

# Silicon-based Neuromorphic Implementation of the Olfactory Pathway\*

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**Abstract** – *Here we describe the component subsystems which comprise the first silicon-based olfactory system, each implemented in analog VLSI/MEMS. These include a biologically constrained neuronal model, chemical micro-sensor array and associated interface circuitry. We present a spiking olfactory bulb model, a reduced 70 element broadly-tuned chemosensor array (25 different chemsensor tunings), alongside details of their silicon implementation. Our results show that the olfactory bulb model is capable of pattern classification and that the odour delivery, uptake and sensor circuitry, as well as the fundamental units of the neuromorphic model (spike-driven synapse and spiking soma), are all functional. Work will continue towards completing a fully-integrated and scalable silicon implementation of the olfactory system.*

**Index Terms** – *neuromorphic aVLSI, chemosensor array, machine olfaction, olfactory bulb.*

## I. INTRODUCTION

To date, neuromorphic silicon analog VLSI (aVLSI) implementations of auditory and visual sensory pathways have been undertaken, which are at varying stages of advancement [1-3]. Due to the significant technical challenges involved in complex odor detection and discrimination, there have been no reports of equivalent implementations of the olfactory pathway.

Although electronic nose technologies exist that have parallels with the biological olfactory pathway (such as exploiting population coding of sensory stimuli), these are in all cases far away from the neuromorphic approach of deploying biologically derived analogue circuitry (in particular spiking neuronal systems) in silicon [4].

Before building such an ambitious system, a key question we should ask is what should such an integrated neuromorphic olfactory system be capable of? Most animals rely on olfactory cues far more than humans - olfaction is fundamental to many animal behaviors, for example, foraging, conspecific mate location, predator avoidance and crypsis (through chemical camouflage). These behaviors rely upon common olfactory detection tasks, which are regularly performed in complex, nonstationary and unpredictable environments. These include:

1. Discrimination between learnt odors, both single and multiple compound (simple and complex),
2. identification of specific learnt odors in a background of undefined interfering, and possibly time varying, chemical compounds,
3. separation of odor sources into Gestalts which can be segmented simultaneously, similar to its counterpart in vision – related to the binding hypothesis[5], and audition – the so-called cocktail party problem [6].

While portable chemosensor detectors are able to routinely perform the first of these olfactory detection tasks (subject to suitably high chemical concentrations), they cannot reach the performance of an animal; inasmuch as the last two detection problems have not yet been solved technologically. For this reason we aim to exploit what is known about the neuronal architecture of the early olfactory pathway in order to improve technologies for, as well as understand more about biology's solution to, complex chemical detection.

Here we describe the subsystems upon which our silicon olfactory pathway implementation is based; including a spiking neuronal model of the olfactory bulb, broadly-tuned chemosensor array with associated interface circuitry, and neuromorphic aVLSI circuitry.

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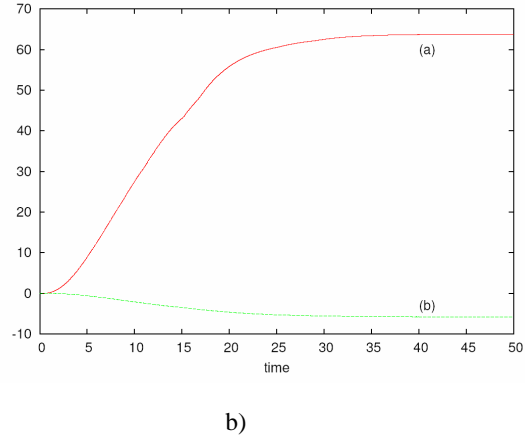
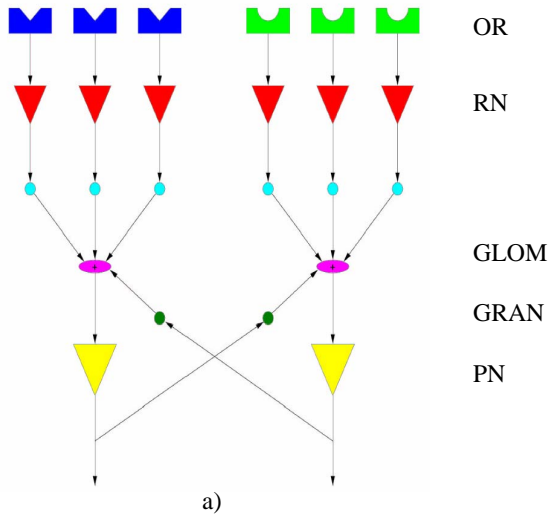


Fig. 1 a) A schematic diagram of the olfactory bulb neuronal model architecture, showing receptor and principal neurons (triangles) and synapses (circles), and b) model response in the learnt (red) and naïve (green) stimulus conditions. OR – olfactory receptors, RN - receptor neurons, GLOM – glomeruli, GRAN – granule cell interaction, and PN – principal neurons.

## II. COMBINED RECEPTOR INPUT AND OLFACTORY BULB NEURONAL MODEL

In vertebrates, a large number of olfactory receptor neurons (ORNs) constitute the front-end of the olfactory system, being responsible for detecting airborne molecules. Cilia of ORNs protrude into the olfactory mucosa, where they come in contact with molecules that are transported by the nasal air flow. On the surface of the cilia, odorant receptors (ORs) bind odorant molecules with a broadly tuned affinity. When an OR binds with an odorant molecule, it triggers in its ORN a biochemical cascade that eventually causes the membrane potential of the ORN to change, potentially leading to the generation of spikes. Each ORN only expresses one type of odorant receptor, while each type of receptor is usually expressed by a large number of ORNs; for example, in mice around 1,000 types of ORs are expressed by millions of ORNs [7].

ORNs project their axons to the olfactory bulb, terminating at spherical neuropil called glomeruli (GLOM), where they synapse onto the dendrites of mitral and tufted (M/T) cells, which act as principal output neurons (PNs). Experimental data indicates that each glomerulus receives axons from only ORNs expressing the same type of OR, while a single PN sends its apical dendrite to a single glomerulus. Inhibitory neurons of the olfactory bulb (granule cells [GRAN]) make reciprocal contacts with many PNs, forming together a complex network constituting the first stage of olfactory information processing. The output of PNs are relayed to higher brain areas for further processing [7].

The neural network model described here is inspired by the olfactory system of vertebrates. The only external signals that the network receives come from the chemosensors (see Section 3), which are responsible for transforming the molecular information of an odorant into signals suitable to constitute

neural input. About 25 types of chemosensors, broadly tuned to different chemicals, are expected to be available for the final silicon implementation.

Fig. 1a shows part of the network, only depicting two types of sensors for the sake of clarity. The diagram has been drawn representing every computational element with an individual device, rather than adopting a biologically realistic representation. The chemosensors are represented by irregular polygons at the top of the diagram; polygons of the same shape represent sensors of the same type.

There are two classes of neurons, Receptor Neurons (RNs) and Principal Neurons (PNs); the smaller and the larger triangles in Fig. 1a represent ORNs and M/T cells, respectively. A single RN receives input from only one chemosensor, and likewise a single chemosensor only projects to one RN. The outputs of the RNs feed into their respective RN-PN synapses (circles). The outputs of the synapses that receive input from RNs fed by sensors of the same type converge onto a summation component (ellipse), where they are summed linearly. The output of any summation component feeds to one respective PN. Every PN projects to every other PN through one of the PN-PN synapses (circles). Because the signals from sensors of the same type are fed forward through neural elements to one and one only PN, the network forms a distinct modular structure, reminiscent of the glomerular organization of the olfactory bulb [7].

The soma of each neuron element is modeled as a leaky integrate-and-fire (IF) unit. Below some threshold,  $V_\theta$ , the dynamics of the “membrane” potential,  $V(t)$ , of the IF neuron are defined by the equation

$$\frac{dV(t)}{dt} = -\frac{V(t)}{RC} + \frac{I(t)}{C}, \quad (1)$$

where  $t$  is time,  $R$  and  $C$  are, respectively, the membrane resistance and capacitance, and  $I(t)$  is the total input current to the neuron. The membrane rest potential is conventionally set equal to 0 V. The membrane time-constant is defined as  $\tau_m = RC$ . The terms contributing to  $I(t)$  are due to sensor responses if the neuron is a RN, and to RNs and lateral interactions if the neuron is a PN. If the potential  $V(t)$  reaches the threshold value  $V_\theta$ , it is immediately reset to the after-hyperpolarization value  $V_{ahp}$  and a spike (action potential) is produced as output of the neuron. The emission of any spike is followed by a refractory time,  $\tau_{refr}$ , during which the neuron cannot fire but still integrates the input currents.

When a spike reaches a synapse, it induces a dendritic current that is fed into the post-synaptic neuron which decays exponentially with a characteristic time-constant, starting from a peak value determined by the synaptic weight. The sign of the current is formally included into the synaptic weight, positive or negative according to whether the interaction is, respectively, excitatory or inhibitory. The currents induced by several pre-synaptic spikes add up linearly at the soma. If a neuron receives the outputs of several synapses, the respective contributions to the total post-synaptic current sum linearly. The total post-synaptic current constitutes the term  $I(t)$  in Eq. 1, which drives the membrane potential of the respective neuron.

The weights of the PN-PN synapses are defined so as to endow the network with associative properties (cf., e.g. [8] for general definitions), though it is not known whether the biological counterpart performs this kind of processing. The network learns odorants by modifying the weights of the PN-PN synapses according to a one-shot Hebbian learning rule, during a training stage. Given any learnt odorant, a function of the firing rates of the PNs is defined (indicator function) that indicates whether the network output is currently representing that odorant; if a learnt odorant is delivered, then the corresponding indicator function should assume a relatively large positive value. As an example, Fig. 1b shows the behavior of the indicator function over time in a simulation of the neuronal model with 25 sensor types that has already learnt one odorant. The odor stimulus is currently delivered simultaneously to all sensors as a step-function of time, starting at zero (time is in units of the PN time-constant, while the y-axis is in arbitrary units); in one case, (a), the odorant present in the stimulus is the one previously learnt, while in the other case, (b), an unknown odorant is delivered. It is clearly possible to dis-criminate between recognition and non-recognition cases.

The small size of the repertoire of sensor types presently available, however, can cause the behavior of the network to vary with different odorants to an extent that normally depends on the complexity of the olfactory task.

### III. CHEMOSENSOR ARRAY

Input to our olfactory bulb model is provided by a combined chemFET/resistive sensor array fabricated using an AMS 0.6  $\mu\text{m}$  CUP CMOS process, employing carbon black (CB) composite sensing materials, with integrated signal processing

circuitry. The sensing materials are a combination of an insulating polymer and conducting carbon. The authors believe the sensor technology differs from previous work in a number of ways. Firstly, it is the first resistive CMOS compatible sensor array integrating different CB polymers into the same array. In addition, it is the largest capacitively coupled FET sensor array using CB materials. Lastly, it is the first time both a chemoresistor and chemFET have been combined with integrated signal processing electronics.

#### A. Combined sensor concept

The resistive sensor component is formed by depositing CB polymer material between two sensor electrodes. The FET section is based on a floating gate concept, where the sensing material is capacitively coupled to the floating gate of a FET. As the gate is floating, any potential created through the interaction of the sensing material with the target gas or odor appears, due to this coupling, on the gate of the FET. It has previously been reported [10] that this is due to a change in workfunction within the sensing material. The floating gate will have an absolute potential subject to variations in the fabrication process. A biasing plate is added underneath the sensing plate and biased to ensure the transistor is turned-on. The capacitive plate is placed in-between the two resistive electrode elements, hence the same sensing material is used for both resistive and FET measurements.

#### B. Sensor Interfacing Circuitry

Included with each sensor is circuitry to drive and process any response. Each resistive/chemFET sensor is driven by a constant current source which can have three different values (1  $\mu\text{A}$ , 10  $\mu\text{A}$  and 100  $\mu\text{A}$ ). This is used to compensate for variations in resistance with different coatings. To remove the DC baseline value of the sensor, an offset cancellation circuit has been added to the design. The circuit allows high gain values to be used without saturating the output. In our design, the DC offset cancellation circuitry uses a ramping DAC with a comparator. The 10-bit DAC ramps to estimate the offset voltage and the value maintained in an internal counter register. The  $\pm 1$  bit error is 5 mV and takes 512  $\mu\text{s}$  (based on 2 MHz clock) to perform a cycle of scanning the offset voltage as all cells are performed in parallel. This baseline removal can be done either before exposure to an odor or in-situ. Hence, any long term drift of the sensor or changes in environmental conditions that alter the DC baseline can be compensated for. Once the baseline has been removed the signal is amplified with gains of 1, 10, 50, 100 or 1,000. These values are programmed externally and can be altered whilst a test is running. Lastly, the signal is conditioned with a low pass filter set at a corner frequency of 1 kHz. The output voltage is at present measured externally using a data acquisition card. The control bits for each cell are contained within 4 D-type flip-flops and are loaded from an external source. A simplified schematic of the offset removal circuitry is given in Fig. 2b.

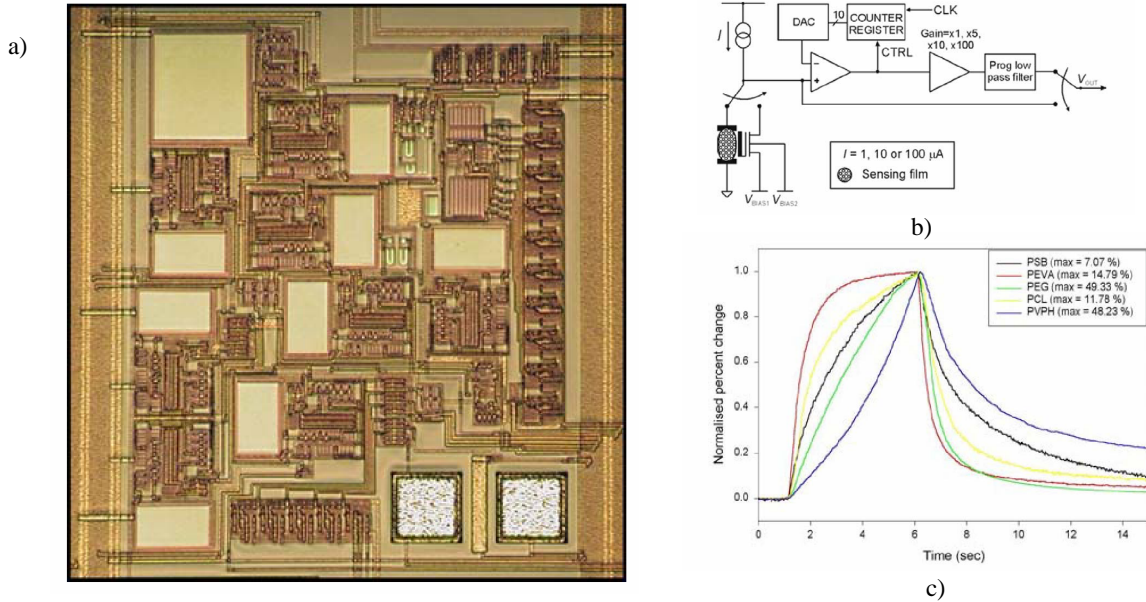


Fig. 2 a) Footprint of the chemosensor array implementation, b) offset cancellation circuitry, and c) representative chemosensor responses, (reproduced from Covington *et al.*, 2004 [9]).

The sensor array was designed and implemented in the AMS 0.6  $\mu\text{m}$  CUP process and has been tiled across the whole chip. Fig. 2a shows the footprint of one cell of the fabricated chip, whilst a close-up of the combined resistor/FET component is shown in Fig. 2b. Before CB polymer deposition, the aluminium electrodes have been gold plated. This is to ensure a stable contact between the CB polymer and the aluminium. Five different CB polymers were used as given in Table 1.

Table 1: Polymer materials used.

Type	Polymer material
1	Poly (styrene-co-butadiene), PSB
2	Poly (ethylene glycol), PEG
3	Poly (Ethyl-co-vinyl acetate), PEVA
4	Poly (4-vinyl phenol), PVPH
5	Poly (caprolactone), PCL

The sensitivity to ethanol vapor, for example of the PSB sensor material, is about 0.00012 %/ppm and 0.00644 %/ppm to toluene vapor. We have also tested other sensors with different coatings to ethanol vapor in air and the results are shown in Fig. 2c. Here the sensor array is exposed to a 5 s ethanol vapor pulse at a flow rate of 25  $\text{ml}/\text{min}^{-1}$ . The results show that different types of polymer films provide different response profiles over time, thus providing added discriminatory information.

#### IV. NEURONAL MODEL SILICON IMPLEMENTATION

The analogue circuit implementation of the synapse corresponding to the circle elements in Fig. 1a is shown in Fig. 3a (top). The input spike  $V_{\text{spike}}$  triggers the injection of a current  $i_{\text{wt}}$  into the capacitor  $C_{\text{SYN}}$ . The output of the synapse is an ex-

ponentially decaying current given by  $i_{\text{syn}}$ . The time constant during the discharge phase is controlled by varying  $I_{\text{BIASSYN}}$ . The weights are stored as a charge on capacitor  $C_{\text{WT}}$  and are updated using a combination of shift registers and switches (not shown in the figure).

The analogue VLSI implementation of the spiking neuron has the following functional blocks. They are, a) leaky integrator, b) comparator and spike conditioner, and c) reset and refractory timer. The analog circuit implementation of the integrate and fire block is shown in Fig. 3a (bottom). The leaky integrator is designed using an operational transconductance amplifier-capacitor (OTA-C) configuration. The output of the integrator is fed to a spike generator circuit. The spike generator circuit consists of a two stage comparator with hysteresis followed by inverters. The reset and refractory period timers are implemented using separate OTA-C circuits (not shown in the figure).  $V_{\text{reset}}$  and  $V_{\text{refrt}}$  signals are the output control signals of the reset and refractory period circuits, respectively.

Initially the  $V_{\text{reset}}$  and  $V_{\text{refrt}}$  signals are at a low state. The output of the comparator  $V_{\text{spike}}$  goes high when the integrator response is above the threshold voltage  $V_{\text{th}} = V_{\theta}$ . The output of the comparator is fed to a reset timer circuit. The reset timer output  $V_{\text{reset}}$  goes high after a finite interval of time, which in turn resets the integrating capacitor  $C_{\text{int}}$ . The time delay of the reset timer circuit determines the pulse width of the neuron spike output  $V_{\text{spike}}$  and is externally programmable. The trailing edge of the pulse triggers the refractory timer  $V_{\text{refrt}}$  to a high state. The  $V_{\text{refrt}}$  signal switches the comparator threshold to a large voltage  $V_{\text{brefrt}}$  thereby inhibiting the neuron from firing. However, the leaky integrator continues to integrate during the refractory period.

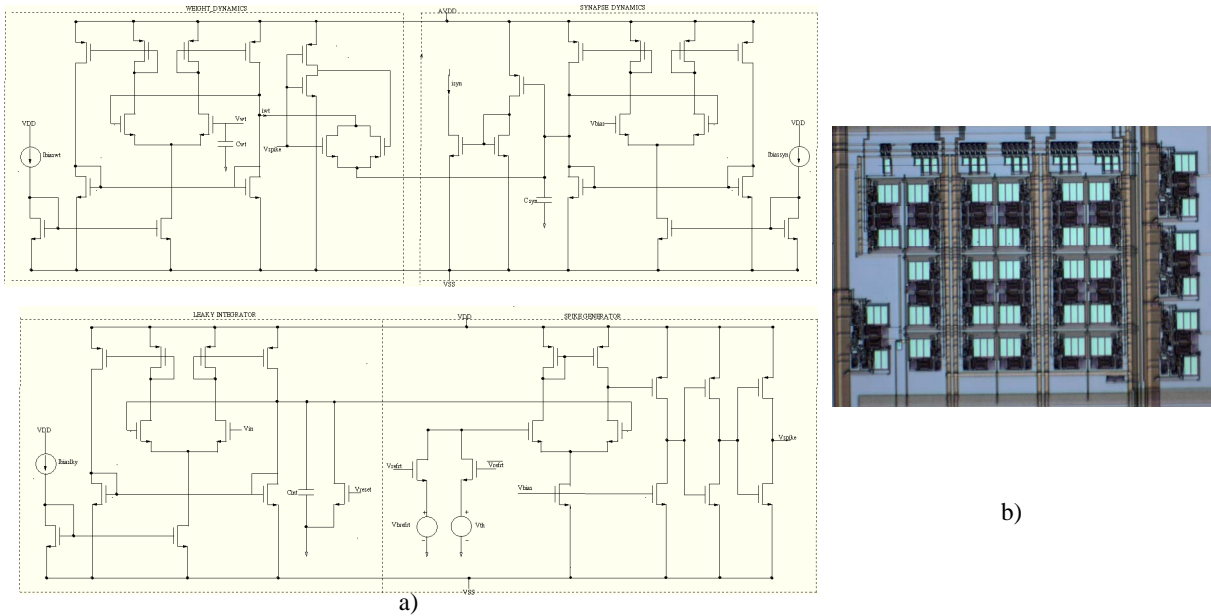


Fig. 3 a) Neuromorphic synapse and soma circuit, and b) footprint of the neuromorphic circuit implementation.

The analogue VLSI implementation of the neuromorphic chip has also been fabricated using an AMS 0.6  $\mu\text{m}$  CUP process. The chip contains 3 spiking neural network models with each model having 3 RNs, 27 synapses and 1 PN, as per the architecture described in Section 2, and is shown in Fig. 3b. The architecture of the chip is designed such that a scalable spiking network can be constructed by interconnecting multiple chips. The spiking neurons have programmable time constant, refractory period, threshold and spike width. The synaptic circuits have individually programmable weights which are stored on chip. The die area of the chip is 31.5  $\text{mm}^2$ .

The synapse circuit was tested by exciting it with a spike input of 1 ms duration. The response of the synapse programmed for a weight input of  $-0.5\text{V}$  and time constant of 75 ms is shown in Fig. 4a. Since the sign of the weight is negative with respect to the baseline, the synapse exhibits an inhibitory response. The response is matched against the synaptic model described in Section 2. It is seen that the chip response closely matches the simulated model.

The response of the synapse to consecutive input spikes is shown in Fig. 4b. A series of 10 consecutive spikes of 1 ms duration are fired with a time interval of 75 ms. During this test, the synaptic weight input was set at  $-0.5\text{V}$  and the time constant is 75 ms.

The neuron testing was carried out by characterizing the response of the leaky integrator separately followed by testing the full spiking neuron circuit. The step response of the leaky integrator on chip is shown in Fig. 4c. The response was again matched against the simulated response of the model described in Section 2. To evaluate the working of the whole spiking neuron circuit, a receptor neuron on the 3-27-1 spiking neural

network was tested using a square wave input with an amplitude of 0.2 V and period of 1 s. For this, the comparator threshold  $V_{th}$  was set at  $+0.18\text{V}$  with reference to the baseline output of the leaky integrator. Fig. 4d shows the neuron firing for a time constant of 150 ms.

## V. CONCLUSIONS & OUTLOOK

We have presented details of the component subsystems of the first aVLSI implementation of the olfactory pathway. These components appear to function correctly, independently of one another and so work will continue to test their combined behaviour in olfactory detection tasks, such as those outlined in the introduction.

One of the key challenges we face in creating a fully integrated solution is the role of time in the system – which is also one of the most interesting aspects of this endeavour. While chemosensors typically operate on the hundreds of ms scale, aVLSI is naturally suited to far higher bandwidths, and so there is great potential for mismatch in the dynamics of the sensor and neuronal model. Large time constants in the aVLSI typically mean large capacitances requiring significant space on the silicon. Solutions exist in the form of multiplexing or buffering between the front-end of the system and the neuronal model, deploying ultra-fast sensors or slowing down the silicon. Time also plays a critical role in terms of the performance of the system. Indeed, a key question we have been addressing is how can the neuronal model we have implemented exploit temporal information in the sensor responses in order to improve detection performance.

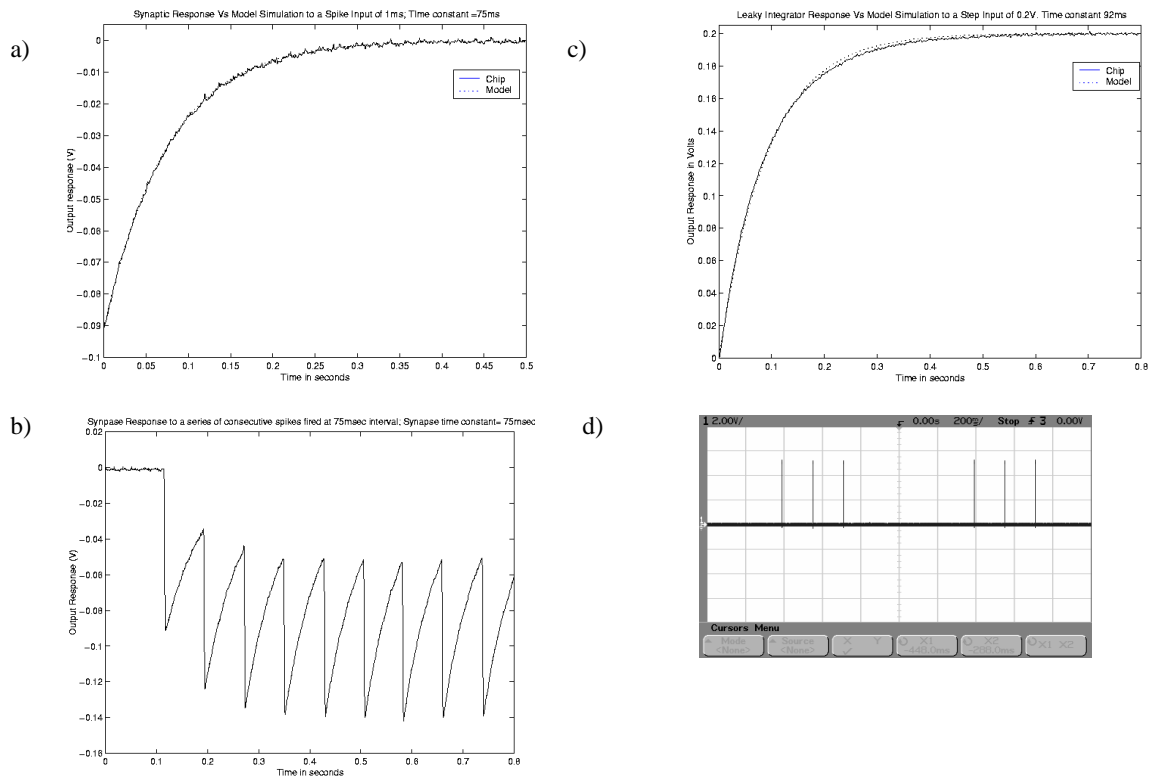


Fig. 4. Representative circuit behaviour of a) single spike synapse response, b) multiple spike synapse response, and c) soma.

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