An Oscillator Based Energy Efficient Computing Architecture for Smart Sensors

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***Abstract*—In the past decade, there is a fast-growing need for sensing technology applications. However, the implementation of sensing and proceeding creates a large burden on data processing. The idea for designing stable cluster state for coupled phase oscillator in pattern recognition is receiving significant attention. This paper gives an overview of an oscillator neural network (ONN) based hierarchical associative memory (AM) architecture using oscillator synchronization and stable cluster state for pattern recognition and how such architecture can be efficiently used in local processing units. The ONN based AM architecture can be easily achieved using CMOS technology on local hardware units. Unlike cloud computing system, our architecture provides an approach when it is under an offline mode which couldn't get responses from the web server. The proposed architecture can help perform sensing and data processing efficiently on the local device without connecting to the Internet.**

***Index Terms*—ONN, synchronization, stable cluster state, energy efficiency, hierarchical AM, pattern recognition**

I. Introduction

Technological innovations of sensors and integrated circuit technology have resulted in wireless sensing for various applications [1], [2], [3], [4]. With the widespread deployment of sensors and the proliferation of Internet-of-Things, there is a critical need for in-situ energy-efficient computational units. Cloud computing has been used to access server and database through the internet [5] such as Amazon Web Services (AWS). The cloud services can be easily connected to the hardware over a web application. However, cloud computing approaches in pattern recognition applications are based on online data processing. While considering the possibility of an offline mode where the server cannot respond to the request of pattern recognition or other required tasks, the local processing unit embedded with computational power can solve the offline data processing problem.

In order to improve the information processing efficiency of computers, researchers have begun to use CMOS process devices to simulate the information processing methods of neurons. Since the 1980s, with the development of CMOS technology, the convergence of learning rules and very large scale integration (VLSI) technologies, the size of the device channel has entered a dozen or even a few nanometers and transistor integration density has grown tremendously which made it is possible to better simulate the nervous system to validate the model and cultivate new biologically inspired ideas [6]. Neuro-inspired computing CMOS architecture based ONN for analog or non-boolean computing has been learned for many years as the recognition tasks on local processing unit [7]. The coupled ONN can perform the pattern recognition tasks with ease than other scheme [8], [9]. As a result, diverse ONN models for computing have been proposed. In recent years, several researchers have proposed the use of multiple coupled oscillators for pattern recognition. There have been several studies that proposed different hardware implementations for the ONN structure to perform pattern recognition. In [10], an AM architecture of ONN that consist of phase-locked loop (PLL) circuit which can store and retrieve dynamic oscillator patterns as synchronization states is performed. Fang et. al. proposed a self-generating power computing system based on BZ-PZ ONN for pattern recognition using the synchronization approach [11]. In [12], CMOS ring oscillators for pattern recognition were proposed. A non-Boolean ring oscillator coupled with a resistor network was proposed to function as a Hopfield network. The computing efficiency in pattern recognition of a variety of coupled oscillator networks has been compared in references [13]. However, the traditional synchronization approach for classifying signal and images is based upon the nearest neighbor theorem can only provide a binary result for pattern recognition. In this paper, we are using a supervised approach, cluster state is used to exhibit more complex behavior for the coupled nonlinear oscillators to perform multiple stable cluster state by calculating the appropriate weights connecting between every two oscillators. Since local data storage and maintenance is a big challenge for the local processing unit. Due to the fact that make improvement on the CMOS scale is approaching the limitation in the near future. As a result, it has become important to consider alternate methods for data processing with higher processing speed and lower energy consumption [14] Therefore, in this paper, we are demonstrating a two-layer hierarchical associative memory architecture based on ONN using traditional CMOS technology for real-time pattern recognition.

The rest of this paper is structured as follows. In Section II, an overview of the hierarchical system is summarized including the hierarchical algorithm and the dynamic coupling structures for two different layers. In section III, our image processing unit is performed. In section IV, we describe our hierarchical AM architecture for pattern recognition. Section V reports the simulation result in pattern recognition. Finally, this paper ends with a discussion and conclusion in Section

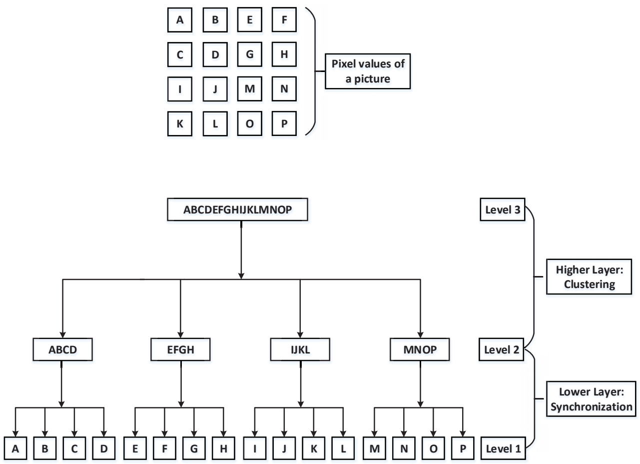

Fig. 1. Hierarchical dendrogram.

VI and VII.

II. Overview of the Hierarchical System

A. Hierarchical AM Model

In this section, we describe our two-layer hierarchical AM architecture and algorithm. In Fig. 1, the top diagram, letter A to P represent the pixel values of an image, the bottom diagram is the two-layer hierarchical dendrogram. During the pattern recognition processing, we divided the 4×4 oscillators in level 3 into four modules in level 2 with each module four oscillators in level 1. Each module in level 2 represents the synchronization output of a coupled ONN in level 1. The outputs of level 2 are read as the inputs of level 3 in the higher layer through clustering.

B. Method Analysis for Two Layers

The Kuramoto model is a commonly used model for studying synchronization phenomenon. It provides a simple but solvable approach to synchronization in coupled oscillators [15]. For this hierarchical data processing, the oscillator data of each module in the lower layer is read by the Kuramoto model as the intrinsic frequency, and the synchronization frequency of each module acts as the intrinsic phase of one of the oscillators in the higher layer. A classification process is then done by using a stable clustering algorithm to classify phase difference between each pair of the oscillator in the higher layer into stable 2-clusters.

III. Image Preprocessing Unit

Our result use human face from ATT Cambridge Database [16]. In our ONN, the image pixel value is stored as the intrinsic frequency of oscillators. When a new photograph is coming, we convert it to the same pixel amount as our stored pattern. Fig. 2 shows how the image pixel values are stored in oscillators and forming the ONN. We assume that each oscillator is connected to a pixel. The ATT Cambridge Database contains 40 person's face image and 10 pictures for each person. However not all of them are suitable for our Algorithm. So we pick three individuals with two photographs for each of them as storage patterns and with one for each as recognition pattern. Fig. 3 shows three images for each of two individuals from the datasets.

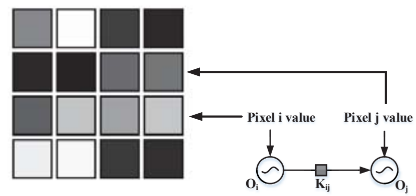

Fig. 2. Image preprocessing unit of the proposed ONN for clustering applications. Oscillator i and oscillator j are connected with pixel i value and pixel j value, respectively. Oscillator i and oscillator j are coupled with K_{ij}, which is one in this system.

Fig. 3. Three sample images for each individuals. In each row, the first and the second are storage patterns, the third is the recognition pattern.

IV. Pattern Recognition Architecture

The behavior of our ONN is governed by the following equation:

$$\frac{\mathrm{d}\phi_i}{\mathrm{d}t}(t) = \omega_i + \sum_{j=1}^{N} K_{ij} H_{ij}\left[\phi_j(t) - \phi_i(t)\right] \quad (1)$$

In general, by choosing appropriate coupling function H_{ij}, any arbitrarily complex behavior can achieve a stable cluster state. In particular, when $H_{ij}\left[\phi_j(t) - \phi_i(t)\right]$ is equal to $sin\left[\phi_j(t) - \phi_i(t)\right]$, then the system becomes Kuramoto model. the oscillator data of each module in the lower layer is read by the Kuramoto model as the intrinsic frequency. Kuramoto model can only show whether a pattern is synchronized or not. While our clustering can provide more than one stable state, it also provides another stable state of pattern compared to the single decision from the Kuramoto model. For a higher layer of the dynamics of weakly coupled oscillators exhibit complex chaotic behavior which cannot be obtained by Kuramoto model using simple sinusoidal coupling function.

By choosing appropriate coupling function H_{ij}, the stable cluster state can be achieved. The algorithm below shows how to design stable 2-cluster [17]. Any H_{ij} can be represented as a Fourier series and choosing a suitable coefficient, the Fourier expansion of H_{ij} to the L-th harmonics is given by,

$$H_{ij} = \sum_{l=1}^{L}[u_l \cos(l\phi) + v_l \sin(l\phi)] \quad (2)$$

Consider a cluster state with M cluster. For stable cluster states, both the tangential eigenvalues and the transverse eigenvalues have to be on the left- half complex plane, which can be satisfied by changing the coefficient u_1, v_1, u_2, v_2 in equation (2). By fixing the cluster phase difference $\phi_1 = 2k\pi$, $\phi_2 = (k+\frac{1}{2})\pi$, and the cluster size $a_1, a_2, N = a_1+a_2, u_1, v_1, u_2, v_2$ can be calculated for each storage pattern.

Based on these oscillators, we can design and build an AM circuit for each stored pattern. When the new pattern is coming. The pattern will compare to all stored patterns to search the closest match. The hierarchical clustering greatly reduced the pattern that needs to be stored through multiple layered processing. In this approach, our AM architecture reduces the time complexity by increasing the space complexity.

A binary pattern ξ,

$$\begin{gathered} \xi = [\ \xi_1 \quad \xi_2 \quad \xi_3 \quad \ldots \quad \xi_{16}\ ], \\ \xi_i = \pm 1, i = 1...16, \xi_j = \pm 1, j = 1...16 \end{gathered} \quad (3)$$

can be designed as a stable 2-cluster and stored into the ONN while the higher layer achieving stable 2-cluster. When the phase difference is $2k\pi$, ξ_i is equal to 1. On the other hand, while the phase difference is $(k+\frac{1}{2})\pi$, ξ_j is equal to -1.

$$\xi_i = 1 \Longleftrightarrow \phi_i - \phi_j = 2k\pi \quad (4)$$

$$\xi_j = -1 \Longleftrightarrow \phi_i - \phi_j = (k+\frac{1}{2})\pi \quad (5)$$

V. Simulation Results

In the higher layer of our system, we assume the topology of this system is cross-connect topology with coupling weight $K_{ij} = 1$. For the coupling function H_{ij}, the parameter $u_1 = \frac{1}{4}, v_1 = -\frac{89}{140}, u_2 = \frac{1}{9}, v_2 = \frac{11}{90}$ was calculated and designed for the first individual. to achieve stable 2-cluster, $u_1 = \frac{1}{4}, v_1 = -\frac{27}{120}, u_2 = \frac{1}{12}, v_2 = \frac{67}{240}$ was calculated and designed as stored pattern for the second individual. And $u_1 = \frac{1}{6}, v_1 = -\frac{23}{120}, u_2 = \frac{1}{9}, v_2 = \frac{43}{180}$ was calculated and designed as stored pattern for the third individual.

We have stored each individuals' image with 64×64 oscillators. The first and second images are stored as storage pattern, the third image is acting as a recognition pattern shown in Fig 3. For each image, in the lower layer, 8×8 oscillators are stored in each module. 8×8 modules are stored in the higher layer. The output of each module in the lower layer is read as the input of the higher layer. For hierarchical sensing process, each oscillator data is read by the Kuramoto model as the intrinsic frequency in the lower layer, and the synchronization frequency of each module acts as the intrinsic phase of the oscillator in the higher layer. Apparently from the simulation result shown in Fig. 4 to Fig. 6, the first storage pattern in Fig. 4 achieves the best matching. A part of the oscillators approach one cluster with phase difference $2k\pi(k = 0 \text{ or } 1)$, when $k = 0, \phi_1 - \phi_1 = 0$, when $k = 1, \phi_j - \phi_1 = 2\pi (j \neq 1)$ and the rest of the patterns approach the other cluster with phase difference close to $(k+\frac{1}{2})\pi$, which means this two groups of oscillators are converged to phase difference $(k+\frac{1}{2})\pi$ and 2π, respectively. We call it stable 2-cluster. In Fig. 5 when the first individual third image using the second individual's H_{ij} function is perform unstable cluster partitions. Fig. 6 shows the status for the first individual third image using the third individual's H_{ij} function.

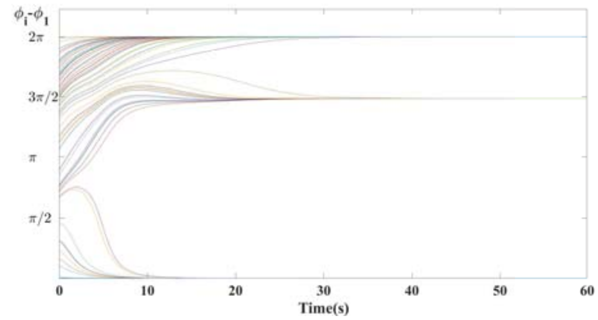

Fig. 4. The simulation results are shown as the first individual third image using the first individual's H_{ij} function which is as a particular stable 2-cluster partitions, where each curve represents the phase difference $\phi_i - \phi_1$

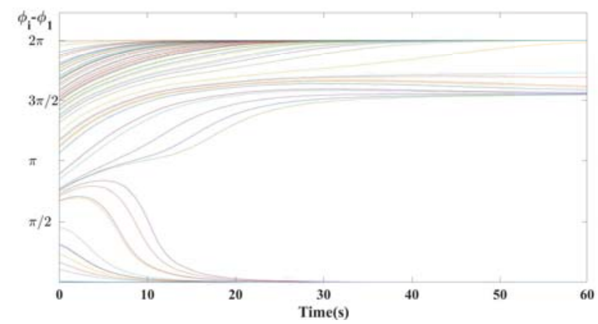

Fig. 5. The simulation results are shown as the first individual third image using the second individual's H_{ij} function which is unstable cluster partitions, where each curve represents the phase difference $\phi_i - \phi_1$

VI. Discussion

Table I shows a comparison of the hierarchical AM model used in this work with a single AM model. The coupling weights are corresponding to the connections of each two oscillators. A simple ONN based AM model implemented in software costs too much time for training as the number of neurons increases [18]. When the number of oscillators is increasing, the hierarchical model uses much fewer connections compared with the single AM model, which is a big

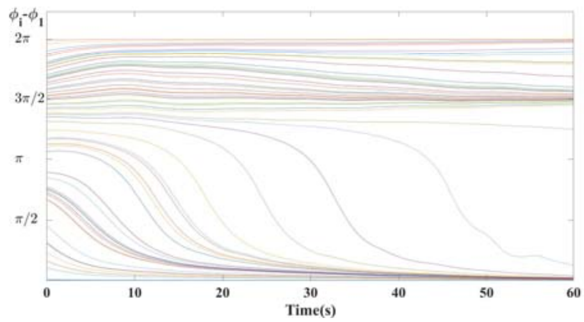

Fig. 6. The simulation results are shown as the first individual third image using the third individual's H_{ij} function which is unstable cluster partitions, where each curve represents the phase difference $\phi_i - \phi_1$

advantage for simplifying ONN. Our aim is to develop an algorithm such that reducing the computational complexity and minimizing the connections of stored pattern without sacrificing recognition accuracy. However, we still cannot guarantee the accuracy of the hierarchical AM model when using it to differentiate two very similar patterns. But with enough training data, we are able to improve the coupling function for more accurate recognition performance.

A weakly coupled phase oscillator theory is analyzed in the case of both linear and nonlinear couplings. For the Kuramoto model, a sinusoidal coupling function is able to exhibit synchronization for pattern recognition applications. The convergence time and frequency of synchronization are considered as indicators of recognition. Moreover, a nonlinear coupling function is utilized and the nonlinear dynamics is represented as a Fourier series. The dynamic coupling function provides an approach for analyzing the nonlinear coupled oscillator. By choosing the specific coefficient and coupling function, a stable 2-cluster is achieved for a sensing application. Since clustering can provide more than one stable state, it also provides another stable state of pattern compared to the single decision from the Kuramoto model. The hierarchical AM model performed in this work can be easily achieved in a local processing unit.

TABLE I
COMPARISON OF THE PROPOSED HIERARCHICAL AM MODEL WITH THE SINGLE AM MODEL.

ONN Characteristics	***Hierarchical AM model***	***Single AM model***
No. of layers	2	1
No. of oscillators	n^2	n^2
No. of oscillators in each layer	n	n^2
Connections (Number of weights)	C^2_{n+1}	$C^2_{n^2}$

VII. CONCLUSION

In this paper, the synchronization and stable 2-cluster for dynamic ONN system have been studied. The ONN based hierarchical AM model which performs sensing and computing on a local processing unit is explored. An application for human face recognition is used to test the functionality and retrieval performance of the hierarchical AM model. Our AM model is possible to use an ONN as a basic unit from nano-oscillator for local processing. Since the recognized pattern will always need to compare with all storage patterns to search the nearest neighbor, instead of a single AM model, we use the two layers hierarchical clustering which greatly reduces the pattern that needs to be stored through multiple layered processing.

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