

Bioinspired Control Method Based on Spiking Neural Networks and SMA Actuator Wires for LASER Spot Tracking

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Abstract This chapter presents a new biologically inspired technique for automatically compensating the light spot deviation from the normal position for laser spot trackers. The method is based on hardware implementation of the spiking neural networks which provides fast response due to real time operation and ability to learn unsupervised when they are stimulated by concurrent events. For increasing the biological plausibility of the method, the spiking neural network controls the contraction of shape memory alloy (SMA) actuator wires that operates as the muscular fibres. These SMA wires are the most suitable actuators for being controlled by the electronic spiking neurons because the contraction force increases naturally with the spiking frequency. From our knowledge the laser spot tracking using spiking neural networks was not performed previously. Moreover, other original ideas represent the use of analogue implementation of the spiking neural networks for real time operation as well as the SMA actuator wires for more biological plausibility. To validate this method we implemented in hardware a spiking neural network structure that processes the input from a one dimensional photodiode array and controls a positioning system based on SMA actuator wires. The results show that the spiking neural network is able to detect the one-dimensional spot motion and to adapt the response time by Hebbian learning mechanisms to the spot wandering amplitude. Moreover, by driving two antagonistic SMA actuator wires the system is able to track the laser spot with low response time and acceptable precision. These results are encouraging to develop bio-inspired low power spot tracking system for enhancing the receiving accuracy in free space optical communications or for enhancing the efficacy of the photo-voltaic systems. Moreover, the light tracking principle based on spiking neural networks and SMA wires can be successfully used in implementation of the light tracking mechanism of an artificial eye.

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Keywords Laser spot tracking • Spiking neural networks • Analogue bio-inspired neuron • Shape memory alloy actuator wires • Photosensitive panel

1 Introduction

The light spot tracking problem was solved in several approaches using artificial intelligence elements such as fuzzy neural networks [5, 8, 28] or multilayer perceptrons [32]. However, despite the multiple approaches of this problem, the use of spiking neural networks represents a new method for light spot tracking. The advantage of this type of neural networks represents their ability to model high complexity functions in a bio-inspired manner while having very low power consumption when implemented in analogue hardware.

The spiking neural networks are adaptable parallel structures that use time for information processing and learning [7, 27]. Typically, the processing unit of these networks is the neuron designed to mimic in the most plausible way the neuronal cell behavior [20]. Several neuron models of biological inspiration such as integrate-and-fire [10, 24] were developed to mimic the information processing elements which are the membrane potential and the detection of activation threshold. Other neuron models suitable for software implementation that mimic the different types of spiking behavior of the biological neurons were developed by Izhikevich [16, 17]. The simulation time of large biologically inspired neural networks can be reduced by designing computationally effective neuron models [9, 22, 23, 26] or by implementing dedicated computational systems [25, 29]. However, the lowest response time and power consumption of the neural networks is achieved when these are implemented in analogue hardware. Thus, the neural network that is used as processing unit for the tracking system presented in this chapter is based on an adaptable electronic neuron [11, 12]. We use this type of spiking neuron that was analyzed in [13] because it is implemented in low power analogue hardware and mimics accurately the natural mechanisms of Hebbian learning [2, 3, 30].

The spiking neural network should control a position mechanism that is able to move the sensor area in order to track the laser spot. The most common method to actuate mechanical parts for the tracking systems represents the brushless or stepper motors. In contrast, for our work we considered for moving the sensor panel the recently implemented and tested SMA actuator wires [4, 31]. This actuation method increases the biological plausibility of the tracking system because the SMA wires operates by contraction as the natural muscles and they are naturally controlled by the spiking neural network because contraction force increases with the spiking frequency generated by the neural network.

Despite the fact that the SMA actuator wires were used for actuation of a prosthetic hand [1] we test for the first time the ability of the spiking neural networks (SNN) to control the SMA wires [15]. Also, the ability of the SNN to

detect the laser spot deviation was performed for the first time [14]. Moreover, this work represents the first attempt to use spiking neural networks and SMA actuator wires for light spot tracking.

2 Neural Network

For compensating the deviation from the normal position of the light receiver, the tracking device should receive the data from a photodiode array and control a positioning mechanism. The processing unit of the tracking device is a spiking neural network that is able to learn by association during light spot tracking. For this research, we implemented the analogue spiking neural network, the photoresistive area and the positioning system based on shape memory alloy (SMA) actuator wires.

Spiking neurons are the most plausible models of biological neurons because they accurately mimic the natural mechanisms of information processing and of adaptation. First category of processes includes temporal integration of the incoming excitatory and inhibitory stimulation, membrane potential, activation threshold and refractory period, while the main properties that give the neural network the ability to learn from previous experience are the short-term potentiation (STP) and long-term potentiation (LTP) of the synapses. These mechanisms as well as the posttetanic potentiation are modelled by the electronic neuron that represents the basic unit of the spiking neural network used for laser spot tracking. One of the advantages of the analogue implementation of the spiking neurons is that they are multiplexed in space obtaining the real time operation of the entire neural network.

2.1 The Learning Mechanism

The strength of a synapse or connection between two neurons is increased with a factor p each time the synapse is activated. A synapse is active when the presynaptic neuron sends information to the receiving or postsynaptic neuron. If two incoming synapses towards the same postsynaptic neuron are concurrently activated in a time window t_p then the strength of the synapses is increased using a factor q [2]. Throughout this chapter we say that two events are concurrent if they take place in the time interval t_p . From the biological point of view, t_p is the duration of the short-term potentiation. The factor p models the posttetanic potentiation contribution to synaptic plasticity and q models the long-term potentiation rate implying that $p \gg q$.

For the neuron model used as the processing unit the weight variation associated with the posttetanic potentiation is described by Eq. (1), while for the long term potentiation the weight varies with the amount given by the Eq. (2).

$$\Delta w_p = V_1 \cdot (e^{-p}) \quad (1)$$

$$\Delta w_q = V_2 \cdot (e^{-q}) \quad (2)$$

where V_1 and V_2 are two constants given by the neuron model design. During the neuron idle state the synapses are depressed with a factor r whose value is significantly lower than q [18]. Therefore, if a trained synapse is not activated in a long period of time the synaptic weight will decrease to the minimum value following the law:

$$\Delta w_q = V_3 \cdot (1 - e^{-r}) \quad (3)$$

where V_3 is a constant dependent on the neuron design.

2.2 The Light Sensing Panel

The network receives the input from two areas of photodiodes placed like in Fig. 1. The tracking area of sensors is used for light spot tracking while the learning area is used for adaptation of the network response to the spot deviation amplitude as well as for tracking.

This structure allows the neural network to learn to associate the effect of the sensors in the learning area with the effect of neurons in the tracking area starting from the initial conditions presented in the sequel.

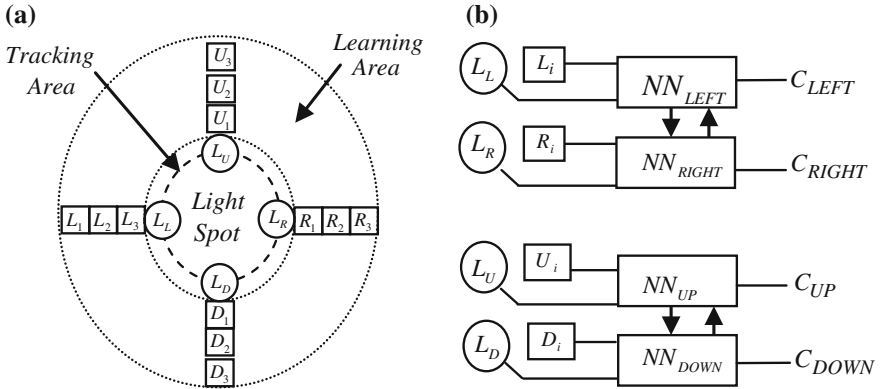


Fig. 1 **a** The panel of the sensors grouped in two areas—for tracking and respectively for learning. **b** The modules of the spiking neural network that generate the signals for controlling the positioning mechanisms of the sensor panel; The inhibitory connections shown by arrows are used when the spot covers two antagonistic tracking sensors simultaneously

In Fig. 1a the sensors from the tracking area L_L and L_R detect the spot movement on the horizontal axis, while the sensors L_U and L_D can be sensitive to the spot deviation on vertical axis. In the same manner the sensors L_i and R_i , $i = \overline{1,3}$ are sensitive to longer deviations of the light spot on the horizontal axis.

In order to make the network adaptable while being able to track the spot, the sensors from the tracking area are simultaneously active when the light spot is centered. For this system the spot size should cover half of the surface of the sensors from the tracking area when it is centered. In this setup small spot deviations determine covering of the whole surface of one sensor when the opposite sensor is not covered. The spot size was chosen for increasing the system detection accuracy because the input neurons from the tracking area activates when the spot moves with half of the sensor. Also, keeping the tracking neurons continuously active when the spot is centered inhibits the synaptic depression for the tracking neurons.

2.3 The Neural Network Structure

In order to control the positioning mechanism for compensating the bi-dimensional deviation of a light spot, the neural network should be divided in four principal modules that receive the inputs for each of the four directions—left, right, up and down. Figure 1b shows the modules of the neural network denoted by NN_{LEFT} , NN_{RIGHT} , NN_{UP} , and respectively NN_{DOWN} that are connected to the corresponding neurons from the tracking area (marked by circles) and from the learning area (marked by rectangles). The outputs of these modules that are designed to control the positioning mechanism for the photosensitive area are denoted respectively by C_{LEFT} , C_{RIGHT} , C_{UP} , and C_{DOWN} . Note that in order to compensate the light spot deviation from the central position the sensor panel should be moved in the same direction. Therefore, despite the fact that the position mechanism is placed behind the sensor panel that faces the laser implying that the motion on *left*–*right* directions is reversed, for simplicity we will refer to the directions of the panel motions as seen from the laser side.

Taking into account that the structure of the neural network that detects the spot deviation on horizontal and respectively vertical axis are similar, for simplicity we implemented and analyzed the operation of the subsystem that tracks the spot on horizontal axis. Thus, the structure of the neural modules NN_{LEFT} and NN_{RIGHT} for controlling the *left* and respectively *right* directions on horizontal axis is presented in Fig. 2.

The neurons $N_{L[i]}$, and $N_{R[i]}$, $i = \overline{1,3}$ are the postsynaptic neurons for the sensors L_i and R_i , $i = \overline{1,3}$ that controls the outputs C_{LEFT} and C_{RIGHT} through the output neurons N_{CL} and N_{CR} , respectively. In the same way the sensors L_L and L_R are connected with the outputs C_{LEFT} and C_{RIGHT} like in Fig. 2. Taking into account that the centred spot covers two sensors with antagonistic effect on the positioning mechanism, the inhibitory neurons I_L and I_R are used for compensation of the

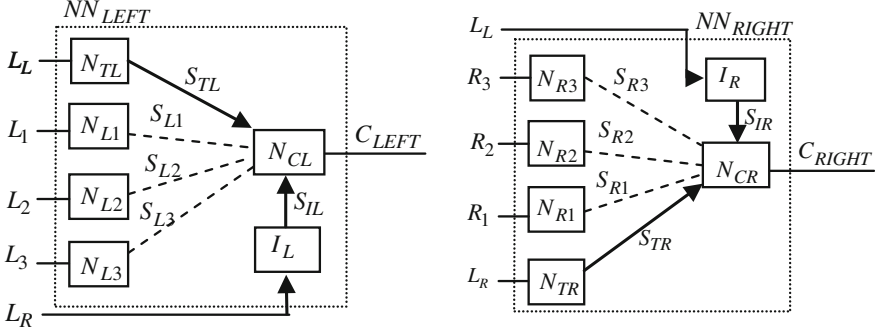


Fig. 2 The neural network structures that includes un-potentiated synapses that can be trained to compensate the spot displacement on *left* and *right* directions; The excitatory synapses S_{TL} and S_{TR} , as well as, the inhibitory synapses S_{IL} and S_{IR} that are connected to the training area are potentiated by PTP while the remaining synapses $S_{L[i]}$, and $S_{R[i]}$, $i = \overline{1, 3}$ are potentiated mainly by LTP

excitatory activity of the tracking neurons N_{TL} and respectively, N_{TR} when the spot is centered. Therefore, when the spot moves to the *left*, the inhibitory activity of the neuron I_R is reduced determining less inhibition on the neuron N_{CL} that is stimulated by the excitatory activity of N_{TL} . Without inhibitory input activity the neuron N_{CL} starts to fire generating energy on the output C_{LEFT} that is used to move the sensory area to the left.

Note that while the spot is centred the two tracking neurons are activated simultaneously. The neural network structure was designed to remain active when the spot is centred in order to keep the synapses S_{TL} and S_{TR} potentiated by PTP to the maximum strengths without setting these strengths artificially. This structure allows the fastest response of the tracking neurons because of the maximum synaptic strengths. The structure of the neural modules NN_{UP} and NN_{DOWN} that control the sensor area motion on the vertical axis can be similar with the structure presented for the horizontal axis. Therefore, for compensating the receiver displacement on the *up* and *down* directions, the C_{UP} and C_{DOWN} outputs should be controlled by the corresponding photodiodes L_U and U_i respectively, L_D and D_i , $i = \overline{1, 3}$ through similar synaptic configurations like in Fig. 2.

2.4 Neural Network Initial State

When the spot is not present on the sensor area and the network is not trained all synaptic strengths are minimum. After the laser is turned on and the spot covers the photodiodes L_L and L_R the synapses included by the corresponding neural paths are potentiated to the maximum values. For this work the maximum strengths of the synapses S_{TL} and S_{TR} that are activated by the sensors from the tracking area and the minimum strengths of the synapses $S_{L[i]}$ and $S_{R[i]}$, $i = \overline{1, 3}$ corresponding to the

learning area represents the initial synaptic configuration of the neural network. This configuration corresponds to the normal position of the spot when no spot deviations occurred previously. Thus, initial synaptic configuration of the neural network allows the sensors L_L and L_R to control a positioning device on the horizontal axis by activating accordingly the outputs C_{LEFT} and C_{RIGHT} , while the sensors L_i and R_i , $i = \overline{1,3}$ have no effect in controlling the positioning mechanism.

2.5 Neural Network Adaptation

The activation of the mechanisms that determine synaptic potentiation depend on the amplitude of the spot wandering. Therefore, if the spot deviation amplitude is higher than the tracking area and the spot reaches the learning area, the network starts learning by concurrent activation of the neural paths activated by the sensors from the tracking and respectively from the learning areas. For example, whether the light spot moves from the normal position to the left the L_L photodiode together with at least one of the photodiodes L_1 , L_2 , L_3 will stimulate simultaneously the neural network. Depending on the spot deviation amplitude the untrained synapses of the neural path between L_i , $i = \overline{1,3}$ and C_{LEFT} are strengthened. After several concurrent stimulations of the sensor L_L and the sensors from L group, the neurons $N_{L[i]}$, from the learning group will be able to activate the output C_{LEFT} in the same way as the tracking neuron N_{TL} . This orchestration of the tracking neurons activity increases the energy of the network response making the response of the tracking system faster. The active neurons for three spot deviation amplitudes when the synapses of the untrained paths are potentiated by *LTP* are shown in Fig. 3.

Thus, when the spot covers the sensor L_L and L_1 as in the Fig. 3a the untrained synapse S_{L1} is potentiated by the concurrent activity of the neurons N_{TL} that activates the postsynaptic neuron N_{CL} and the neuron N_{L1} .

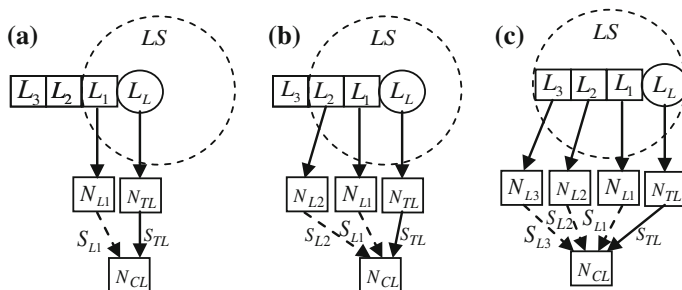


Fig. 3 Active synapses during the light spot (LS) deviation where the potentiated synapses are shown with *continuous arrows*; the un-potentiated synapses when the spot reaches **a** one, **b** two, or **c** three sensors from the learning area are shown with *dashed arrows*. These synapses are strengthened by *LTP* when the spot covers simultaneously at least one sensor corresponding to a trained neural path

Similarly, the synapses S_{L2} and S_{L3} are potentiated when the tracking neuron N_{TL} activates the output neuron N_{CL} as in Fig. 3b, and respectively in Fig. 3c. Therefore, the synapses marked with the dashed arrows are trained when the spot covers the tracking sensor L_L and the sensors L_i , $i = \overline{1,3}$ from the learning area. Taking into account that for *left-right* directions the network uses the same operation principles, the groups of photodiodes UDL and R will take progressively the role of L_L and respectively L_R during the training process. Therefore, the photodiodes placed in the tracking area act like supervisors for the activity of the photodiodes from the learning area.

On the other hand if the spot is static or the wandering amplitude is lower than the tracking area than the network starts learning at a lower rate by PTP. In this case the synaptic potentiation is determined only by presynaptic neuron activation. This mechanism is useful for potentiation of the synapses from the tracking area at the beginning of the experiment. After the synaptic strength S_{TL} increases above the threshold that makes it capable of activating N_{CL} , the neuron N_{TL} activation will strengthen the concurrent activated synapses, such as S_{L1} , S_{L2} and S_{L3} , depending on the spot deviation amplitude. Thus, if the spot wandering amplitude is high enough to cover the photodiodes L_1 , L_2 and L_3 the corresponding input neuron N_{TL} will trigger long-term potentiation for the untrained synapses.

Due to the biological plausibility of the neuron model, the synapses that are not used are continuously depressed at a very low rate. Thus, whether the spot is steady in the normal position for a period of time that is longer than the duration of the complete synaptic depression, the learning process can start again from the initial conditions if the spot deviation amplitude increases. The synaptic depression ensures that the configuration of the synaptic strengths is suitable for compensating the spot wandering considering only the recent deviation history. This adaptation mechanism can reduce the unnecessary power that drives the SMA wires reducing panel oscillations and increasing the SMA wire lifetime.

2.6 The Positioning Mechanism for the Sensor Panel

The positioning mechanism of the system presented in this chapter is able to control the sensor area by moving it on the horizontal axis. The most common approach to implement the positioning systems represents the DC motors. Thus, the outputs of the neural network generate spikes whose frequency depends on the network activity. By integration of these spikes the analogue signals that can be decoded by a motor driver are obtained. The problem of controlling a DC motors speed using spikes was approached in [19] where the spiking neural network was designed in VLSI and implemented in FPGA.

However, the control of the DC motors using spiking neural networks implies the use of artificially designed circuit for conversion of the spiking activity of the

Table 1 Technical data for actuator wires used for actuating the sensor area

Diameter	Resistance	Pull force	Current for contraction	Stroke	Cooling time
0.006"	55 Ω/m	321 g	~410 mA	4 %	2 s

output neurons into the signals that rotates the DC motor. In contrast for implementation of our system we used SMA wires that are naturally driven by the spiking neural network because they actuate by contraction as the natural muscular fibres. This type of actuators brings more biological plausibility to the control system we proposed.

The outputs C_{LEFT} and C_{RIGHT} of the neural network generate spikes which frequency depends on the network activity. By integration of these spikes we obtained the characteristic of the network outputs as analogue signals that are amplified to power the actuator wires.

2.6.1 SMA Wires

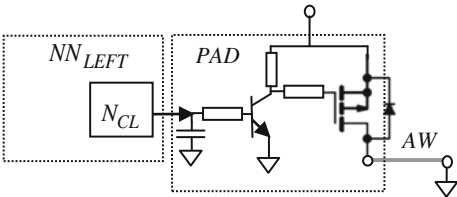
The actuator wires are implemented with shape memory alloy (SMA) that contracts due to heating when they are electrically driven [31]. They are used mainly in robotics especially for hand prostheses because they are silent and model the muscular fibers behavior [1, 21]. In our experiments we used 0.006" actuator wires type Flexinol LT. The technical data for the actuator wires is given in the Table 1 [6].

These wires are suitable to model the behaviour of natural muscles because they can act by contraction which intensity can be determined directly by the spikes frequency generated by the neurons. Thus, by increasing the spiking rate of the neural network output the current that drive the wires is increased bringing more contraction force to the SMA wires.

2.6.2 Positioning Mechanism Structure

The neural network generates continuous signals which energy is amplified to power the SMA wires. The schematic of the signal amplifier suitable for the system we implemented is shown in the Fig. 4.

Fig. 4 The power adaptation device (PAD) for driving the SMA actuator wires (AW) using the signal generated by the output neuron N_{CL}



The neural network generates on each output spikes with different frequencies that depends on the number of input neurons activated simultaneously and on their spiking frequency. The role of power adaptation device (PAD) is to convert the spiking frequency into continuous analogue signals and to amplify the power of these signals for actuating the SMA wires. For example as shown in Fig. 4 the output of the NN_{LEFT} is integrated by a capacitor and the signal energy is amplified using the pair of transistors NPN-MOSFET that powers the actuator wire (AW).

Therefore, in order to implement a biologically plausible mechanism that can move the photosensitive area according to a light spot deviation from normal position we used SMA actuator wires because they are silent and operate as natural muscular fibres. These wires have limited stroke of about 4 % which implies that the wire length has to be significantly longer than the spot maximum deviation. In order to reduce the wire length while increasing the maximum spot wandering amplitude that can be compensated by the positioning system we implemented a lever mechanism as in Fig. 5.. The PA is mounted on a lever that is rotated by the actuator wires around a fixed point. Because for this system the force that is needed to move the PA is very low, we chose a much shorter lever for the SMA wires than the lever for PA. This ratio increases the PA motion amplitude and reduces the SMA wire stroke necessary to move the PA.

However, for this setup the PA follows a circular trajectory that might be unwanted if the spot deviates in a straight line. In order to be able to test the operation of the positioning device correctly we placed the laser module (LM) on a similar lever fixed at the same height as the lever of the positioning device. The lever length for the LM was adjusted to obtain the centred position of the light spot on the sensor panel.

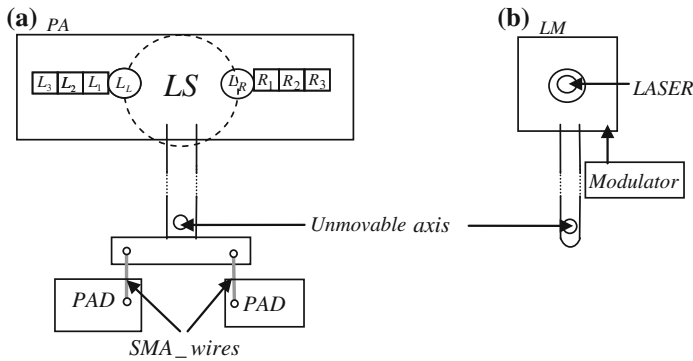


Fig. 5 **a** The structure of the positioning device for the photosensitive area (PA); the PA area is actuated by two SMA wires with antagonistic action controlled by two PADs. For increasing the ratio between the PA motion amplitude and the SMA wire stroke we placed the PA on an lever that is able to rotate around a fixed point (FP); **b** the laser module (LM) used for testing the positioning device. The LM is mounted at the same height as the PA. For actuation of the PA's lever we used two PADs with antagonistic activity that were controlled by the neural networks NN_{LEFT} and respectively NN_{RIGHT}

3 Results

The experiments included three phases when we evaluated the spiking neural network response time, we test the adaptation abilities of the electronic synapses when the LASER spot moved across the sensor area and we tested the ability of the SMA wires to move the photosensitive area to track the LASER spot when they are controlled by the electronic neural network.

The response time evaluation was performed using a microcontroller that simulated the activity of sensors when the spot deviates with constant speed across the sensors. For testing the adaptation abilities of the neural network that represents the second phase of the experiment the learning process is considered finished. In this case the photodiodes from the learning area are able to compensate the spot wandering as the sensors from the tracking zone. During the last phase of the experiment we evaluated the performance of a tracking device based on SMA wires controlled by the electronic neural network of biological inspiration when the spot was deviated deliberately from the centered position.

For all phases of the experiment one mono-synaptic neuron was connected to every sensor as presented in the Fig. 2.

3.1 Neural Network Response Time Evaluation

In order to test the neural network nonlinearity and learning rate when it is used for compensating the spot movement, we implemented a preliminary hardware device based on a microcontroller for generating the neural network input. Because the neural network modules have the same structure, in this section we simulated the activity of the photodiodes U_1 , U_2 and U_3 that would detect the spot deviation towards up . This simulation is the same for all neural network modules that detect the spot wandering on the corresponding directions.

3.2 Spiking Output

The microcontroller was programmed to simulate the output of the photodiodes auxiliary circuit when PDs are covered by the light spot.

During this period the corresponding input neuron will generate action potentials like in Fig. 6. The spikes amplitude and duration depends on the synaptic weight and on the maximum energy generated by one impulse. For the maximum synaptic weights of the neural network used in this experiment, the spike duration is $60 \mu s$ and the amplitude is $V_s = 1.64 mV$.

Considering that the spot size is constant, the moving velocity of the spot between the tracking sensors is proportional with the distance between the

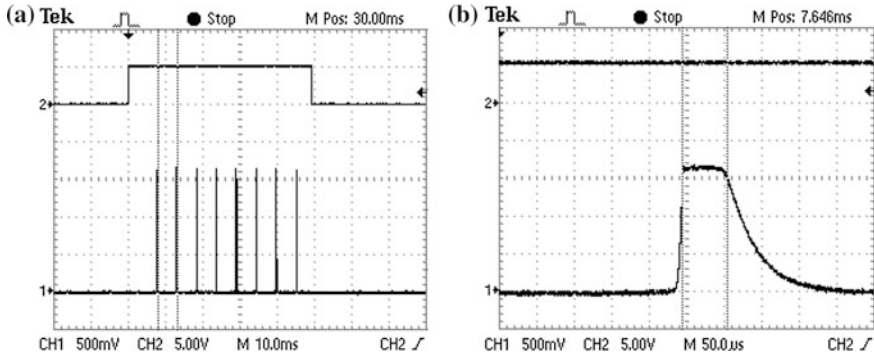


Fig. 6 The output of the neural network (*upper signal*); the microcontroller output modelling the activity of the U sensor (*lower signal*)

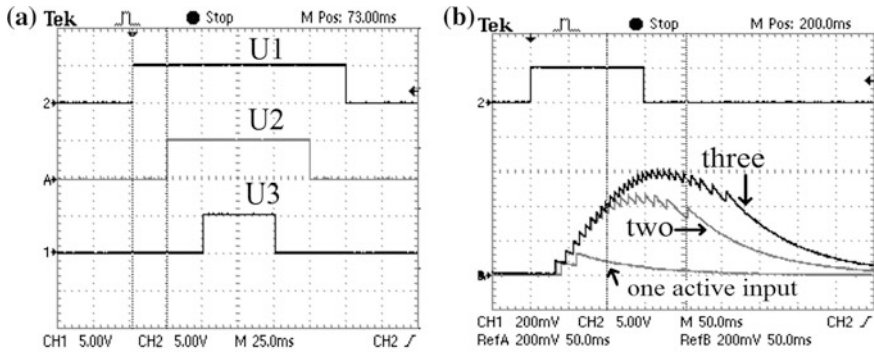


Fig. 7 **a** The simulation of the photodiode activity when the spot is moving across the sensors with constant velocity. **b** The difference between the network response when one, two and respectively three active network inputs

photodiodes d_i . The time T_l while the spot travels between two adjacent receivers decreases if the speed is higher. Thus, by controlling T_l and measuring the network output energy as well as the elapsed time until the network responds, it is possible to evaluate the network performance at different spot wandering velocities. The examples of the network output given in Fig. 7 were recorded for photodiode area edge of 3 mm and for $T_l = 25.2$ ms. Taking into account that $d_l = 9$ mm we obtain the spot wandering velocity $v = 0.36$ m/s for which we simulate the photodiode activity. Therefore, in order to assess the network ability to discriminate between the numbers of concurrently active sensors we recorded using an oscilloscope the neural network output.

The signals in Fig. 7a simulate the output of the sensors L_U , U_1 and U_2 if the spot passes across them at constant velocity from L_U to U_2 and backwards. The upper signal in Fig. 7b, represent the neural network input and the lower signal is

the integrated response of the output neuron for three valid configurations of the active inputs. The presented results were obtained after the NN_{UP} neural network was trained meaning that each synapse was strengthened above the value that allows the presynaptic neurons to reach the postsynaptic action potential for the stimulated neurons. The waveform (b) allows measuring of the time lag of about 30 ms between the stimulus onset and the neural network response. Also, note the difference between the network output energy when the microcontroller simulates the activity of one, two or three sensors. The diagram shows that the neural network produces higher energy if the spot displacement is higher which means that the neural network acts as a regulator for compensating the light spot deviation.

The energy generated by the supervising neuron N_{LU} is maxim because this neuron used for tracking has to ensure that the light spot moving at normal speed remains centered when the synapses in the learning area are untrained. Also, the activity of these neurons increases the learning rate for the neurons that are connected to the photodiodes from the learning area.

3.3 Evaluation of the Network Adaptation Abilities

The role of the neurons in the learning area is to increase the nonlinearity of the neural network response in order to increase the device performance in spot tracking. For assessing the training rate of the neural network we evaluate the duration of the learning process by measuring the time t_L elapsed from the beginning of the network stimulation and the first spike generated by the output neuron N_{CD} that is the effect of the neuron activation. The initial weights of the synapses are zero meaning that the network is untrained.

The learning duration was measured when the synapses are potentiated by posttetanic potentiation (PTP) respectively by the short term and long-term potentiation (STP-LTP) mechanism.

The results presented in the Table 2 show that the learning period decreases with the number of active neurons for both learning mechanisms. The durations presented in the PTP column were obtained when the N_{LU} neuron was inactive. The learning rate significantly increases when LTP was triggered by the activity of the learning neuron N_{LU} due to the fact that the rate of the synaptic potentiation by STP-LTP is significantly higher.

Table 2 Learning duration

Active neurons (n_A)	Posttetanic potentiation PTP (s)	Long-term potentiation LTP (s)
1	2'52"	~ 3
2	30"	~ 3
3	20"	~ 1

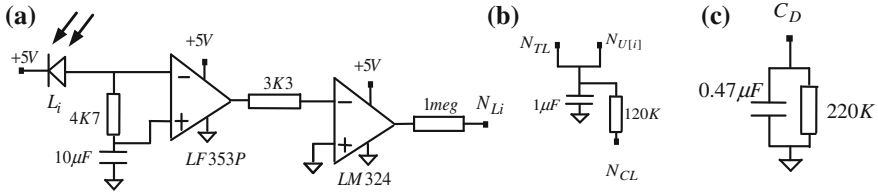


Fig. 8 **a** Light detecting circuit connected to the neural network inputs. **b** Auxiliary input circuit for neurons from hidden and output layers. **c** Circuit for integration of the network output energy

3.4 Laser Spot Movement Detection Experiment

The presence of the light spot on the photodiode surface is signalled to the corresponding neural network by the circuit presented in Fig. 8a. The photodiode resistance is converted by this circuit in a digital signal that is in high logic level when the light spot generated by a LASER type ADL-65055TL covers the photodiode type BPW20RF. The LASER spot diameter was adjusted using lens type CAY046 and for this phase of the experiment the LASER current was 30 mA.

Figure 9 presents the results obtained after the neural network activity was evaluated using the input generated by the photodiode area. The signal diagrams (a) and (b) presents the neural network output integrated using the circuit presented in Fig. 8c when the same test was performed in two different days.

In this case when the LASER spot moved across the photodiodes, the behaviour of the neural network was similar with that obtained when the network was stimulated by the microcontroller. The number of active neurons from the learning area determines the power of the network output and the response time.

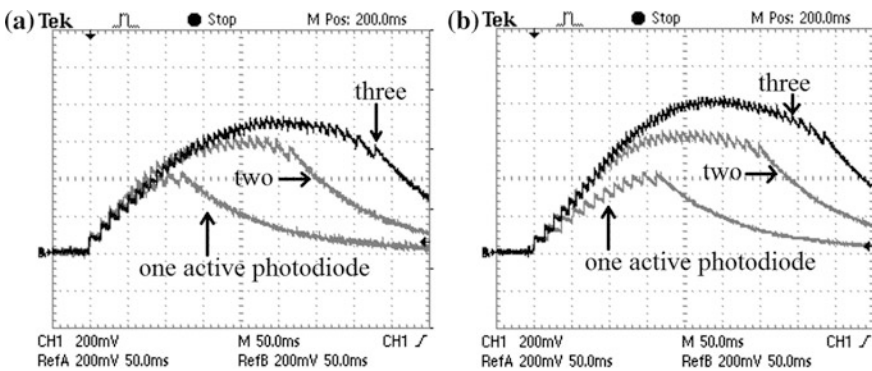


Fig. 9 Two network responses when the laser beam covers simultaneously one, two and respectively three photodiodes. The recordings (a) and respectively, (b) were performed after the network training in two different days

Thus, as shown in Fig. 9 if more neurons from the learning area are active, the output energy is higher and the response time is slightly decreased. The energy generated by the neural network can be calculated using the spike duration and amplitude which are given by the synaptic weights.

Because more neurons were activated when the spot displacement from normal position was higher implies that the network is sensitive to the amplitude of the spot deviation. This aspect increases the performance of the tracking system because the system reaction is amplitude dependent.

4 Laser Spot Tracking Experiment

The most important phase of the experiment represents the evaluation of the ability of the SMA wires to actuate the positioning device in order to compensate the spot wandering on the sensor area. The main goal of this experimental phase was to determine if the SMA actuator wires can react sufficiently fast when the light spot deviates from the central position because SMA wires contracts due heating that may delay their response. For this experiment we used the structure of the neural network presented in the Fig. 2 that uses one excitatory neuron driven by each photodiode included in the corresponding signal detection circuit shown in the Fig. 8. Also, the neural network uses two inhibitory neurons that are activated by the antagonistic sensors L_L and L_R from the tracking area.

4.1 Experimental Arrangement

Figure 10 presents several pictures of the experimental setup for testing the performance of the laser spot tracking system.

The first picture (a) shows the optical arrangement that includes the laser module facing the photosensitive area that is moved on *left-right* directions, on a circular trajectory, actuated by SMA wires. The PA pictured in the Fig. 10b uses four photodiodes for detection of the spot deviation in each direction. The spot normal position is centered between the photodiodes from the tracking area. The length of the levers for the sensor area and respectively for the laser module is 17.5 cm and the distance between the laser and the photosensitive area is 15 cm. The photosensitive area is actuated by two SMA wires of 27 cm length that are able to compensate on each direction the maximum spot deviation amplitude of 5 cm as shown in the Fig. 10d. When the PA is in normal position the wires are not tensioned because each wire should allow the antagonistic wire to contract. Thus, as pictured in Fig. 10d when the sensor area is moved to one side by contraction of the

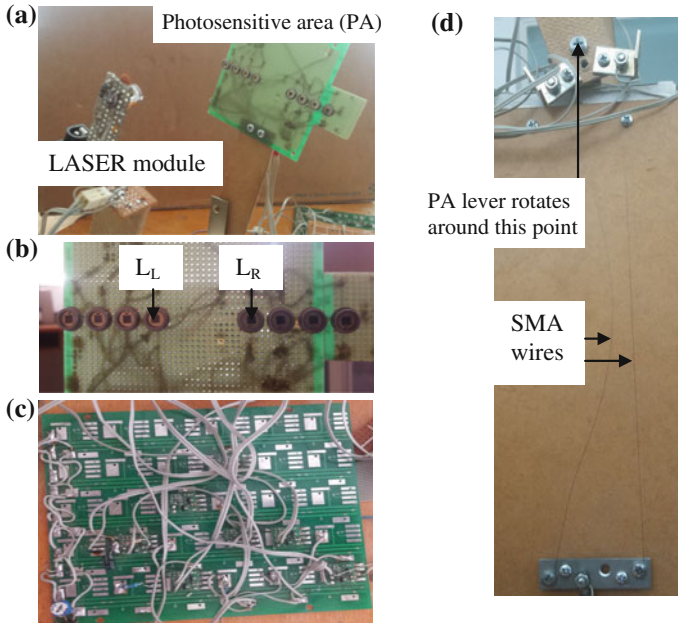


Fig. 10 Laboratory experimental setup for testing the performance of the tracking system based on spiking neural networks and actuator wires. **a** Optical arrangement. **b** Photosensitive area (PA). **c** PCB implementation of one network module (NN_{RIGHT}). **d** SMA actuator wires

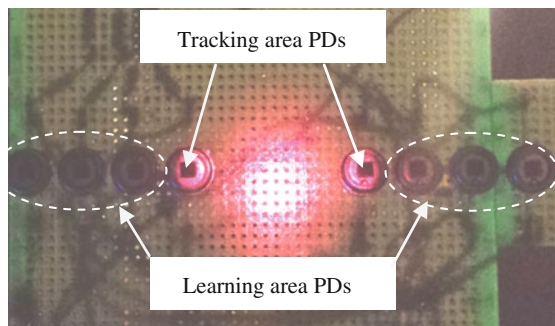
corresponding wire, the antagonistic wire is relaxed and stretched. Taking into account that the wire maximum stroke is 4 % meaning that during contraction the 27 cm wire is shortened by ~ 1 cm, our experimental setup increases the wire contraction influence to 5 cm which represents a significant improvement of the ratio between the wire contraction and the maximum compensable deviation of the light spot.

The spot deviation from the normal position is detected by the electronic neural network. Figure 10c presents one module of the neural network implemented in PCB hardware that detects the spot deviation to the right. This neural network includes four presynaptic excitatory neurons and one postsynaptic neuron. The output power of the postsynaptic neuron is amplified to drive the actuator wires.

4.2 Tracking Performance Evaluation

The experimental results presented in the previous sections showed that the neural network responds sufficiently fast when the spot deviates and adapts its response to spot wandering amplitude. In this section we will determine the system response

Fig. 11 The spot is centered between the two tracking sensors; the tracking neurons are inactive



time when it tracks the spot by controlling the position of the sensor panel. For this part of the experiment the synaptic strengths were set to the maximum values in order to determine the fastest system response time. Also, because neural network adaptation facility is not used and the simultaneous activation of the tracking neurons from both sides of the spot is not necessary, the spot size was slightly reduced in order to keep all the input neurons silent when the spot is centered as in the Fig. 11.

The spot diameter can be estimated taking into account that the distance between the centers of the tracking PDs is 3.2 cm and the distance between the PDs from the learning area is 1 cm. The spot size ease the evaluation of the tracking system response time by monitoring only the neural network activity as presented in the sequel.

All results presented in this section were obtained by moving deliberately the laser lever. Before each test the lever was steady a period of time longer than 3 s that allows the SMA wires to cool down. Also the room temperature that influences the SMA wire relaxation state was around 28 °C.

In order to determine the system response time we use the laser diode (LD) type ADL-65075TR/L. For keeping active the inputs of the neural network we modulated the laser at 100 Hz using the external function generator G5100. The laser modulation was necessary because the auxiliary circuit for the photodiodes is designed to respond only to sudden changes in the received light intensity for reducing the ambient light influence on the neural network activity. This aspect determines continuous activation of the input neurons when the light spot covers the corresponding PDs. In order to obtain an acceptable optical power taking into account the spot diameter of 4 cm at 15 cm from the laser source, we set the current for the LD to 60 mA and connected a 40 pF capacitor in parallel with the LD.

Because for the experiments presented in the previous chapters the light was not modulated we started this phase of the experiment by preliminary evaluation of the neural network activity when the spot covers one or two spots. The activity of the spiking neural network was monitored using an oscilloscope type Tektronix TDS-210.

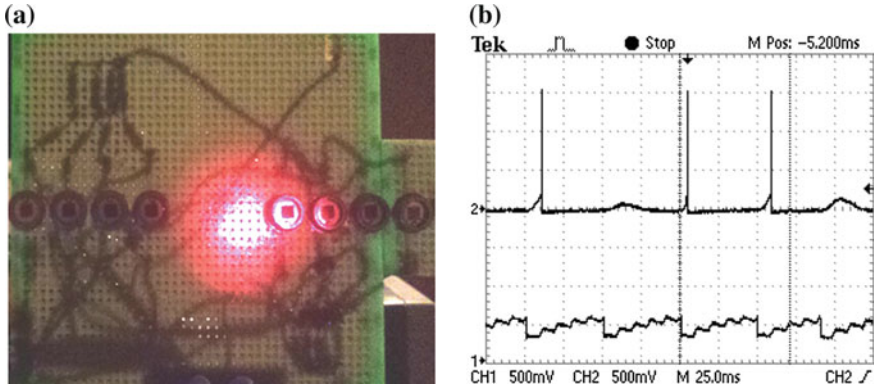


Fig. 12 **a** The laser spot covers the sensor from the tracking area. **b** The output of the postsynaptic neuron (*upper signal*) when activated by the tracking neuron whose input represents the *lower signal*

Figure 12 presents the activity of the neural module NN_{RIGHT} when the spot covers the photodiode L_R from the tracking area as in Fig. 12a. In order to be able to evaluate the neural network activity and to record the signals, during this preliminary test the power for the SMA wires was disabled. Figure 12b shows the activity of the output neuron N_{CR} when it is activated by the presynaptic neuron which input potential is shown by the lower signal. During normal operation the PAD integrates and amplifies the N_{CR} activity.

Similarly, Fig. 13a shows the picture of the photosensitive area when the spot covers two sensors— L_R from the tracking area and R_1 from the learning area. The waveform from Fig. 13b presents the output of the N_{CR} (*upper signal*) and the input potential of the presynaptic neuron N_{R1} that activates N_{CR} .

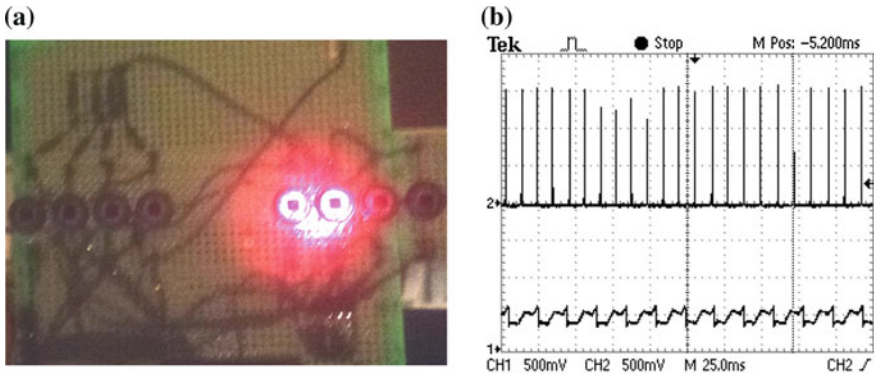


Fig. 13 **a** The light spot covers one sensor from the tracking area and one sensor from the learning area. **b** The *upper signal* shows the activity of the output neuron and the *lower signal* represents the input potential variation for the learning neuron L_{R1}

Note that the output neuron which activity is shown in Fig. 12b fires at maximum frequency of 18 Hz while in Fig. 13b the spiking frequency of the output neuron is about 100 Hz. As supposed, the spiking frequency of the network output is significantly higher when the light spot covers simultaneously two sensors than only one. This fact implies that the neural network is able to clearly discriminate between spot deviation amplitudes which increase the network sensitivity to the spot wandering amplitude.

In order to evaluate the ability of the tracking system to control the position of the photosensitive area for keeping the laser spot centered, we evaluated the response time and the tracking accuracy of the system.

4.2.1 Tracking System Response Time

In order to determine the period of time while the spot deviation is compensated we measured the duration of the tracking neurons activity that are stimulated directly by the photodiodes auxiliary circuit. Note that the tracking neurons are active only when the light spot stimulates the corresponding photodiode from the tracking area implying that when the spot is centered the neural network is silent. The duration of the neurons activity was evaluated based on the waveforms recorded on the oscilloscope.

Several results obtained when the deviated laser spot covers two sensors for each direction are shown in Fig. 14. These results are obtained when the maximum current that drives the SMA wires was limited to 300 mA representing 73 % of the maximum current mentioned by the wires manufacturer shown in the Table 2.

Fig. 14 shows the tracking neurons response when the laser spot deviation is compensated. In this case the wire that will contract is fully stretched and relaxed.

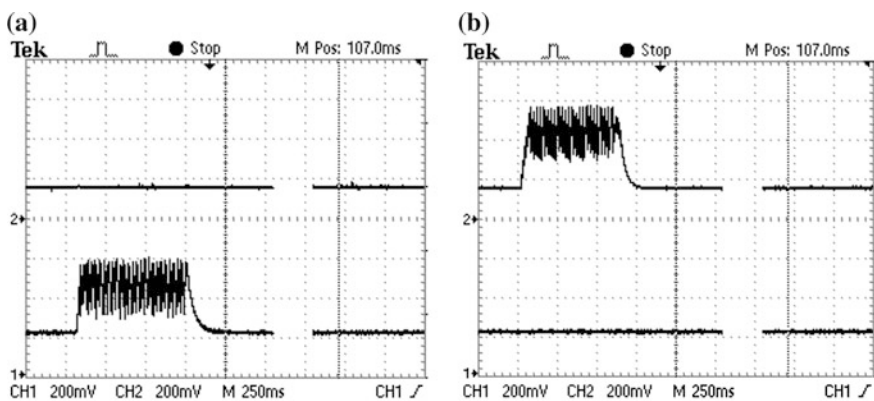


Fig. 14 The tracking neurons activity for evaluation of the response time t_L and t_R of the tracking system when the spot deviates towards the **a left** or **b right**; Before contraction the SMA wire is fully stretched and relaxed; The maximum driving current for the SMA wires is $I_A = 300$ mA

Table 3 Response time for the tracking system (t_L and t_R)

Initial state of the wire	Fully stretched		Normal	
Maximum current for SMA wires (mA)	t_L (ms)	t_R (ms)	t_L (ms)	t_R (ms)
$I_A = 300$	813	766	1033	1160
$I_A = 350$	713	846	846	886
$I_A = 400$	560	506	700	706

This configuration is achieved, for example, by placing the panel to the maximum right position with the spot centered.

Thus, in the Fig. 14a the spot deviation to the left is compensated in the period t_L . The upper signal represents the input of the tracking neuron N_{TR} and the lower signal represents the input activity of N_{TL} . Similarly, the spot deviation to the right is compensated in the time t_R as shown in Fig. 14b. The gaps that appears on both signals are introduced by the oscilloscope when the time per division is greater than 100 ms. For having a qualitative view of the network response time we can estimate that $t_L = 700$ ms and $t_R = 630$ ms taking into account that one vertical division on the oscilloscope represents $M = 250$ ms.

Several values of the measured response time of the tracking system are given in the Table 3.

Each value represents the average of three time measurements performed using the oscilloscope cursors that were placed at the beginning of the first stimulation of the neuron input and respectively at the last neuron activation. The first two columns of the Table 3 present the response time for left and respectively right deviation of the sensor panel when the SMA wire was stretched before contraction. The last two columns present the values for the same parameters when the sensor panel lever was vertical before SMA wire contraction. On each row we present the response time for several values of the maximum current that drives the actuator wires.

4.2.2 Tracking Precision

The normal position of the light spot is centered when the sensor panel lever is vertical. Therefore, the system should be able to track the spot starting from this position implying that the SMA actuator wires are not stretched when they are relaxed. This may add a delay in the system response time because the panel is actuated after a period of time elapsed before the wire is tensioned. Indeed, in this case the network response time increases to $t_{OSC(L)} = 1.150$ s for left deviation and to $t_{OSC(R)} = 1$ s for right deviation as shown in the Fig. 15a, b. Note that for the deviations in both directions the opposite tracking neuron activates showing that the sensor panel deviates in the opposite direction determining the activation of the opposite photodiode from the tracking area. Therefore when the SMA wire is not

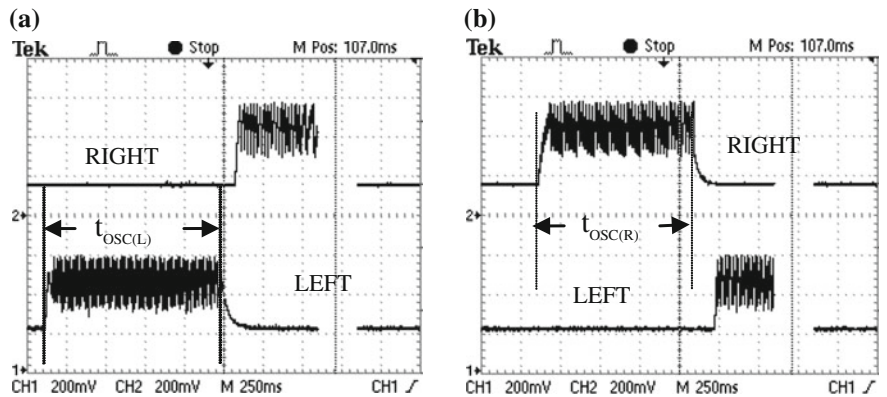


Fig. 15 The tracking neurons activity for evaluation of the response time of the tracking system when the spot deviates towards **a Right. b Left** starting from the normal position; The maximum SMA wire current is $I_A = 350$ mA

fully stretched the sensor panel is actuated sharply making the sensor area to oscillate due to inertial forces and slightly due to panel weight.

Several values of the $t_{OSC(L)}$ and $t_{OSC(R)}$ for $I_A \in \{300, 350, 400\}$ mA are given in the Table 4. These values were obtained using the same method that gives the data presented in the Table 3.

Our results showed that for $I_A = 300$ mA and $I_A = 350$ mA the oscillation of the sensor panel does not occur when the actuating wire is stretched before contraction.

For a qualitative illustration of the panel oscillation Fig. 16 presents two waveforms recorded from the oscilloscope that capture panel oscillations. The waveform (a) shows that the spot deviation to the left that is compensated in about 760 ms when the sensor panel is pulled by the corresponding SMA wire. The wire contraction force determines the panel deviation in the opposite direction. The time difference t_i between the last activation of the input neuron N_{TL} and the first stimulation of N_{TR} gives us information about the panel velocity that in this case is estimated to $v_p = 0.4$ m/s. This value is in concordance with the value $v = 0.36$ m/s of the spot wandering simulated using the microcontroller (see Sect. 3.2). Similarly, t_f gives information about the panel velocity in the opposite direction. Note that

Table 4 Oscillation duration when inertial forces affects the sensor panel control

Initial state of the wire	Fully stretched		Normal	
	$t_{OSC(L)}$ (s)	$t_{OSC(R)}$ (s)	$t_{OSC(L)}$ (s)	$t_{OSC(R)}$ (s)
$I_A = 300$	no osc.	no osc.	1.8	2.09
$I_A = 350$	no osc.	no osc.	1.4	1.89
$I_A = 400$	1.36	1.49	2.03	1.99

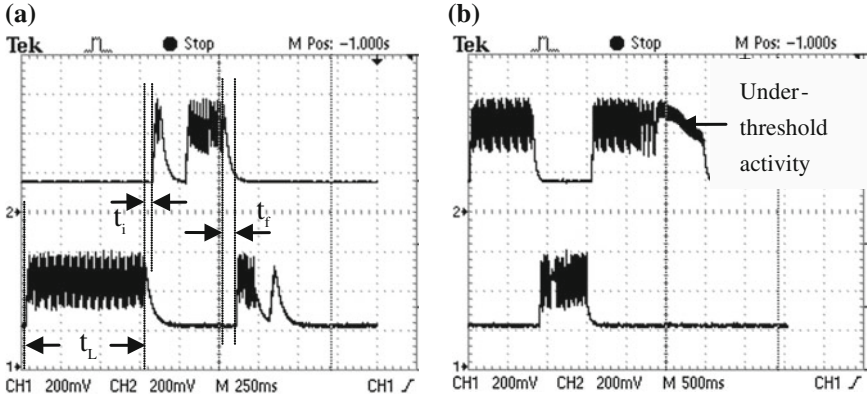


Fig. 16 Activity of the tracking neurons when the spot deviates from normal position (the panel lever is vertical) for $I_A = 400$ mA

$t_f > t_i$ implying that the spiking neural network acts to reduce the oscillation amplitude.

However, the panel velocity that gives information about the inertial forces represents only estimation and is not the subject of the research presented in this chapter.

Similar behavior is observed in Fig. 16b that presents the tracking neurons activity when the spot deviates to the right starting from normal position. The unusual activity of the tracking neuron N_{TR} that is pointed by the arrow on the upper signal represents under-threshold stimulation of the neuron. This activity stopped because the panel is still moving slightly pulled by the actuator wire that is cooling down.

5 Discussions

The research presented in this chapter demonstrates the principle for mono-dimensional light spot tracking using a biologically plausible system. Despite the fact that we tested the laser spot tracking for horizontal axis, the same principle can be easily used to implement a control module that tracks the spot on vertical axis. Because the spot tracking on horizontal and respectively vertical axis is performed by independent modules that operates in parallel the combination of the two systems is able to perform bi-dimensional laser spot tracking.

In this experiment we limited the maximum current I_A that can drive the actuator wires to several values and determined the response time and regulatory performance of the control system. The results show that when the laser spot deviates, the tracking system respond for highest I_A in around 0.5 s to compensate the laser spot displacement. This implies that the SMA wires reacts unexpectedly fast when the

light spot covers at least the diode from the tracking area taking into account that the wire contraction occurs due heating.

One of the interesting aspects is the fact that because the response of the actuator wires is fast, the inertial forces for the sensor panel occur. Due to these forces and to the contraction of the antagonistic actuator wire when the light reaches the opposite tracking sensor the panel tends to oscillate but it stabilizes after one or two oscillations.

However, our experiments showed that the cooling time of the wires, that according to the datasheet is 2 s, becomes a problem during fast oscillations of the laser spot. This problem could be easily solved using thinner wires for which the cooling time is as low as 0.15 s. Moreover, according to the technical characteristics of the SMA actuator wires among the cooling down methods the most effective is water with glycol [6].

Another behavior that affects the system tracking precision represents the panel area oscillations. These oscillations occur when I_A is near the maximum constructive value or when the wires are not stretched before contraction. This problem was solved partly by reducing the maximum current that drives the SMA wires with penalty in the system response time. Also, the oscillation problem could be solved by reducing the weight of the photosensitive panel.

6 Advantages of the Nature-Based Method for Control Systems

This chapter describes a biologically inspired method for laser spot tracking based on spiking neural networks and SMA actuator wires. The spiking neural network is able to track a laser spot by detecting the spot deviation from a central position using the output of two areas of photodiodes and by driving the photodiode panel using two antagonistic SMA actuator wires. The neural network is based on a neuron model that mimics the main mechanisms of the biological neurons regarding the information processing and the associative learning. The SMA wires mimic the behavior of muscular fibers because they act by contraction when they are stimulated by currents.

The spot tracking system presented in this chapter represents a high complexity control system because it is responsive to perturbations that vary in a continuous range and adapts continuously for better compensation of these perturbations. Despite the high complexity function of the control system, the design of the regulatory unit is simple because it uses spiking neurons implemented in analogue hardware that model intrinsically high complexity functions as the neural cells. Thus, this type of neurons allowed us to implement the processing unit of the tracking system for the horizontal axis using only ten excitatory neurons and two inhibitory neurons.

Moreover, the spiking neural network controls naturally the contraction of SMA actuator wires that reacts fast but smoothly as the natural muscular fibers. This behavior ensures a biological-like behavior of the tracking system that controls the position of a sensory area for keeping the light spot centered.

The advantages of the spiking neural network implemented in analogue hardware represent the real-time response because all neurons operate in parallel as well as the very low power consumption. For example, taking into account that one neuron with one synapse needs around $0.5 \mu\text{W}$ to operate, the power consumption of the whole neural network that performs the high complexity control function for spot tracking is about $6 \mu\text{W}$. This value is significantly lower than the necessary power for any microcontroller that would implement even lower complexity control functions. Moreover, modeling higher complexity functions using algorithms increases the response time of the processing unit.

The control functions for the classical systems are designed to fulfill specific goals and when an unpredicted situation occurs the system may not be able to deal with the unknown perturbations. In contrast, the spiking neural network is adaptable being able to adjust the power that drives the actuator wires according to the previous perturbations. Moreover, when using spiking neural networks the exact model of the process is not necessary for designing the regulatory unit because spiking neurons act as regulators.

Considering all mentioned above the main advantages of the bio-inspired method for the control system represents the adaptability, model-less design of the regulatory unit, very low power consumption and the real time response control unit. Moreover, using the proposed method the light tracking mechanism of the eye could be modeled.

7 Conclusions

The light spot tracking is a necessity for enhancing the quality of the link stability in FSO communications or for increasing the received light power in photovoltaic systems. Moreover, the most complex light tracking function is performed by the eye and the corresponding neural areas. Thus, the most suitable processing unit for solving this task can be the analogue implementation of the spiking neural networks due to highly non-linear behavior, fast response time and very low power consumption.

After testing the neural network performance by simulation of the light sensors activity using a microcontroller, the results showed that the velocity of the spot movement in strait line can reach easily 0.36 m/s while the consumed power of the active neurons is less than $6 \mu\text{W}$. One important aspect represents the significant dependency of the network response energy on the number of neurons that are concurrently active. Similar network behavior was obtained when it was tested in real conditions using a laser spot that was moving across the photodiode area.

The compensable speed of the spot wandering using the spiking neural networks (SNN) makes SNN suitable for laser spot tracking in turbulent environment when used in free space optical communications.

However, the type of SMA actuator wires used in our experiment might be more suitable for compensation of the spot wandering in weak turbulence due to relatively high response time and very high cooling time.

The low power neural networks that control the actuator wires are suitable for improving the efficiency of the photovoltaic power supplies by continuously tracking the light spot of maximum intensity.

Considering the response time of our system and its smooth biological like behaviour the unidirectional light tracking principle demonstrated by our system is most suitable to be used in modelling and explaining the light tracking mechanisms of the eye. This mechanism for the light spot tracking could be the following: when the spot deviates from a central position on the retina the muscles contracts to rotate the eye for compensation of the spot displacement on the retinal sensorial area.

One of the future directions of our research will be based on this idea when we intend to model the light sensitive retinal cell using photodiodes and the muscles that rotate the eye using SMA actuator wires.

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Nature-Inspired Computing for Control Systems

Ponce, H. (Ed.)

2016, XII, 289 p. 179 illus., 62 illus. in color., Hardcover

ISBN: 978-3-319-26228-4