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# Recognition of the Korean Character Using Phase Synchronization Neural Oscillator

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**Abstract** : Neural oscillator can be applied to oscillator systems such as analysis of image information, voice recognition and etc. Conventional learning algorithms(Neural Network or EBPA(Error Back Propagation Algorithm)) are not proper for oscillatory systems with the complicate input patterns because of its too much complex structure. However, these problems can be easily solved by using a synchrony characteristic of neural oscillator with PLL( phase locked loop) function and a simple Hebbian learning rule. Therefore, in this paper, it will introduce an technique for Recognition of the Korean Character using Phase Synchronization Neural Oscillator and will show the result of simulation.

**Key words** : Neural Oscillator, Korean Alphabet, Phase Locked Loop, Hebbian learning rule, Phase Synchronization Neural Oscillator

## 1. Introduction

Oscillatory systems are ubiquitous in nature and also, principally, in neuron and neuro-physiological dynamics including interaction of human cardiovascular and respiratory systems. Information processing mechanism of neurons in brain is based on its rhythmic activity and synchronization phenomena of neuronal spiking. However, much of neural network research are still focusing only on the non-oscillatory sigmoidal neuron activities. Futhermore, the precise timing manipulation of neuronal firing and its control strategy usually had been neglected[1].

Therefore, it is necessary to understand the information processing mechanisms of oscillatory neurons in brain, specially an synchrony of coupled neural oscillators should be studied with estimation of certain relations between their phases, frequencies, and periodic activity[2]. Such neural synchrony dynamics in oscillation can be modeled as a neural oscillator in Fig. 1 and has a similar function as PLL models. It is assumed that an oscillatory

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neural network has the same neuro-computational properties as the standard Hopfield network. Ermentrout, Pascal, and Gutkin have recently researched using the reduced-phase method that when an interacting pair of neurons, one excitatory and one inhibitory, are coupled to other excitatory-inhibitory pairs through the excitatory neurons as shown in Fig. 1, synchronous or near-synchronous soluti ons are stable throughout a wider range of firing rates compared to networks involving only excitation. In other words, adding local inhibitory interactions to networks dominated by excitation can enhance synchronization.

The synchronization in networks of coupled excitatory-inhibitory pairs (so called, type I neuron) depends on firing rate in the same way that synchronization in all-excitatory networks does: The synchronous or nearsynchronous solution is stable at lower firing rates and breaks down gradually as firing rate increases. The inclusion of inhibition leads synchrony or near-synchrony to break down at higher and higher rates, extending the range of firing rates over which interactions promote synchrony. Frank C. Hoppensteadt and Eugene M. Izhikevich proposed an architecture of an oscillatory neural network that can be built using off-the-shelf PLL's, e.g., LMC568 or LM565 series by *National Semiconductor*. Their network were memorizable and reproducible complex oscillatory patterns in which all neurons oscillate with the same frequency but different phase relations. There are still unsolvable issues such as learning rule and tedious phase locking time of oscillatory network to the memorized patterns[1].

In this paper, the recognition system of the Korean Character using Phase Synchronization neural oscillator shall be implemented by improvement of Hebbian learning rule and neural oscillator model. We can postulate an extreme assumption that each neuron exhibits periodic sinusoidal oscillation. And also, comparing to the results of Frank C. Hoppensteadt and Eugene M. Izhikevich[1], its pattern recognition time by phase synchrony of neural oscillators with an acceleration factor shall be substantially shortened and also its recognition appearance shall be clarify by using a linear threshold function.

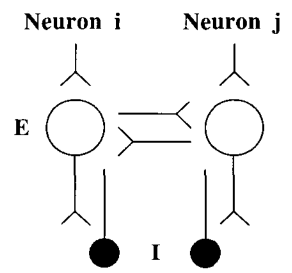



**Fig. 1 Architecture Structure of Neural Oscillator with the interaction of Coupled Excitatory (E) and Inhibitory (I) neuron pairs**

## 2. Phase model of neural oscillator

### 2.1 Phase modeling of neural oscillator as PLL and synchronization

We can implement a neural oscillator as PLL in Fig.2. If a stable and sinusoidal oscillation is assumed, a phase synchronizer of neural oscillator stands for *'Phase-Locked Loop'* and is basically a closed loop frequency control system, which functioning is based on the phase sensitive detection of phase difference between the input and output signals of the controlled oscillator. The phase detector is a device that compares two input frequencies $f_{IN}$ and $f_{FD}$, generating an output frequency $f_{OUT}$. That is a measure of their phase differences. If, for example, they have some frequency deviations, they can occur periodic outputs at the different frequencies. Therefore, a neural oscillator is similar to the principle of PLL.

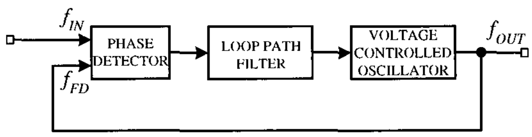



**Fig. 2 Basic Architecture of PLL**

### 2.2 Canonical model of weakly connected neurons

The general equations for a system of n coupled neural oscillator are given by

$$\dot{x}_i = F_i(t, x_1, x_2, x_3, \cdots, x_n) \tag{1}$$

where $x_i$ denotes the membrane potential, gating variables, and other electrophysiological variables of the i-th neural oscillator, and the function $F_i$ with the assumption of $2_\pi$ period encapsulate both the internal dynamics of the i-th neural oscillator and its coupling to the other oscillator. Because the influence of all the oscillator is the sum of terms each one of which represents the influence of one of the other oscillators, for the weakly connected neurons, we can rearrange eq.(1) by using the synaptic connection weight $c_{ij}$ describing the influence of oscillator $j$ on oscillator $i$. The assumption of weakly connected neuron is based on the fact 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 a weak neuronal connection is assumed, its mathematical model can be described as following.

$$\dot{x}_i = f_i(x_i, \lambda_i) + \varepsilon \sum_{j=1}^{n} c_{ij}\, g_{ij}(x_i, x_j) \tag{2}$$

Where $f_i$ means a function describing the internal potential dynamics of the i-th oscillator. Each $\lambda_i$ denotes the biophysical parameter of the i-th neural oscillator. The function $g_{ij}$ is the $2\pi$ periodic sinusoidal function describing the coupling of pairs of oscillators. The dimensionless parameter $\varepsilon \ll 1$ is small, reflecting the strength of connections between neurons. The type of coupling among pairs of oscillators is determines by the function $f_i$. Usually, the membrane potential between neuron and neuron shows oscillatory phenomena. If their variables change continuously by the periodic spikings of neuron, Eq. (2) for an weakly connected network can convert into Eq. (3).

$$z_i' = (r_i + i\omega_i)z_i - z_i|z_i|^2 + \sum_{j=1}^{n} c_{ij} z_j \tag{3}$$

Here, $i = \sqrt{-1}$, and each complex variable $z_i$ describes oscillator activity of the i-th neuron. If , in Eq. (3), all neurons have equal frequencies $\omega_1 = \cdots = \omega_n$ and have synchronized same phase as in the PLL, and the connection matrix $C = (c_{ij})$ is $c_{ij} = \bar{c}_{ij}$, then the given network always converges to an oscillatory pattern. If they have nearly equal frequencies, then the network can be transformed into the generalized phase canonical model as following.

$$\varphi_i' = \omega_i + \sum_{j=1}^{n} H_{ij}(\varphi_j - \varphi_i) \tag{4}$$

Where each $\varphi_i$ is a one-dimensional variable that describes the phase of the $i$-th oscillator in PLL, and each $H_{ij}$ is a connection function.

## 3. Generation of input patterns and hebbian learning

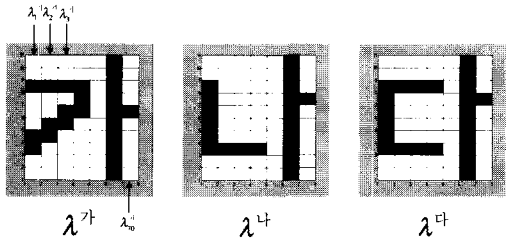
The phase model that Eq. (4) can be transformed into the Eq. (5) by setting as $\varphi_i' = -\partial U / \partial \varphi_i$

$$U(\varphi) = \frac{1}{2} \sum_{i,j=1}^{n} R_{ij}(\varphi_j - \varphi_i) \tag{5}$$

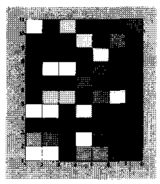
Where $R_{ij}$ is the antiderivative of $H_{ij}$ that is, $R_{ij}' = H_{ij}$. We see that if the matrix of synaptic connections is symmetric, then the network synchronizes with a certain pattern of phase relations, which is determined by Eq. (5). Suppose we are given a set of key vectors to be memorized.

$$\lambda^k = (\lambda_1^k, \lambda_2^k, \cdots, \lambda_n^k),\ \lambda_i^k = \pm 1,\ k = 0, \cdots, p \tag{6}$$

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




(a) Normal Patterns to be memorized.



(b) Noisy Pattern of '가' to be Recognized

**Fig. 4 Schematic diagram for Patterns**

We use the learning rule to train the network with three images "가", "나", and "다" depicted in Fig. 4 (a). A simple Hebbian Learning Rule with a learning accelerator factor $1 \le \eta_{ij} \le 3.2$ and regulation factor $\alpha_k$ is given as following.

$$\varphi_i' = \omega_i + \eta_{ij} \sum_{j=1}^{n} s_{ij} H_{ij}(\varphi_j - \varphi_i) \tag{7}$$

$$s_{ij} = \frac{1}{n} \sum_{k=0}^{p} \alpha_k \lambda_i^k \lambda_j^k \tag{8}$$

If the value of $\alpha_k$ is not set within the above boundary, the periodic oscillation is disappeared or the phase synchronization is never obtained. And, the success for recognition is strongly assured when the

$\alpha_k$ is given only for the noisy pattern to be recognized. When the initial phase distribution corresponds to a distorted image "가", the neural oscillators lock to each other with an appropriate phase relation : in-phase or anti-phase. That is referred to recall an associative memory for the stored patterns as Fig. 4(b). We also plot two outputs, $V(\theta_1)$ and $V(\theta_2)$, and their phase deviations, $\varphi_1$ and $\varphi_2$. We use the learning rule to train the network with three images "가", "나", and "다" depicted in Fig. 4(a). However, in biological system, memorized associative patterns are not stationary, but dynamic and oscillatory in which neurons fire periodically in phase with nonlinear relations between their phases and frequencies. For example, the human cardiovascular and respiratory system do not acts independently and are comparatively weak coupling by an unknown form of cardio-respiratory interaction through synchronization during paced respiration. Therefore, the stable oscillation and the phase synchronization are necessary.

## 4. Recognition of pattern using phase synchronization

We consider a similar dynamical system to [1] as following.

$$\dot{\theta}_i = \omega_i + \eta_i \sum_{j=1}^{n} s_{ij} V(\theta_i) V(\theta_j - \frac{\pi}{2}) \quad (9)$$

Here $\theta_i$ is the phase of the voltage controlled neural oscillators. In Eq. (9), the convergence time and its learning stability are dependent largely on the value of $\eta_i$. 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.

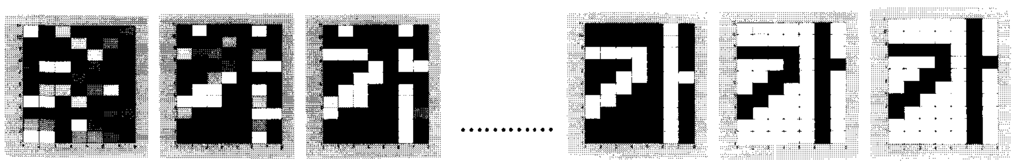
We are given a set of key vectors to be memorized.

$$\lambda^{\text{가}} = (\lambda_1^{\text{가}}, \lambda_2^{\text{가}}, \cdots, \lambda_{10}^{\text{가}}), \quad \lambda_i^{\text{가}} = \pm 1 \quad (10)$$

To memorize such phase patterns, we can apply the complex Hebbian Learning Rule as Eq. (8)). Recognition progressing sequences of the patterns can be represented as Fig. 5.

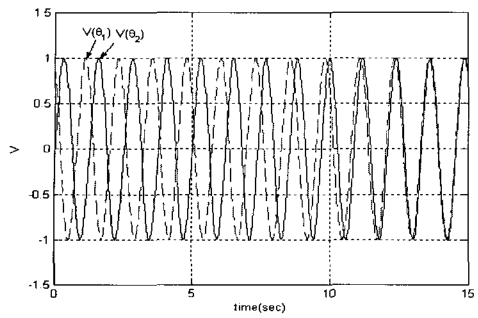
When the $V(\theta_i) = \sin\theta$ is assumed, two outputs $V(\theta_1)$ and $V(\theta_2)$, their phase deviations $\varphi_1$ and $\varphi_2$ were shown in Fig. 7.

In Fig. 6 and 7, the result of recognition for pattern using phase synchronization of neural oscillator was represented. Each pixel is 70 spaces all to $\lambda_1^{\text{가}}$, $\lambda_2^{\text{가}}$, $\cdots$, and $\lambda_{70}^{\text{가}}$. It was simulated

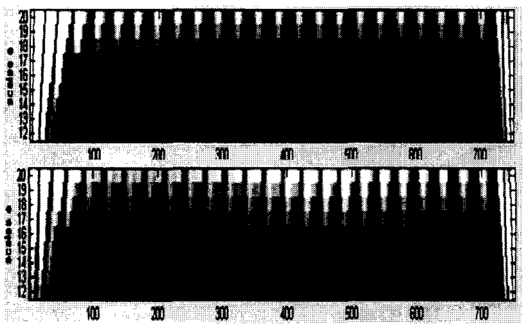


0[sec] 1.5[sec] 3[sec] ............ 12[sec] 13.5[sec] 15[sec]

**Fig. 5 Recognition Sequences of Pattern "가"**




(a) Waveforms of $V(\theta_1)$ and $V(\theta_2)$



(b) Wavelet Transform Analysis for $V(\theta_1)$ and $V(\theta_2)$ (sampling time : 20[msec])

**Fig. 6 Synchronization of Neural Oscillator Phases**

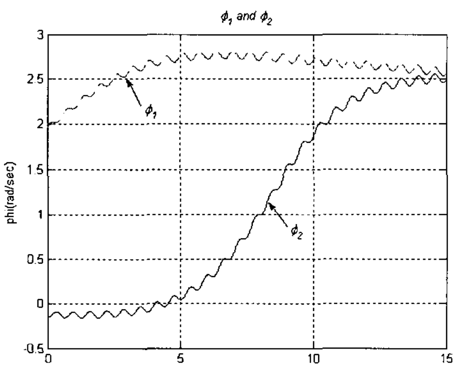



**Fig. 7 Convergence of Phase Difference for Synchronization**

over 15 seconds and sampling time of each sequence output was set as 1.5 seconds. Also, CWT(Continuous Wavelet Transform) can give us important evidence for the seizure of a synchronization state. CWT provided a means of (joint) time-frequency analysis with the property that spectral/temporal widths (or resolutions) were the same for all basis elements. Let's now take a closer look at the implications of uniform resolution. Consider two signals $V(\theta_1)$ and $V(\theta_2)$ composed of sinusoids with same frequencies. It is important to seizure the symptom of for synchronization between neural oscillators using CWT. Our observation of characteristic for pattern recognition drops in synchronization as a criterion index. In this paper, we used this phenomenon for the characterization of $V(\theta_1)$ and its distinction from $V(\theta_2)$. CWT using Daubechies wavelet function was applied to consider $\varphi_1$ and $\varphi_2$ as the phase synchronization process of two oscillators. In Fig. 7(b), we can observe that the phase synchronization pattern of $V(\theta_2)$ as a neural oscillator is clearly appeared over 6~10 [sec] by CWT. This gives rise to an information for periodicity and synchronization detections based on the periodicity of wavelet transforms defined by generalzed Daubechies wavelets and implemented by wavelet averaging methods. Specially, in Fig. 6(b), the phase synchronization pattern of $V(\theta_2)$ as neural oscillator is clearly appeared over 6-10[sec] by Continuous Wavelet Transform using Daubechies Wavelet function.

## 5. Conclusion

In this paper, that proposed recognition technique of the Korean Character using Phase Synchronization of Neural Oscillator shows successful results. Specially, neural oscillator with a Complex Hebbian Learning Rule is more simply algorithm than a generalized neural network with EPBA. But there are still some issues that have been takes much time that take in pattern recognition. Neural oscillator will be widely applied to nonlinear oscillatory systems such as analysis of image information, voice recognition and etc.

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