Abstract*- This paper validates and exams the improvements of the system for obtaining velocity spectral information from electroneurogram (ENG) recordings using multi-electrode cuffs (MECs). The present study adopts a fundamentally non-linear velocity classification approach based on a type of artificial neural network (ANN). The new method can operate in real-time, is shown to be robust in the presence of noise and also to be relatively insensitive to the form of the action potential waveforms being classified, consequently, real time data analysis and optimization become necessary. However, the system needs verification and examination the ability of sensing APs signal and distinguish between the spikes correctly. An amplitude-threshold APs detector approach is used in the current paper for verification from whose performances with simulated statistical analysis on both conventional and ANN approaches. The present paper deals with the detection and validation of VSR for sorting of APs and the able to distinguish the activity from single fibre from the signals recorded by MEC. This study tackles two considerable issues: the system ability for function in real-time for long term implantation; and high performance characteristics such as unsupervised adaptive (automatic classification and detection), fast detection and accurate selectivity. Hence, these challenges have been dealt with ANN signal processing and the acceleration achievable with FPGAs.

***Keywords*— Biomedical signal processing, Biomedical transducers, Microelectronic implants, Neural prosthesis, Artificial neural networks**

I. Introduction

One component of neuroprosthetic systems is the neural input through which information is transformed from the physiological to the artificial. Tripolar recording from peripheral nerves cannot generally extract much of the information in the neural traffic, so we and others have been investigating velocity selective recording (VSR) since it allows the possibility of increasing the information extracted from peripheral nerves (electroneurogram-ENG) by carrying out a spectral analysis in the velocity domain [1-9]. The resulting spectrum shows not only the direction of action potential (AP) propagation (afferent or efferent) but also provides a measure of the differential level of excitation of the fibre populations in the nerve. Since there is a well-established relationship between AP propagation velocity and fibre diameter that is approximately linear for myelinated fibres, VSR provides a method for assessing the level of activity in nerve fibre populations of different diameter as well as establishing the direction of propagation. This information potentially allows more information to be extracted from an intact nerve for use in applications requiring sensory feedback such as neuroprostheses [1-4].

II. MATERIALS AND METHODS

A. *Algorithms Design.*

In order to study and validate VSR recording based on ANN method for detection and spike sorting performance in the simulation and real time environment, a statistical analysis has been presented in this paper using Matlab and FPGA implementation. In addition, a comparison study has been used for examination the performance of neural signal detection and sorting for both approaches in statistical analysis. Moreover, a hardware design has been proposed for complete system included spike detection and classification signal processing on costume FPGA board for both approaches. Indeed, this study based on previous result which has been already published in [10-12]. Fig. 1 demonstrates the overall diagram of the spike sorting and detection which has been used in this work. The both structure of conventional VSR and ANN methods have been applied with bandpass filter, smoothing and threshold unit respectively for each matched velocity.

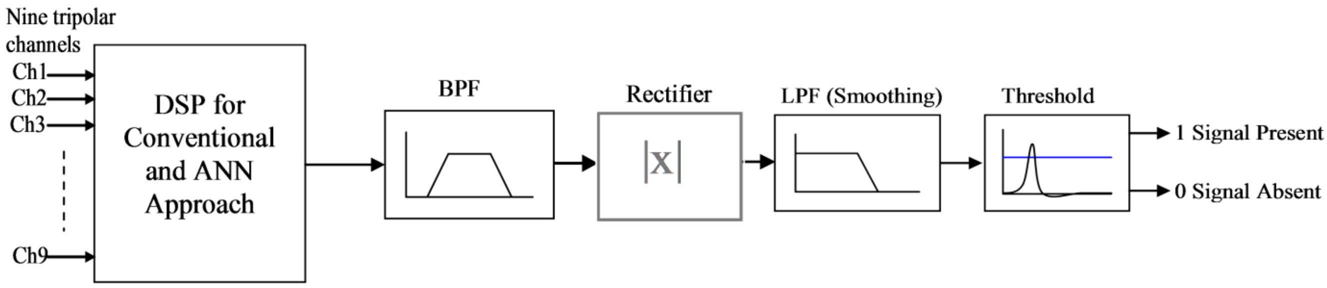


Fig. 1 Overall diagram of spike detection and classification

1) BPF Design.

Several studies were published [5-9], which described the conventional approach based on delay and add as well as the nonlinear (ANN) method [10-12] to match VSR system in the *velocity* domain. Though, in order to evaluate the system in simulation and real time environment and compare the enhancements possible using bandpass filters (BPF) for both. All neural network and delay and add outputs signals are filtered with 8th order Infinite impulse response (IIR) Butterworth BPF filter correspond with each matched velocity (the hardware design and implementation have been described in [5-12]). The electrode space $d = 3mm$ and matched velocities have been selected at these value (10, 20, 30...100 m/s), and the centre frequencies for BPF filters are calculated depend on constant length which are chosen corresponding to each matched velocity (Table 1), the theoretical concept and equation for calculating the centre frequency for each BPF have been described in more details in [5-9]. So this study used the BPF design parameters it are already chosen and tested in [5-9]. However, a hardware design has been provided in this study for the whole system for both approaches included the BPF and spike detector.

Table 1

THE CENTRE FREQUENCIES (F_o) FOR EACH MATCHED VELOCITY [5] .

Matched velocity (m/s)	f_o (kHz)
20	1.6
30	2.4
40	3.2
50	4
60	4.8
70	5.6
80	6.4
90	7.2
100	8

Fig. 2 shows an example of the output of single side amplitude spectrum for both one tripolar channel and delay and add of sinusoidal signal input before applying the BPF. The red line presents one tripolar channel response, while, the green line presents unfiltered output of conventional approach. The system has been chosen to mach 20 m/s and the conduction velocity for the inputs channels 20m/s as well, where the electrode pitches 3 mm and sampling frequency is 32.5 ks/s.

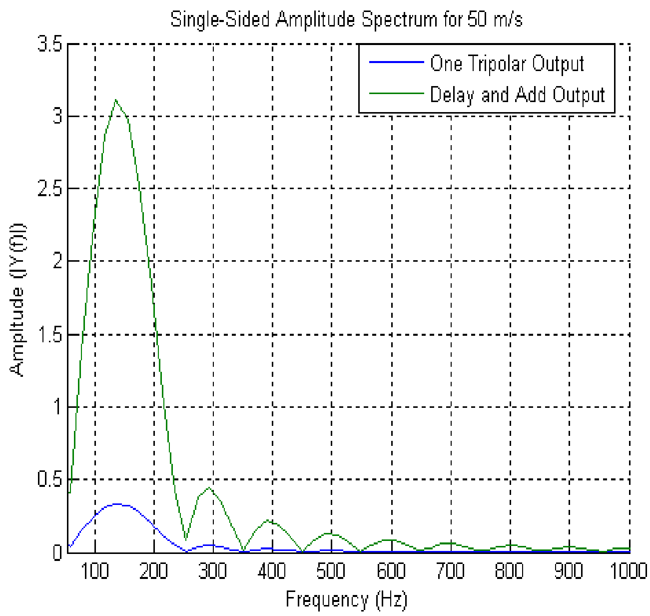


Fig.2 FFT spectrum for sinusoidal input and output using delay and add.

Fig. 3 demonstrates the time domain response of the system after applying the BPF with matched delay (Ts, 2Ts, 3Ts….45Ts), where the input is Trans-Membrane Action Potential (TMAP) TMAP #1 at conduction velocity 20 m/s. As it seen, the system response is peaking on the artificial delay equal to the natural delays. The time domain response of the delay and add outputs for three maximum outputs cases have been shown in Fig. 4.

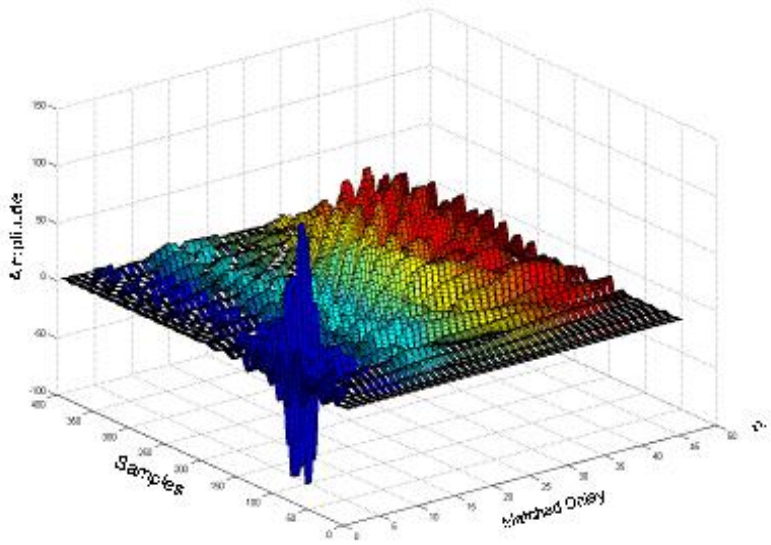


Fig.3 BPF outputs response for 20m/s conduction velocity.

As shown in Fig. 3, the simulated outputs of the matched velocity v_o, corresponding to matched delays and electrode pitch (d).The time response of the outputs of BPF shows that the maximum response occur at matched delay $5T_s$ which is correspondence to 20m/s matched velocity. Nevertheless, the delay and add at $4T_s$ and $6T_s$ outputs in this case are quite close to the matching velocity, and that cause limitation in the selectivity and detection in the conventional approach as shown in Fig. 4. Indeed, this issue clearly appear at high conduction velocity range as it has been described before in [5-9].

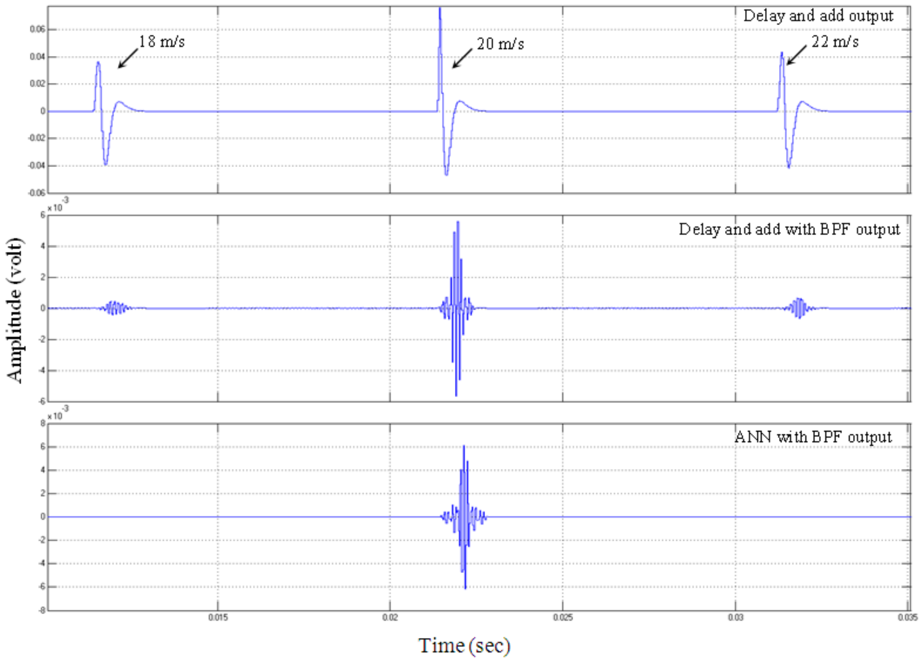


Fig.4: The BPF filter response for three matched delay cases for Conventional approach and ANN at 20m/s conduction velocity.

This issue have been tackled with nonlinear ANN method by setting the target as pulse output instead of using the delay and add [11,12], also the other outputs have been set to be zero. In fact, this part is achieved by choosing the nonlinear transfer function for the ANN, meanwhile the other parts of the ANN include delay line, weights and biases play as conventional approach. The results show significant improvements at both the reactivity and detection. Moreover, these improvements have been achieved at high conduction velocity not just on the low velocity range as shown in Fig. 5.

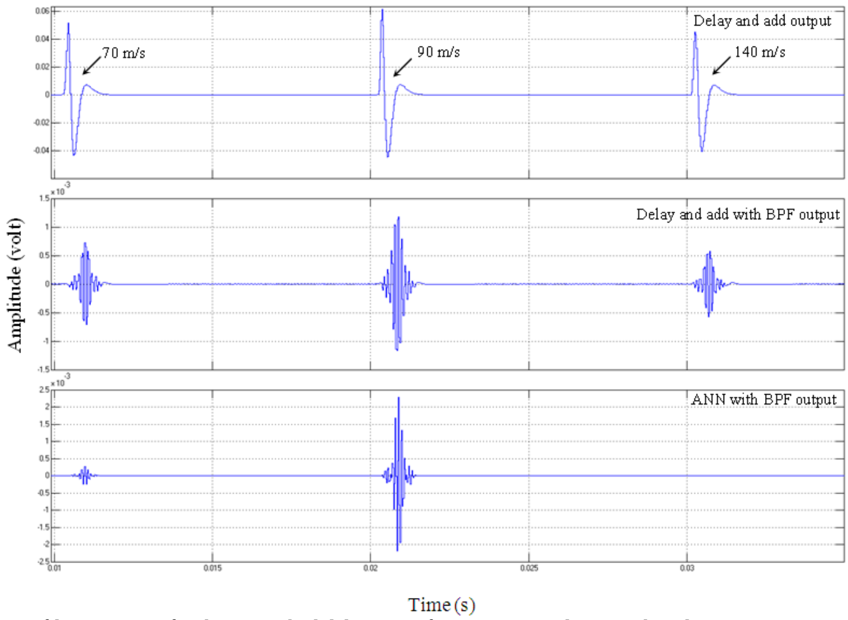


Fig.5: The BPF filter response for three matched delay cases for Conventional approach and ANN at 90m/s conduction velocity.

2) Threshold Detector Design

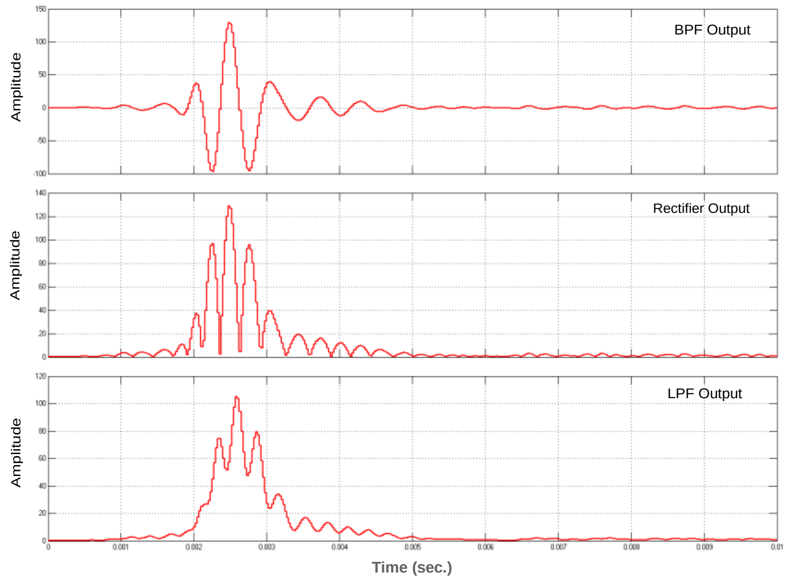


Fig. 6 BPF, rectifier and LPF outputs.

The threshold detector stage flows the BPF unit; a simple rectifier and smoothing unit have been used between the BPF and the detector. This procedure has been achieved by applying each BPF output through rectifier and smoother with 4th order finite impulse response (FIR) LPF before applied them for threshold unit for detection process. The rectifier process has been executed with simple absolute value function on outputs of the BPF, it is similar to using a positive and a negative threshold, thus will be leading the larger of the two phases to be detected. The LPF filter is design at sample frequency 32.5 ks/s and cut-off frequency corresponding to BPF centre frequency for each matched velocity. Fig. 6 shows the outputs of the above stages for one matched velocity in time domain where y- axis represents the sample value in digital term and the x- axis is the time domain.

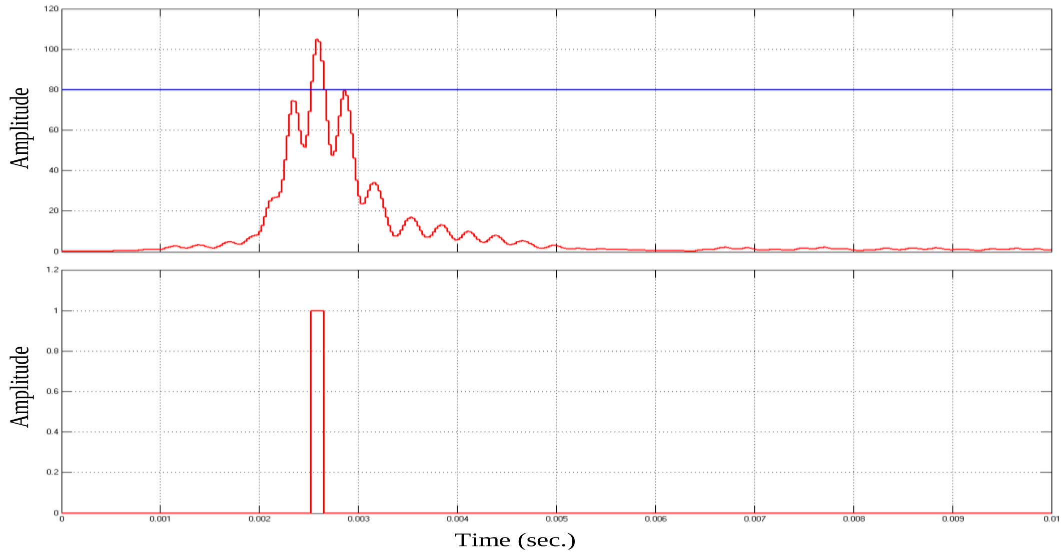


Fig.7: Threshold detection method

The amplitude threshold detection method has been adopted in this work as it most easy and common used with automatic detection APs[13, 14]. A simple threshold level adjustment based on the root-mean-square (rms) voltage measured over a finite window has been presented for the detection process as shown in Fig. 7. There are two main parameters for adjustment the detector with threshold approach. Firstly selective the proper value for threshold crossing the data to detect the APs. Secondly, the lowest time interval that ought to the AP across before another AP is detected in running windows.

The spike detection algorithm compares the amplitude action potentials accurately with the threshold voltage level. Simulation evaluation process is employed to optimize the procedure parameters for each matched velocity, and that would be led for further enhanced on the APs detector process.

After the threshold and comparison unit a statistical probability distribution for correct detection is used for each matched velocity. These analyses are achieved by passing (960) APs within conduction velocity range from 4-100m/s in nine tripolar channels through both approaches process. In addition, this procedure has been repeated for difference SNR values 1, 5, 10, 25, 50 and 100. Indeed, these processes required huge data; however, using multi AP generator which is described in [10-12] makes it possible.

3) Evaluation of Performance.

The performances of spike detection and classification algorithm have been examined with statistical analysis that calculates the True Positive (TP) and False Positive (FP) for each matched velocity. Moreover the True Negative (TN) and False Negative (FN) (TN-FN) have been determined that would be presented the noise peaks or incorrect matched velocity peak (APs propagate at different velocity from matched velocity)[13-14]. These four parameters have been used to determined sensibility (Se) as shown in eqn(1), the probability that a noise peak might be identified by this approach, and specificity (Sp) as shown in eqn(2), the probability that a spike might not be identified by algorithm. Moreover, Positive Predicted Value (PPV) and Negative Predicted Value (PPV) have been determined as shown in eqn (3) and (4) respectively, where the PPV is the probability of test-positive where peak must be a spike at matched velocity and the NPV is test-negative where peak must be noise or different conduction velocity.

$$Se = \frac{TP}{TP + FN} \quad \text{...Eqn. 1}$$

$$Sp = \frac{TN}{TN + FP} \quad \text{...Eqn. 2}$$

$$PPV = \frac{TP}{TP + FP} \quad \text{...Eqn. 3}$$

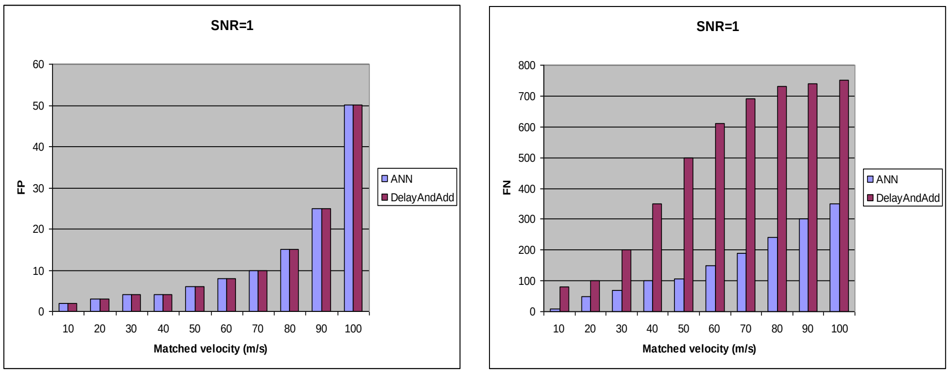
$$NPV = \frac{TN}{TN + FN} \quad \text{...Eqn. 4}$$

The Se, Sp , PPV and NPV are used to assess and exam both approaches detection and selectivity depends on the true and false detection probability. Moreover, it is employed to demonstrate the selectivity performance under different level of noise.

The classification algorithm used in this work is based on VSR method. The detected AP is investigated in 0.3 ms window, testing if it is the maximum peak occurs at matched velocity above threshold level this is TP, otherwise it is FN. While the TN tests shows if there is no maximum peak more than threshold level occurs at other velocities, otherwise it is FP.

III. RESULTS

Fig. 8 shows the ANN and conventional method have the same number of FPs, while, the ANN has the smallest number of FNs, due to improvements in the selectivity in the ANN method. However the number of FNs in both approaches gradually increases in the high velocity domain.



(a) (b)

Fig.8 Test results for SNR=1 on simulated signals. (a) FP-False Positive, (b) FN-False Negative.

Further, The nonlinear approach more adaptive than linear approach: it recognizes a small number of FNs occurred by noise.

The Se (Fig. 9 (a)) and Sp (Fig. 9 (b)) are calculated using TP, FP,TN and FN as shown in eqn. (1),(2),(3) and (4) at SNR equal to one. The results show that the sensibility and specifity for the ANN higher than the conventional approach along the velocity domain, the highest value for Sp and Se occurs at 10 m/s while the lowest value occurs at 100m/s for both approaches. The proposal approach outperform the conventional method by factors 1.35 and 1.11 for Se and Sp respectively at SNR=1 and 100m/s, Meanwhile, this improvement increase once the SNR is rose to 100, On the other hand, the both approaches decline in high conduction velocity range due to the limitation and noise in both approaches.

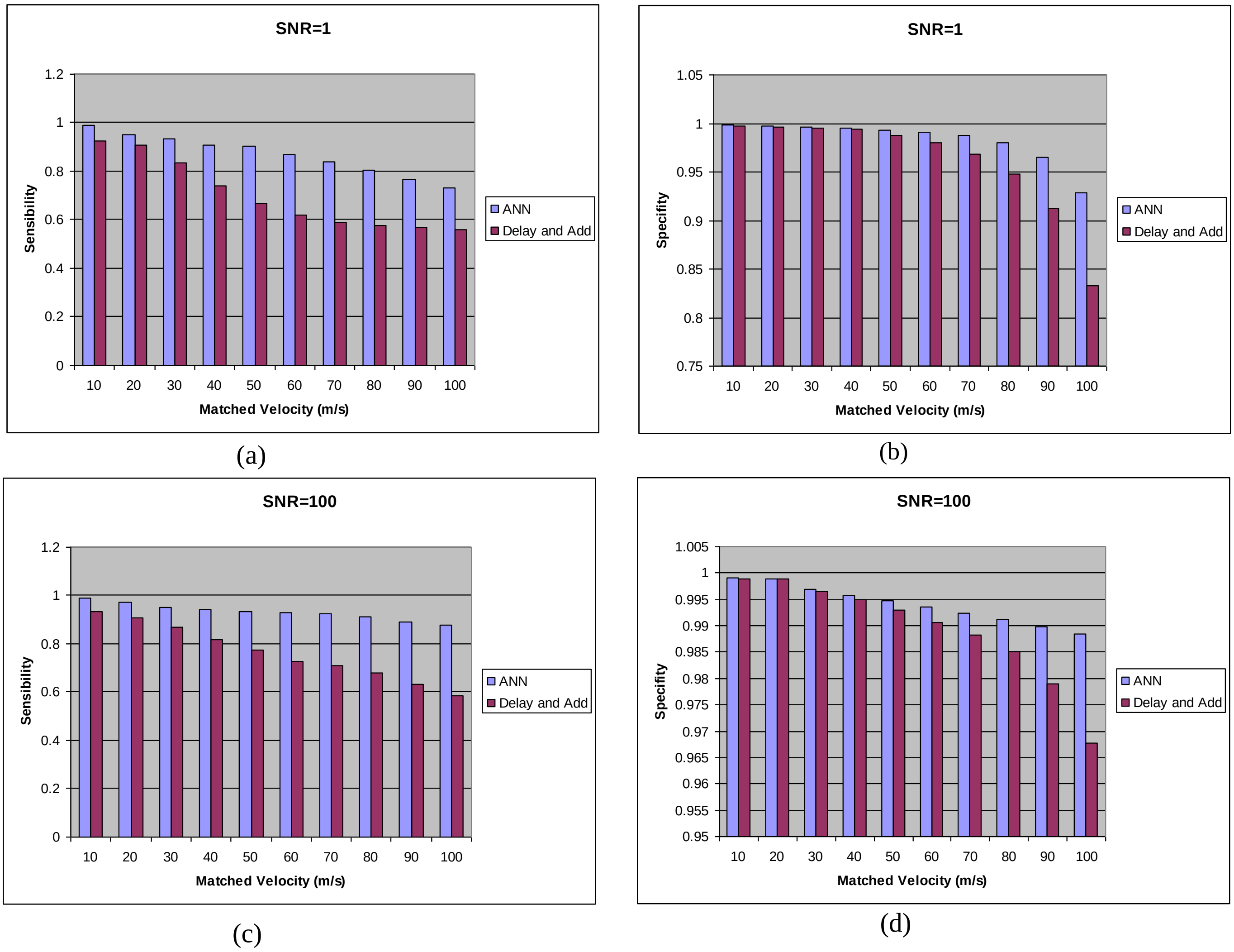


Fig.9 Results for (a,c) Se-Sensibility SNR=1and 100 respectively, and(b&d) Sp-Specificity at SNR=1and 100 respectively.

As it seen in Fig. 10, the PPV results shows that the both approaches have the same number of TP which mean no positive tests (AP at matched velocity) have been missed in both approaches even with noisy case as shown in Fig. (a, c). However, Fig. (b,d) shows the NPV for both approaches decline when the matched velocity increases but always ANN has high NPV than conventional approach. The NPV shows the parentage of system distinguish AP propagate at conduction velocity not equal to the matched velocity and that mean the ANN has NPV value about 40% more rejection than the conventional approaches in the high velocity domain. The significant advantage of NPV is to show the amount velocities have been rejected by the system because they are not matching the matched velocity. However, the results demonstrate similarity performance in the PPV term.

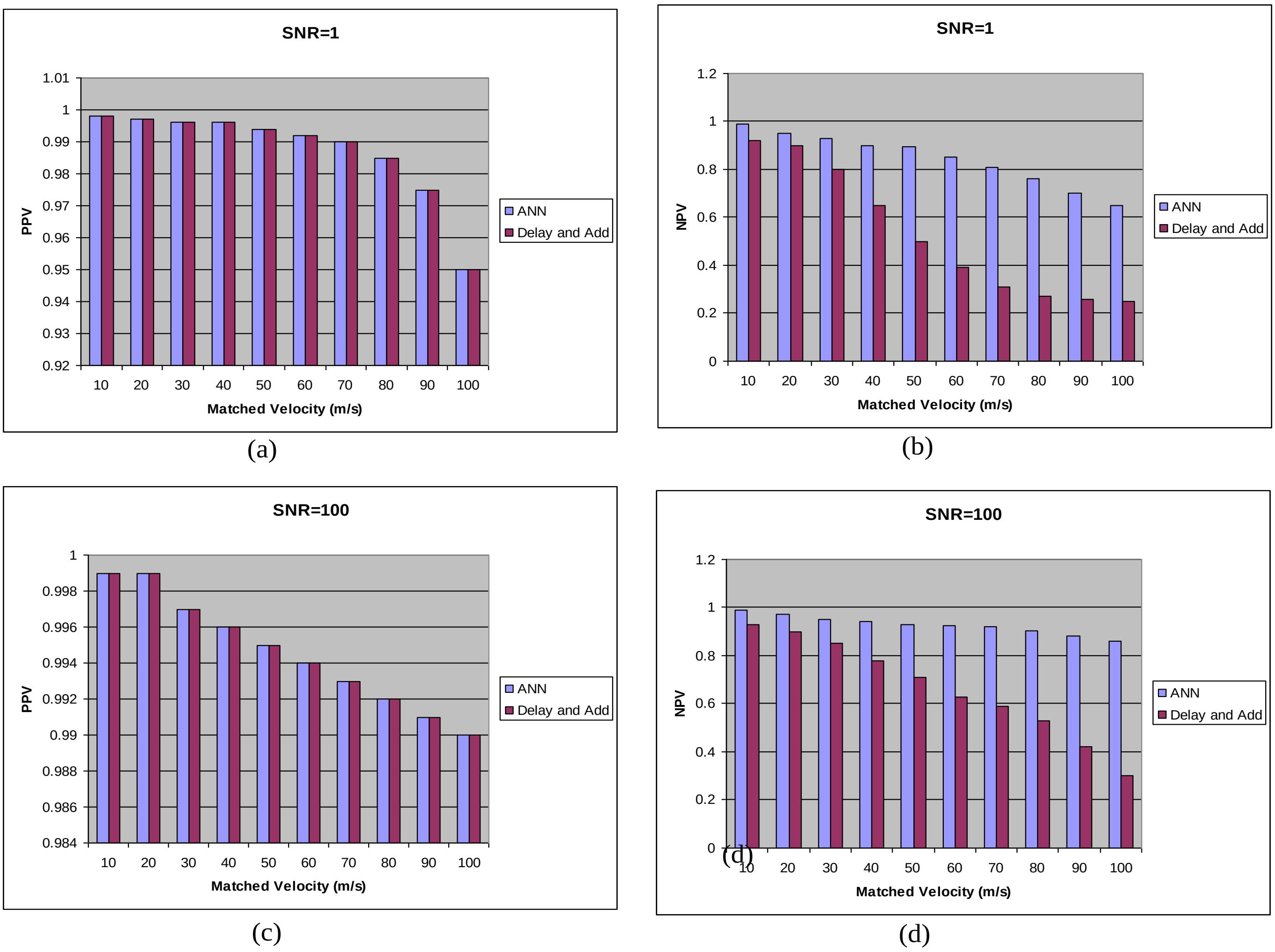


Fig.10 Results for (a,c) PPV at SNR=1and 100 respectively, and (b&d) NPV at SNR=1 and 100 respectively

Further tests have been used to verify the system response with different TMAP, a nine tripolar channels with TMAP#2 applied on the both approaches at the same sampling frequency 32.5ks/s, and the same number of attempts at SNR 1, 5, 10, 25, 50 and 100. In these results, just PPV and NPV at SNR= 1 are presented here to avoid the repetition.

The PPV and NPV comparing the abilities of the two methods discussed to sort the velocities of APs generated from a TMAP (TMAP#2) different from that used in the training process (TMAP#1). The slate blue bar represent TMAP#1 and the brown ones TMAP#2, all the comparisons are made using a nominal AP propagation velocity of 10 m/s to 100m/s and with SNR=1. The Fig. 11 (a,b) shows the effect of swapping TMAPs on the PPV and NPV for the standard delay-and-add type classification while the Fig. 11 (c) & (d) show the effects of this process on non-linear ANNs respectively.

For the delay-and-add case it is noticeable that the PPV for TMAP#2 gradually decrease once the matched velocity increase because the centre velocities for each matched velocity shifted when the TMAP has been changed. Meanwhile the NPV for the TMAP#2 in comparison to TMAP#1 is slightly decreased. The reasons for this effect are wider bandwidth spectrum for TMAP #2. The c and d plots show how the performances of the non-linear ANNs are affected by a swap in TMAP function. this case the networks were trained with a noiseless version of TMAP#1 as a template (see [11,12]) and were then tested with TMAP#2 as an input. The centre velocity (v_0) is reduced for TMAP#2 in high matching velocity range. Moreover, the velocity selectivity is reduced and that cause reduction in PPV and NPV, however, with this reduction the delay-and-add still has less PPV and NPV along velocity domain compare with ANN method.

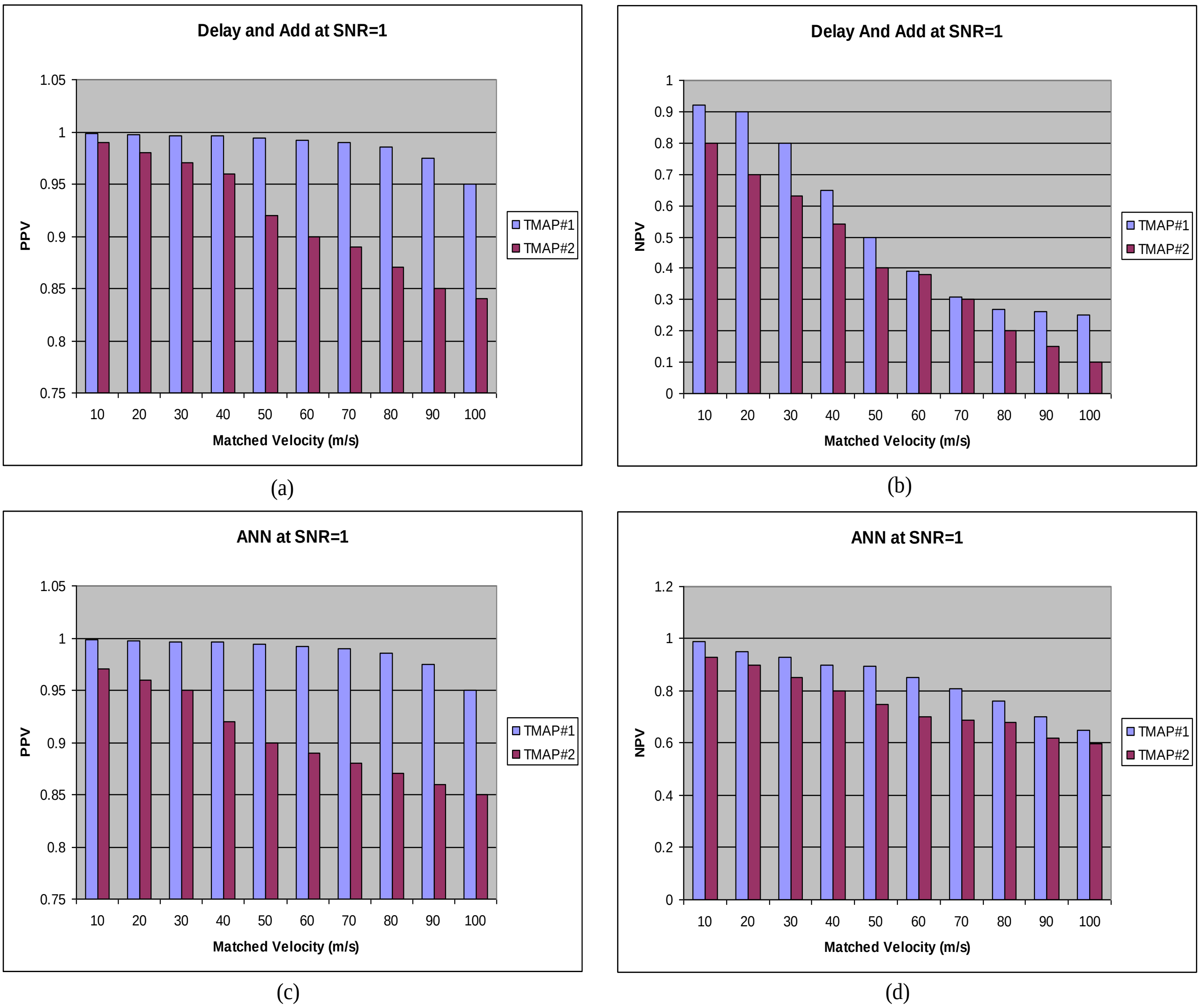


Fig. 11 Results for (a,b) PPV and NPV for delay and add method at SNR=1for TMAP#1and2 respectively, and (c,d) PPV and NPV for ANN at SNR=1for TMAP#1and2 respectively

Fig. 9 shows that the ANN method better than the conventional approach even with SNR equal to one. It performs successfully at low SNR and generate (<15% error) in detection correct AP with correct matched velocity even when the SNR 0dB, while, It shows high incorrect velocity rejection rate level (<40% error).

The results show the ANN more effective and high accurate in selectivity terms than the conventional method. These results highlight the beneficial of using ANN method instead of conventional method for neural recording in noisy environment.

IV. Conclusions

An adaptive spike detector has been presented with statistical analysis to measure the selectivity using artificial neural data. Moreover, a comparison investigation on the performance for both approaches (the proposed method and traditional delay and add algorithm) are simulated and presented. The results show that the TP and TN generated by the proposal approach higher than conventional methods (delay and add). Also it shows the FP and FN obtained by ANN method are low than the delay and add method. The simulations demonstrate that a higher selectivity and gain would improve performance considerably.

The threshold processor is found depend on the amplitude and time period of the action potential waveform under detection. Consequently, the better results for TP, TN, FN and FP will be for detecting the spikes whose SNR high. Since, the detection corresponding on the amplitude of the spike and the threshold time window, so it is better to use the rectifier processor, as it is similar to using a positive and a negative threshold, thus will be leading the larger of the two phases to be detected.

Finally, this investigation in this study has shown that the selectivity performance of the neural signal is highly related to the spike detector's performance, not just the SNR and amplitude. Therefore, choosing high selectivity approach with simplest threshold detector processor much better than using low selectivity approach.

Finally, the results show a significant gain has been achieved on the proposal approach in the simulation term, and show the capability of this approach within noisy environment application.

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