Investigation of contrast enhancement by numerical methods for an optical cellular neural network

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ABSTRACT - A numerical model of a nearest-neighbor interconnected cellular neural network is described. The cells consist of optically driven autonulling circuits that generate analog output signals. From the numerical analysis we demonstrate that the 2D array provides lateral inhibition properties. Control of the image enhancement is obtained through the weights associated with a 2D convolution operator.

KEYWORDS: cellular neural network (CNN), spatial filtering, lateral inhibition, edge enhancement, image enhancement, nearest-neighbor and autonulling dc bridge (ADCB)

Introduction

Artificial neural networks have been developed to enhance features or edges for pattern recognition and classification [1]. The optical cellular neural networks (OCNNs) use signals from photodiodes or phototransistors to drive a nearest-neighbor interconnected neural network to an equilibrium state, generating a 2D matrix corresponding to a pre-procssed image. We present the results from a numerical model of a feedback system that uses an array of phototransistors, with each phototransistor configured in an autonulling bridge [2]-[3]. The bridge circuits and interconnections are designed to reduce electronic noise from the input devices as well as spatially filter background noise, analogous to spatial filtering techniques used in image processing.

A nearest-neighbor interconnected neural network utilizing the autonulling dc bridge (ADCB) as the unit *cell* shown in Figure 1 has been simulated using PSpice and numerical techniques. In the first microfabricated implementation of the OCNN, each bridge *cell* will be configured as shown in Figure 1 with a phototansistor as the DUT and a bipolar transistor as the VCR, described in [2]. A second variation of this embodiment is being fabrcicated to use a photodiode array as the input for each of the bridges in which the bridge circuitry is connected in close proximity to the array to reduce pick up.

Numerical Model

Each of the bridge integrators will have outputs that are governed by the following coupled differential equations

$$\frac{dV_{i,j}}{dt} = A_{i,j}\left(V_{1,i,j} - V_{2,i,j}(V_{r,i,j})\right)$$

where $V_{1;i,j}$ and $V_{2;i,j}$ correspond to node voltages of each bridge in the array and i and j correspond to the row and column in the array. $V_{1;i,j}$ corresponds directly to the input signal being transduced by

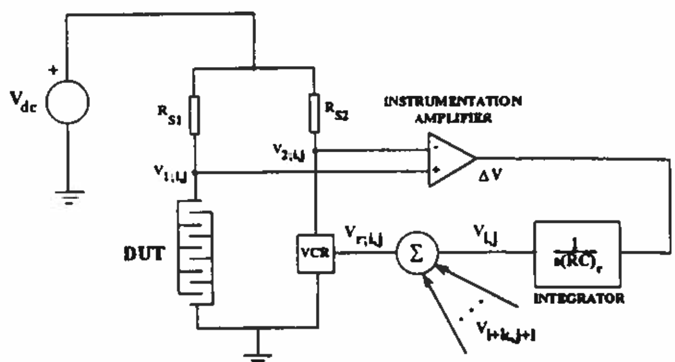

Figure 1. Dynamic autonulling *Cell* of the OCNN with the integral feedback and a summer in the loop generating V_r from the neighbors and itself. DUT represents a device under test that responds to an applied dc voltage, and VCR is a voltage controlled resistance used to null the bridge.

each *cell* and $V_{2;i,j}$ is the voltage driven by the feedback to follow the input node. $A_{i,j}$ are the respective gains on each of the instrumentation amplifiers in each of the bridges. The collection data from an array of transducers suffers from spatial noise due to thermal affects on the transducers and local electrical noise at each transduction point. The nearest-neighbor interconnection emulates a cellular neural network that enables spatial convolution or integration over the image. It provides the weighted interconnection of the feedback signals in the following manner in order to generate the voltage required to balance each bridge in the network,

$$V_{r,i,j} = \sum_{k,l=-1}^{1} w_{k,l} \cdot V_{i+k,j+l}$$

where $w_{k,l}$ are the interconnection weights of each of the neighborhoods. The above summation is for k and l over the range of -1 to 1 which denotes only nearest-neighbors, but this can be extended indefinitely depending on the shape and corresponding function of the convolution kernal. The weights of the interconnections determine the type of spatial filtering that is carried out by the network and can be positive or negative to mimick different types of kernals. At equilibrium, each of the bridges will be at null, so the signal $V_{r;i,j}$ that controls the VCR of each bridge will correspond to the input signal on that bridge, but the signal $V_{i,j}$ will be the signal corresponding to a spatially filtered output from that point in the array. The weighted interconnection of the bridge

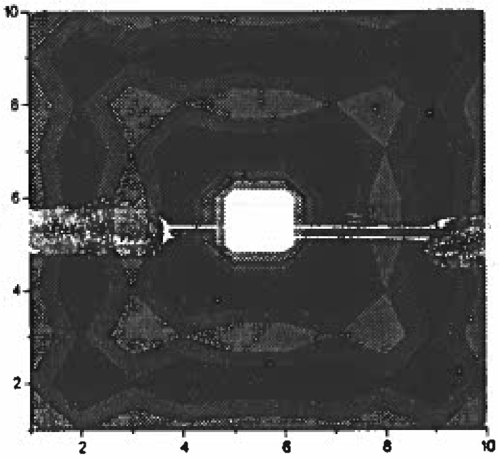

Figure 2. Gray-scale contour plot for the equilibrium solution of the numerical simulation of a point source response for a 10x10 optical cellular neural network (OCNN). Lateral inhibition is evident in diminishing low then high bands around the source.

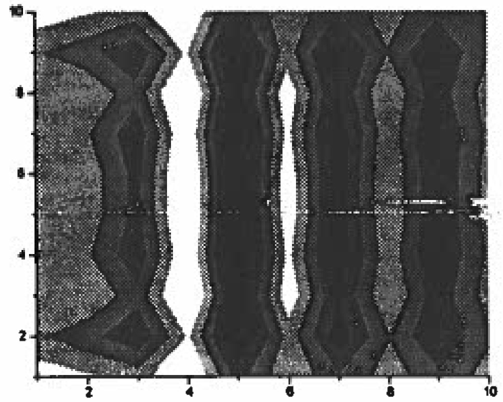

Figure 3. Gray-scale contour plot for the equilibrium solution of the numerical simulation of a spatial edge response for a 10x10 optical cellular neural network (OCNN). Lateral inhibition is evident in diminishing Mach bands away the source [9].

feedback signals generates a two-dimensional pre-processed image. The technology used in this network is compatible with microfabrication and therefore offers itself to miniaturized operation.

The system equations for the OCNN are similar to a general formulation developed by Cohen and Grossberg [5]-[8] for the state equation of shunting inhibitory neural networks,

$$\frac{d}{dt}x_i = a_i(x_i)\left[b_i(x_i) - \sum_{j=1}^{n} c_{ij} d_j(x_j)\right],$$

As was demonstrated by this generalization, the state equations we have discussed can also be applied to many other paradigms of neural networks (e.g. content addressable memory, short term memory) implying that the interconnected ADCB offers itself to other applications besides the optical OCNN. This type of state equation also demonstrates the capability of the system to be applied as an analog processor for spatial signals that are not necessarily transduced using sensors, but for general computation (analog computation). Other schemes besides linear weighted sums of the neighbor signals (e.g. products, derivatives) are also feasible yielding a variety of spatial filtering algorithms incorporated into the system.

Results

The linear model derived using the coupled differential state equation for the OCNN was solved using numerical techniques. The node voltages from each of the bridges was represented by the following linear models for the phototransistor and bipolar transistor feedback element

$$V_{1i,j} = V_{dc} - \frac{\beta R_s(V_{in;i,j} - 0.7)}{R_b} \quad \text{and} \quad V_{2i,j} = V_{dc} - \frac{\beta R_s(V_{1i,j} - 0.7)}{R_b}$$

In the simulations, a Runge-Kutta algorithm was used to solve the system. In these equations, $R_{S1}=R_{S2}=R_S$ and in the input to the system was simulated using the voltages $V_{in;i,j}$. Two tests are carried out on the OCNN to test its lateral inhibition capabilities: (i) point source response and (ii) spatial edge response. The equilibrium results of the system in response to these spatial signals are shown in Figures 2 and 3.

Conclusions

This configuration is being investigated for use in three situations: (1) for two-dimensional optical transduction that can either be mounted under a substrate properly passivated for cellular or chemical deposition to monitor transmission of light signals through the chemical system; (2) as a focal plane array; or (3) signals transduced from substrate-based electrodes or sensors (e.g. temperature or pressure) as the input method in which case a two-dimensional electrical image will be transduced. It is also possible that the dc bridge configuration be modified to an autonulling ac configuration described in [4] in which the photocapacitance be monitored instead of equivalent resistance. In view of the similarity between the state equation of the OCNN and the shunting neural networks, the OCNN with the autonulling dc bridge as the dynamic cell offers itself to many neural network implementations besides that of the proposed optical pre-processing system.

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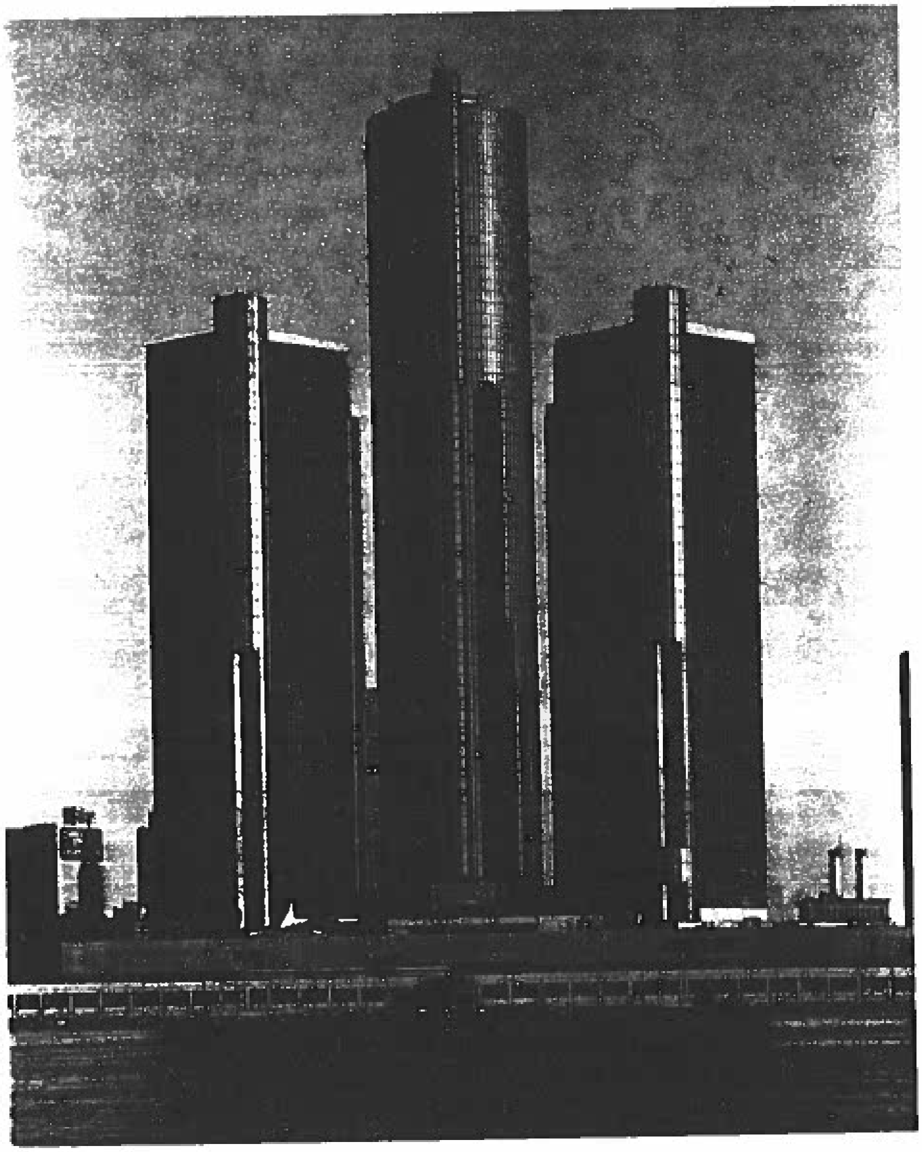

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