A NEW METHOD TO OBTAIN NON VOLATILE MEMORY FOR NETWORKS OF SPIKING NEURONS

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In this paper we describe a new method for long term keeping of the electronic synapses potentiation after the neural network training. Using the main properties of our biologically inspired electronic neuron which includes plasticity mechanism of the natural synapses, this method is based on neural network recurrence. Therefore, keeping in mind that the synaptic weights stored by capacitors are lost in time in case of no synaptic activity, the network recurrence compensates this synaptic depression. This new method was tested on a network of spiking neurons which was trained in two phases: first one was to recognize simple words formed by vowels and the second one was to build long term recurrence while keeping the ability to detect previously trained words. Our final goal, however, is not to make a speech recognition system but developing a neural system able to explain the long term and short term memory mechanisms of the human brain

Key words: electronic neurons, long term memory, recurrence, spiking neurons.

1. INTRODUCTION

Until now, the mechanisms that underlie the operation of the biological brain are less understood. To solve this problem, it is possible to study the behavior of biological neurons by making experiments directly on neural tissue in vivo or by developing physiologically correct model of neurons and study the behavior of networks of such neurons.

The mechanisms that govern the natural neuron physiology could be implemented in software by developing the mathematical model of the neuron operation or in hardware by building an electronic schematic which operation mimics the main aspects of the natural neuron physiology. Despite the main advantage of first approach which is the easiness of the model development, the mathematical model of the neuron has one important disadvantage: the dependency of the network response time on the number of neurons [13]. On the other hand, due to parallel operation of the electronic neurons, the hardware approach in obtaining the artificial neural network has the main advantage of independency between network response time and the number of neurons. However, one important aspect which needed to be taken into consideration represents the long-term memory of the neural network which implies the necessity of using non-volatile storage of the synaptic weights. This request is an easy task for the software implementation of the neural networks but for the electronic model this implies the use of some advanced techniques such as floating-gate transistor [8], [3]. The gate of such transistor has the ability to store the electronic charge for unlimited period of time due to its insulation cover. However, the disadvantage of this method to obtain non-volatile memory represents the necessity of using UV radiation or high voltages to alter the charge protected by the high-quality insulator [2].

Therefore, artificial models of neurons implemented in software and hardware could help in understanding of the brain activity. The electronic model of neuron brings real time operation to the neural network despite the difficulty in obtaining non-volatile storage of the synaptic weights.

2. NEURON MODEL

Artificial neurons should mimic the spiking nature and the synaptic strengths variability of the biological neurons. To achieve this goal, the electronic neuron design started from the operation principles of the *integrate-and-fire* model elaborated by McGregor, which are the integration of incoming stimuli using a capacitor and detection of the neuron activation threshold [14]. The neuron activation resets the input potential and generates a voltage spike. Keeping these basic principles of the McGregor model, the electronic neuron used for this work integrate new features such as membrane potential, neuron excitation and inhibition, refractory period, activation threshold, as well as the natural mechanisms of learning such as posttetanic potentiation (PTP), long term potentiation (LTP) and short term potentiation (STP). From the biological point of view every time the neuron fires, the PTP increases at a low rate the presynaptic stimulation strength and the STP increases temporary the postsynaptic sensibility which begins to decrease asymptotically to the pre-firing value. In case of postsynaptic action potential during the STP the synaptic sensibility is fixed at current value triggering the LTP for that synapse [1]. Synaptic depression represents a decrease of the synaptic efficiency which lowers the stimulation strength. The causes that trigger these mechanisms are not known, but it is supposed that synaptic depression happens when a neuron is stimulated just under its activation threshold without producing its action potential [15]. On the other hand, a group of scientists supposed for their neuron model that the postsynaptic neuron activation potentiates the synapses activated short before postsynaptic potential (PSP) while depressing the others which are activated short after PSP [18].

Our neuron strengthens the synapses activated prior to its action potential, while leaving unchanged the ones with post PSP activity. The gain in synaptic efficiency depends on the time interval elapsed until PSP in a way that the shorter the interval is, the more potentiated the synapse will be.

2.1. NEURON STRUCTURE

The electronic neuron was designed to model the critical features of the biological neuron physiology using only passive and semiconductor electronic elements. The neuron, with the structure from Figure 1, is divided in three functional units which are the input module (IM), spike generation module (SGM) and efficiency control module (ECM). Because we made detailed description of the neuron operation in our previous work [10], this paper will focus mainly on the ECM properties.

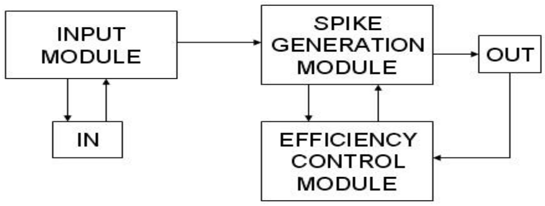

Fig. 1. The basic structure of the artificial neuron.

The integration of the incoming stimulation and detection of the neuron activation threshold is performed by IM, while the SGM generates action potentials in order to stimulate the postsynaptic neurons. The energy of every generated action potential or spike depends on the value stored inside the ECM.

2.2. IDEAL MODEL OPERATION

To easy understand the basic principles of the artificial neuron operation the schematic in Figure 2 represents an ideal model of electronic neuron. The saturation of the transistor Q_{NPN} represents the neuron action potential when it is considered that the neuron is active. Thus, when the integration of the received spikes made by the capacitor C reaches the V_{BE} of the threshold detection transistor, the neuron will fire. The saturation of Q_{NPN} and respectively Q_{PNP}, determine some current flows which alter the synaptic weight stored by LC.

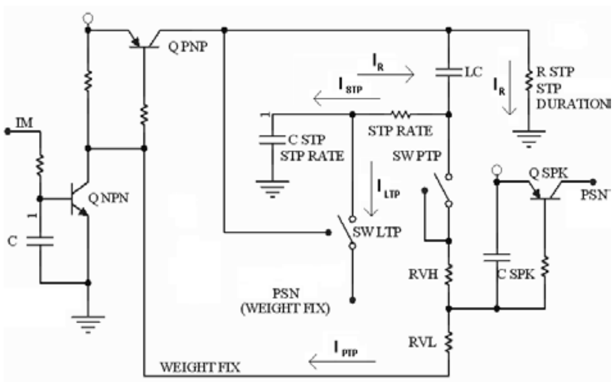

Fig. 2. Electronic schematic for illustration of the neuron ideal operation. Switches SW LTP and SW PTP isolate the ideal capacitor LC which stores the synaptic weight.

Therefore, the action potential of the neuron closes the SW_{PTP} determining the current I_{PTP} which increases the synaptic weight. This mechanism models the *posttetanic potentiation (PTP)* of the biological synapses which means that the stimulation intensity increases with every neuron activation. During the action potential, saturation determines another current which discharges an amount of LC inside another auxiliary capacitor. This process determines a temporary increase of the synaptic efficiency. During the neuron idle state, the electronic charge stored temporarily by C_{STP} returns to LC at a rate determined by current. The charge restoring period determine the duration of the *short time potentiation (STP)* while the synaptic efficiency returns to its pre-firing state. It is requested that the current limited by resistor R_{STP} during *STP* to determine SW_{PTP} closing. Thus, the postsynaptic neuron activation determines a sudden discharge of the C_{STP} by current I_{LTP}, fixing the synaptic weight at current value. This behavior models the *long term potentiation (LTP)* of the natural synapses. Equation (1) gives the energy of every spike generated by the electronic neuron, which is a consequence of charge.

$$E = UIt \tag{1}$$

The LC discharging increases the charge variation from C_{SPK} through voltage divisor RV_H - RV_L, which will increase the time interval while Q_{SPK} remains open. From (1) we deduce that when impulse amplitude U and intensity I remain constant, the spike energy increases proportionally with t. Therefore, the variation of the synaptic weight memorized by LC alters the spike energy generated by the neuron, modifying the efficiency of the synaptic transmission.

2.3. ARTIFICIAL MECHANISM OF LEARNING

Taking into account the principles of the ideal neuron behavior described above, it is necessary to spot on some aspects which make the real electronic neuron operation possible. Thus, the synaptic efficiencies are memorized by the ECM – which schematic is shown in Figure 3 – using, like for ideal model, a capacity LC. Depending on the natural mechanism of learning modeled, the activation moments of the presynaptic and postsynaptic neurons could alter the LC charge in three ways. Thus, the action potential of the presynaptic neuron triggered by saturation of Q_T and Q_A determines the electronic *PTP* by discharging the capacitor LC through $R_{PTP} = RV_H + RV_L + RD$, and the electronic *STP* by discharging LC in C_S. After the neuron firing, by closing the pair Q_T - Q_A, the charge stored temporary by C_S is regained asymptotically by LC through RS, pulling the synaptic weight to its pre-firing state.

Taking into account that the V_{ADJ} sub-module increases the Q_L base potential by an under saturation threshold value, the postsynaptic neuron activation occurrence during presynaptic *STP* will fix the synaptic efficiency to its current state triggering the electronic *LTP*. The postsynaptic neuron activation is signaled by pulling the input PSN to ground which holds Q_L open while $V_{STP} > 0$. In other words C_S will be discharged until the lost equilibrium between C_S and LC will be established. To maximize the effect of associative learning mechanisms *STP* and *LTP,* the *PTP* rate was chosen much lower than the *STP* rate which probably is in concordance with the way the biological synapses behaves.

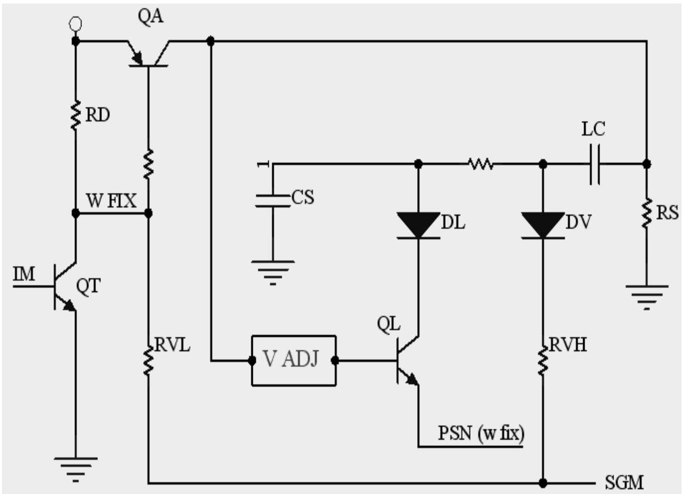

Fig. 3. The schematic of the ECM where pico ampere diodes DL and DV are used to keep the synaptic weights stored in LC.

2.4. ELECTRONIC SYNAPSE DEPRESSION

One important aspect about real hardware implementation of the neural networks represents the synaptic weights non-volatile storage. Considering the electronic schematic shown in Figure 3 which models synaptic mechanism of learning, experimental data showed a variation of the synaptic weights in a way that determines synaptic depression. This was caused by the leakage currents of the diodes D_L and D_V which are used instead of mechanical switches of the ideal model. These diodes recharge LC in case of no synaptic activity making the neuron to lose its memory. However, the synaptic depression rate is lower than that of learning but higher than would be normal to be in concordance with the biological neuron. Therefore, the leakage current of the diode should be as low as possible. The technology available today permits obtaining pico amperes diodes (PAD) where reverse current of diode decreases down to pA. Some examples of PAD would be PAD1, PAD2 or PAD5 but for the neuron model developed we use *BAS45* with $I_R^{\max} = 1nA$ at $V_R = 125V$. The measured leakage current at $V_R = V_{NOV} = 1,6V$ is $I_R \approx 100\,pA$ where V_{NOV} represents the *neuron operating voltage.* The experimental results show that for LC capacity $C_{LC} = 1\mu F$ and $R_S = 1M\Omega$ the LC charge varies with about *1% per hour* in case of no neuronal activity. During neuron firing this modification of the synaptic strength will induce a negligible variation to the generated spike energy. Therefore, for ECM, the use of PADs associated with capacitors represents an acceptable solution to store the weights of the electronic synapses.

Thus, despite the leakage currents induced by diodes, the use of PADs coupled with capacitors represents a simple and very reliable option for weights storage of the electronic neural networks.

2.5. ELECTRONIC NEURON LONG TERM MEMORY

The design of the electronic neurons which mimic the natural neuron physiology permits the frequency dependent potentiation of the synapses. Thus, with every action potential of the neuron the mechanism which models the *PTP* increases the efficiency of the synapse at a very low rate. Taking into account the depression of the electronic synapse in case of no neuronal activity and the electronic *PTP*, it is clear that proper frequency of stimulation could compensate the artificial neuron losing of memory. The equilibrium of these mechanisms could keep the electronic neural network infinitely trained. Moreover, this behavior of the artificial neural network could be in concordance with the biological brain physiology which loses its memories if they are not reactivated for long periods of time.

The action potential of the artificial neuron used for this work lasts about $t_a = 40\,us$. This value coupled with the capacity $C_{LC} = 1\mu F$ and the resistance $R_{PTP} = RV_L + RV_H = 71k\Omega$ gives the charge lost by LC during single neuron activation. Taking for example $V_{C0}^A = 1.9V$, during neuron activation which corresponds to a value of $V_{C0}^I = 1V$ during neuron idle state $\left(V_{C0}^I = V_{C0}^A - V_{NOV} + 0.7V\right)$ we obtain $V_{C1}^A = 1.8989V$ after $t_a = 40us$, which means that LC loses about $\Delta V_C = 12mV$ from its initial charge. Considering that the leakage current of the diode recharges the LC with about *0.9%* per hour and the charge lost by LC during neuron action potential $\left(\Delta V_C\right)$ corresponds to *1.2%* from V_{C0}^I results that it is necessary one action potential every 80 minutes in order to keep the synaptic memory. The vowel recognition experiment performed for our previous work [9] showed that the network was able to compute whether the frequency of stimuli was higher than 10 Hz. Therefore, it is clear that this weight refreshing mechanism does not affect the normal activity of the neuron.

3. NEURAL NETWORK RECURRENCE

The recurrence of the biological neural networks represents a mechanism which effect on neural computation is not fully understood [1]. For the first time it was inferred by Hebb who thought that the information is kept by these recurrent connections until the short-term memory is transformed in long-term memory. Thus, the feed forward neuron activity is diluted inside next layers of the neural network to come back for reintegration at the neuron which generated it. In other words, the neuron action potentials become orchestrated by the network activity implying that the neuron is present at different levels of integration depending on the topology and previous activity of the network. It was discovered that inside of a neocortical column the neurons could present reverberations of order higher than two, but the effect of this behavior is not known [1]. The great complexity of the neural network increases the probability that these recurrent connections include both excitatory and inhibitory neurons which participate to self training of the initial feed forward connections.

3.1. RECURRENCE FOR ARTIFICIAL NETWORKS

The calculation done earlier demonstrates that the neuron activation at a time interval compensates the loss in synaptic efficiency. One way to achieve these refreshing action potentials that hold the electronic weights in place could be achieved by network recurrence. We chose to investigate this kind of refreshing mechanism because it could be obtained naturally by network training without any additional hardware or software equipment. Moreover, the recurrent connections are present inside the biological neocortical columns [1]. Therefore, it is supposed that the electronic feed forward stimuli train the neural network to that point that is capable to transform the short term memory into long term memory. The network should potentate the synapses to make the desired task, as well as, to form another neural circuit which help to maintain its pervious trained synapses.

For exemplification of how the artificial recurrence mechanisms should be applied on feed-forward neural connections, it was considered a network able to be trained to execute a simple task like vowel detection using sounds specific formants like in Figure 4. For simplicity in illustration of the basic principles of artificial recurrence, we use constant frequency stimuli as input for the network. Both input neurons are stimulated by the same formant of /a/ vowel using a signal adaptation device described in the sequel.

The connections of this kind of long term memory are formed by strengthening the auxiliary synapses s_2, s_3, s_4 and s_5 to drive the information back to the task solving neurons. The synapses [v]s1, [v]s2 and [v]s3 are considered to be potentiated during first phase of the network training by vowel repetition. The activity of the recurrent connections will trigger the *PTP* for all synapses of [v]N3 including [v]s1. The role of the loop formed by neuron [r]N2 and network area [r]NA3 during second phase of learning is to generate trains of impulses which frequency is divided by the group of neurons [r]NA4. The high frequency impulses generated by [r]N2 decreases because of the integration properties of neurons contained [r]NA4, which determine the time interval between refreshing spikes.

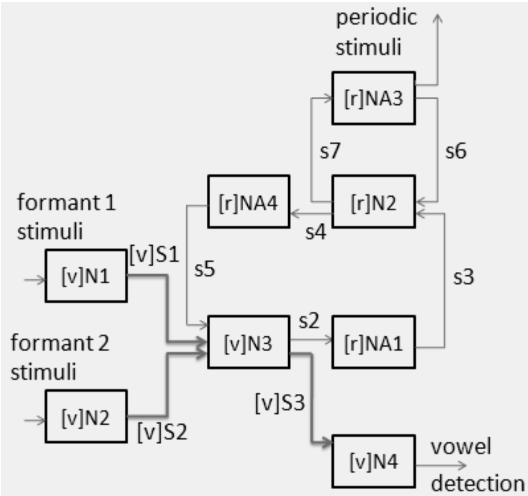

Fig. 4. A simple model of neural network for vowel detection to illustrate the basic principles of recurrence in obtaining long term memory. The network input neurons [v]N1 and [v]N2 are stimulated by vowel formants and the output neuron [v]N4 generates trains of impulses when both inputs are active.

Therefore, the theoretical model of recurrent network described above, and the fact that there is evidence that some natural neurons are able to build recurrence inside the brain, encourage us to use it for keeping the learning of the word recognition network in our long term memory experiment presented in the sequel.

4. LONG TERM MEMORY EXPERIMENT

To validate this method to obtain long term memory, we performed an experiment which started from a network structure stimulated by bursts of impulses that represent vowel specific formants. The learning process is based mainly on the use of supraliminal stimuli generated by external medium which increase the rate of synaptic potentiation. To test the capacity of a network of spiking neurons to keep its synaptic weights we wired additional neurons in a topology able to maintain the network previous training.

4.1. NETWORK INPUT STIMULATION

The vowel specific formants are generated by an electronic device which splits audio spectrum into frequency channels that stimulates the input layer of the network like in Figure 4. After training, the neural network activates one output neuron for every vowel recognized. Thus, the /*e*/ *vowel detection network* (EVDN) generates a train of impulses when the inputs *ch1*, *ch2*, *ch3*, *ch4* are stimulated by *2134 Hz* and *1808 Hz* /*e*/ vowel specific formants. Depending on the network level of training, the EVDN output could be activated by 3 or 4 netwok inputs. This means that higher synaptic weights will make the network to respond to fewer activated inputs, as well as more stimulated inputs will increase the output frequency.

The speech is split into frequency channels with central frequencies which vary from 1031 Hz to 3901 Hz. These central frequencies shown in Figure 5 were deduced by a group of researchers from The University of Texas who made a speech recognition experiment on human subjects in order to determine the number of channels necessary to understand speech [12].

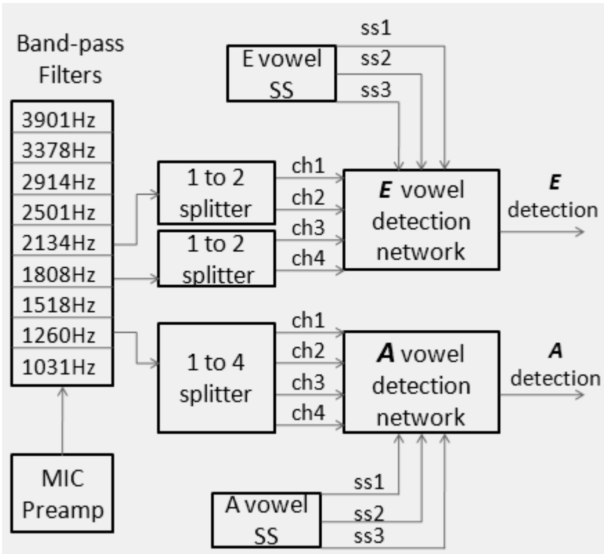

Fig. 5. The electronic device which stimulates the vowel detection neural networks. Audio signal from a microphone is split into frequency channels using band-pass filters characterized by central frequencies and then transformed into parallel trains of impulses by channel splitters.

For this work, every frequency channel generates trains of impulses which are split into more network specific trains of impulses in order to obtain more stimulation power for our vowel detection networks. The frequency channel stimuli are reintegrated by *1to2* and *1to4 splitters* and converted into trains of impulses by the network input layer. As an example the output of vowel /a/ specific band pass filter (BPF) with central frequency of 1260 Hz is presented in Figure 6 (a). The Figure 6 (b) shows the reintegration performed by *1to4 splitter* (signal 1) and the burst generated by the corresponding input layer neuron (signal 2). One important aspect which needed to be mentioned is the fact that the train of impulses ends after the channel stimulation finishes. This property was considered for our experiment in order to obtain the coincidence of stimuli generated by spoken vowels during words recognition. The */e/ vowel SS* and the */a/ vowel SS* modules represents some switches that activate some neurons inside EVDN and respectively, AVDN in order to obtain the LTP for the synapses activated by vowel reception. This mechanism is used to increase the learning rate of the synapses which activity was concurrent with the supraliminal stimuli.

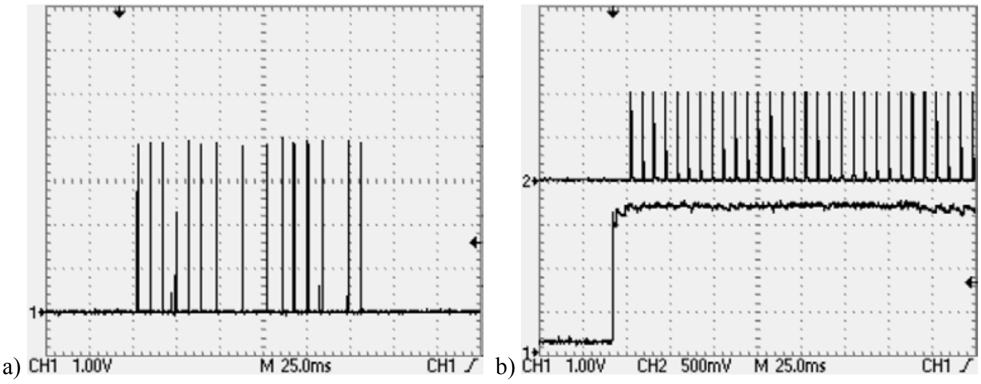

Fig. 6. The network input signals. a) BPF output, b) BPF output reintegration by splitter (signal 1) and input layer neuron generated spikes.

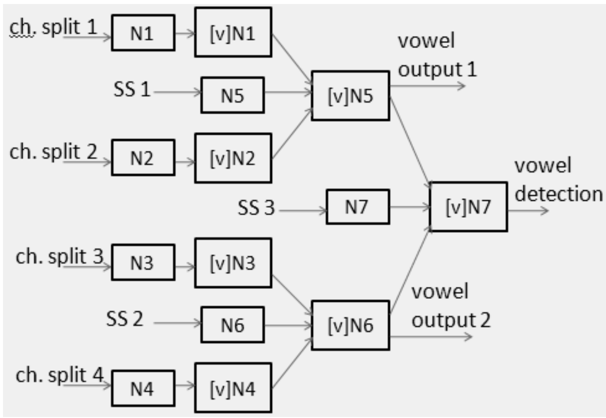

Fig. 7. The four-inputs and one-output vowel detection neural network. The network is stimulated by split frequency channels specific for one vowel. The supraliminal stimuli SS1, SS2 and SS3 increase the learning rate and the output neuron [v]N7 activity signals the vowel detection. The *vo1* and *vo2* signals the vowel of reception but with lower accuracy.

The topology of the vowel detection network is shown in Figure 6. The neurons N1, N2, N3 and N4 form the network input layer used as a filter between external stimuli and the neural network hidden layers. The neurons [v]N1, [v]N2, [v]N3 and [v]N4 are able to form connections with neurons [v]N5, and respectively [v]N6. By integrating the activity of the last ones, the neuron [v]N7 is able to perform vowel detection. The stimulation of inputs SS1, SS2 and SS3 will make the neurons N5, N6 and respectively N7 to oscillate. These oscillations will potentiate the activated synapses by PTP which will send supraliminal stimuli inside the neural network activating the postsynaptic neurons. These auxiliary connections which increase the rate of synaptic potentiation for the new synapses by LTP are referred throughout this work as supraliminal stimuli (SS). Thus, the SS could control the formation of the network topology when they are activated concurrently with the speech stimuli.

4.2. NETWORK ACTIVITY

The input neurons stimulate the following layer formed by neurons [v]N1, [v]N2, [v]N3 and [v]N4. Because the activity of these neurons when stimulated is similar, figure 7 shows the variation of input potentials for N1 (signal 2) and [v]N1 (signal 1).

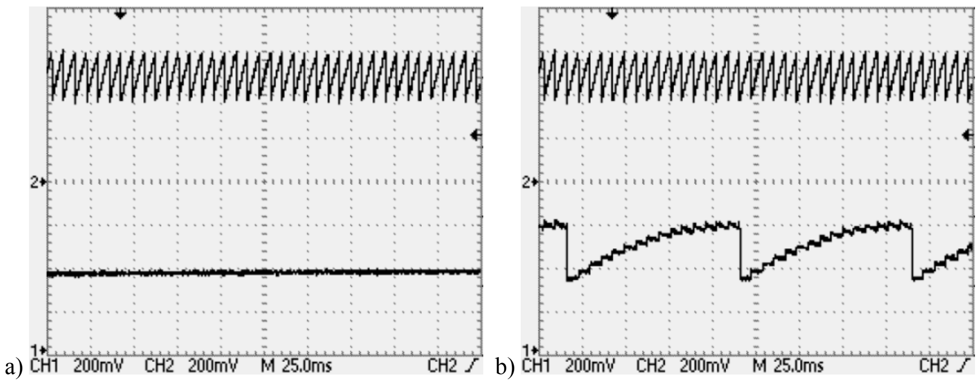

Fig. 8. Connection training by repetition. Signal 2 in (a) and (b) is N1 input during vowel reception, signal 1 in (a) is [v]N1 activity before training and in (b) during training when the N1 stimulation produces [v]N1 activation (sudden decrease of input potential).

Some aspects about the training process of the incoming synapses to [v]N7 using SS3 are spotted by signal diagrams from Figure 9. Therefore, the initial subliminal stimulation of the layer 2 neurons (waveform a) is transformed into supraliminal activity by continuously speaking of vowel /*a*/ (waveform b). Signal 1 on both diagrams represents the input potential of the N1 which is activated by /*a*/ reception, while signal 2 shows the synaptic stimulation power before training and after few repetition of /*a*/ vowel. The connections to the next network layer formed by [v]N5 and [v]N6 were formed using SS1, and respectively, SS2.

The action potentials of neuron [v]N6 represents the sudden decreases of the potential on diagrams a), b) and c) which means that the neuron is sending stimuli to vowel detection neuron [v]N7. Signal 1 on the same diagrams represents the input potential for the postsynaptic neuron [v]N7 in three phases of the synaptic potentiation: before learning (a), during learning when the SS3 activity is present (b), and when SS3 is missing (c). As shown in (d), after training [v]N7 is activated once by the presynaptic neurons [v]N5 and [v]N6. Signal 2 on this diagram (d) shows the idle state of SS3.

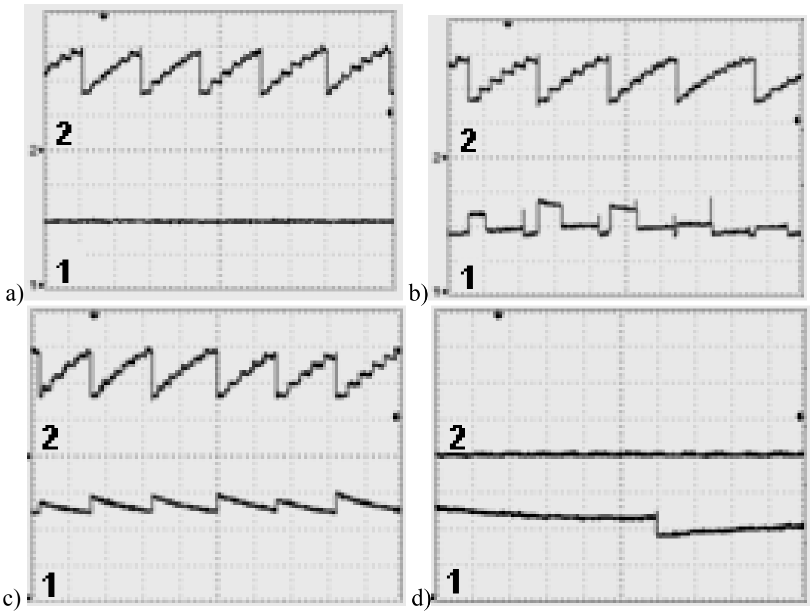

Fig. 9. Vowel detection neuron training. Signal 2 in (a), (b) and (c) [v] N6 input potential activated by [v]N3 and [v]N4, (d) inactive SS3; signal 1 represents the input potential of the [v] N7: (a) before training, (b) during training in presence of SS3, (c) during training in absence of SS3, (d) after training where it is activated by presynaptic neurons.

Concluding, every vowel is detected using less than 15 electronic neurons which are stimulated by vowel formants converted into trains of impulses. The network is trained using supraliminal stimuli which activity is controlled by a supervisor and the vowel recognition is made using input stimuli association.

4.3. WORD RECOGNITION

As was mentioned above the vowel recognition is performed by association of the formants with concurrent activity. Considering that the splitters which make the conversion of BPF output to network specific stimuli were designed to keep the network stimulation for a short period of time after vowel reception, it is clear that successive spoken vowels will stimulate the network input layer concurrently. This fact permits the word detection by association of the frequency channels generated by the vowels that word contains. Figure 9 illustrates the behavior of two input neurons when the network receives the word /*ea*/ specific stimuli. The presence of /e/ vowel specific formants into audio signal spectrum is shown by signal 2 while vowel /a/ specific stimuli are presented by signal 1. It could be observed that after the onset of the /e/ stimulus, the network receives concurrent stimulation from both vowels.

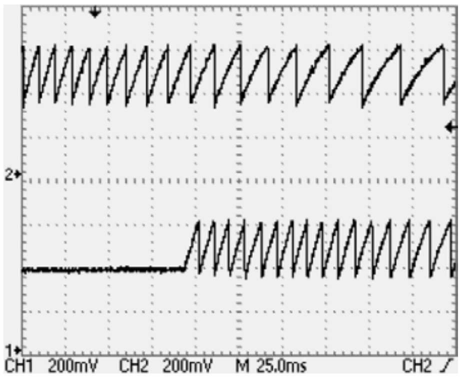

Fig. 10. The input neurons activity during word /*ea*/ reception where signal 2 represents the /e/ vowel stimulation while signal 1 represents /a/ vowel stimulation.

The network topology from Figure 11 could be trained to perform word recognition using the same principles as vowel recognition network. Thus, the network input layer uses two channels for every vowel which stimulates the same neurons as in vowel recognition part of the experiment. Thus, the neurons [a]N1 and [a]N2 activate [a]N5 during /a/ reception while the [e]N1 and [e]N2 activate [e]N5 when /e/ specific channels stimulate the network input layer. As it was shown above by the first part of the learning process, the pairs of synapses (*s1, s2*) and (*s3*, *s4)* are potentiated in order to perform vowel recognition.

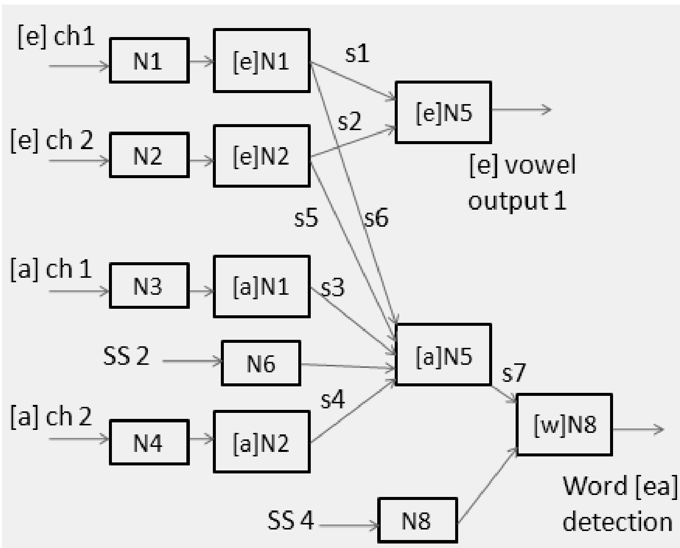

Fig. 11. A network topology able to perform word recognition as vowel successions. The input neurons N1 and N2 are stimulated by /e/ vowel while the N3 and N4 receive stimulation from specific channel of /a/ vowel. The word detection neuron [w]N8 is activated by concurrent stimuli generated by both vowels.

The new part of the experiment represents the strengthening of the synapses *s5* and *s6* through which the /e/ specific neurons [e]N1 and [e]N2 stimulates /a/ specific neuron [a]N5. The potentiation mechanisms are triggered by vowels coincidence when the supraliminal activity of *s3* and *s4* takes the role of *SS2.* Therefore, after some repetitions of word /ea/ the /e/ vowel specific channels *[e]ch1* and *[e]ch2* are able to activate neuron [a]N5. This does not affect the vowel /a/ detection mechanism because both [v]N5 and [v]N6 should fire in order to activate [v]N7 (see figure 6). Until now, like it is shown by signal 1 in Figure 12 (a) and (b), the neuron [a]N5 is activated independently by both vowels.

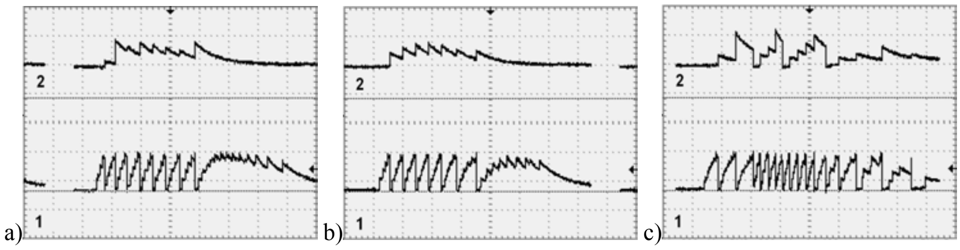

Fig. 12. The input potential of neurons [a]N5 (signal 1) and [w]N8 (signal 2) after network training when (a) vowel /e/ is spoken, (b) vowel /a/ is spoken, (c) word /ea/ is spoken. The neuron action potentials are given by sudden decreases of signals.

Thus, it is necessary to use other neurons able to perform discrimination between vowels and the word received. This word detection mechanism is ensured by neuron [w]N8 which is activated when both vowels stimulates the network. The training of the synapse *s7* which stimulates [w]N8 is made using *SS4*. Signal 2 in Figure 12 (a) shows the input potential of [w]N8 when vowel /e/ is received, while in Figure 12 (b) shows the same input potential during /a/ reception. It could be observed that the independent stimulation of the two vowels is not able to activate the postsynaptic neuron [w]N8, as it happens in figure 11 (c) when both vowels stimulate the network during /ea/ reception.

4.4. LONG TERM MEMORY FOR WORD RECOGNITION SYNAPSES

Due to the fact that the synaptic weights are stored by capacitors which naturally alter their charges in case of no network activity, it is necessary to refresh the synaptic efficiencies after network training. This goal is achieved by using some loops which permits reactivation of every synapse or a group of synapses in order to obtain long term memory. The recurrence mechanism described at the end of previous chapter could be used successfully to keep the synapses potentiated in case of no network activity. The calculation which was done earlier shows that the optimum reactivation period for a synapse is approximately 80 minutes.

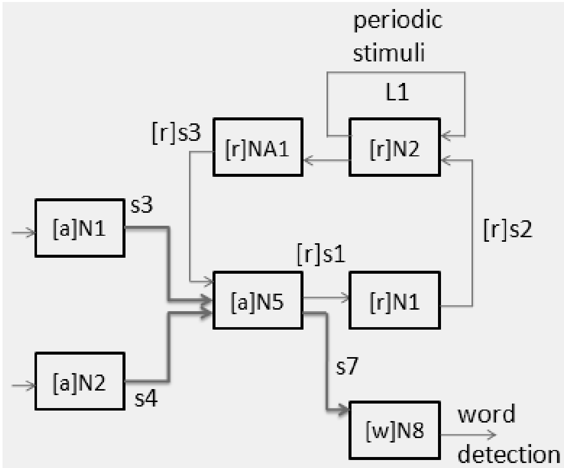

Fig. 13. A reccurent network for keeping the potentiation of the synapse *s7* from the word detetion network. The frequency of stimulation generated by [r]s3 is divided by network area [r]NA1.

Figure 13 shows a recurrent network for keeping the synapse *s7* potentiated. In order to obtain recurrent connections which return the information back to the feed forward neuron in a long period of time, there is necessary one secondary neural loop *L1* which for our model generates trains of impulses with $f \approx 40Hz$. This frequency returns to neuron [w]N8 divided by the network area [r]NA1 composed of excitatory and inhibitory neurons. By activating the loop *L1* and by strengthening the synapses which drive the [r]NA1 stimuli back to [a]N5, it is obtained the [a]N5 reactivation. This will prevent the *s7* for being depressed. It is needed to mention that because the complexity of architecture of spiking neurons, the network area [r]NA1 is not able to generate impulses at exactly 80 minutes. This aspect does not put any problems to the word recognition network because our previous experiments on this kind of neural networks demonstrate that it is not necessary to use highly precise values for the synaptic weights. Therefore, in order to keep the synapse s7 potentiated, the time interval between the spikes generated by [r]NA1 could be lower than 80 minutes, but not higher.

5. CONCLUSIONS

The main advantage of the analogue neural networks is the real time operation. In other words by parallel execution of the hardware implemented neurons the artificial network could respond faster than the biological neural network. This is a crucially advantage over software developed models for which the neural computation speed represents a major disadvantage [1]. However, the problem of electronic networks represents the necessity of mechanisms that are able to keep the network trained in case of long periods of external stimuli inactivity. In order to increase the period of time the electronic synapses remain potentiated after offset of the external stimuli, we use some pico ampere diodes which lower the variation of capacitor charge down to one percent in about 80 minutes. Moreover by using the posttetanic potentiation mechanism of the electronic neuron, the weights variation due to these leakage currents of the diodes could be compensated by reactivation of the neuron. This goal is achieved by using network recurrence which permits reintegration of the generated information. To test these long term memory principles we developed a network topology able to be trained to recognize spoken vowels by formant association and to recognize words formed by previous trained vowels.

This work solved two problems encountered in our previous research activity which are the decrease of the depression rate of the electronic synapses by using pico ampere diodes, and to obtain network long term memory by using recurrent connections. Moreover, by using more neurons for vowel recognition network and the use of channel splitters which reintegrate the impulses generated by BPF we improved spoken vowel detection accuracy, as well as word detection accuracy. The next research aims are to include recognition of consonants to word recognition neural network and to improve the network recurrence mechanisms.

REFERENCES

1. BAUDRY M., DAVIS J.L., THOMPSON R., *Advances in Synaptic Plasticity,* The MIT Press, Cambridge, MA, 1999, 133–137; 257–259.
2. HASLER P., *Floating Gate Devices: They are not Just for Digital Memories Anymore*, Proceedings of the 1999 IEEE International Symposium on Circuits and Systems, ISCAS '99, July 1999, **2**, 388–391.
3. HASLER P., LANDE T.S., *Overview of floating gate devices, Circuits and Systems*, IEEE Transactions on Circuits and Systems – II: Analog and Digital Signal Processing, January 2001, **48**, 1, 1–2.
4. HASTINGS A., *The Art of Analog Layout*, Prentice-Hall, Upper Saddle River, New Jersey, 2001, 77–84.
5. HASTLER P., DUGGER J., *Analog VLSI Implementations of Neural Networks*, The Handbook of Brain Theory and Neural Networks, November 2002, The MIT Press, Cambridge MA, 1–3.
6. HOPFIELD J.J., BRODY C.D., *What is a moment? Cortical sensory integration over a brief interval*, Proceedings of the National Academy of Sciences of the USA, 2000, 13919–13924.
7. HOPFIELD J.J., BRODY C.D., *What is a moment? Transient synchrony as a collective mechanism for spatiotemporal integration,* Proceedings of the National Academy of Sciences of the USA, 2001, 1282–1287.
8. HSU D., FIGUEROA M., DIORIO C., *Competitive Learning With Floating-Gate Circuits,* IEEE Transactions on Neural Networks, May 2002, **13**, 3, 732–744.
9. HULEA M., *A biologically inspired model of spiking neurons suitable for analog IC design*, ICAI 2008 Proceedings, July 2008, Las Vegas Nevada, USA, 807–812.
10. HULEA M., *A model of silicon neurons suitable for speech recognition*, CEAI Journal, 2008, **10**, 4, 32–41.

11. IZHICHEVICH E.M., *Simple Model of Spiking Neurons*, IEEE Transactions on Neural Networks, November 2003, **14**, 6, 1569–1572.
12. LOIZOU P.C., DORMAN M., *On the Number of Channels Needed to Understand Speech*, The Journal of Acoustical Society of America, October 1999, **106**, 4, 2097–2103.
13. LOVELACE J.J., *A Very Simple Spiking Neuron Model That Allows for Modeling of Large, Complex Systems*, Neural Computation, January 2008, **20,** 1, 65–90.
14. MAASS W., BISHOP C.M., *Pulsed Neural Networks*, November 1998, Cambridge MA: The MIT Press, 23–42.
15. O'REILLY R., MUNAKATA Y., *Computational Explorations in Cognitive Neuroscience*, Cambridge MA: The MIT Press, September 2000, 115–117.
16. SAINT C., SAINT J., *IC Layout Basics – A Practical Guide*, McGraw–Hill, New York, 2002, 143–222.
17. STEVENS K.N., *Acoustic Phonetics*, Cambridge MA: The MIT Press, January 1999, 204–214.
18. SWIERCZ W., CIOS K.J., *A New Synaptic Plasticity Rule for Networks of Spiking Neurons*, IEEE Transaction on Neural Networks, January 2006, **17**, 1, 94–99.
19. ⁂ The Blue Brain Project – URL: http://bluebrain.epfl.ch/page18699.html.

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