Decentralized Sensor Fault Diagnosis for Wireless Structural Health Monitoring Systems Using Artificial Intelligence of Things

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ABSTRACT

Structural health monitoring (SHM) is a non-destructive evaluation technique that utilizes sensor data for assessing the condition of civil infrastructure. Sensors in SHM systems may experience faults, which may influence the accuracy, reliability, and performance of SHM systems. The timely detection, isolation, and accommodation of sensor faults in SHM systems has been the focus of sensor fault diagnosis (FD) approaches, which have increasingly been employing artificial intelligence (AI) algorithms due to the effectiveness of AI in sensor FD. However, current AI-based FD approaches require transmitting large amounts of raw sensor data to centralized servers for offline analysis, resulting in inefficiencies as well as computational burdens on centralized servers. This paper introduces a decentralized sensor fault diagnosis (DSFD) approach for wireless SHM systems using Artificial Intelligence of Things (AIoT). In particular, AI-based FD models are embedded into wireless sensor nodes of SHM systems to detect, isolate, and accommodate sensor faults. By embedding the FD models into the wireless sensor nodes, only high-level information, specifically the status of the sensors, is transmitted to centralized servers. As a result, data transmission inefficiencies as well as computational burdens on centralized servers are reduced. The proposed DSFD approach is validated in a controlled laboratory experiment, in which custom-built wireless senor nodes are installed on a test structure that is dynamically excited using a shake table. After training and embedding the AI-based FD models into the custom-built wireless sensor nodes, sensor faults are artificially injected into the sensor data, demonstrating the ability of the DSFD approach to diagnose sensor faults in a decentralized manner. The results of the validation test corroborate the capability of the proposed approach to efficiently ensure the accuracy, reliability, and performance of SHM systems.

INTRODUCTION

Structural health monitoring (SHM) is a non-destructive evaluation technique that utilizes data recorded by sensors (“sensor data”) for assessing the condition of civil infrastructure [1]. SHM systems may primarily be based on accelerometers [2], strain gauges [3], temperature sensors [4], fiber optic sensors [5], or mobile sensing devices, such as unmanned aerial vehicles [6] or legged robots [7]. With technological

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advancements, and owing to the low installation costs, increased scalability, and reduced installation time, trends in SHM systems have slowly transitioned from wired to wireless systems. Additionally, developments in artificial intelligence (AI) and Internet of Things (IoT) technologies have considerably improved the ability of wireless SHM systems to monitor and assess civil infrastructure.

Sensors deployed in SHM systems may experience faults due to hardware or software malfunctions, power outages, environmental impacts, or signal interferences, resulting in incorrect assessments of civil infrastructure [8]. As the accuracy, reliability, and performance of wireless SHM systems rely on the quality of the sensor data, efforts towards sensor fault diagnosis (FD) in SHM systems have been reported, mostly based on physical or analytical redundancy. The high cost, power consumption, and maintenance demands of physical redundancy approaches have motivated the adoption of analytical redundancy [9]. In analytical redundancy, sensor faults are detected by evaluating residuals between sensor data and outputs of models, i.e. AI models, developed to predict the sensor data using threshold logic or hypothesis testing [10]. In [11], a distributed similarity test, an artificial neural network (ANN), as well as a correction function have been used to detect, identify, and accommodate sensor faults. In [12], signal processing techniques combined with AI have been used to detect and identify sensor faults. In [13], sensor FD has been extended from the time domain to the frequency domain. However, current AI-based FD approaches in wireless SHM require transmitting large amounts of raw sensor data to centralized servers for offline analysis, resulting in data transmission inefficiencies as well as computational burdens on centralized servers.

This paper introduces a decentralized sensor fault diagnosis (DSFD) approach for wireless SHM systems using the Artificial Intelligence of Things (AIoT) paradigm, which combines AI with IoT technologies [14]. The AIoT paradigm enables efficient utilization of computational capabilities of embedded devices in modern sensor nodes of wireless SHM systems. Embedded computing minimizes bandwidth consumption by transmitting only high-level information (the status of the sensors) to centralized servers instead of voluminous raw data, avoiding data transmission problems as well as computational burdens on centralized servers. The proposed DSFD approach consists of (i) AI models for sensor FD embedded into (ii) wireless sensor nodes with information transmission capabilities based on IoT technologies, supporting real-time data visualization, data storage, as well as SHM system interaction.

The remainder of the paper is structured as follows: First, the DSFD approach is described, followed by a validation test under controlled laboratory conditions, using a test structure dynamically excited by a shake table. Next, the validation results are presented and discussed. Finally, the work presented herein is summarized and an outlook on future work as well as potential improvements are suggested.

DECENTRALIZED SENSOR FAULT DIAGNOSIS USING ARTIFICIAL INTELLIGENCE OF THINGS

In this section, the DSFD approach using the AIoT paradigm is presented. First, the conceptual basis is discussed and, then, the hardware design, customized to the proposed approach, is illuminated.

AI-based decentralized sensor fault diagnosis

The AIoT-based DSFD approach extends the "adaptive FD approach based on analytical redundancy" (AFDAR) proposed by the authors in [15]. The AFDAR approach combines ANN models with signal processing techniques to develop AI-based FD models capable of detecting, isolating, and accommodating sensor faults in SHM systems, such as complete failure, complete failure with noise, outliers, drift, bias, and gain.

The AFDAR approach comprises four steps: (i) initialization, (ii) fault detection, (iii) fault isolation, and (iv) fault accommodation. In the *initialization* step, correlated sensors within the SHM system are investigated through data analysis, from which sensor data is used to train ANN models. Then, in the *fault detection* step, adverse sensor behavior is detected by comparing sensor data with outputs of ANN models, predicting the sensor data ("virtual outputs"). In the *fault isolation* step, the location of the faulty sensor is determined by analyzing the moving average of individual sensor data around the fault occurrence time. Finally, in the *fault accommodation* step, the faulty sensor data is substituted with virtual outputs.

AIoT wireless sensor nodes for SHM systems

The hardware design of the custom-built AIoT wireless sensor nodes follows a four-layer IoT architecture, which encompasses (i) a physical layer, (ii) a middleware layer, (iii) an application layer, and (iv) a security layer.

The *physical layer* includes hardware components of the SHM system, such as microcontrollers and sensors. The physical layer is responsible for recording sensor data, processing the sensor data locally using embedded computing, and transmitting information between devices based on IoT communication protocols. The *middleware layer* facilitates communication as well as data storage and management between different applications and services within the SHM system. Furthermore, in the middleware layer, the AI-based FD models are embedded for decentralized sensor data processing, i.e. facilitating DSFD. The *application layer* offers user interfaces, such as dashboards and control panels, for sensor data visualization and system control. Finally, the *security layer* leverages cross-layer security mechanisms to safeguard sensor data and communication processes.

The four-layer IoT architecture is implemented as follows: On the *physical layer*, the wireless sensor nodes, shown in Figure 1, are assembled using low-cost components, specifically, an Espressif ESP32-S3 microcontroller, an Adafruit BNO085 accelerometer, an Adafruit BME280environmental sensor, as well as transistors, resistors, and capacitors. The hardware components are mounted on a printed circuit board (PCB) designed to ensure stable connections and robustness.

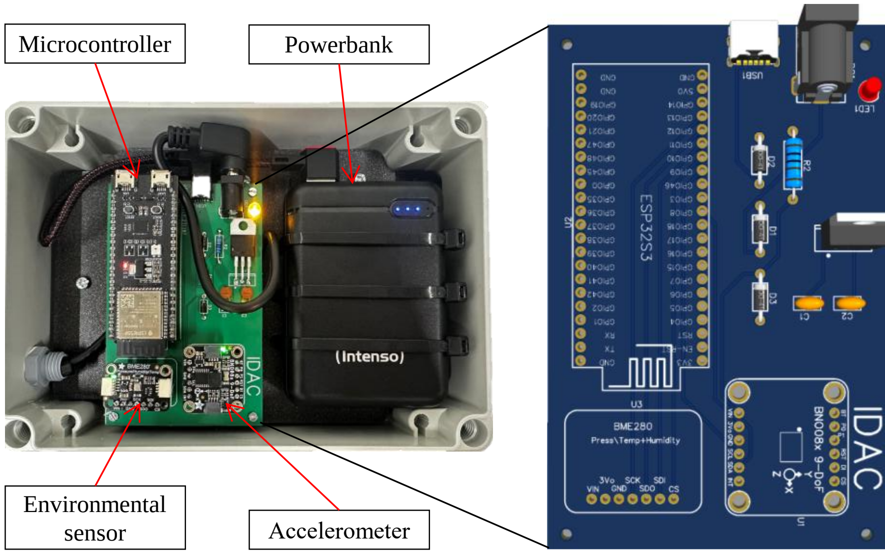

Figure 1. Physical layer of the custom-built wireless sensor nodes.

The *middleware layer* is realized using a Raspberry Pi 4 Model B, functioning as a portable main station. The portable main station is used for bidirectional data transmission between the custom-built wireless sensor nodes and for sensor data management through storage hubs. Data transmission is handled using Node-RED and the Message Queuing Telemetry Transport (MQTT) protocol, which is a lightweight publish-and-subscribe communication protocol suitable for IoT applications. An MQTT server manages the communication, processing both sensor data transmitted from the custom-built wireless sensor nodes and user commands sent for configuring the SHM system. A data management hub is set up using Telegraf, which collects the sensor data from the MQTT server and stores it efficiently in a time-series database, implemented via InfluxDB. Furthermore, in the middleware layer, AI-based FD models are embedded for decentralized sensor data processing. The communication flow between the physical layer and the middleware layer is illustrated in Figure 2.

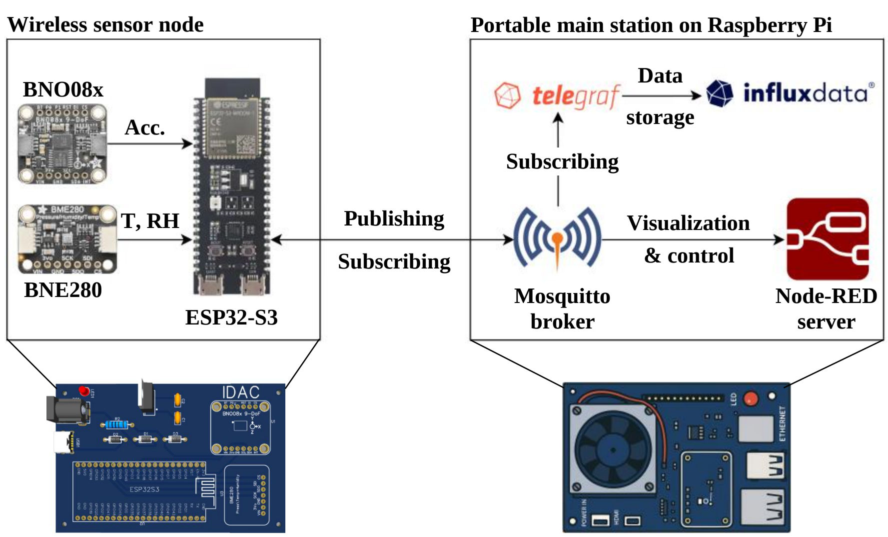

Figure 2. Communication flow between the physical layer and the middleware layer of the custom-built wireless sensor nodes.

The *application layer* provides a web-based user interface, built using Node-RED. The web-based user interface includes a control panel for configuring operational parameters, such as sampling rates and data collection durations, and a dashboard for sensor data visualization. Additionally, the dashboard displays alerts generated by the embedded AI-based FD models implemented in the portable main station. The web-based user interface is hosted locally on the Raspberry Pi, allowing authenticated users to remotely access the SHM system. Finally, the *security layer* implements user-authentication mechanisms based on usernames and passwords to ensure secure access to the SHM system. The applicability of the AIoT-based DSFD approach is corroborated in validation tests, presented in the following section.

VALIDATION OF THE AIoT-BASED DECENTRALIZED SENSOR FAULT DIAGNOSIS

The DSFD approach is validated in controlled laboratory experiments, in which four custom-built wireless senor nodes for SHM systems are installed on a test structure that is dynamically excited using a shake table. As shown in Figure 3, the wireless sensor nodes (WSN1, WSN2, WSN3, and WSN4) are installed on a metallic shear-frame structure with a height of 60 cm, and plate dimensions of 18 cm (length), and 13 cm (width). The shear-frame structure is mounted on the shake table, which is equipped with a stepper motor and a microcontroller capable of controlling both the amplitude and frequency of dynamic excitation remotely via IoT technologies [16].

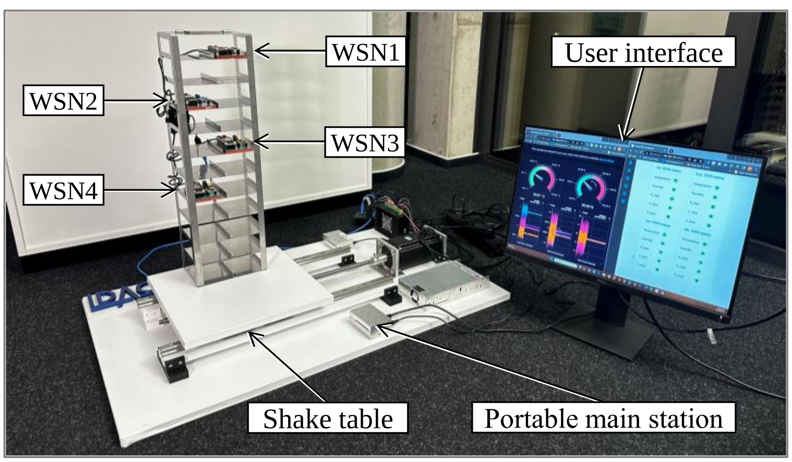

Figure 3. Validation test set-up.

To simulate real-world operational conditions, the DSFD approach is validated as follows: (i) Acceleration measurements are recorded by each wireless sensor node over a two-hour interval at 100 Hz sampling rate, while the test structure is subjected to dynamic excitation by the shake table with an amplitude of 1 cm and a frequency of 5 Hz; (ii) the acceleration measurements are divided into training (70%), validation (20%), and testing (10%) sets to train the AI-based FD models, i.e. the embedded ANN models [15]; (iii) upon completing training, the ANN models are embedded into the portable main station and integrated into a script for data processing and FD; (iv) the wireless senor nodes transmit new acceleration measurements via MQTT, which is analyzed by the embedded ANN models; (v) two sensor faults are artificially injected into WSN1, specifically a bias fault is injected, represented by an offset equal to 3 cm/s^2, as well as a complete failure fault, simulated by disconnecting the accelerometer; (vi) the DSFD approach diagnoses both faults and triggers a fault detection alarm in the web-based user interface validating the accuracy, reliability, and performance of the approach. The results of the validation test are presented and discussed in the next section.

RESULTS AND DISCUSSION

The results of the validation test confirm the effectiveness of the DSFD approach to diagnose sensor faults in a decentralized manner. As illustrated in Figure 4, the acceleration measurements are collected along the *y*-axis (the axis of the dynamic excitation generated by the shake table. The results of the validation test are divided into four phases, each evaluating the fault diagnosis capability of the DSFD approach:

- ***Phase 1*** (first minute – normal operation): All sensor nodes operate under fault-free conditions. The control panel displays green status indicators for each node, confirming baseline system integrity.
- ***Phase 2*** (second minute – bias fault detection and isolation in WSN1): A bias fault is artificially injected into the acceleration measurements recorded by WSN1. The embedded AI model detects the bias fault in real time, with a red status light indicating the anomaly. Then, the fault is isolated to WSN1, demonstrating fault isolation capabilities of the proposed approach.
- ***Phase 3*** (third minute – fault accommodation): The bias fault is accommodated, restoring WSN1 to normal operation, in which the faulty acceleration measurements are replaced with virtual outputs predicted by the FD ANN models.
- ***Phase 4*** (fourth minute – complete failure of WSN1): In this phase, the WSN1 is disconnected to simulate a complete failure. The FD ANN models detect the absence of acceleration measurements across all axes, and, consequently, the web-based user interface is updated with red indicators, confirming a complete failure of WSN1.

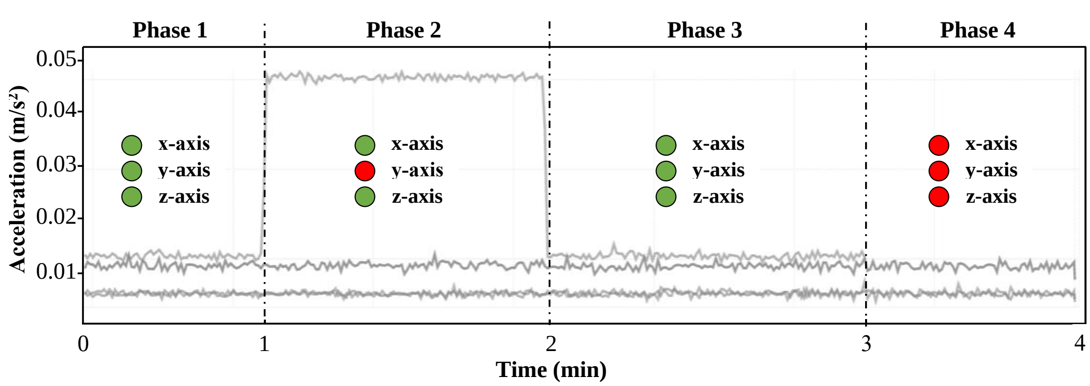

Figure 4. Validation test result for DSFD using AIoT.

The results of the validation test confirm the effectiveness of the DSFD approach to diagnose sensor faults in a decentralized manner, thus ensuring the accuracy, reliability, and performance of SHM systems. Upon fault detection, the SHM system issues alerts in the web-based user interface. Thereby, maintenance actions may be considered, minimizing data loss and ensuring reliable condition assessment.

Decentralized senor fault diagnosis is performed on site, specifically, using embedded AI models into the portable main station, eliminating the need for transmitting large amounts of raw sensor data to centralized servers for offline analysis. As a result, the communication bandwidth consumption is reduced by transmitting only high-level information, specifically the status of the sensors, to centralized servers instead of large volumes of raw data. In turn, data transmission problems are avoided along with alleviating computational burdens on centralized servers.

A current limitation faced during the implementation and validation of the DSFD approach is the computational capacity of the Raspberry Pi, which does not support on-device model training, thus, in this study, the AI-based FD models have been trained offline and deployed on the portable main station for FD. Achieving fully decentralized training of AI-based FD models requires either more powerful embedded hardware or further optimization of the FD models, representing a potential future research direction.

SUMMARY AND CONCLUSIONS

Sensors deployed in SHM systems may experience faults, which may influence the accuracy, reliability, and performance of SHM systems. Efforts undertaken towards sensor FD have increasingly been employing AI algorithms due to the effectiveness of AI in sensor FD. However, current AI-based FD approaches require transmitting large amounts of raw sensor data to centralized servers for offline analysis, resulting in data transmission problems as well as high computational burdens on centralized servers.

This paper has presented a decentralized sensor fault diagnosis (DSFD) approach for wireless SHM systems using the AIoT paradigm. For sensor FD, the DSFD approach has been built upon the “adaptive FD based on analytical redundancy” (AFDAR) approach proposed by the authors in a previous work [15]. The AIoT paradigm has enabled efficient use of the increasing computational capabilities of embedded devices present in modern sensor nodes of wireless SHM systems. The DSFD approach has been implemented using custom-built wireless sensor nodes for SHM systems. The applicability of the AIoT-based DSFD approach is validated in controlled laboratory experiments, in which four custom-built wireless senor nodes have been installed on a metallic shear-frame structure that is dynamically excited using a shake table. The validation tests results have proven the capability of the DSFD approach to diagnose sensor faults in a decentralized manner, thus ensuring the accuracy, reliability, and performance of SHM systems. In future research, the DSFD approach may be extended to include sensor fault identification to classify the sensor fault type, as well as differentiating between sensor faults and structural damage.

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