Uncertainty in Noise-Driven Steady-State Neuromorphic Network for ECG Data Classification

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***Abstract*—The pathophysiological processes underlying the ECG tracing demonstrate significant heart rate and the morphological pattern variations, for different or in the same patient at diverse physical/temporal conditions. Within this framework, spiking neural networks (SNN) may be a compelling approach to ECG pattern classification based on the individual characteristics of each patient. In this paper, we study electrophysiological dynamics in the self-organizing map SNN when the coefficients of the neuronal connectivity matrix are random variables. We examine synchronicity and noise-induced information processing, influence of the uncertainty on the system signal-to-noise ratio, and impact on the clustering accuracy of cardiac arrhythmia.**

Keywords-ECG data classification, neuromorphic network, SNN, uncertainty, noise.

I. Introduction

Classification of irregularities or variations in the morphological pattern in a recorded ECG waveform can be very challenging task for a wearable ECG acquisition and classification system due to the uncertainty and imbalanced classes among signals, contaminations of signals to physiological artefact and external noise, and substantial inter-patent variations in the pathophysiological processes, or within the single patient over different temporal or physical conditions. Several methods for generic ECG classification based on signal processing techniques exists; however, in general, the inter-patient variations of the ECG signals, and the stochastic nature of the main pathophysiological processes result in the inconsistent performance, and consequently, to significant variations in their accuracy and efficiency. In this context, spiking neural networks (SNNs), which provide principal mechanism for the neuromorphic engineering, are an effective platform to provide personalized prognosis by combining the heterogeneous sources of available information within the sensor fusion framework, as well as, by identifying meaningful patterns in data (e.g. convolutional neural networks (CNN) [1], recurrent neural networks (RNN) [2]).

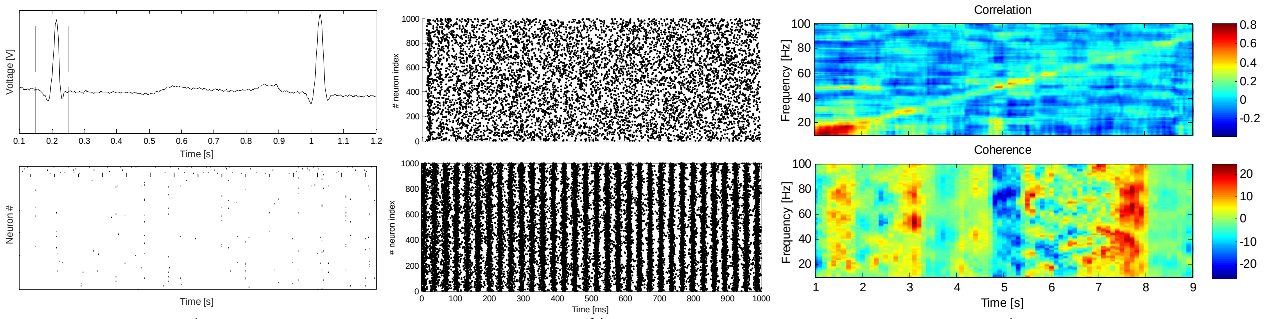
In this paper, we examine electrophysiological dynamics and synchrony in the neuromorphic self-organizing map (SOM) SNN [3]-[6]. Consequently, we distinguish between synchronized and unsynchronized spikes generated in a neural population, and we examine how noise induce spontaneous transitions in information channels and influence the clustering accuracy of several forms of cardiac arrhythmia.

II. Stochastic Uncertainty and Synchronity

The noise originates from the quantal releases of neural transmitters, the random openings of ion channels, the coupling of background neural activity, etc. Subsequently, the noise induces neuronal variability, increase the neuron sensitivity to environmental stimuli, influence synchronization between neurons, and facilitate probabilistic inference. The impact of noise on neuronal dynamics is analysed in [7], and extended in [8]. In comparison, we study the impact of noise on the dynamics of the firing probability of spiking neurons. We derive the uncertainty model as a Markov process where stochastic integration is interpreted as an Itô system of stochastic differential equations

$$d\Gamma(t) = \left(-\psi\Gamma(t) + \lambda f\left(\dot{\Gamma}(t)\right)\right)dt + \sigma\big(\Gamma(t)\big)d\omega(t) \qquad (1)$$

where Γ is the synaptic drive at time t, λ is the gain, which regulates *exponential* decay of the synaptic voltages, and mimics a spike-time dependent scaling of the input conductance, and function $f_i(.)$ represents the neuron firing rate. The first and second terms in the right hand side of (1) are the deterministic drift and stochastic diffusion parts of the stochastic differential equations, respectively, where we define $\Gamma(t)\triangleq[\Gamma_1(t), \Gamma_2(t),\ldots, \Gamma_n(t)]^T$, $f(\Gamma)\triangleq[f_1(\Gamma_1), f_2(\Gamma_2),\ldots, f_n(\Gamma_n)]^T$, $\psi\triangleq[1/\tau_1, 1/\tau_2,\ldots, 1/\tau_n]^T$, $\lambda\triangleq\mathrm{diag}[\lambda_1, \lambda_2,\ldots, \lambda_n]^T$. $\omega(t) = [\omega_1(t), \omega_2(t),\ldots, \omega_n(t)]^T$ describes noise in the input voltage and is represented by Brownian motion, i.e. an n-dimensional standard Wiener process, and $\sigma(\Gamma)=\mathrm{diag}[\sigma_1(\Gamma), \sigma_2(\Gamma),\ldots,\sigma_n(\Gamma)]^T$ represents the state-dependent noise matrix for the Gaussian white noise process $d\omega(t)$. Solving (1) requires first finding $\sigma(\Gamma)$ and then obtaining its matrix square root. In our experiments we used the stationary statistics of open channels in the Markov channel model to define the noise processes in the conductance models. The general method for constructing $\sigma(\Gamma)$ from deterministic drift is by Goldwyn method. From Itô's theorem on stochastic differentials, *variance-covariance matrix* $K(t)$ of $\Gamma(t)$ with the initial value $K(0)=E[\Gamma\Gamma^T]$ can be expressed in differential Lyapunov matrix equation form. Standard techniques for small dense Lyapunov equations such as the Bartels-Stewart method or Hammarling method [9] efficiently evaluate small to medium scale circuits. Alternatively, large dense Lyapunov equations, such as those in large scale circuits, are solved by sign function based techniques [10].



a) b) c)

Figure 1: a) Top: ECG signal; Bottom: Example of population temporal coding in a SOM. The amount of input neuron spikes needed for activation to occur determines the latency of the network, and can be modified by potentiation or depression of the synapses linking the input and grid neurons; b) Top: Asynchronous irregular regime in the network; Bottom: in the oscillatory state the majority of neurons fire in tight synchrony; c) The temporal synchrony between two output spike patterns.

III. Experimental Results

We use the multi-parameter ECG data from MIT-BIH Arrhythmia Database. The ECG classification is performed with SOM neuromorphic network [5]. In the SOM, synaptic delays enable the formation of polychronous groups, i.e. distinctive clusters of neurons that fire together in response to a specific input stimulus [4]. If the synaptic communications between neurons are non-instantaneous, the network is characterized with stable n-cluster states for a wide set of parameters (the number of clusters in such states typically increases linearly with the inverse of the delay). In these states the network is subdivided into n groups of neurons. Within each group, neurons fire in synchrony (Fig. 1a) (while a nonzero phase shift exists between groups), unless strong noise is present in the network. If the amplitude of input noise is sufficiently large, firing is no longer exact but may happen even though the noise-free processing has not yet reached threshold. Subsequently, the neurons fire in an asynchronous manner (Fig. 1b) and the activity of the network is time-invariant. The temporal synchrony between output spike patterns and individual spike timing dependencies can also be examined in the frequency domain, using spike-spike coherence (Fig. 1c). The neurons respond with variable strength to repeated, identical stimuli offered to the system. This uncertainty is shared among neurons causing correlations in trial-to-trial responsiveness of a neuronal population. Consequently, correlations reduce the signal-to-noise ratio (SNR) of a pooled population response, as shared fluctuations in response cannot be averaged away.

The effect of uncertainty on the clustering accuracy of several selected forms of cardiac arrhythmia (normal beat, left bundle branch block beat, right bundle branch block beat, premature ventricular contraction, atrial premature beat, pace beat, ventricular flutter wave) is 4.6%, 8.5%, 7.9%, 7.4%, 11.6%, 7.3%, and 8.8%, respectively. The clustering of each beat is evaluated based on the dominant beat type in a cluster. If the fluctuations in the synaptic current are large, the spontaneous transitions between the two stable states are induced in a random manner, and the examined features of the beat cannot fit within its cluster leading to the loss of the accuracy. Due to its small P-R interval atrial premature beats are the most impacted.

IV. Conclusions

SNNs offer effective platform for advanced personalized prognosis and healthcare. In this paper, we study electrophysiological dynamics of SOM neuromorphic network when the coefficients of the neuronal connectivity matrix are random variables. We examine how noise induce spontaneous transitions in information channels and influence synchronous firing of the neuron populations. This approach provides key insight required to address signal-to-noise ratio, response time, and linearity of the network, and subsequently, the clustering accuracy of several selected forms of cardiac arrhythmia.

References

[1] S. Kiranyaz, *et al.*, "Real-time patient specific ECG classification by 1-d convolutional neural networks," *IEEE Tran. Biomed. Eng.*, vol. 63, no. 3, pp. 664-675, 2016.

[2] C. Zhang, *et al.*, "Patient-specific ECG classification based on recurrent neural networks and clustering technique", *IEEE Int. Conf. Biomed. Eng.*, pp. 63-67, 2017.

[3] S.R. Rogal Jr, *et al.*, "Automatic detection of arrhythmias using wavelets and self-orgainzed artificial neural networks," *IEEE Int. Conf. Intel. Syst. Des. App.*, pp. 648-653, 2009.

[4] R. Dlugosz, *et al.*, "Realization of the Conscience Mechanism in CMOS Implementation of Winner-Takes-All Self-Organizing Neural Networks," *IEEE Tran. Neur. Netw.*, vol. 21, no. 6, pp. 961-971, 2010.

[5] J. Mes, *et al.*, "Neuromorphic self-organizing map design for classification of bioelectric-timescale signals" *IEEE Int. Conf. Embedded Comp. Syst.*, pp. 1-8, 2017.

[6] J. Kim, P. Maxumder, "Energy-efficient hardware architecture of self-organizing map for ECG clustering in 65-nm CMOS," *IEEE Tran. Circ. Syst.-II*, vol. 64, no. 9, pp. 1097-1101, 2017.

[7] B.W. Knight, "The relationship between the firing rate of a single neuron and the level of activity in a population of neurons," *J. Gen. Physiol.*, vol. 59, pp. 767-778, 1972.

[8] W. Gerstner, "Population dynamics of spiking neurons: fast transients, asynchronous states, and locking," *Neural Comp.*, vol. 12, pp. 43-89, 2000.

[9] L. Arnold, *Stochastic Differential Equations: Theory and Application*, New York: Wiley, 1974.

[10] A. Zjajo, *et al.*, "Stochastic analysis of deep-submicrometer CMOS process for reliable circuits designs," *IEEE Tran. Circ. Syst.-I.*, vol. 47, no. 5, pp. 655-674, 2011.