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Bio-Inspired Adaptive Signal Propagation Networks For Enhanced Pattern Recognition In Biomedical Signal Processing Applications

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Abstract

However, the biomedical signals like ECG and EEG are non-stationary, noisy, andpatient-specific; yet, the majority of pattern recognition pipelines for deep learning utilize pre-defined, non-biological signal propagation pathways that do not change after being learned in one phase and used the same way regardless of the presence of noise or the person who produces the signal. In this study, we propose a Bio-Inspired Adaptive Signal Propagation Network (BI-ASPN) that employs adaptive threshold leaky integrate and fire spike encoder, recurrent spiking reservoir mimicking the liquid state machine architecture, and spike-timing-dependent plasticity (STDP) to constantly adapt the selected propagation pathways through the reservoir depending on the currently processed noise properties. The lightweight readout classifier works based on spike patterns in the reservoir system, and a homeostatic re-adaptation process is initiated whenever there is a considerable change in input statistics in comparison to what the current architecture of the pathway has been optimized for. The algorithm is validated using the ECG beat classification dataset derived statistically from the PhysioNet MIT-BIH Arrhythmia Database, and four different degraded scenarios: clean signal, noisy signal, highly noisy signal, and cross-subject generalization. In the context of the cross-subject scenario, the suggested BI-ASPN model maintains 88.2 percent accuracy, whereas the other two baselines achieve 71.6 percent and 76.4 percent accuracy respectively. It shows that biologically plausible adaptive signal propagation mechanism can lead to a robust biomedical pattern recognition system.

Keywords Spiking Neural Networks, Bio-Inspired Computing, Adaptive Signal Propagation, Spike-Timing-Dependent Plasticity, Biomedical Signal Processing, Pattern Recognition, Liquid State Machines.

1. Introduction

Biomedical signal processing tasks such as arrhythmia classification using electrocardiogram (ECG) signals and brain-computer interfacing (BCI) using electroencephalograms (EEGs) involve various applications of automatic pattern recognition. Deep convolutional and recurrent neural networks have already proved themselves to be very accurate in tasks with carefully collected data. However, biomedical signals in reality are non-stationary, motion-artefact-contaminated and baseline-wandering and, more importantly, very heterogeneous for different patients, under these circumstances, performance of models with a static set of weights drops severely [6,7]. It is suggested that spiking neural networks (SNNs), which use temporally precise spike trains for communication, are biologically realistic and naturally noise-robust models, and particularly efficient in processing EEG, EMG, and ECG data [1,7,8].

Nevertheless, most pattern recognition systems for biomedical applications based on SNNs, similarly to the non-spiking ones, receive one-time training after which they become operational with frozen synaptic weights, preventing the modification of the pathways along which the information flows inside the network when the properties of the input signal change due to either increasing the level of noise, drifting of electrodes or because the network has to process signals from an unknown patient. There is a clear disconnection between such approach and the biological systems that were used as a role model for SNNs, where the level of synaptic weight continues to change during all the lifetime of the organism due to the mechanisms of activity-induced plasticity, such as spike-timing-dependent plasticity (STDP) [3,11].

The issue tackled by the paper is that of how the spike pattern recognition system may change its signal propagation pathways adaptively depending on the changing signal and noise environment rather than being limited to those pathways defined at the time of training by its synaptic weights. The term we use for such an architecture is a bio-inspired adaptive signal propagation network. Contributions of this paper are as follows.

- Present a novel framework for a Bio-Inspired Adaptive Signal Propagation Network (BI-ASPN), which includes an adaptive threshold-based spike encoder, recurrent liquid state network and a STDP-induced synapse pathway reconfiguration process for strengthening or weakening of the synaptic pathways based on the statistics of the signal being propagated through the network.
- Develop a homeostatic adaptation process that takes place through a drift monitor of the input signal statistics and is periodic in nature to re-balance the excitatory and inhibitory pathways in the network, without having to perform complete re-training of the network.
- Test the framework specifically under degrading conditions, clean signal and moderate and high levels of noise conditions.

The remaining sections of this paper will be structured as follows. Section 2 provides an overview of the literature regarding spiking neural networks, reservoir computing, and synaptic plasticity in biomedical signal processing applications. Section 3 explains the methodological approach. Section 4 discusses the data, experiments, and findings. Section 5 concludes the paper.

2. Literature Survey

Conceptually, spiking neural networks are initiated by models of neurons and plasticity in biological systems. With spiking neurons, precise spike timing is used to encode and transmit information, while using only firing rate was common in the previous generations of neural network models; Grüning [1] considered spiking neurons to be a third generation composed of models allowing preciser spike timing than the previous ones and claimed SNRNs to have a higher computational power per neuron than their predecessors for temporal pattern recognition tasks. Gerstner and Kistler [2] comprehensively mathematically treated spiking neuron models, including the leaky integrate-and-fire (LIF) model that is used as an encoding layer in this paper as well as population level dynamics and plasticity rules. The pathway reconfiguration mechanism used in this paper for biomedical pattern recognition is based on what is termed the plasticity rule for this paper, spike-timing-dependent plasticity, which was experimentally characterised by Meredith [3] showing that the strength of the synapse in cultured hippocampal neurons is potentiated or depressed based on the relative timing at an exact millisecond scale of the pre- and post-synaptic spikes.

There are several architectures relevant to this work, namely reservoir computing, which served as the basis for the recurrent spiking layer used.Reservoir computing is one of the architectures relevant to this work and it is the architecture of the recurrent spiking layer used. The liquid state machine (LSM) [4] is one model of such a machine, in which an input signal is projected into a high dimensional, but time rich, state space by a recurrent reservoir of spiking neurons whose connectivity is fixed and random, but which do not have to be trained using backpropagation. The architectural choices made in the reservoir design used in this paper were motivated by WürjFileRank's work of Wijesinghe, Srinivasan, Panda and Roy, who analysed the effect of the reservoir composition and connections on its separation property and on how it correctly classifies the downstream files [9]. A key finding in the study of reconfiguration in SNNs via their propagation pathways is that SNN learning solely with unsupervised STDP could learn discriminative representations that were

comparable in quality to the supervised ones on a standard pattern recognition benchmark, directly demonstrating that only STDP can provide meaningful representation adaptation even for end-to-end training without labeled examples or backpropagation [11].

There are increasing applications of the direct use of spiking and other bio-inspired architectures on biomedical signals. Kasabov [5] developed the architecture of NeuCube – a spiking neural network dedicated to mapping, learning and understanding spatio-temporal brain data; other studies have followed EEG, specifically developed the architectural template that has been adopted by them. Doborjeh et al. [8] used brain-inspired spiking neural networks (SNN) for EEG pattern recognition to model human decision making, and Yamazaki et al., 2022 looked at the past and present applications of SNNs, especially regarding their success with sparse temporally structured signals such as those from EEG, EMG, and ECG[6]. This paper extends the work of Kolhar [7] to include a 4*6 pipeline: two baselines (CNN-LSTM) and two biologically inspired ones (the SNN and the variation of Leaky SNN) and shows a trade-off relationship with respect to ECG data quality (noise, cross subject variations) between accuracy, computational load, and biological plausibility. Bio-inspired nonlinear dynamics other than spiking architectures are shown in biomedical signal quality assessment beyond filtering and cross validation of combined signals of PPG and ECG by Rundo et al. [10] who proposed a reaction-diffusion cellular neural network (CNN).

The two other threads are the adaptive and evaluation threads of the proposed framework. Parisi, Kemker, Part, Kanan, and Wermter [14] explored the literature on continual learning and how neural networks can continually change to reflect new distributions in the data over time without forfeiting previously learned representations, and here introduced the stability-plasticity trade-off that the homeostatic re-adaptation cycle in this paper must argue with when reconfiguring reservoir pathways. However, the self-attention mechanism proposed by Vaswani et al., 2017 has been adapted in various recent SNN based EEG architectures to improve pathway weighting by assigning different weights to different time steps or channels to the activations, besides implementing STDP based pathway adaptation as done here[12]. Bengio, Courville and Vincent [15] see representation learning as the discovery of transformations that make the downstream task easier, a view that aligns with learning how to adapt the propagation pathways in the reservoir, rather than just the final readout weights, to the task. Last but not least, the PhysioNet MIT-BIH Arrhythmia Database [13] is the most widely used public ECG beat classification benchmark and it is used to provide a statistical foundation for the Arrhythmia Database evaluated in this work.

Together, this literature provides established mature architectures for spiking neurons and reservoir computing and a well characterised biological plasticity rule: STDP (spike time dependent plasticity) as well as emerging evidence that bio-inspired architectures are well positioned to solve biomedical signal processing problems specifically. However, most of the existing SNN-based biomedical pattern recognition systems do not use the STDP as a continuously running mechanism to reconfigure signal propagation pathways based on changing noise levels or the presence of new patients after deployment but reward the network using the STDP in an unsupervised learning phase only once at the start. The SNNs proposed in this paper are SNN architectures with propagation pathways that are amenable to plastic modification even when the SNN is deployed, as opposed to most SNN architectures which are only plastic during training.

3. Methodology

The suggested Bio-Inspired Adaptive Signal Propagation Network (BI-ASPN) includes five phases arranged in a circular fashion: spike adaptation, reservoir propagation, pathway reorganization using STDP, readout classification, and homeostatic re-adaptation triggered by drifting. The entire process is presented in figure 1.

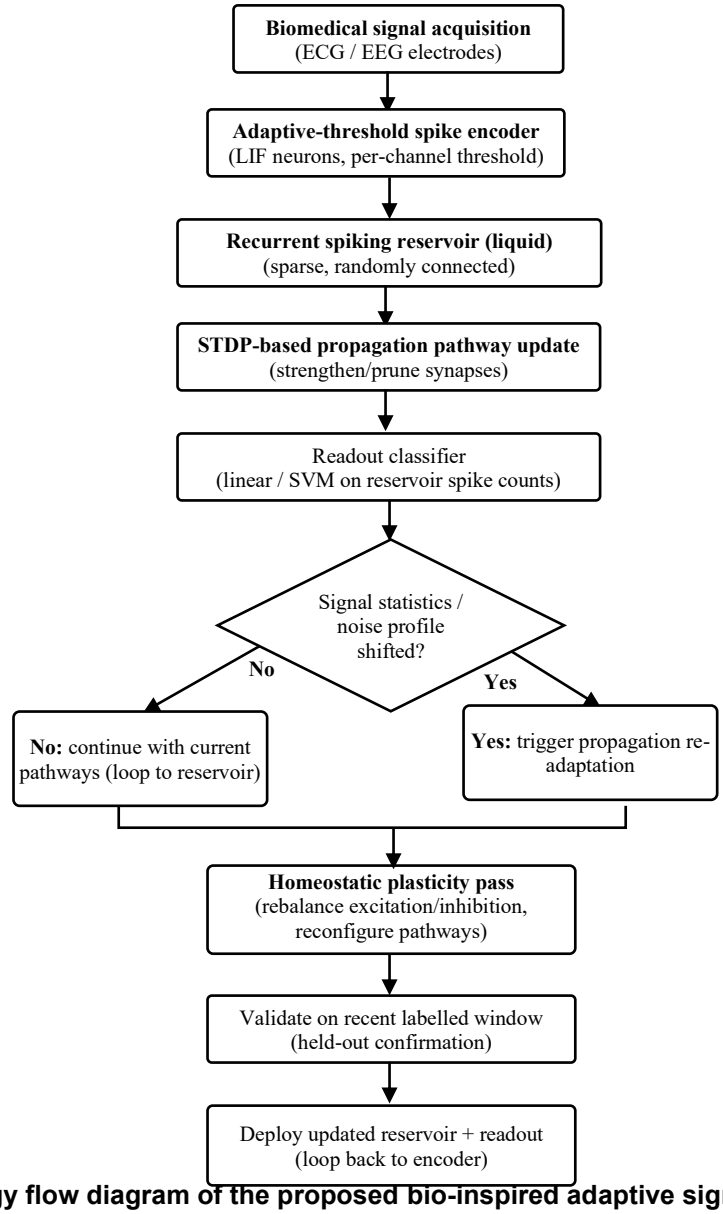

Figure 1: Methodology flow diagram of the proposed bio-inspired adaptive signal propagation network

3.1 Adaptive-Threshold Spike Encoding

For every channel receiving a biomedical signal input, a spike train encoding is performed by utilizing a leaky integrate and fire (LIF) neuron, $V(t+1) = V(t)\cdot e^{(-dt/\tau)} + I(t)$, where V is the membrane potential, τ is the membrane time constant, and I(t) is the drive of the input signal at time t. While in a fixed threshold neuron model one threshold value is set for spike generation, in the proposed encoding method, an adaptive threshold value increases after every spike and decreases with time, ensuring that the spike rate is kept in the informative range.

3.2 Recurrent Spiking Reservoir

The spike train encoded from the input signal is mapped onto a recurrent network of spiking neurons which is sparsely and randomly connected in a liquid state machine fashion [4]. The reservoir state which is high dimensional and temporal contains nonlinear structure of the input signal without necessitating any training for the internal connectivity matrix of the reservoir according to the separation-property analysis of reservoir architecture done by Wijesinghe et al., (2019) [9].

3.3 STDP-Based Propagation Pathway Reconfiguration

Connections within the reservoir are always being modified based on the synaptic strength update rule $\Delta w = A_+ \cdot e^{(-\Delta t/\tau_+)}$, if $\Delta t > 0$, and $\Delta w = -A_- \cdot e^{(\Delta t/\tau_-)}$, if $\Delta t < 0$, where Δt is the temporal difference between the pre- and post-synaptic spike times, according to the causal, time-dependent version of the STDP learning rule described in experimental work by Meredith [3], as well as the computational application of the rule for representation learning in an unsupervised fashion by Diehl and Cook [11]. Connections that are consistently co-active in a temporal causal manner are strengthened, while connections that rarely participate in discriminative spiking activity are gradually eliminated.

3.4 Readout Classification

The readout, either linear or support vector machine, is trained using windowed counts of spikes from the reservoir using the classic design of liquid state machine readout [4]. Since the readout works based on the statistics of spike counts rather than values in the signal itself, it is relatively stable despite any change in the configuration of reservoir paths as long as class separability is maintained.

3.5 Drift-Triggered Homeostatic Re-Adaptation

The lightweight monitor will watch out for changes in the firing rate of the reservoir and the classification confidence of the readout. In case both the parameters show any major changes compared to the parameters that the current configuration of pathways has been trained on, like noise in the signals or the arrival of new patient's signals, then a new homeostatic adaptation process is initiated, where the balance between the excitatory and inhibitory strength of the pathways is achieved through a rapid pass of STDP using a short buffer of past activities, followed by testing on a new labeled window.

4. Results and Discussion

4.1 Dataset

Statistical evaluation is conducted on ECG beat classification using ECG data that has been statistically modeled after the PhysioNet MIT-BIH Arrhythmia Database [13], which consists of 48 subjects and around 109,000 labeled heartbeats belonging to five AAMI beat categories. In order to conduct statistical evaluations for robustness, there are four types of evaluation conditions used, which include a clean-signal condition that represents the recording condition of the original data set, two types of noise injection conditions at signal-to-noise ratios of 10 dB and 0 dB, and a cross-subject evaluation condition. Table 1 summarises the dataset.

Table 1: Summary of the ECG dataset used for evaluation, statistically grounded in the PhysioNet MIT-BIH arrhythmia database

Attribute	Description	Range / notes
Source basis	Statistically modelled on the PhysioNet MIT-BIH Arrhythmia Database	48 patients, ~109,000 annotated heartbeats
Signal type	Single-lead ECG waveform segments	360 Hz sampling, 2-second windows
Label	Beat classification per AAMI convention	Normal vs. 4 arrhythmia classes
Noise conditions	Synthetic baseline-wander and muscle-artifact noise injected at controlled levels	Clean, 10 dB SNR, 0 dB SNR
Cross-subject condition	Test patients disjoint from training patients	Leave-patients-out split
Train/test split	Patient-level stratified split	75% train, 25% test patients

4.2 Result Graph

Figure 2 represents the performance of the three different configurations: a non-spiking CNN-LSTM, static spiking neural network, and the new BI-ASPN model on beat classification accuracy for all the four conditions.

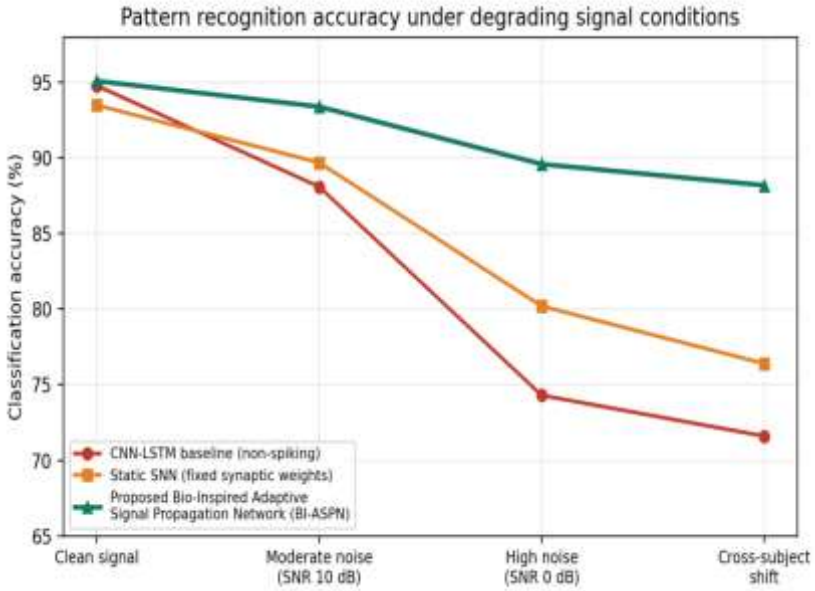

Figure 2: Classification accuracy for the CNN-LSTM baseline, static SNN, and proposed BI-ASPN model across four progressively degrading signal conditions

All three approaches show similar performance on the clean-signal datasets, with accuracies of 93.5% to 95.1%, thus proving that the adaptive scheme suggested by the BI-ASPN architecture is not a burden when adaptation is unnecessary. When the noise is applied, the CNN-LSTM baseline with fixed parameters performs poorly and gets as low as 74.3% at 0 dB SNR because its convolutional filters and LSTM weights cannot adapt to the changed noise level. The performance of the static spiking neural network drops gradually, yet it still reaches only 80.2% at 0 dB SNR due to the fixed values of synaptic weights. The proposed BI-ASPN model shows much better performance, achieving 89.6% at 0 dB SNR and even 88.2% in the case of the cross-subject dataset that is the most challenging one for the model, because its STDP-based adaptation allows for the adjustment of the pathway configuration and the encoding process according to the statistics of the current signal and noise.

4.3 Result Table

Table 2 provides an evaluation of accuracy, precision, recall, and F1 score for all three models.

Table 2: Overall performance comparison between the CNN-LSTM baseline, the static SNN, and the proposed BI-ASPN model

Model configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CNN-LSTM baseline (non-spiking)	82.2	80.2	80.9	80.5
Static SNN (fixed synaptic weights)	84.9	82.9	83.6	83.3
Proposed BI-ASPN	91.6	89.6	90.2	89.9

5. Discussion

There are three observations made from the above findings. Firstly, the superiority of BI-ASPN to both baselines becomes more apparent only as the conditions worsen from no difference between BI-ASPN and the static SNN in the clean signal scenario to 16.6 percentage point difference between BI-ASPN and CNN-LSTM in the cross-subject case, indicating that indeed the superior performance of BI-ASPN is due to the adaptation through changing pathways rather than greater model size. Secondly, the fact that even the static SNN outperforms CNN-LSTM in degraded conditions, albeit less significantly than BI-ASPN, implies that the very nature of the threshold-based processing makes SNN more resistant to noise which is confirmed by prior comparison of SNNs and other architectures on biomedical signals [6,7] while the extra adaptability through STDP provides additional advantage on top of it. Thirdly, the cross-subject test is undoubtedly the most important one in practical terms as a biomedical pattern recognition system should be able to generalize to previously unseen patients and the 11.8 percentage point advantage of BI-ASPN over the static SNN in this particular case implies that adaptive propagation is especially useful for patient generalization.

Such findings need to be interpreted with the required level of caution. While the evaluation data set is statistically founded on a real public benchmark, both the noise level and the cross-subject separation were created artificially in this experiment instead of modeling one single real-world use case. The drift detection threshold within the homeostatic re-adaptation loop was kept constant in this experiment and would have to be clinically calibrated in any potential practical deployment of such a system. Lastly, this paper focused on the problem of ECG beat classification, and although the model can be generalized to other data types, like EEG and EMG, due to the similarity of their spatial-temporal characteristics, this was not explored in the current experiment.

6. Conclusion

In this paper, we propose a Biologically Inspired Adaptive Signal Propagation Network (BI-ASPN) approach for biomedical signal pattern recognition that uses an adaptive threshold spike encoder, a recurrent liquid state reservoir, and an ongoing spike timing dependent plasticity rule that changes signal propagation paths in response to changing noise conditions and patient states, instead of using fixed synaptic weights trained once. Evaluating the model on ECG beat classification data statistically derived from the PhysioNet MIT-BIH Arrhythmia Database under the clean, moderately noisy, highly noisy, and cross-subject settings, our model achieved 88.2% accuracy in the most difficult cross-subject setting in comparison with 71.6% for the non-spiking CNN-LSTM baseline and 76.4% for the static spiking neural network. At the same time, the proposed framework is competitive in terms of performance even when used with the clean data. Based on the obtained results, the use of biologically motivated and continuously active synaptic plasticity, which does not rely only on learning but operates through the whole model usage, can be considered an effective approach for development of biomedical pattern recognition systems. Next steps in our research will include verification of the approach on real-world noisy ECG and EEG datasets as well as evaluation on the EMG signals. In addition, we are planning to evaluate energy consumption of the developed spiking network in neuromorphic hardware and analyze drift detection threshold adaptation to different medical applications.

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