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An analogue recurrent neural network for trajectory learning and other industrial applications

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Abstract

A real-time analogue recurrent neural network (RNN) can extract and learn the unknown dynamics (and features) of a typical control system such as a robot manipulator. The task at hand is a tracking problem in the presence of disturbances. With reference to the tasks assigned to an industrial robot, one important issue is to determine the motion of the joints and the effector of the robot. In order to model robot dynamics we use a neural network that can be implemented in hardware.

The synaptic weights are modelled as variable gain cells that can be implemented with a few MOS transistors. The network output signals portray the periodicity and other characteristics of the input signal in unsupervised mode. For the specific purpose of demonstrating the trajectory learning capabilities, a periodic signal with varying characteristics is used. The developed architecture, however, allows for more general learning tasks typical in applications of identification and control. The periodicity of the input signal ensures convergence of the output to a limit cycle. On-line versions of the synaptic update can be formulated using simple CMOS circuits. Because the architecture depends on the network generating a stable limit cycle, and consequently a periodic solution which is robust over an interval of parameter uncertainties, we currently place the restriction of a periodic format for the input signals. The simulated network contains interconnected recurrent neurons with continuous-time dynamics. The system emulates random-direction descent of the error as a multidimensional extension to the stochastic approximation. To achieve unsupervised learning in recurrent dynamical systems we propose a synapse circuit which has a very simple structure and is suitable for implementation in VLSI.

Index Terms— Artificial neural network (ANN), Electronic Synapse, trajectory tracking, Recurrent Neurons.

I. INTRODUCTION

Recently, interest has been increasing in using neural networks for the identification of dynamic systems. Feedforward neural networks are used to learn static input-output maps. That is, given an input set that is mapped into a corresponding output set by some unknown map, the feedforward net is used to learn this map. The extensive use of these networks is mainly due to their powerful approximation capabilities. Similarly, recurrent neural networks are natural candidates for learning dynamically varying input-output. For instance, one class of recurrent neural networks which is widely used are the so-called Hopfield networks. In this case, the parameters of the network have a particular symmetric structure and are chosen so that the overall dynamics of the network are asymptotically stable [1]. If the parameters do not have a symmetric structure the analysis of the network dynamics becomes intractable. Despite the complexity of the internal dynamics of recurrent networks, it has been shown empirically that certain configurations are capable of learning non-constant time-varying motions.

The capability of RNNs of adapting themselves to learn certain specified periodic motions is due to their highly nonlinear dynamics. So far, certain types of cyclic recurrent neural configurations have been studied. These types of recurrent neural networks are well known, especially in the neurobiology area, where they have been studied for about twenty years. The existence of oscillating behaviour in certain cellular systems has also been documented [1-3,10]. Such cellular systems have the structure of what, in engineering applications, has become known as a recurrent neural network. Thus the neural network behaviour depends not only on the current input (as in feedforward networks) but also on previous operations of the network [4].

II. ANN FOR TRAJECTORY TRACKING

In this paper we treat a neural network configuration related to control systems. We describe a class of recurrent neural networks which are able to learn and replicate autonomously a particular class of time varying periodic signals.

Neural networks are used to develop a model-based control strategy for robot position control. In this paper we investigate the feasibility of applying single-chip electronic (CMOS IC) solutions to track robot trajectories.

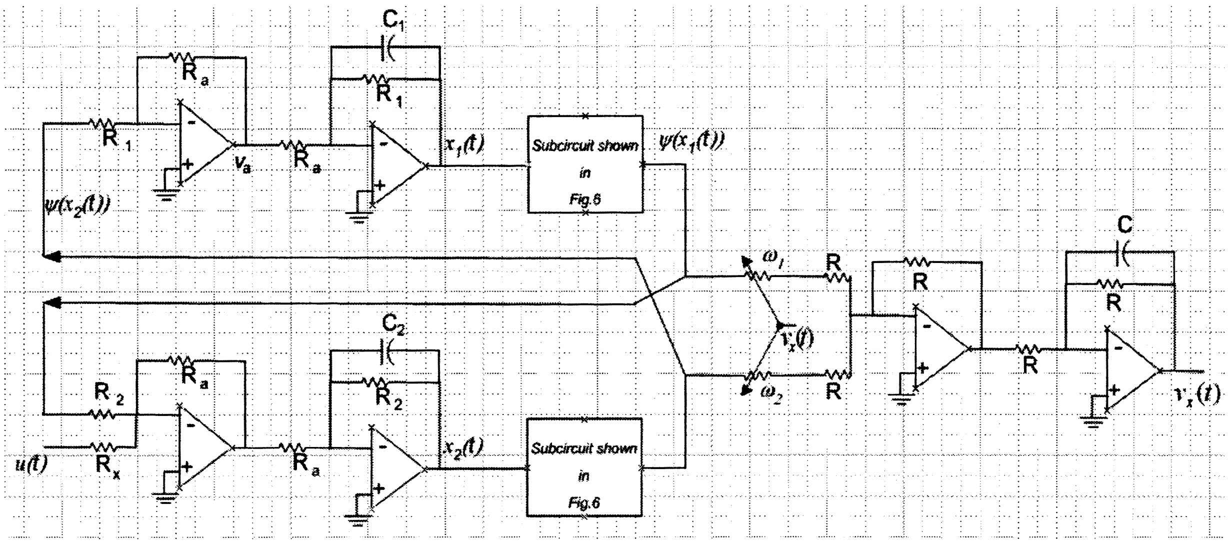


Fig. 1. The block diagram of the proposed recurrent neural network.

Neural network with dynamic neurons

The block diagram of the type of network under study is illustrated in the Fig. 1. In this figure $u(t)$ is the input and $v_x(t)$ is the output of the network. A recurrent network of the type depicted in the Fig. 1 is described by the following system of differential equations

$$x_1 = -\frac{R_1}{R_a}v_a - R_1C_1\frac{dx_1}{dt} \quad = -\frac{R_1}{R_a}v_a - \tau_1\dot{x}_1$$

$$v_a = -\frac{R_a}{R_1}\psi(x_2)$$

$$\tau_1\dot{x}_1 = -x_1 - \frac{R_1}{R_a}v_a = -x_1 + \frac{R_1}{R_a} * \frac{R_a}{R_1}\psi(x_2)$$

$$= -x_1 + \psi(x_2)$$

Similarly,

$$\tau_2\dot{x}_2 = -x_2 + \psi(x_1) + u(t) \tag{1}$$

Finally, for the output of the circuit, we have,

$$\tau\ \dot{v}_x = R\ C\ \dot{v}_x$$

$$= -v_x - \frac{R}{R}\left[-\omega_1\frac{R}{R}\psi(x_1) - \omega_2\frac{R}{R}\psi(x_2)\right]$$

$$= -v_x + \omega_1\psi(x_1) + \omega_2\psi(x_2)$$

The time constants τ, τ_1, and τ_2 govern the dynamics of the network, providing first order low-pass filtering in the evolution of the neuron state variables. A more elaborate model of neural dynamics would incorporate individual adjustable time constants at the level of the synaptic contributions [5-7].

An alternative type of RNN that can be described by the differential equations given below can also be built with the electronic neurons discussed in the next section. We see that the above schematic (Fig. 1) implements the neural network with only two dynamic neurons (neuron circuit is shown in Fig. 2.). The equations of the branch currents (I_{M1} and I_{M2}) discussed in the next section suggest the synapses are suitable to implement both types of RNN represented by either (1) or (2).

The simulated network contained six fully interconnected recurrent neurons with continuous-time dynamics. The simulated neural network can be described by a general set of equations such as the ones given below.

$$r\dot{y}_i = \gamma' + W_i - \exp(y_i) - \lambda\sum_{j=1,\neq i}^{N}\exp(y_j)$$

$$= \gamma' + W_i - (1-\lambda)\exp(y_i) - \lambda\sum_{j=1}^{N}\exp(y_j) \tag{2}$$

with $x_i(t)$ the neuron state variables constituting the outputs of the network, $x_i(t)$ the external inputs to the network, and $\sigma(.)$ a sigmoidal activation function. The value for τ is kept fixed and uniform in the present implementation. There are several free parameters, to be optimally adjusted by the learning process. For example if we implement a fully interconnected RNN, there will be 36 connection strengths W_{ij} and 6 thresholds θ_j.

The so called triggering nonlinear function of the neurons associated with this network is taken as $tanh(x_i)$ and is shown in the Fig. 1 as $\psi(x_i)$. However, it is likely that a larger class of triggering functions with the same properties of oddity, boundedness, continuity, monotonicity and smoothness could be considered. Such triggering functions include arctan(x), $(1+e^{-x})^{-1}$, e^{-x^2} etc. In the next section we will introduce a synaptic circuit that implements the ω_i shown in Fig. 1.

III. RECURRENT NEURON CHARACTERISTICS

In the synaptic circuit, the current of M_5, which we denote as I_{M5} acts as an excitatory current which increases the membrane potential v_c, while the currents of M_1 and M_2, which we denote as I_{M1} and I_{M2}, respectively, act as lateral- and self-inhibitory currents which decrease the membrane potential. In this synaptic circuit, the node equations at the node v_c are as follows:

$$C\dot{v}_c = I_{M5} - I_{M1} - I_{M2}$$

where I_{Ma} stands for the current of transistor Ma of the synaptic circuit. It should be noticed that the left side of the above equation represents the current of the capacitor, while the right side of the equation is given by the linear combination of saturation currents of MOS transistors operating in the subthreshold (weak inversion) region. The input transistors are operated in weak inversion for two reasons. In this configuration, (1) they deliver maximal transconductance for a given current and (2) low v_{gs} and v_{ds} voltages are needed for large swing. This implies that the network can easily be implemented by the MOS circuit of Figure-2 operating in the subthreshold region [8].

A transistor can be biased in different ways by choosing the dependent variable as current or voltage. For voltage biasing, the gate-source voltage of the device is the same and current is the dependent variable. For current biasing, the current in the devices is the same but the voltage is the dependent variable. Current-mode circuits should be biased deep in saturation for best accuracy. In the case of voltage-mode circuits, best accuracy is obtained in weak-inversion.

In the subtrhreshold region of operation, I_{M2} is ideally given by

$$I_{M2} = I_o \exp(v_c / \eta V_T)$$

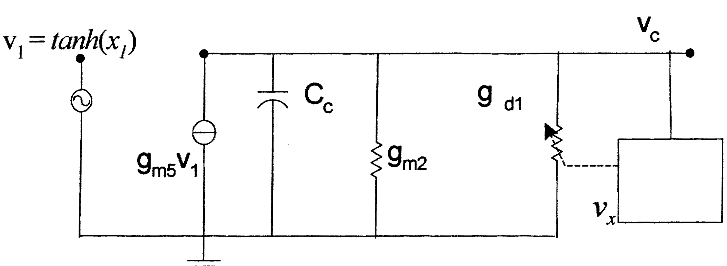


Figure 3. Small-signal equivalent of the synaptic circuit.

Similarly, I_{M1} is given as

$$I_{M1} = I_o \exp(v_x / \eta V_T)$$

in terms of the gate-source voltage v_x of M_1, as long as it operates in the saturation region ($v_x \geq 4\ V_T$). where v_x represents a transformed variable possessing the dimension of a voltage, $V_T = kT/q$ (k is the Boltzmann's constant, T the temperature, and q the charge of an electron), η measures the effectiveness of the gate potential, v_{in} is an external input voltage, C represents a capacitance, I_o is a MOS transistor parameter, and β represents a gain constant. We have conformed to the standard notation in writing the CMOS equations above to represent the dynamics of the circuit [9].

The current mirror consisting of M_2 and M_3 implies that the output current of the synaptic circuit I_{M3} is equal to I_{M2}. The current I_{M5} which depends on the input v_{in} acts as an excitatory input and is given by $I_{M5} = I_o \exp(v_{in} / \eta V_T)$. The voltage v_c is amplified by the common source amplifier consisting of transistor M_3 and its load M_4.

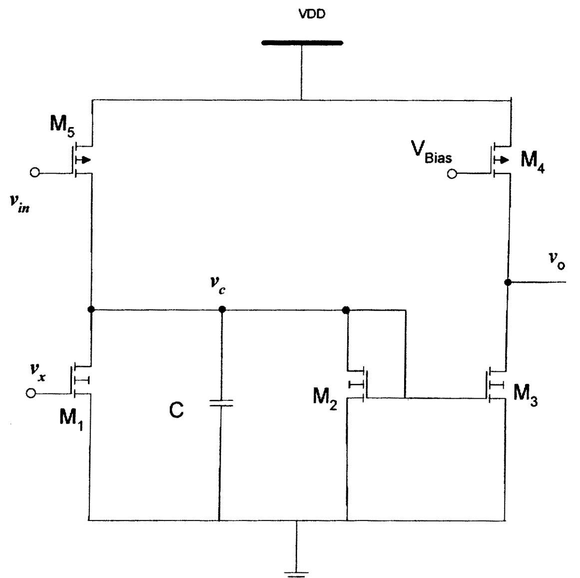


Fig. 2. The circuit diagram of the proposed recurrent neuron.

Analysis of the synapse circuit

The synaptic circuit can be realized in two different formats. The format shown in Fig.2 implements the synapse as a gain controlled voltage amplifier. An alternate format of the synapse (shown in Fig. 4) is based on a transimpedance gain function. The main difference between these two circuits is the presence of an additional feedback transistor placed between v_c and output v_o (Compare Figs. 2 and 4.). In both cases the gate terminal of transistor M_1 can be used to control the gain of the synapse. In this case the small-signal equivalent circuit shown in Fig. 3 can be used to show that the voltage gain is given by :

$$\frac{v_c(s)}{v_1(s)} = \frac{-g_{m5}}{g_{m2} + g_{d1} + sC_c}$$

In this case, the output of the synapse, $\omega_1 * \psi(x_1)$ goes through the output stage integrator and the voltage v_x is used to control the gate of transistor M_1 of the synapse. Hence the synapse behaves like a variable gain amplifier controlled by the variable conductance g_{d1}. In other words, ω_1 is a function of the state v_x.

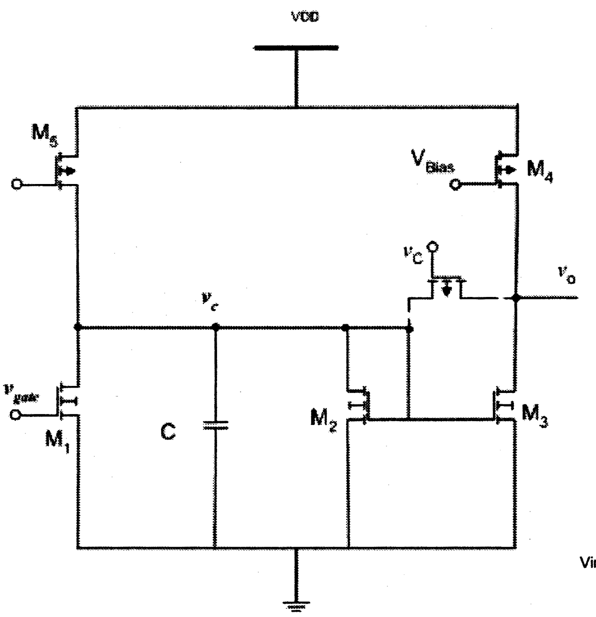


Fig. 4. The circuit diagram of the proposed synapse that implements a transimpedance gain function $Z_T(s)$.

IV. A NEURAL NETWORK BASED CONTROLLER FOR ROBOT POSITION CONTROL.

We train a neural network to learn and mimic movement of a robot manipulator. A block diagram of such a setup is depicted in Fig. 5. The neural network learns the behaviour of the robot manipulator over certain time horizon. The neural network also optimizes the control action such that the error between the output of the robot manipulator and the reference (desired) trajectory is minimized.

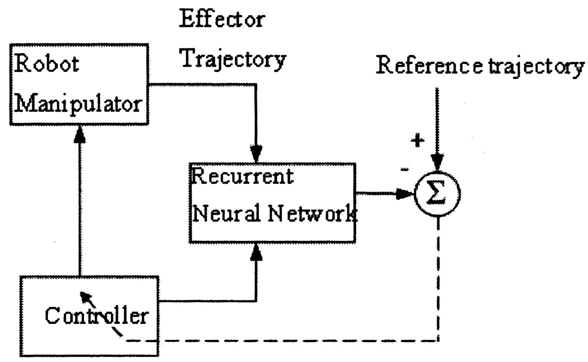
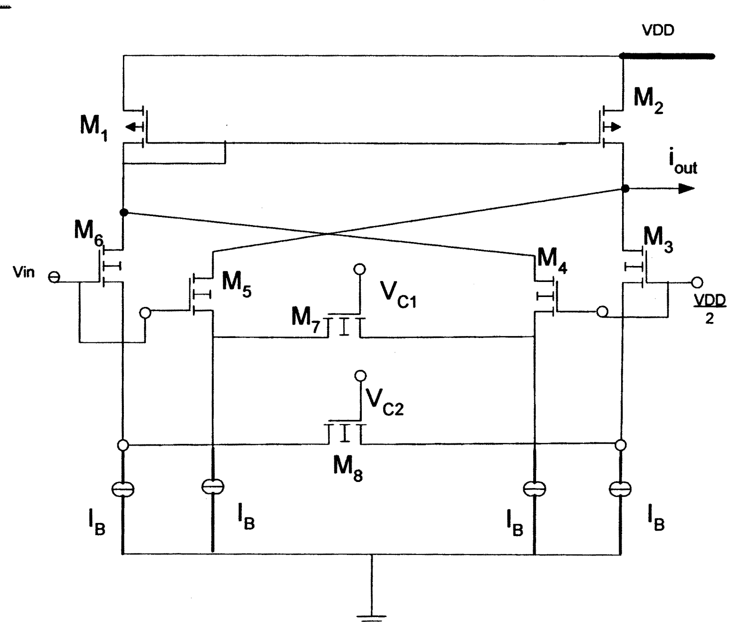


Fig. 5. Block diagram of a neural network based robot control system.

Neural network with sigmoidal neurons

In the proposed recurrent neural network (Fig. 1) we need a sigmoidal $\psi(x_i)$ function. This sigmoidal circuit shoule be suitable for implementation in CMOS. We will introduce a simple circuit that can implement the sigmoidal function $\psi(x_i)$.

Fig. 6. Circuit diagram to implement the $\psi(x_i)$ function.



The circuit shown in Fig. 6 is a linearized transconductor whose output current i_{out} is proportional to $\tanh(v_{in})$. In this circuit, the G_m is derived from a cross coupled pair of matched transistors (M_7 and M_8) operating in the triode region. In this configuration, the G_m is controlled with gate voltages V_{C1} and V_{C2}.

The possibility of building the entire electronic system discussed in this paper using CMOS technology is currently explored. In the absence of such a hardware system, we are studying the performance by simulating an operational amplifier based conceptual circuit model.

V. SIMULATION OF THE PROPOSED SYSTEM

The novel concepts formulated in this paper can be experimentally verified by the manufacture of a prototype electronic system. The circuits needed for such implementation are presently simulated using CAD packages. For example the circuits of sigmoidal transfer function (Fig. 6) and synaptic networks (Figs. 2 and 4.) were designed using 0.18 micron CMOS technology. These simulations confirmed the scalability of the modularized architecture of the learning algorithm. We are verifying the robustness of the architecture under technology parameter perturbations. These simulation results will be discussed during the presentation at the conference.

As an alternative to the experimental verification, we have simulated the system of differential equations that represent the proposed recurrent neural network. The task set for this verification is to apply a variety of input waveforms to the simulator and observe the output waveforms. The inputs to the simulator explored comprise a variety of waveforms such as triangular, saw-tooth, square and sinusoids. All these input waveform characteristics such as frequency, amplitude and phase were varied and the ability of the neurons to settle to a limit cycle were observed.

VI. INDUSTRIAL APPLICATIONS

The architecture of an analog recurrent network that can learn a continuous-time trajectory is presented. The presentation shows that the RNN does not distinguish parameters based on a presumed model of the signal or system for identification. Simulation of such an autonomous tracking of a trajectory is shown in Fig. 7. The vertical (y-axis) shows the robot joint position in radians and the horizontal (x-axis) shows time in msec.

In many decision making processes such as manufacturing, aircraft control, robotics etc, we come across problems of control systems that are highly complex, noisy, and unstable. A tracking system or *agent* must be built that observes the state of the environment and outputs a signal that affects the overall system in some desirable way. The RNN presented here is suitable for such tasks because it is general and robust enough to respond effectively to conditions not explicitly considered or completely modelled by the designer.

The architecture of the analog RNN discussed here is easier to implement in CMOS VLSI technology. The RNN presented is a very small network consisting only of two synaptic weights. However, it was able to learn periodicity from the applied signals in unsupervised mode. It should be noted that this network is scalable. A large RNN of this structure can be built with relatively little hardware and can be used for a variety of applications in control, instrumentation and signal processing applications.

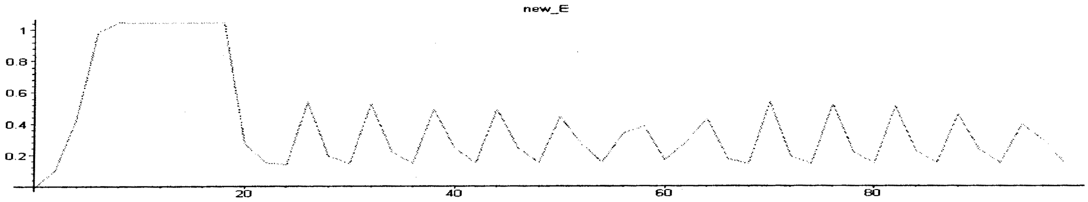


Fig. 8. Output of the RNN for an applied varying input.

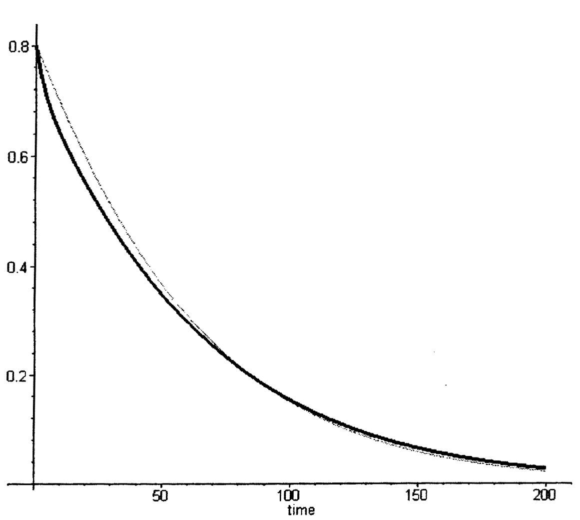


Fig. 7. The reference trajectory (red) compared with tracking RNN output.

VII. CONCLUSIONS

The complexity of real world systems often defy mathematical analysis, and, most interesting tasks in these environments are too hard for designing a controller strategy by hand. Both of these problems can be avoided by learning from direct interaction given two essential components: a simulator that behaves like the environment, and a learning mechanism that is powerful enough to solve the task.

In this paper we discussed the application of an analogue recurrent neural network to learn and track the dynamics of an industrial robot. The observations made from this study suggest that RNNs (similar to those in Fig. 1) can be applied to the control of real systems that manifest complex properties – specifically, high-dimensionality, non-linearity and requiring continuous action. Examples of these real systems include aircraft control, satellite stabilization, and robot manipulator control.

We conclude that robust controllers of partially observable (non-Markov) systems require real-time electronic systems that can be designed as single-chip Integrated Circuits (CMOS IC). This paper explored such techniques and identified suitable circuits.

VIII. REFERENCES

[1] S. Townley, et al., "Existence and Learning of centerline Oscillations in Recurrent Neural Networks", *IEEE Trans. Neural Networks* **11**: 205-214, 2000.

[2] E. Dijk, "Analysis of Recurrent Neural Networks with application to speaker independent phoneme recognition", M.Sc Thesis, University of Twente, June 1999.

[3] G. Cauwenberghs, "An Analog VLSI Recurrent Neural Network Learning a Continuous-Time Trajectory", *IEEE Trans. Neural Networks* **7**: 346-361,Mar. 1996.

[4] M. Mori et al., Cooperative and Competitive Network Suitable for Circuit Realization", IEICE Trans. Fundamentals, vol. E85-A, No.9, 2127-2134, Sept. 2002.

[5] H.J. Mattausch, et al., "Compact associative-memory architecture with fully parallel search capability for the minimum Hamming distance", *IEEE J. Solid-State Circuits*, vol.37, pp.218-227, Feb. 2002.

[6] G. Indiveri, "A neuromorphic VLSI device for implementing 2-D selective attention systems", *IEEE Trans. Neural Networks*, vol. 12, pp.1455-1463, Nov. 2001.

[7] C.K. Kwon and K. Lee, "Highly parallel and energy-efficient exhaustive minimum distance search engine using hybrid digital/analog circuit techniques", *IEEE Trans. VLSI syst.* vol. 9, pp. 726-729, Oct. 2001.

[8] T. Asai, M. Ohtani, and H. Yonezu, "Analog Integrated Circuits for the Lotka-Volterra Competitive Neural Networks", *IEEE Trans. Neural Networks*, vol. 10, pp. 1222-1231, Sep. 1999.

[9] Donckers, et al. "Design of complementary low-power CMOS architectures for loser-take-all and winner-take-all" Proc of 7th Int conf. on microelectronics for neural, fuzzy and bio-inspired systems, Spain, Apr 1999.

[10] A. Ruiz, D. H. Owens and S. Townley, "Existence, learning and replication of limit cycles in recurrent neural networks", *IEEE Transactions on Neural Networks,* vol. 9, pp. 651-661, Sept. 1998.