Soft-neuromorphic artificial touch for applications in neuro-robotics

Giacomo Spigler, Calogero M. Oddo and Maria Chiara Carrozza

Abstract—We propose an artificial mechanotransduction system based on a 2x2 MEMS array touch sensor, and evaluate a neural model which is designed to convert raw sensor outputs into neural spike-trains. We show that core tactile information is preserved in the neural representation, and that the resulting modulation via spikes can be used in surface discrimination tasks. In this research study the first neural stage (i.e., at mechanoreceptor level) of somatosensory system was mimicked in a soft-neuromorphic fashion, while future works will target the implementation of the 2nd order stage (Cuneate neurons) to further understand the biological mechanisms underlying maximum transfer and fast processing of tactile information.

I. INTRODUCTION

The availability of a tactile sensory system with an embedded spike-like encoding of information would enable the direct connection of the robotic artifact to the nervous system, as well as contribute to a better understanding of the biological system itself. The development of upper limb prostheses interfaced to neuromorphic artificial sensory afferents is an increasingly emerging topic in neuro-robotics [1]. This research study addresses the understanding of the tactile system mechanotransduction mechanisms [2], with the aim to emulate or substitute the human tactile capabilities by means of a robotic artifact. This topic was investigated as part of a years-long research [3] [4] which provided the framework to collect both biological data via human microneurography [5] in parallel to artificial data via a 16 channels MicroElectroMechanical System (MEMS) array touch sensor [6] [7]. In this framework, we specifically addressed the conversion of raw sensor outputs to spike codes. This research activity is oriented towards the implementation of a neuromorphic architecture emulating the first stage of a more advanced model (including the Cuneate Nucleus, important relay for pre-cortical processing [8] [9]) of the somatosensory system, with potential contributions to the better understanding of the biological system. The advantages of this approach are related to its applications to building advanced prostheses eventually connected at different levels of the human afferent pathways, provided that technological advancements would be available to allow such hybrid-bionic system [10]. Other applications we are currently investigating are the use of such biologically-inspired event-driven system in manipulation and tactile discrimination tasks in humanoid robotics.

In this preliminary attempt, we address the spike-like encoding of tactile information in a soft-neuromorphic way, meaning that in the neuro-bio-inspired system the spike trains are the result of a processing operation applied to a system which is not intrinsically spiking, as opposed to a hard-approach, where the spiking neural-like events are the direct result of the physics of the system. In practice, we applied our neural model to raw sensor outputs instead of implementing the firing behavior in hardware; based on the experience gained with this approach, a following research activity will be undertaken to achieve the hard event-driven encoding immediately at the mechanotransduction level.

In the following of this paper we will present a set of results to support a loss-less representation of raw sensor outputs via soft-neuromorphic spiking units which code tactile information, and we show that the relevant discriminatory features are preserved and enhanced. Section II reports on the hardware and the sensors we used to perform the experiments and the neural model we applied to sensor outputs under a soft-neuromorphic approach. Section III outlines the outcomes of the spiking behaviour implemented in our artificial tactile sensory system, and Section IV gives a glance on future research activities.

II. MATERIALS & METHODS

Our experiments have been run by using a custom biomimetic fingertip together with a mechatronic platform...
allowing the implementation of passive-touch stimulation protocols while acquiring experimental data. Sensor data was then processed and fed as input to artificial neurons simulated using the Izhikevich model [11].

A. Biomimetic fingertip

The biomimetic fingertip used in the experiments, which is shown in Fig. 1, consists of a 2x2 array (with a 2.36\,mm pitch) of integrated MEMS sensors [4] [6] [7]. Each sensor integrates 4 piezoresistors at the base of a cross-shaped structure (see Fig. 2), providing 4 coupled channels showing responses which are function of the kind, intensity and direction of the applied tactile stimulus. Overall, we have 16 channels transducing mechanical stimulation applied to an area of about 22.3\,mm$^2$ of the fingerpad. The equivalent average density of input units is 72 units/cm$^2$, that is close to the 70 units/cm$^2$ of human Merkel-SA1 mechanoreceptors and half of the approximate density of human Meissner-RA1 units, which have been shown to encode roughness [7] [12]. The 16 channels provided by the 4 sensors are directly acquired at 375 Hz by means of a high-resolution (24 bit) Analog to Digital Converter (ADS8345) interfaced to a FPGA (Altera Cyclone II), and then transmitted via ethernet protocol to a PC for processing operations.

B. Model for analog to spike conversion

The raw output-voltages coming from the sensors were first pre-processed (using an on-line algorithm described in the following paragraph) and then used as inputs for artificial neurons simulated using Izhikevich’s model.

1) Pre-processing: Pre-processing was carried out to normalize incoming sensor data, avoiding sensor calibration. Because of the sensor’s design and the known correlations between channels belonging to the same sensor [13], we decided to build some sort of channel opponent units, whose output was given by

$$X_i(t) = x_i(t) - x_j(t) - k_i$$  \hspace{1cm} (1)

$$k_i = x_i(0) - x_j(0)$$  \hspace{1cm} (2)

Also, we set $X_i(t) = 0 \forall t : X_i(t) \leq 0$ to provide polarized inputs to the artificial neurons. Here, $x_i$ is the $i$-th channel, $x_j$ is its associated opposite channel on the
same sensor. $k_i$ was introduced to level inputs among different channels and was also tested using the mean of the difference in batch mode for performance analysis. Following this approach we can almost completely level the sensors’ channels output range with no calibration or knowledge of specific sensors’ parameters and contrast is enhanced.

2) *Izhikevich Neurons*: Izhikevich Neurons are an efficient model of the spiking dynamics of neural systems, combining the biological plausibility of Hodgkin-Huxley dynamics [14] and the computational efficiency of integrate-and-fire neurons [15]. The model is described by the evolution of two variables $v$ and $u$, representing respectively the voltage potential and membrane recovery. Dynamics is determined by

$$
\frac{dv}{dt} = Av^2 + Bv + C - u + \frac{I_{input}}{C_m}
$$

(3)

$$
\frac{du}{dt} = a(bv - u)
$$

(4)

$$
v_{output} = f(v)
$$

(5)

\[\text{TABLE I}
\text{PARAMETERS USED IN THE SIMULATIONS.}
\]

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>$C_m$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.04 s$^{-1}$V$^{-1}$</td>
<td>5 s$^{-1}$</td>
<td>140 s$^{-1}$V</td>
<td>1 F</td>
</tr>
</tbody>
</table>

with fixed parameters (Table I)

Also:

- the supplied input current $I_{input}$ was computed for the channel opponent potential $X_i$ of the tactile sensor

$$
I_{input}(t) = \frac{X_i(t)}{R}
$$

(6)

introducing a resistance $R$ to regulate the input current, setting the appropriate range specific to our sensor ($R = \frac{1}{\alpha C_m}$, $\alpha = 200s$);

- we reset the variables every time $v \geq v_{thr}$

\[
v \leftarrow c
\]
\[
u \leftarrow u + d
\]
Fig. 4. 440µm input - channel 1 (left) and 2 (right) are shown as raw signal along with the output from the corresponding Izhikevich unit.

<table>
<thead>
<tr>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>vthc</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.02 s⁻¹</td>
<td>0.2 s⁻¹</td>
<td>-65 mV</td>
<td>8 mV</td>
<td>30 mV</td>
</tr>
</tbody>
</table>

- in the experiments we mostly tested a Regular Spiking behavior given by (Table II)

- \( v_{output} \) was added on top of the standard Izhikevich model as a function of the state variable \( v \) so that the result is tuned to a possible amplitude range of the firing behavior of human mechanoreceptors [5]. Specifically \( f(v) \) is

\[
f(v) = \frac{v + c}{K}
\]

with \( K = 8000 \) (empirically tuned) in this model.

It is well known [11] that, by adjusting the four free parameters, this model can reproduce the spiking and bursting behavior of all known biological neurons.

The differential equations were integrated using Euler’s method, testing different timesteps.

C. Experimental protocol

Experiments were carried out by first collecting data using our artificial fingertip in a passive-touch scenario [5], recording sensors’ outputs on a set of surfaces, while modifying the applied force and the stimulus’ moving speed on different runs. Specifically, every recording session consisted in sliding the test surface 3 times over the sensor, with a little pause between each one. The recorded data was then processed and fed to the individual neural units whose output approximated the response of surface-located type 1 mechanoreceptors. Final output consisted of numerous data, tracking information across all stages, thus featuring raw sensor data, channel opponent outputs and neural responses, both as time series and, by computing their spectrogram, by means of short time Fourier transform. We then analyzed and compared the quality and the properties of all this data according to two subsequent approaches

Tactile stimuli were applied with a combination of a set of different properties (Table III) but due to limited space all the graphs shown in this paper were computed using Table IV.

We observe [4] that the principal frequency of oscillation \( f_p \) in sensors’ signals can be computed as

\[
f_p = \frac{v}{\Delta p}
\]

with \( v \) being the stimulus’ moving speed and \( \Delta p \) the spatial period of the tested grating.

III. RESULTS

In this paragraph we describe results relative to the response of the model at the different stages of processing to the same input stimulus, thus verifying the preservation of the principal input features. We will then discuss the usage...
of the Izhikevich units in discriminating surfaces made by gratings with different spatial frequencies, therefore comparing the response of the model to different tactile stimuli. The pictures show two groups of graphs, relative to data coming from channel 1 and 2, with each one featuring raw sensor readings and the processed Izhikevich units’ output, both as time series (two runs on the same input) and through their corresponding spectra. An example output computed with the soft-neuromorphic approach from experimental data is shown in Fig. 3.

A. Same stimulus

As we can see in Fig. 4, the output units preserve the frequency information from the original signal, representing it in a normalized and stable response. Principal frequency, which matches the predicted $f_p$ associated to the input surface (which is computed using Eq. 8), is retained through neural coding, and can be read out through spectral analysis. We can clearly identify the $\sim 23\text{Hz}$ peak in the Figure, and most importantly its preservation throughout the processing steps in our model. It does seem that the system can be effectively used as a complete replacement of raw sensor outputs, while providing its response in a soft-neuromorphic spiking fashion and thus being potentially capable of direct interface to a neuroprosthetic device.

B. Different stimuli

Given that the Izhikevich units in our model retain the main features of the raw input, at least in the frequency space, we expect them to be able to discriminate different input surfaces just like the raw input was first used [4]. Actually the stimulus perception is still subject to variability with the speed at which it is moving, but this appears to be a property of biological mechanoreceptors [12], as well, and is further processed and separated at higher stages of the tactile system hierarchy.

Discrimination is possible if we account for speed, though, and we can clearly see an example of this in Fig. 5, where we compare two surfaces characterized by different spatial frequencies ($360\mu m$ and $440\mu m$) and the same velocity ($v = 10\text{mm/s}$) through both the spectrogram of the raw sensor outputs and that of the output of the associated Izhikevich units.

IV. CONCLUSIONS

Results are encouraging and will be further verified by using our units as the first stage of more complex tactile system models, specifically working on the Cuneate $2^{nd}$ order neural stage, for a better understanding of tactile discrimination of surfaces in the biological system, and bio-robotic emulation for neuro-robotic applications such as upper limb prosthetics. Further work will also tend to compare different theories of information encoding in spiking neurons.

V. ACKNOWLEDGMENTS

A special acknowledgment goes to Dr. Lucia Beccai from CMBR IIT@SSSA for previous collaboration in the development of the biomimetic fingertip, and to Prof. Johan Wessberg from the Department of Physiology of University of Gothenburg for meaningful discussions on the human tactile system and for having provided unrestricted access to human microneurography data.

REFERENCES