Processing EMG signals using reservoir computing on an event-based neuromorphic system

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***Abstract*—Electromyography (EMG) signals carry information about the movements of skeleton muscles. EMG on-line processing and analysis can be applied to different types of human-machine interfaces and provide advantages to patient rehabilitation strategies in case of injuries or stroke. However, continuous monitoring and data collection produces large amounts of data and introduces a bottleneck for further processing by computing devices. Neuromorphic technology offers the possibility to process the data directly on the sensor side in real-time, and with very low power consumption. In this work we present the first steps toward the design of a neuromorphic event-based neural processing system that can be directly interfaced to surface EMG (sEMG) sensors for the on-line classification of the motor neuron output activities. We recorded the EMG signals related to two movements of open and closed hand gestures, converted them into asynchronous Address-Event Representation (AER) signals, provided them in input to a recurrent spiking neural network implemented on an ultra-low power neuromorphic chip, and analyzed the chip's response. We configured the recurrent network as a Liquid State Machine (LSM) as a means to classify the spatio-temporal data and evaluated the Separation Property (SP) of the liquid states for the two movements. We present experimental results which show how the activity of the silicon neurons can be encoded in state variables for which the average state distance is larger between two different gestures than it is between the same ones measured across different trials.**

***Index Terms*—EMG, Neuromorphic chips, Intelligent sensors, Biomedical signals**

I. Introduction

The sEMG technique is a non-invasive method for measuring the electrical signals associated to the muscle activities by means of surface electrodes located above the skin. The amplitude of sEMG signals is classically associated with the number of action potentials discharged by a population of motor neurons that were neurologically or electrically activated. The signals produced can be used to extract information about desired movements of the subjects under investigation and, in particular, sEMG signals have been used for the control of upper limb exoskeletons aimed at augmenting [1] or restoring human capabilities (e.g., post-stroke rehabilitation [2]). To understand muscular recruitment it is necessary to monitor the electrical activity of a large number of individual neurons simultaneously. To this end, many parallel measurements are required, increasing the amount of data that needs to be transmitted, if off-line processing approaches are adopted. This high amount of data can be significantly reduced if processed, analyzed and classified directly at the source (i.e., on the wearable device). Employing such intelligent sensors will reduce the overall cost, bandwidth and power requirements of future generations of human-machine interfaces.

Neuromorphic technology offers a solution to the challenge of directly processing the data on the sensor, on-line and in real-time. Specifically, spiking neuromorphic VLSI devices use brain-inspired neural networks with on-line learning abilities for processing bio-signals massively in parallel, using very low power, and in very compact packages. This makes them ideal candidates for integration in wearable devices, to extract signal features and classify them on-line.

In this paper we describe a feasibility study that represents the first steps toward the realization of a neuromorphic event-based neural processing system that can be directly interfaced to an sEMG sensor for the extraction of signal features and classification of the motor neurons output activities. This classification can be done using different neural network topologies. Specifically, Recurrent Neural Networks (RNN) have been shown to be suited for classification of temporally changing data since the connections between their units form a directed cycle which allows it to exhibit dynamic temporal behavior. However, training RNN networks based on more Deep Network approaches [3] requires the use of the Back Propagation Through Time (BPTT) algorithm [4] which is not feasible to be implemented on neuromorphic Spiking Neural Network (SNN) chips. Nevertheless, the LSM type of RNNs proposes the ingenious idea of a two layer network comprised of spiking neurons with dynamic synapses in which first layer is set up with randomly connected recurrent weights to project the input signal to a higher dimensional space [5]. The complex dynamics of the synapses and neurons, and the high dimensional space provide a pool of basis functions on which the projected data can be separated because of the Kernel properties of the LSM [6]. As a result, the second layer can simply be trained on the basis of a gradient decent learning rule which is powered by the already separated data from the first random layer. The synapse and neural dynamics are directly and faithfully emulated by the analog circuits of neuromorphic chips [7], and the high variability of the LSM, imposed in software by the randomness of the first layer weights is easily achieved on the neuromorphic chips when using sub-threshold analog circuits to implement the neuron and synapse circuits.

In this paper we used a recently developed multi-core neuromorphic chip that has these features and in addition allows

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for easy configuration of LSM topologies by implementing flexible and programmable routing schemes [8]. To validate the network we use sEMG signals that represent two movements of open and closed hand gestures of one subject recorded by the Myo armband that sense electrical activity in the forearm muscles [9]. We explain how we encode this data into spike events as the input to the neuromorphic chip, in section II-A. We then explain the details of the LSM implemented on such chip in section II-C. The experimental results and data analysis are presented in the last Section, showing the SP of the network [5].

II. Materials and Methods

The main motivation of the proposed work is to investigate the internal state of a hardware implementation of a LSM for two different sEMG signal classes. The first step was to acquire sEMG data to feed into the network. The network was implemented on a neuromorphic chip called DYNAP-SE (Dynamic Neuromorphic Asynchronous Processor). This chip was chosen because it allows the implementation of reconfigurable, real-time neural networks based on mixed-signal arrays of spiking neurons [8]. The setup, with the Myo and the DYNAP-SE board is shown in Figure 1.

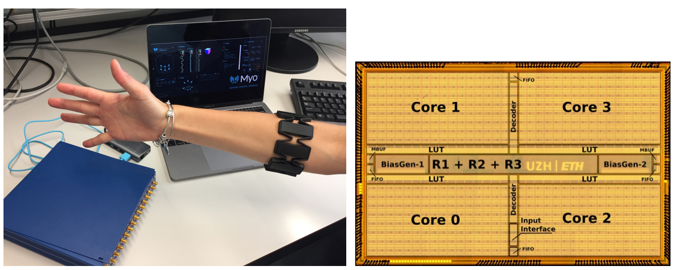

Fig. 1. The sEMG sensor placed on the arm and the DYNAP-SE board. When the hand moves or holds the gesture, the MYO interface records the muscle electric activity with 8 channels, and send them to a Matlab interface. Each DYNAP-SE board is composed by 4 DYNAP-SE chips, shown in the right Figure. The chip comprises 4 cores, each with 256 neurons.

A. EMG data acquisition and conversion

In order to evaluate the SP of the network, two forearm sEMG signals were recorded: open and fully closed hand.

To record the gestures, a Myo [9] gesture control armband was used. The Myo is composed of 8 equally spaced non-invasive sEMG sensors that provide a sampling rate of 200 Hz. The armband was placed approximately around the middle of the forearm and the sensor records 8 channels of sEMG data. A data set consisting of several sEMG signals of both hand gestures was acquired, each lasting for 500 ms. Since the network has spiking neurons, the two sEMG signals need to be converted into spikes to be processed in the LSM. The solution adopted to convert the data from the 8 electrodes of the armband to spikes is the delta-sigma ADC algorithm proposed in [10], [11][1]. This algorithm outputs two channels of UP and DOWN spike: the UP (DOWN) spikes are generated

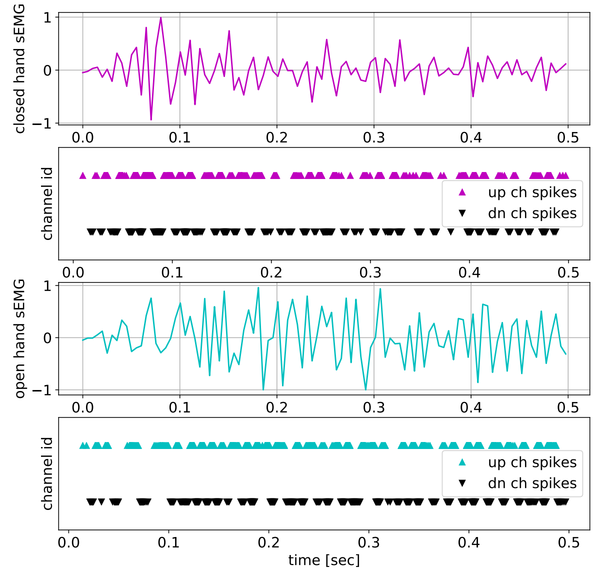

Fig. 2. Example of recorded sEMG muscle activity with relative spikes conversion. The Figure shows the activation of the Palmaris Lungus muscle activity during the open and close hand gestures.

when the positive (negative) change in the input signal exceeds a certain threshold. The amplitude of the threshold chosen for the spike conversion is 0.05, since it is the best trade-off value for the number of input spikes to the network and the accuracy of signal reconstruction. With this threshold the mean firing rate, averaged across channels over 0.5 s, is 491.0 spikes/s for open hand and 560.5 spikes/s for the closed one. Figure 2 shows an example of the activation signal[2] of one of the movements in the data set and its spike conversion.

Since each armband electrode generates two, UP and DOWN, channels, only 4 electrode signals were chosen and used as inputs for the LSM. The 4 chosen sEMG signals are the ones that showed the highest difference in the trace shape, corresponding to the most involved muscles activation. In particular, the back pack of forearm *flexor pollicis lungus, flexor digitorum profundus* and the *palmaris lungus*.

B. Neuromorphic hardware

The DYNAP-SE is a fully custom asynchronous mixed-signal SNN processor. It comprises analog spiking neurons that emulate the biophysics of their biological counterpart and neuromorphic circuits able to emulate the synaptic dynamics in real time. Specifically, it comprises 4 four-core chips with 1k adaptive exponential integrate-and-fire neurons (AEI&F) per chip and four different synapse types can be chosen for each synapse (slow/fast, inhibitory/excitatory). Each neuron has a Content Addressable Memory (CAM) block, containing 64 addresses representing the pre-synaptic neurons that the neuron is subscribed to. Digital peripheral asynchronous input/output logic circuits are used to receive and transmit spikes by using the AER communication protocol [12]. In this representation, each neuron is assigned an address that is encoded as a digital word and transmitted as soon as they produce an event

[1] https://github.com/federicohyo/ecgheartbeat

[2] https://developer.thalmic.com/docs/api_reference/platform/index.html

TABLE I
PARAMETERS OF THE LSM IMPLEMENTED ON THE CHIP

Connection	Exc to Inh	Exc to Exc	Inh to Exc	Inh to Inh
Time constant	1.67 ms	13 ms	3.5 ms	26 ms
λ	2	2	4	4
C	0.2	0.3	0.4	0.1

using asynchronous digital circuits. The chip presents a fully asynchronous inter-core and inter-chip routing architecture that allows flexible connectivity with microsecond precision under heavy system loads. The analog circuit parameters governing the behavior and dynamics of the neurons and synapses are set by an on-chip programmable bias generator [13] that supplies 25 parameters for each core.

C. Hardware implementation of LSM

The liquid of the LSM was implemented with one population of 31 x 31 spiking AEI&F neurons using one chip of the DYNAP-SE board. Eighty percent of the population is randomly programmed as the excitatory neurons of the liquid and the remaining 20% as the inhibitory neurons. The highly reconfigurable synaptic dynamics present on the DYNAP-SE chip is ideal for implementing the dynamics of the liquid. For example, we are exploiting the fast and slow synaptic dynamics of the DYNAP-SE to introduce dynamics in different time scales. The slow synapses are used as the recurrent connections within the excitatory and inhibitory populations and the fast synapses are utilized to connect the inhibitory and excitatory populations to each other. Table I summarizes the time constant values used to implement the network. For the neurons we set the chip biases to model a time constant of $26\,ms$. The recurrent connectivity between any two neurons is constructed randomly under a probabilistic distribution function such that the wiring probability and the synaptic connection strength of two neurons drops exponentially with the distance between them which implements a spatial Gaussian Kernel: $Cexp(-D(N1, N2)/\lambda)^2$, where $D(N1, N2)$ is the euclidean distance between neurons $N1$ and $N2$. Parameters C and λ are chosen as suggested in [5] and for convenience are summarized in Table I. Spike trains from Section II-A are given to 30% of the neurons in the liquid [5].

III. RESULTS AND DISCUSSIONS

As the preliminary step in testing the behavior of LSM, we evaluated the SP of neuron populations in the liquid given spike train inputs as is suggested in [5]. Spike-encoded signals of open $O(t)$ and closed $C(t)$ hand gestures (6 trials for each class), generated with the scheme explained in section II-A, were generated and injected (in separate trials) as input to the LSM. The resulting trajectories of the states of the liquid ($X_O(t)$ and $X_C(t)$) were recorded for each of these time-varying inputs $O(t)$ and $C(t)$. The states measured in one randomly selected trial for each movement type are shown in Figure 3 as the raster plots of the spiking neurons on the chip. The mean firing rate of the network is 67.63 spikes/s for the open hand and 77.04 spikes/s for the closed. The SP is

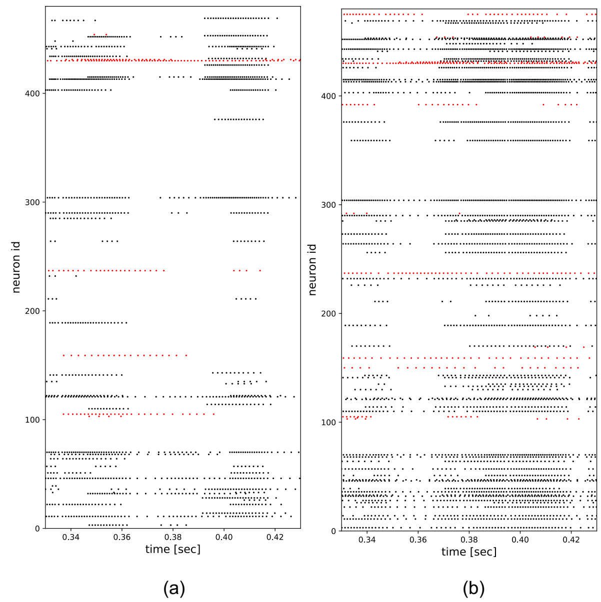

Fig. 3. Raster plots representing the state of the liquid for the open (a) and closed (b) hand gestures. Only 50 % of the neurons in the liquid are randomly shown. The ratio of the excitatory (black) to inhibitory (red) neurons are kept in the figure.

calculated as the euclidean distance between the mean activity of the neurons in the liquid for the two kinds of inputs. The average SP (mean $\pm$ SE across trials) is reported in Figure 4 as a function of the time t after the onset of the input. These curves show that the distance between these liquids states is well above the noise level which is calculated by giving the same input to the chip twice indicated by the gray line. The blue (green) curve illustrates the euclidean distance between the states of the network given different trials of closed (open) hands. However, the distance of the network between open vs closed gestures diverges from the other curves. Even though it is possible to see peaks at $0.2\,ms$ and $0.28\,ms$, the maximum euclidean distance for a longer windows is present at the end of the movement (as highlighted in orange shading). Each of the presented curves was measured under the same network initial conditions, i.e. with the same matrix of connectivity, weight and input connectivity.

The subplots depict the 2D representations of the mean activity of the neurons in the reservoir for the open and closed gestures at the time points indicated in the figure. The color coding represents the mean firing rate of each neuron in the liquid measured in a window of $50\,ms$. The subplots show the different firing activity of the liquid in response to the two movements which is also approved by the euclidean distance.

IV. CONCLUSIONS

The main aim of the presented work is to investigate the SP of a spiking LSM, implemented on an event-based neuromorphic system, when two classes of sEMG signals are presented: open and closed hand gestures. The scope is to quantify the network's ability to separate the input signal in a higher dimensional space. High separability means higher

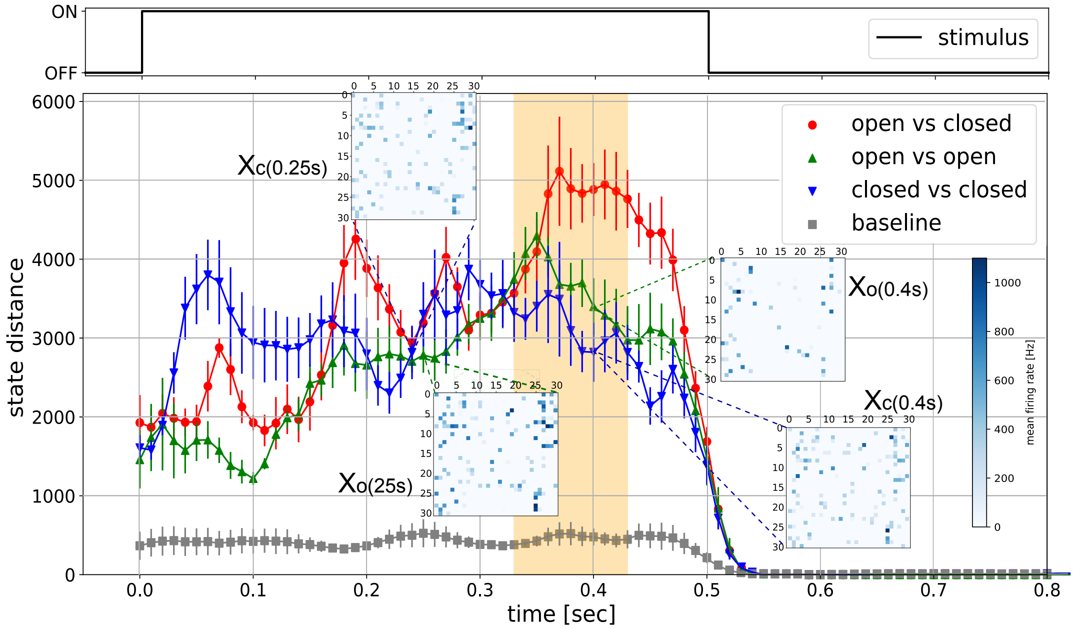

Fig. 4. Average state distance (mean ± SE, on 6 trials) of the liquid for the the two different types of input movements (open vs closed), for the same type of input movement (open vs open, closed vs closed), and for the same input movement (baseline). The black curve on the top depicts the stimulus duration. The time window of highest SP is highlighted by the orange shading. Subplots show the mean firing rate of the individual neurons in the liquid measured in one trial for both movement types at the indicated times.

classification accuracy at the linear read-out. In addition, this approach can help to understand when to perform the read-out, that will be when the network the highest separation.

The sEMG data was acquired by using the Myo armband and then converted into UP and DOWN channels spikes to feed into the network. To quantify the SP, the euclidean distance between the neurons activity was measured in 3 different scenarios: closed vs closed, open vs open and open vs closed. As shown in Figure 4 the network presents the highest distance for the closed vs open case. In particular, in a window of 0.1 s centered at the end of the input application (around 0.4 s), the network maximizes the distance between its liquid states for the input classes.

These results provide an important basis for building a quantitative model for a the classification of sEMG signals and other biomedical signals with temporal dynamics (e.g. ECG, EEG). Future steps will include the read-out phase, in particular a spiking read-out phase, in order to implement a complete wearable system on a neuromorphic system.

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