**Fault Tolerant WSN-based Structural Health Monitoring**

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*Abstract*— Wireless sensor networks (WSNs) are emerging as sensing paradigms of structural health monitoring (SHM) systems due to their low cost, high scalability and easy deployment. However, fault tolerance remains a challenging issue due to the harsh deployment environment and the long deployment time. Existing fault-tolerant schemes are either centralized or unable to meet the requirements for SHM applications. In this paper, we address fault tolerance problem in WSN-based SHM. We target faulty sensor reading, one of the most difficult types of sensor fault to be detected, and propose a fault-tolerant SHM approach. Our approach uses two types of structural dynamic characteristics: natural frequencies and mode shapes which are extracted from measured data. Redundancy in natural frequencies is used to detect faulty sensor nodes while mode shapes are used to accurately detect possible structural damage. The effectiveness of the proposed approach is demonstrated through both simulation and real implementation.

Keywords- structural health monitoring, fault tolerant

# Introduction

Structures like high-rise buildings, dams, bridges, etc. are critical components of the economic and industrial infrastructure. However, these structures are aging with years and are also subjected to harsh loading scenarios and severe environmental conditions that are not foreseen during the design and construction. Therefore, it is important to monitor the integrity of these structures and detect and pinpoint the locations of any possible damage. This is the objective of structural health monitoring (SHM).

In a SHM system, an array of sensors, usually accelerometers, strain gauges or piezoelectric sensors, are deployed on the structure to be monitored to periodically collect its responses to ambient or forced excitation. From these measurements, SHM algorithms are carried out to extract damage-sensitive vibration characteristics and compares these characteristics with reference ones which are obtained when the structure is healthy. From the change of the features, information about structural damage can be obtained[1].

Recently, wireless sensor networks (WSNs) have become an increasingly compelling platform for SHM applications. In a WSN-based SHM system, low-cost wireless sensor nodes are used to substitute conventional costly data acquisition system and wireless link is adopted to replace cables. Correspondingly, WSN-based SHM systems are low cost, easy deployment and high flexibility.

When implementing WSN-based SHM systems, significantly efforts have been paid on issues such as energy consumption, sensing synchronization, and reliable delivery of large amount of data etc. However, one important issue which has received much less attention is fault tolerance.

Fault tolerance problem is much more severe in WSN-based systems than in the wire-based counterparts due to the following reasons. First, the hardware platforms of low cost wireless sensor nodes are intrinsically not as stable as centralized data acquisition systems used in wire-based systems. Second, due to the low cost, the number of sensor nodes in a typical WSN-based SHM system can be very large, which increases the number of potential faulty nodes. Third, many WSN-based SHM systems are deployed for the long-term purposes. The long monitoring time and harsh outdoor environment increase the probability that a wireless sensor node becomes faulty.

Wireless sensor nodes can experience various types of faults. Among them, some faults can be easily identified. For example, in the presence of some hardware problems (e.g. battery depletion, transceiver failure, etc.) or software problems (e.g. bugs or memory overflow), senor nodes seized to perform their designated tasks (i.e. receive/transmit information or respond to external commands). These indications can be used to detect these types of faults.

On the contrary, another type of faults which is quite common in WSN-based SHM but much more difficult to be detected is faulty sensor readings: sensor nodes seem to work properly, but the values returned by them are incorrect. A very common reason of this fault is that sensor nodes partially or completely debond from host structure [ref]. Sensor degradation or breakage also can cause faulty reading. Since this type of fault cannot be easily identified, its can directly affect the damage detection capability of the system. A SHM system detects structural damage by examining the changes of the vibration characteristics extracted from the measurements of sensor nodes. However, both structural damage and sensor fault incur the changes of these vibration characteristics. Without detecting faulty sensor nodes, false alarm will be issued by the system.

In this paper, we proposed an SHM approach which is tolerant to faulty sensor readings. This scheme adopts a multi-layer approach to perform structural health monitoring in the presence of faulty nodes. In this system, sensor nodes deployed on a structure is partitioned into clusters and detection of faulty sensor nodes as well as structural damage is implemented in each cluster. In the first layer, faulty sensor nodes are detected based on the premise that natural frequencies identified from normal sensor nodes in each cluster are similar but different from those obtained from faulty nodes. After faulty nodes have been detected, a second layer algorithm uses extracted mode shapes to detect possible structural damages. This approach is lightweight and is able to disambiguate structural damage from faults in the sensor readings. The effectiveness of the proposed approach is demonstrated through both simulation and a real implementation.

The structure of the paper is organized as follows. In section II, we introduce the related works proposed by researchers in both computer science engineering and civil engineering. In section III, we present the proposed method. In section IV and V, the results based on a simulated suspension bridge and on a real implementation are described respectively.

# Related Work

Fault tolerance in WSNs has been studied extensively by researchers in computer science engineering. The application background is mainly event or target detection in battlefield surveillance, habitat monitoring, or environment monitoring etc. The main objective is that in the presence of faulty sensor nodes, how to detect or locate specific events or targets over a specific region.

A widely adopted fault-tolerant strategy is through decision fusion. Fig. 1 shows the basic theory of decision fusion[2]. If event or target H occurs or appears, each sensor (Si) observes it via signal yi and makes a local decision ui which is typically, a binary value. The local decisions are sent to a fusion center, where the final decision u0 is made by combining these local decisions. It is assumed the occurrence of event will be detected by more than one sensor nodes. This redundancy will be utilized in the fusion algorithm. Optimal fusion algorithms have been sought under the Bayesian or the Neyman-Person performance criterion. Using the scheme, event/target can still be correctly detected in the presence of faulty sensor nodes.



Figure Fault-tolerant decision fusion strategy

To make the above strategy more applicable for wireless sensor network, a distributed version was proposed in [3]. In this algorithm, each sensor node communicates with its neighbours and collects their binary decisions and implements fusion algorithm. The basic idea of the fusion algorithm is that if most neighbour nodes have the same value as its particular value, a node considers that its sensor is correct (i.e. majority voting). This scheme is illustrated in Fig.2 (a), where sensor node S0 receives the local conclusions from its neighbours (S1~S6) to confirm whether its own conclusion is correct. This scheme is further improved in [4~5] by using only part of neighbour nodes in fusion so as to further decrease the energy consumption and traffic congestion. This scheme is illustrated in Fig. 2(b), where S0 only receives part of its neighbours, particularly, S1,S3 and S5, to make conclusion.



Figure Decision fusion scheme in WSNs (see [13] and [15])

The fault-tolerant methods proposed above use decision fusion. Another kind of fusion which can make the system fault-tolerant is value fusion. Different from decision fusion, sensors in value fusion exchange their measured values first and then make their decisions[16].



Figure Value fusion. The grey sensors are faulty (from [16])

Through simulation, it is concluded in [16] that value fusion is superior to decision fusion when the sensor network is highly reliable. However, as faulty sensors are introduced in the system, the performance of value fusion degrades faster than the performance of decision fusion and decision fusion becomes superior to value fusion.

Although the proposed fusion schemes have proven to be fault-tolerant for many WSN applications including target/event detection, they are not suitable to be applied to a particular monitoring application, structural health monitoring (SHM).

Detection of event in SHM (i.e. structural damage) uses different approach from most of the existing monitoring applications of WSNs. To detect structural damage, the vibration characteristics of structures are first identified from measured vibration data and damage is then detected based on examining the changes of these vibration characteristics. An important property of SHM is that the accurate identification of vibration characteristics of a structure always requires data-level collaboration of multiple sensor nodes[26-27].

For the decision fusion in Fig. 1, faulty sensor nodes are detected in the process of event detection: if a sensor node gives different decision about the occurrence of event from others, it is regarded as faulty. This approach is valid for many event and target detection applications since each sensor node makes its local decision by comparing the received energy, in terms of light, vibration, temperature, etc, emitted by events or targets to a threshold. While in SHM, the occurrence of event (i.e. structural damage) cannot be reliably detected by individual sensor node, even the sensor itself is not faulty. Therefore, the decision fusion scheme is no longer applicable for SHM.

This value fusion scheme in Fig. 3(a) is also not applicable to SHM. In the existing WSNs applications such as target tracking or event detection, sensed data from each node can be simple as a single or a few byte data. While in SHM, to capture damage-sensitive information contained in the measured vibration signals, sensors nodes need to sample at hundreds of Hz and the data length required from each sensor node is generally larger than one thousand. Exchanging the raw data among the sensor nodes is not applicable considering the possible communication cost, energy consumption in wireless sensor network.

It also should be noted that the above value fusion and decision fusion are able to mask the effect of faulty sensor nodes. In other words, the event can still be correctly detected without isolating the faulty sensor nodes. However in SHM, damage detection always relies on the data-level collaboration of multiple sensor nodes which means that, the raw data from multiple sensor nodes are processed simultaneously, generally through various matrix computations such as eigen decomposition, singular value decomposition etc. This property of SHM algorithms imply that, once the measurements from faulty sensor nodes are involved, it is almost impossible to mask their effects. Consequently, it is necessary to first identify the faulty sensor nodes and then detect damage using data from the remaining sensor nodes.

There is also some previous work in civil engineering community to detect sensors which give faulty readings. In [31], two approaches were proposed which based on the comparison between the subspace of response and the subspace generated by the lower modes of a structural model. In [32], the detection of sensor failures relies on an auto-associative neural network which is known to implement principle component analysis (PCA). Another procedure based on PCA was proposed in [33] which is able to perform detection, isolation and reconstruction of a faulty sensor. However, these approaches assume that the structure is healthy when implementing sensor fault detection. They are not able to discriminate between a sensor fault and structural damage. In addition, they are all centralized and need the raw measurement data from all the sensor nodes to be aggregated to a central unit. Implementing neural network method [32] in WSNs will also cause substantial computational overhead because wireless sensor nodes have limited computational power. Based on the discussion above, they are not suitable for a fault-tolerant WSN-based SHM system.

# Proposed Method

In this section, the proposed method will be described. The whole strategy is divided into two stages: faulty nodes detection and structural damage detection.

Two types of structural dynamic characteristics, namely natural frequencies and mode shapes, are extracted from measured data and used in the above two stages. Redundancy in natural frequencies is used in the first stage to detect faulty sensor nodes. After faulty nodes have been detected and isolated, mode shapes extracted from healthy nodes are adopted to detect and locate structural damage.

Before we introduce the method, we will first briefly introduce natural frequencies and mode shapes.

Every structure has tendency to oscillate with much larger amplitude at some frequencies than others. These frequencies are called natural frequencies. Natural frequencies are internal vibration characteristic of structure and are different for different structures. When a structure is vibrating under one of its natural frequencies, the corresponding vibration pattern it exhibits is called a mode shape for this natural frequency.

For example, we deploy a total of m sensor nodes on a structure and extract a total of p mode shapes from the measurement of these sensors. The corresponding natural frequency set and mode shapes are denoted respectively as:

|  |  |  |
| --- | --- | --- |
|  |  | (1a) |

where (k=1…p) is the kth natural frequency;

|  |  |  |
| --- | --- | --- |
|  |  | (1b) |

where mode shape (k=1,...p) is the mode shape corresponding to . (i = 1, 2, …,m) is the value of at the ith sensor. As an example, Fig. 4 illustrates the first three natural frequencies and corresponding mode shapes of a typical cantilevered beam, extracted from the measurements of the deployed 12 sensor nodes.



Figure The mode shapes of a cantilever beam

The differences of natural frequencies and mode shapes can be observed by comparing Eq. (1a) with Eq. (1b). Theoretically speaking, the natural frequencies are global parameters of a structure which means that, using sensor nodes deployed on different location of a structure, the same set of natural frequencies can be obtained. This redundancy in natural frequency can be used to detect faulty sensor nodes since the natural frequencies extracted from the faulty sensor nodes will be different from those obtained from healthy nodes. However, also because the global property of natural frequency, we cannot use the extract natural frequencies from sensor nodes to detect the location of possible damage on the structure since natural frequencies do not contain any spatial information.

On the other hand, it can be seen from Eq. (1b) that mode shape has an element corresponding to each sensor node and thus contain spatial information. By comparing the mode shapes identified before and after damage and identify the sensor node where the maximum change occurs, we can obtain possible damage locations. Also can be seen is that the more number of sensor nodes used, the more elements are contained in . Another important characteristic of mode shape is that elements in only represent the relative vibration amplitudes of structure at corresponding sensor nodes. That is, = ζ, where ζis any non-zero real number. This property will be re-visited when we formulate the clustering problem in next section.

In this paper, faulty sensor nodes are first detected by exchanging the extracted natural frequencies. After faulty nodes have been detected and isolated, mode shapes of the structure are identified and from which possible structural damages are detected.

## Clustering

The first stage of the paper is to divide the deployed sensor nodes into a number of clusters. The implementation of clustering is due to the following reasons:

First, although natural frequencies are theoretically global parameters for a structure, it is practically impossible for every sensor node to get the same set of natural frequencies due to the structural nonlinearity and the environmental noise. For example, in a suspension bridge, the natural frequencies extracted from the sensor nodes deployed on cables, piers, or spans can be significantly different. Therefore, to still use the redundancy in natural frequencies to detect faulty sensor nodes, it is therefore necessary to partition the sensor nodes into different clusters where sensor nodes in each cluster belong to the same substructure (or component) of the structure. Sensor nodes deployed on the same substructure will record similar vibration pattern of the measurements and therefore maintain the redundancy in the natural frequencies.

Second, through clustering, we should guarantee that sensor nodes in each cluster are within the single hop communication range to the cluster head (CH). This single-hop constraint is caused by the synchronization error and wireless communication. The identification of natural frequencies and mode shapes requires that the measurement data of involved sensor nodes should be synchronized. The synchronization error should also be within 1ms to avoid any consequent effect on the accuracy of identified parameters. Currently time synchronization protocols, such as FTSP, will accumulate with the number of hops. Another reason for this single-hop constraint is that relaying raw data through multiple hops consumes energy as well as already limited wireless bandwidth.

Besides the substructure and single-hop constraints, we also require that all the clusters are connected together through the overlapping nodes. This constraint is associated with the approach we used to identify mode shapes. In this paper, the mode shapes for each cluster are first identified and then stitched together to obtain mode shapes defined on all of deployed sensor nodes. However, since mode shape vectors identified in a cluster only represent the relative vibration amplitudes at cluster sensor nodes, mode shapes of different clusters may not be able to be assembled together. This can be demonstrated in Fig. 5a, where the deployed 12 sensor nodes in Fig. 4 are partitioned into three clusters to identify the 3rd mode shape. Although the mode shape of each cluster is correctly identified, we still cannot obtain the mode shapes for the whole structure. The key to solve this problem is overlapping. We must ensure that each cluster has at least one node which also belongs to another cluster and all the clusters are connected through the overlapping nodes. For example, in Fig. 5b, mode shapes identified in each of the three clusters can be assembled.

Figure Mode shape assembling when (a) clusters do not overlap (b) clusters overlap

Under these constraints, we need to minimize the number of clusters since the amount of wireless data transmitted when estimating natural frequencies and mode shapes is decreased with the cluster size, and the number of faulty sensor nodes that can be detected is also increased with the cluster size.

Therefore, the objective is to divide the deployed sensor nodes into a minimum number clusters under the following constraints:

1. Sensor nodes in each cluster belong to the same substructure
2. Sensor nodes in each cluster a within the single hop communication range to its cluster head (CH)
3. All the clusters are connected together through the overlapping nodes.

To formulate the above clustering problem more formally, we assume that formulated as follows: Given a sensor network G = (V,E), find a clustering scheme that can cluster these V sensor nodes into q clusters, denoted as C = {S1, S2, S3, · · ·, Sq}, subject to the following constraints:

1) ∪Si∈C = V

2) Let the sub-graph for Si is G(Si,Ei), where Ei E. Then Si ∈ C, si ∈ Si, such that there is an edge aij Ei between si and any other sj ∈ Si(si ≠ sj)

3) Si, Sj ∈ C, (i ≠ j),

4)

Objective: Minimize q

The first constraint is set because we wish to find the mode shapes defined on all the deployed sensor nodes. The second constraint is to ensure only single-hop clusters are generated. Constraints 3 and 4 are used to describe that generated clusters are overlapping and connected.

By reducing the set cover problem into the decision version of this problem, it can be proved that the decision version of the clustering problem is NP complete. Obviously, the original clustering problem is also NP-Complete. The detailed proof is omitted for brevity.

We design a greedy centralized algorithm to solve our clustering problem. Our algorithm uses the similar idea of designing the greedy algorithm for the set cover problem but with significant modifications to handle the extra constraints of clustering. The algorithm has two parts. First, given the graph G = (V,E), it will define a cluster set for every sensor node i ∈ V . Each contains a CH, i.e. i, and all its one-hop neighbours. All the cluster sets will be treated as subsets in the set cover problem. Then the greedy approach is adopted to select the most cost-effective cluster that overlaps with the existing clusters, one at a time, until all the sensor nodes in V have been covered.

There is another centralized algorithm for our clustering problem which uses the similar greedy approach, but with different way to handle constraint associated with overlapping. Instead of constructing the overlapping clusters, this algorithm first covers all the nodes in V in a greedy matter without considering overlapping constraints, then it will test if all the clusters are connected through the overlapping nodes and add extra clusters to connect them if necessary. To achieve this, we need to first identify all the isolated cluster groups (ICGs) from the obtained clusters. Clusters within an ICG are connected through overlapping nodes but do not overlap with clusters in other ICGs. Then extra clusters are established to connect these ICGs (by the use of the minimum spanning tree (MST)). The detailed description is omitted for brevity.

We will use a simple example to demonstrate the two algorithms above. Fig. 6(a) plots the topology of 18 nodes deployed on the same substructure of the structure to be monitored. A total of 7 clusters are obtained using the first algorithm and illustrated in Fig. 6(b). Note that all these 7 clusters are connected through the overlapping nodes. Using the second algorithm, a total of 6 clusters are generated after all the 18 nodes have been covered (see Fig. 7(a)). However, these 6 clusters constitute three ICGs illustrated in Fig. 7(b). By constructing the MSP to connect these ICGs, two extra clusters, namely #7 and #8 in Fig. 7(d), are generated to connect these isolated clusters.



Figure Example of using the 1st Algorithm (a) Graph G(V,E), (b) The Generated 7 Clusters



Figure Example of using the 2nd Algorithm (a) the Initially Generated 6 clusters, (b) ICGs for (a), (c) Minimum Spanning Tree for the ICGS (d) Final Obtained 8 Clusters

For the second algorithm, we have the following theorem:

**Theorem.** *If the optimal solution for the clustering problem has*  *clusters, then our solution will produce a solution with at most*

*Proof:* It has been shown that for set cover problem, the greedy algorithm will produce sets [1]. Our algorithm will need one additional step to make sure all the sets are connected through overlapping. In the worst case when there is no overlapping node between any pair of clusters, we will need additional sets to connect them. Hence the total is .

## Extract Natural Frequency Set in Each Cluster

After clustering, sensor nodes in each cluster belong to the same substructure. In each cluster, we use the extracted natural frequency set from each sensor node to find out the faulty nodes. This is based on the premise that the healthy sensor nodes in each cluster have the similar natural frequency set. For the faulty sensor nodes, for example nodes which debond from the attached structure or experience sensor breakage, the ‘natural frequency sets’ estimated from these sensor nodes will be significantly different from normal ones.

A very intriguing property of this method is that it can discriminate sensor faults from structural damage. As was described, sensor faults will cause the significant deviation of the extracted natural frequency set from others in the same substructure. On the contrary, structural damage does not have this effect. The natural frequency set in the damaged structure is still a global parameter which means that the natural frequency set extracted from each sensor node will still match with each other after structural damage (although the natural frequency set is different from that obtained when the structure is healthy). Therefore, when the natural frequency set from a node is significantly different from others, particular from those in the same cluster, the possible cause should be sensor fault instead of structural damage.

The problem then becomes how to identify the natural frequency set using data from each sensor node. In this paper, we first calculate the power spectral of sensor nodes and then use the peak-picking method to identify natural frequencies. From the deployed sensor nodes in each cluster, we calculate the power spectral density (PSD) of the CH and cross spectral density (CSD) between the CH and each of the cluster members. PSD and CSD functions are estimated using:

|  |  |  |
| --- | --- | --- |
|  |  | (2) |

where Gxy(ω) is the CSD between two vibration signals, x(t) and y(t), measured from CH and a cluster member, respectively. X(ω) and Y (ω) are the Fourier transforms of x(t) and y(t), and ’\*’ denotes the complex conjugate. nt is time length of each record xi(t) or yi(t). nd is the number of averages mainly for denoising purpose and nd practically ranges from 10 to 20. When calculating Gxy, consecutive records of xi(t)(also yi(t)) generally overlap. When y(t) in Eq. 2 is replace by x(t), the PSD of CH is obtained.

After obtaining the CSD and PSD, the peak-picking (PP) technique proposed by [36] is adopted to extract natural frequencies. In PP, each node picks the p largest peaks from its CSD (for the CH, the PSD is used) by scanning for frequencies at which the value of the spectrum is significantly and consistently higher than the value of the spectrum at surrounding frequencies. If less than p peaks are found, zeros will be returned in place of the missing peaks. A typical CSD and the natural frequencies using the PP method are illustrated in Fig. 8, where the extracted natural frequency set is [6,34,37,99,194,317, 470].



Figure A typical CSD function and the natural frequencies extracted using the PP method (each red dot corresponds to a natural frequency)

## Natural Frequency Matching

After the frequency set of each sensor node has been identified in a cluster, faulty sensor nodes can be identified by comparing these frequency sets. However, it should be noted the identified natural frequency set from each sensor node is a vector (we define natural frequency set from node i as , where (k=1…p) is the kth natural frequency of ). Due to the environmental noise, different deployed locations, we cannot guarantee that the kth natural frequency of two sensor node correspond to the same vibration pattern of the structure. Some sensor nodes, although they are healthy, may miss identifying some true natural frequencies or erroneously obtain several pseudo frequencies. For example, assume the first four natural frequencies of a structure is

|  |  |  |
| --- | --- | --- |
|  |  | (3a) |

The identified natural frequency sets from two healthy sensor nodes can turned out to be as:

|  |  |  |
| --- | --- | --- |
|  |  | (3b) |
|  |  | (3c) |

By comparing with , contains a pseudo natural frequency 3.0 while missed a true natural frequency 5; One the other hand, missed natural frequency 1 while falsely identified 13. If natural frequencies in and are directly compared according to their orders, false positive alarm will be issued (see Fig. 9 (a)). Only when the pseudo frequencies in and are deleted, the remaining frequencies can be compared: , , where the small differences can be attributed to noise. Fig. 7 (b) illustrates these two comparable natural frequencies of and (connected by the dashed line).



Figure 9 (a) Non-comparable and (b) comparable natural frequency sets,

Based on the example above, it is important first to identify the comparable natural frequencies of different sensor nodes. However, of a structure is never known precisely and what we know are the natural frequency sets from available sensors. This increases the difficulty to identify the comparable frequencies in sensor nodes. This problem becomes even more complicated if sensor faults exist in sensor nodes.

Given a collection of natural frequency sets from sensor nodes, we use the following method to find out the comparable natural frequencies and the faulty sensor node. Before we describe the method, we will give a formal definition of comparable natural frequencies and how to select these comparable natural frequencies.

Assume using PP method, we extract natural frequencies from m sensors, each sensor having p natural frequencies. These frequencies are arranged in a m-by-p matrix

|  |  |  |
| --- | --- | --- |
|  |  | (4) |

where (i=1,…m, k=1,…,p) is the kth natural frequency extracted using the data from ith sensor. Each row of (i.e. belongs to the natural frequency set of a particular node. Analogous to the ‘adjacency list’, we define a ‘comparability list’ for each , denoted as . contains all the comparable frequencies in . The comparability lists of all the natural frequencies constitute a matrix:

|  |  |  |
| --- | --- | --- |
|  |  | (5) |

For a frequency which can be added into ’s comparability list, it must first satisfy:

|  |  |  |
| --- | --- | --- |
|  |  | (6) |

where is a threshold defined by user. Depending on the measurement noise, generally ranges from 5 to 15.

The equation above can be easily interpreted in terms of the error bar. The ranges defined by and are , , respectively. If these two ranges overlap, they satisfy the above equation.

There are some additional requirements that must satisfy to add into . First, since the comparability aims to match natural frequencies of different sensors, the comparability list of a natural frequency would not contain natural frequencies from the same sensor. Second, since we aim to establish a one-to-one mapping relationship between natural frequencies among different sensors, frequencies of the same sensor cannot be contained in the same list. Third, due to the same reason, the same natural frequency cannot be contained in more than one comparability lists of the same node. Here, we use three examples in Fig. 9 to illustrate these requirements. Two sensors, S1 and S2, each having two natural frequency sets, , . Each natural frequency is represented as a node in Fig. 10. Two frequencies are connected if they satisfy Eq.(6). The violations of the three additional requirements are illustrated in Fig. 10(a), (b) and (c), respectively, where red X indicates the illegal comparability.



Figure Three typical types of non-comparability

More formally, given and the current comparability list of (denoted as ), a frequency must satisfy the following conditions to be added into :

|  |  |  |
| --- | --- | --- |
|  |  | (7a) |
|  |  | (7b) |
|  |  | (7c) |
|  |  | (7d) |

The pseudo code for calculating is illustrated in Algorithm 1.

|  |
| --- |
| Input: natural frequency sets in  Output: |
| for i =1, i<m, i++ %% for each row of (i.e. )  for k =1, k<=p, k++ %% for each    for j=i+1, j<m, j++ %% for each  find in which minimize )  If this distance  add the location of into  block from using by other frequencies in  end  end  end  Release the block of all the frequencies in  end |

After calculating , we also obtain a supplementary matrix denoted as . has the same size of with each element containing the number of natural frequencies in the comparability list of .

Based on , we evaluate the comparability of each sensor node. This can be calculated, by adding all elements of each row of together:

|  |  |  |
| --- | --- | --- |
|  |  | (13) |

is the summation of the ith row of , which corresponds to the ith sensor nodes. A significant smaller value in indicates that on average, natural frequencies of sensor i have low comparability with others and therefore, this sensor have much larger chance to be faulty. The threshold for removing can be determined by the standard deviation in . After these nodes have been deleted, the , and are updated. This procedure will iterate until the standard deviation of is smaller than a pre-defined threshold.

We use an example to illustrate the above frequency matching procedures in a step by step manner. Assume we have four sensors S1~S4, each identifying 5 natural frequencies:

|  |  |  |
| --- | --- | --- |
|  |  | (8) |

Assume , the comparability list for each frequency in can be obtained using algorithm 1:

|  |  |  |
| --- | --- | --- |
|  |  | (15) |

This is illustrated in Fig. 12, where each frequency is connected with those in its comparability list.



Figure The of Eq. (8)

The supplementary matrix and are calculated as

|  |  |  |
| --- | --- | --- |
|  |  | (9a) |
|  |  | (9b) |

From Eq. (9b), S4 shows a much smaller value in than others and this indicates that the natural frequencies from S4 is the most incomparable to others. S4 is therefore deleted. The updated is shown in Eq.(10)

|  |  |  |
| --- | --- | --- |
|  |  | (10) |

The supplementary matrix becomes:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  | | (11a) | |
|  | | (11b) | |

The frequency matching strategy is that it can be used at the first stage to detect faulty sensor nodes, particularly with severe faulty readings. The natural frequencies identified from these sensor nodes are significantly different from others are detected in the matching procedure. However, for the sensor nodes with slight faulty readings, they may not be detected only using the matching procedure. Only when the Hotelling control chart is implemented, can these sensor nodes be detected. This conclusion will be demonstrated through a simulated example in section 4.

## Structural Damage Detection using Normal Sensor Nodes

After faulty sensor nodes have been detected, structural damage detection can be implemented using the measurement from the remaining sensor nodes.

In this paper, we adopted mode shape curvature method to identify structural damage. This method is proposed in [39] and its effectiveness has been demonstrated in many practical SHM applications. The mode shape curvature has high sensitivity to damage and does not require accurate analytical model of the structure, which believe to be very difficult to obtain in practical condition.

One issue which has not been addressed in the damage index method is how to calculate the mode shapes As was required to identify natural frequencies in section 3.2.2, we also require that the mode shapes can be calculated based on ambient vibrations (i.e. the input excitation is not measured). This problem can be addressed by employing the NExT in conjunction with the eigensystem realization algorithm (ERA)[28]. Using the NExT technique, we obtain the CSDs of sensor nodes. The inverse Fourier transform is implemented on the functions and the cross-correlation functions (CCFs) are obtained. ERA uses these functions to build a state space system whereby mode shapes of the structure are identified.

It is noteworthy that in the previous section when detecting faulty sensor nodes, we implemented distributed CSD and used peak-picking technique to find out natural frequency set for each sensor node. Here, we can slightly modify the above procedures and extract mode shapes for structural damage identification: after each sensor node obtaining the CSD with the reference node, these CSDs are inverse Fourier transformed to obtain the CCFs. These CCFs are transmitted to the CH. The CH implements ERA method to calculate mode shape. Mode shapes in different clusters are assembled together using the overlapping nodes. From the obtained mode shape, the mode shape curvature of this structure is calculated and structural damage is detected. The increase of the mode shape curvature at a sensor point indicates the possible damage at the corresponding location.

It can be seen from above that structural damage detection has effectively integrated with sensor fault detection. The CSD functions which were to be used for sensor fault detection can be utilized for damage detection. The actual cost associated with sensor fault detection is low.

Fig. 9 illustrated the architecture of the scheme. In each round, a number of samples are collect at each sensor nodes. Based on the measured data, each sensor nodes identify its natural frequencies. After the natural frequency matching, the sensor nodes with severe faulty readings are detected and isolated. Using the obtained the UCF sets, sensor nodes with slight faulty readings can also detected using the Hotelling control chart. After the faulty sensor nodes are detected and isolated, mode shapes of each cluster are identified and assembled together. Possible structural damage existing in the structure is then detected and located by examining mode shape curvatures.

In this paper, two vibration characteristics of structure, natural frequency and mode shape/curvature, have been used respectively to fulfill the two objectives: sensor fault detection and structural damage detection. The spatial redundancy of natural frequencies is used to detect sensor fault and the temporal change (i.e. before and after damage) of mode shape curvature is used to detect possible damage. It may reasonably to think of using only one characteristic to accomplish both tasks so as to save energy as well as computational cost. For example, the change in natural frequencies before and after damage can also be used to for damage identification. Unfortunately, the change of natural frequency is not a sensitive indicator to detect structural damage. Similarly, for mode shape/mode shape curvature, it cannot be used to detect sensor fault since the identification of mode shape rely on a centralized ERA algorithm which requires all the CSDs in a cluster. Data from a faulty sensor node will affect the identification of the mode shapes on all the sensor nodes, not restricted to the faulty one.



Figure The architecture proposed in this paper.

# Prototype and Evaluation

## System Description

In this paper, we use a simulated suspension bridge illustrated in Fig. 15(a) to test our proposed algorithm. The bridge is generated by SAP2000 [42]. A total of 114 sensor nodes are used to monitor the vibration at the transverse direction (z direction in Fig.15 (a) ) of the deck of the bridge. These sensors are evenly spaced at the outer side and inner side in the middle span of the deck with distance of 2m (see Fig. 15(b)). The number of sensor nodes in the left span, middle span and right span are 28, 58 and 28, respectively.



Figure The Dimensions of the Suspension Bridge and the Sensor Locations (a) TheDimensions of the Suspension Bridge (3D), (b) the Sensor Locations (X-Y plane)

In the simulation, data from these sensor nodes are generated when the bridge is under a transverse impact located at the center. The time series were sampled at 100Hz. 2% zero-mean Gaussian noise was added to the sensor data at each sample. The impact test was repeated 20 times and during each test, 1024 data are stored in each sensor. We also assume the communication range of each node is 10m.

The wireless sensor nodes deployed on the structure are divided into three substructures according to the spans they belong. Hereinafter, we use the sensor nodes in the middle span to test our propose approach. From the 58 sensor nodes, we randomly select 5 sensor nodes and generate sensor fault on these sensors. Without loss of any generality, we assume they are #10, #20, #30, #40 and #50 ( the numbering of these nodes are illustrated in Fig. 16.). According to the severity, two types of sensor faults are generated. We assume that the first three sensor nodes have slight faulty readings which will cause 3% right shift on the natural frequencies of these sensors. The last 2 sensor nodes have more severe sensor fault which causes 30% right shift on the obtained frequencies. In the following sections, we will demonstrate the proposed scheme is able correctly disambiguate faulty sensors from structural damage.

## Clustering

First, the sensor nodes in the middle span are divided into overlapping clusters. The results using the first and the second proposed methods are illustrated in Fig. 16 (a) and (b), respectively. It can be seen that both methods partition the 58 sensor nodes into 6 clusters. Particularly, using the second method, 5 clusters are obtained at the first stage and they form 3 isolated cluster groups. Accordingly, an extra cluster (i.e. VI in Fig. 16(b)) is added to make them overlap.



Figure 14 Results of using (a) the 1st and (b) the 2nd Algorithms

## Extract Natural Frequency Set in Each Cluster

In this section, we will use natural frequencies to detect faulty sensor nodes. For each cluster, the PSD of CH and the CSD for each cluster member are calculated. After obtained its CSD, each sensor node implements the PP method to extract 8 largest peaks. In this paper, the ith point of a CSD is a peak if:

|  |  |  |
| --- | --- | --- |
|  |  | (12a) |
|  |  | (12b) |

where , and are the (i-1)th, ith, and (i+1)th points of CSD, respectively. is a positive threshold that can be adjusted according to the historical data. If less than 8 peaks are found, zeros will be returned in place of the missing peaks. If more than 8 peaks are found, the largest 8 peaks are adopted. Eq. (12) also applies to PSD for CH. The CSDs and corresponding peaks from some of sensor nodes in cluster I of Fig. 16(a) are illustrated in Fig. 17.



Figure CSD and peaks from 8 sensors

The peaks in each CSD correspond to the natural frequencies extracted by the corresponding sensor. The extracted natural frequencies from all 16 sensors are illustrated in Fig. 18.



Figure The extracted natural frequencies from 58 sensor nodes

It is clearly seen from Fig. 18 that although we assume no faulty sensor nodes, frequencies from different sensor nodes do not match with each other according to the order in the frequency set. The frequency matching is therefore necessary. We first calculate the comparability and the supplementary matrix . Fig. 20 shows , the comparability for each sensor. From Fig. 20, we can see that sensors #1,#6,#29,#49 have much smaller value than others. These sensors are negative sensor nodes and are deleted. After the and is updated accordingly, a total of four UCF sets have been found and are illustrated in Fig. 21, where the frequencies in the each UCF are connected using a dashed line.



Figure The comparability for each sensor node

After generating the faulty sensor data, we come to the stage of online monitoring. The frequency matching is implemented again using the contaminated data. Fig. 22 shows the comparability for these 54 sensors using the calculated . Note that in this figure, the values corresponding to the four negative nodes have been set to zeros. From Fig. 22, we can see that sensors #10, #40, #50 have much smaller values than others. These sensors are negative sensor nodes and are deleted. It is interesting to find that even without Hotelling control chart, three faulty sensor nodes, including all the sensor nodes with server fault, are detected using the frequency matching technique only. This again demonstrates our conclusion that this matching technique can be used as the first stage to detect sensor fault. After the and are updated accordingly, a total of four UCF sets have been found as before. This is illustrated in Fig. 23.



Figure The comparability for each sensor node (#10,#20,#30,#40,#50 are faulty sensor nodes)



Figure The obtained four UCF sets using sensor data containing faulty sensor nodes

Using the previously obtained mean , covariance matrix and control limits (, ) frequencies and the newly obtained UCF sets, the Hotelling T2 statistic for each sensor is calculated as Eq. (7). The Hotelling control chart is illustrated in Fig. 24. It can be clearly observe that the remaining two slightly faulty sensor nodes #20 and #30, have been successfully detected. The Hotelling control chart can be regarded as the second stage of faulty sensor node detection which is more sensitive than the frequency matching. From this simulation, all of the 5 faulty sensor nodes have been successfully detected. Two sensor nodes with severe damage (#40,#50) and one with slight damage (#10) have been detected using the frequency matching, and the remaining two slight faulty nodes (#20,#30) are detected using the consequent Hotelling control chart.



Figure Hotelling Control chart for faulty sensor detection

## Structural Damage Detection and Localization

After all the faulty sensor nodes (#10, #20,#30,#40 and #50) and the healthy but negative sensor nodes (#1, #6, #29 and #49) have detected and isolated, the remaining 49 sensor nodes are used to detect possible structural damage.



Figure The remaining sensor nodes in the middle span

The CSD of each sensor is transformed into the cross-correlation function and send back to the cluster head, where the ERA is implemented to extract the mode shapes. In this test, mode shapes for the first four modes are extracted. Sensor nodes in the upper side and lower side of the middle span are classified into different groups and the mode shape curvatures for these two groups are examined respectively.

Before we calculate mode shape curvatures using Eq. (20), one thing that should be noted is that some faulty sensor nodes or negative sensor nodes have been deleted. Corresponding, values of the mode shape at these sensor nodes do not exist. To further increase the damage detection capability, if a sensor has been deleted in the faulty node detection stage, the corresponding value of mode shapes at this sensor is estimated using the cubic spline interpolation [43]. In this test, for the mode shapes of the sensor nodes at the upper side of the bridge, values are estimated for sensor #1, #6, #10,#20,#29 and #30 are estimated. For the sensor nodes at the bottom side, values for sensor #40,#49 and #50 are estimated. Mode shape curvature calculated based on the interpolated mode shapes have a higher accuracy that based on the originally obtained mode shapes. Fig. 26 and Fig. 27 illustrated the interpolated mode shapes and mode shape curvatures for the upper side and lower side sensors, respectively. By examining the mode shape curvatures from damaged structure, the damage can detected which is at the points with high abnormality on mode shape curvatures (in Fig. 26, damage is detected at locations corresponding to #12 and #13, in Fig. 27, damage is detected at locations near #41 and #42). This damage location information coincides well with the simulated damage locations. The abnormality can be observed more clearly by using the gapped-smoothing method (GSM) [44]. But for brevity, this method is not omitted in this paper.



Figure The interpolated mode shapes and mode shape curvatures for the upper side sensors



Figure The interpolated mode shapes and mode shape curvatures for the lower side sensors

# Conclusion and Future Works

In this paper, we proposed a fault-tolerant scheme for WSN-based SHM systems. This scheme is able to detect structural damage in the presence of the most ambiguous and misleading type of sensor fault: sensor nodes which give faulty readings. Faulty sensor detection strategy utilizes the spatial redundancy existed in the extracted natural frequency sets among different sensor nodes. Natural frequencies of different sensor nodes are extracted in a distributed way and based on the extracted frequencies, frequency matching and Hotelling control chart is implemented to detect sensor fault. After faulty nodes have been detected and isolated, mode shape curvature method is used to detect structural damages. Faulty sensor detection and structural damage detection is efficiently integrated together and the proposed scheme is able to disambiguate structural damage from sensor faults. The effectiveness of the proposed algorithms is demonstrated through both simulation and a lab structure

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