A Novel Architecture for implementing Large-Scale Hopfield Neural Networks using CDMA Communication Technology

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Abstract—**We propose a novel LSI architecture that allows silicon LSIs to implement mutual-coupled neural networks. The architecture reduces wiring areas of Hopfield neural networks by using CDMA protocols for communicating between neurons. As an example, we propose a CDMA-Hopfield neural network, aiming at examining retrieval properties of the network. Extensive simulation results indicated that the CDMA-Hopfield neural network of N neurons could retrieve signal patterns from P memory patterns when $P/N \approx 0.1$.**

Keywords—**CDMA, integrated circuits, neural networks**

I. Introduction

In mutual-coupled neural networks, the number of connections between neurons increases exponentially as the number of neurons increases. This increase in connections (wires between neurons) prevents us from implementing large-scale neural networks on silicon VLSIs because of the increase in wiring areas. Thus, implementing mutual-coupled (fully connected) neural networks such as the Hopfield neural networks [1][2][3] is difficult . To overcome this difficulty, we have to develop a new system architecture that differs from conventional ones in which connections between neurons correspond to the physical wiring on a chip.

On the other hand, optical neural networks, which utilize lights to represent the connections between neurons, have been proposed in the literature [4]. In the networks, optical signals (output of neurons) travel through a three-dimensional medium such as air. Constructing a large-scale network with optical wires is thus easy compared with implementing the network on VLSIs. However, implementing the optical network on silicon VLSIs is difficult because of the terrible mismatch of the fabrication processes in the optical devices and VLSIs. In this report, we propose a new architecture that enables us to implement a large-scale neural network on silicon VLSI by using current device manufacturing technology. The development of large-scale neural networks leads to useful applications that utilize novel functions of neural networks.

II. Implementing Fully Connected Neural Networks on 2D Silicon LSIs

Figure 1 shows the conventional architecture of fully connected neural networks. Because the network consists of N-neurons and N^2-synapses, the total area of a synapse device increases exponentially as N increases. The Hopfield neural network is a typical example of a fully connected neural network. However, the number of synapse devices in a fully connected neural network with uniform connection strength can be significantly reduced, as shown in Fig. 2, because each input of the neurons is given by a common input that corresponds to the sum of the outputs of all neurons [5]. This 2D architecture is very suitable for implementing the network

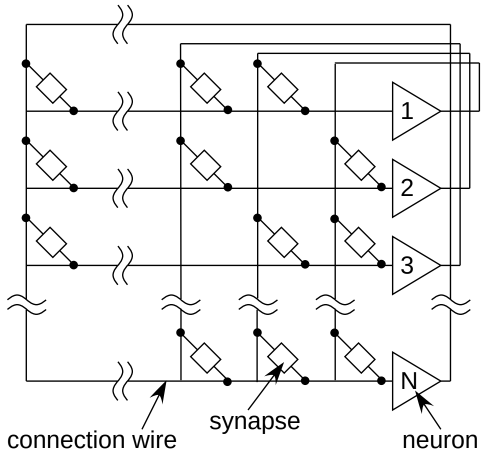

Fig. 1. Conventional architecture of fully connected neural networks (N neurons and $N(N-1)$ synapse devices)

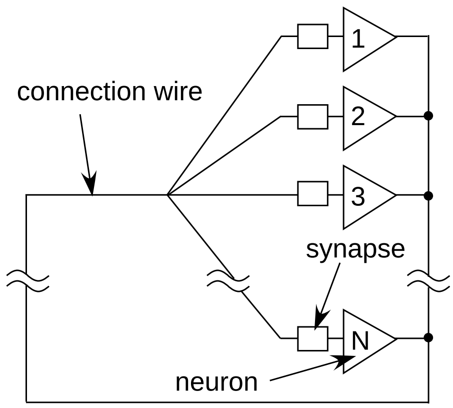

Fig. 2. Fully connected neural network with uniform connection strength (N neurons and N synapse devices)

on a 2D-silicon VLSI. To construct the Hopfield neural network using the 2D-VLSI architecture, each wire must be shared with all the neurons. The sharing (multiplex) method is commonly used in telecommunication systems [6][7]. A CDMA bus interface for conventional digital systems has also been proposed in the literature [8][9]. In the following section, we propose a novel VLSI architecture that is designed for constructing a large-scale Hopfield neural network using CDMA (one of the multiplex method). The network reduces the number of physical connections between neuron circuits.

III. Networks Using the CDMA System

Modern telecommunication systems make use of time division multiple access (TDMA), frequency division multiple access (FDMA), and code division multiple access (CDMA) systems for multiplex operation. As shown in Fig. 3, TDMA and FDMA operate by dividing time and frequency while CDMA operates by dividing a channel into identifying codes that are assigned to each user [6][7][10][11]. Because the TDMA system divides a transmission channel into time slots, configuring a neural network with this system would mean that only one neuron could transmit a signal at one time (other neurons would have to wait). The TDMA system is therefore not conducive to a neural network that performs real-time processing. The FDMA or CDMA system, however, should be appropriate for configuring a real-time system.

The signal demodulation process in CDMA has the task of separating signal components from the transmitting signal (the signal from the other party) and noise components (signals unrelated to the other party). This signal/noise separation computation is the same as that of individual neuron inputs (local fields) in a Hopfield neural network, and it was this realization that prompted us to study a CDMA-Hopfield neural network that combines a Hopfield neural network and a CDMA communications system.

A. CDMA System

The CDMA system has found widespread use in the field of mobile communications. In contrast to TDMA and FDMA, CDMA can transmit and receive communications even if different signals coexist in time or frequency [10][11]. That is, CDMA allocates a specific code (spreading code) to each user and enables them to communicate by having the system check for these codes on the receiver side. The following explains the basic principles of the CDMA system using the Direct-Sequence CDMA (DS-CDMA), which is one type of CDMA, as an example.

The CDMA system multiplies the information signal by an unrelated noise signal (spreading code) thereby spreading the frequency band (called spreading). In this regard, the DS-CDMA uses a periodic random sequence of numbers that takes on the values of ± 1 as a spreading code. Figure 4 shows the mechanism behind the modulation and demodulation in the DS-CDMA for two users.

In this example, each of two information signals (data1, data2) takes on the values of ± 1 in amplitude.

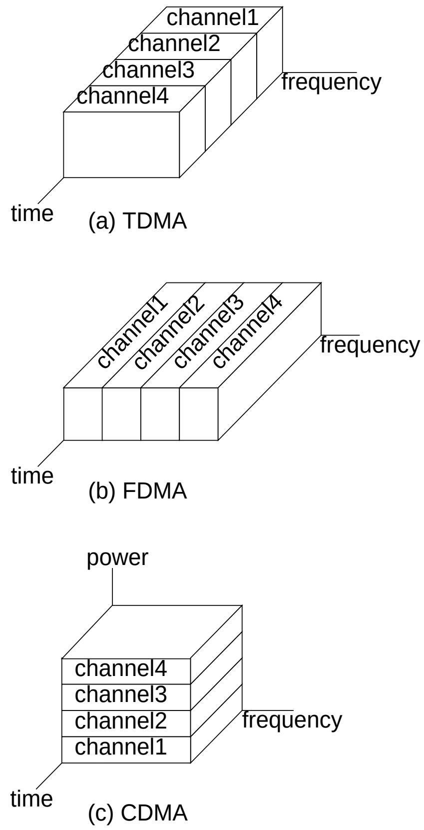

Fig. 3. Multiplex method used in modern telecommunication systems

The value of such a signal changes every time period T, called the symbol rate. On the transmitter side, the system multiples these information signals using spreading codes (code1, code2) that change every time period $T_c (< T)$, called the chip rate. This multiplication spreads the frequency band having the information signal (spreading operation), and the resulting bandwidth is determined using the ratio of the symbol to chip rate (T/T_c). For T/T_c equal to N, called the spreading factor, the frequency band that has the information signal spreads out by about N times ($N = 6$ in Fig. 4). The system now takes the spread information signals of each user and adds them together on a wireless channel for transmission. Then, on the receiver side, the system multiplies the received signals using the spreading codes of each user that wishes to communicate (despreading operation). The signals resulting from this operation are then integrated over symbol rate T of the original information signal leaving its high-frequency components. These operations enable information to be conveyed between users. The restored signal $D_i(n)$ of user i obtained after a series of calculations can be expressed as follows.

$$D_i(n) = \frac{1}{T}\int_{nT}^{(n+1)T} c_i(t)\sum_{a=1}^{P} d_a(t)c_a(t)dt, \qquad (1)$$

Here, T is the symbol rate, $c_i(t)$ is the spreading code of user i, $d_i(t)$ is the information signal of user i, n is the

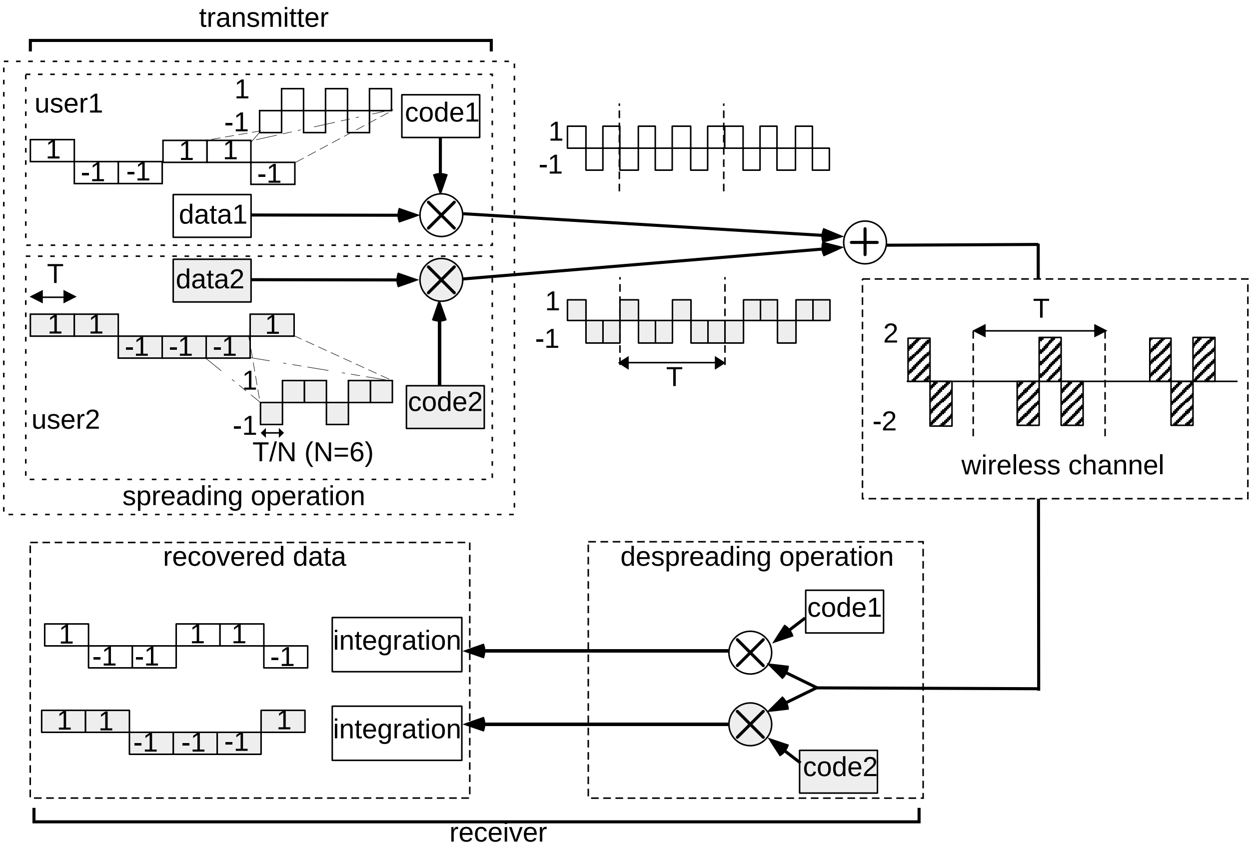

Fig. 4. Mechanism behind modulation and demodulation in DS-CDMA for two users

nth bit of the information signal, and P is the number of users.

B. CDMA-Hopfield Neural Network

The following equation represents the dynamics of a Hopfield neural network.

$$\tau \frac{du_i}{dt} = -u_i + \sum_{j \neq i}^{N} J_{ij} f(u_j), \tag{2}$$

Here, $u_i$is the membrane potential of a neuron, f is the transfer function, and N is the number of neurons. In addition, J_{ij} is the connection strength given as follows (P is the number of patterns to be stored, and ξ^μ is the μth pattern to be stored).

$$J_{ij} = \frac{1}{N} \sum_{\mu=1}^{P} \xi_i^\mu \xi_j^\mu, \tag{3}$$

The Hopfield associative memory model normally uses a sigmoid function that monotonically increases as a transfer function. The use of a non-monotonic function for a neuron's transfer function, however, means new features for the network. For example, storage capacity could increase by about three times, or a phase could appear in which noise components that hinder memory recall completely disappear [12][13]. Accordingly, when using a non-monotonic transfer function to construct a Hopfield neural network using a CDMA system, disappearing CDMA noise may affect it. Anticipating this effect, we adopted a Hopfield type of network to be operated in continuous time.

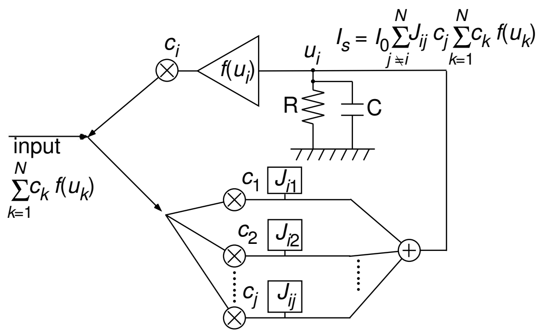

Fig. 5. Neuron unit of CDMA-Hopfield neural network

Figure 5 shows the configuration of a neuron unit in a Hopfield neural network using a CDMA system. To transfer the signal in the CDMA system, neuron output $f(u_i)$ is multiplied by a spreading code $[c_i f(u_i)]$. The received signal here is the sum of signals sent by all neurons. In the CDMA system, the received signal is sub-

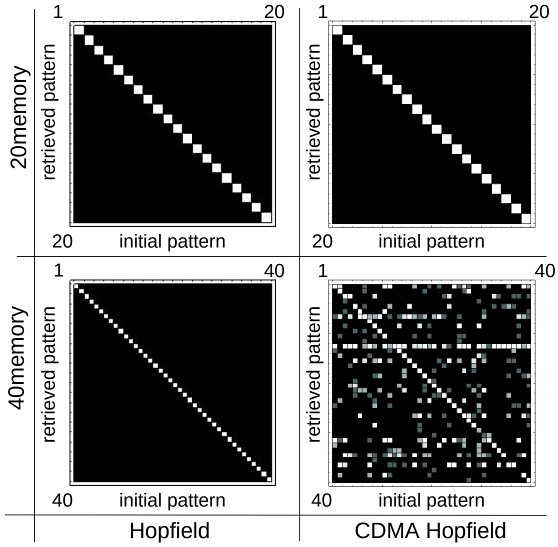

Fig. 6. Results of associative memory simulation

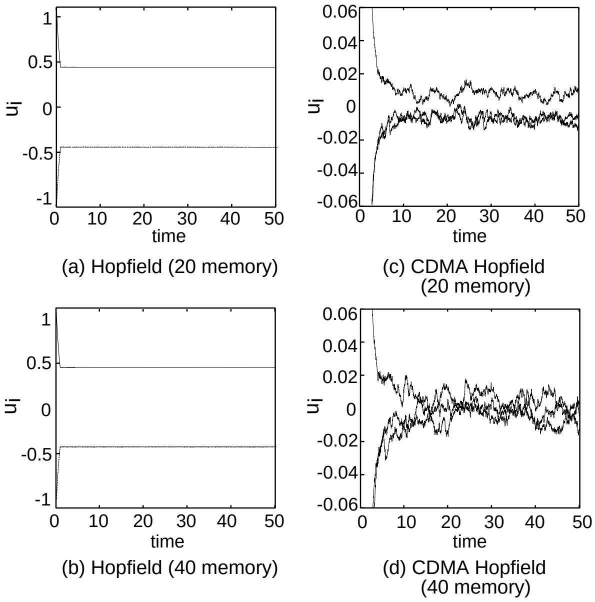

Fig. 7. Changing of membrane potential over time in recall process

jected to a despreading operation and then integrated over symbol rate T and finally divided by T. A Hopfield neural network, however, operates in continuous time, which means that dividing time and integrating as in the CDMA computation of (1) cannot be done. This integration, though, can be included in the dynamics of a Hopfield neural network, as described below.

The dynamics of this Hopfield neural network can be expressed as follows.

$$\tau \frac{du_i}{dt} = -u_i + \frac{1}{\tau} \sum_{j \neq i}^{N} J_{ij} \left(c_j \sum_{k=1}^{N} c_k f(u_k) \right), \tag{4}$$

Here, an increase or decrease in u_i follows a time delay on the order of time constant τ. That is, u_i is the timewise superpositioning of the u_i value τ seconds before (time integration from arbitrary time t_o to $t_o + \tau$). Thus, if τ is made the symbol rate (because the neuron output is not a periodic signal), (4) will include the integration computation on the right side of the CDMA computation of (1).

C. Simulation Results

Associative memory simulations for the CDMA-Hopfield neural network of (4) were performed. We stored 20 random patterns in the network, which had 200 neurons ($N = 200$). In these simulations, we wished to verify whether phenomena such as increases in storage capacity and disappearances of noise between stored patterns as seen in Hopfield neural networks that are non-monotonic would occur in one that are CDMA based. We therefore simulated a CDMA-Hopfield neural network using a non-monotonic transfer function. Furthermore, in addition to the above case of 20 stored patterns, we also performed simulations for storing 40 patterns in the same network.

In the network, a noise pattern consisting of 40 inverted bits within a stored pattern was taken as an initial value, and 50 noise patterns were generated for each stored pattern as initial values.

Figure 6 shows the simulation results. Associative-memory results for an ordinary Hopfield neural network (not using CDMA) are also shown for comparison purposes. The horizontal axis represents initial patterns whose noise patterns are based on the corresponding stored pattern, while the vertical axis indicates stored patterns that are retrieved. We note here that some retrieved patterns did not match any stored pattern. When this happens, the system calculates the correlation between the retrieved pattern and each of the stored patterns and counts the stored pattern showing the highest correlation as a retrieved pattern. The number of retrievals for a certain stored pattern by an initial pattern is indicated in the figure on a grayscale basis: retrieving the highest possible number of stored patterns is indicated in white while retrieving nothing at all is indicated in black.

For a Hopfield neural network storing 20 (or 40) patterns, we see that the number of diagonal elements was 20 (or 40), demonstrating that memory recall is correct. For a CDMA-Hopfield neural network storing 20 patterns, the number of times that a pattern other than a stored pattern was retrieved was small (discussed later). For the same network storing 40 patterns, however, correct recall was nearly impossible. The same kind of simulation was also performed for a CDMA-Hopfield neural network using a monotonic transfer function, and similar results were obtained.

The results of Fig. 6 do not provide a complete assessment of associative-memory capability. We therefore define recall rate (R_r) as follows to provide a quantitative assessment of associative memory:

$$R_r = \frac{N_{cr}}{N_{ip}}, \quad (5)$$

where R_r, N_{cr}, and N_{ip} represent the recall rate, the number of patterns correctly recalled, and the number of initial patterns given, respectively. In this study, correct recall was assumed to occur when the correlation between a stored (the basis of an initial value) and a retrieved pattern exceeded 0.95. When 20 stored patterns in 200 neurons were used, the recall rate for a CDMA-Hopfield neural network using monotonic neurons was 0.898, and that for one without these neurons was 0.899. While these values represent a drop in performance compared to the 1.000 recall rate of an ordinary Hopfield neural network, they nevertheless demonstrate that memory recall was being accomplished. However, when 40 stored patterns were used, the recall rates of the networks with and without the monotonic neurons were 0.000 and 0.001, respectively. These results indicate that virtually no memory recall was being accomplished, suggesting that a CDMA-Hopfield neural network does not possess characteristics such as a noise-disappearance effect or an increase in memory capacity due to the use of non-monotonic neurons.

We next extracted three of the 200 neurons and examined the change in membrane potential over time in the recall process. Figure 7 shows the simulation results of a Hopfield neural network using a transfer function that is non-monotonic. When using no CDMA, the membrane potential was essentially $\pm\theta$ (θ is the threshold value of a non-monotonic transfer function and is here set to 0.4) for both the 20 and 40 stored patterns (Figs. 7(a), (b)). In contrast, the membrane potential in a CDMA-Hopfield neural network was unstable, and its amplitude was nearly zero.

This is because noise due to spreading remains at the neuron input because complete restoration cannot be achieved at the CDMA communications section.

Denoting the signal restored with a spreading code at neuron i as $D_i(n)$, the CDMA section in a CDMA-Hopfield neural network is given as follows.

$$D_i(n) = \frac{1}{T} c_i(t) \sum_{a=1}^{P} d_a(t) c_a(t), \quad (6)$$

Here, $d_i(t)$ is the information signal transmitted by neuron i, n is the nth bit of the information signal, $c_i(t)$ is the spreading code of user i, T is the symbol rate, and P is the number of users. The signal component of neuron i is $d_i(t)$, and the noise component is$\sum_{a\neq i}^{P} d_a(t)c_a(t)$. Because information signal $d_i(t)$ and spreading code $c_i(t)$ both take on values of ± 1, this noise component had an average of zero and resembled Gaussian noise with dispersion P. An increase in the number of users P is accompanied by an increase in noise dispersion (approaching white noise). Nevertheless, the fact that correct recall (Fig. 6) can be performed (for an $N = 200, P = 20$ network) is an extremely interesting result.

D. Network operating in discrete time

In the previous section, we configured a Hopfield neural network that operates in continuous time using a CDMA system. Our expectation here was to obtain an increase in memory capacity and a disappearance of noise as can be obtained in a Hopfield neural network consisting of neurons that have a non-monotonic transfer function. For this reason, we configured the network using a CDMA system that changes form in continuous time and omitted integration at the time of signal restoration. In contrast, a network that operates in discrete time indicates that a CDMA system that does not change form can be used. Specifically, letting T_d be the time step of a network operating in discrete time, we made this T_d the same as the symbol rate in the CDMA system. This indicates that the signal transmitted at each neuron can be completely restored by integrating a received signal over T_d. This, in turn, means that exact network operation and an increase in scaling can be achieved.

IV. Conclusion

We proposed a novel VLSI architecture to implement mutual-coupled neural networks. Sharing one connection wire with all neurons allows us to implement large-scale neural networks on silicon LSIs by reducing wiring areas. As an example, a configuration for a Hopfield neural network using CDMA was presented. First, an associative memory simulation was run for that network, which had 200 neurons. Second, we extracted three of the 200 neurons and examined the change in membrane potential over time in the recall process. The first simulation showed that the CDMA-Hopfield neural network of N neurons could retrieve signal patterns from P memory patterns when $P/N \approx 0.1$. However, an enhancement in storage capacity due to using non-monotonic neurons was not observed. The second simulation showed that noise due to spreading remains at the neuron input because complete restoration cannot be achieved at the CDMA communications section. We will hereafter develop a structure for the CDMA-Hopfield neural network to eliminate noise and will construct a large-scale Hopfield neural network, one that will have a higher storage capacity.

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