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신경 진동자를 이용한 한글 문자의 인식 속도의 개선에 관한 연구

A study for improvement of Recognition velocity of Korean Character using Neural Oscillator

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Abstract

Neural Oscillator can be applied to oscillatory systems such as the image recognition, the voice recognition, estimate of the weather fluctuation and analysis of geological fluctuation etc in nature and principally, it is used often to pattern recognition of image information. Conventional BPL(Back-Propagation Learning) and MLNN(Multi Layer Neural Network) are not proper for oscillatory systems because these algorithm complicate Learning structure, have tedious procedures and sluggish convergence problem. 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. And also, Recognition velocity of Korean Character can be improved by using a Neural Oscillator's learning accelerator factor η_{ij}.

Keywards : Neural Oscillator, Korean Character, 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, much of neural network research is still focusing only on the non-oscillatory sigmoidal neuron activities.

In this paper, Recognition system of Korean Character shall be implemented by improvement of Hebbian learning rule and neural oscillator model. 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 appearence shall be clarify by using a linear threshold function.

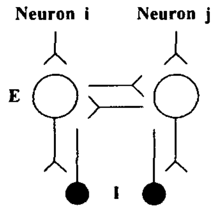


Fig. 1 Architecture Structure of Neural Oscillator with the interaction of Coupled Excitatory (E) and Inhibitory (I) neuron pairs

2. Basic Neural Oscillator

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

$$\frac{d\theta}{dt}=\omega_0 \quad (1)$$

where $\omega_0=2\pi/T$ for the period T of the oscillator. If two oscillators are weakly connected, the phase dynamics can be given as

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

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

$$n\omega_1 \approx m\omega_2 \quad (3)$$

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

$$\phi_{n,m}(t)=n\phi_1(t)-m\phi_2(t) \quad (4)$$

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

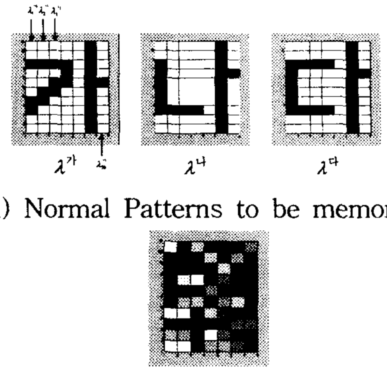
$$\frac{d\theta_{n,m}}{dt}=n\omega_1(t)-m\omega_2(t)+\varepsilon V(\theta_n(t),\theta_m(t)) \quad (5)$$

3. Generation of Pattern Vector and Recognition Technique

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

$$\lambda^k=[\lambda_1^k,\lambda_2^k,\cdots,\lambda_N^k],\ \lambda_i^k=\pm 1,\ k=1,2,\cdots,p \quad (6)$$

where the real number $\lambda_i^k=\lambda_j^k$ means that the i-th and the j-th oscillators are in-phase; $\phi_i=\phi_j\pm 2\pi[rad]$, and $\lambda_i^k=-\lambda_j^k$ means they are anti-phase; $\phi_i=\phi_j\pm\pi[rad]$. $\lambda_i^k=-1$ 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. 2(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. 2 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.

$$s_{ij}=\frac{\eta_{ij}}{N}\sum_{k=1}^{p}\alpha_k\lambda_i^k\lambda_j^k \quad (7)$$

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.

4. Recognition Results of Pattern using Phase Synchronization

We can implement an neural oscillator as PLL in Fig.3. 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. 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.

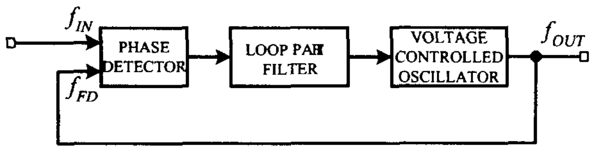


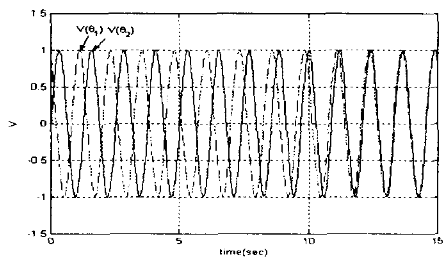
Fig. 3 Basic Architecture of PLL

We consider a dynamical system(PLL system).

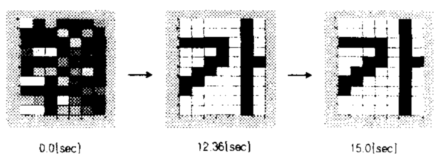
$$\theta_i = \Omega + V(\theta_i) \sum_{j=1}^{n} s_{ij} V(\theta_j - \frac{\pi}{2}) \tag{8}$$

When the $V(\theta_i) = \sin\theta_i$ is assumed, the simulation was divided into the three 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.

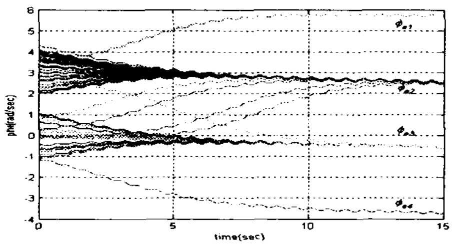
At the first step, when only one pattern was memorized, the recognition was successful. See Fig. 4. However, the long convergence time and the phase synchronization characteristics were very similar to the results of Ref. 1.



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



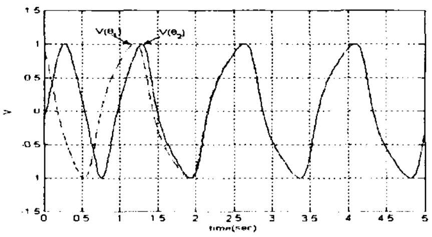
(b) Output Patterns of Image



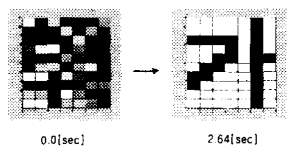
(c) Convergence Patterns of Phases

Fig. 4 Application Results of Regulation of Factor α_k

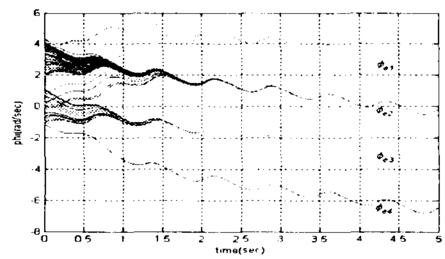
At the second step, fig. 5 shows the successful recognition results for the noisy "가" when the factors are given as $\eta_i = 5, \alpha_1 = 1$ and $\alpha_2 = \alpha_3 = 0$. But, we can observe that the output waveforms of $V(\theta_1)$ and $V(\theta_2)$ do not sustain sinusoidal oscillations with the 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.



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



(b) Output Patterns of Image



(c) Convergence Patterns of Phases

Fig. 5 Application Results of Regulation Factor α_k and Accelerator Factor η_i

At the third step, fig. 7 shows also the successful recognition results as fig. 6 when the factors are given as $\eta_i=9.9$, $a_1=5$, $a_2=a_3=0$. 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. 6.

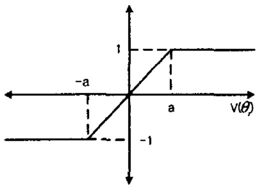
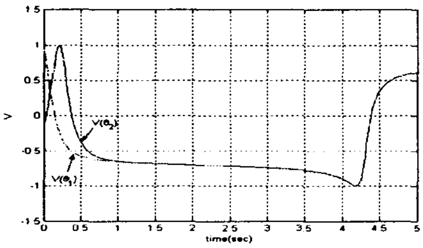


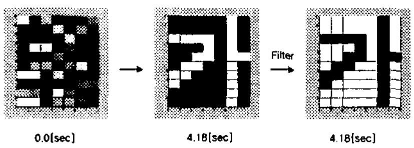
Fig. 6 Linear Threshold Function

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

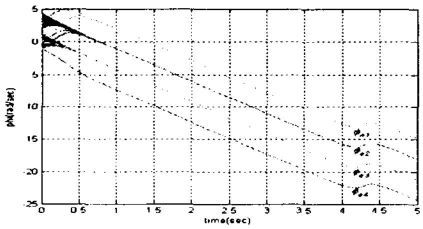
$$V(\theta_i)=\begin{cases} 1 & \cdots\cdots\cdots for \quad a<V(\theta_i) \\ V(\theta_i) & \cdots\cdots\cdots for \ -a\le V(\theta_i)\le a \\ -1 & \cdots\cdots\cdots for \ -a>V(\theta_i) \end{cases} \qquad (9)$$



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



(b) Output Patterns of Image



(c) Convergence Patterns of Phases

Fig . 7 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 act 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 Character using phase synchronization of Neural Oscillator was more successful than the conventional theories [1,2]. Specially, we could get a superiority of neural oscillator with a simple Hebbian learning rule using the convergence accelerator factor η_{ij} and regulation factor.

In the future, the neural oscillator shall be widely applied to the nonlinear oscillatory systems such as estimate of the weather fluctuation and analysis of geological fluctuation, voice recognition and etc.

6. REFERENCE

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