# A Coupled Schmitt Trigger Oscillator Neural Network for Pattern Recognition Applications

Ting Zhang, Mohammad R. Haider, Iwan D. Alexander
*Dept. Electrical and Computer Engineering*
*University of Alabama at Birmingham*
Alabama, AL, USA
$\{emmating, mrhaider, ialex\}$@uab.edu

Yehia Massoud
*School of Systems and Enterprises*
*Stevens Institute of Technology*
Hoboken, NJ, USA
ymassoud@stevens.edu

***Abstract*—This paper demonstrates a coupled Schmitt trigger oscillator based oscillator neural network (SMT-ONN) for pattern recognition applications. Unlike previous ONN models, the SMT-ONN can be easily realized in both hardware and software levels. A mathematical model of the Schmitt Trigger Oscillator as well as the corresponding CMOS circuit are presented to validate the mathematical model. The SMT-ONN can realize the pattern recognition task by considering the convergence time and frequency as the recognition indicators. A Kuramoto model based frequency synchronization approach is utilized, and simulation results indicate less than 160 ms convergence time and close frequency match for a simplified pattern recognition application.**

***Index Terms*—Schmitt Trigger, oscillator neural network, synchronization, pattern recognition**

## I. Introduction

Technological innovations of sensors and integrated circuit technology have resulted in wireless sensing for various applications [1]- [2]. With the widespread deployment of sensors and proliferation of Internet-of-Things, there is a critical need of *in-situ* energy-efficient computational units. Recently, neuro-inspired computing architecture, oscillator neural networks (ONN), has attracted researchers' attentions, which has demonstrated more efficient computational characteristics than the conventional Von-Neumann architecture [3]. Oscillation is a common phenomenon in nature. It was performed in different areas including physics, neuroscience, and engineering [4]- [6]. Based on its synchronization phenomenon, the coupled oscillatory network can perform the classification and pattern recognition tasks with ease than other schemes [7].

To study the dynamics of coupled oscillator network, different mathematical models are reported. The Kuramoto model is an authoritative model for studying synchronization phenomenon, which provides a simple but solvable approach to the coupled oscillators [8]. In recent years, multiples of coupled oscillators for pattern recognition have been proposed by different researchers. Fang *et al.* develops a new chemo-mechanical oscillating material, BZ-PZ oscillator network for pattern recognition [9]. In [10], CMOS ring oscillators for pattern recognition are proposed. In this paper, we propose a coupled Schmitt trigger oscillator neural network (SMT-ONN) with a simplified Kuramoto model based approach to realize the pattern recognition task. The proposed neural network uses Schmitt Trigger oscillator and can solve noise problems due to its hysteretic characteristics [11]. Both a mathematical model and an analog circuit implementation of the Schmitt trigger oscillator are presented in the paper. The advantage of this approach is that it makes it possible to test the algorithm in a practical way through experiment. This also facilitates energy-efficient hardware implementation and low-level signal processing using ONN other than computation intensive software simulation.

The organization of the paper is as follows. In Section II, an overview of the ONN system is summarized including the coupled topology between oscillators, the hardware architecture of Schmitt trigger oscillator, Simulink block module, and the introduction of the coupled approach, Kuramoto model. We show the simulation results for pattern recognition using Kuramoto model and coupled oscillator network in Section III. Finally, this paper ends with a conclusion in Section IV.

## II. Overview of the ONN System

Pattern recognition is to classify the samples through the calculation according to the characteristics of the sample. Pattern recognition system is basically composed of three parts – data acquisition, data processing, and classification decision or model matching. Our goal is to compare the stored pattern with the detective pattern. There can be multiple stored patterns. We define the pattern recognition task with the convergence time and frequency to the stored pattern. The initialized detective pattern the closest convergence time and frequency exhibit the best match between the detective pattern and store pattern. If the time and frequency difference are asymptotic to zero, the detective pattern is synchronized with the stored pattern, which we consider as recognition. However, if the frequency does not synchronize or the time and frequency differences are bigger than $\varepsilon$ ($\varepsilon$ depends on different recognition system), it is considered lack of recognition. The functional flow diagram for pattern recognition using ONN is shown in Fig. 1.

### *A. Topology of the Proposed System*

In this section, we present the topology of the overall system used in the neural network design. The coupled oscillators are separated into two categories: stimulus oscillators and recognition oscillators. We assume that the topology between

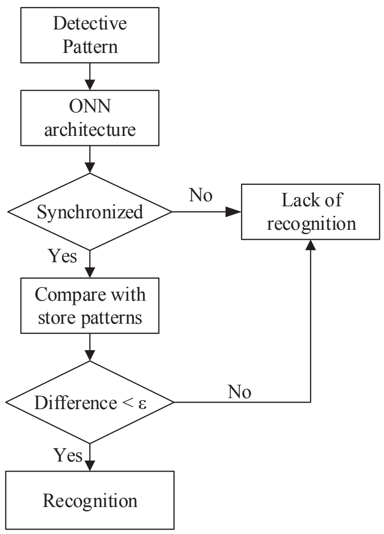


Fig. 1. Functional block for pattern recognition using ONN.

each oscillator is cross-connected with different weight $w_{ij}$ shown in Fig. 2. The advantage of cross-connected topology is that if one oscillator fails, only the failed oscillator is unable to send or receive data [12].

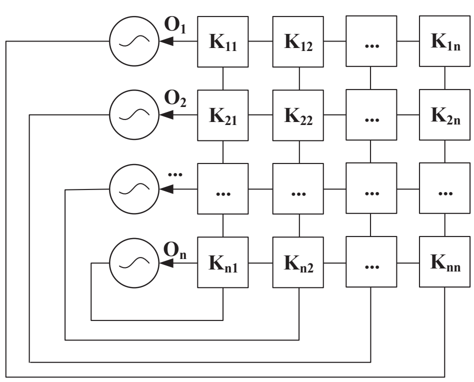


Fig. 2. Topology of coupled oscillators.

### *B. Basic Schmitt Trigger*

A Schmitt trigger is used as CMOS neuron in ONN circuit. A Schmitt trigger is a digital transmission gate with hysteresis characteristics. Its output state depends on the input state and will change only when the input voltage crosses a certain predefined voltage: higher switching threshold voltage ($V_{sph}$) and lower switching threshold voltage ($V_{spl}$). When the output is high and the input exceeds $V_{sph}$, the output switches low. On the other hand, the input voltage must go below $V_{spl}$ before the output can switch high again. In this project, by utilizing this hysteresis property, a relaxation oscillator will be formed and later on, by coupling a series of oscillators, an oscillatory neural network will be established for computation such as pattern recognition.

This system has been designed using IBM cmrf8sf 130 nm CMOS process with Cadence. By providing a triangular signal (increasing from 0 $V$ to 1 $V$, then decreasing to 0 $V$) as input, the output switched when inputs are equal to 574 $mV$ and 272 $mV$. From simulations, we got the threshold for our Schmitt trigger: $V_{sph}$= 574 $mV$, $V_{spl}$= 272 $mV$, a hysteresis value $h$= $V_{sph} - V_{spl}$= 302 $mV$, which can be used to match the Simulink model.

The architecture of a Schmitt trigger oscillator was shown in Fig. 3, the resistor $R = 222k\Omega$ and capacitor $C = 1pF$ is used to determine the frequency of the oscillator. $t_1$ is the time when the voltage cross $C$ is equal to $V_{spl}$, given by equation (1)

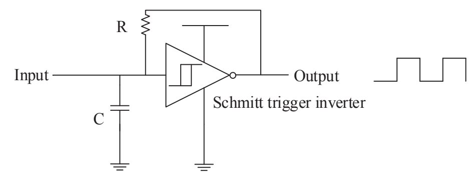


Fig. 3. Oscillator using a Schmitt trigger.

$$t_1 = RC \cdot ln\frac{V_{sph}}{V_{spl}} \tag{1}$$

$t_2$ is the time When the voltage through capacitor is charged from $V_{spl}$ to $V_{sph}$ as

$$t_2 = RC \cdot ln\frac{Vdd - V_{sph}}{Vdd - V_{spl}} \tag{2}$$

The frequency of this Schmitt trigger oscillator, without regard to the delay of Schmitt trigger, is defined by

$$f_{osc} = \frac{1}{t_1 + t_2} \tag{3}$$

### *C. System Modeling*

In this paper, a basic Schmitt trigger Oscillator architecture was described as a close loop system, which included a low pass filter module and a binary switch with hysteresis as shown in Fig. 4. The low pass filter is defined as the transfer function in equation (4), R and C value were set the same as R and C value in Fig. 3. The function of transfer function module and the hysteresis are to determine the frequency. The transfer function for low pass filter is defined by,

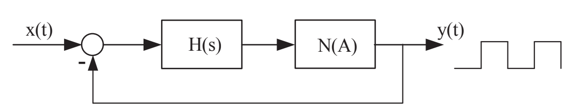


Fig. 4. First-order Schmitt trigger oscillator.

$$H(s) = \frac{1}{RCs + 1}, H(j\omega) = \frac{1}{\frac{j\omega}{\omega_p} + 1} \tag{4}$$

The limit cycle frequency was obtained [13], [14],

$$\omega = \frac{\omega_p \pi}{h}, \omega_p = \frac{1}{RC} \tag{5}$$

The frequency of the Schmitt trigger oscillator is obtained from equation (4) and (5),

$$f = \frac{1}{RC * h} \tag{6}$$

The same model has been realized in MATLAB-Simulink as shown in Fig. 5. The low pass filter is modeled as a transfer function. The binary switch is modeled as a relay to a threshold. The binary switch was specified 'on' or 'off' value by comparing the input to the specified thresholds from Cadence simulation $V_{sph}$= 547 $mV$ and $V_{spl}$= 272 $mV$. The on and off state of the relay is not affected by input between the high threshold and low threshold.

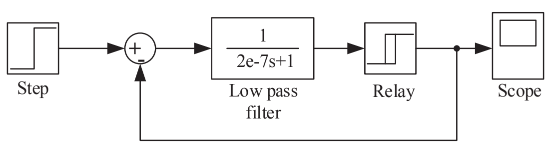


Fig. 5. Simulink module of Schmitt trigger oscillator.

### D. Pattern Recognition with Kuramoto Model

Frequency synchronization is common in nature, and we can observe this phenomenon when the frequencies of the oscillators converge to the same value by coupling. The Kuramoto model is a well-known model for studying the synchronization phenomenon of oscillators. Many of the synchronization phenomena are studied on the basis of the Kuramoro model [15], and the Kuramoto model is also widely used in the fields of biology, physics, chemistry, and sociology. The oscillators are coupled using Kuramoto equation is given in [16],

$$\frac{\mathrm{d}\phi_i}{\mathrm{d}t}(t) = 2\pi \left\{ f_i + \sum_{j=1}^{N} A_i A_j k_{ij} sin\left[\phi_j(t) - \phi_i(t)\right] \right\} \tag{7}$$

Where $\phi_i$ is the phase of oscillator i, $f_i$ is its intrinsic frequency, $A_i$ is the amplitude and $k_{ij}$ is coupling constant. Coupled oscillators are synchronized if they are at the same frequency and phase locked [17].

## III. Results

This paper exhibited an example for pattern recognition with Kuramoto model. The structure of the ONN architecture was shown in Fig. 2. The couplings between the ten oscillators comprised with two stimulus oscillators: $O_1$ and $O_2$, and eight recognition oscillators $O_3$, $O_4$, $O_5$, $O_6$, $O_7$, $O_8$, $O_9$, $O_{10}$. The coupling constant is $k_{ij}(i \neq j)$, we set $k_{ij} = 1$, except $k_{12} = k_{21} = 0$. $A_1 = 4$, $A_2 = 4$, $A_3 = A_4 = ... = A_{10} = 1$. The weight between each oscillator is $K_{ij}$,

$$K_{ij} = A_i * A_j * k_{ij} \tag{8}$$

The weight between each recognition oscillator is $K_{ij} = 1, i \neq j$. The weights between the two stimulus oscillators are $K_{12} = K_{21} = 0$. The weight from stimulus oscillator to recognition oscillator is $K_{ij} = 4, i = 1$ and $2, j = 3...10$, while the weight from recognition oscillator to stimulus oscillator $K_{ij} = 0, i = 3...10\ j = 1$ and 2. The weights between these ten oscillators are shown as,

$$K_{ij} = \begin{bmatrix} 0 & 0 & 4 & 4 & 4 & 4 & 4 & 4 & 4 & 4 \\ 0 & 0 & 4 & 4 & 4 & 4 & 4 & 4 & 4 & 4 \\ 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 \end{bmatrix} \tag{9}$$

### A. Initialization of the Network

By choosing an appropriate value for $K_{ij}$, a binary pattern $\xi$ can be stored in the network, $\xi$ = 1 or 4. The coupling weight $K_{ij}$ can also be represented by $\xi_i$* $\xi_j$. In this example, we choose ten different intrinsic frequency and weight for each oscillator, the frequency vector and weight vector are shown below,

$$f = \begin{bmatrix} 21 & 14 & 10 & 15 & 20 & 25 & 12.5 & 17.5 & 17.5 & 22.5 \end{bmatrix} \tag{10}$$

$$\xi = \begin{bmatrix} 4 & 4 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix} \tag{11}$$

Fig. 6 shows the synchronization diagram of the ten coupled oscillators. The stored pattern synchronized with the coupling approach of Kuramoto model. The convergence time of the stored pattern is 1.576800e-01 s, the convergence frequency is 17.5 Hz. The ten coupled oscillators intrinsic frequencies are in different colors.

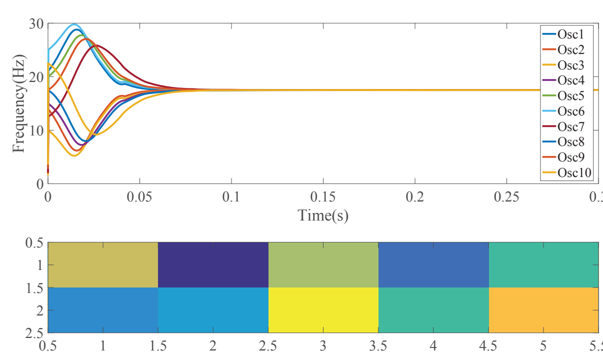


Fig. 6. Convergence time and frequency (top), and weight vector diagram of the stored pattern (bottom).

### B. Pattern Recognition

From the simulation results of the stored pattern, we detect the synchronizing time and frequency. The next critical step for ONN system is the pattern recognition. A detective pattern was given, with one or more oscillators are in different intrinsic frequencies from stored pattern. With the same coupling approach, the coupling weights are the same as the stored pattern, the synchronizing time and frequency of detective pattern determine the process of pattern recognition. In this example, by changing the intrinsic frequency of the oscillator from 15 Hz to 10 Hz at coordinate (2, 2) and measuring the convergence time of the detective pattern is shown in Fig. 7. Those ten oscillators eventually synchronized in 1.550100e-01 s and the convergence frequency is 17.3 Hz. When changing the ninth oscillator's frequency with coordinate (1, 5) to a more than twice the average value of those ten oscillators in store pattern. The coupled oscillators were not synchronized.

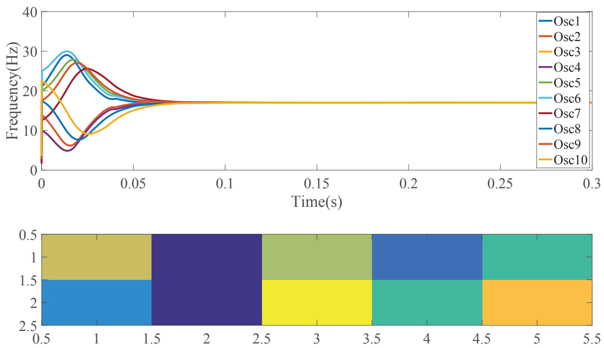


Fig. 7. Convergence time and frequency (top), and weight vector diagram of the recognition pattern (bottom).

Table I summarizes the synchronized convergence time and frequency for the stored pattern and the detective pattern. The difference in convergence time and synchronizing frequency between the detective pattern and the store pattern illustrate the pattern recognition status. Once the network frequency is synchronized, we measure the convergence time and frequency of the detective pattern and compare to the stored patterns convergence time and frequency.

TABLE I
SIMULATION RESULTS OF CONVERGENCE TIME AND FREQUENCY AS RECOGNITION INDICATORS.

| **Synchronization Pattern** | **Convergence** | |
|---|---|---|
| | ***Time(s)*** | ***Frequency(Hz)*** |
| Stored | 1.576800e-01 | 17.5 |
| Recognition | 1.550100e-01 | 17.3 |
| Recognition upper threshold | 2.742600e-01 | 19.3 |
| Recognition lower threshold | 1.841300e-01 | 16.5 |
| Lack of Recognition | No Convergence | No Convergence |

## IV. Discussion and Conclusion

In this work, we have demonstrated an ONN that can be realized both in mathematical models in Simulink and with CMOS hardware module. We have shown a coupled approach using Kuramoto model to exhibit the synchronization for pattern recognition. The convergence time and frequency of synchronization are considered as the indicators of recognition. The learning happens by changing the natural frequency of the oscillator in the ONN. We presented the ONN in both digital and analog CMOS circuitry. This enables not only to achieve computing energy efficiency, but also to perform on a small scale device. Our Mathematical algorithm can match up with the hardware implementation in theory.

## Acknowledgment


This work was supported by the NSF-CPS (Cyber-Physical Systems) program with award number CNS-1645863.


## References


[1] H. Bauer, M. Patel, and J. Veira, ”The Internet of Things: Sizing up the opportunity,” Article-December 2014, section: The Technological Challenges. source online: http://www.mckinsey.com/industries/high-tech/our-insights/the-internet-of-things-sizing-up-the-opportunity

[2] M. R. Haider, S. K. Islam, and M. R. Mahfouz, ”A low-voltage low-power injection-locked oscillator for wearable health monitoring systems,” *Analog Integrated Circuits and Signal Processing,* vol. 66, issue 2, pp. 145–154, Feb 2011.

[3] P. Maffezzoni, B. Bahr, Z. Zhang and L. Daniel.“Oscillator array models for associative memory and pattern recognition,” IEEE Transactions on Circuits and Systems I: Regular Papers, 62(6): pp.1591-1598, 2015.

[4] M. Bennett, M.F. Schatz, H. Rockwood, and K. Wiesenfeld, “Huygens’s clocks,” Proceedings: Mathematics, Physical and Engineering Sciences, pp.563-579, 2002.

[5] M. Breakspear, S. Heitmann, and A. Daffertshofer, “Generative models of cortical oscillations: neurobiological implications of the Kuramoto model,” Frontiers in human neuroscience, 4, 2010.

[6] M. H. Y. Wong, R. S. T. Lee and J. N. K. Liu, “Wind shear forecasting by Chaotic Oscillatory-based Neural Networks (CONN) with Lee Oscillator (retrograde signalling) model,” 2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence), Hong Kong, pp. 2040-2047, 2008.

[7] D. Vodenicarevic, N. Locatelli, J. Grollier, and D. Querlioz, “Synchronization detection in networks of coupled oscillators for pattern recognition. In Neural Networks,” (IJCNN), 2016 International Joint Conference on. IEEE, pp. 2015-2022, 2016.

[8] E. Vassilieva, G. Pinto, J. A. De Barros, and P. Suppes. “Learning pattern recognition through quasi-synchronization of phase oscillators,” IEEE Transactions on Neural Networks, 22(1), 84-95, 2011.

[9] Y. Fang, V. V. Yashin, S. P. Levitan, et al. “Pattern recognition with materials that compute,” Science advances, 2(9): e1601114, September 2016.

[10] M. J. Cotter, Y. Fang, S. P. Levitan, D. M. Chiarulli, and V. Narayanan, “Computational architectures based on coupled oscillators,” In VLSI (ISVLSI), 2014 IEEE Computer Society Annual Symposium on, pp. 130-135, July 2014.

[11] O. H. Schmitt, “A thermionic trigger,” Journal of Scientific Instruments, 15(1): 24, 1938.

[12] M. Itoh, and L.O. Chua, “Star cellular neural networks for associative and dynamic memories,” International Journal of Bifurcation and Chaos, 14(05): pp.1725-1772, 2004.

[13] T.Matic, T. Svedek, and M. Herceg, “Limit cycle frequency jittering of an asynchronous sigma-delta modulator,” In Telecommunication in Modern Satellite, Cable, and Broadcasting Services. TELSIKS’09. 9th International Conference on IEEE, pp. 198-201, October, 2009.

[14] S. Ouzounov, E. Roza, J.A. Hegt, G. van der Weide, and A.H. van Roermund, “Analysis and design of high-performance asynchronous sigma-delta modulators with a binary quantizer,” IEEE Journal of Solid-State Circuits, 41(3): pp.588-596, 2006.

[15] F.C.Hoppensteadt, and E.M. Izhikevich, “Oscillatory neurocomputers with dynamic connectivity,” Physical Review Letters, 82(14): p.2983, April, 1999.

[16] Y. Kuramoto, “Chemical Oscillations, waves, and Turbulences,” New York: Spinger-Verlag, 1984.

[17] E.M. Izhikevich, and Y. Kuramoto. “Weakly coupled oscillators.” Encyclopedia of mathematical physics 5, pp.448, 2006.