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Recognition of the Korean Alphabet using Phase Synchronization of Neural Oscillator

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Abstract

Neural oscillator can be applied to oscillatory systems such as analyses of image information, voice recognition and etc. Conventional EBPA (Error back Propagation Algorithm) is not proper for oscillatory systems with the complicate input's patterns because of its tedious training procedures and sluggish convergence problems. However, these problems can be easily solved by using a synchrony characteristic of neural oscillator with PLL(Phase Locked Loop) function and by using a simple Hebbian learning rule. Therefore, in this paper, a technique for Recognition of the Korean Alphabet using Phase Synchronized Neural Oscillator was introduced.

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

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, many neural network researches 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[1,2,3].

Therefore, it is necessary to understand the information processing mechanisms of oscillatory neurons in brain, specially a synchrony of coupled neural oscillators should be studied with estimation of certain relations between their phases, frequencies, and periodic activity[3]. 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 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 solutions 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 neurons) 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 the 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 networks 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 Alphabet using phase model synchronization of 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,

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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.

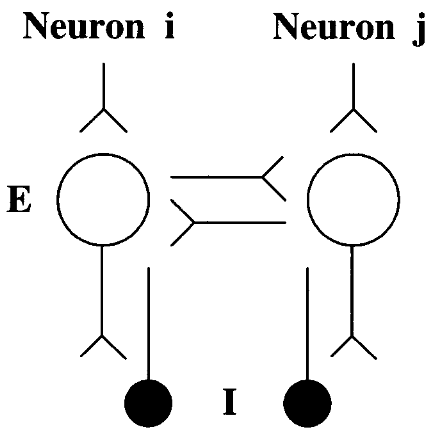


Fig. 1. Architecture Structure of Neural Oscillator with the interaction of Coupled Excitatory (E) and Inhibitory (I) neuron pairs

2. PHASE MODEL OF NEURAL OSCILLATOR

2.1 Neural Oscillator as PLL

We can implement an 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 difference. If, for example, they differ in frequency, it gives a periodic output at the difference frequency. Therefore, a neural oscillator is similar to a PLL.

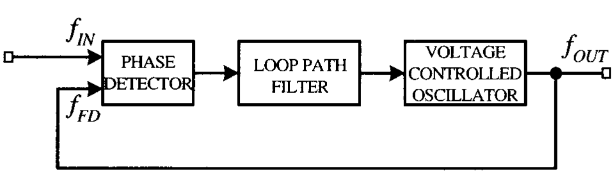


Fig. 2 Basic Architecture of PLL

2.2 Canonical Model of Weakly Connected Neurons

1) Basic Neural Oscillator [4]

Basically, the stable periodic self-sustained oscillations are described by a stable limit cycle in the dynamics about phase φ from the relation $\theta(t)=\omega t+\varphi(t)$ as

$$\frac{d\theta}{dt}=\omega_o \tag{1}$$

where $\omega_o=2\pi/T$ for the period T of the oscillator. If two oscillators are weakly connected, the phase dynamics can be given as

$$\frac{d\theta_i}{dt}=\omega_i+\varepsilon f_i(\theta_i,\theta_j) \tag{2}$$

where ε is the coupling coefficient and the functions f_i [$i=1,2$] depict the coupling relation with 2π [rad] period. If each of the intervals corresponds to a $n:m$ synchronization region, for some integer n and m, the frequencies $\omega_i[i=1,2]$ in resonance are represented as

$$n\omega_1\approx m\omega_2 \tag{3}$$

Therefore, the phase difference obtained from the Fourier expansion of the f_i [$i=1,2$] is as

$$\varphi_{n,m}(t)=n\varphi_1(t)-m\varphi_2(t) \tag{4}$$

and its dynamic equation is a first order ordinary differential equation as

$$\frac{d\theta_{n,m}}{dt}=n\omega_1(t)-m\omega_2(t)+\varepsilon V(\theta_n(t),\theta_m(t)) \tag{5}$$

This equation has two type solutions of fixed points and periodic relations of $\varphi_{n,m}(t)$. The first corresponds to perfect phase synchrony $\varphi_{n,m}(t)$ =const. And the last means a quasiperiodic motion with unequal frequencies $\omega_i[i=1,2]$. But in general, the nonresonant terms are existing in neural oscillation modes as

$$|\ n\varphi_1(t)-m\varphi_2(t)-\delta\ |<const \tag{6}$$

where δ is infinitesimal and represents an average amplitude of the oscillating phase perturbation. Therefore, the phase difference is oscillating with the amplitude δ and is disappeared for very weakly connected oscillators. As above mentioned, in order to obtain an equation describing the oscillatory phase dynamics, the variations of their amplitudes were neglected.

2) Weakly Coupled Neural Oscillator

If the N neural oscillators are coupled each other, the phase dynamics are given as

$$\varphi_i = F_i(t, \varphi_1, \varphi_2, \varphi_3 \cdots, \varphi_N) \quad (7)$$

And the function F_i with the assumption of 2π 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 s_{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]). Resultantly, if a weakly neuronal connections are assumed and we consider the connection weights s_{ij} and the acceleration convergence factor η_i , its mathematical model can be described as following.

$$\dot{\theta}_i = \omega_i + \eta_i \sum_{j=1}^{N} s_{ij} V(\theta_i, \theta_j, \theta_{ij}) \quad or \quad \dot{\theta}_i = \omega_i + \varphi_i \quad (8)$$

And also, if the input $V(\theta_i)$ is applied to the voltage controlled oscillator embedded in the i -th PLL of fig. 2, the VCO output signals are phase shifted by a delay angle of $-\pi/2$ [rad].

Therefore, eq. (7) is rewritten as

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

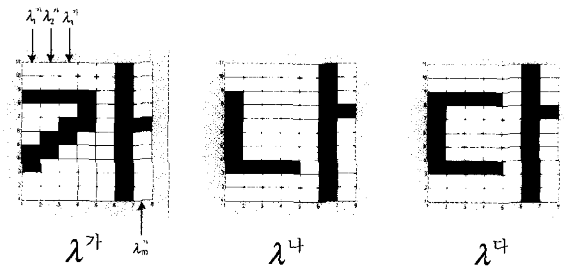
Where, when the $\theta_i(t) = \omega_i t + \varphi_i(t)$ is given, the phase deviations defined as vector $\Phi(t) = [\varphi_1(t), \varphi_2(t), \cdots, \varphi_N(t)]$ are converge to the phase equilibrium points Φ^*. The proof for their convergences is succinctly described in Ref. [1]. In case of the pattern recognition problems, the phase equilibrium points can be dependent on the number of modes to be represented in order to recognize the pattern images. That is, in the color image modes, it needs many equilibrium points, but in the black and white ones, it needs only two equilibrium points.

3. Generation of Pattern Vectors and Its Recognition Technique

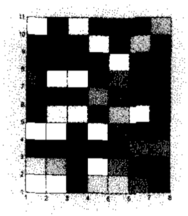
The real vector arrays for the p patterns with the dimension of each 10x7 to be memorized as '가', '나' and '다' were mapped as Fig.3 and their vectors are given as.

$$\lambda^k = [\lambda_1^k, \lambda_1^k, \cdots, \lambda_N^k], \lambda_i^k = \pm 1, k = 1, 2, \cdots, p \quad (10)$$

where the real number $\lambda_i^k = \lambda_j^k$ means that the i-th and the j-th oscillators are in-phase; $\varphi_i = \varphi_j \pm 2\pi$ [rad], and $\lambda_i^k = -\lambda_j^k$ means they are anti-phase; $\varphi_i = \varphi_j \pm \pi$ [rad]. $\lambda_i^k = -1$ means the black color and $\lambda_i^k = 1$ means for the white color. And their values restricted between -1 and 1 shall be depicted as the gray color. Fig. 3(a) shows the three image Patterns of "가", "나" and "다" to be memorized.



(a) Normal Patterns to be memorized.



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

Fig. 3. 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 simple Hebbian Learning Rule with a learning accelerator factor $1 \le \eta_{ij} \le 3.2$ and the regulation factor α_k is proposed as following.

$$s_{ij} = \frac{1}{N} \sum_{k=1}^{p} \alpha_k \lambda_i^k \lambda_j^k \quad (11)$$

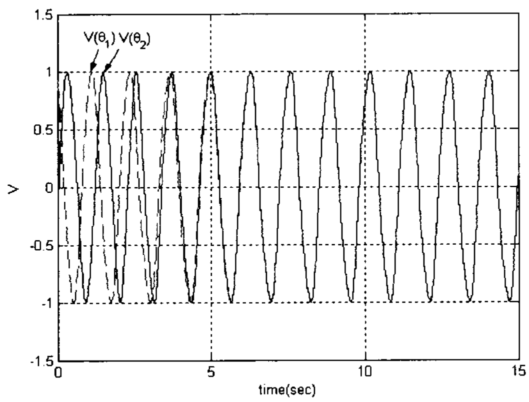
If the value of α_k is not set within the above boundary, the periodic oscillation is disappeared or the phase synchronization is never obtained. And, the success for recognition is strongly assured when the α_k is given only for the noisy pattern to be recognized. When the initial phase distribution 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.

4. Recognition Results of Pattern using Phase Synchronization

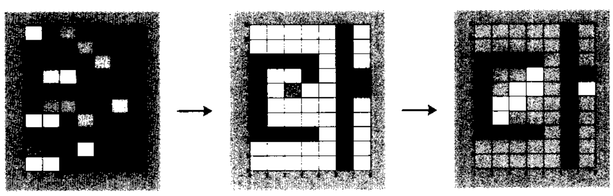
When the $V(\theta_i)=\sin\theta_i$ is assumed, the simulations were divided into the four steps; those are, application of the conventional technique[1], application of the regulation factor α_k and applications of the convergence accelerator factor η_i and the linear threshold function for post-processing.

At the first step, as the method of Ref .1, three pattern vectors were memorized and all the factors α_k and η_i were set as 1. Two outputs $V(\theta_1)$ and $V(\theta_2)$, their phase deviations φ_1 and φ_2, and $\varphi_i[i=1,2,\cdots N]$ were shown in Fig. 4. Comparing to the results of Ref.1, the synchronization time was substantially reduced but the phases were not converged into the fixed points as Fig. 4(d). The phases were approximately synchronized into the four values as $\varphi_{el}[l=1,2,3,4]$. If we consider the periodic duration of 2π [rad], we can conclude to be $\lambda_i=-1$ for $\varphi_{e1}=\varphi_{e3}\pm 2\pi[rad]$ and $\lambda_i=1$ for $\varphi_{e2}=\varphi_{e4}\pm 2\pi[rad]$. Therefore, all the recognition results were not successful. Fig. 4 shows that the noisy "가" is falsely recognized as "다" .

At the second step, when only one pattern was memorized, the recognition was successful. See Fig. 5. However, the long convergence time and the phase synchronization characteristics were very similar to the results of Ref. 1.

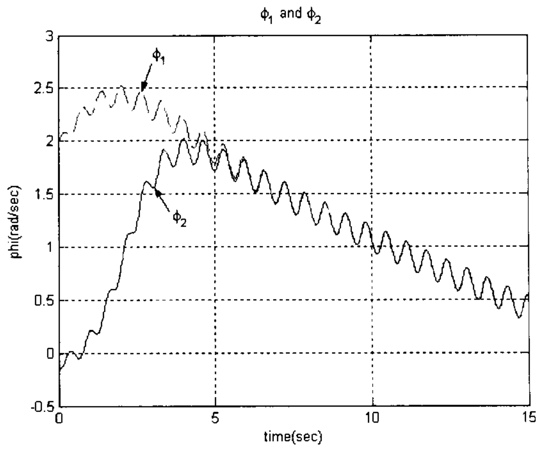


(a) Waveforms of $V(\theta_1)$ and $V(\theta_2)$

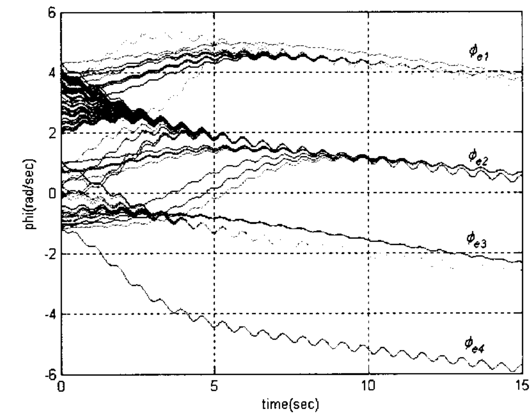


0.0[sec] 5.0[sec] 15.0[sec]

(b) Output Patterns of Image

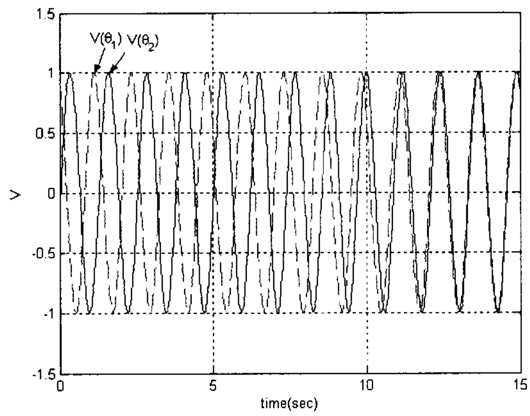


(c) φ_1 and φ_2

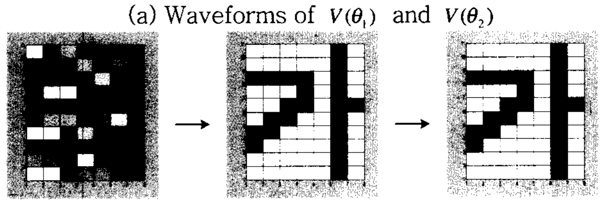


(d) Convergence Patterns of Phases

Fig. 4. Application Results of Conventional Technique

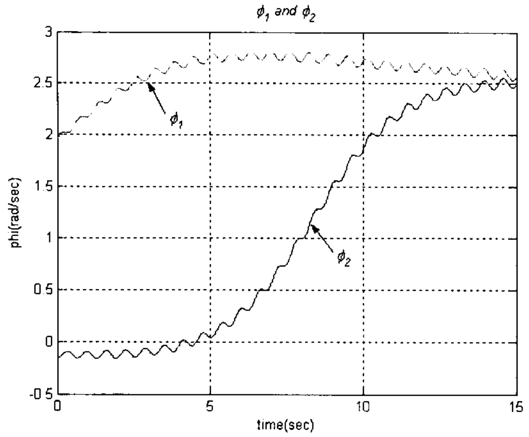


(a) Waveforms of $V(\theta_1)$ and $V(\theta_2)$

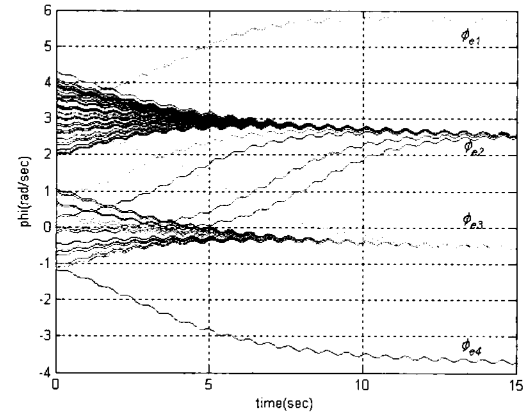


0.0[sec] 12.36[sec] 15.0[sec]

(b) Output Patterns of Image

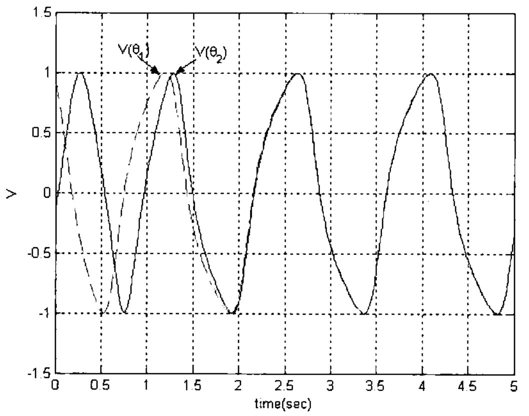


(c) φ_1 and φ_2

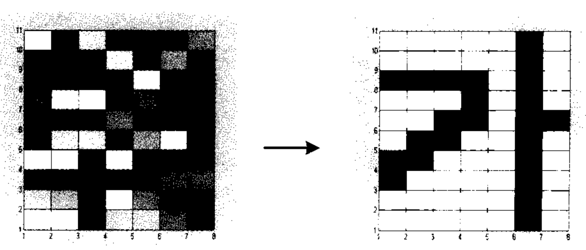


(d) Convergence Patterns of Phases

Fig. 5. Application Results of Regulation of Factor α_k

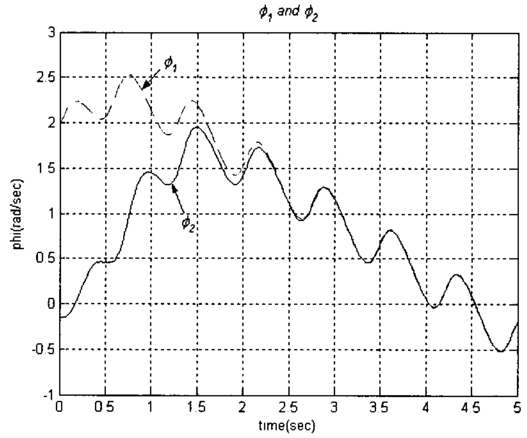


(a) Waveforms of $V(\theta_1)$ and $V(\theta_2)$

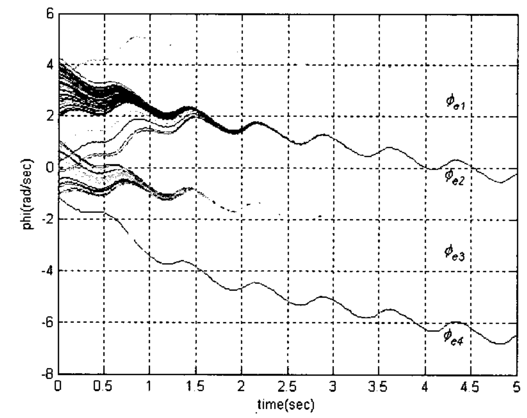


0.0[sec] 2.64[sec]

(b) Output Patterns of Image



(c) φ_1 and φ_2



(d) Convergence Patterns of Phases

Fig. 6. Application Results of Regulation Factor α_k and Accelerator Factor η_i

At the third step, Fig. 6 shows the successful recognition results for the noisy "가" when the factors are given as $\eta_i = 5, \alpha_1 = 1, \alpha_2 = \alpha_3 = 0$. But, we can observe that the output waveforms of $V(\theta_1)$ and $V(\theta_2)$ do not sustain sinusoidal oscillations with the lower frequencies 4.36[rad/sec] than the applied frequency $\omega_i = 5$ [rad/sec]. At the same time, the amplitudes of the phases oscillating with the synchronized limit cycle modes are somewhat increased.

At the 4th step, Fig. 8 shows also the successful recognition results as Fig. 6 when the factors are given as $\eta_i = 9.9, \alpha_1 = 5, \alpha_2 = \alpha_3 = 0$. In this case, because the resultant recognition values are reversed and have the unclean images, they must be post-processed through the threshold filter as Fig. 7.

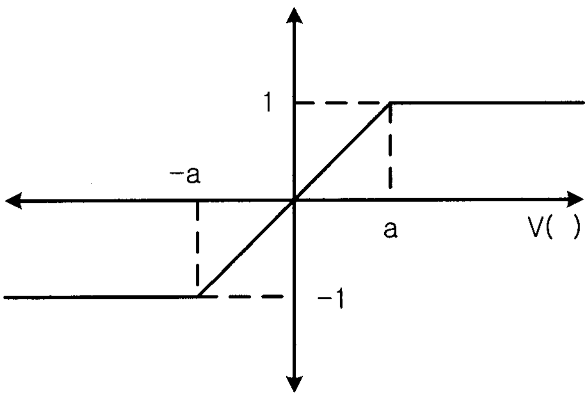
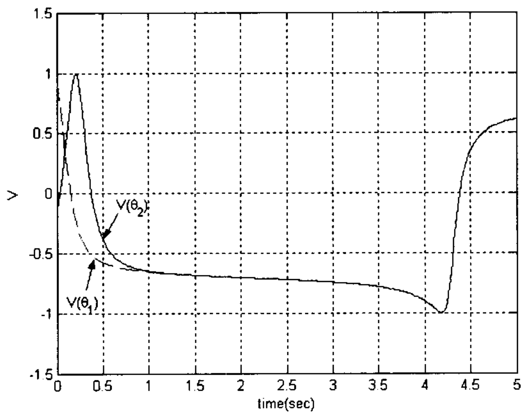


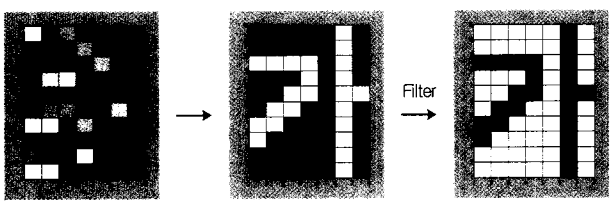
Fig . 7 Linear Threshold Function

This threshold filter has a function to clarify the recognized gray patterns for below $V(\theta_i) = -0.2$ and over $V(\theta_i) = 0.2$.

$$V(\theta_i) = \begin{cases} 1 & for \quad a < V(\theta_i) \\ V(\theta_i) & for \ -a \le V(\theta_i) \le a \\ -1 & for \quad -a > V(\theta_i) \end{cases} \qquad (12)$$

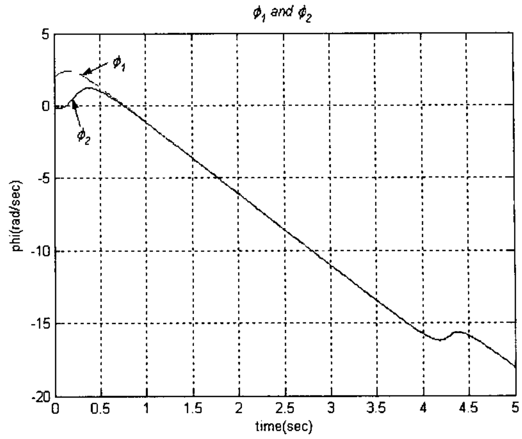


(a) Waveforms of $V(\theta_1)$ and $V(\theta_2)$

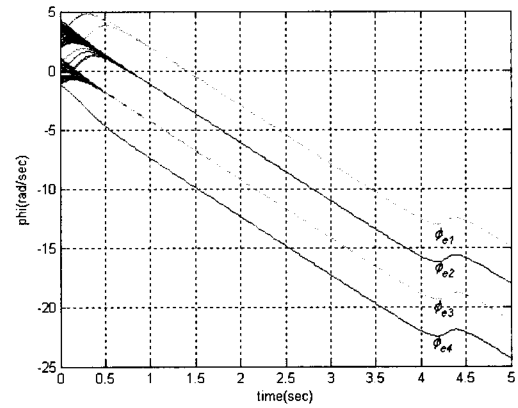


0.0[sec] 4.18[sec] 4.18[sec]

(b) Output Patterns of Image



(c) φ_1 and φ_2



(d) Convergence Patterns of Phases

Fig. 8. Application Results of Linear Threshold Function

However, in the biological system, the 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.

5. CONCLUSION

In this paper, it shows that the proposed elementary recognition technique of the Korean alphabet using Phase Synchronization of Neural Oscillator was more successful than the conventional theories [1,2]. Specially, we could get more a superiority of neural oscillator with a simple Hebbian learning rule to a generalized neural network with EPBA. But there are still some issues about the convergence time and the stability including the sustainable stable oscillation.

In the future, the neural oscillator shall be widely applied to the nonlinear oscillatory systems such as analysis of image information, voice recognition and etc.

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