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Unsupervised heart-rate estimation in wearables with Liquid states and a probabilistic readout

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ABSTRACT

Heart-rate estimation is a fundamental feature of modern wearable devices. In this paper we propose a machine learning technique to estimate heart-rate from electrocardiogram (ECG) data collected using wearable devices. The novelty of our approach lies in (1) encoding spatio-temporal properties of ECG signals directly into spike train and using this to excite recurrently connected spiking neurons in a Liquid State Machine computation model; (2) a novel learning algorithm; and (3) an intelligently designed unsupervised readout based on Fuzzy c-Means clustering of spike responses from a subset of neurons (Liquid states), selected using particle swarm optimization. Our approach differs from existing works by learning directly from ECG signals (allowing personalization), without requiring costly data annotations. Additionally, our approach can be easily implemented on state-of-the-art spiking-based neuromorphic systems, offering high accuracy, yet significantly low energy footprint, leading to an extended battery-life of wearable devices. We validated our approach with CARLsim, a GPU accelerated spiking neural network simulator modeling Izhikevich spiking neurons with Spike Timing Dependent Plasticity (STDP) and homeostatic scaling. A range of subjects is considered from in-house clinical trials and public ECG databases. Results show high accuracy and low energy footprint in heart-rate estimation across subjects with and without cardiac irregularities, signifying the strong potential of this approach to be integrated in future wearable devices.

1. Introduction

Heart-rate monitoring is ubiquitous in modern wearable devices such as a smart watch (Aarts & Ouwerkerk, 2006; Phan, Siong, Pathirana, & Seneviratne, 2015) or Electrocardiogram (ECG) necklace (Penders, van de Molengraft, Altini, Yazicioglu, & Van Hoof, 2011). ECG sensors (Gyselinckx et al., 2005; Mukhopadhyay, 2015) attached to these devices monitor the electrical potential caused by the systolic activity of heart and then propagated through cardiac muscles. The recorded electrical data are post-processed, either locally on the sensor (Van Helleputte et al., 2015) or on a device (Krasauskas & Telksnys, 2015) attached to the sensor to estimate heart-rate. Detecting Q, R, S peaks (Fig. 1) in ECG is fundamental to heart-rate estimation. Although QRS detection have matured over the years (Kohler, Hennig, & Orglmeister, 2002), this topic still remains relevant for wearables (Gyselinckx et al., 2005; Otto, Milenkovic, Sanders, & Jovanov, 2006) due to the following.

- ECG sensor recordings are often contaminated with motion artifacts and baseline drifts due to the motion of the wearables; and
- devices processing the ECG sensor recordings are constrained in terms of area, power consumption and computational capabilities.

Several software approaches have been proposed to detect QRS from wearable ECG. In Ravanshad, Rezaee-Dehsorkh, Lotfi, and Lian (2014), a modified level-crossing analog-to-digital converter

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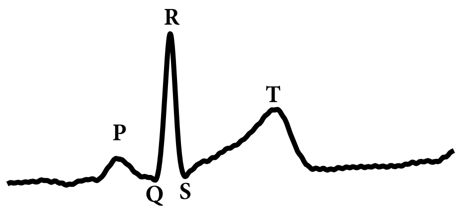

Fig. 1. QRS complex in ECG.

is introduced to convert analog ECG data to a meaningful representation. Based on this representation, an algorithm is proposed to detect the RR intervals. In Zidelmal, Amirou, Ould-Abdeslam, Moukadem, and Dieterlen (2014), S-Transform is introduced to isolate QRS complexes in time–frequency domain. Shanon energy is then computed on these isolated spectrums to localize R-waves in time domain. In Karimipour and Homaeinezhad (2014), a real-time signal processing is proposed, which includes high frequency noise filtering and baseline drift reduction using discrete wavelet transform. In Ramakrishnan, Prathosh, and Ananthapadmanabha (2014), QRS detection is performed based on first derivative of ECG signals. There are also other software approaches for QRS detection (refer to Jain, Ahirwal, Kumar, Bajaj, & Singh, 2017 for a summary). In general, software-based QRS detection is performed on generic computing components (such as CPU core). One advantage of this approach is the ease of updating an existing algorithm or implementing a new use-case (such as arrhythmia detection). However, power consumption of these techniques is usually of the order of $\approx 10\,\mu$W. Recently, low-power dedicated QRS-detection hardware is investigated (Deepu, Zhang, Heng, & Lian, 2016; Ieong, Mak, Vai, & Martins, 2016; Kim & Mazumder, 2017; Van Helleputte et al., 2015). Although, sub-μW power consumption is achieved, limited flexibility is available to implement new algorithms or use-cases. To overcome this, the usual approach is to perform QRS detection on the sensor hardware, with use-cases, such as the arrhythmia detection, implemented on the attached device (Tekeste, Saleh, Mohammad, Khandoker, & Elnaggar, 2017).

Recently, machine learning-based QRS detection is investigated to address flexibility and power consumption. In Silipo and Marchesi (1998), artificial neural network is used for ECG classification to detect arrhythmia, myocardial ischemia and other chronic alterations. In Saini, Singh, and Khosla (2013), K-nearest neighbor classifier is used for ECG classification. The ECG signal is post-processed using a digital band-pass filter to reduce false detection with gradient of the signal used as a feature for the classifier. In Arbateni and Bennia (2014), radial basis function is used for QRS detection. This technique also uses a filter to adjusting R-peak positions. In Magrans, Gomis, and Caminal (2016), support vector machine is used in to classify QRS segments. In Acharya, Fujita, Lih, Adam et al. (2017); Acharya, Fujita, Lih, Hagiwara et al. (2017), 11 layer deep convolution neural network is proposed as an alternative. These approaches use supervised learning, success of which depends on availability of large amount of hand labeled data, generic to be applied to subjects with and without cardiac irregularities.

In this work we use spiking neural networks (Maass, 1997), which are powerful and biologically realistic computation models, inspired by the dynamics of human brain. Spiking neural networks are recently used for pattern recognition (Buonomano & Merzenich, 1999; Kasabov, Dhoble, Nuntalid, & Indiveri, 2013), function approximation (Iannella & Back, 2001) and image classification (Diehl & Cook, 2015; Diehl et al., 2015; Samadi, Lillicrap, & Tweed, 2017) tasks. These networks can also be implemented efficiently in hardware (Fusi & Mattia, 1998; Hsieh & Tang, 2012; Indiveri, Chicca, & Douglas, 2006). Examples are the large scale neuromorphic computing systems such as TrueNorth (Akopyan et al., 2015), CxQuad (Indiveri, Corradi, & Qiao, 2015), NeuCube (Kasabov, 2014), SpiNNaker (Khan et al., 2008), NeuroGrid (Benjamin et al., 2014) and HICANN (Schemmel et al., 2010), among others (refer to Schuman et al., 2017 for a survey). Some of these systems are originally designed for high-performance computing (e.g., TrueNorth and SpiNNaker), while others are designed for low-power embedded systems (e.g., CxQuad and HICANN). In this work we report energy usage on CxQuad, a low power spiking hardware with 1024 neurons and 64K synapses (Indiveri et al., 2015).

Our work differentiates from existing studies on ECG-based heart-rate estimation by (1) using spiking neural networks, which can be implemented on energy efficient neuromorphic hardware; (2) encoding analog ECG signal directly into spike trains, which are then used to excite the network of spiking neurons; and (3) designing an unsupervised readout, facilitating learning from subject-specific ECG to estimate heart-rate. The overall approach allows personalization and eliminates the need to manually annotate training data. We envision our approach to be integrated inside an ECG sensor node. Analog ECG signal is encoded directly into spikes, which are used to excite a reservoir of recurrently connected spiking neurons. These neurons are interconnected using plastic synapses, with weight updates using Spike Timing Dependent Plasticity (STDP) (Brader, Senn, & Fusi, 2007; Rao & Sejnowski, 2001). Additionally, homeostatic synaptic scaling (Carlson, Richert, Dutt, & Krichmar, 2013; Galtier & Wainrib, 2013; Liu, 2011) is used to stabilize the plastic mechanism, preventing run-away behaviors. At the readout stage of the architecture, we use particle swarm optimization (Eberhart & Kennedy, 1995) to select contributions from a subset of the spiking neurons. Cumulative responses from the selected neurons are clustered to infer heart-rate using Fuzzy c-Means clustering (Bezdek, Ehrlich, & Full, 1984). To validate our approach we used CARLsim (Beyeler, Carlson, Chou, Dutt, & Krichmar, 2015) spiking neural network simulator with ECG data from in-house clinical trials and other open-source databases. We compared our approach with (1) software-based (Van Helleputte et al., 2015), (2) neural networks-based (Acharya, Fujita, Lih, Hagiwara et al., 2017), and (3) support vector machine-based (Magrans et al., 2016) QRS detection. Results demonstrate high accuracy of our approach, with applicability to subjects with and without cardiac irregularities.

Contributions: Following are our novel contributions:

- a technique to encode time-series data directly to spike train, capturing its spatio-temporal properties;
- a novel architecture inspired by the computation model of Liquid State Machine;
- a novel learning-rule with soft winner-take-all implementation;
- an unsupervised readout for heart-rate estimation using Fuzzy c-Means;
- a technique to improve clustering accuracy by selecting neurons responses using swarm intelligence; and
- a real-life medical benchmark for neuromorphic computing community.

2. Overview of our approach

Evolving spiking neural network architectures (Schliebs & Kasabov, 2013; Soltic & Kasabov, 2010) have been proposed recently targeting a wide-range of applications such as image recognition, time series prediction etc. These architectures offer trade-offs in terms of storage complexity, classification/prediction accuracy and computation requirements. Our approach is based on