Active sensing acousto-ultrasound SHM via stochastic time series models

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ABSTRACT

In this work, a statistical damage diagnosis scheme using stochastic time series models in the context of acousto-ultrasound guided wave-based structural health monitoring (SHM) has been proposed and its performance has been assessed experimentally. Three different methods of damage diagnosis were employed, namely: i) standard autoregressive (AR)-based method, ii) singular value decomposition (SVD)-based method, and iii) principal component analysis-based method. For estimating the AR model parameters, the asymptotically efficient weighted least squares (WLS) method was used. The estimated model parameters were then used to estimate a statistical characteristic quantity that follows a chi-squared distribution. A statistical threshold derived from the chi-squared distribution that depends on the number of degrees of freedom was used instead of a user-defined margin to facilitate automatic damage detection. The method's effectiveness is assessed via multiple experiments under various damage scenarios using damage intersecting as well as non-intersecting paths.

Keywords: Ultrasonic waves, Damage detection and identification, Time series models, Autoregressive models

1. INTRODUCTION

With the recent emphasis on the cyber-physical systems paradigm, incorporating structural health monitoring (SHM) approaches and algorithms in the civil, mechanical, and aerospace structures have become inevitable in order to impart intelligence, such as self-diagnostic and self-sensing capabilities.[1] In addition, SHM ensures enhanced reliability and increased safety of a structure.[2] An SHM process involves automatic extraction of damage sensitive quantities or features from a series of periodic measurements coming from an array of permanently installed sensors on a structure/system and performing statistical analysis of these quantities to establish the current structural state of the system.

For the local monitoring of a structure, a wide variety of methods are available based on ultrasound, eddy current, acoustic emission, and thermal field principles. On the other hand, for the global monitoring of a structure, the vibration-based family of methods is usually employed, which utilizes random excitation/response signal, statistical model building, and statistical decision making to infer the current health state of the structure/system. The fundamental premise is that small changes (cause or damage) in a structure force its vibration response to be changed (effect), which may be detected and associated with a specific cause (damage type).[3–5] However, a tiny change or damage may not be manifested in the vibration response signal, thus may remain undetected. Although vibration-based methods can detect global changes and are more robust in the face of environmental and operational conditions (EOC), they may be less sensitive to the local effects.

On the contrary, when it comes to active sensing SHM approaches, ultrasonic guided wave-based methods, which use guided Lamb wave propagation within a thin structure, are extremely sensitive to local changes and can detect tiny changes or damages within a structure or on the surface.[6,7] The most widely used method for damage detection using guided waves is the concept of damage/health indices/indicators(D/HI), where features of the signal for an unknown structural state are compared to that coming from the healthy structure. The features may be based on the specific mode wave packets of the guided wave signal, the amplitude/magnitude

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or the energy content of the signal. These conventional DI-based approaches have been extensively used in the literature for their simplicity, damage/no-damage binary detection paradigm, and ease of decision making. In addition to the time-domain DIs, the use of frequency domain or mixed domain DIs can also be noticed in the literature. However, these methods are deterministic in nature and do not account for uncertainty nor allow for the extraction of the appropriate confidence intervals for damage detection.[8,9] In the face of the stochasticity in the signal and under the evolution of complex damage types with the presence of varying environmental and operational states, these DI-based methods may become ineffective. In order to circumvent these difficulties, the use of stochastic time series models may be an appropriate option.

The main objective of this work is the investigation and performance assessment of a novel damage detection and identification scheme using stationary stochastic time series models such as autoregressive (AR) models in the context of the guided wave-based damage diagnosis process. Three damage diagnosis methods have been considered, namely: i) standard AR-based method, where all of the estimated model parameters have been used; ii) SVD-based method, where only the first few significant parameters have been used; iii) PCA-based method, where model parameters have been projected onto a lower dimansional subspace and a few truncated parameters have been used. AR model parameters were estimated by the asymptotically efficient weight least squares (WLS) method, and the performance of the three damage diagnosis processes was evaluated for damage intersecting as well as damage non-intersecting paths. The method's effectiveness was shown to outperform the traditional DI-based damage detection approach. According to the authors' best of knowledge, this is the first study that explores the use of stochastic time series models in the context of active sensing acousto-ultrasound-based SHM.

2. STOCHASTIC IDENTIFICATION AND DAMAGE DETECTION THEORY

Guided waves are inherently non-stationary due to their time-dependent (evolutionary) characteristics and are heavily influenced by environmental and operating conditions. However, in the case of weak non-stationarity, an auto-regressive (AR) model can be used to represent a guided wave signal for damage detection and identification.

An AR(n) model is of the following form:[10]

$$y[t] + \sum_{i=1}^{n} a_i \cdot y[t-i] = e[t] \qquad e[t] \sim \text{iid}\,\mathcal{N}\big(0, \sigma_e^2\big) \tag{1}$$

with t designating the normalized discrete time ($t = 1, 2, 3, \ldots$ with absolute time being $(t-1)T_s$, where T_s stands for the sampling period), $y[t]$ the measured guided wave response signals as generated by the piezoelectric sensors of the structure, n the AR polynomial order, and $e[t]$ the stochastic model residual (one-step-ahead prediction error) sequence, that is a white (serially uncorrelated), Gaussian, zero mean with variance σ_e^2 sequence. The symbol $\mathcal{N}(\cdot,\cdot)$ designates Gaussian distribution with the indicated mean and variance, and iid stands for identically independently distributed.

The identification of an AR model involves determination of the AR order n, which is referred to as the *model structure selection*, and the estimation of the model parameter vector $\boldsymbol{\theta}$, referred to as the *model parameter estimation*, where,

$$\boldsymbol{\theta} = [\ a_1\ a_2\ \ldots\ a_n\ ]^T \tag{2}$$

The unknown parameter vector $\boldsymbol{\theta}$ can be estimated via minimization of the Ordinary or Weighted Least Squares (OLS/WLS) criteria.

The damage detection and identification of a structure can be based on a characteristic quantity $Q = f(\boldsymbol{\theta})$, which is a function of the parameter vector $\boldsymbol{\theta}$ of an AR model. In addition to using $d = \dim(\boldsymbol{\theta}) = n$, a truncated version of the parameter vector $\boldsymbol{\theta}$ may also be used in an effort to simplify the damage detection procedure. In this study, singular value decomposition (SVD) and principal component analysis (PCA)-based truncation approach have been adopted (for details see[3,11]).

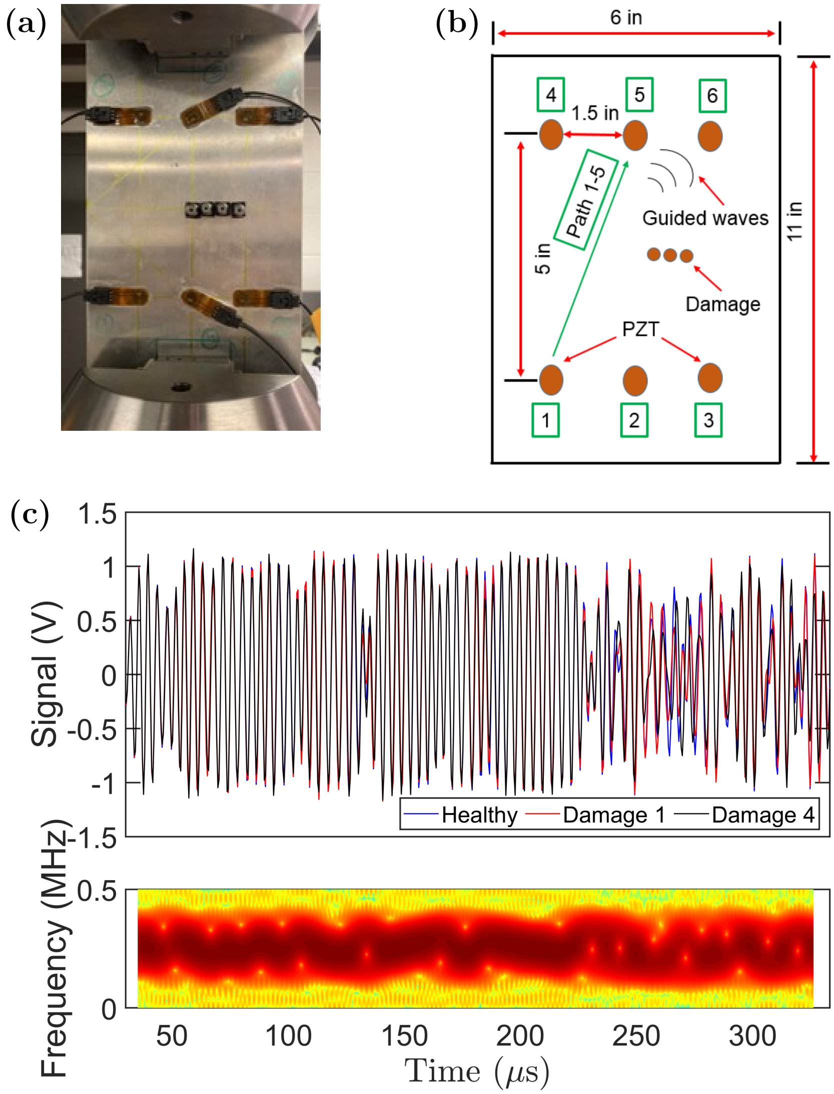

Figure 1. (a) The aluminum plate used in this study with simulated damage; (b) a schematic of the plate's sensor layout and dimensions; (c) realization of the guided wave signal for healthy and damaged cases with a representative non-parametric spectrogram analysis.

3. EXPERIMENTAL SETUP

In this study, a 152.4×279.4 mm (6×11 in) 6061 aluminum coupon (2.36 mm/0.093 in thick) was used (Figure 1(a)). Using Hysol EA 9394 adhesive, six lead zirconate titanate (PZT) piezoelectric sensors (type PZT-5A, Acellent Technologies, Inc) of 6.35 mm (1/4 in) diameter and a thickness of 0.2 mm (0.0079 in), were attached to the plate and cured for 24 hrs in room temperature. Figure 1(b) shows the dimensions of the plate, placement of the PZT transducers and the path naming convention. Up to four three-gram weights were taped to the surface of the plate starting from its center point to simulate local damage (Figure 1(b)).

Actuation signals in the form of 5-peak tone bursts (5-cycle Hamming-filtered sine wave, 90 V peak-to-peak, 250 kHz center frequency) were generated in a pitch-catch configuration over each sensor consecutively. Data was collected using a ScanGenie III data acquisition system (Acellent Technologies, Inc) from selected sensors during each actuation cycle at a sampling frequency of 24 MHz. 20 signals for each sensor path (wave propagation path) and damage condition were recorded. This led to a total of 410 data sets. For the time-series modeling,

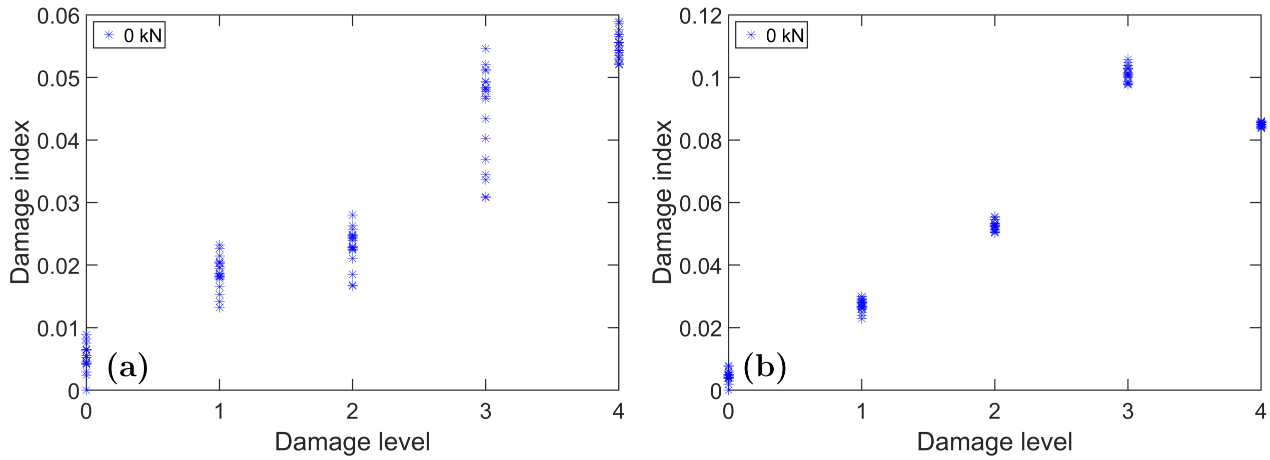

Figure 2. The evolution of the damage index[11,12] as applied to indicative actuator-sensor paths: (a) damage non-intersecting path 1-4; (b) damage intersecting path 2-6.

the acquired signals were down-sampled to 2 MHz. This process resulted in 612-sample-long signals. Figure 1(c) presents an indicative non-parametric spectrogram analysis of the acquired signal*.

4. RESULTS AND DISCUSSIONS

In the context of the active sensing guided wave based method, there are often multiple sensors installed at the area being monitored, and every actuator sensor path in the network has to be examined in order to assess the integrity of the component. In the present study, Figure 1(b) shows the actuator-sensor layout and six sensors/actuators have been used. Damage starts from the center of the plate and grows in magnitude to the right. In this study, simulated damages have been used in the form of weights mounted to the plate with tacky tapes. It has been shown that when the guided wave signal crosses the damage (known as the damage-intersecting path), a significant change can be observed in the signal with the increase in the damage size. On the other hand, for a damage non-intersecting path, one can observe that the received signals sustain significantly smaller change with the increase in damage size. Thus information from the damage non-intersecting path naturally carries less information when it comes to damage detection and identification compared to damage-intersecting paths. In order to support this point, one state-of-the-art DI from the literature was explored to see how damage intersection affects damage detection using the DI approach. Figure 2(a) and (b) show the evolution of the DI with increasing damage size for a damage non-intersecting and intersecting path, respectively. It can be observed that the magnitude of the DI for the damage non-intersecting path is much smaller than the damage intersecting path. As a result, damage detection and identification are challenging using a damage non-intersecting path.

In order to detect and identify damage using an AR model, it is first necessary to identify the system in its healthy state. Figure 4 shows the AR model identification process of the structure in its healthy states for path 2-6.

An AR model selection involves selecting the appropriate model order na. The RSS/SSS (Residual Sum of Squares/Signal Sum of Squares) criterion, describing the predictive ability of the model, was employed for the model selection process. AR orders from $na = 2$ to $na = 15$ were considered to create a pool of candidate models. Among all these models, the best model was chosen where the RSS/SSS values start to show a plateau. Following this criterion, the best model occurred for $na = 4$. In addition to the RSS/SSS criterion, the Bayesian Information Criterion (BIC), which rewards the model's predictive capability while penalizing model complexity for increasing model order, was also taken into account. Model validation took place via examination of the whiteness, or uncorrelatedness, normality hypothesis of the model residuals. It should be mentioned here that

*window length: 30 samples; 98% overlap; NFFT points: 30000 (zero-padding took place to obtain smooth magnitude estimates); frequency resolution $\Delta f = 666.66$ Hz.

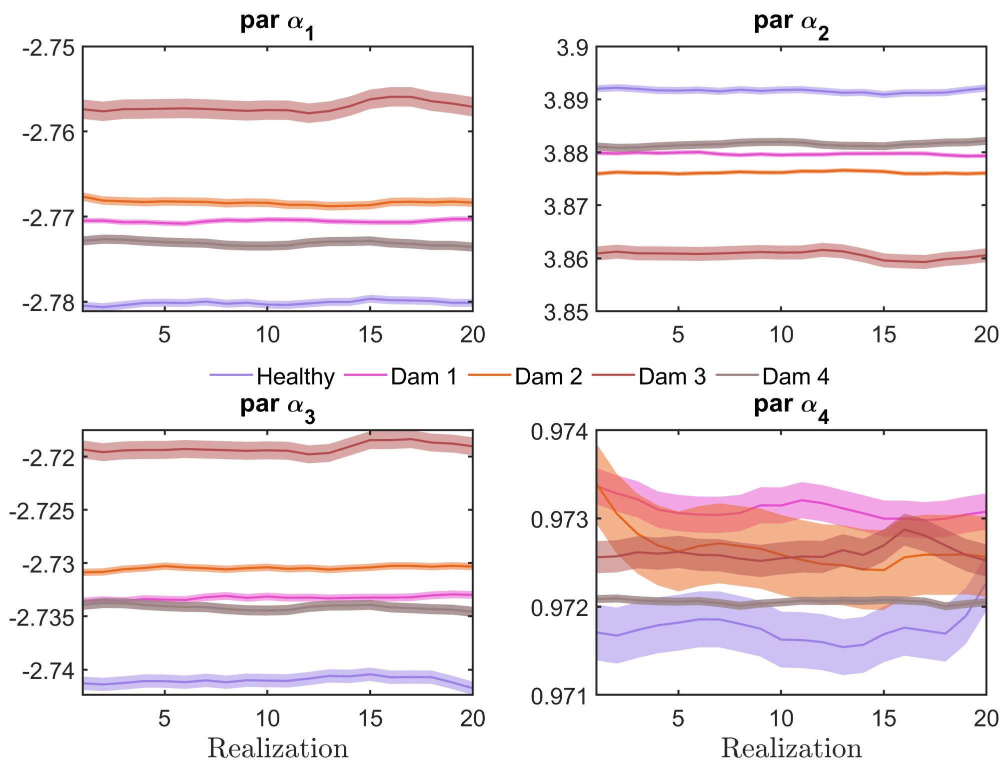

Figure 3. AR(4) model parameters for different structural states. The mean parameter values are shown as solid lines and the associated ± 2 experimental standard deviations are shown as shaded regions.

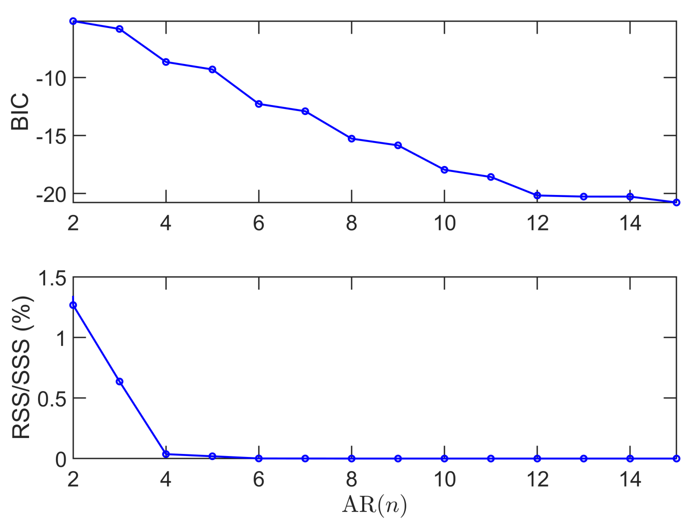

Figure 4. Model order selection via the BIC (top) and RSS/SSS (bottom) criteria.

as stationary AR models are being used to model a non-stationary response signal, perfect white residuals are not expected with an arbitrarily large model order keeping a reasonable sample per parameter value (SPP).

Figure 3 depicts the AR model parameters for all different states, namely: healthy, damage level 1, damage level 2, damage level 3, and damage level 4. For each state, 20 realizations are shown. The solid lines represent the mean parameter values, and the shaded regions represent the ± 2 experimental standard deviations for damage intersecting path 2-6. As the model order $na = 4$, the number of estimated parameters is also four. However,

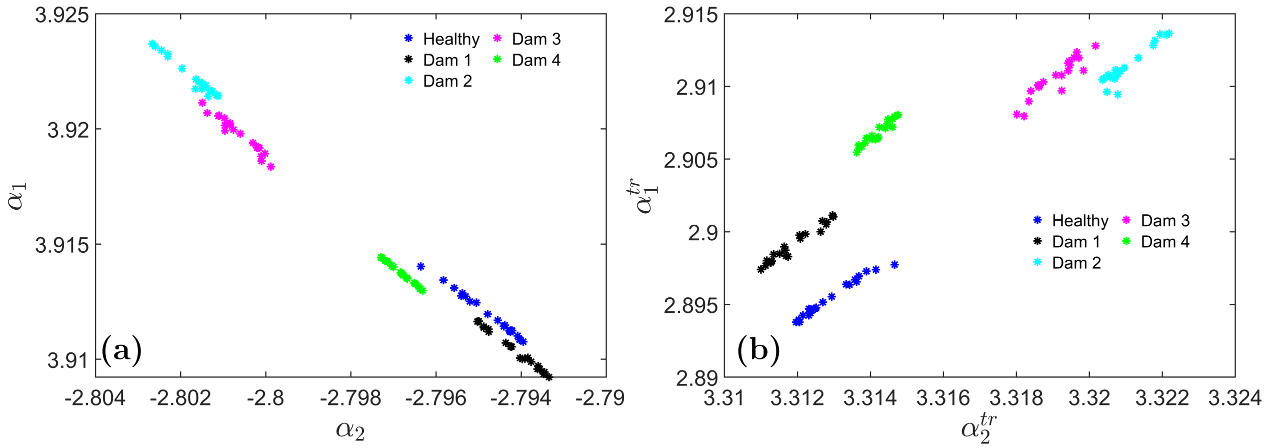

Figure 5. Correlation between the parameters: (a) shows that parameter α_1 and α_2 are highly correlated; (b) shows that after PCA transformation, the parameters become uncorrelated.

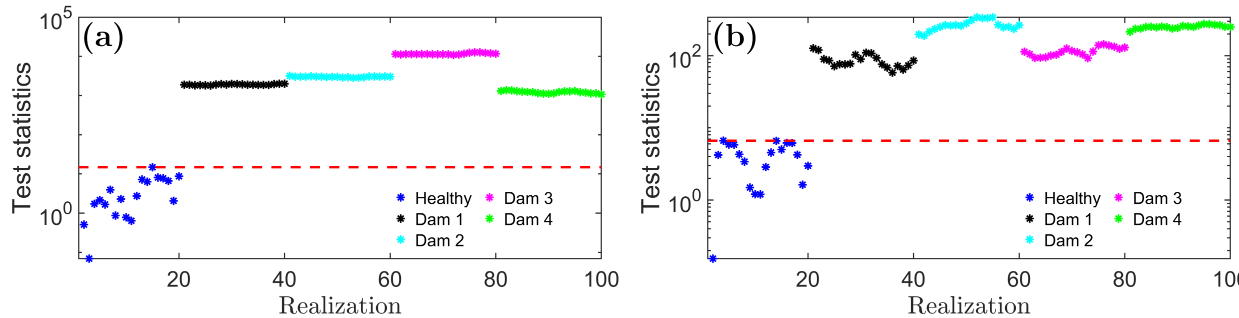

Figure 6. Damage detection performance of the standard AR-based method using the covariance matrix derived from 20 experimental healthy signals: (a) damage intersecting path 2-6; (b) damage non-intersecting path 1-4.

for damage detection, all four parameters may not be needed. Again, parameters might be correlated among themselves, and the correlated parameters may hamper the performance of the damage diagnosis process. Two approaches have been taken in this regard. One is referred to as the SVD-based approach, and the other is known as the PCA-based approach. Figure 5(a) shows the correlation of the two parameters α_1 and α_2. Note that parameters of different states are closely spaced. After performing PCA transformation, parameters of different states become well separated as shown in Figure 5(b). These well separated parameters of different states result in better damage detection and identification of the system.

Figure 6(a) and (b) show the damage detection performance of the standard AR-based method (all four parameters have been used) for the damage intersecting path 2-6 and damage non-intersecting path 1-4, respectively. In this case, the covariance matrix was derived from 20 experimental healthy signals. Note that perfect damage detection was achieved with no missed damage. Figure 7 shows the damage detection performance of the damage intersecting path 2-6 using the SVD and PCA-based approach. In this case again, the covariance matrix was derived from the 20 experimental healthy signals. It can be observed that for both cases, perfect damage detection was achieved. The α level used for the SVD and PCA-based case was 0.1 and 1×10^{-11}, respectively.

Figure 8(a) and (b) show the damage detection performance of the damage non-intersecting path 1-4 using the AR(4)-based covariance matrix. Note that the SVD-based method shows poor performance, and the damage level 1 is completely missed. However, the PCA-based method circumvents this poor diagnosis, and perfect damage detection was achieved. This is because, as shown earlier (Figure 5(b)), PCA transformation helps the parameters of different states to be well separated. This good separation between the parameters helps achieve better damage detection and identification capabilities. The α-level was manually adjusted when using

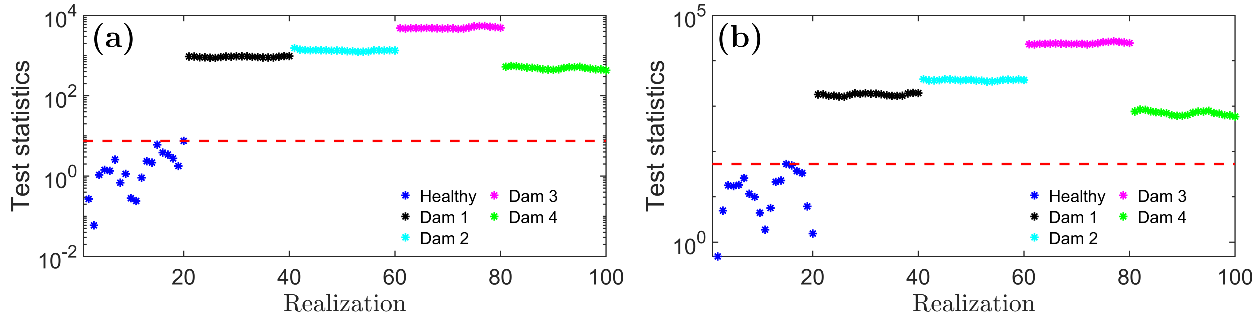

Figure 7. Damage detection performance for damage intersecting path 2-6 using the covariance matrix derived from 20 experimental healthy signals: (a) SVD-based approach; (b) PCA-based approach.

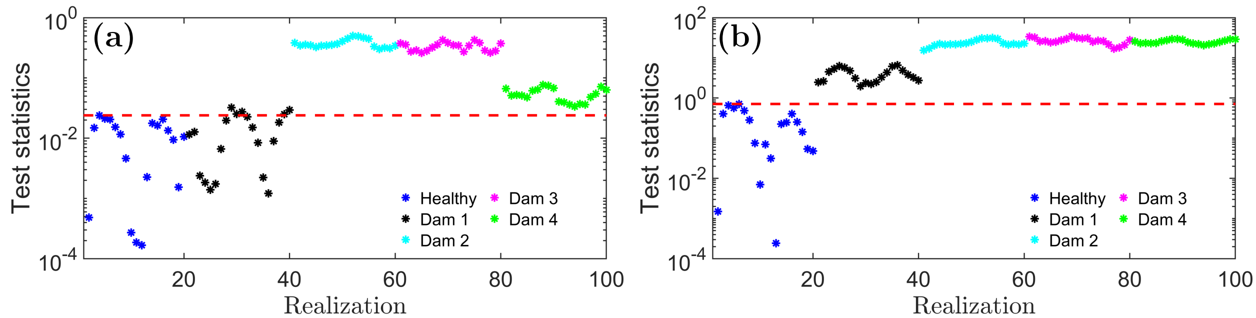

Figure 8. Damage detection for damage non-intersecting path 1-4 using AR(4)-based covariance matrix: (a) SVD-based approach (b) PCA-based approach.

AR(4)-based covariance matrix.

Figure 9 shows the damage identification results of the four different damage states for damage non-intersecting path 1-4. The covariance matrix was derived from 20 experimental healthy signals. Note that perfect identification was achieved for each damage state. The appropriate α- level was used for each case.

5. CONCLUDING REMARKS

The objective of this work is the formulation and numerical assessment of a statistical damage diagnostic scheme in the context of ultrasonic guided wave-based damage diagnosis using stationary autoregressive models. At first, standard AR-based damage diagnosis was considered where all the estimated model parameters were used. Then the SVD-based approach was used, where model parameters were sorted according to the highest magnitude of the eigenvalues obtained from the parameter matrix. Another approach used was the PCA-based truncation approach, where model parameters were projected onto a lower dimensional space. It was found that for both the damage intersecting path 2-6 and damage non-intersecting path 1-4, all three methods perform well using the experimental covariance matrix. However, when using AR(4)-based covariance matrix, PCA-based method performs better for damage non-intersecting path 1-4, and standard AR-based and SVD-based method perform better for damage intersecting path 2-6. It is to be mentioned here that different parameter estimation methods may have effects on the damage diagnosis process. The methods shown here for damage diagnosis are easy to use, statistical in nature and have potential for full automation.

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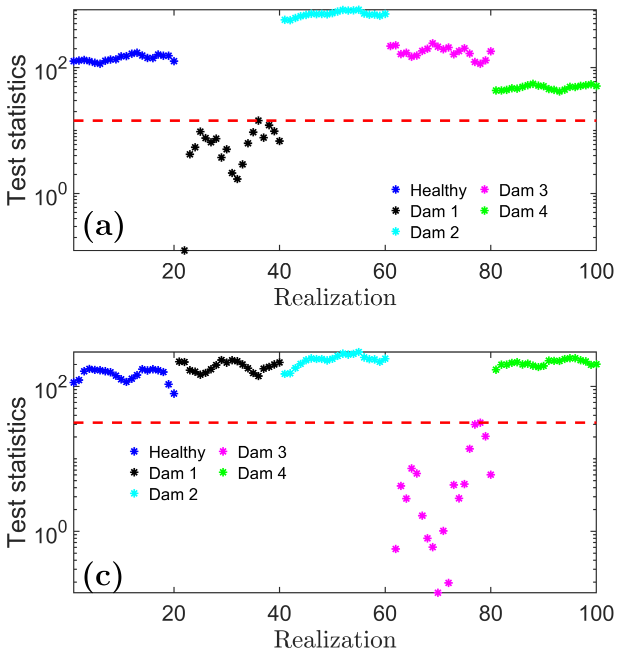

Figure 9. Damage identification results for the damage non-intersecting path 1-4 using the standard AR-based approach: identification of (a) damage level 1; (b) damage level 2; (c) damage level 3; (d) damage level 4.

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