Damage Identification for Guided Wave Testing of Composite Structures Using Statistical Features

SHRUTI SAWANT, SAUVIK BANERJEE and AMIT SETHI

ABSTRACT

Guided wave structural health monitoring (GW-SHM) is essential for detecting damage in composite materials. Conventional damage identification approaches require knowledge of material properties to calculated deviation of monitoring signal from baseline and are limited to specific damage types or materials. Deep learning has emerged as a more automated method, but it requires high computational power. To address this, we propose using two features: correlation coefficient deviation (CCD) and root mean squared deviation (RMSD). CCD captures the changes in phase of monitoring signal due to presence of the damage. RMSD on the other hand is sensitive to changes in the amplitude. When combined with a binary random forest classifier, these features achieve performance comparable to deep learning. We tested our algorithm on two datasets with different damage types, recording accuracy of 94.4% for Open Guided Waves (OGW) dataset and 99.2% for NASA Prognostic Center of Excellence-Guided Waves (PCoE) dataset. These lightweight models are suitable for in-situ monitoring, offering practical application for damage identification.

INTRODUCTION

GW-SHM systems employed for detecting defects in large civil infrastructure such as bridges, aircraft, railway tracks etc. consist of a large number of sensors mounted on the structure to perform a variety of measurements. Quantifying deviation of monitoring signal from baseline using various statistical relations or features is crucial for damage identification. The conventional approach involves extracting wave mode, which shows a change in amplitude or/and phase in the presence of damage using group velocity. This step requires knowledge of material properties, such as group velocity of various wave modes or dispersion curve of the material [1]. Such methods work for particular damage types or materials, and are not scalable. When the variations in environmental/operational conditions such as temperature, moisture etc. cannot be neglected, a conventional approach highly unreliable [2, 3].

In recent years, deep learning (DL) techniques have been shown to successfully cir-

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cumvent the need for feature computation in damage identification using GW-SHM [4–6]. However, the lack of sensor data corresponding to different damages is a challenge for the development and validation of DL algorithms. Most supervised DL models lack robustness and generalizability when trained using this limited data. The large size of typical deep learning architectures containing convolutional layers with millions of trainable parameters requires the deployment of trained models on cloud or powerful desktop/server-grade GPUs for damage assessment.

The utility of easy-to-compute statistical metrics obtained from time-domain signals for machine fault diagnosis was shown by Bandyopadhyay et al. [7]. For GW-SHM system, feature engineering is still in nascent stages. Liu et al. reported a feature selection method based on binary particle swarm optimization with a new fitness function proposed in combination with least-squares support-vector machine for damage identification in variety of challenging practical scenarios for switch rail damage [8]. Recently, Sawant et al. demonstrated the effectiveness of features for damage classification in composite sandwich structures [9].

In this work we propose using two features; namely, CCD and RMSD. CCD captures the changes in phase of monitoring signal due to presence of the damage. RMSD on the other hand is sensitive to changes in the amplitude. When used with binary random forest classifier for identifying the damage in composite materials, these features give performance comparable to DL methods reported in the literature. We demonstrated the proposed algorithm using two public domain datasets, i.e., OGW dataset [10] and NASA PCoE dataset [11], having different damage types of added mass and edge notch damage, respectively. Damage identification accuracy of 94.4% was recorded for OGW dataset, whereas 99.2% for NASA PCoE dataset.

METHODOLOGY

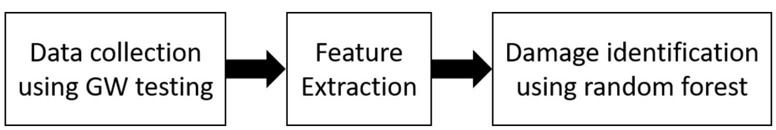

Figure 1. Proposed method using feature extraction for damage identification in GW-SHM systems

The proposed ML pipeline for damage identification in GW-SHM systems is illustrated in Figure 1. GW-SHM system for composite structures considered in this study uses PZT (peizoelectric) transducers to collect data non-invasively for sensor paths on a panel having two different geometries. Features play crucial role in quantifying deviation of monitoring data from the baseline data. We computed two features described below :

Correlation Coefficient Deviation (CCD)

The correlation coefficient measures the linear relationship between two signals and quantifies the similarity or dissimilarity between them. In GW-SHM, the correlation coefficient is used to compare the measured wave responses with a reference or baseline signal obtained from a healthy structure.

$$CCD = 1 - \sqrt{\frac{\{\int^T f_b(t) f(t) dt\}^2}{\{\int^T f_b(t)^2 dt \int^T f(t)^2 dt\}}} \tag{1}$$

Root Mean Square Deviation (RMSD)

The RMSD is a statistical measure that quantifies the difference or deviation between baseline signal $f_b(t)$ and monitoring signal ($f(t)$) by taking into account the average magnitude of the differences or residuals between corresponding data points of the two signals.

$$RMSD = \sqrt{\frac{\int^T [f(t) - f_b(t)]^2 dt}{\int^T [f_b(t)]^2 dt}} \tag{2}$$

The correlation coefficient and RMSD are complementary measures in GW-SHM. By using both measures together, SHM practitioners can gain a comprehensive understanding of the structural condition. The correlation coefficient and the phase change features in the received signal change as the damage size and location change [11]. On the other hand, increased RMSD value signifies a larger magnitude of deviation. The combination of these measures can enhance the detection, localization, and quantification of structural damage or changes, facilitating effective decision-making.

Finally, for the task of damage identification, binary classifier is trained. The classifier learns the patterns and relationships in the training data to discriminate between healthy and damaged states. Once the binary classifier is trained and evaluated, it can be deployed for damage identification in real-time monitoring scenarios. GW signals obtained from the structure under surveillance are fed into the classifier, and based on the learned patterns, the classifier predicts whether the structure is in a healthy or damaged state. This information can be used for early detection, localization, and severity assessment of structural damage.

EXPERIMENTAL RESULTS

OGW Dataset

The publicly available OGW dataset, containing temperature-affected guided wave data collected on CFRP plate of dimensions $500\,\mathrm{mm} \times 500\,\mathrm{mm} \times 2\,\mathrm{mm}$ using an array of twelve transducers, was used to evaluate the proposed method [10]. Figure 2 shows the layout of the composite plate and network of transducers. Added mass defect was introduced (on 4 locations, one location at a time) using an aluminum disk with diameter $10\,\mathrm{mm}$ and thickness $3\,\mathrm{mm}$ bonded to the structure with double-sided adhesive tape on CFRP panel [10]. The performance was evaluated with data from 36 out of total 66 paths for which the transmitter and receiver are on opposite sides of the plate (as shown in

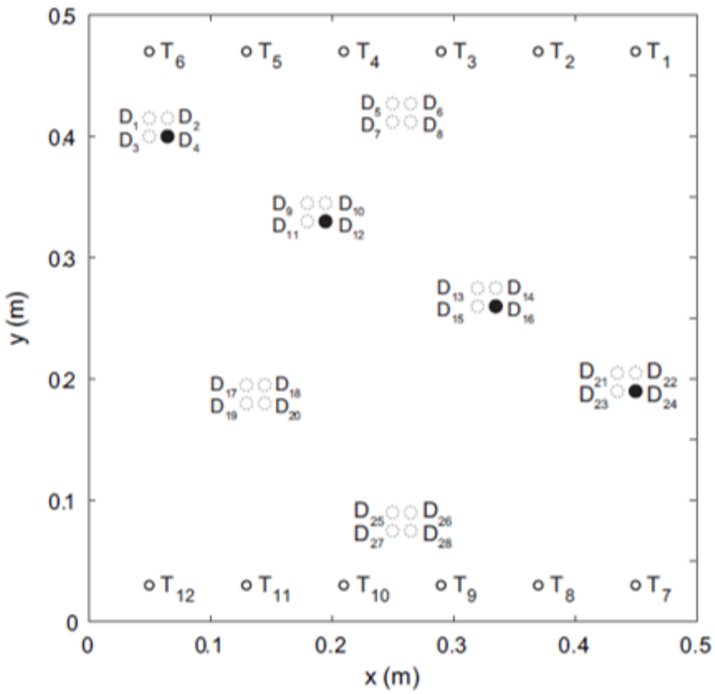

Figure 2. Layout of composite plate with network of 12 transducers in OGW dataset [10]

Figure 2) collected at temperatures ranging from $20\,°\mathrm{C}$ to $60\,°\mathrm{C}$. We considered damage location D16 and temperature of $20\,°\mathrm{C}$ for our study. For OGW dataset, twelve different frequencies are available from $40\,\mathrm{kHz}$, $60\,\mathrm{kHz}$, $\ldots$, $260\,\mathrm{kHz}$. Lower frequencies of actuation ($40\,\mathrm{kHz}$, $60\,\mathrm{kHz}$ and $80\,\mathrm{kHz}$) have been reported to be more sensitive to the added mass defects [5].

NASA Dataset

In this dataset, fatigue experiments were conducted on a dog bone specimen with an edge notch (Figure 3 [11]). The specimen was made of 12 plies of uni-directional T700G composite material. The study focused on a quasi-isotropic layup-1 configuration. PZTs were arranged in a parallel array on both sides of the specimen, with PZTs 1–6 used for actuation and PZTs 7–12 used for sensing. The experiments involved recording thirty-six actuator-sensor paths for each excitation frequency ranging from $150\,\mathrm{kHz}$, $200\,\mathrm{kHz}$, $\ldots$, $450\,\mathrm{kHz}$. . For our study, we used a dataset consisting of signals corresponding to 20,000 cycles. The initial state of the structure, which includes an edge notch, consisting a total of 252 baseline signals, is considered as the baseline [12].

For binary classification, each dataset was split in the proportion $75 : 20\ (\%)$ for training and test purpose. The training dataset, consisting of the extracted features and corresponding labels (healthy or damaged), is used to train the binary classifier. After evaluation of various ML models such as logistic regressor, Naive Bayes, support vector machine, decision tree, we selected used random forest algorithm for this purpose as it gave the highest accuracy. After training, the performance of the binary classifier was evaluated using test dataset, which contains GW signals that were not used during training.

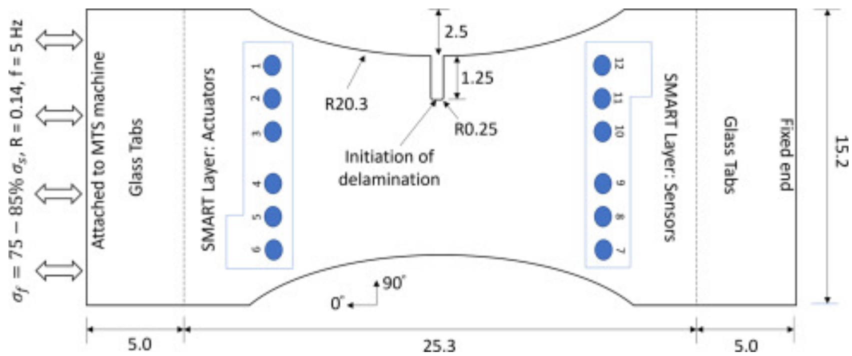

Figure 3. Geometry of dog-bone specimen used in NASA-PCoE dataset [11]

TABLE I. Comparison of our work with previously reported damage assessment methods validated using OGW dataset (NR denotes 'not reported')

Reference	Damage identification accuracy	Method
Rautela et al. [6]	100%	Unsupervised deep learning using 2D representations
Bosse et al. [13]	NR	Feature engineering, supervised classifier & regressor
Amer et al. [14]	95%	Stochastic non-parametric models with Z-statistics
Sawant et al. [5]	100%	Unsupervised deep transfer learning using 1D-CNN
This work	94.4%	Supervised classifier with statistical features

A comparison of our work to various reports on OGW dataset in literature is presented in Table I. Most results reported in the literature on DL models in supervised or unsupervised setups require cloud computing or powerful GPUs for deployment and training. The method proposed in this work overcomes this limitation using classical ML models with features, and we have shown damage identification accuracy of $94.4\,\%$ for D16. For NASA dataset, Rautela et al. reported perfect accuracy using unsupervised deep learning approach [6]. Peng et al proposed a probabilistic framework for location and size determination for delamination in carbon–carbon composites and used Lamb wave-based damage detection features to make probability image of delaminated area with the Bayesian updating technique [11]. To the best of our knowledge, there is no approach report of feature based damage identification for NASA dataset.

CONCLUSION AND FUTURE WORK

We presented a feature-based damage identification method for the GW-SHM system for composite structures. The method presented in our work uses two statistical features computed using time domain signals. The proposed approach was validated on two pubic domain datasets containing different geometries. It gives performance comparable to state of the art DL methods with near perfect accuracy. Using statistical features with classical ML models, we achieved performance comparable to DL architectures reported in the literature. The vast reduction in computations enables deployment on an edge device and thus is a promising development for truly portable GW-SHM systems without dependence on cloud computing or desktop/server-grade GPUs for data processing. CCD plays a crucial role in quantifying the phase change in GW signals. RMSD effectively captures amplitude change in time domain. The OGW dataset contains temperature-affected data corresponding to only one type of damage (added mass), of only one severity (i.e., weight) at known locations. In the future, we wish to investigate the feasibility of the method proposed in this work for temperature variations, different types of structures, damages and severity. We shall also explore implementation of the proposed method on the edge device in order to realize truly portable GW-SHM systems.

ACKNOWLEDGMENT

This work was partially supported by Indian Space Research Organization (ISRO) [grant no. RD/0118-ISROC00-006].

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