Class-Associative Structural Health Pattern Recognition using Oscillatory Neural Network

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Abstract

The next generation intelligent infrastructures mandates ubiquitous sensing, monitoring, and assessment for maintenance, structural health status evaluation, and initiation of preventive actions for impending dangers. The massive scale of sensor data from an infrastructure creates a burden to the property owner to process and extract the meaningful information. To tackle this challenge, a sensor level analog computational platform is proposed in this work using an oscillatory neural network (ONN) for its increased computational efficiency. In this work, an array of sensors is considered for structural health monitoring and the sensor outputs affect the coupling weights of the ONN. The beauty of ONN structure is, it can store a pattern (i.e. sensor output) through the coupling weights and exhibits a synchronized output for a close-in-match input pattern or sensor data. Any predefined deviation of sensor outputs result in desynchrony in ONN and indicate the anomaly in structural health. The inherent computational power in ONN obviates the power-hungry digital processor and facilitates data reduction and reduced computational burden for the central data center. In this work, a Kuramoto model based ONN consisting of 10 oscillating nodes is designed and simulated. An array of 10 strain sensors is considered to affect the coupling weights of the oscillating nodes, and demonstrate network level computation. Based on MATLAB simulations, the proposed ONN architecture can successfully detect the close-in-match pattern through synchronization, and differentiate the far-out-match pattern through loss of synchronization in the oscillating nodes.

1. Introduction

The state of art of the communication technology is constantly evolving benefit from the increased communication bandwidth and frequency, the scale of the Internet of Things (IoT) has shifted from a single point-to-point communication to a mesh communication between sensors. [3] However, the massive sensors serving in the infrastructures create the burden in the energy harvesting, real-time monitoring, self-calibrating and even in the data analyzing.

Sensors act as significant role in intelligent infrastructures for health monitoring, status evaluation and assessment for maintenance. In conventional sensor detection technology, whether it is an active sensor or a passive sensor, the sensor works independently in the monitoring scenario. In the process of rapid development of the IoT, a large number of different sensors communicate as sensor networks, so the kind of point-to-point sensors has great limitations in redundant data processing, energy harvesting, and efficiency decreasing [1].

In wireless sensor network, transmission units are the largest energy consumers. In sensor nodes. Reducing transmission data between node and base station can prolong the lifetime of the sensor node significantly [4]. It is necessary to find an efficient, optimized approach to [8]. Oscillatory neural network (ONN) is a high-efficiency data processing method by simulating neurons [3]. Based on the synchronization phenomenon of the coupled oscillatory network, classification and pattern recognition can be performed [7]. ONN stores different patterns by coupling weights between different oscillators. When the coupling weights change, the ONN exhibits pattern recognition from the synchronous output in each oscillator [6].

In this paper, ten oscillators coupled ONN based on Kuramoto model is presented. The rest of the paper is organized as follow. Section 2 gives a short overview of the ONN sensing system shown in Fig.1. The data forming the coupling weights are generated from the infrastructure's sensor array. Section 3 shows the simulation results for pattern recognition of synchronization, asynchronization, and the robustness when different stimulus data from the sensor is performed to the system. Finally, section 4 provides a discussion and conclusion of the work.

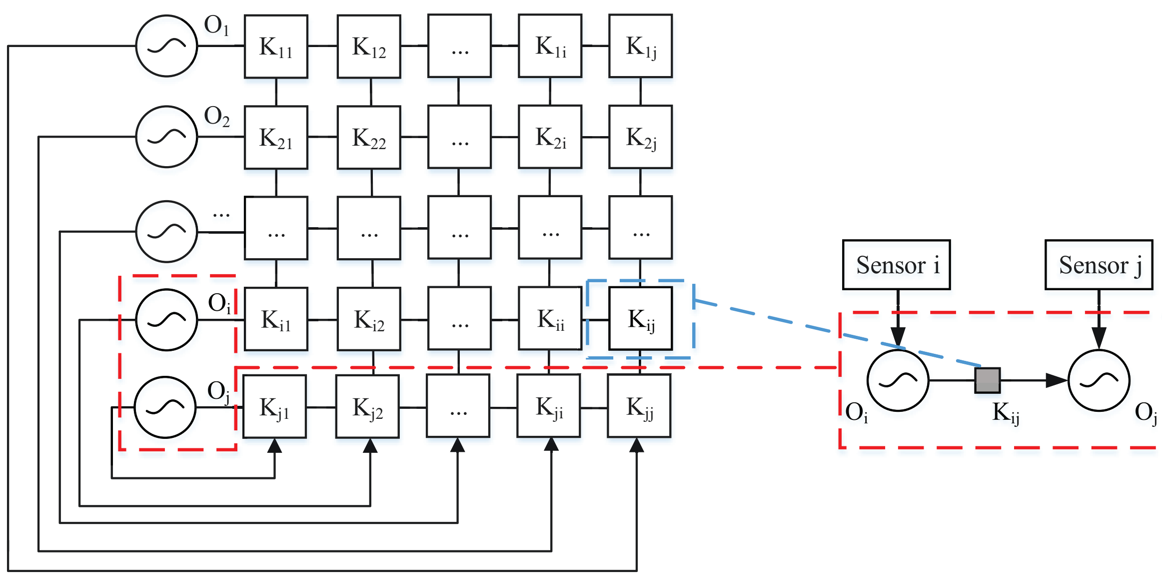

Fig.1 Schematic showing the connection between each oscillator. The coupling strength A_i and A_j of oscillator i and oscillator j are getting from the data measured from the sensor i and sensor j.

2. System Architecture

Frequency synchronization between different oscillators is a common phenomenon in nature. This can be observed when the frequencies between oscillators converge to a single value because of the weight coupling. This paper proposed an ONN based on the Kuramoto model. The equation of coupled oscillators using the Kuramoto model [5] is shown as,

$$\frac{d\varphi_i}{dt}(t) = 2\pi\{f_i + \sum_{j=1}^{N} K_{ij}\sin(\varphi_j - \varphi_i)\} \tag{1}$$

Where the φ_i, f_i are the phase and intrinsic frequency of i^{th} oscillator. The oscillator coupling weight between two different oscillators represented by $K_{ij} \in \boldsymbol{K}$. The weight between the oscillator i to j is generated form sensor i and j output. The coupling weight K_{ij} which forms the weight matrix $\boldsymbol{K}$ is equal to

$$K_{ij} = k_{ij} * A_i * A_j \tag{2}$$

A is the coupling strength which is affected by the sensor, k_{ij} is the coupling constant. In this proposed ONN system, there are 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, and O_{10}. In this paper, the sensing data ε comes from the accelerometer. The values of coupling strength A comes from the sensing data which are normalized to the range of 1 to 4.

$$\varepsilon = \sqrt{\Delta x^2 + \Delta y^2 + \Delta z^2} \tag{3}$$

Δx , Δy , Δz are the difference between the current sensing coordinates values and the stored coordinates values. The coupling constant between oscillators is $k_{ij}(i \neq j)$. In the stored pattern we set $k_{ij} = 1$, except $k_{12} = k_{21} = 0$, $A = [4, 4, 1, 1, 1, 1, 1, 1, 1, 1]^T$, the weight matrix **K** is shown below,

$$\mathbf{K} = \begin{bmatrix} 0 & 0 & 4 & 4 & 4 & 4 & 4 & 4 & 4 & 4 \\ 0 & 0 & 4 & 4 & 4 & 4 & 4 & 4 & 4 & 4 \\ 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 \end{bmatrix}$$

3. Simulation Results

Matlab simulation is designed to simulate the proposed ONN system. The intrinsic frequencies of the oscillator are chosen from 10 to 30 Hz low frequency to simulate infrastructures. The simulation result for a stored pattern and two recognition patterns are shown in the top images in Fig. 2-4. In the bottom of the images in Fig. 2-4, the different color represent the different coupling strength for each oscillator. The ten oscillators are arranged in 2 rows and 5 columns. The vertical & horizontal axes are the position of each oscillator.

3.1 Stored Pattern

The stored pattern simulation result is shown in Fig.2. The coupling strength vector is $A = [4, 4, 1, 1, 1, 1, 1, 1, 1, 1]^T$, the intrinsic frequency vector of the oscillators $f_0 = [14, 21, 12, 15, 18, 27.5, 10, 17.5, 17.5, 22.5]$.

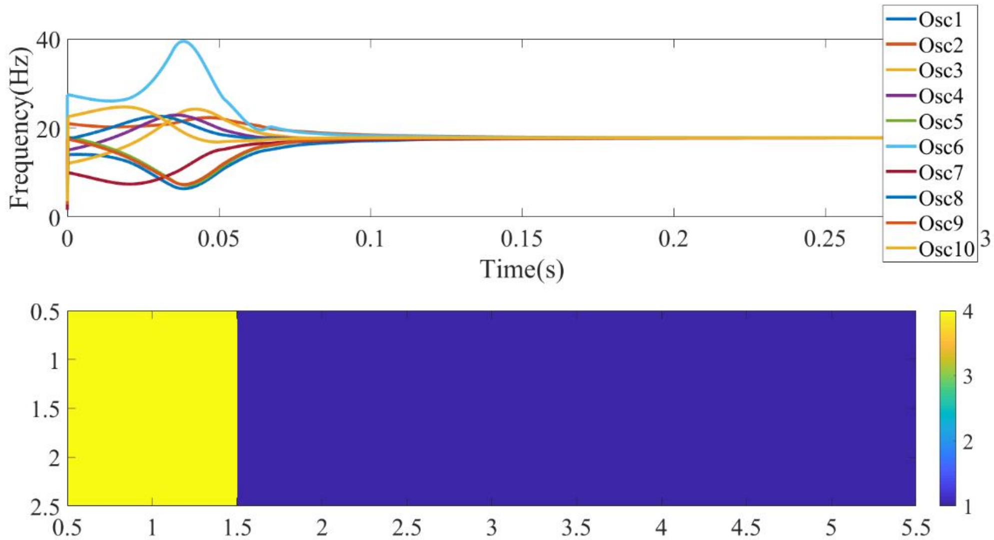

Fig.2 Synchronous time, frequency (top) and coupling strength diagram for stored pattern (bottom)

As shown in Fig.2, the convergence time of the store pattern is 0.1829 seconds and the synchronous frequency is 17 Hz. The color diagram is a 2 by 5 matrix represents the weight vector k. Color bar from blue to yellow represent the coupling strength value from 1 to 4.

3.2 Asynchronous Pattern

As the coupling strength values are normalized to a range of 1 to 4 when a detorted pattern is performed which means the sensor sensed a significant change compared to the stored pattern. The ONN system will be involved in a different pattern as shown in Fig.3. When the coupling strength vector is $A = [4, 4, 1, 1, 1, 2, 1, 1, 1, 1]^T$, the intrinsic frequency vector of the oscillators $f_0 = [14, 21, 12, 15, 18, 27.5, 10, 17.5, 17.5, 22.5]$.

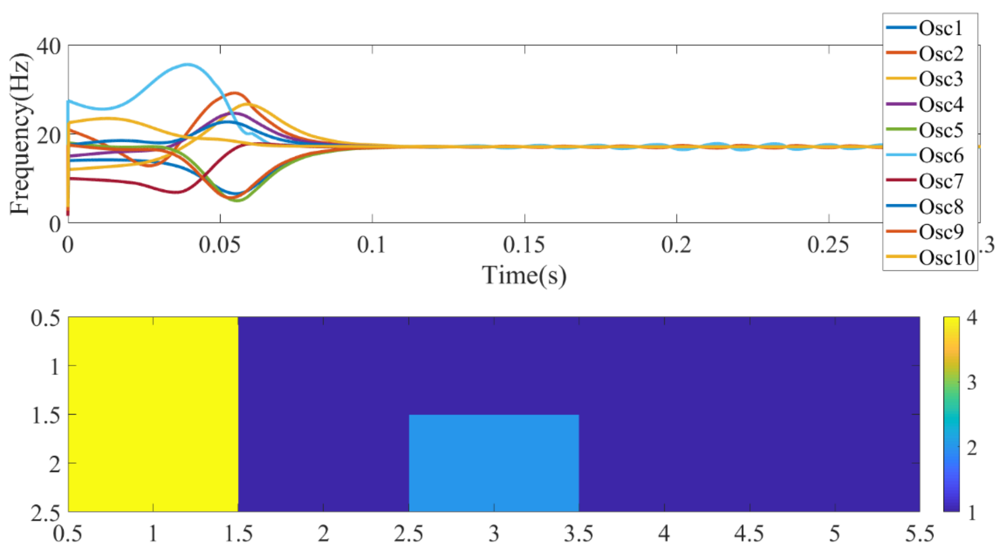

Fig.3 Asynchronous time, frequency (top) and coupling strength diagram (bottom)

Fig.3 shows an asynchronous pattern, which ONN is under an asynchronous situation with no synchronous time and frequency due to the significant change of sensor output.

3.3 Robustness simulation

Robustness detection is one of main detection indicator for ONN anti-interference performance. In practical scenarios, the excellent robust performance of the system is not only the resistance to noise signals but also the recognition efficiency of the overall system and the reduction of energy consumption which is important in a sensor network. In the simulation, a white noise signal vector is added at the store weight vector k = [4.0498, 4.0960, 1.0340, 1.0585, 1.0224, 1.0751, 1.0255, 1.0506, 1.0699, 1.0891]^T, the intrinsic frequency vector of the oscillators f_0=[14, 21, 12, 15, 18, 27.5, 10, 17.5, 17.5, 22.5].

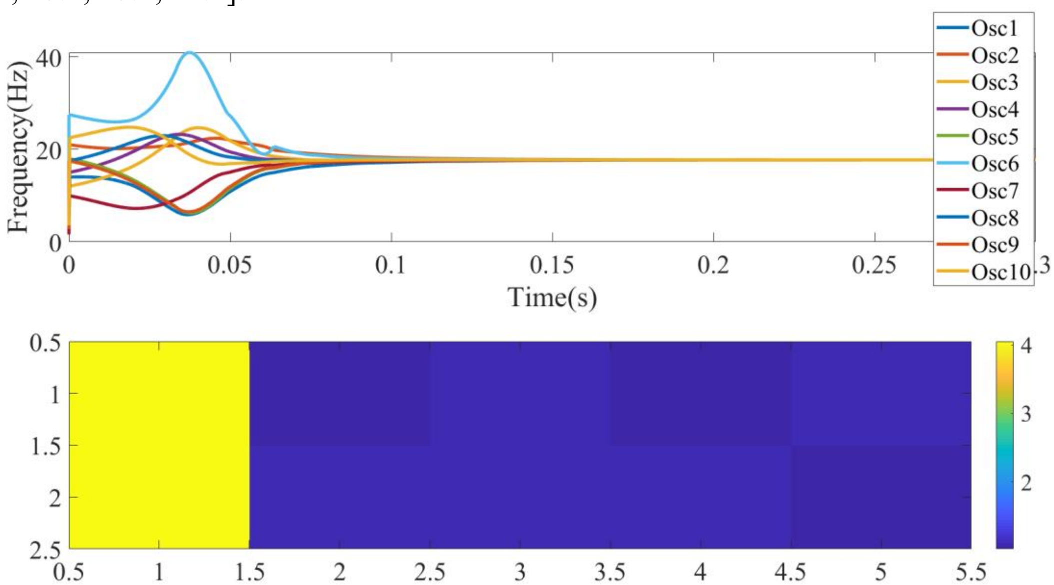

Fig.4 Synchronous time, frequency (top) and coupling strength diagram in robustness (bottom)

As shown in Fig.4, the convergence time and synchronous frequency under the coupling strength added a noise signal is 0.26185 second and 17.2Hz separately. This explains when the sensing data has a small change, the system is able to restore to steady. This has proved the robustness of this system.

4. Discussion and Conclusion

In intelligence infrastructures with sensor network applications, quickly and accurately identify the various states of the sensors to provide a fundament for the recognition of the life state of the basic facilities. An ONN system based on the Kuramoto model is designed and simulated in this paper. We showed a coupled approach using Kuramoto model to exhibit the synchronization for pattern recognition. The convergence time and frequency to synchronization were considered as the indicator of recognition. Based on MATLAB simulations, the proposed ONN architecture can successfully detect the close-in-match pattern through synchronization, and differentiate the far-out-match pattern through loss of synchronization in the oscillating nodes. In wireless sensor network, transmission units are the largest energy consumers. By only transmitting the data with lossing of synchronization, ONN have been shown to have a big benefit on low power comsumption though data reduction.

Acknowledgment

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