Structural Damage Detection using Wireless Intelligent Sensor Networks

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Abstract

Structural health monitoring (SHM) is the science of assessing the integrity of structures such as buildings, bridges and aerospace structures. SHM systems strive to detect and locate damage in structures as early as possible. Today most automated SHM system has been suggested that wireless sensing can potentially bring about a dramatic reduction in cost by doing away with the cabling cost. Self-organizing dense wireless sensor networks that are cheap and easy to install can potentially bring significant benefits to SHM systems. This paper introduces a wireless sensor network system based SHM, the system includes the self-developed sensor node for SHM and the artificial intelligence routing for data transmission. Using offline processing and online processing methods in artificial intelligence routing, it can discovery backbone for wireless sensor networks with low average dissipated energy and average delay.

Keywords: *structural health monitoring, structural damage detection, sensor node, routing algorithm, Wireless sensor network, self-organizing map*

1. Introduction

Much attention has been focused on the research of structural health monitoring (SHM). The SHM is researched for devoted to predict the onset of damage and deterioration in structural condition with the observation of a system over time using periodically sampled dynamic response measurements from an array of sensors. There are several advantages to using a SHM system over traditional nondestructive testing, such as reduced down time, elimination of component tear down inspections and the potential prevention of failure during operation. Marine, aerospace, ground and civil structures can receive unexpected damage that may compromise integrity during their life span. Therefore, the development of the SHM system can save revenue and lives depending upon the application. A lot of developments have been made to prove that the structural health monitoring technology is a promising one [1-3].

Traditionally, the cable-based SHM systems for aircraft structures might involve large number of wires employed for communication among sensors and centralized data acquisition systems. Centralized data processing makes test programs lack efficiency and intelligence. To tackle these problems, wireless sensor network technologies have been explored in recent years. Mitchell, *et al.*, [4] proposed the use of distributed computing and sensing to detect damage in critical locations. Krishna [5] proposed a NETSHM system based on wireless sensor network and used flood routing to minimize communication overhead. J. Wu, *et al.*, [6] proposed a wireless sensor network node designed for exploring structural health monitoring applications and used directed diffusion routing algorithm to monitor the strain distribution.

The research in this paper aims to develop a low-cost, low-power, dedicated wireless sensor node to develop the SHM system, and to present a new routing algorithm for SHM which introduces artificial intelligence techniques to measure the Qos supported by the network. The wireless SHM system can enhance network self-control capability and resource efficiency, and prolong the whole network lifetime.

2. The Wireless Sensor Node Design

The fundamental objective of the wireless sensor network based SHM system is the design of a dedicated high-precision wireless strain sensor node. High-precision means the testing random error is small and replicated measurements can provide closely similar results.

In this paper, this design aims to achieve a node testing accuracy of ±0.1%. The wireless sensor node in this paper is designed with integrated bridge voltage circuit which enables precise strain measurement, so the resistance strain gauges might be directly connected to the designed wireless sensor nodes and need no other additional instruments. In order to have good testing precision, the bridge voltage provided to the Wheatstone-bridge must have enough accuracy. Because the strain measurement has low-voltage and varying-load features, the series reference scheme is selected for better initial tolerance, temperature coefficient and power dissipation than using shunt reference [7].

In Figure 1, a series reference IC named REF5030 is used for providing the constant voltage for the Wheatstone-bridge circuit. The REF5030 is able to provide a 3V high precision power with excellent temperature drift (3 ppm/℃) and high accuracy (0.05%). The instrumentation amplifier AD623 is adopted to amplifier the bridge circuit output and it can offer excellent accuracy. The maximal input offset drift of AD623 is no more than 2 μV/°C. The maximal supply current of AD623 is no more than 575 μA. Since strain gauges are usually adopted to monitor static signals, a low-pass filter is designed to eliminate the high frequency noise. The voltage follower is adopted to output the filtered voltage signal.

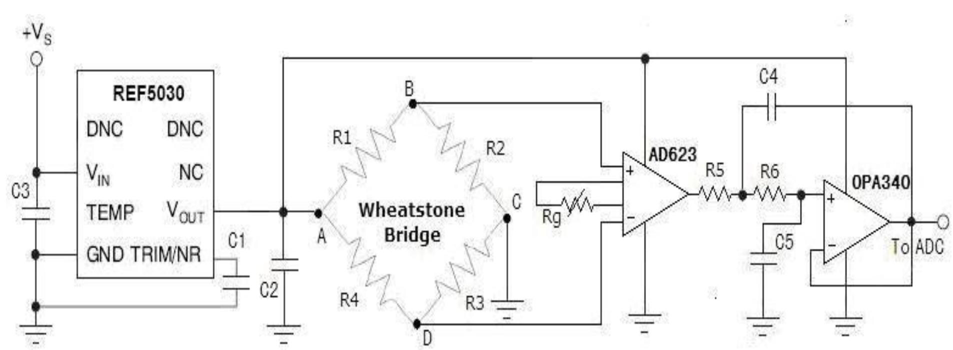

Figure 1. The Schematic Circuit Diagram for High-precision Strain Measurements

A 10-bit analog-to-digital (A/D) converter with a sampling rate of 15 KSPS integrated in an Atmel Mega128 MCU is adopted directly in the node design. It has eight multiplexed single ended input channels. Specifically, in the wireless communication design a TI CC2420 RF transceiver is chosen instead of a CC1000 for the communication capability improvement provided. The CC2420 is a true single-chip 2.4 GHz IEEE 802.15.4 compliant RF transceiver designed for low-power and low-voltage wireless applications. With 2.4 GHz RF frequency and -25 dBm output power, the wireless transceiver only draws 8.5 mA of current while actively transmitting, guaranteeing the low-power characteristics of the designed wireless node. The circuits of the WSN node are divided to be manufactured on three four-layer printed circuit boards. A dedicated installation box is designed to attach these boards. The reasons for adopting the four-layer circuits and divided design is to sufficiently separate the analog and digital circuit components. The other benefit obtained from the design is that each part can easily be upgraded according to different application requirements. Figure 2 shows the picture of the designed wireless strain node, PZT node and shock-proof encapsulation for lightweight installation. The power to supply the wireless sensor node is designed to use 5V direct current (DC) power since all the components are low-power. Thus, four normal AA batteries can power the complete wireless sensor node.

Figure 2. The Picture of the Designed Wireless Strain Node, PZT node, Station Node and Shock-proof Encapsulation

3. Evaluation Systems Setup for SHM

In order to validate the efficiency of the artificial neural networks routing schemes for SHM, an aircraft plate structure as the typical engineering structure is adopted. Two typical structure states which may be monitored by sensor arrays and indicate structural damages are researched such as joint failure and strain distribution change. The system is used for bolt loosening monitoring which based on the structural vibration response.

The setup of the practical system is shown in Figure 3. The structure is a 2m$\times$1.2m aviation hard aluminum (the type is LY12) plate with 2.5mm thick, fastened to a steel frame by 64 bolts. The bolts are deployed around the frame with a distance of 100mm. Except for the edge area with 100mm x 110mm area to arrange the bolts; the whole structure is divided averagely into eight substructures with the dimension of 450mm$\times$490mm. Each substructure is divided into 9 sub-areas which are all embedded four strain gauges. The dimension of every sub-area is 150mm×140mm. 12 piezoelectric ceramic sensors with 10mm diameter are fixed on the corners of each substructure. Based on the designed multi-agent wireless sensor network architecture, this evaluation system should demonstrate following functions: the sensor network can automatically choose sensor nodes, self-organize wireless sensor network backbone formation , integrate suitable sensor data to localize the joint failure around the frame, and the static load on the structure which cause the strain distribution change in the structure. In this paper, a loading equipment is used to change the strain distribution in the plate. When the concentrated load is applied on the structure or the applied position changes, the strain distribution changes correspondingly and the output mode of the strain sensor nodes changes too. The different pattern data decide the different load position. The pattern recognition method is the minimum-distance classification. The distance between two patterns is calculated using the Euclidean distance.

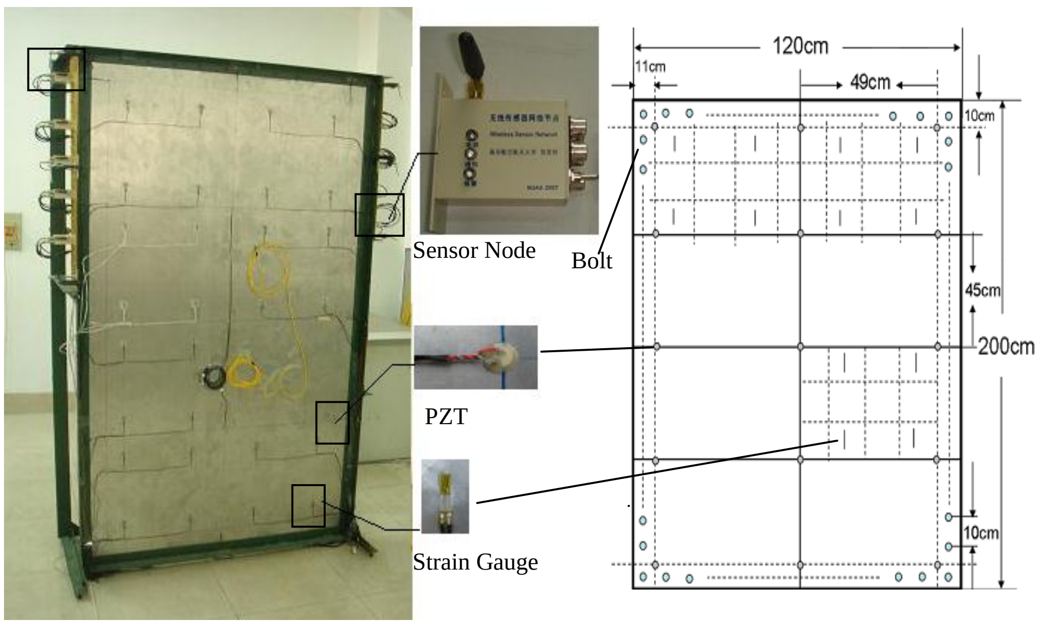

Figure 3. The Picture of the Evaluation Structure and System

4. Artificial Intelligence Routing Algorithm

In our research, a novel routing algorithm is proposed, which is called Artificial Neural Networks Routing (ANNR) algorithm. As is depicted in Figure 4, a data transmission path is selected to localize the joint failure around the frame. In this scenario, every node has a radio transmitter power and a radio receiver sensibility, which defines an average radio range. Following each node in the transmission path, sensor data can be sent to the base station. This processing is called *network backbone formation*. Our method to enhance this solution is based on the introduction of artificial intelligence techniques in the WSNs: fuzzy logic [8], artificial neural networks and expert systems. Although several approaches which used different AI techniques [9-11] have been proposed to deal with the issue, only a few [12-13] have considered the possibility of implementing an AI technique inside a sensor node.

Due to the processing constraints, we have to consider in a sensor node, the best suited, among all these techniques, is self-organizing-map (SOM). This kind of artificial neural network is based on the self organization concept; it can form a novel backbone through the shortest path algorithms, and keeps the well Qos in each sensor node at the same time.

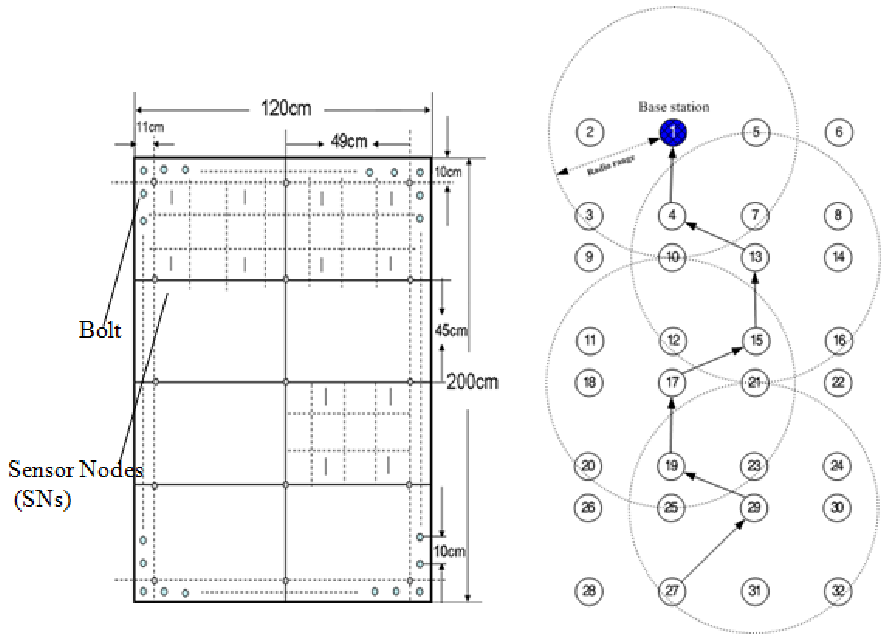

Figure 4. Event Transmission from a Source to a Base Station

4.1. Network Backbone Formation

To form a network backbone, we should find paths from the base station v_r to every node with minimum cost. This problem is similar to the shortest path finding, which has been studied in mathematics as a particular discipline called Graph Theory. For a wireless sensor network with n sensors, we can define it as communication graph. A communication graph can be viewed as an undirected digraph G (V, E), where V represents the set of all sensor nodes in the network and E represents the set of edges. Two nodes v_i and v_j are said to have an edge in the graph if the distance between them is less than transmission range. And we assume that all the links in networks are symmetrical, that is, if node v_i reach node v_j, then the node v_j and also reach the node v_i.

In 1959, Edsger Wybe Dijkstra devised a simple algorithm for computing shortest paths in a graph. We propose a modification on Dijkstra’s algorithm to adapt to wireless sensor networks. The new algorithm is called Artificial Neural Networks Routing, ANNR. The proposed algorithm can be depicted as Figure 5. Each pair ($v_{r,}$ v_i) in the wireless sensor network executes the following four steps: initialization, main loop, forward extension and backward extension.

Algorithm 1 shortest path algorithm in WSNs

Let d d be an $n \times n$ matrix and let H be an empty priority queue

For each pair $(v_r, v_i) \in V \times V$ **do** {initialization}

  if $(v_r, v_i) \in E$ **then** $d[v_r, v_i] \leftarrow \omega(v_r, v_i)$

    else $d[v_r, v_i] \leftarrow +\infty$

  Add edge (v_r, v_i) to H with priority $d[v_r, v_i]$

while H is not empty **do** {main loop}

  extract from H a pair (v_r, v_i) with minimum priority

  for each edge $(v_i, v_j) \in E$ leaving v_i **do**

    {forward extension}

   if $d[v_r, v_i] + \omega[v_i, v_j] < d[v_r, v_j]$ **then**

    $d[v_r, v_j] \leftarrow d[v_r, v_i] + \omega[v_i, v_j]$

   decrease the priority of (v_r, v_j) in H to $d[v_r, v_j]$

  for each edge $(v_j, v_r) \in E$ entering v_r **do**

    {backward extension}

   if $\omega[v_j, v_r] + d[v_r, v_i] < d[v_j, v_i]$ **then**

    $d[v_j, v_i] \leftarrow \omega[v_j, v_r] + d[v_r, v_i]$

   decrease the priority of (v_j, v_i) in H to $d[v_j, v_i]$

return d

Figure 5. Shortest Path Algorithm in WSNs

The algorithm maintains a matrix d that contains at any time an upper bound to the distances in the network graph. The upper bound $d[v_r, v_i]$ for base station node and other sensor node of pair (v_r, v_i) is initially equal to the edge weight $\omega(v_r, v_i)$ if there is an edge between v_r and v_i, and $+\infty$ otherwise. The algorithm also maintains in a priority queue H each pair (v_r, v_i) with priority $d[v_r, v_i]$. The main loop of the algorithm repeatedly extracts from H a pair (v_r, v_i) with minimum priority, and tries to extend at each iteration the corresponding shortest path by exactly one edge in every possible direction. This requires scanning all edges leaving v_i and entering v_r. Finally, the shortest path is formed.

Once a minimum cost path from the base station node to other nodes is formed, a way of measuring the edge weight parameter $\omega(v_r, v_i)$ must be defined. Considering network reliability, availability, communication security and robustness in wireless sensor networks, the edge weight parameter $\omega(v_r, v_i)$ cannot be defined simply as the number of hops or the physic distance, it should take account into the Quality of Service.

Due to the distributed feature of sensor networks, we define the Qos level in a spread way. Each node v_i tests every neighbor v_j link quality with the periodical transmissions of a specific packet named ping. Because the ping requires acknowledgment (ACK), the way node v_i receives this ACK determines a specific Qos environment, expressed on the four metrics elected: latency, throughput, and error rate and duty cycle. These are the four metrics we have defined to measure the related Qos parameters. Once a node has tested a neighbor link Qos, it calculates the distance to the root using the obtained Qos value qos. The expression (1) represents the way a node v_j calculates the distance to the base station node v_r through node v_i, where qos a variable whose value is obtained as an output of a neural network. According to this strategy, data from source nodes travel through dynamic paths, avoiding the region with the worst quality of service levels.

$$d\left[v_j, v_r\right] = d\left[v_i, v_r\right] \cdot qos \tag{1}$$

4.2. Self-organizing Map

Self-organizing map (SOM) is a data visualization technique invented by Professor Teuvo Kohonen [14] which reduces the dimensions of data through the use of self-organizing neural networks. SOM is a type of unsupervised learning. The goal is to discover some underlying structure of the data. Kohonen's SOM is called a topology-preserving map because there is a topological structure imposed on the nodes in the network. A topological map is simply a mapping that preserves neighborhood relations. Every neuron is organized in a unidirectional two layers architecture (Figure.6.). The first one is the input layer, formed by m neurons, one per each input variable. The second layer is output layer which usually formed by a rectangular grid with $n \times n'$ neurons. Each neuron is represented by an *m-dimensional* weight. And we assume that the network is fully connected - all nodes in input layer are connected to all nodes in output layer. In SOM we can distinguish two phases, the training process and the mapping process. Due to the constrains on data processing and power consumption in WSNs. The training process with a high computational cost should be implemented over a central data processing unit (also called *offline processing*). Contrary to this, the mapping process does not implies a high computational cost and can be implemented on every sensor node (also called *online processing*).

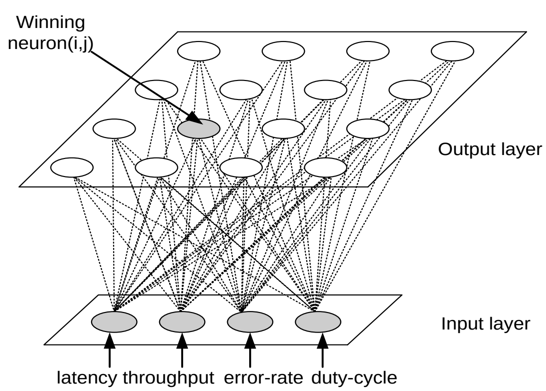

Figure 6. Self-organizing Map Architecture

In the training phase, neurons from the second layer compete for the privilege of learning among each other, while the correct answer is not known. In order to train the network, we construct a self-organizing map using a high performance neural network tool on a personal computer instead of on wireless sensor network. We call this process *offline training process*. Once we have ordered the neurons on the Kohonen layer, we identify each one of the set of 150 input samples with an output layer neuron. According to this procedure, the set or 150 input samples is distributed over the SOM. These samples allocated in the SOM form groups with similar characteristics. This way, we obtain a map formed by clusters, where every cluster corresponds with a specific QoS and is assigned a neuron of the output layer.

In the mapping process, every sensor node measures the QoS periodically running a ping application with every neighbor, which determines an input sample. After a node collected a set of input samples, it runs the wining neuron election algorithm and obtains the QoS value qos. This value is employed to modify the distance to the base station node using the expression (1). Because the mapping process is implemented by the wireless sensor network, we have called this process online mapping processing.

5. Evaluation Experiment Results

For the wireless strain node, the relationship between the output of the voltage change ΔV and the strain parameter variation $\Delta\varepsilon$ is as following: $\Delta V = \frac{K}{4} * \Delta\varepsilon * V$. K is the sensitivity coefficient of the strain gauge , $K = 2$. V is the bridge voltage provided, $V = 3v$. Table 1 shows the strain data from SN9 to SN12. These strain data could be used for the trained data to decision making of static load localization. Table 2 lists a part of the monitoring result when bolt 1, 2, 3 is loosening respectively.

Table 1. Strain Data from SN9 to SN12 in Evaluation Structure (unit: $\mu\varepsilon$)

SN	Loading Locallization									
	No load	1	2	3	4	5	6	7	8	9
9	0	18	18	4	25	32	16	272	80	33
10	0	269	36	23	0	3	-8	-25	-7	-8
11	0	37	46	25	39	50	45	106	121	324
12	0	8	45	320	-10	-4	-9	-68	-35	-31

Table 2. The Euclidean Distance of Different Modes

Mode	1	2	3
0	2.36	2.01	2.31
1	$\boxed{1.03}$	3.18	2.2
2	2.54	$\boxed{0.74}$	2.21
3	1.35	1.98	$\boxed{1.28}$
4	2.15	3.18	2.7
5	1.43	2.61	2.08
6	1.91	2.67	2.21
7	1.86	1.58	2.25
8	1.75	3.24	2.35
9	2.54	2.56	2.45
10	2.33	2.58	2.15

6. Conclusions

In this paper, we develop a miniature, high-precision, and shock-proof wireless sensor node to develop the SHM system, which is designed for multi-channel strain gauge signal conditioning and monitoring. An evaluation system for SHM is built to test the artificial intelligence routing schemes. Using *offline processing* and *online processing methods* in artificial intelligence routing, it can discovery backbone for wireless sensor networks with low average dissipated energy and average delay. For future work, we would like to have a better study of noise influence in the physical channel in order to make experiments in real SHM environments.

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