F LASKY, J. B.: 'Wafer bonding for silicon-on-insulator technologies', *Appl. Phys. Lett.*, 1986, **48**, pp. 78–80
G MACIVER, B. A., and JAIN, K. C.: 'J-MOS transistors fabricated in oxygen-implanted silicon-on-insulator', *IEEE Trans.*, 1986, **ED-33**, pp. 1953–1955
H SCHRODER, D. K.: 'The concept of generation and recombination lifetimes in semiconductor', *ibid.*, 1982, **ED-29**, pp. 1336–1338
I SCHRODER, D. K., WHITFIELD, J. D., and VARKER, C. J.: 'Recombination lifetime using the pulsed MOS capacitor', *IEEE Trans.*, 1984, **ED-31**, pp. 462–467

SEMIPARALLEL MICROELECTRONIC IMPLEMENTATION OF NEURAL NETWORK MODELS USING CCD TECHNOLOGY

Indexing terms: Biomedical electronics, CCD technology

A new generic architecture for realising the basic functions of neural networks is described. In the proposed configuration the $N \times N$ interconnectivity problem is accomplished by a simultaneous combination of horizontal and vertical shifting of CCD arrays. The proposed devices can be implemented with present-day technologies.

The increasing interest in neural network (NN) theories that have evolved during the past few years[1,5] has created a demand for reliable and efficient hardware implementations of these theories. Efforts to implement NN models by using VLSI techniques[6,7] were hitherto limited by the 'connectivity problem', namely, the fact that in direct electronic implementations each neuron has to be electrically connected to all other neurons. This problem limits the size and complexity of the NN that can be implemented in a device, and reduces the reliability of the device performance. In this letter we present the underlying principle of a new microelectronic implementation based on CCD technology, which obviates this problem.

For the sake of clarity we shall describe first an implementation of the basic Hopfield model with synchronous updating. In the basic Hopfield model the NN consists of N binary neurons which are connected to each other by the synapses. The state of the system is given by the vector $\boldsymbol{V}$:

$$\boldsymbol{V} = (V_1, \ldots, V_i, \ldots, V_N) \tag{1}$$

where V_i is the state of the ith neuron ($V_i = 0$ or $V_i = 1$). The strength of the 'synaptic' interaction between the neurons is given by the matrix $\boldsymbol{T}$, where T_{ij} is the strength of the interaction from the jth neuron to the ith neuron. (For the Hopfield model $T_{ij} = T_{ji}$ and $T_{ii} = 0$). The dynamics of the system are conducted by the following procedure: each neuron is being updated according to the total input that flows into it, and is given for the ith neuron by

$$I_i = \sum_{j=1}^{N} T_{ij} V_j \tag{2}$$

The new state of the neuron is decided by a threshold function which is given for the ith neuron by

$$\tilde{V}_i = \begin{cases} 1 & \text{if } I_i \geq U \\ 0 & \text{if } I_i < U \end{cases} \tag{3}$$

where $\tilde{V}_i$ is the new value assigned to the ith neuron. We limit ourselves here to the case of synchronous updating of the network, namely in each updating cycle each neuron is being updated according to the state of the network in the previous cycle.

Given a set of vectors $\zeta^{(s)}$, $s = 1, \ldots, p$, to be stored in the system, the synaptic interactions matrix $\boldsymbol{T}$ is defined by applying a 'learning rule' which impresses these vectors, $(\zeta^{(s)})$, as the stable states of the system. This is done by finding the matrix T_{ij} such that when it operates as in Reference 2 on any $\zeta^{(s)}$ the result using Reference 3 is the $\zeta^{(s)}$.

It is now expected that if the initial state of the system is not one of its stable states, it will be attracted by the dynamics to the stable state $\zeta^{(s)}$ most similar to the initial state. In this respect the system performs as an associative recall.

A schematic description of the device is presented in Fig. 1. For the sake of clarity we shall concentrate first on an implementation of the original Hopfield model.

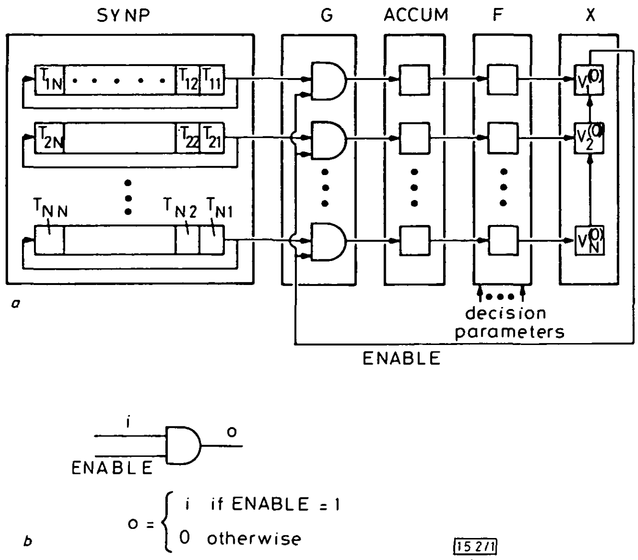

Fig. 1 *Layout of basic elements used in electronic realisation of electronic neural network*

Consider Fig. 1*a*:

(i) SYNP is an $N \times N$ CCD of analogue registers divided into N-dimensional, self-connected rows (the rightmost element feeds the leftmost element).

(ii) $\boldsymbol{G}$ is a column of N AND gates with a common enable port and analogue input and output (see Fig. 1*b*).

(iii) ACCUM is a column of N analogue registers; each accumulates the analogue signal which is fed into it from the respective output of $\boldsymbol{G}$.

(iv) $\boldsymbol{F}$ is a column of N threshold functions of the type described in eqn. 3. Each element of $\boldsymbol{F}$ produces a binary output (the next state, $\tilde{V}_i$), as a response to an analogue input (the total input I_i).

(v) $\boldsymbol{X}$ is an N-dimensional binary CCD column of registers where each element can be fed directly from the respective $\boldsymbol{F}$ element, and the entire contents can be read out sequentially through the top element.

Fig. 1 does not contain the logic units, the clocks, the set/reset ports and the input/output units.

Prior to the operation of the device the synaptic interaction matrix $\boldsymbol{T}$ is loaded into SYNP, and the initial state vector $\boldsymbol{V}^{(0)}$ is loaded into $\boldsymbol{X}$ as described in Fig. 1*a*.

(i) After RESET the common ENABLE of $\boldsymbol{G}$, which is supplied by the upper element of $\boldsymbol{X}$, is $V_1^{(0)}$, and the inputs to $\boldsymbol{G}$ are supplied by the rightmost column of SYNP, i.e. T_{i1}, $i = 1, \ldots, N$. The registers of ACCUM are set by the reset to zero.

(ii) After the first clock pulse the outputs of $\boldsymbol{G}$, namely $T_{i1}V_1$, $i = 1, \ldots, N$, are accumulated into the respective elements of ACCUM. The common enable of $\boldsymbol{G}$ is now $V_2^{(0)}$, and the respective inputs into the $\boldsymbol{G}$ elements are T_{i2}, $i = 1, \ldots, N$.

(iii) The next terms $T_{ij}V_j$, $j = 2, 3, \ldots, N$, are thus accumulated into the respective ACCUM elements, until after the Nth clock pulse they contain the sums

$$\sum_{j=1}^{N} T_{ij} V_j \qquad i = 1, \ldots, N$$

(iv) The $(N + 1)$th clock pulse activates the decision function $\boldsymbol{F}$, which produces the new state of the system $\boldsymbol{V}^{(1)}$.

(v) $\boldsymbol{V}^{(1)}$ is set into $\boldsymbol{X}$ by the next RESET.

The system thus continues to update itself until a stable state is reached. (For the sake of clarity the part of the device which identifies a stable state is not described.)

The operating speed of the device can be characterised by τ, the time required for the complete network to be updated (i.e. the time it takes for the network to transform from state $V^{(1)}$ to state $V^{(i+1)}$). It can be easily verified that a complete update requires $(N + 2)$ clock pulses. Therefore τ is given by

$$\tau = (N + 2)/f_0 \quad (5)$$

where f_0 is the clock frequency of the device. The state-of-the-art of the CCD technology is now limited to devices with approximately 10^6 elements ($N = 10^3$), and a clock frequency of $f_0 = 10$ MHz. For such a device we obtain $\tau = 10^{-4}$ s. Thus the network is completely updated 10^4 times per second.

The speed of operation and simplicity of structure render this device very attractive for implementing the basic Hopfield model. The use of the same underlying principles for the implementation of more sophisticated models is now being studied. Possible future development will include replacing the CCD shift registers by CCD detector arrays which will enable optical parallel loading of $\boldsymbol{T}$ and $V^{(0)}$.

The device described here can thus serve as a convenient and flexible tool for the purpose of investigating possible applications of neural-network models. The fact that it is based on state-of-the-art microelectronic technology gives it *a priori* a high degree of reliability. Its main disadvantage lies in the fact that it is limited in dimension to the currently available CCD technology ($N \simeq 2000$ at the present time). It should be borne in mind, however, that other existing implementations are currently limited to a much lower dimension[7] and their improvement depends on improving the state-of-the-art of microelectronic technologies as well.

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27th March 1987

References

1 LITTLE, W. A.: 'The existence of persistent states in the brain', *Math. Biosci.*, 1974, **19**, pp. 101–120
2 HOPFIELD, J. J.: 'Neural networks and physical systems with emergent collective computational abilities', *Proc. Naut. Acad. Sci.* 1982, **79**, pp. 2554–2558
3 MCCLELLAND, J. L., and RUMELHART, D. E.: 'Parallel distributed processing' (MIT Press, Cambridge Massachusetts, 1986)
4 PERSONNAZ, L., GUYON, I., and DREFUS, G.: 'Information storage and retrieval in spin-glass like neural networks', *J. Phys. Lett.*, 1985, **46**, pp. L359–L365
5 AMIT, D. J., GUTFREUND, H., and SOMPOLINSKY, H.: 'Spin-glass models of neural networks', *Phys. Rev. A*, 1985, **32**, pp. 1007–1018
6 SAGE, J. P., THOMPSON, K., and WITHERS, R. S.: 'An artificial neural network integrated circuit based on MNOS/CCD principles'. Snowbird, Utah, 1985

YAG RESONATOR

Indexing terms: Piezoelectric devices and materials, Resonators

A resonator made of a YAG rod has been excited, in an extensional mode, by the capacitive effect. An alternating voltage was applied across a capacitor formed by one of the free metallised ends of the rod and a fixed metal plate placed at a short distance. A Q-factor of $1{\cdot}9 \times 10^6$ was measured at the resonance frequency of 195·76 kHz.

Introduction: In a previous letter[1] we showed that a resonator made of a crystal of sapphire (Al_2O_3), a material which is not piezoelectric, could be excited by the thermal effect. The vibrations were detected optically. The Q-factor of this resonator placed in a primary vacuum enclosure was 8×10^5. Subsequent experiments with better suspended crystals have even given Q-factors greater than 2×10^6, i.e. greater than Q-factors obtained with quartz crystals.

These resonators, made of a sapphire bar vibrating in a flexural mode, were excited by periodically heating a resistive layer of chromium deposited on one side of the bar. The suspending wires were used as conductors. These resonators could also be excited by an intensity-modulated laser beam locally heating a small zone of a side of the bar.

In addition to sapphire, other materials can compete with quartz crystals as far as the Q-factor is concerned. Yttrium and aluminium garnet (YAG) is an example. Its acoustic wave attenuation factor is even less than that of sapphire (YAG: 0·6 dB/μs; Al_2O_3: 1·2 dB/μs; quartz: 7 dB/μs at 2 GHz[2]). Consequently, we have mounted a resonator with a single crystal of YAG. This crystal, normally intended for a laser, was neodymium-doped.

The object of this letter is to describe the relevant experiments, which differ from our previous ones performed with sapphire in three ways: (i) the mode of vibration is extensional instead of flexural; (ii) the resonance frequency (~200 kHz) is ten times greater; (iii) the excitation of the resonator is capacitive instead of thermal.

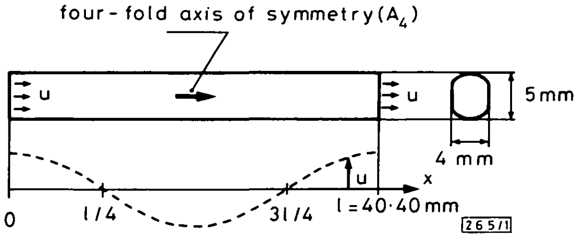

Fig. 1 *YAG rod*
Extensional vibration u along axis $x \parallel A_4$ is indicated by broken line

Experiments: YAG crystals belong to the cubic crystallographic class of symmetry: m3m. The crystal used for our experiments had the shape of a rod, the length of which was along a four-fold axis of symmetry. It was provided with two flat parts as indicated in Fig. 1. The diameter of the cylindrical part was 5 mm and the length $l = 40{\cdot}40$ mm. For the rod to vibrate longitudinally in a second overtone mode it was held at two points: $l/4$ and $3l/4$. This overtone mode was preferred to the fundamental one because holding the rod at two points instead of one prevents low-frequency mechanical vibrations and also facilitates optical detection.

Thus the expected frequency f_0 of vibration was

$$f_0 = \frac{V}{l}$$

where $V = 1/[\sqrt{(\rho s_{11})}]$, for $\rho = 4550\,\text{kg m}^{-3}$ and $s_{11} = 3{\cdot}60 \times 10^{-12}\,\text{m}^2/\text{N}$. Thus

$$f_0 = 193\,\text{kHz} \quad (1)$$

A 1000 Å-thick gold layer was deposited on to one end and on to a flat part of the rod as shown in Fig. 2. This end layer was then connected to a suspending wire and formed the moving electrode of a capacitor, the other electrode of which was a fixed metal plate placed near the rod end.

For a gap e and a surface area S, a voltage v applied across the capacitor of capacitance C generated a force F on the rod

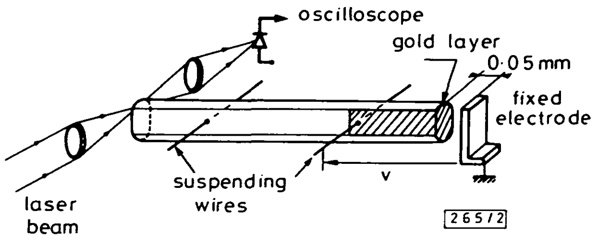

Fig. 2 *Excitation of vibration by capacitive effect and detection by optical wedge method*