USING SPIKING NEURAL NETWORKS FOR LIGHT SPOT TRACKING

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ABSTRACT

This paper introduces a new method for automatically compensating the light spot displacement from the normal position in 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. To validate this method we implemented in hardware a spiking neural network structure able to process the input from a photodiode array and to control a positioning system. The performance of the neural network that is based on an electronic neuron of biological inspiration was tested using the output of the photodiode array placed in strait line. The results show that the rapport between the energy consumed by the spiking neural network and the accuracy in compensating the spot moving on horizontal or vertical directions is significantly better than the rapport which is obtainable when programmable computing devices solve the same task. These results are encouraging to develop low power spot tracking system for enhancing the receiving accuracy in free space optics or for enhancing the efficacy of the photovoltaic systems.

Index Terms— *spiking neural networks, tracking device, associative learning*

1. INTRODUCTION

The light spot tracking problem was solved in several papers using artificial intelligence elements such as fuzzy neural networks [1], [2] and [3] or multilayer perceptrons [4]. 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 using this type of neural networks is that they are able to model high complexity functions in a biomimmetic manner while having very low power consume when implemented in analogue hardware.

Therefore, spiking neural networks are parallel structures which use time in information processing and learning [5] and [6]. The processing unit of these networks is the neuron designed to mimic in the most plausible way the neuronal cell behaviour [7]. Several neuron models of biological inspiration such as McGregor [8] and Hopfield [9] were developed to mimic the information processing elements such as membrane potential and detection of activation threshold. Other models of neurons suitable for software implementation that mimic the different types of spiking behaviour of the biological neurons were developed by Izhikevich [10] and [11]. The simulation time of large biologically inspired neural networks can be reduced by designing computationally effective neuron models [12], [13], [14] and [15] or by implementing dedicated computational systems [16] and [17]. 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 device presented in this paper is based on a neuron model introduced in [18] and [19]. We use this type of spiking neuron that was analyzed in [20] because it is implemented in low power analogue hardware and mimics accurately the natural mechanisms of associative learning described by neuroscientists in [21], [22] and [23].

NEURAL NETWORK

For compensating the displacement 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 work, it was implemented the analogue spiking neural network and tested its performance by simulating the activity of the sensors area using a microcontroller.

1.1 The learning mechanism

The strength of a synapse or connection between two neurons is increased with a factor p each time the synapse is active. We say that the 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 active in a time window t_p then the strength of the synapses is increased using a factor q [24] and [25]. Throughout this paper it is considered 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 processing unit for the tracking device the weight variation associated with the posttetanic potentiation is described by equation (1), while for the long term potentiation the weight varies with the amount given by the equation (2).

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

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

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* [26]. 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:

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

where V_3 is a design dependent constant.

1.2 The neural network input

The network receives the input from two areas of photodiodes placed like in figure 1. The *tracking area* (T) of sensors is used for light spot tracking while the *learning area* (L) is used for network training.

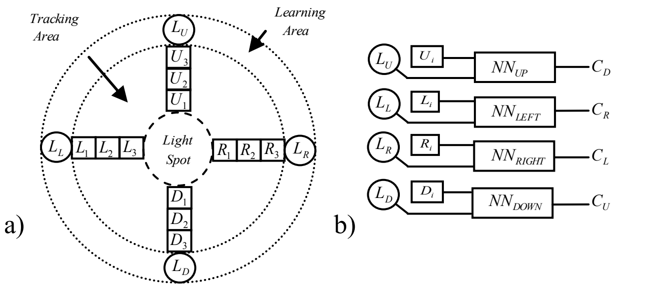

Figure 1. a) The light sensors areas; b) the spiking neural networks that generate the control signals

This structure allows the neural network to learn to associate the effect of the sensors in learning area with the effect of neurons in the tracking area starting from the initial conditions presented in the sequel.
Thus, in figure 1 (a) the sensors L_U and L_D detect the spot movement *up* and *down* on vertical axis, while the sensors L_L and L_R are sensitive to *left* and *right* spot displacement on horizontal axis.

1.3 The neural network structure

The neural network is divided in four principal units that receive the inputs for each of the four directions and are able to control the positioning mechanism for compensating the light spot movement. The structure of the neural network modules NN_{UP} and NN_{DOWN} for controlling the *up* and respectively *down* directions on vertical axis is presented in figure 2. The neurons $N_{U[i]}$, and $N_{D[i]}$, $i = \overline{1,3}$ are the input neurons for the sensors U_i and D_i, $i = \overline{1,3}$ that controls the outputs C_D and C_U through the neurons N_{CD} and respectively N_{CU}. In the same way the sensors L_U and L_D are linked with the outputs C_D and C_U like in figure 2.

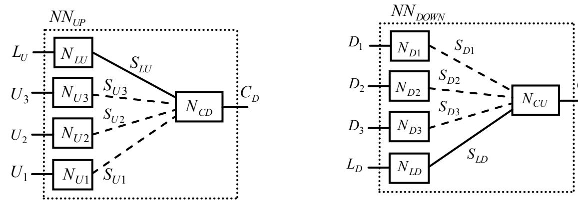

Figure 2.The neural network structures that can be trained to compensate the spot displacement on *up* and *down* directions; initially, the weights of the synapses that are connected to learning area are maximum and the rest of the weights are minimum.

The structure of the neural modules NN_{LEFT} and NN_{RIGHT} that control the receiver area movements on horizontal axis is the same as that presented for vertical axis. Therefore, for compensating the receiver displacement on the *left* and *right* directions, the C_R and C_L outputs are controlled by the corresponding photodiodes L_L and L_i respectively, L_R and R_i, $i = \overline{1,3}$ through similar synaptic configurations like in figure 2.

1.4 Neural network initial state

The initial synaptic configuration of the neural network allows the sensors L_U and L_D to control a positioning device on vertical axis by activating accordingly the outputs C_D and C_U, while effect of the sensors U_i and D_i, $i = 1,3$ position mechanism control is null. Thus, before network training the synapses S_{LU} and S_{LD} are strengthened to the maximum value, while the weight of the synapses S_U and S_D are set to the minimum.

1.5 Learning phase

The involved mechanisms in the network learning depend on the amplitude of the spot wandering.

1) If the amplitude is high and the spot reach the learning area, the network starts learning by concurrent activation of the sensors from the tracking area with the corresponding sensor from the learning area. For example, whether the light spot is displaced upwards from the centre, the U_1, U_2, U_3 and L_U photodiodes will stimulate simultaneously the neural network strengthening the synapses of the neural path between U_i and C_D. After a number of concurrent activations of the photodiode L_U and the sensors from *U* group, the tracking neurons $N_{U[i]}$, $i = \overline{1,3}$ will be able to control the output C_D in the same way like the learning neurons N_{LU}.

Taking into account that for all four directions the network uses the same operation principles, the groups of photodiodes *U, D, L* and *R* take progressively the role of L_U, L_D, L_L and respectively L_R during the training process. Therefore, the photodiodes placed in the learning area act like supervisors for the activity of the photodiodes from the tracking area.

2) If the amplitude is lower than the tracking area than the network starts learning at a lower rate by posttetanic potentiation when the synaptic efficacy is increased during the presynaptic neuron activation. After the neuron weight S_{U1} increases above the threshold that makes it capable of activating N_{CD}, this neuron will strengthen the concurrent activated synapses, such as S_{U2} and S_{U3}, depending on the spot moving amplitude. Therefore, if the spot wandering amplitude is high enough to hit the photodiodes U_1, U_2 and U_3 the corresponding input neuron N_{U1} will trigger long-term potentiation for untrained synapses S_{U2} and S_{U3}. If the spot covers only U_1 and U_2 then the LTP will potentiate only the synapse S_{U2}.

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 maximum amplitude of the spot wandering is reduced to zero for a period of time longer than the duration of the complete synaptic depression, the learning process can start again if the spot displacement amplitude increases. The synaptic depression ensures that the network synaptic configuration is suitable for compensating the present patterns of the spot wandering.

1.6 Positioning mechanism

The positioning mechanism has to be able to control the sensor area position by moving it on the horizontal and vertical axis using two stepper motors. The outputs C_L, C_R, C_U and C_D of the neural network generate spikes whose frequency depends on the network activity. By integration of these spikes it is obtained the characteristic of the network outputs as analogue signals that can be decoded by a motor driver. The problem of controlling a DC motor speed using spikes was approached in [27] where the spiking neural network was designed in VLSI and implemented in FPGA. Because the research presented in this paper is focused on the implementation and test of an analogue spiking neural network that is able to learn by STP-LTP mechanisms when it is stimulated by the output of a photodiode array, the positioning device for the tracking system will be implemented during future research.

2. EXPERIMENTAL SETUP

The learning process is considered to be finished when the photodiodes in the tracking area are able to compensate the spot wandering without the activity of the sensors in the learning zone. For this experiment, we used one neuron connected to every photodiode as presented in figure 2.

2.1 Preliminary experiment

In order to test the neural network nonlinearity and learning rate when used for compensating the spot movement, it was built a preliminary hardware device based on a microcontroller for generating the neural network input.

Neural network response

The microcontroller was programmed to simulate the output of the receivers when they are hit by the light spot by keeping a digital signal in high logic level.

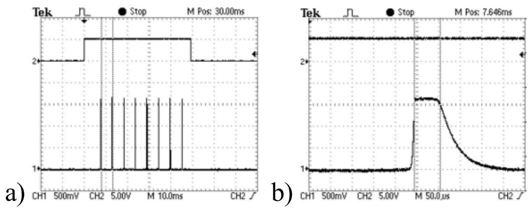

Figure 3. The output of the neural network (upper signal); the microcontroller output modelling the activity of the U sensor (lower signal).

During this period the corresponding input neuron will generate action potentials like in figure 3. 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 60µs and the amplitude is 1.64mV.

Considering that the spot size is constant, the moving velocity of the light between the tracking sensors is proportional with the distance between the photodiodes d_I. The time T_I while the spot travels between two adjacent receivers decreases if the speed is higher. Thus, by controlling T_I and measuring the network output energy as well as the time lapsed until the network responds, it is possible to evaluate the network performance at different spot wandering velocities. The examples of the network response given in figure 4 were recorded for photodiode area edge of 3 mm and for T_I = 25.2 ms. Taking into account d_I = 9 mm we obtain the spot wandering velocity v=0.36m/s for which we simulate the photodiode activity. Therefore, to assess the network ability to discriminate between the numbers of concurrently active sensors we recorded using an oscilloscope the neural network output.

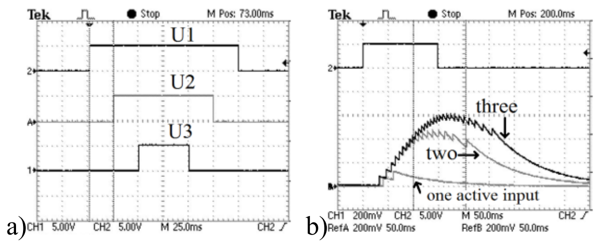

Figure 4. a) The simulation of the photodiode activity when the spot is moving across the sensors with constant velocity; b) the difference between the network response when one, two and respectively three active network inputs.

The signals in figure 4 (a) simulate the output of the sensors U_1, U_2 and U_3 if the spot passes across them at constant velocity from U_1 to U_3 and backwards. The upper signal in figure 4 (b), 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 pre-

sented 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 image (b) allows measuring of the time lag of about 30ms between the stimulus onset and the neural network response. Also, notice 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 an auto-regulating mechanism for light spot movement.
The energy generated by the supervising neuron N_{LU} is maxim because this neuron used for learning has to ensure that the light spot moving at normal speed remains in the photodiode area when the neural network is untrained. Also, the activity of these neurons increases the learning rate for the neurons that are connected to the photodiodes from the tracking area.
The goal of using the neurons in the tracking 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 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.

Learning Rate

The learning duration was measured when the synapses are potentiated by posttetanic potentiation (PTP) respectively by short-term and long-term potentiation (STP-LTP) mechanisms.
The results presented in table 1 show that the learning rate given by the measured learning time intervals increases with the number of active neurons for both learning mechanisms. The durations presented in the PTP column were obtained

TABLE I
TRAINING DURATION

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

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 increase by STP-LTP is significantly higher.

2.2 LASER spot movement detection experiment

The presence of the light spot on the photodiode surface is signalled to the corresponding neural network input by the circuit presented in figure 5 (a). The input given by the photodiode is converted by the circuit in a digital signal that is in high logic level when the light spot generated by a LASER type ADL-65055TL hits the photodiode type BPW20RF.The LASER spot diameter was adjusted using lens type CAY046 according to the setup presented in figure 1 and the LASER current was 30 mA.

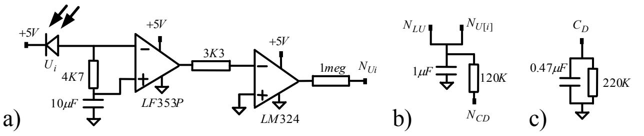

Figure 5. a) Light detecting circuit connected to the neural network inputs; b) auxiliary input circuit for neurons from hidden and output layers; c) circuit for integration of the network output energy.

Figure 6 presents the results obtained after the neural network behaviour was evaluated using the input given by the photodiode array. The signal diagrams (a) and (b) presents the neural network output integrated using the circuit in figure 5 (c) when the same test was performed twice.

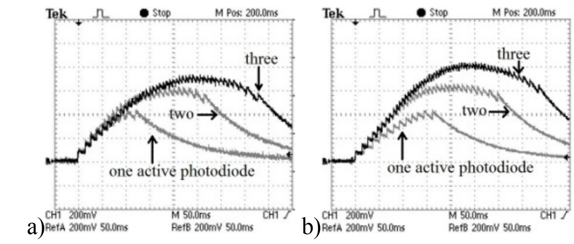

Figure 6. Two network response when the laser beam hits simultaneously one, two and respectively three photodiodes. The recordings were performed after the network training in two different days.

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 n_A from the tracking area determines the power of the network output and the response time.
Thus, as shown in figure 6 if more neurons from the tracking 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 the network learning state. Because more neurons were activated when the spot displacement from centre position was higher implies that the network behaviour is suitable for adjusting the position of the light spot.

3. CONCLUSIONS

The light spot tracking is a necessity for enhancing the quality of the link stability in FSO communication or for increasing the received light power in photovoltaic systems. Also, the consumed energy of the tracking devices should be very low for providing more portability to the communicating devices and for increasing the efficiency of the photovoltaic power supplies. Thus, the most suitable processing unit for solving this task can be the analogue implementation of the spiking neural networks due to non-linear behaviour, fast response time and the very low power operation.

After testing the neural network performance by simulation of the light receiver activity using a microcon-

N_{LU}

troller, the results showed that the velocity of the spot movement in strait line can reach easily 360 cm/s while the consumed power of the active neurons is less than 10 μA. Also, similar nonlinearity of the network behaviour was obtained when it was tested in real conditions using a LASER beam that was moving across a photodiode area. The spot wandering speed which might be compensated by the spiking neural network makes this type of tracking device suitable for free space optics communications. Moreover, these low power neural networks are suitable for improving the efficiency of the photovoltaic power supplies by continuously tracking the light spot of maximum intensity.

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