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Development of ANN Based Improved Model of Amplitude Response in Suppression State of Axonal Memory

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In this paper, three single-layered functional link artificial neural networks (FLANNs) based adaptive models are developed for generating improved responses for three high-frequency stimulations (HFS). It is in general observed that all the proposed FLANN models generate axonal responses which are in good agreement with the corresponding responses obtained from experiments. Further, it is demonstrated from simulation results that the responses obtained by the proposed model match better than that obtained by the theoretical model reported in the literature. Out of three FLANN models developed, the trigonometric FLANN model of suppression state of axonal memory is the best as it offers lowest of MAPE and MSE compared to those obtained by other two ANN models proposed in the paper.

Keywords: Neuro-spike Communication, Axonal Memory, Suppression State, Modelling of Suppression State Response, Functional Link Artificial Neural Network (FLANN)

Introduction

Neuronal communication refers to communication among neuronsand is termed as neuro-spike communication. The review of related literature in the area of neuro-spike communication[4]reveals that the research work pertaining to the effect of axonal memory on spike communication through axon is few. The results of theoretical study during suppression state reported[1] do not fully match with the experimental responses[2,3] obtained due to stimulation at different frequencies. Hence, there is a scope of development of other alternative ANN[5,7] models which will generate responses in the axon that will have better agreement with the experimental observations. The modelling of the responses using conventional back propagation based ANN[5,7] is complex and takes more training time compared to the FLANN. However, performance wise they are similar. Hence, in this paper the FLANN model is chosen for generating the responses. To fulfil this research gap, an attempt has been made in this paper to develop three types of FLANN[6] models such as Trigonometric FLANN (TFLANN)[6], Polynomial FLANN (PFLANN)[6] and Chebyshev FLANN (CFLANN)[6] and to use those for generating experimentally closer responses. The organisation of the paper proceeds as follows: in Section 2, the materials and methods relating to background of suppression state of axonal memory are dealt. In Section 3, the methodology of modelling of different types of FLANNs for the generation of responses during the suppression state of axonal memory is presented. The simulation results are obtained from the three proposed models at different frequencies, and the results are compared and discussed in Section 4. Finally, the conclusion and scope for further work are provided in Section 5.

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Materials and Methods

In this section, a concise presentation on physiological studies and communication channel model for axonal transmission are presented.

Axonal Transmission

Signal and Channel Modelling of Neuron

The hippocampal pyramidal neurons are stimulated by paired pulse with different inter pulse intervals (IPIs) changing between 1 to 500 milliseconds. The axon is modelled as a low pass filter and trains of high-frequency stimuli (HFS) with frequencies 50, 100 and 200 Hz are applied as input to obtain the axonal response. These frequencies are chosen as the axonal response to these stimulations is reported in the literature[2].The model of axonal channel comprises of spike to rectangular pulse converter, low pass filter and spike generator. In the converter the impulses are changed to rectangular pulses. When a spike comes, the level of pulse changes and it remains in that state until the new spike arrives. Then these pulses are passed through a second order Butterworth filter[1]. Finally, the spike generator converts the filtered pulses to impulses.

Model of Axonal Function

Based on research study and experiments conducted on CA region of the brain, the axonal memory consists of four states[3].

a. Resting State: In this state the axonal response is of base line spike. But if the neuron receives many stimuli with small IPIs, the axonal response decreases. Hence it passes to suppression state.
b. Suppression State: In this state the amplitude of the response is less than the amplitude of base line spike. If more stimulation continues the neuron remains in this state. But depending upon the time of rest, it moves to one of fast or slow recovery or resting states.
c. Fast Recovery State: The neuron attains this state if it gets little rest after undergoing heavy depolarization in suppression state. In this state the response recovers fast but depends on frequency. If the rest time is very small, the recovery of neurone is poor and its refractory period changes.
d. Slow Recovery State: In this state the recovery of response of the axon does not depend on the magnitude of previous stimulations.

Response of Axon

Suppression State

The model of the function in this state depends on the refractory period(R).

Case 1 (R=0)

In this state the neuron is recovered fully during prior stimulations and its R is not changed. There is no suppression of frequencies below 25 Hz. However, application of higher frequency simulation for one minute causes the depolarization of axonal response to various levels. However the amplitude degradation stops.

Case 2 (R=1)

In this case, the neuron after a heavy stimulation recovered during a small time gap. By providing a small time gap during HFS there is an increase in the value of R of the neuron.

Data Generation

The response of the axonal memory during suppression state for R=0 is very important. To find the performance of this state, trains of stimuli with frequencies 50 Hz, 100 Hz and 200 Hz are applied to the suppression state model presented in the previous section. The objective is to obtain the variations of axonal response during application of train of spikes. The input stimuli with these frequencies are chosen because axonal responses of these frequencies are reported in the literature[2]. The experimental and theoretical[1] responses for the three cases of input frequencies presented in Fig. 6 of [1] are examined. From the experimental and theoretical results, 201 normalised amplitude values are obtained between 0-60 seconds with a time interval of 0.3 seconds for each of the three frequencies. Out of these 201 data points, 161 values (80%) are used for training. The three FLANN models and remaining 40 data points are applied for validation of the models.

Modelling of Different Types of FLANN

A generalised FLANN model for generating amplitude response during suppression state of axonal memory is shown in Figure 1. The nonlinear functional expansion used in this study are trigonometric, polynomial and Chebyshev types. The expanded values for an input x(k) in all the three cases are shown in Table 1. By trial-and-error, the number of expansions is fixed to 21, 15 and 9for TFLANN, PFLANN and CFLANN models respectively. These numbers of functional expansion

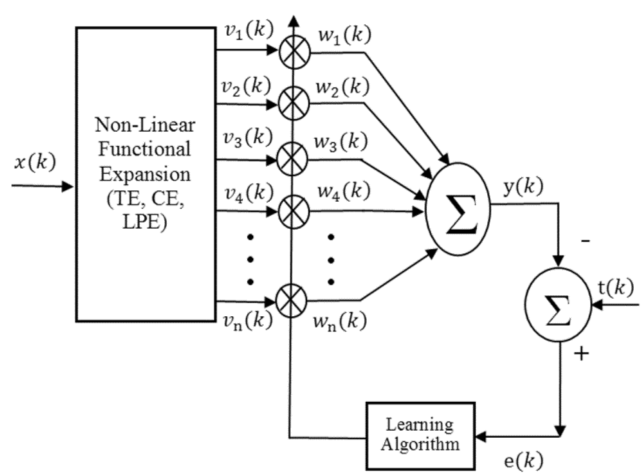

Fig. 1 — A generalised FLANN model for response simulation of axonal memory

Table 1 — Specifications of the FLANN models used in simulation study

Models	No. Of Expanded Terms (N)	Learning Rate (μ)	Expanded Terms
TFLANN	21	0.01	$x_1(k)$, $\sin(\pi x_1(k))$, $\cos(\pi x_1(k))$, $\sin(2\pi x_1(k))$, $\cos(2\pi x_1(k))$, ... $\sin(10\pi x_1(k))$, $\cos(10\pi x_1(k))$.
PFLANN	15	0.01	$x_1(k)$, $x_1^2(k)$, $x_1^3(k)$, ..., $x_1^{15}(k)$.
CFLANN	9	0.01	$T_0(x(k))$, $T_1(x(k))$, ..., $T_8(x(k))$ where $T_0(x(k))=1$, $T_1(x(k))=x(k)$, and $T_{n+1}(x(k))= 2xT_n(x(k)) - T_{n-1}(x(k))$

Table 2 — Comparative performance study in terms of MAPE and MSE of different models at three different frequencies

Models	Frequencies	Number of Expanded Terms (N)	Proposed MSE	Proposed MAPE	MSE	MAPE
TFLANN	50Hz	21	0.0007	0.0492	0.0249	0.2988
	100Hz	21	0.0003	0.0563	0.0055	0.1619
	200Hz	21	0.0001	0.0501	0.0051	0.1794
PFLANN	50Hz	15	0.0011	0.0577	0.0249	0.2988
	100Hz	15	0.0006	0.0470	0.0055	0.1619
	200Hz	15	0.0013	0.0512	0.0051	0.1794
CFLANN	50Hz	9	0.0021	0.0677	0.0249	0.2988
	100Hz	9	0.0020	0.0751	0.0055	0.1619
	200Hz	9	0.0044	0.1131	0.0051	0.1794

provides best possible results in each case. The functionally expanded values are normalised to provide better performance. The output of the TFLANN, PFLANN and CFLANN are computed according to (1), (2) and (3) respectively

$$y(k) = w_1 x(k) + \sum_{n=1}^{10} w_{2n+1} \cos nx(k) + \sum_{n=1}^{10} w_{2n} \sin nx(k) \quad \text{... (1)}$$

$$y(k) = \sum_{n=1}^{15} w_n(k) x^n(k) \quad \text{... (2)}$$

$$y(k) = \sum_{n=1}^{9} w_n(k) T_{n-1}(k) \quad \text{... (3)}$$

Where

$$T_{n-1}\big(x(k)\big) = 2xT_n\big(x(k)\big) - T_{n-1}\big(x(k)\big), T_0\big(x(k)\big) = 1 \text{ , and } T_1\big(x(k)\big) = x(k) \quad \text{... (4)}$$

During training phase when a particular input x(k) is applied, the model produces the output y(k). It is then compared with the target experimental output t(k). Comparison of these two values produces the error e(k) which is computed as

$$e(k) = t(k) - y(k)$$

Subsequently, each n^{th} weight for k^{th} input sample is updated according to

$$W_n(k+1) = W_n(k) + \alpha . \mathrm{e(k)} . \mathrm{v_n(k)} \quad \text{... (5)}$$

where α= learning rate lying between 0 and 1, and $1 \le n \le N$, N= number of expanded terms

Results and Discussions

All the 161 input values are used as inputs during training period and in each case, the weights are updated according to (5). The training process is continued for all the three frequencies and for all the three models until the squared error is minimised to the lowest possible value. After completion of the training, the weights of all the nine models are frozen. Then, the performance of each of the models is evaluated. The theoretical[1], experimental[2,3] and simulated responses in each of the nine cases are obtained and plotted. Since more discrepancy is observed between the theoretical and experimental results in case of 50 Hz stimulation, the plots for 50 Hz frequency are obtained. However, for TFLANN it is presented in Figure 2. To compare the performance of these plots with the corresponding experimental response, the MAPE and MSE values are computed according to

$$MAPE = \frac{\sum_{k=1}^{K} |t(k) - y(k)|}{K} \quad \text{... (6)}$$

$$MSE = \frac{\sum_{k=1}^{K} [t(k) - y(k)]^2}{K} \quad \text{... (7)}$$

where K = number of input samples.

These results are listed in Table 2. It is observed that for 50 Hz case, the TFLANN model yields the

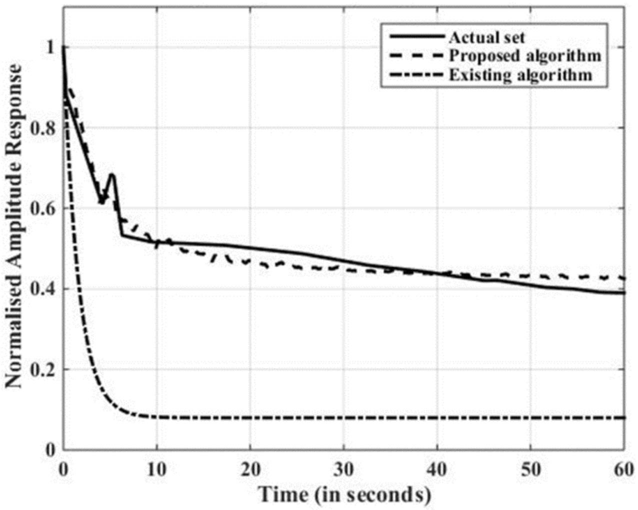

Fig. 2 — Comparison of amplitude response of theoretical[1], experimental[2,3] and proposed TFLANN model at 50 Hz

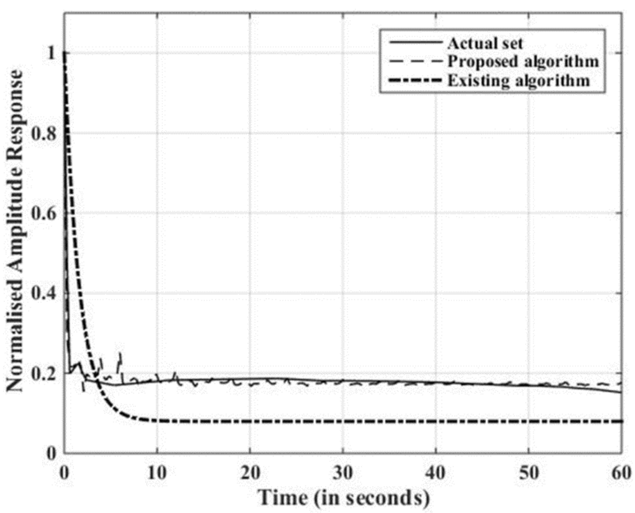

Fig. 3 — Comparison of amplitude response of theoretical[1], experimental[2,3] and proposed TFLANN model at 100 Hz

least MSE and MAPE compared to those obtained by the other two models. Thus it is demonstrated that the TFLANN is a superior model and its amplitude response is in close agreement with experimental response compared to the theoretical response reported[1]. In addition, the plots of TFLANN, experimental as well as theoretical responses in Figure 3 and 4 respectively for 100 and 200 Hz are presented. In these two cases also improved performance in matching of amplitude response obtained by TFLANN is observed. In general, the various plots and the results presented in Table 2 demonstrate that based on performance, the ranking of the models is observed to be TFLANN, PFLANN and CFLANN.

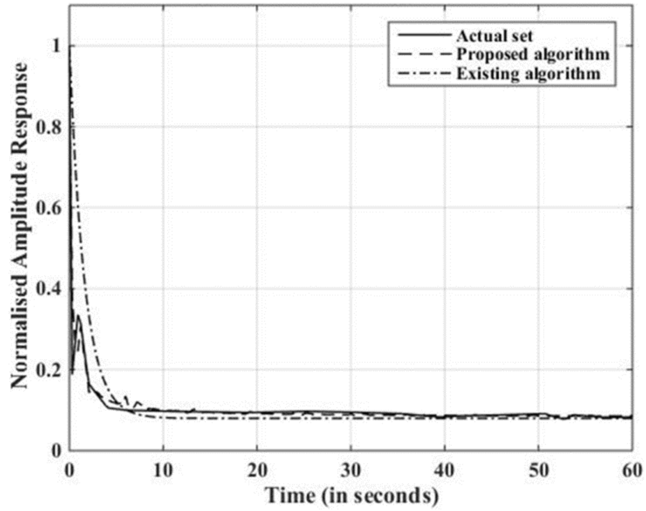

Fig. 4 — Comparison of amplitude response of theoretical[1], experimental[2,3] and proposed TFLANN model at 200 Hz

Conclusion

The characteristics of neuro-spike communication are different from the conventional communication system. In neuro-spike communication, the axonal memory plays an important role but not yet fully explored. This paper has developed three different FLANN adaptive models which generate theoretical normalised amplitude responses during suppression state of axonal memory for HFS of three different frequencies. The comparison of MAPE and MSE obtained from the comparison of theoretical proposed, and experimental responses show that the outputs of all three FLANN models match with the experimental responses better than the reported theoretical ones1. Further, it is observed that the performance of TFLANN is the best as it yields minimum MSE and MAPE values than that offered by PFLANN and CFLANN models. Further research work can be carried out to develop similar ANN models to generate responses corresponding synaptic propagation state of neuro-spike communication and can be compared with the corresponding theoretical responses.

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