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Recognition of the Korean alphabet Using Neural Oscillator Phase model Synchronization

Yong-Bum Kwon*, Jun-Tak Lee*
*Dept. of Electrical Eng Dong-A Univ
Dong-A University, Hadan 2dong, Saha Gu, Busan ,Korea
Email : ybkwonic@donga.ac.kr

Abstract – **Neural oscillator is applied in oscillatory systems (Analysis of image information, Voice recognition. Etc...). If we apply established EBPA (Error back Propagation Algorithm) to oscillatory system, we are difficult to presume complicated input's patterns. Therefore, it requires more data at training, and approximation of convergent speed is difficult. In this paper, I studied the neural oscillator as synchronized states with appropriate phase relation between neurons and recognized the Korean alphabet using Neural Oscillator Phase model Synchronization.**

I. INTRODUCTION

Oscillatory systems are ubiquitous in nature and, particular, in neuron and brain dynamics. Information processing system of neurons in brain has rhythmic activity and synchronization of neuronal firing. However much of neural network research still focuses on non-oscillatory sigmoidal neurons. The precise timing of neuronal firing is usually neglected.

Therefore, to understand possible neuro-computational properties of oscillatory neural networks we consider an extreme case when each neuron exhibits periodic activity. Such networks can be described by phase models. Oscillatory neural network has the same neuro-computational properties as the standard Hopfield network.

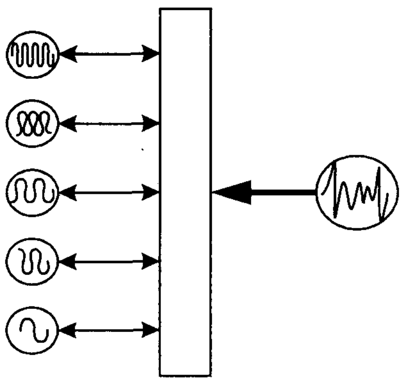

Fig. 1.Neural Oscillator

In this paper we suggest an implementation of the recognition systems of Korean alphabet using neural oscillator phase model synchronization. Such a success has been achieved when we consider neuron firing whose activity is near a bifurcation, which often occurs when the membrane potential is near the threshold value.

II. Neural Oscillator Phase Model

A. Canonical Neural of Weakly Connected Neurons

The assumption of weak neuronal connections is based on the observation that the averaged size of a postsynaptic potential is less than 1[mV], which is small in comparison with the mean size necessary to discharge a cell (around 20[mV]) or the averaged size of the action potential (around 100[mV]).

If connection is weak, mathematical model represent as following.

$$\dot{x} = f(x_i,\lambda_i) + \varepsilon\sum_{j=1}^{n} g_{ij}(x_i,x_j,\varepsilon) \qquad (1)$$

Here each vector x_i denotes membrane potential, gating variables, and other electrophysiological variables of the i-th neuron. Each vector λ_i denotes various biophysical parameters of the neuron. The function f describes connections between the neurons. The dimensionless parameter $\varepsilon << 1$ is small, reflecting the strength of connections between neurons. Eq(1) can be transformed into the canonical form(Eq(2)). Particulars of the functions f and g_{ij} and the value of the parameters λ_i do not affect the form of the canonical model, bat only the values of the parameters r_i and s_{ij}. The canonical model(2) has only one non-linear term, namely, y_i^3, and two internal parameters, r_i and s_{ij}.

The Cohen-Grossberg-Hopfield convergence theorem applies, which mean that canonical model has Eq(2).

$$y_i' = r_i - y_i^3 + \sum_{j=1}^{n} s_{ij} y_j \qquad (2)$$

The Cohen-Grossberg-Hopfield convergence theorem represent as following.

$$E(y) = -\sum_{i=1}^{n}(r_i y_i - \frac{1}{4}y_i^4) - \frac{1}{2}\sum_{i,j=1}^{n} s_{ij} y_i y_j \qquad (3)$$

Eq(3) is a potential function for Eq(2) in the sense that $y_i' = -\partial E / \partial y_i$.

B. Neural Oscillator Phase Model

Usually, membrane potential between neuron and neuron shows oscillatory phenomena. If do that variables change continuously in such periodic shock, Eq(1) that indicate weakly connected network can convert into Eq(4).

$$z_i' = (r_i + i\omega_i) z_i - z_i |z_i|^2 + \sum_{j=1}^{n} c_{ij} z_j \qquad (4)$$

Here, $i = \sqrt{-1}$, and each complex variable z_i describes oscillatory activity of the *i*th neuron. If Eq(3) all neurons have equal frequencies $\omega_1 = \cdots = \omega_n$ and the connection matrix $C = (c_{ij})$ is $c_{ij} = \bar{c}_{ij}$, then the network always converges to an oscillatory pattern.

Suppose that neurons in the weakly connected network(1) exhibit periodic spiking; see Figure 2(Morris-Lecar Model). Morris-Lecar Model is a figure what reaction Neurons represent in case external stimulation is given. If they have nearly equal frequencies, then the network can be transformed into the phase canonical model(Eq(6)).

$$\varphi_i' = \omega_i + \sum_{j=1}^{n} H_{ij}(\varphi_j - \varphi_i) \qquad (6)$$

Where each φ_i is a one-dimensional variable that describes the phase of the *i*th oscillator, and each H_{ij} is a connection function.

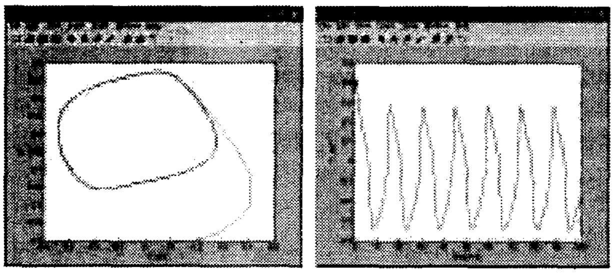

Fig. 2. This figure exhibit periodic oscillating(Morris-Lecar Model).

C. Synchronization of the Phase Model

The phase model that Eq(6) can be transformed into the Eq(7) by $\varphi_i' = -\partial U / \partial \varphi_i$.

$$U(\varphi) = \frac{1}{2}\sum_{i,j=1}^{n} R_{ij}(\varphi_j - \varphi_i) \qquad (7)$$

Where R_{ij} is the antiderivative of H_{ij} ; that is, $R_{ij}' = H_{ij}$. We see that if the matrix of synaptic connections is symmetric, then the network synchronizes with a certain pattern of phase relations, which is determined by Eq(6).

Suppose we are given a set of key vectors to be memorized.

$$\xi^k = (\xi_1^k, \xi_2^k, \cdots, \xi_n^k),\ \xi_i^k = \pm 1, k = 0, \cdots, p \qquad (8)$$

where $\xi_i^k = \xi_j^k$ means that the *i*th and the *j*th oscillators are in-phase $(\varphi_i = \varphi_j)$, and $\xi_i^k = -\xi_j^k$ means they are anti-phase $(\varphi_i = \varphi_j + \pi)$.

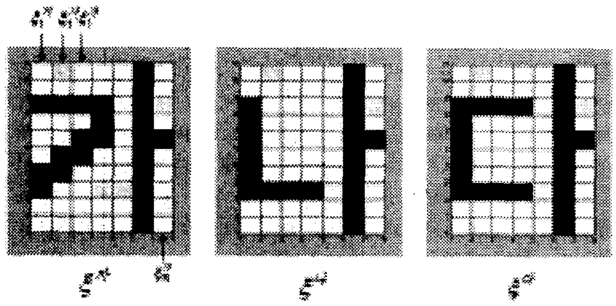

Fig. 3. Patterns to be memorized

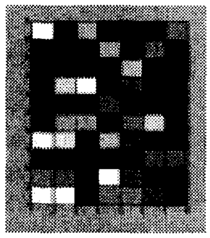

Fig. 4. Pattern to be Recognized

We use the learning rule to train the network with three images “가”, “나”, and “다” depicted in Fig. 3. A Hebbian learning rule is the simplest one.

$$s_{ij} = \frac{1}{n}\sum_{k=0}^{p} \xi_i^k \xi_j^k \qquad (9)$$

When the initial phase distribution corresponds to a distorted image “가”, the oscillators lock to each other with an appropriate phase relation; see Fig. 4. We also plot two outputs, $V(\vartheta_1)$ and $V(\vartheta_2)$, and their phase deviations, φ_1 and φ_2.

D. Recognition of pattern using synchronization of the Phase Model

We consider a dynamical system

$$\dot{\vartheta}_i = \Omega + V(\vartheta_i)\sum_{j=1}^{n} s_{ij} V(\vartheta_j - \frac{\pi}{2}) \qquad (10)$$

Here ϑ_i is the phase of the voltage controlled neural oscillators. The connection matrix can be expressed compactly as $c_{ij} = \overline{c_{ji}}$ for all *i* and *j*, where c_{ij} is a complex synaptic coefficient, and $\bar{c}$ means complex conjugation.

We are given a set of key vectors to be memorized

$$\xi^{\text{가}} = (\xi_1^{\text{가}}, \xi_2^{\text{가}}, \cdots, \xi_{10}^{\text{가}}),\ \xi_i^{\text{가}} = \pm 1 \qquad (11)$$

To memorize such phase patterns we can apply the complex Hebbian learning rule(Eq(9)).

Recognition of the patterns can be represented as

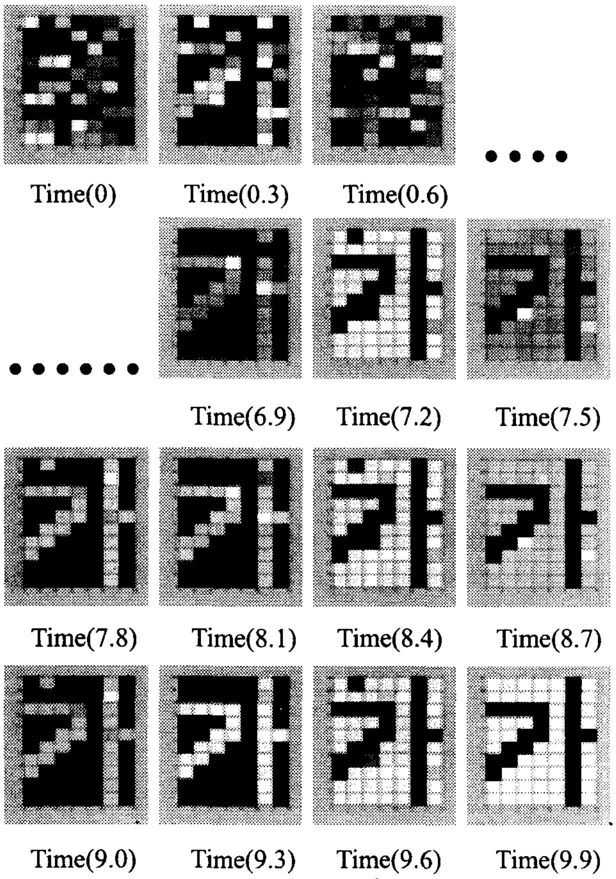

Fig. 5. Pattern recognition of "가" by neural oscillator with Hebbian learning rule

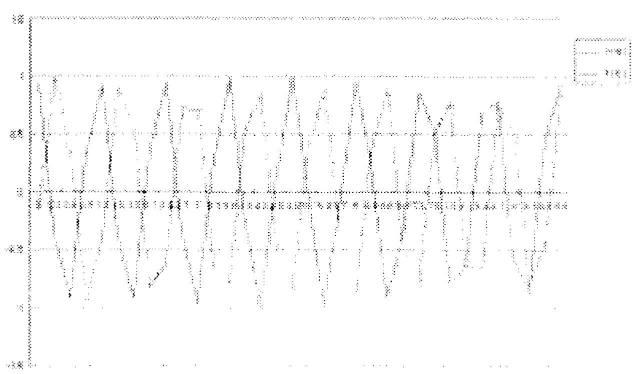
Fig. 6. Output $V(\vartheta)$ of neural oscillators

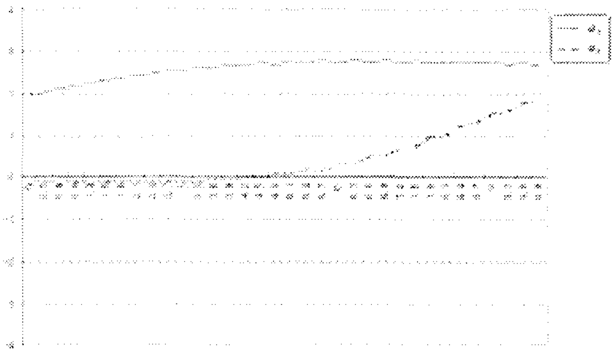
Fig. 6. The proceeding of Phase Synchronization

Fig. 5 represented result that recognize pattern using phase synchronization of neural oscillator. Each pixel is 70 spaces all to $\xi_1^{\text{가}}$, $\xi_2^{\text{가}}$, ... , and $\xi_{70}^{\text{가}}$. All times that take in awareness of pattern is 10 seconds and sampling time is 0.3 seconds.

III. Conclusion

In this paper I suggested recognition of the Korean alphabet using Neural Oscillator Phase model Synchronization. Specially, we could get more detailed result comparing neural oscillator with general neural network. But there are still some issues that have been takes much time that take in pattern recognition. Neural oscillator will be applied to systems(Analysis of image information, Voice recognition. Etc...) that oscillation is accompanied.

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