Information Processing Using Intelligent Materials— Information-Processing Architectures for Material Processors

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ABSTRACT: One of the goals in the intelligent materials area is to develop material systems that can process information by using the material's own properties. To develop such systems, we must first find an information-processing method that is achievable using the material itself. Several potential distributed information-processing architectures are described.

INTRODUCTION

INTELLIGENT materials are a new and exciting field of research. One of the goals in this area is to develop material systems that can process information by using the material's own properties, what I call "material processors". To develop such systems, we must first find an information-processing method that is achievable within the material itself. Neural networks and other non-Neumann architectures will be necessary for developing these material processors. The purpose of this paper is to introduce some non-Neumann architectures that might be used as material processors. I hope that it will stimulate the reader's thinking in this area.

DISTRIBUTED INFORMATION-PROCESSING ARCHITECTURES

There are two basic ways that we can use new materials for information processing. One is to construct conventional electronic devices, such as transistors, functional devices, and logic units from the new material, and then interconnect them to construct electrical circuits that perform the information processing. This approach is illustrated in Figure 1(a). The problem is that integrated circuits made of new materials would have a hard time competing with silicon LSI, which is a well-established, mature technology.

The more promising approach is to directly use the material's physical properties to perform the information processing, as shown in Figure 1(b). This means using the material's atoms or molecules as the processing elements. From this we can develop material processors that provide new functions. With these new material processors, however, we can no longer use conventional Neumann-type computing architectures. We need a new "distributed" information-processing architecture.

Unlike LSI devices, we cannot interconnect atoms or molecules in the material; they only interact with close neighbors [Figure 2(a)]. In order to achieve useful information processing under these restrictions, we must use a "distributed" information-processing architecture [Figure 2(b)]. This is a special information-processing method that uses many identical processing elements, each of which operates only with its neighboring elements.

In the following, I will present for future discussion a few candidates for this special type of information-processing architecture. They are: holonic systems, neural networks, cellular automata, and analog devices. They all use a distributed-parallel information-processing method and are different from conventional programmed computing.

HOLONIC SYSTEMS

A holonic system is a distributed information-processing system that uses a synthesizer and a memory composed of many unit oscillators (called holons), each of which has excitatory/inhibitory interactions with its neighbors. It can perform pattern recognition by using entrainment among the holons in the synthesizer and the memory.

Figure 3 shows the basic structure of this system. An input plane senses the input pattern and excites the synthesizer. The synthesizer extracts the information from the input pattern and compares the data with sample patterns stored in its memory. When the data matches one of the sample patterns, entrainment occurs between the synthesizer holons and the corresponding memory holons, and the input pattern is classified.

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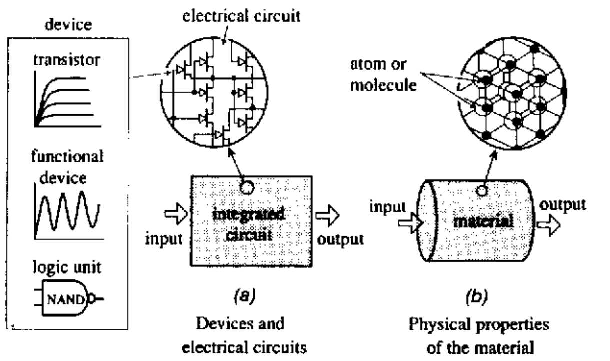


Figure 1. Two ways to process information: (a) use an electrical circuit constructed with electronic devices (integrated circuit) or (b) use the material's own properties (material processor).

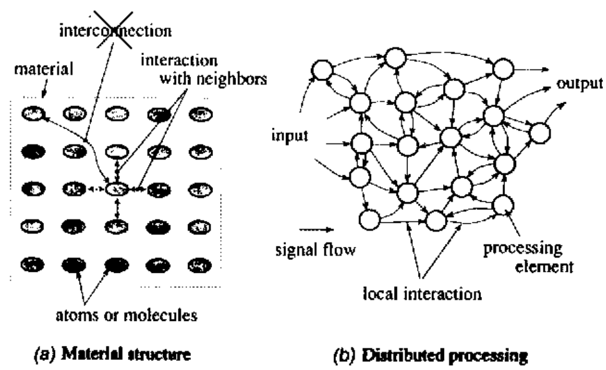


Figure 2. Distributed information-processing architecture. A special information-processing method that uses many identical processing elements, each of which operates only with its neighboring elements.

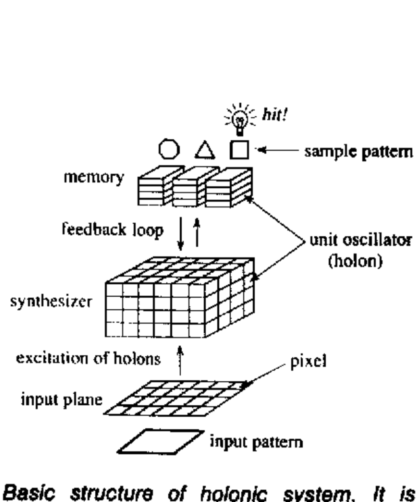


Figure 3. Basic structure of holonic system. It is a pattern-recognition system that utilizes entrainment among the holons in the synthesizer and the memory.

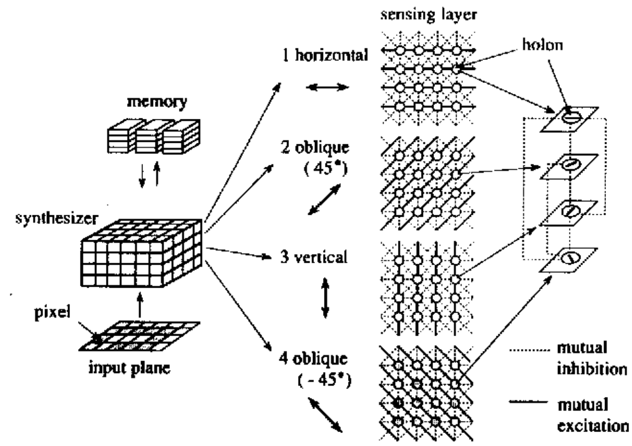


Figure 4. Synthesizer structure. It consists of many holons, each of which has excitatory/inhibitory interactions with its neighbors.

There are various types of synthesizers. Figure 4 shows a simple-version model. It consists of four sensing layers that extract four directional lines of information (vertical, horizontal, and two oblique directions). Each sensing layer consists of regularly arrayed holons, each of which is excited by a pixel signal from the input plane. Nonlinear oscillators, e.g., van del Pol oscillators with dumping and interaction terms, are used as holons. The holons on each sensing layer interact only with their neighbors. Holon interactions are excitatory in a specific direction and inhibitory in the other directions. Moreover, the four holons corresponding to a pixel inhibit each other. See Shimizu and Yamaguchi (1987, 1991) for a complete description of system operation. Improved holonic systems have been investigated. More recent versions can perceive the topographical relationships of the input-pattern lines, sides, and vertexes. They can also recognize rotated patterns.

Holonic systems have only been theoretically discussed, not implemented. It is difficult to construct a holonic system with existing electronic devices because it requires an enormous number of such devices, even for a simple model. We should therefore investigate constructing holonic systems using the material's structure and properties. It may be that large holonic systems can be achieved by using electron dynamics in three-dimensional semiconductor superlattices, or molecular dynamics in liquid crystals (Figure 5).

NEURAL NETWORKS

A neural network is a distributed information-processing system characterized by self-organization. The network is composed of many identical inter-connected processing elements (neurons), and automatically modifies the internal connections (signal channels) by learning to produce required information-processing capabilities. There are several neural-network architectures, as listed in Table 1. Neural networks can carry out various information-

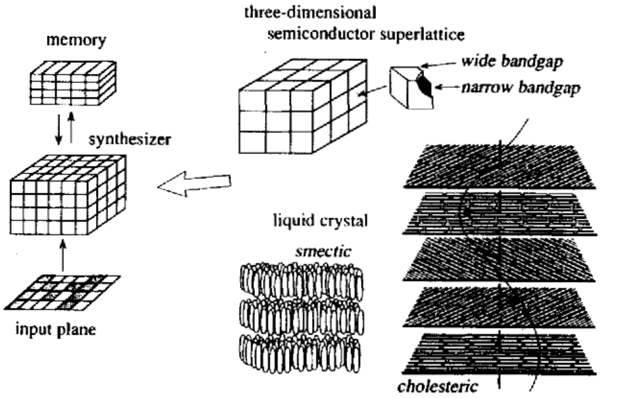


***Figure 5.** Material holonic system. Large holonic systems may be achieved by using three-dimensional semiconductor superlattices or liquid crystals.*

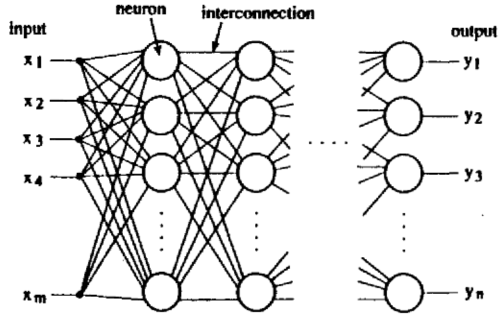


***Figure 6.** Basic structure of neural network. Backpropagation neural network is shown here.*

processing tasks such as mapping, combinatorial optimization, and associative operation.

Figure 6 shows the basic concept of neural networks. An example of the backpropagation neural network (one of the most useful neuro-architectures) is given. The network has a hierarchical structure consisting of fully interconnected layers of neurons. Each neuron is comprised of several processing elements with local memory, as will be explained below. The information processing that the backpropagation neural network carries out is the approximation of a mapping from a subset of m-dimensional input space to a subset of n-dimensional output space, by means of training on example data of the mapping. For example, in an application to character recognition, the input to the network is a set of picture array signals from an image sensor, and the output is a code that indicates which of the characters the input represents. At first the network gives no correct output because stored values in the local memory are not optimized, so it is trained with example data. On each individual training trial, the network is supplied with an example input and an error data that indicates the difference between the actual output and the desired output. In the training process, the network modifies values stored in the local memory to produce the correct output.

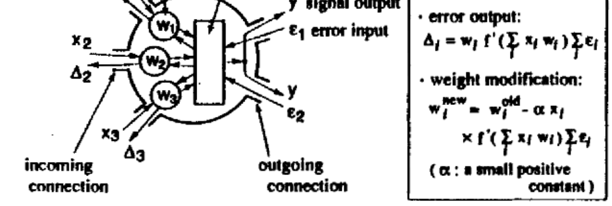
Each of the backpropagation neurons has a number of incoming and outgoing connections [Figure 7(a)]. The incoming connections receive input signals from the preceding neurons and at the same time send error signals back to the preceding neurons. The outgoing connections send an output signal to the following neurons, and in turn receive error signals. Each neuron has local memory to store weight values, which determine the coupling constants of the connections. The operation of each neuron is completely local. Each one produces an output signal which depends only on the current input signals and the weight values in memory. At the same time, each neuron automatically modifies its weight values in accordance with a learning law to produce the correct output. The computing/learning algorithm is shown in Figure 7(b). See Rumelhart and McClelland (1986) and Hect-Nielsen (1990) for a more detailed discussion.

In order to achieve material neuron operation, we first need to find an effective computing/learning architecture that is achievable with material properties. Among various neuro-architectures, the deterministic Boltzmann machine (a variant of the Boltzmann machine) seems to be achievable because of its simplicity in learning operations (Morie and Amemiya, 1990), but I have not been able to confirm this in actual materials. Further investigation of new architectures is needed.

There has been some success in implementing neural networks using LSIs. It is difficult, however, to prepare a sufficient number of neurons for practical use because each neuron requires a great many devices. We should therefore attempt to construct large-scale material neural networks. For example, we might attempt to use conductive long-chain

***Table 1.** Neural network architectures.*

- Backpropagation
- Boltzmann machine
- Hopfield network
- Neocognitron
- Self-organizing feature map
- Learning vector quantization
- Radial basis function model



(a) Connections and signal flow (b) Computing/learning algorithm

***Figure 7.** Backpropagation neuron and its operation: (a) connections and signal flow and (b) computing/learning algorithm of the backpropagation model.*

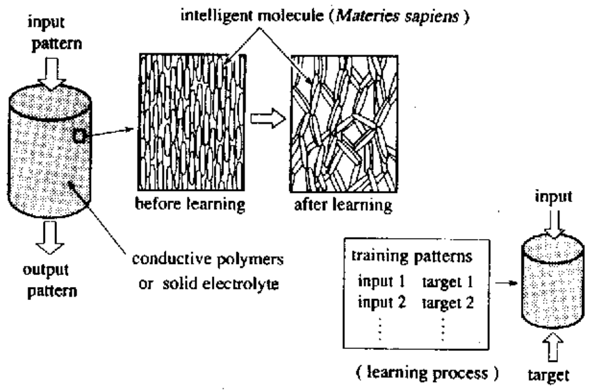


Figure 8. Material neural network. Large neural networks might be constructed by using conductive long-chain polymers or solid electrolytes.

polymers or solid electrolytes. We can achieve large-scale neurocomputing by using these materials, provided that we can find an effective method for electrically rearranging their network structures (Figure 8).

CELLULAR AUTOMATA

A cellular automaton is a distributed information-processing system consisting of a large number of simple identical processing elements with local interactions. Figure 9 shows the basic concept of a cellular automaton. It consists of many processing elements (cells) regularly arrayed on a plane. Each cell has two or more states, and the cells change their states synchronously in discrete time steps according to local interaction rules. Each cell determines its state based only on the values of neighboring cells. It contains no control center, but is capable of complex behavior.

A cellular automaton has several possible applications. One is transducers, which produce an output information pattern in response to an input information pattern. As an example [Figure 10(a)], we assume that each cell has two states, 0 or 1. Consider the eight neighbors in setting each cell state and follow the local interaction rule shown in Figure 10(b)(called the Game of Life rule). We start with the initial cell-state pattern shown in Figure 11(a)(step 0). With

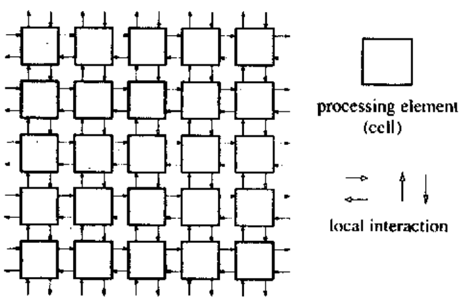


Figure 9. Cellular automaton. An information-processing system consisting of a large number of simple identical cells with local interactions.

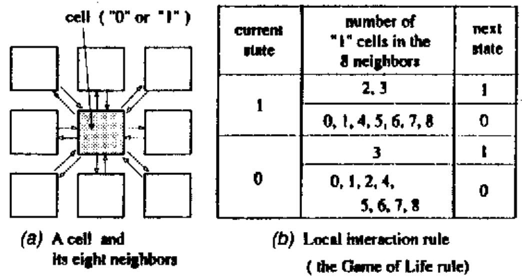


Figure 10. Example of cellular automaton operation. The Game of Life rule operation is shown here.

time steps, we can observe the pattern transition as shown in the figure (step 1–step 7). As another example, we input the simple pattern (A) in Figure 11(b). A number of steps later, we obtain the complex output pattern (B); they may have a topological relationship with each other. There are many other interaction rules and therefore various behaviors. A three-dimensional structure has also been studied. See Preston and Duff (1984) and Toffoli and Margolus (1987) for details.

With proper rules and structures, we could obtain some useful pattern transformations. As an example, I give an application to noise removal in picture processing (Figure 12). If a given picture is binary valued (black and white), noise that is smaller than the picture detail can be removed by a processing of contraction and expansion. The contraction step changes all black pixels to white if they have any white neighbors, and the expansion step changes all white pixels to black if they have any black neighbors. The contraction deletes black noise points, and the expansion deletes white noise points. By combining both steps, we can obtain fine pictures from noisy ones.

In order to implement cellular automata in materials, we should search for interaction rules that satisfy the dual requirements for producting useful information processing and for being achievable with the material properties. We should investigate materials such as semiconductor-quantum boxes, liquid-crystal molecules, and superconductive electron pairs. In this microscopic world, we can no longer use electricity for interaction signals; instead we must use other media, like lattice elasticity, Coulomb force,

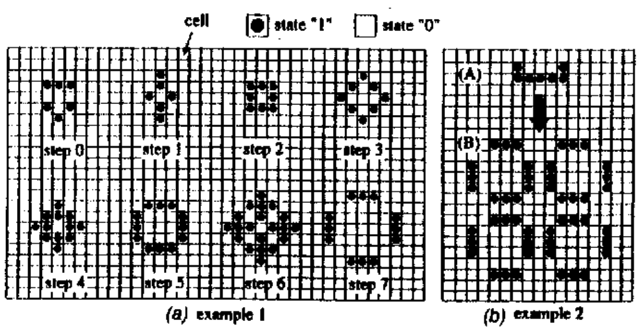
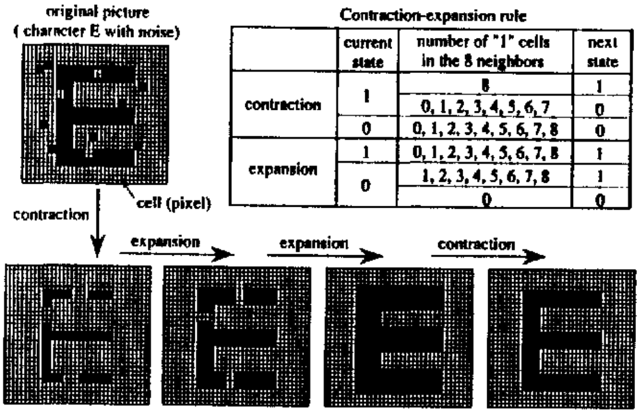


Figure 11. Pattern transformation. Two examples following the Game of Life rule are shown.



	current state	number of "1" cells in the 8 neighbors	next state
contraction	1	8	1
		0, 1, 2, 3, 4, 5, 6, 7	0
	0	0, 1, 2, 3, 4, 5, 6, 7, 8	0
expansion	1	0, 1, 2, 3, 4, 5, 6, 7, 8	1
	0	1, 2, 3, 4, 5, 6, 7, 8	1
		0	0

Figure 12. Noise removal by cellular-automaton operation. An example following the contraction-expansion rule is shown.

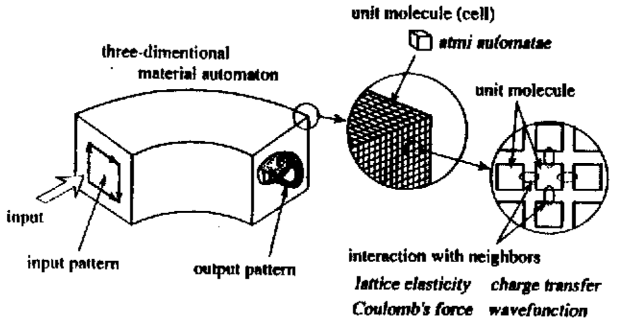


Figure 13. Material cellular automaton. Large cellular-automaton systems may be achieved by using semiconductor-quantum boxes, liquid-crystal molecules, or other intelligent materials.

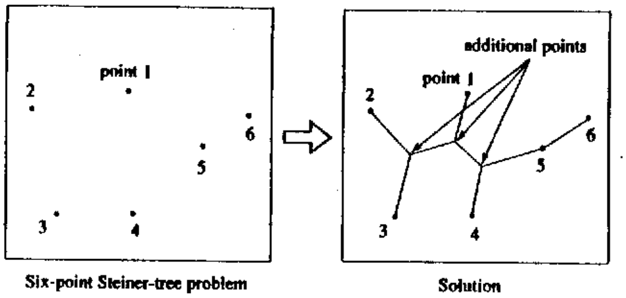


Figure 14. The minimum Steiner-tree problem. Connect given points on a plane with a graph of minimum overall length. This is difficult to solve using existing computers because it requires enormous computing time.

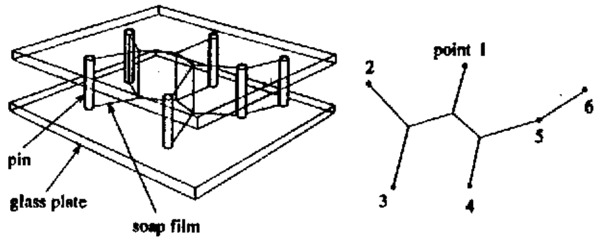


Figure 15. A soap-film solution to the minimum Steiner-tree problem. The problem can be quickly solved by utilizing the equilibrium of the soap film tension.

charge transfer, and wavefunction. One report has already discussed the possibility of using semiconductor-quantum boxes for the cells (Obermayer, Teich, and Mahler, 1988). If we can find the molecules or crystal units that provide useful functions for the cells, we can then construct large-scale cellular automata by using these materials (Figure 13).

ANALOG DEVICES

An "analog device" is a mechanical-material system that solves a specific problem by applying an analogy of its structure or behavior to the elements of the problem. It is a simulation machine rather than an information-processing system.

As an example, consider the following problem (Figure 14). Connect n points on a plane with a graph of minimum overall length, allowing the use of additional points. This is an example of an NP-complete problem, and is called the minimum Steiner-tree problem. It requires enormous computing time to solve because presently known algorithms need 2^n computational steps. Nevertheless, there is an ingenious mechanical-material system that can quickly solve this problem (Figure 15). Prepare two parallel glass plates and insert n pins between the plates to represent the points; then dip the structure into a soap solution and withdraw it. The soap film connects the n pins in an approximate Steiner-tree network. The equilibrium of the soap film tension is well utilized in this analog device.

Similar devices have been devised for other problems (the least squares problem, the longest path problem, and so forth). See Isenberg (1978) and Dewdny (1984, 1985) for details. At present, all of these analog devices are merely for fun. They may, however, provide some guidance for our intelligent material study.

SUMMARY

One of our goals is to develop material processors that can perform information processing by directly using the structure and properties of the material itself. To do this, we must first find an information-processing method that is achievable with the material. Several candidates for this kind of information-processing architecture were presented. Their development requires further study.

REFERENCES

Dewdny, A. K. 1984. "Computer Recreations", *Scientific American*, 250(June):15–19.

Dewdny, A. K. 1985. "Computer Recreations", *Scientific American*, 252(June):12–17.

Hect-Nielsen, R. 1990. *Neurocomputing*. Addison-Wesley Pub. Co.

Isenberg, C. 1978. *The Science of Soap Films and Soap Bubbles*. Tieto Ltd.

Morie, T. and Y. Amemiya. 1990. "Deterministic Boltzmann Machine Learning Improved for Analog LSI Implementation", *IEICE Trans. Electron.*, E76-C:1167–1173.

Obermayer, K., W. G. Teich and G. Mahler. 1988. "Structural Bases of Multistationary Quantum Systems", *Phys. Rev. B*, 37:8096–8121.

Preston, K. and M. Duff. 1984. *Modern Cellular Automata*. Plenum Press.

Rumelhart, D. E. and J. L. McClelland. 1986. *Parallel Distributed Processing*. MIT Press.

Shimizu, H. and Y. Yamaguchi. 1987. "Synergetic Computer and Holonics", *Physica Scripta.*, 36:970–985.

Shimizu, H. and Y. Yamaguchi. 1991. "The Self-Organization of Neuronal Representations of Semantic Information of Vision", in *Neurocomputers and Attention – Vol I*. Manchester Univ. Press., pp. 383–403.

Toffoli, T. and N. Margolus. 1987. *Cellular Automata Machines*. MIT Press.