A Model of Silicon Neurons Suitable For Speech Recognition

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Abstract: In this paper we describe the structure of an artificial neuron designed using only basic electronic components such as transistors, resistors, capacitors and diodes which could be successfully implemented as the computation unit for a neural analogue integrated chip. Being able to associate between temporal events and to extract similarities from physical data, these neurons could be used as a tool for speech recognition or image processing problems. To test the performance of the electrical neural network under real conditions it was developed a tool which could perform speaker independent vowel recognition. The final goal of this approach is to manufacture an analogue integrated chip with similar behaviour as the neocortical column which is the basic functional unit of the biological brain.

Keywords: spiking neurons, Hebbian learning, vocals classification, silicon neurons

1. INTRODUCTION

The neuron represents the processing unit of the neural networks, its operation properties being inspired from the natural neuron physiology. In concordance with the biological behaviour, the spiking neurons generate trains of impulses when they are stimulated by changes of the external conditions [1]. Being able to detect events and generate a response when these events are concurrent, the spiking neurons have a great potential for obtaining good results in physical environment understanding. Moreover, offering the possibility of synaptic activity direct observation, the use of these neurons helps in understanding of the interactions that take place inside the biological neural network.

The behaviour of these artificial neurons could be programmed in software by developing a mathematical model or by implementing an electrical scheme which operation mimics the main features of the natural neuron. The hardware approach offers real time computation speed while using low energy. Moreover, the high degree of parallelism implied by electrical scheme offers high reliability to the network.

The principle of computation using spiking neurons is that they integrate the incoming positive and negative trains of impulses, the synapses being potentiated by almost concurrent stimulation [3]. Moreover, by delaying the information received from some sensors the neurons could associate events which happen at different time intervals. Therefore such neural networks learn to detect patterns of temporal events.

The use of the electronic neuron as computation unit for artificial neural networks offers a good alternative for developing the control modules of the intelligent machines. Providing a very good accuracy in modelling the natural neuron physiology, it could be, also, used to understand the mechanisms which determine some neurological diseases.

2. NATURAL NEURON

The connections between neurons are known as synapses. The neural message inside the neural network propagates unchanged through the neurons and altered through the synapses [1]. Thus the intensity of each stimulus depends on the synaptic transmission efficiency which depends on neurons activity. Therefore, the processing power of the natural neural networks is given by the synapses. The structural components of the biological synapse are the presynaptic and postsynaptic membranes as well as the ion channels. These components provide the neuron with the ability to transmit the information inside the network and to learn from previous experience.

2.1. Information processing

The signals inside the natural network are carried by different types of mediator which are released from presynaptic membrane. The mediator molecules are driven through synaptic gap to the postsynaptic membrane where they are opening the ion channels. The mediating substances are able to increase the postsynaptic membrane potential (PMP) by opening Ca^{2+} and Na^{+} ion channels or to decrease it by stimulating the Cl^{-} ion channels [1]. The neurons which stimulate the positive ion channels are excitatory while in the other are inhibitory. One neuron could produce only one type of mediator and could receive stimulation from both types of neurons.

The basic principle of the neural information processing represents the spatial and temporal integration of the incoming stimulation. This means that the PMP depends on the stimulation moment and on the place from where this stimulation comes. The increasing of the PMP above a threshold known as action potential, determines the postsynaptic neuron activation. During activation, the neuron releases the mediator from the presynaptic membrane into synaptic gap determining excitation or inhibition of the postsynaptic neurons. After neuron firing, the postsynaptic membrane is polarised under the equilibrium potential for a short period of time known as refractory period. During this time interval the sensitivity of the membrane decreases lowering the neuron capacity to fire [1].

Despite the fact that the action potential inside the neuron's body propagates instantly, the migration of the mediating molecules inside the synaptic gap induces a delay in the neural message transmission. This latency period between the mediator releasing and the postsynaptic action potential is one of the important aspects of the natural neuron physiology [1].

2.2. Associative learning

The natural neural networks have the ability to detect concurrent stimulation by modifying its synaptic efficiency in order perform events association. During neuron activation the mediator released from presynaptic membrane opens the specific ion channels from the postsynaptic membrane. This fact triggers some structural alterations of the stimulated synapses which determine their temporary potentiation [2]. The action potential of a postsynaptic neuron fixes at the current values the efficacies of the synapses which contribute to its activation. The long-term potentiation represents the basic mechanism of the associative learning [2]. This increases the weights of the synapses which were activated synapses in a period of time preceding the postsynaptic neuron action potential. Considering multiple impulses and the synaptic behaviour described above, it is clear that the concurrent activated synapses which participate to neuron activation will be more strengthened than the ones which have no contribution to any postsynaptic activity.

Another behaviour which determines synaptic efficiency alteration represents the increasing of the quantity of mediator released per neuron activation [1]. This feature and the long-term potentiation bring a great contribution to synaptic dynamics which are responsible for neural networks long-term learning.

3. NEURON MODEL

There are two models of spiking neurons which could represent the starting point in developing the hardware implementation of the artificial neuron. One is the conductance model (Hodgin – Huxley) which offers better accuracy in simulating the natural neuron physiology but the high complexity of the scheme increases the costs for large neural networks. In contrast, the integrate-and-fire model (McGregor) has a simplified spike generation mechanism while providing an accurate membrane potential approximation, neuron excitation and inhibition, as well as learning from previous experience [4]. The basic principle of the integrate-and-fire model consists of a capacitor C charged by a current I implying a potential U. The increasing of the potential U above a threshold V will make the artificial neuron to fire by generating an electrical impulse to each of the following neurons [3].

A model of spiking neurons which combines the biologically plausibility of Hodgin-Huxley model and the computationally efficiency of integrate-and-fire model was developed by Izhichevich (2003) [14]. Another model which is one of the newest models of spiking neurons was developed by Lovelace (2008) [15]. These two models were developed to decrease the network response time when the activity of thousands of neurons is simulated on a single processor.

On the other hand the artificial neurons developed for this work were designed to provide independency between network response time and the number of neurons. Therefore, due to the fact that operation of these neurons is based on physical laws which governs the electronic components – such as resistors, capacitors, transistors and diodes – an analogue network offers real time computation independent of the number of neurons.

3.1. Neuron structure

The electronic neuron whose structure is presented in figure 1 was designed to model the critical features of the biological synapse physiology while being suitable for silicon integration.

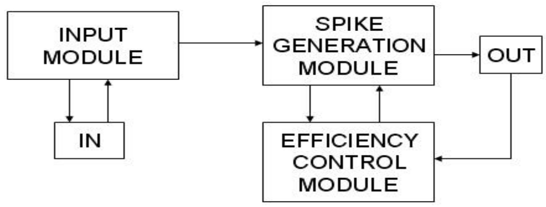


Fig. 1. The basic structure of the artificial neuron

The artificial neuron's body implemented using only simple circuit elements is divided functionally into three modules. These are the input module (IM) responsible with simulation of the postsynaptic membrane features, the spike generation module (SGM) responsible with information transmission and the efficiency control module (ECM) which models the natural mechanisms of learning.

3.2. Neuron stimulation

The IM – whose electrical circuit is presented in figure 2 – integrates the incoming impulses by charging the capacitor C through resistors R. It also activates the SGM when the integrated voltage from C reaches the NPN transistor base-emitter voltage.

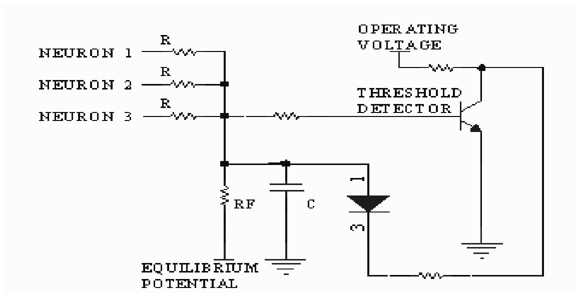


Fig. 2. Input module scheme. The capacitor C integrates the incoming impulses through resistors R and the neuron activation threshold is given by base-emitter voltage of the NPN transistor.

During development process the equilibrium potential of the artificial neuron was set to 0.4 V. The duration of the refractory period which begins after the neuron activation depends on the value of the resistor RF which limits the charging current of the capacitor C. Being composed only of resistors, capacitors, transistors and diodes this module is suitable for IC manufacture which is an important goal of the future work.

3.3. Synaptic weights adjustment

One important aspect of the biological neural networks physiology is the ability to learn from previous experience. Thus, the natural synapses could change their efficiency by increasing the mediator quantity released from presynaptic membrane or by improving the postsynaptic membrane sensibility.

The scheme of the efficiency control module (ECM) of the electronic neuron is shown in figure 3. An important task solved by the ECM represents the simulation of the natural mechanism of synaptic weights adjustment using only basic electronic components while keeping the scheme as simple as possible [12].

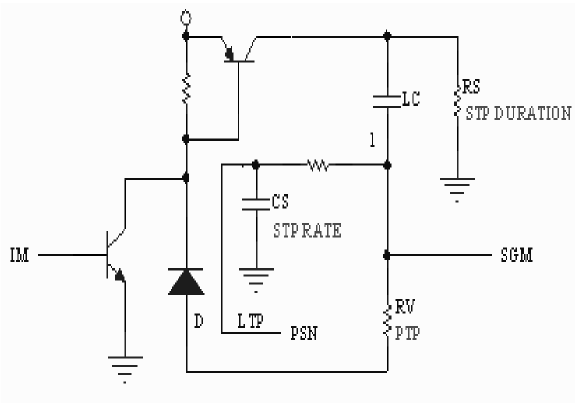


Fig. 3. The artificial neuron learning mechanism. The integration module (IM) triggers the STP and PTP by saturating the NPN transistor and the postsynaptic neuron (PSN) triggers the LTP. The synaptic efficacy stored by the capacity LC is given as input for spike generation module (SGM).

As presented by previous chapter, the short-term potentiation (STP), long term potentiation (LTP) and posttetanic potentiation (PTP) bring an important contribution to network weights dynamics. The synaptic efficiency is stored in a learning capacitor (LC) whose charge is a consequence of the neuron previous activity [5]. To simplify the electrical scheme design, the maximum charge of the LC represents minimum efficiency of the synapse, and the minimum voltage reached by LC during electronic neuron normal operation models maximum weight of the synapse. When the neuron is activated the charge stored by LC affects the impulse duration, the corresponding voltage being used as input by the SGM. The variation of the synaptic strength is modelled by exponential and logarithmic functions which describe the capacitor's charging and respectively, discharging.

The stimulation from presynaptic neurons integrated by the IM saturates the NPN transistor which opens the PNP transistor. This triggers the processes which simulate the natural synapses efficiency alteration. For the STP modelling, the LC is temporary discharged during neuron activation with an amount determined by STP learning rate. Because the STP is a reversible process, the charge lost by LC is stored in another capacitor CS. For this work it is considered that the postsynaptic neuron (PSN) activation triggers the mechanism which transforms the STP in LTP. If this mechanism is not initiated the potentiation of the electrical synapse is continuously decreased to almost its pre-firing efficiency. This process is determined by recharging the LC from CS through resistor RS. Therefore the duration of the temporary potentiation of the artificial synapse is proportional with resistor RS value and the STP rate is given by the parameter CS [5].

The presynaptic component of learning PTP is modelled by the current limited by resistor RV which discharges the capacitor LC when the neuron is activated. To model another important aspect of the natural neuron physiology, the PTP rate – determined by RV parameter – was chosen much lower than the STP rate [1]. If the postsynaptic neuron is activated during STP the capacitor LC voltage is fixed at the current value by the sudden discharge of CS. This will stop the synaptic strength decreasing which determines the LTP of the synapse.

Because the mechanisms which underlie the natural synapses depression are a subject of debate for neurosciences [1], this biological feature was modelled by continuous charge of the LC through diode D. The very low reverse current of the diode makes the synaptic depression a very slow process which happens in case of no synaptic activity. Being the reverse process of the synaptic potentiation the synaptic depression implies the decreasing of the synaptic weights.

3.4. Spike generation

Another important aspect regarding biological neuron behaviour is the activity of the natural presynaptic membrane which transmits the neural message to the following neurons. Thus, the SGM of the artificial neuron generates electrical impulses during neuron activation. The strength of every impulse depends on the ECM module output. Therefore, the weight of the synapse is proportional with the impulse duration. The variation of the stimulation intensity could also be modelled by spike amplitude alteration. However, the SPICE simulations of the circuit showed that the neuron discrimination power was lower than that obtained by spike duration modelling. Moreover, this would introduce a limitation in lowering the neuron operating voltage which is in contradiction with the future goals of analogues integrated chip development.

The spike generation module SGM – whose scheme is shown by figure 4 – generates a voltage impulse during neuron activation. The duration of each spike is given by the ECM and depends on the charge stored by the LC. Thus, the spike lasts longer if the voltage given by ECM is lower.

One biological feature simulated using the capacity CF and resistor RF is the fatigability. CF is charged during PNP transistor saturation with an amount which depends on the capacitor value. This will lower the power of the following stimulation by decreasing the amplitude and duration of the

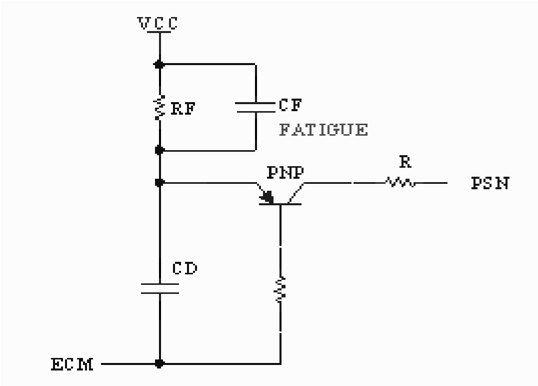


Fig. 4. The spike generation module (SGM) scheme with fatigue mechanism. The efficiency control module (ECM) opens the PNP transistor which will generate a spike to the PSN.

impulse. During idle state of the electronic neuron the CF is discharged by a current limited by resistor RF. High frequencies of stimulation will break the equilibrium between CF charging and discharging lowering the potential from PNP emitter. Therefore, the neuron will not be able to fire until the charge from CF is lost. This property makes the neuron a filter for high frequency stimulation.

3.5. Artificial Neuron Implementation

First step in natural neuron physiology modelling was the SPICE simulations of the circuit operation which provided good results for neuron development, but for large networks the simulation became time consuming. Therefore, a board design represented a better solution for network studying and testing under real conditions. However, because of the big physical dimensions, this approach in hardware implementation becomes difficult to handle when we deal with large networks of such neurons.

To solve this problem the electrical scheme of the artificial neuron was developed using only electronic components such as transistors, diodes, resistors, and capacitors which are suitable for silicon integration [6], [7]. Therefore, this will help in designing an analogue integrated chip with the same operation characteristics as the board, while taking the advantage of a substantially reduced size. Moreover, the SPICE simulations of the circuit showed that the values of the critical components could vary more than ±20% for capacitors and more than ±30% for resistors without affecting the overall operation of the neuron. This parameter variation is in concordance with the tolerance needed when designing the integrated chip which is an important aspect considered for the future work. The neuron model uses nanofarads of capacitance which is more than a single die could economically include during normal fabrication process [6]. Therefore, the manufacture of the integrated chip requires a special dielectric such as barium strontium titanate (BST) [9]. Another aspect that will be taken into consideration is the replacing of the LC with a floating-gate transistor which represents a better solution for on-chip non-volatile storage of the synaptic weights [10].

In the biological brain the neurons are organised into basic functional units which communicate between them, each containing about 10 000 highly connected neurons. These units known as neocortical columns are repeated million of times across the cortex [13]. The electronic model of one of these basic neural volumes containing ten thousand neurons could be integrated on approximately four square centimetres of die area when BST material is used for capacities implementation.

4. NEURON OPERATION

The main properties of the electronic neuron operation which are in concordance with the biological neuron physiology were illustrated using the board implementation of the artificial neuron. It were tested the spatial and temporal integration of the incoming stimulation, as well as the presynaptic and postsynaptic components of learning. Therefore, the signal diagrams presented forward spot on the posttetanic potentiation, short-term potentiation and long term potentiation of the artificial synapse.

4.1. Spatial and temporal integration of the incoming stimulation

The output layer of the artificial network shown in figure 5 is composed of one postsynaptic neuron which receives voltage spikes from two presynaptic neurons as it is illustrated by the signal diagrams from figure 6. Therefore, the diagrams (a) and (b) shows the input potential of the presynaptic neurons Pre 1 and respectively, Pre 2 which are activated by the input neurons IN1 and IN2.

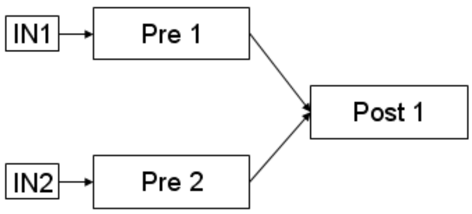
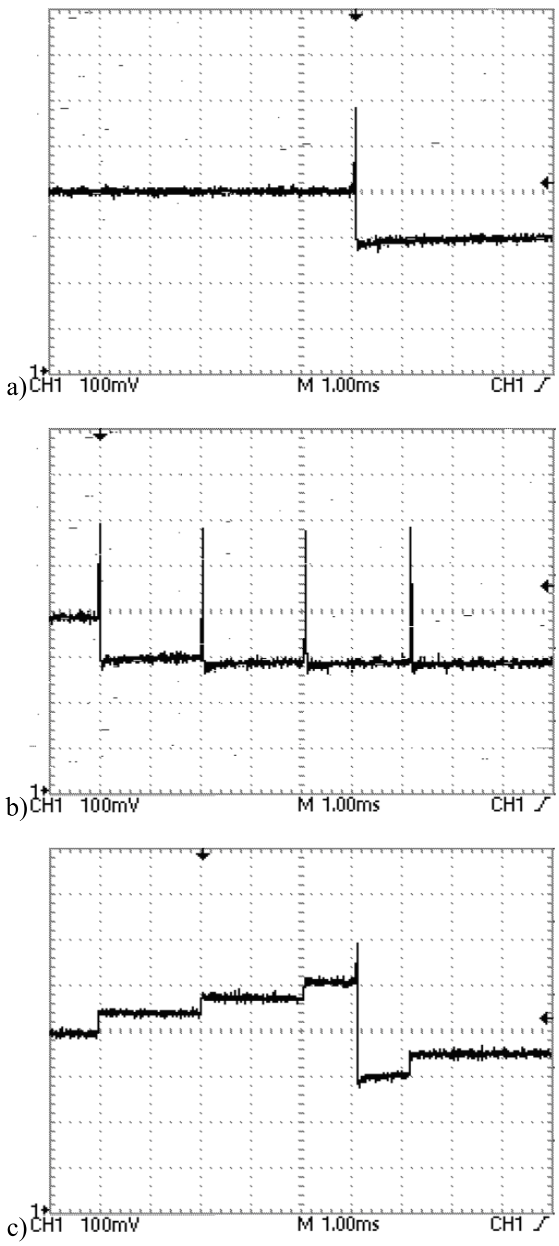


Fig 5. The structure of a network composed of two presynaptic neurons (Pre1 and Pre2) and one postsynaptic neuron (Post1)

The waveform (c) represents the input voltage of the postsynaptic neuron Post 1 which integrates the incoming stimulation from the Pre1 and Pre2. Thus, the neuron Pre2 whose activity is illustrated by diagram (b) increases the input potential of the Post1 without triggering its action potential. The postsynaptic neuron will fire as a consequence of neuron Pre1 activation. This behaviour is illustrated by the Pre1 input potential shown in figure 6 (a) and by the Post1 input potential presented by figure 6 (c).

Another property modelled by the artificial neuron is the refractory period which begins after the neuron firing is characterised by a temporary decrease of the input voltage below the equilibrium potential. The equilibrium potential is set to 400 mV below the V_{BE} voltage of the NPN transistor, while the beginning of the refractory period pulls down the input voltage of the neuron at 300 mV.



vertical div.= 100mV; horizontal div.= 1ms

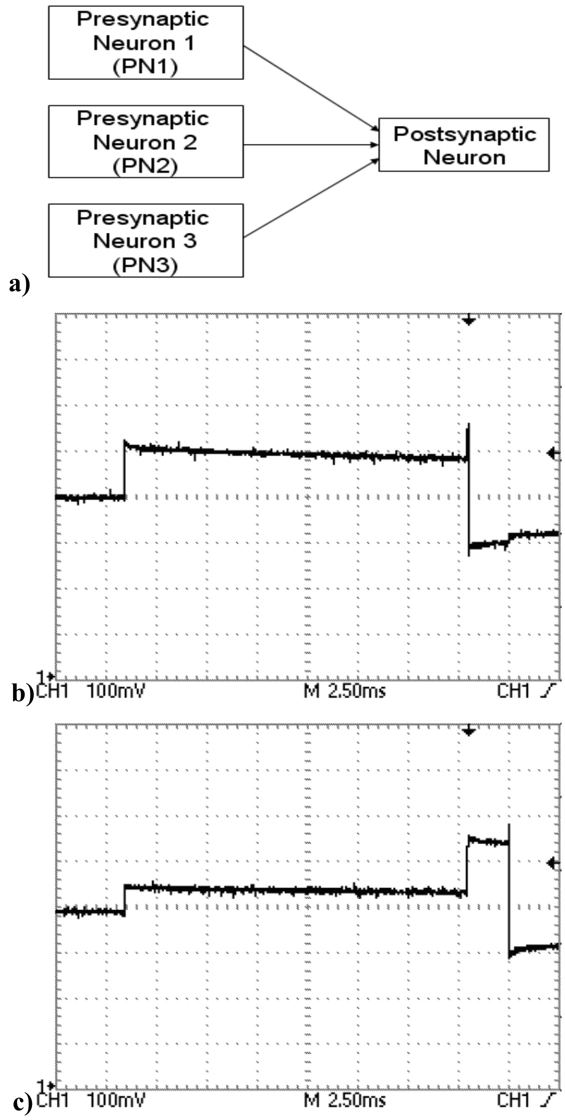
Fig. 6. (a) and (b) the input potential for two presynaptic neurons; (c) the input of a postsynaptic neuron.

For all signal diagrams shown in this paper the corresponding voltage of one vertical division is 100 mV and is shown below the diagram after 'CH1'. The corresponding time for one horizontal division is specific for every waveform and is shown below the diagram after letter 'M'.

4.2. Artificial mechanism of learning

The main rule of the synaptic weighs adjustment which is inspired from biology is that all the synapses which participate to the postsynaptic neuron activation are potentiated. On the other hand, the efficiency of the activated synapses after the postsynaptic action potential remains the same.

To illustrate the ability of the electronic synapses to change their efficiency, it was considered a network of electronic neurons whose topology is presented in figure 7 (a).



vertical div.= 100mV; horizontal div.= 2.5ms

Fig. 7. a) Network topology for underlying the rule which governs the synaptic potentiation; b) The influences of the presynaptic neurons on the postsynaptic input potential when during training the second one triggers the LTP only for previous activated neuron. c) The inverted proportionality between the potentiation rate of the synapses and the time elapsed until postsynaptic action potential was triggered by the third neuron.

The aim of the simulation was to spot on the importance of the LTP when almost concurrent events stimulate the network input. Thus, each of the presynaptic neurons PN1, PN2 and PN3 stimulates the postsynaptic neuron a number of times, each time the PN2 activating the postsynaptic neuron. The time intervals between the PN1 and PN2 activations, and respectively, between PN2 and PN3 activations are the same for all iterations. The action potential of the PN2 triggers the LTP only for previously activated PN1. Thus, after the network training the PN1 synapse should be more potentiated than the PN3. The second goal of the simulation was to spot the dependency between the gain in synaptic efficiency and the time elapsed until the postsynaptic neuron activation. The training is started again from null synaptic weights for PN1 and PN2, but this time PN3 activates the postsynaptic neuron triggering the LTP for the previous activated neurons. After the second phase of the experiment the first activated synapse should be less potentiated than the second one.

The signal diagram from figure 7 (b) confirms the supposition made showing the significant difference between the potentiation of the PN1 and the PN3 synapses when the postsynaptic neuron is stimulated by sets of three excitatory impulses. For the neuron PN1 the increase in synaptic strength was determined by the LTP which was triggered by the postsynaptic neuron activation, while for PN2 the synaptic efficacy was increased only by the PTP process. The waveform (c) confirms the inverted proportionality between the gain in synaptic strength and the time interval elapsed from presynaptic neuron activation and the postsynaptic action potential. Thus, the PN1 synapse is less potentiated than the PN2 synapse due to the fact that the PN2 activation moment is closer to postsynaptic action potential. This behaviour of the artificial neurons learning mechanism is used as the basic principle for the word recognition process which will be detailed in the next chapter.

5. WORD RECOGNITION EXPERIMENT

To test the ability of the artificial neurons in association of temporal events it was considered a network which performs vowel classification by frequencies association. The neural network which will be presented in the sequel is stimulated by sets of concurrent impulses which represent the activation of frequency channels specific for each vowel. After training, reception of each vowel will be signalled by activation of a hidden neuron [12]. Moreover the output neuron will be able to detect a word formed by these vowels.

The word recognition using spiking neurons was previously done by Hopfield and Brody with their *mus silicium.* That was an integrated chip containing about 1000 neurons which could be trained to recognise ten spoken words [16]. The speech was split into 20 frequency channels, each channel stimulating 20 neurons with different frequency decay rates. The word recognition was made by detection of the almost concurrent impulses generated by different frequency channels which activates neurons with different frequency decay rates [17].

In contrast, the network used for the experiment described in the sequel learns to detect words using same type of neurons which were described previously in this paper. Moreover, the neurons are generating singular impulses per stimulation. The successions of spoken sounds – i.e. vowels – are detected using delaying neurons. Therefore, the main differences between Hopfield approach and my approach is that my neural network uses the same parameters for all the neurons which provides generality to the use of the neural network. Another difference is that these neurons fires once per channel stimulation while the Hopfield's neurons generates a frequency which decays in time with different rates. For word detection my network uses delaying neurons which compensates the time intervals between spoken sounds. This will shorten the time intervals between the corresponding stimulations on the word detection neuron. Another original aspect regarding my network represents the use of previously trained neural paths in order to improve the learning rate.

5.1. Biological background

The biological ear splits the audio signal into frequency channels using the resonance of different segments of the basilar membrane and sends channel dependent impulses to the brain [11]. Some experiments on human subjects showed that high performance in speech understanding does not require a detailed spectral representation of the speech signal. Therefore, asymptotical performance in speech understanding was obtained when only 8 frequency channels were presented to the subjects [8]. Thus, each sound could be identified by its specific audio frequencies and considering that spoken vocals are some of these sounds, the experiment presented forward focuses on the basic aspect of the speech recognition. The output of the activated channels is suitable to be processed by networks of spiking neurons which perform events association.

5.2. Audio module

For the performed experiment the vocal spectrum of the audio signal is split into frequency channels using band-pass resonant filters. Each of these channels sends voltage impulses to an input neuron of the artificial network when the specific frequency is received. Obviously, the specific channels for one vowel will stimulate the network almost concurrently increasing the weighs of the activated synapses. Figure 8 presents the structure of the audio module which transforms the audio signal into impulses which stimulate the input layer of the neural network. The amplified signal from the microphone is split into frequencies by the resonant filters (RF) and the positive peaks of each channel are transformed into spikes suitable for network stimulation.

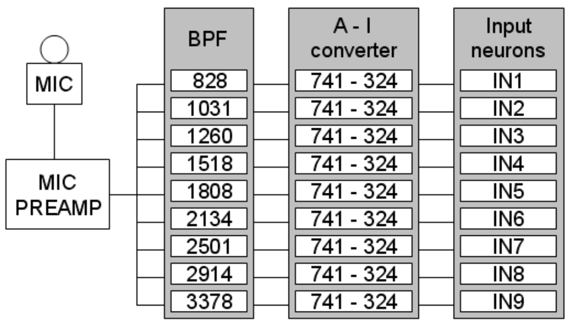


Fig 8. The structure of the audio module which converts audio signal into voltage impulses for the input layer of the neural network.

The output of each RF is amplified using a ßA741 operational amplifier and transformed into impulses by a LM324. The peak threshold for each channel could be modified by variable resistors connected to the negative input of the LM324 op-amps.

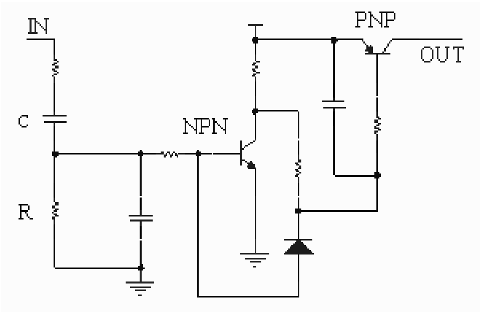


Fig. 9. Input neuron of the neural network; its main role is to make spike amplitude and duration adaptation.

For proper operation of the network, the input neurons make the limitation of the impulse amplitude to 1.6 V and of the spike duration to 30us. Considering the electrical scheme shown by figure 9, it is clear that the voltage adaptation is made by the NPN and PNP transistors, while the impulse duration is proportional with the capacity C value.

5.3. Network topology

To test the classification power of the electronic neurons presented in this work it was considered a network of excitatory neurons able to perform audio channels classification into spoken vowels. Moreover, the output layer of the network is able to associate the two vowels if they are said almost concurrently to form a word. To easily asses the results, for each vowel were chosen the most significant pair of frequency channels. Thus, based on direct observation on the oscilloscope of the audio module behaviour, the ‘a’ vowel activates the frequency channels:

fa1 = 828 Hz; fa2 = 1260 Hz

while the ‘e’ vowel is mainly characterised by the frequencies:

fe1 = 1808 Hz; fe2 = 2134 Hz

As it was previously supposed in our work [12], the activated channels do not depend on the speaker or the voice tone which is an important aspect of the speaker independent speech recognition.

It is clear that any speech sound – by unique activated channels configuration – will make a unique alteration to the synaptic weighs configuration of a large neural network. However, the simple topology of network presented in figure 10 helps in understanding the basic principles of almost concurrent events association.

The presynaptic neurons aFN1 and aFN3 are stimulated by the input neurons IN1 and respectively, IN3, while the neurons eFN5 and eFN7 receive impulses from IN5 and respectively, IN7. Each channel activates one of the presynaptic neurons and the time interval between the spikes received is specific to every vowel. This time interval depends also on the amplitude of the audio signal. The short duration of this interval helps in illustrating the ability of the artificial network to associate concurrent events. After network training, the neurons aFN1 and aFN3 activate the neuron aN when vowel ‘a’ is said at the microphone. The vowel ‘e’ is recognised similarly by the action potential of eN which is stimulated by neurons eFN5 and eFN7.

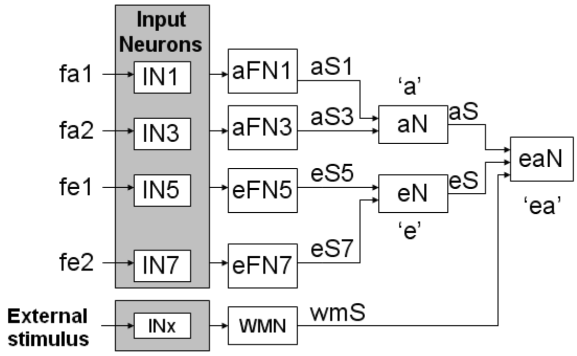


Fig. 10. The topology of a network composed of two hidden layers of excitatory neurons which classifies frequency channels into spoken vowels and vowels into words. The WMN action potential activates eaN neuron.

5.4. Network training

Network training is made by repetitive stimulation of the network input layer by pairs of spikes that are specific for every vowel. The neurons eFN5 and eFN7 will be activated for ‘e’ vowel reception when the fe1 and fe2 frequency channels stimulate the input layer of the network. Similarly, the neurons aFN1 and aFN2 will be activated by vowel ‘a’ reception signalled by fa1 and fa2 channels. At the beginning of the experiment, all the synaptic strengths were set to minimum that means that they have no influence on the postsynaptic neurons in case of presynaptic activity.

When the input layer receives the specific stimulation for ‘e’, the synaptic efficiencies of the synapses eS1 and eS3 are increased only by PTP which is a low power component of learning. After several stimulations of the network input layer by ‘e’ vowel specific channels the postsynaptic neuron eN reaches its activation threshold triggering the LTP for participating synapses eS5 and eS7. This strong potentiation of the synapses will make the neuron eN to be the vowel ‘e’ detector. Similarly, the ‘a’ vowel is detected by the hidden neuron aN, which triggers the LTP for synapses aS1 and aS3.

Thus, the reception of ‘e’ vowel will make the neuron eN to fire while the ‘a’ vowel will activate the neuron aN. Because of the great complexity and diversity of the biological neural network it is supposed that exists a third neuron eaN which is able to associate the almost concurrent activations of the neurons eN and aN with a third supraliminal stimulus which activates the postsynaptic neuron eaN. Therefore this neuron is able to detect the vowel combinations ‘ea’ or ‘ae’ by triggering the LTP for previous activated neurons eN and aN. For this experiment it was considered only de word ‘ea’ recognition because in Romanian language during normal speech the ‘a’ vowel is easier to link after ‘e’ vowel. The activation of the input neuron INx simulates the receiving of an external stimulus which is considered to be previously known by the network. As an example, the external stimulus represents an image which could be associated with the word received. Taking into account the similarity with the experience gained in time by a biological neural network, the neural path which is activated by this stimulus is previously trained. Therefore, the synapse wmS is able to activate the neuron eaN. However, the activation of this neural path could be obtained by repeated stimulation of the input neuron INx which determines the potentiation of the synapse wmS by PTP mechanism. This process could be repeated until the neuron WMN is able to trigger eaN action potential.

5.4. Experimental results

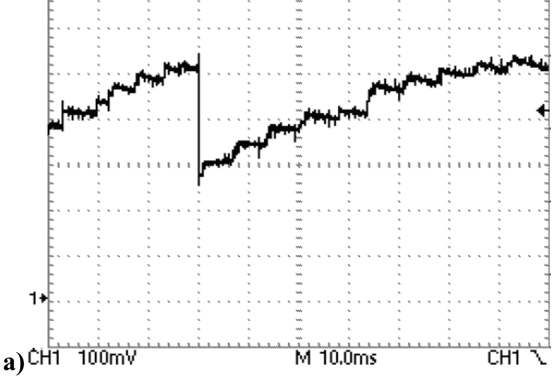
The network behaviour proves our supposition that the neurons make the vowel detection by synaptic strength adaptation to the input stimulation. The experiment proves also the ability of the neurons to make word detection by vowel association.

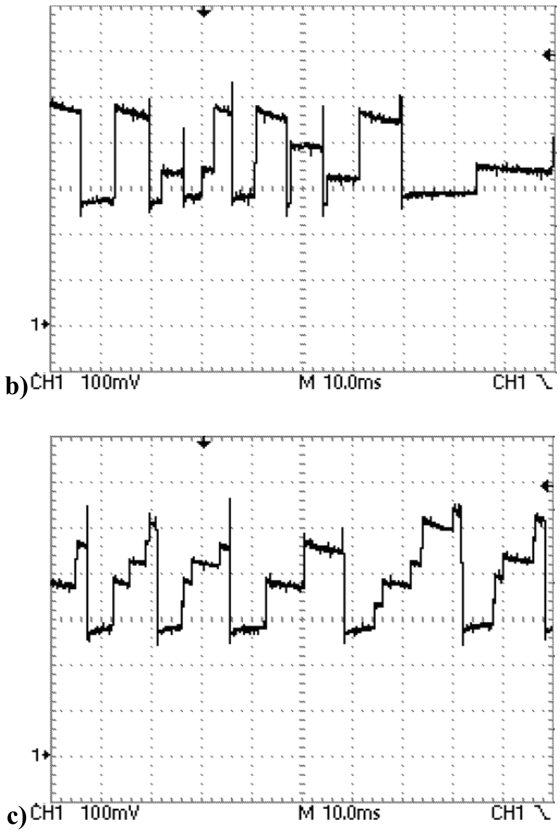
5.4.1. Vowel detection

The signal diagrams (a) and (b) from figure 11 show the input potential of the neuron aN during the network training. The sudden decrease of the voltage illustrates the neuron activation determined by the concurrent action of the synapses aS1 and aS3. The waveform (a) illustrate the integration of the incoming stimulation which determines the first activation of aN is illustrated by the waveform (a). After this training iteration, the efficiency of the aS1 and aS3 is increased by the LTP until it determines the neural activations shown by signal diagram (b).

The illustrations of the network behaviour after frequency classification is illustrated in figure 11 (b) and (c). The waveform (b) represents the input potential of the neuron aN activated by the ‘a’ vowel reception. Similarly, waveform (c) illustrates the activation of the neuron eN after network training when the frequency channels which are specific for ‘e’ vowel stimulate the input layer of the network.

Therefore, eN makes the vowel ‘e’ detection while the ‘a’ vowel is detected by aN neuron. The eN and aN neurons activations are illustrated by the sudden decreases of the voltage which represents the beginning of the refractory period. The successive pronunciation of these vowels implies successive activations of these two neurons which could be associated by a third neuron in order to perform word detection.





vertical div.= 100mV; horizontal div.= 10ms

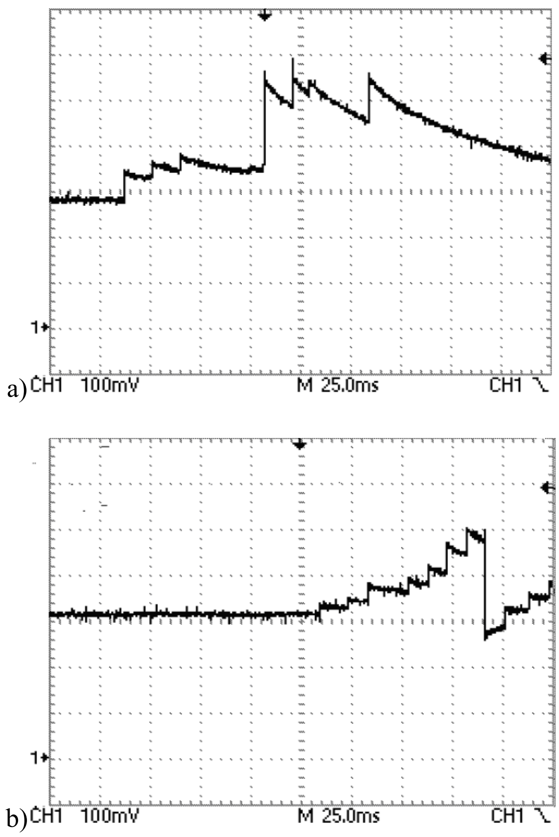
Fig. 11. a) The influence of the presynaptic neurons on aN input potential during first activation of the aN; b) and c) The input potentials of the neurons eN and aN after training. The sudden decreases of the input voltage illustrate the neuron activations.

5.4.2. Word detection

As it is shown by the network topology from figure 8 the eN and aN neurons are connected to a postsynaptic neuron eaN. The last one receives voltage impulses from both presynaptic neurons during the ‘e’ vowel and respectively ‘a’ vowel receptions.

The signal diagram (a) from figure 12 shows the input potential for the eaN during network training when the eN and aN presynaptic neurons are not powerful enough to activate the postsynaptic neuron. The LTP process increases the gain in synaptic efficiency per neuron activation. Thus, the potentiation of the synapses eS and aS is stronger when the mechanisms of LTP are triggered by the postsynaptic neuron. The eN and aN presynaptic neurons are stimulating the neuron eaN prior to activation of the neuron WMN. During the eN and aN activity the corresponding synapses aS and respectively, eS are temporary potentiated by the STP process. The last one will determine the postsynaptic action potential which will fix the temporary potentiated synapses.

Thus, after few repetitions of the corresponding stimulations for vowel ‘e’ followed by ‘a’ and than ‘external stimulus’, the action potential of aN neuron which activation is closer to supraliminal influence of WMN, will activate the neuron eaN.



vertical div.= 100mV; horizontal div.= 25ms

Fig. 12. The input potential for neuron eaN which detects the ‘ea’ vowel combination; a) before training was finished; b) after training. The gap between the first three voltage steps which is longer on diagram (a) illustrates the pause between ‘e’ and ‘a’ vowels.

This means that the successive spoken vowels ‘ea’ have the same response inside the neural network as the external stimulus (activation of the neuron eaN). From this point, the stimulation of the input neuron INx is not necessary because aN will trigger the LTP for eN like in figure 12 (b). First three voltage steps are caused by the vowel ‘e’ reception, while the last voltage steps illustrates the neuron aN influence on the eaN input. Therefore, the neural network learns to make an association between the vowel combination and the external stimulus which could be an previously known image.

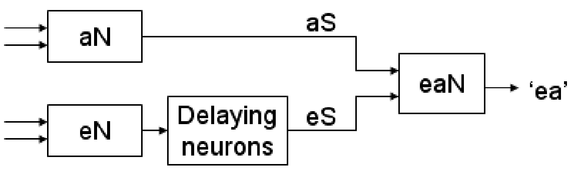


Fig 13. The insertion of a delaying neuron into neural path of ‘e’ vowel detection.

The sensitivity of word detection increases when the gap between vowel receptions is shorter. This fact could happen when the neural path from the network input to the word detection neuron for vowel ‘e’ is longer than the neural path for vowel ‘a’. Due to latency period of the neuron, the length of a neural path is proportional with the delay introduced in neural message transmission. Thus, the time interval between successive receptions of spoken vowels could be compensated by the neural path delay. This will shorten the time interval between the vowels stimulations on the word detection neuron. The topology of the network tested for this experiment (figure 10) could be modified by introducing some neurons on vowel ‘e’ neural path like in figure 13. These neurons will delay the stimulation of the postsynaptic neuron eaN by the eN, improving word detection due to the shorter time interval between stimulations implied by the two vowels reception.

The operation of this artificial network encourages us to extend it successfully to recognise all vowels and speech sounds. Moreover, the behaviour of the output neuron demonstrates the ability of this neural network to recognise words which makes it suitable for speaker independent speech recognition.

6. CONCLUSIONS

This paper describes a new biologically inspired electronic model of neurons. The main goal of this new design is to obtain large neural networks without the disadvantage of computation time increasing. This model uses simple electronic components which makes it suitable for analogue integrated chip design while providing good simulation of natural neuron crucial features. The basic electronic components could be seen as high-complexity program functions governed by physical laws with parallel execution, which linked in a circuit provides the overall operation of the neuron. Same neuron behaviour could be obtained when this circuit is simulated in software, but in this case the computation time increases substantially. The analogue design of electronic neuron offers almost unlimited power for temporal events discrimination. The external events will be reflected in neural network activity and the concurrent stimulation will modify the synaptic configuration of the network. The artificial synaptic efficiency depends on a capacitor charge which is a simple solution to model the activity dependent alteration of the synaptic geometry. However, for the analogue IC development this capacitor will be replaced with a floating gate transistor which is a better solution for on-chip non-volatile storage.

As was shown by the performed classification experiment, the efficiency of the concurrent activated synapses which participate to postsynaptic neuron activation is substantially increased, while the sensitivity of the unused ones remains the same or decreases. Thus, the network could develop in an unsupervised manner its own topology which depends only on its previous activity. Considering that the brain synaptic configuration is a consequence of the natural selection (along generations by environment validation of the fittest genetic mutations), it is possible for an electronic network having electricity as source of energy to build the same synaptic configuration as the biological one. This would be useful for neurosciences when it is needed the activity simulation of the different parts of the brain, or for developing the control modules of the intelligent machines.

The neocortical column (NCC) which contains about 10 000 neurons connected in an intricate way represents the functional unit of the biological brain. The main difference between the human brain and the mice brain represents the number of such processing units. Therefore, it may be possible that the intelligence degree will increase proportionally with the number of such units which build the biological brain. The development of a system that provides more intelligence than human brain hits the problem of parallel activity simulation of billions of high complexity neurons. Based on the biological neuron physiology and providing real time operation the silicon integration of the electronic neuron could be successfully used to model the behaviour of the NCC. Considering that 10 000 electronic neurons could be integrated on about four square centimetres of silicon, it is clear that a computing architecture of 100 000 neural ICs will take approximately 40 m² of die area. Due to the low current consumed by the artificial neuron, the power needed for proper operation of such a system oscillates around 480 Watt.

Thus, despite the production costs of the integrated chips and the difficulties which could appear in making the connections between all the artificial NCC, the real time operation of the electronic neuron makes the brain like artificial neural network containing one billion neurons, to be practically feasible.

REFERENCES

A. Hastings. "The Art of Analog Layout", Prentice-Hall, Upper Saddle River, New Jersey, pp 77 – 84, 2001.

C. Saint, J. Saint. "IC Layout Basics – A Practical Guide", McGraw–Hill, New York, pp 143 – 222, 2002.

Eugene M. Izhichevich, „Simple Model of Spiking Neurons", IEEE Transactions on Neural Networks, Vol 14, No. 6, pp. 1569 – 1572, November 2003.

Explorations in Cognitive Neuroscience", Cambridge MA: The MIT Press, pp.32-37, September 2000.

J. J. Hopfield and C. D. Brody „What is a moment? Transient synchrony as a collective mechanism for spatiotemporal integration" Proceedings of the National Academy of Sciences of the USA", pp. 1282 – 1287, 2001.

J. J. Hopfield, C. D. Brody „What is a moment ? *Cortical* sensory integration over a brief interval", Proceedings of the National Academy of Sciences of the USA, pp. 13919 – 13924, 2000.

Jeffrey J. Lovelace, „A Very Simple Spiking Neuron Model That Allows for Modeling of Large, Complex Systems", Neural Computation, Volume 20, issue 1, pp. 65 – 90, January 2008.

Kenneth N. Stevens. "Acoustic Phonetics", Cambridge MA: The MIT Press, pp.204 - 214, January 1999.

M. Baudry, J.L. Davis and R. Thompson, "Advances in Synaptic Plasticity", Cambridge MA:The MIT Press, pp.133-137, November 1999.

M. Hulea. "A biologically inspired model of spiking neurons suitable for analog IC design" ICAI 2008 Proceedings, CSREA Press, Las Vegas Nevada, USA, pp 807-812, July 2008.

M.Azuma. "Barium Strontium Titanate Integrated Circuit Capacitors and Process for Making the Same", US Patent 6285048, pp. 14.

M.Hulea. "A Biologically Inspired Rule for Electronic Synapses Plasticity", SACCS 2007 Proceedings, Editura Politehnum Iasi, Romania, pp. 89-93, November 2007.

P. Hastler, J. Dugger. "Analog VLSI Implementations of Neural Networks", The Handbook of Brain Theory and Neural Networks, Cambridge MA: The MIT Press, pp. 1 – 3, November 2002.

P.C. Loizou, M. Dorman. "On the Number of Channels Needed to Understand Speech", University of Texas at Dallas, pp 1 – 15.

The Blue Brain Project – URL: http://bluebrain.epfl.ch/page18699.html.

W. Maass, C.M. Bishop "Pulsed Neural Networks", Cambridge MA: The MIT Press, pp.23-42, November 1998.

W. Swiercz, K.J. Cios, "A New Synaptic Plasticity Rule for Networks of Spiking Neurons" IEEE Transaction on Neural Networks, vol 17, Issue 1, pp. 94-99, January 2006.