Force Control for Anthropomorphic Fingers Actuated by Shape Memory Alloy Wires

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Abstract—**High accuracy in modelling the behavior of human hand and fingers is obtained using control devices of high biological plausibility. Such devices are typically based on neural networks and are able to control in parallel multiple artificial muscles. This paper presents the structure of an electronic spiking neural network that was implemented to control the force of two opposing fingers of an anthropomorphic hand. In order to increase the level of bio-inspiration, the artificial muscles are implemented using shape memory alloy wires which actuates by contraction as the natural muscles. Moreover, the contraction force of the SMA actuators is directly related to the spiking frequency that is generated by the artificial neurons. The results show that using few excitatory and inhibitory neurons the neural network is able to set and regulate the contraction force of the SMA actuators.**

Index Terms—**Force control, shape memory alloy, spiking neural networks, antropomorfic hand.**

I. INTRODUCTION

Modelling the motor abilities of the human hand and fingers represents a challenging task for robotics due to smoothness and diversity of the natural motions. The design of the control devices for such robotic hands should model the behaviour of the motor neural areas (MNA) and their bidirectional communication with the muscles. The natural MNA stimulates the muscles through efferent neural pathways that includes the motor cortex and the central pattern generators. In the opposite direction, through afferent pathways, the MNA receives information from spindles about the muscle stretch during relaxation [1], and from Golgi tendon organs during contraction [2]. Considering that the frequency generated by the spindles increases with the muscle stretch by an external force [3], the spindles output can be used to determine the rotation angle of the articulation. However, this function cannot be applied when the muscle contracts because spindles response to acceleration dominate their response during the passive stretch [4]. When the muscles contract the Golgi organs respond to the force applied on the tendons providing information about the muscle activity [5].

Starting from this idea, in the sequel we will evaluate experimentally the ability of a biologically plausible structure of spiking neurons to control the contraction of artificial muscles. The neural network uses the output of a force sensor that provides information about muscle contraction as the Golgi organs.

The spiking neurons represents the most accurate model of the natural neurons [6] and their implementation in

analogue hardware benefits from very fast response due to parallel operation of neurons, low power consumption and ability to process high complexity functions. The spiking neurons used in this work have these advantages and, being implemented on PCB hardware, makes the prototyping of the synaptic configuration easier.

In order to achieve the smoothness and accuracy of the natural motions the artificial muscles should mimic the behaviour of the muscular fibres. Thus, in this work the artificial muscles are implemented with shape memory alloy (SMA) which actuates by contraction as the biological muscles [7]-[9]. Moreover, the contraction strength can be determined directly by the frequency of the electronic spiking neurons. The research done in this field, shows that the SMA actuators are suitable for actuation of bioinspired systems [9] starting from artificial fingers [10], insect legs [11] and wings [12] to an artificial jellyfish [13] and an anthropomorphic arm [14].

In SMA based applications the control of the contraction force of these actuators plays a critical role [15]–[17]. The precise control of SMA actuators force was performed using algorithms programmed on a microcontroller in a clamping vice [15]. Another method suitable for SMA control is represented by the neural networks (NNs) that were used to implement actuators for lightweight applications [16] including a SMA based endoscope [17]. The NNs are suitable, also, in robotics for the force control of different types of servomotor-based manipulators [18], [19].

In this work we used the newest class of NNs which represents the spiking neural networks (SNN) to control the contraction force of SMA wires that actuate two opposing fingers of an anthropomorphic hand. The earliest research that approached SNN to control the SMA actuators was performed by our group [20]. In this direction, we evaluated experimentally the ability of SNN to control the contraction of SMA in positioning of a robotic junction [21] and in laser spot tracking [22].

II. GENERAL CONCEPT

The results reported previously [21] show that networks with few spiking neurons are able to control the rotation angle of a robotic joint when the mobile lever moves towards target positions. In that case the spiking neural network behaves as a regulator for the rotation angle even when the mobile lever is slightly loaded.

A. Artificial Fingers

Based on these observations we implemented and tested experimentally for this work a neural structure that behaves

as a regulator for the force of two anthropomorphic fingers that opposes each other as presented in Fig. 1. These fingers can be flexed using SMA actuators that are connected with one end on the fingers apex.
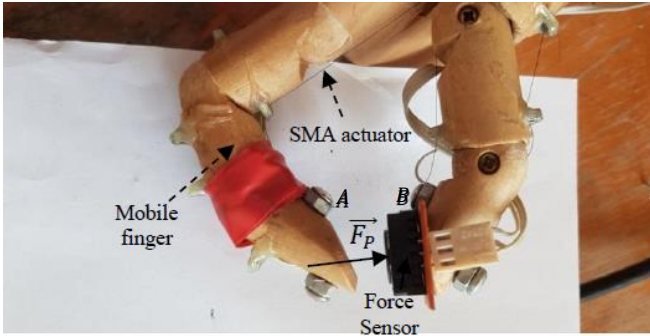

Fig. 1. The implementation of the anthropomorphic hand with two opposing fingers connected to the SMA actuators (points A and B); The force sensor is placed on the thumb to measure the push force $\vec{F}_P$ of the index finger.

The spiking neural network controls the contraction of only the index finger that presses with $\vec{F}_P$ on the force sensor (FS) connected to the opposing thumb.

B. Bioinspired System Structure

The general structure of the fully analogue bioinspired system that is used for force control is presented in Fig. 2. This system includes the SNN that controls the SMA driver to power the actuators and receives input from the force sensor through the potential controller.
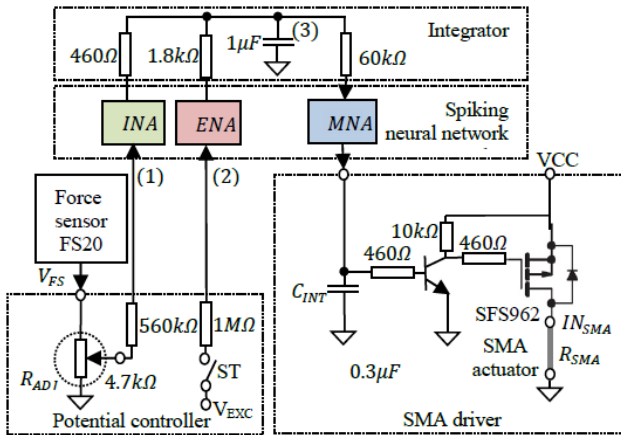

Fig. 2. The bioinspired system structure including the SNN, the SMA driver and the potential controller.

The synaptic configuration of the SNN is bioinspired and was tested experimentally in our previous work for arm positioning [21]. Also, we evaluated previously by simulation the feasibility of a system based on SNN for force control when the pair force sensor - SMA actuator was approximated by a current controlled voltage generator [23]. The SNN includes an excitatory neural area ENA that determines the contraction of the SMA actuator through the motor neural area MNA (see Fig. 2). The activity of the MNA is reduced by an inhibitory neural area INA that is activated by the force sensor. The force is converted into the potential V_{FS} that is adjusted to the activation threshold of the artificial neurons using the adjustable resistor R_{ADJ} included in the potential controller. The resistor R_{ADJ} determines the value V_{FS} where the inhibitory neurons start to fire and consequently, the maximum force level of the finger.

Thus, the SMA actuator pulls the finger until the inhibitory activity reaches the spiking frequency generated by the area ENA. The power that determines the SMA actuator contraction is generated by the SMA driver which integrates the output of the excitatory neurons in the motor area MNA. The switch ST starts the activity of the excitatory neurons in ENA which fire at a constant frequency that depends on the potential V_{EXC}.

III. SPIKING NEURAL NETWORK STRUCTURE

The synaptic configuration of the SNN is detailed in Fig. 3. The excitatory neurons EN_{1-4} activate the motor output neurons $MN_{1,2}$ which actuate the SMA wires until the inhibitory neurons IN_{1-8} compensates for the activity generated by EN_{1-4}. Thus, the neurons IN_{1-8} reduces the frequency of $MN_{1,2}$ and, consequently, the contraction of the SMA actuators.
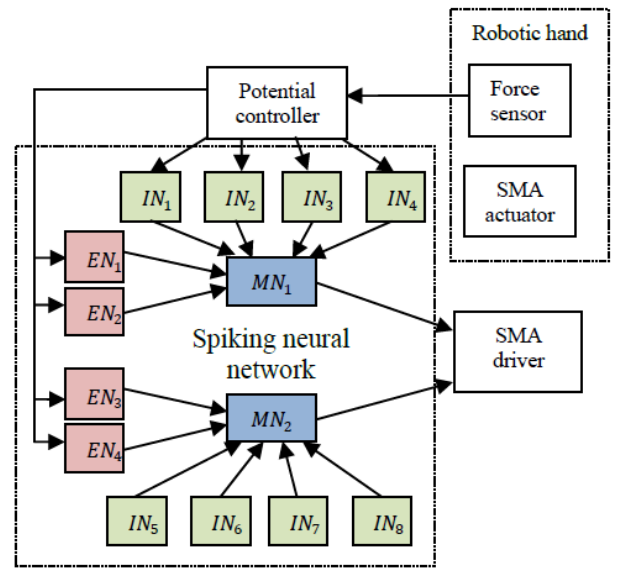

Fig. 3. The spiking neural network structure including the motor neurons MN_1 and MN_2 which activation is controlled by the neurons $EN_{\overline{1,4}}$ (excitatory) and $IN_{\overline{1,8}}$ (inhibitory); The potential controller and SMA driver interfaces the SNN with the force sensor and respectively with the actuator.

Note that the neurons EN_{1-4}, IN_{1-8} and $MN_{1,2}$ shown in red, green, and respectively blue build the neural areas ENA, INA and respectively MNA highlighted in Fig. 2 by the same color.

IV. THE ARTIFICIAL NEURON MODEL

The spiking neural network that is used for force control is based on an artificial neuron model which schematic is presented in Fig. 4 (a) [24]. This neuron implements two main classes of bioinspired properties that are related to the coincidence detection of the input stimuli and to the synaptic plasticity. The electronic circuit that implements this neuron includes one artificial soma (SOMA) and one or more artificial synapses (SYN).

A. Artificial Soma

The natural neurons integrates the output of the presynaptic neurons and activate when the postsynaptic membrane potential reaches their activation threshold. Similarly, the artificial soma integrates the incoming spikes and activates when the input voltage in the capacitor C_{IN} reaches the base-

emitter voltage of the transistor T_M. When the artificial neuron activates, the soma triggers the activity of all connected artificial synapses which generate a pulse at OUT_{SYN}.

For simplicity, in Fig. 4 (a), the SOMA is connected to only one SYN that can generate excitatory or inhibitory spikes depending on the preset position of the switch SW. During the neuron activation, T_M saturates pulling the voltage in the capacitor C_{IN} below the equilibrium potential V_M of the artificial neuron modeling the onset of the refractory period. After activation, if the input potential is above V_{BE}, the neuron is reactivated and a new spike is generated. The activation frequency of the artificial neuron can be determined by counting the output spikes or the sudden decreases of IN_{SOMA} in a given period of time. Fig. 4 (b) shows an example of the input potential IN_{SOMA} when the electronic neuron is activated by the continuous voltage $V_{EXC} = 3V$ through a resistor $R_M = 1M\Omega$ connected to the neuron input.
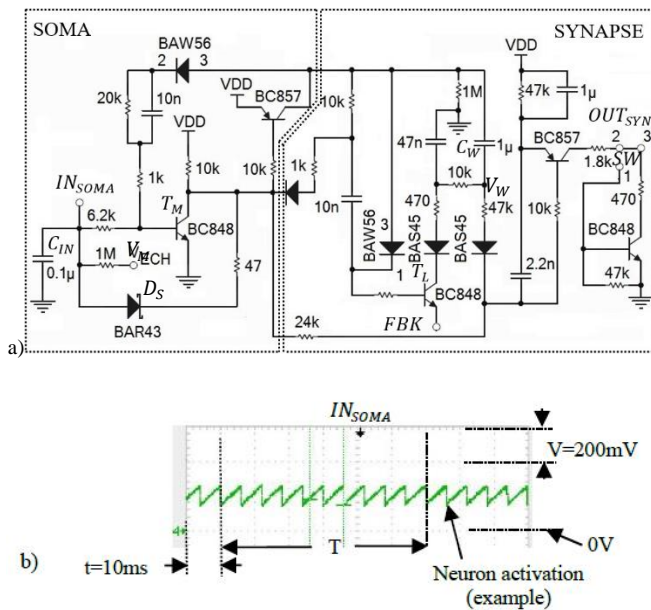

Fig. 4. (a) The electronic circuit which implements the artificial neuron that includes one SOMA and at least one synapse which generates excitatory or inhibitory spikes according to the synaptic weight; (b) Sample signal read on the SOMA input when the neuron is activated with constant frequency.

The neuron activation frequency is $\sim 166Hz$ determined by the number of falling edges of IN_{SOMA} during the interval T.

B. Artificial Synapse

The synaptic weight is stored by the artificial synapse in the capacitor C_W which charge determine the duration of the generated spike. For this neuron model, the voltage V_W read on the lower shield of the capacitor C_W is proportional with the synaptic weight. The electronic synapse is potentiated when the potential V_W decreases. This variation occurs during neuron activation when C_W is discharged through the opened transistor T_M modeling posttetanic potentiation of the biological synapses. Also, during the postsynaptic neuron activation, V_W decreases through the transistor T_L that opens conditioned by prior activation of the neuron in a time interval. This behavior models the long term potentiation of biological synapses [25] which determines adaptability in the brain. The activation of the postsynaptic electronic neurons is

signaled through the FBK input that connects the transistor T_L to the transistor T_M of the postsynaptic neuron.

From the biological point of view if the postsynaptic neuron activates before the presynaptic neuron in a time interval long term depression occurs (LTD) [26]. This neuron model implements only the LTP because during normal activity of biological synapses the LTP is stronger than LTD [26]. However, for the electronic neuron, the decrease of the synaptic weight occurs during neuron inactivity due to the leakage current of the diodes (see Fig. 4). This models empirically the long term depression of the biological synapses without taking into account the relative timings of the neurons activations.

V. EXPERIMENTAL SETUP

During the experiments we tested the hand ability to squeeze and hold an elastic tweezers with different force levels. These were set by adjusting empirically R_{ADJ} to several values that match the predefined distances $d \in \{0, 1, 2, 3, 4\}mm$ between the tweezers heads.
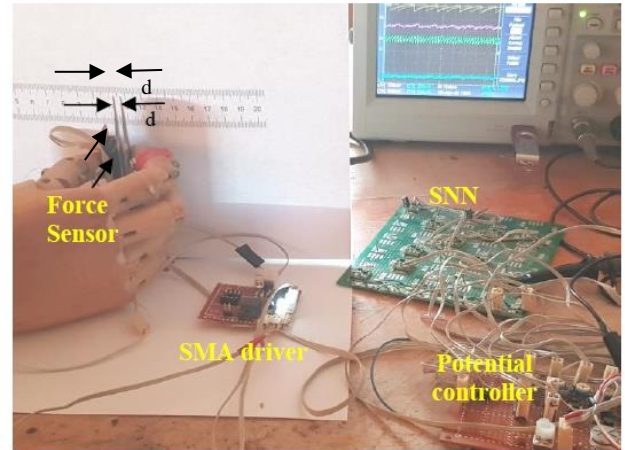

Fig. 5. Laboratory prototype of the bioinspired system for the force control.

For each value of d the voltage generated by the force sensor and the activity of several neurons were monitored. A picture of the laboratory prototype of this bioinspired system including the anthropomorphic hand, the SNN and the auxiliary electronic circuits is shown in Fig. 5. The power supply was $VDD = 1.6V$ for the electronic neuron, and $VCC = 14V$ with the current limited to $I_{MAX} = 400mA$ for the SMA actuators. The fingers were actuated by 0.006" Flexinol wires that support maximum load of 321g which represents 3.15 N. The force sensor was powered by 5V which, according to the datasheet, ensures the output variation between $V_{OMIN} = 0.5$ V and $V_{OMAX} = 4.5$ V for the push load variation between 0 and $m_{LMAX} = 0.5Kg$.

VI. RESULTS

The diagrams in Fig. 6 show several signals of interest for the SNN operation. The inputs of an inhibitory, excitatory, and motor neurons are presented by the yellow, green and respectively, magenta signals recoded in the nodes (1), (2) and respectively, (3) shown in Fig. 2. The output V_{FS} of the force sensor is shown by the dark green signal.

Based on the voltage generated by FS and taking into account that the linearity error of the FS output is lower than $\pm 1\%$ we determined the force $\vec{F}_P$ on FS that occurs due to SMA actuator contraction as:

$$\vec{F}_P = (V_{FS} - V_{OMIN}) \cdot \frac{m_{LMAX}}{V_{OMAX} - V_{OMIN}} \cdot g \qquad (1)$$

where g is the gravitational acceleration. Table 1 shows the obtained values of $\vec{F}_P$ for the distances d (see Fig. 5) that were considered in the experiments.
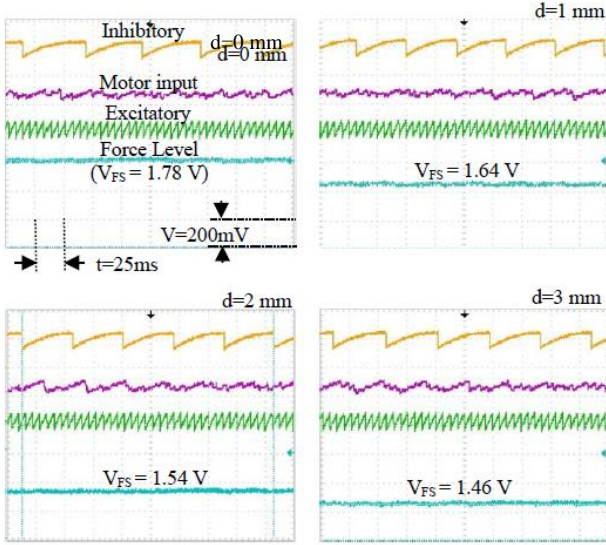

Fig. 6. The SNN activity and FS output for different distances d between tweezers heads.

TABLE I: FORCE CONTROL SYSTEM OUTPUT

Parameters		
d(mm)	$V_{FS}(V)$	$F_d(N)$
0	1.78	1.57
1	1.64	1.40
2	1.54	1.28
3	1.46	1.18
4	1.36	1.05

The measurements show that despite the fact that the force varies with the distance d, the frequency of the inhibitory neurons (yellow signal in Fig. 6) have similar values, as expected [23]. Moreover, the oscillation of the FS output is reduced, implying that the SNN represents a good regulator for the SMA actuator force in nominal conditions when F_P is significantly lower than the maximum force of 3.15 N.

VII. CONCLUSIONS

In this paper we evaluated experimentally the ability of the spiking neural networks to control the contraction force of artificial muscles implemented with shape memory alloy wires. By using a few excitatory neurons which determine the contraction of SMA actuators, and several inhibitory neurons driven by a force sensor the neural structure is able to control the level of quasi constant force applied on an object. One of the main advantages of the system is the high biological plausibility due to: *i)* the bioinspired structure of the SNN that is based on an bioinspired neuron model, *ii)* the SMA wires that actuates by contraction as the natural muscles, *iii)* the neuromorphic force sensor that generates spikes as the biological spindles or Golgi organs. Besides this advantage, the implementation in analogue hardware of the SNN, which allows the parallel control of multiple SMA actuators, brings real-time operation to the system.

As a future work we intend to improve the SNN structure and to evaluate the linearity of its response to the force level. As an application of this research we intend to implement an adaptive neural structure that is able to learn to actuate the fingers to target positions where it was stopped by an external force during the training process.

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