NEURAL AND NERVOUS REFLEX NETWORKS: A NEW APPROACH TO INTEGRATED CONTROL

Alexandru M. PANAIT[1], Alexandru M. MOREGA[2]

Rețelele neuronale sunt privite ca soluție "exotică" la problemele nelineare şi se preferă implementarea lor software pe maşini cu arhitectură clasică, cum ar fi maşinile Von Neumann sau echivalente, sau chiar pe controllere specializate, denumite "computere neuronale". Această lucrare reprezita o direcție alternativă la cercetarea rețelelor neuronale artificiale, pentru că propune o implementare hardware prin particularizarea un tip special de oscilatoare în inel inventate de Mark Tilden. Rețeaua neurală tip Tilden este adaptată pentru a comanda un tracker solar, necesitând foarte puține componente şi având un cost mult mai mic, păstrând fiabilitatea, robustețea şi flexibilitatea soluțiilor clasice ca parametri de bază. Ideea originală constă în adaptarea acestei clase de rețele pentru comanda directă de poziționare a unui motor, şi în conceptul de control distribuit în sensul asigurării unei anumite autonomii efectorilor din sistemele complexe, folosind circuite cu răspuns imediat la modificarile unor parametri monitorizați.

Neural networks have always been regarded as an exotic solution to non-linear problems and often thought to be more effective as code implemented on a classical architecture machine, such as a Von Neumann machine or equivalent, or even given a controller class of their own, the "neural computer". This work represents a breakpoint with that line of thought, as it proposes a hardware alternative to the neural network implementation, by particularizing a specific type of ring oscillator invented by Mark Tilden. The Tilden neural network is adapted to drive a solar tracker, requiring only a fraction of the component list and with a minimal cost, while keeping robustness and flexibility as core parameters. The original idea is adapting this class of neural networks to directly control the positioning of a motor, and describing a type of integrated control where distributed limited autonomy "slave" controllers also exist, enabling immediate response to changes in the monitored parameters.

Keywords: Neural Net, automated control, solar tracking, stability tests, reflex neural networks theory

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1. Introduction

Nervous networks are a complementary concept to neural networks. If the latter have learning abilities and several information processing levels, nervous networks exhibit only a delay generation function and sequence repeating of inputs received form a neural network. Complex oscillatory patterns can thus be achieved from a single input pulse. The combining of the two systems, the neural and nervous network has a synergetic effect, integrating the central control, local pattern generators to drive the subsystems, sensors and effectors (actuators, motors) in a structure that resembles biologic organisms more than a classical automated feedback loop-based control.

The structures often exhibit emergent behaviors, despite their simplicity and lack of programmed elements. Unlike their counterpart, the classical neural networks, the reflex networks, both neural and nervous, do not use a pre-programmed internal representation of the environment, such as look-up tables and such, using sensory data as coefficients in the transfer function instead. Thus the transfer function is adaptable directly to changes in the structure's environment. These systems are inherently adaptable, while all the classic systems are adjustable. The control law in these systems is an arbitrary one, changing in reaction to modifications of the data from the sensors, which constructively impose the limits of sensory input; the system is in an indifferent (or marginal) equilibrium state, ensured by the intrinsic property of self-stabilization found in these structures [1, 2, 5, 7].

This type of reflex networks is comprised of one or several entities named „neurons", built around a hysteresis invertor or opamp, using an RC group to ensure the needed integrating or differentiating characteristic. The type of RC group used determines the characteristic and separates NU and NVs [8].

The transfer function of these artificial neurons has all the well-known properties: sigmoid shape, refractory period when no excitation can occur, inhibitory or activator effect (positive or negative-going output pulses). By the nature of these neurons we differentiate between nervous and neural networks. Mixed-type reflex networks do exist also, but they can be regarded as neural and nervous interconnected networks. Reflex networks of any kind must have at least one loop. In a way, they are equivalent to what the classical theory calls "degenerate networks". The neural reflex networks used in this application exhibit the property of square signal generation, having a variable fill factor and frequency, based on input from sensors or inhibitory/excitatory connections.

Nervous reflex networks, by contrast, do not generate pulses by themselves, they need an external pulse generator but once they are connected, they repeat the pulse without significant losses and modulate it, creating complex oscillatory patterns, depending on their structure, input, and influencing connections with sensors.

The current stage of development for reflex neural and nervous networks has only recently passed enthusiast experimentation phase. In 1999, a scientific military report commissioned by DARPA for the US Army evaluated the technology and found it to be unsuitable for its intended military use, because the governing equations of the neural networks were not yet determined and budget cuts stopped the project in an early phase [2]. Independent studies have been conducted since and a basis of operation was outlined; the present paper establishes the needed formulae and procedures to precisely design such a network and describes a simple application in which such a construct is used to control a simple solar tracker, currently under works.

2. Operation of neural and nervous reflex networks

The two studied types of reflex neurons, as described by their creator, M, Tilden et al. [1] and Rietman and Willis [2], can be classified by the response to the input pulse in integrating (NV's as in Nervous neurons) and differentiating (NU's as in neural/cortical structures).

Let us analyze the simple NV integrating neuron. This structure has the following layout (fig 1.1). To induce a refractory state, similar to that of biological neurons, hysteresis trigger-Schmidt invertors of the 74HC14 series were used [1].

The logic state change in these NV neurons has the following particularities:

- A circuit time constant $\tau = RC$ exists, and it gives its refractory period. The refractory period, like its analogue in biology, represents the time after a transition of the output in which any other input is ignored. In this case, from the inactive „1" logic state of the output, a transition to the „0" logic state can occur if the neuron has received a pulse on the input port, A, (see fig. 1) as a positive-going TTL/CMOS pulse, and it is not in its refractory period.
- A descending front of the input signal having a duration less than τ, works as a neuron reset, causing the output to go inactive („1" logic state, the NV neurons are active-low devices).

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These properties can be demonstrated using a simple experimental setup, consisting in a function generator (pulse injector in this case), neural board, power supply and oscilloscope. By connecting the logic pulser in the polarizing node B of a neuron in the loop, we can observe its response to induced square wave oscillations having variable frequencies, and to constant potentials.

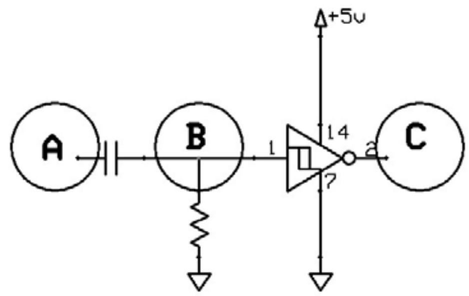

Fig.1 Structure of a NV neuron A = input, B = polarizing node, C = output.

The experiment concluded that: injecting a square wave oscillation having a period smaller than the circuit time constant τ, leads to a similar oscillation of the output, but in antiphrasis to the input. Increasing the frequency until it is greater than τ, and thus the resonant frequency of the neuron, we witness the neuron entering the refractory stage. The refractory stage is relative, as it depends on the intensity of the injected stimulus, just like in biology. Injecting a fast pulse in the polarizing node B, or setting it to a high potential, the output C (fig. 1) has a transition to the active state. If we increase the frequency over a certain value we will find the critical point from beyond which the neuron does not entry the active state anymore, regardless of the stimulus (respecting the voltages within the safe operating limits for the neural network, given by the 74HCT 14's specifications).

Using the fact that the NU-ring structure is unidirectional, and utilizing the weight matrix – eq. 1, in [2] – yields

$$W = \begin{bmatrix} 0 & \dots & \dots & w_{n,1} \\ w_{1,2} & 0 & \dots & 0 \\ 0 & w_{2,3} & \dots & 0 \\ 0 & \dots & w_{n-1,n} & 0 \end{bmatrix}. \tag{1}$$

We point out that *W* has the weights $w_{n-1,n} = -1$, because of the inverting functions of each neuron, coupled with a delay given by the *RC* constant of the circuit. A static analysis is needed to assess the time stability, because frequency stability is ensured by the existence of an absolute refractory period that equals the circuit time constant $\tau = RC$. It will be shown that the NU-network stability is an intrinsic property. The weight matrix structure for the NU neurons shows that each neuron *n* has direct connections only to the next neuron $(n+1)$ and that the network is cyclic, the output of the neuron *n* being connected to the input of neuron 1 forming a uni-directional ring structure.

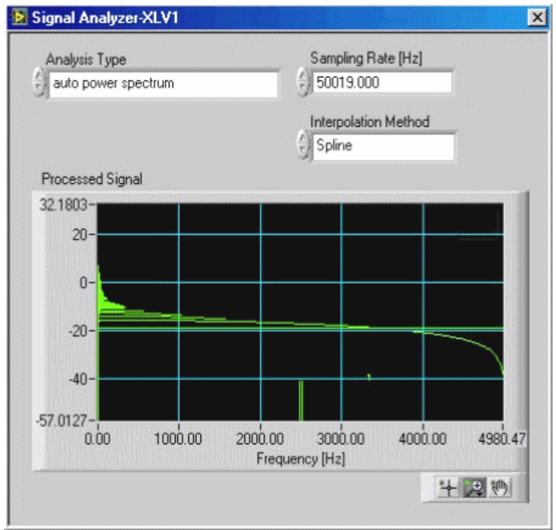

Fig.2 A Lab View simulation of the output signal's power spectrum for a NV neuron. Although it contains a wide range of frequencies, it is not infinite since it represents a sigmoid function.

3. Equations and mathematical formalization of the design

For the transfer function in a neural network usually a sigmoid function is used, written as

$$\sigma(x) = \frac{1}{1 + e^{-ax}}, \tag{2}$$

where a is a parameter named steepness that gives the incline of the sigmoid function, but the analysis of the practical examples indicate a sufficiently good approximation of the model by using that proposed by Blum and Wang in 1995, using a function that expresses transitions in such a structure

$$\Psi(x) = 2[\sigma(x) - 0.5] = \frac{1 - e^{-ax}}{1 + e^{-ax}}. \tag{3}$$

Let us consider a loop of *n* neurons, and agree to note the states of each neuron „*i*" at the moment $t = p$ by $x_p^{(i)}$, and let the transition function be $F : X_n \to X^n$ having $X = \{0,1\}$ as the set of possible states. Under these assumptions, X^n gives the state space for the *n*-neuron structure. We can thus write

$$F(x_{p+1}^{(1)},...x_{p+n}^{(n)}) = (f(x_{p+1}^{(1)}),...f(x_{p+n}^{(n)})), \quad (4)$$

and if we accept $f = \Psi$, where Ψ is given by eq. (3), we can describe a constraint for a stable state of the network: the neural network described by eq. (4) is stable as long as the $f = \Psi$ function has at least one periodic point. That is equivalent to inferring that in the given network, at least one oscillation of a given frequency occurs. The harmonics of this oscillation are possible only if the equation eq. (4) has several fixed points. For eq. (4) to have a periodic point, it must have a minimum period with $q < n$ and q | n, and if a point $x = \left(x^{(1)}, x^{(2)},..x^{(n)}\right)$ is a periodic point, then any point $x^{(i)}$ with $i = 1\ldots n$ must be a fixed point for the f function.

By analyzing Ψ, we conclude that for $a \le 2$ (steepness parameter for the sigmoid transfer function) the equation has an attractor in the solution space, in (0, 0...0), and it is also the only periodic point; however, for $a \ge 2$ the function has a large number of periodic points, (3n), that also describes the number of the network's oscillation modes (possible harmonics). Out of these possible modes, only 2^n are stable, the rest being saddle points.

The NU and NV neural networks are a class of self-stabilizing structures. In these structures the marginal stability is manifested, the system evolving on the edge of chaos, in the calculated saddle points, leading to their saturation. The saturation is a process that physically manifests itself by the apparition of a large number of harmonics and the entry of all the neurons in the refractory state for an undetermined period of time. Needless to say, this rends the neural network non operational [2]. From this point on, we will refer to a stable oscillation in the network as a „process”.

There is a way to stop this situation form occurring, by building and coupling a process injector/initiator, that has the role to suppress the harmonics, bringing the network back to stable state. This process „pacemaker” injects in one network node a frequency that is far lower than the *RC* threshold of the refractory period, and establishes a rhythm for the base oscillation of the network. This rhythm can be modified by injecting signals in the B (polarization) nodes of the neurons in the network (fig. 1) where the sensors will be connected.

4. Neural and Nervous Reflex Controllers

Considering the structure for a NV neuron, discussed earlier, by switching the resistor and capacitor components we find a similar structure, but having different properties. This newfound structure is an analogue of the neurons in the central nervous system; we shall call it a „ nervous neuron”, or NV, by contrast to the neural neuron, or NU. This nervous neuron can also form ring oscillator structures, but as it has an increased immunity to noise and it is difficult to influence (as it has an integrating behavior and it suppresses noise, vs. the differentiating one in the NU) is least suited to be connected to sensors. It excels however in forming pulse-generating structures, and transmitting those pulses in neural networks.

The basis application for these structures is the construction of „pattern generators" similar to those in biologic organisms, and having similar functions, in coordinating complex cyclic functions (as the walking sequences for example), that imply a coordination of several elements, effectors, etc by the NV neurons. A neural controller built upon this paradigm means one or several rhythm generators, sensors and several nervous structures. Its functioning is unique by the fact that it does not use programmed routines and microprocessors, but reacts adaptively to the environment using sensory input as weights for its neurons. A prototype of this system is functioning in the IEM laboratory and will control a solar tracker. Results from preliminary testing are presented below.

The network operation can be synthesized in what follows: the neuron in fig 3.1 consists in a trigger-Schmidt inverter having a hysteresis of approx 0.7 V, built on a CMOS 4093 series chip, powered at 5 V, and an RC low pass filter, that confers the assembly a differentiating behavior. The time constant for R = 5,1 MΩ and C = 0.01 μF is 178 ms. These values were used by DARPA military experts in the assessment of the neural networks of this type, and were replicated by the author. Other configurations using other values and the 74HCxx series chips have been tested. The switching thresholds are 2.9 V and 2.2 V, when the IC is powered at 5 V. This neural structure accepts both excitatory and inhibitory inputs (*i.e.*, positive and negative, high and low logic pulses in the B biasing node).

In the relaxed state (absence of input) the output is in high logic state; if a signal strong enough or lasts enough to charge the capacitor (threshold implementation), the voltage in point B on the diagram 1 becomes positive and the output of the inverter goes low, and the capacitor will discharge through the resistor to ground. In this state the neuron is active (transmits a negative-going pulse at its output). Then, after the capacitor discharges, the neuron output goes high again, yielding

$$V_{in} = V_h \cdot \left[u(t - t_1) - u(t - t_0)\right], \tag{5}$$

where V_h is the output in high state (in this case 5 V) and $u(t)$ is the step unit function, centered in 0

$$u(t) = 0, \quad t < 0, \quad u(t) = 1, \;\; t > 0, \tag{5}$$

describes the functioning of the neuron and the input the following neuron in the loop receives. The neuron active time (active signal front) is

$$t_2 - t_1 = -RC \cdot V_{t_{HL}} \Big/ \left[V_H \cdot \left(1 - e^{-(t_1 - t_0)/(RC)}\right)\right], \tag{6}$$

where

- RC is the time constant of the circuit;
- $V_{t_{HL}}$ is the negative-going front threshold;
- V_H is the positive going front threshold;
- t_1 and t_0 are the moments of pulse injection, initial and final.

We found that a long pulse applied to the input outputs a long pulse, and a shorter one will output a shorter pulse. A consequence of this fact is that in some neural networks of this type, the faster pulses can „catch up” with the slower ones and cause a temporary instability of the network, followed by a re-establishing of the equilibrium of the oscillation in another configuration (frequency and pattern). In general, injecting a pulse in the network having one stable oscillation pattern, leads to the change of the equilibrium state, and establishing of a new limit cycle, having the following expression for its duration [eq. (7) describes the time for one pulse to propagate along the network]

$$T = Nt_{LH} + Nt_{HL} + NRC + Tr, \tag{7}$$

Where

- N = the number of neurons in the loop;
- t_{LH} = transition time, low-high;
- t_{HL}= transition time, high-low;
- RC= the time constant of the circuit;
- Tr = period of the injected pulse (it affects only one cycle of the pulse as it travels along, altering the time constant of the affected neuron).

Shifts in frequency can be observed as long as the pulse is active, and the network normally returns to the idle state when sensory input is not active. Starting from a simple network as described in [1, 2] and using these observations, the authors have built and tested a phototropic motor controller that can be used in solar tracking applications (fig.3). These findings are in concordance with [5].

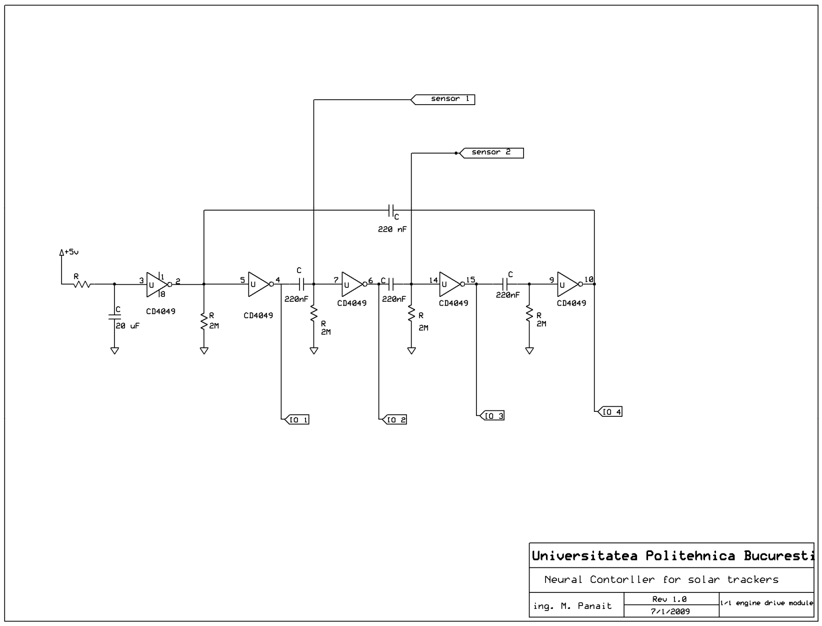

Fig.3. The neural controller designed using the eqs. (1)-(7). The inputs, marked "sensor" on the diagram, show the connection points for a differential photodiode bridge light sensor (not shown). The ports marked IO 1-4 are the controller's outputs that need to be buffered before connecting one monopolar stepping motor.

5. Testing the neural reflex controller

Using eqs. (1)-(7) and a simple experimental setup consisting in a logic pulser, neural board, power supply and a PC-interfaced multiscope, we have found that for each neuron, the oscillation of a known time constant $\tau = RC$ is delayed by the switching times of the used circuit, and, overall, a mean value for the delays of the *RC* groups can be observed. The frequency was measured using the following experimental set-up: PC, digital oscilloscope with serial interface (RS 232), at 9.6Kbaud, measuring two channels simultaneously, one live and one not connected (connected to a dummy resistor NOT in the circuit for noise level measurements), and a quad core of four NV neurons and one NU neuron for pulse initialization/stabilizing behavior. The equation 7 gives the period for the free oscillation of the network, $T = \frac{1}{0,22} = 4,(45)$ – ignoring the very small switching times. The frequency value, at the network initialization was about 3.33 Hz (under the influence of the NU node having a 0.4 Hz frequency- ten times lower than the network itself), which was rapidly amortized and the network stabilized at 4.40Hz, in about two minutes form start-up. The supply voltage ripple was low, below 0.01 mV (tracking stabilization power source), and can be neglected, the schematic having a capacitor type filter consisting of two capacitors in parallel over the supply lines, a 10 μF one and a 1 pF one for high frequency suppression).

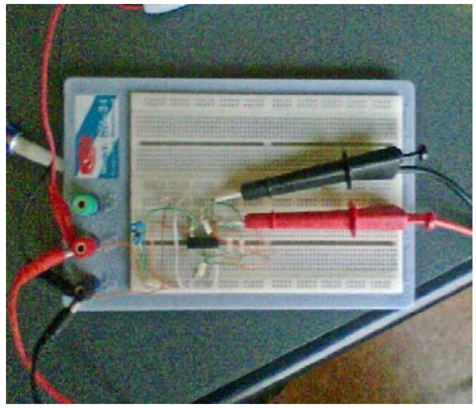

Fig. 4. Experimental set-up, the neural controller on a quick board.

The next stage is the direct light sensors coupling, and the analysis of the network behavior under light gradients will be studied. Modifying the output waveform by frequency/fill factor self-adjustment allows for the PWM control of the small motors, or phase drive for special machines. For the control of larger motors, a current amplifying buffer/optical insulation and smokeless *H*-bridges will be used. A further stage is the integration of the power stage and command electronics, sensors and motors on a one-or two-axis mobile mount.

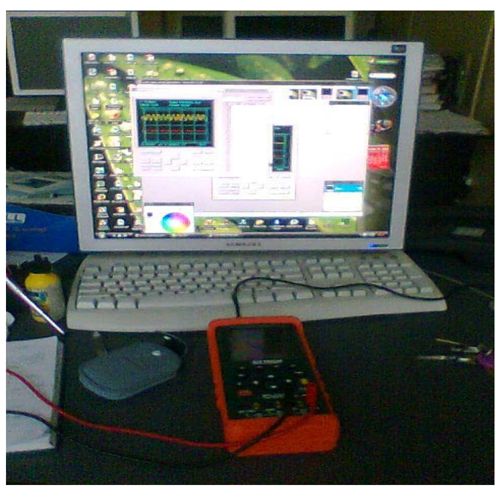

Fig.5 Experimental set-up, the data collection part comprised of an EXTECH multiscope, courtesy of the Laboratory of Electrical Engineering in Medicine, and a PC.

6. Conclusions

Using minor adaptation one can successfully convert the reflex neural network, pioneered by M.Tilden, to the use on a solar tracker. The main advantages of this solution are the reduced costs, and system flexibility and modularity (the networks can be built as modules, easily interchangeable). These networks can be used in low-cost tracking applications of any nature, and do not need a controller, as long as adequate sensors are provided [3,6]. The power supply is not a critical network parameter. The system can also be built for rapid reaction, but this is not suitable for a slow moving tracking target, such as the Sun, because the low thresholds induce unwanted oscillation that leads to high-energy consumption.

Another different approach to implementing hysteresis is by using a TTL compatible differential sensor that has an adjustable sensitivity. This system will be presented in a future paper. The described neural network controller is capable of implementing a reflex fuzzy control paradigm, responding directly to environmental changes by generating pulses of variable frequency and fill factor.

Fig. 6 shows the output waveform of the neural controller, in accordance to eqs. (1)-(7).

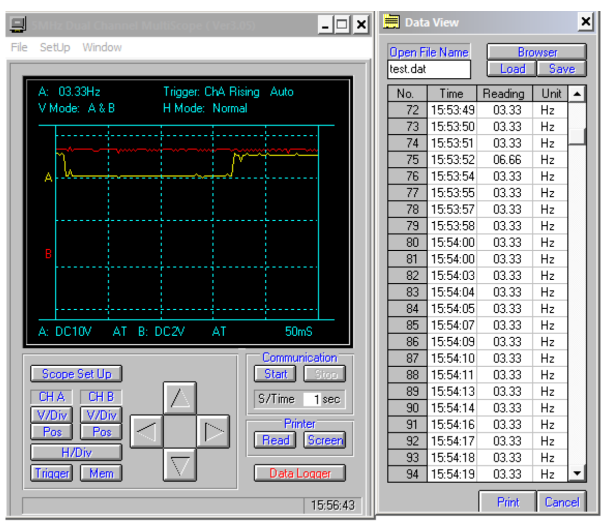

Fig.6. The output waveform of the neural controller.

The waveforms agree well to the theoretic predictions [4, 5,7,8]; the stability of the waveforms were observed, along with the frequency stability previously explored. In fig. 6, the „stability test" started, and the power-up frequency of 3.33 Hz can be observed. During the no-sensors test the circuit was operated at low and normal power, at 2.3 and 4.5 V, drawing below 10, and 20 mA in the second case.

The authors built and tested a neural controller similar to that described in this work, and adapted it to solar energy conversion applications such as optimizing the power output of solar panels by ensuring proper orientation with respect to the Sun [9].

The theory of operation of such devices was studied and further observations were made, that ensured superior performance: the NOT gates are, as we have determined, less stable as the NAND gates in negator configuration, and we preferred the latter because of their faster response time and because of their characteristic, which is closer to optimal transfer. Also, a fully reversible motor drive operating on phase drive wave was developed and tested by the authors using the theory in the present work.

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