Implantation Study of an Analog Spiking Neural Network in an Auto-Adaptive Pacemaker

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***Abstract*—The goals of this research are to develop an analog spiking neural network so as to improve the performance of biventricular pacemaker (CRT devices). Implantation in silicon uses the analogical neural network approach that requires the development of a technical solution satisfying the requirement of very low energy consumption. Targeting an alternative analog solution in 0.18µm CMOS technology, this paper presents a new approach in analog spiking neural network for the delay prediction by using a Hebbian learning algorithm.**

I. INTRODUCTION

That biventricular pacemaker also known as "Cardiac Resynchronization Therapy (CRT) device" is aimed at patients also suffering from circulatory deficiency [1]. The principle of this device is based on the stimulation synchronization of both ventricles in reference with the natural signal of the sinus node. The Adaptive CRT device [2, 3] aims at controlling the contraction of both ventricles for each heartbeat, in order to improve the ejection volume of each ventricle (the Stroke Volume: SV) during contraction. One of the basic characteristics of this resynchronization is therefore atrioventricular (AV) delay and interventricular (VV) delay, which represent respectively the time separating the contractions of right atria and ventricle (RA – RV) and the delay of contractions between the right and left ventricular (RV – LV). The use of "hemodynamic" sensors allows volume measurement of blood ejected by each ventricle [4] and is therefore used for optimization of the AV and VV delays, in order to maximize the SV. However, this optimization rule is very variable. It changes from patient to patient, requiring an optimal manual adjustment for each patient during implant procedure. Furthermore, it may change for the same patient in function of the cardiac rhythm, physical activity, and the physiological condition of the heart. In addition, it may also show short-term variation [5] through ageing or general health of the patient. This very important situation variability has prescribed a solution based on the use of neural networks which have the advantage of the capacity of sequence classification , as well as a massively parallel hardware implementation [6] satisfying the target requirements of reduced dimensions and very low energy i.e. 720nW, for the analogical element. Thus up to date the project uses the AI Medical Semiconductor Adaptive CRT device based on a Spiking Neural Network (SNN). The overall approach for the CRT device will be concisely examined in section II. In Section III we will describe the new architecture of the analog spiking neural network, its algorithm and simulations. The section IV will address a conclusion and its potential impact on the future research.

II. GLOBAL DESCRIPTION OF AI MEDICAL SEMICONDUCTOR ADAPTIVE CRT DEVICE

The adaptive CRT device receives at entry the signal of three electrodes (RA, RV and LV) of Input/Output type and the signal of two Input type only hemodynamic sensors, placed in the RV and LV. At the exit, the CRT sends a series of impulses towards the electrodes RV and LV for depolarization stimulation. These electrical impulses exciting RV and LV are sent in accord with the delay described above and determined by the internal controller. The internal functional unit of the CRT contains five sub-units (Fig. 1):

- An entry interface (receiving the signal of sensors and electrodes);
- A cardiac impulse generator (exciting the heart via electrodes);
- A general controller (GC) functioning as master of the CRT;
- Two SNNs working as slaves of the general controller, which we will name SNN1 and SNN2;
- A programming interface.

The core of the device is based on the connection of GC with both SNN. The choice of the master-slave principle between the GC and the SNN allows accepting or rejecting the prediction made by the SNN [2] and maintaining the adjustments they suggest in the brackets defined by the medical corpus. The clinical practitioner will program the initial AV and VV delays, via the programming interface, during the clinical test following the CRT implantation. These

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initial values will have to be learned by the first SNN (SNN1) in nonadaptive mode before the GC can toggle into adaptive mode. In this adaptive mode, the CRT will adjust the AV and VV delays by itself, in order to maximize the SV. Improvement of the optimization is achieved by a second SNN (SNN2) already in place, aimed at recognition of all physiological situations of the heart, but not described herein.

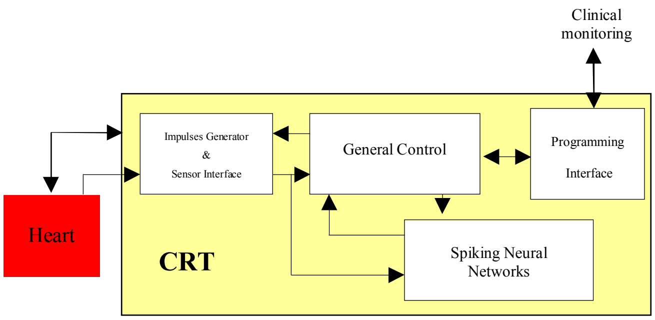


Figure 1. Internal bloc description of the AI Medical Semiconductor Adaptive CRT device

The adaptive CRT has three modes: Nonadaptive, Adaptive and Reinforce. It starts always in the nonadaptive mode under the supervision of a clinical practitioner while the patient is on cardiac monitoring. In this mode, the practitioner will initialize AV and VV delays on the monitor. The CRT is thus only a simple cardiac battery (classic pacemaker) for the patient. The GC transmits to the heart impulses corresponding to the delays specified by the practitioner. We will name these fixed delays P_{AV} and P_{VV} respectively (P: Pacing). On the inside, the SNN1 in the background learns to predict these programmed delays with the best possible accuracy. When the GC approves the forecast of SNN1 as "good", then it slides into adaptive mode.

The startup of adaptive mode is done with correct delays. In this mode, we target the optimization of the SV (volume ejected by each ventricle) through optimal control of the AV and VV delays. In the higher control level (Reinforce), the aim is the optimization of the Hebbian plasticity/stability dilemma. Whereas in this presentation, we focus on the first mode.

III. The Delay Prediction Network (SNN1)

A. *Functional description of the Network*

1) *The targets assigned to SNN1*

The target is twofold. In nonadaptive mode, SNN1 should learn to reproduce the AV and VV delays programmed by the practitioner. These delays are then adjusted by using the Hebbian Learning algorithm. In the adaptive mode, we toggle to the "online learning" algorithm. The different times determined by the network are relative to the instant t_0, corresponding to an impulse captured by the RA electrode. Each decision is made in one cardiac period.

2) *Network Structure*

The SNN1 is composed of two I&F neurons, each with 200 dynamic synapses at entry. We shall distinguish the neurons N_1 and N_2 that respectively deliver an impulse with delay to t_0 of T_1 and T_2 (also T_i with $i \in \{1, 2\}$). Each neuron is dedicated to our ventricular timing (RV or LV), i.e. dedicated to P_{AV} and P_{VV}. In order to distinguish the synapses, we will name them S_{ij} with i being the number of neurons and j, the row of synapse, i.e. $j \in \{1{,}200\}$. We will break the neuron up into three modules (Fig. 2). The first module is a "temporal synchronizer decoder" synchronized to the signal RA of the IEGM via the analogical entry interface. After detection of the depolarization impulse RA, it triggers a sequential stimulation of the second module's synapses like a "shift register". The time shift between the two consecutive stimulations of a synapse is predefined for duration of 5ms called delay. The second module is composed of 200 "dynamic synapses" per neuron. Each synapse, receiving the shifted stimulation from module 1, emits an impulse called Post Synapse Response (PSR) towards the neuron. The PSR is an impulse balanced by the synaptic weight. The third module comprises the "Leaky Integration" part and the "Fire" part of the I&F neuron which respectively collects the 200 PSRs from the second module as an accumulator and works as a comparator with a threshold.

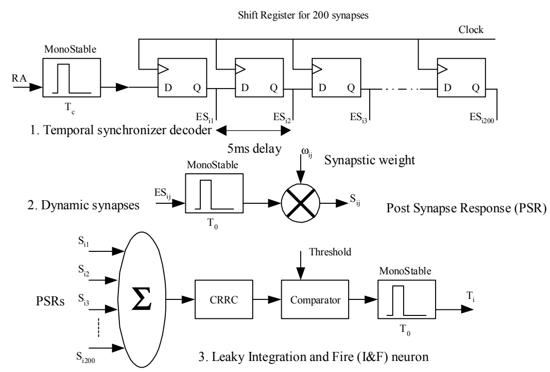


Figure 2. Synopsis of the three analog modules of the SNN1

3) *The analog I&F neuron architecture*

We choose a classic CRRC cell from the high energy particle physics experiments [7] as an analog leaky integration architecture of the third module for the following three reasons:

- We must stack temporal excitations in order to trigger a neuron N_i to exceed an internal threshold;
- The idea of accumulation of excitation is also associated with the concept of energy integration;
- The CRRC presents an impulse response stretching over time, which allows the "addition" of excitations followed by stacking up of the amplitudes and the leak of the incoming energy.

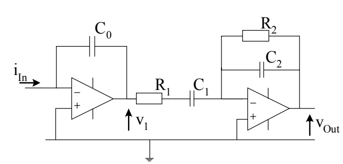


Figure 3. Schema of the CRRC

Fig. 3 shows the schema of the CRRC that produces a similar response of a classic I&F neuron. The mathematical relationship between a Dirac excitation and the output response (the impulse response) is $t.e^{-at}.u(t)$ where $u(t)$ is a Heaviside function. We can find (1) in Laplace transform:

$$H(P)=\frac{v_{Out}}{i_{In}}=\frac{1}{C_0 p}\cdot\frac{R_2C_1p}{(1+R_1C_1p)(1+R_2C_2p)} \tag{1}$$

In seeking the closest formula of Laplace transform, we can also infer the formal equations (2, 3) for the VHDL-AMS description by supposing $R = R_1 = R_2$, $C = C_1 = C_2$, which justify the name of CRRC.

$$H(P)=\frac{a_0+a_1P}{b_0+b_1P+b_2P^2} \tag{2}$$

$$a_0=\frac{1}{\tau\cdot C_0}, a_1=0, b_0=\frac{1}{\tau^2}, b_1=\frac{2}{\tau}, b_2=1, \tau=RC \tag{3}$$

4) The variation of output amplitudes of CRRC depending on excitations

In Fig. 4, we can easily observe that the peaking time (Pk) and the delay (5ms) between two excitations are two important parameters to analyze this variation. The Pk points do not correspond to the maximal amplitude outputs of CRRC, usually a little bit later. Furthermore, the Pk can change both the amplitude output and maximum asymptotic line. We define a coefficient N = Delay / Pk in order to well choose suitable balance values. In the case of CRRC, $Pk = \tau = RC$.

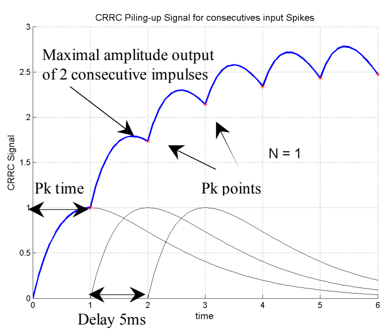
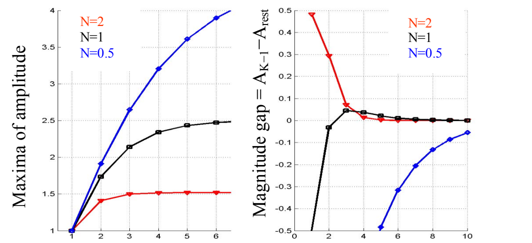


Figure 4. Variation of the output amplitudes of the CRRC by having six consecutive excitations

5) Choice of the threshold

According to the nature of the I&F neuron, if the amplitude output of the CRRC crosses over the threshold, T_i is fired as the I&F neuron output, and then all the shift registers will be reset to 0 and suppress all the following PSRs. Thus the choice of the threshold should be particular. In order to avoid the mistaken firing, the threshold should be set to fulfill the following conditions. If we are short of the last impulse of a consecutive series, which can trigger the neural response, the target firing will not occur until the appearance of another complete consecutive series. Moreover, by taking into account the noise impact, the threshold should not be chosen in a position too close to the nearby maximum of the amplitude output. For this sake, we have successfully simulated the maximum asymptote depending on the coefficient N. Fig. 5 (a) which presents influence of the coefficient N on the maximal CRRC amplitude output of a series of consecutive impulses. When N = 1, the asymptote reaches its maximum after 5 impulses. Fig. 5 (b) shows the gap between the affect of $(K-1)^{th}$ impulse (A_{K-1}) and the influence of the remainders (A_{rest}) on the neuron output. Only in the cases of N near to 1, $A_{K-1} > A_{rest}$ when $K-1 = 3$. Therefore, we can set a threshold which needs absolutely 4 consecutive impulses to trigger.



(a) Affect of N on the maxima of amplitude (b) Magnitude Gap = $A_{K-1}-A_{rest}$

Figure 5. Study on the choice of the threshold

6) Simulation

The simulation of the CRRC under the description of VHDL-AMS is presented in Fig. 6. The PSR signal here is supposed to be bounded to [0, 1]. With the help of the simulation software (MATLAB, SMASH), the optimal value of N is 1 and we should have at least 4 consecutive unitary impulses to trigger the I&F neurons. In other words, the fourth impulse will be the discriminant.

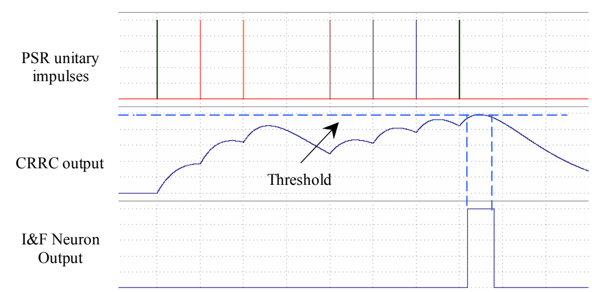


Figure 6. The firing of I&F neuron after four consecutive impulses

7) The Hebbian learning algorithm

The Hebbian learning algorithm [8], which is applied in the nonadaptive mode, aims to get the neural response T_i which matches the value P_i preset by the clinician. With the following equation (4), we can adjust those synaptic weights.

$$\omega_{ij}=\omega_{ij}+\eta*\boldsymbol{R_{ij}} \tag{4}$$

where η is the learning rate. Actually, the real modification of the synaptic weight depends on R_{ij} that is determined by this algorithm, which is an evolution of the [9]. The main difference is that Shift Register is reset to zero after the I&F neuron has been fired. The target of the adjustment with those synaptic weights is to generate a coherent excitation for a group of 3 to 5 synapses which will excite the I&F neuron and that will reach the internal threshold so that it emits an impulsion at the right moment (AV or VV delay). This algorithm acts as a finite state machine which proposes to use two variable states: “I&F Neuron State” (NS) and “dynamic Synapse State” (SS) (Fig. 7). The state NS gets the value Hit when $|T_i - P_i| < 15$ms or the value Miss in the others cases. For each synapse, we measure the delay (TS_{ij}-T_i) between the excitation instant of the synapse S_{ij} and the trigger instant of the neuron. The variable states of the synapse S_{ij} are defined in the following four cases for Δ=20ms (four impulses) :

- $(TS_{ij} - T_i) \in [-2\Delta, -\Delta]$, SS = PostHebb;
- $(TS_{ij} - T_i) \in [-\Delta, 0]$, SS = Hebb;
- $(TS_{ij} - T_i) \in [0, \Delta]$, SS = PreHebb;
- $(TS_{ij} - T_i) \notin [-2\Delta, \Delta]$, SS = Out.

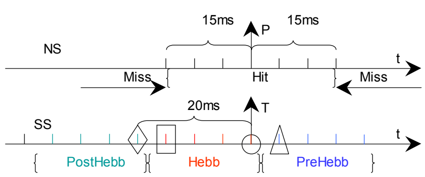


Figure 7. Definition of “I&F Neuron State” and “dynamic Synapse State”

The algorithm will increase ($R_{ij} = +1$) or decrease ($R_{ij} = -1$) these synaptic weights according to a logic combination of these two variable states NS and SS by using (4) and the table I below:

TABLE I. R_{ij} SETTING WITH HEBBIAN LEARNING ALGORITHM

R_{ij}	*States of NS*	*States of SS*		
		PostHebb	***Hebb***	***PreHebb***
$T_i < P_i$	Hit		$-1\square^*$	$+1\Delta^*$
$T_i > P_i$	Hit	$+1\Diamond^*$	$-1\circ^*$	
$T_i < P_i$	Miss		-1	$+1$
$T_i > P_i$	Miss	$+1$	-1	

* corresponds to the specified impulse of the selected state of SS in Fig. 7

B. Analog architecture investigations through system simulations

For the best optimization of the system concept, a development of a complete behavioral model has been written in VDHL-AMS integrating an electromechanical model of the heart developed jointly by the LTSI laboratory and the System-ViP society and a model of the AI Medical semiconductor adaptive CRT device [2, 3]. It permits us to investigate and test various technical and architectural analog solutions for an analog implementation of the neural network SNN1. We have developed a behavioral model of the analog parts of the neural network. The models we have already developed for other projects [10, 11] directly inspire this one. For modulation of the energy conveyed by the PSRs, two strategies were investigated: an amplitude modulation and an impulse density modulation. Our study will investigate the best choice, which will depend on the precision constraints on synaptic weights in relation to the focus of learning in a few seconds. Analysis of this constraint requires the simulation of the neuron within the complete system. Power consumption should be the second elected criteria. Finally, a compromise between the surface, i.e. the number of components, and power consumption will have to be researched. This design work influences also the synapse structure. A PSR amplitude control requires an analog multiplier while the impulse density control involves only nonlinear functions. The modeling of various solutions has offered a global simulation.

IV. CONCLUSIONS

The above result shows some analogical solutions for the analog spiking neural network to be implemented in the adaptive CRT devices. Future work is needed to be more specified. This project has required the development of a number of behavioral models at the system level as well as the various analog behavioral models. The actual design will be based on simulations of a comprehensive system, which will permit the establishment of optimal specifications. The presentation was focused on the method used to reach a first analog solution adapted with the whole system.

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REFERENCES

[1] K. A. Ellenbogen & all, “Device Therapy for Congestive Heart Failure”, Philadelphia, Pennsylvania, Elsevier Inc., 2004, pp 47-91.

[2] Rom R., Erel J., Glikson M., Rosenblum K., Ginosar R., Hayes D., “Adaptive Cardiac Resynchronization Therapy Device: A Simulation Report”, Pacing and Clinical Electrophysiology. 2005; 28(11):1168-1173.

[3] Rom R., Erel J., Glikson M., Rosenblum K., Lieberman R, Binah O., Ginosar R., Hayes D., “Adaptive Cardiac Resynchronization Therapy Device Based On Spiking Neurons Architecture”, IEEE Transaction on Neural Network, vol. 18, no 2, March 2007, pp542-550.

[4] F. Braunschweig, B. Kjellstrom, F. Gadler, C. Linde, “Optimization of Cardiac Resynchronization Therapy by Continuous Hemodynamic Monitoring: A case Report”, Journal of Cardiovascular Electrophysiology, Vol. 15, January 2004, pp 94-96.

[5] D. Odonnell & all, “Long Term Variations in Optimal Programming of Cardiac Resynchronization Therapy Devices”, Pacing and Clinical Electrophysiology, vol. 28, January 2005, suppl. 1, pp S24-S26.

[6] P.J. Antsaklis, “Guest Editorial: Special Issue on Neural Networks in Control Systems”, IEEE Control Systems magazine, April 1990.

[7] F. Anstotz, Y. Hu, J. Michel, J.L. Sohler, D. Lachartre, “FILTRES: a 128 channels VLSI mixed front end read out electronic development for microstrip detectors”, Nuclear Instruments and Methods A412 (1998), pp. 123-134

[8] D.O. Hebb, “The organization of Behavior”, New York:Wiely, 1949.

[9] A.H. Klopf, “A neuronal model of classical conditioning”, Psychobiology, 16, (1988), 85-125, (ch. 3,5,7)

[10] J. Michel and Y. Herve; “VHDL-AMS Behavioral Model of an Analog Neural Networks Based on a Fully Parallel Weight Perturbation Algorithm Using Incremental On-Chip Learning”, IEEE ISIE 2004 conference ; Ajaccio (France) Mai 2004

[11] M. Ghorbel, J. Michel and Y. Herve; “Conservative behavioral modeling of neural systems using VHDL-AMS”, IEEE SSD 2005 conference ; Sousse (Tunisia) Mars 2005