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Structural health monitoring for condition assessment using efficient supervised learning techniques

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An Introduction to Structural Health Monitoring

- Structural health monitoring (SHM) is an active and practical process that essentially aims to evaluate the health of civil, mechanical, and aerospace structures for damage diagnosis and prognosis.

- The process of SHM is based on monitoring features that should be sensitive to damage and consists of sensing, data acquisition, feature extraction, and feature discrimination or classification.

Importance of SHM

- Assessment of the health and safety of structures
- Increase in structural performance
- Prevention of destructive damage to vital structures
- Reduction of maintenance costs

Levels of SHM

- Level 1: Damage detection
- Level 2: Damage localization
- Level 3: Damage quantification

→ Damage diagnosis

- Level 4: Damage prognosis

❑ Methods of SHM

- **Model-based methods** that need finite element modeling and model updating
- **Data-based methods** that only utilize vibration responses without finite element modeling and model updating
- Most of the data-based methods rely upon statistical pattern recognition.

❑ Methods of SHM

SHM can be implemented by statistical pattern recognition through four main steps:

- Operational evaluation
- Data acquisition
- Feature extraction
- Statistical decision making for feature classification

❑ Machine Learning

- Machine learning is a technique for data analysis, pattern recognition, and decision-making based on the only data.
- The statistical decision-making for feature classification is usually implemented under the theory of machine learning.

❑ Types of Machine Learning in SHM

- **Supervised learning** that needs features or datasets of both undamaged and damaged conditions to learn a statistical model.

- **Unsupervised learning** that needs only features or datasets of undamaged conditions to learn a statistical model.

❑ Parts of SHM Based on Statistical Pattern Recognition

- SHM based on statistical pattern recognition paradigm and machine learning generally contains two main phases:

1. *Training or Baseline Phase* → Only undamaged conditions (Unsupervised Learning) | Undamaged & damaged conditions (Supervised Learning)

2. *Monitoring or Inspection Phase* → Current condition

Main References for Feature Extraction in Time Domain

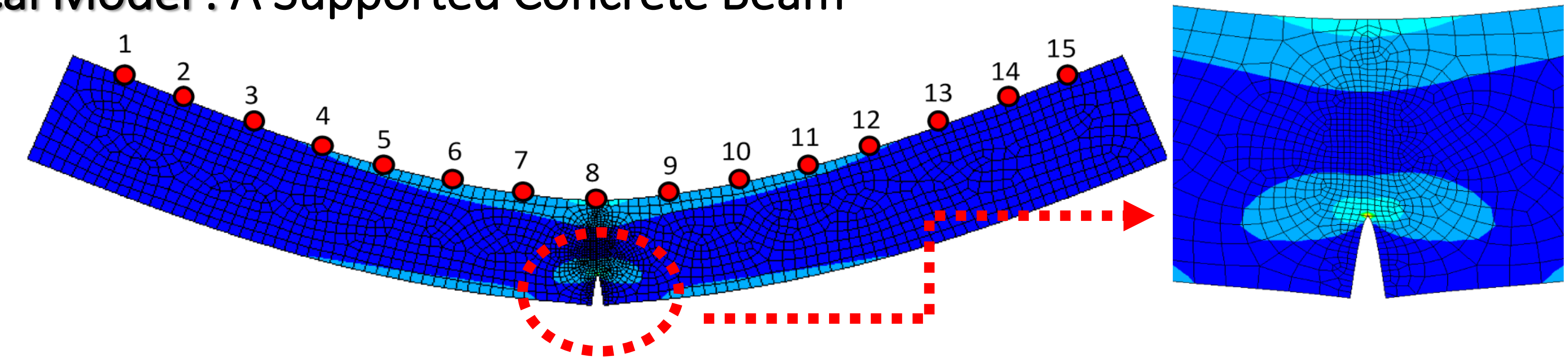
Time series modeling		Principle component analysis (PCA)
Autoregressive (AR) Model		
Coefficients	Residuals	
Sohn, et al. (2000) Gul and Necati Catbas (2009) de Lautour and Omenzetter (2010) Datteo and Lucà (2017)	Fugate, et al. (2001) Mattson and Pandit (2006) Zheng and Mita (2009) Yao and Pakzad (2012)	Sophian et al. (2003) Zhong et al. (2006) Trendafilova et al. (2008) L. Mujica, et al. (2011)

❑ Feature Extraction and Classification Methods

- Extracting damage sensitive features by Autoregressive (AR) time series model and principal component analysis (PCA) from the raw vibration time-domain responses

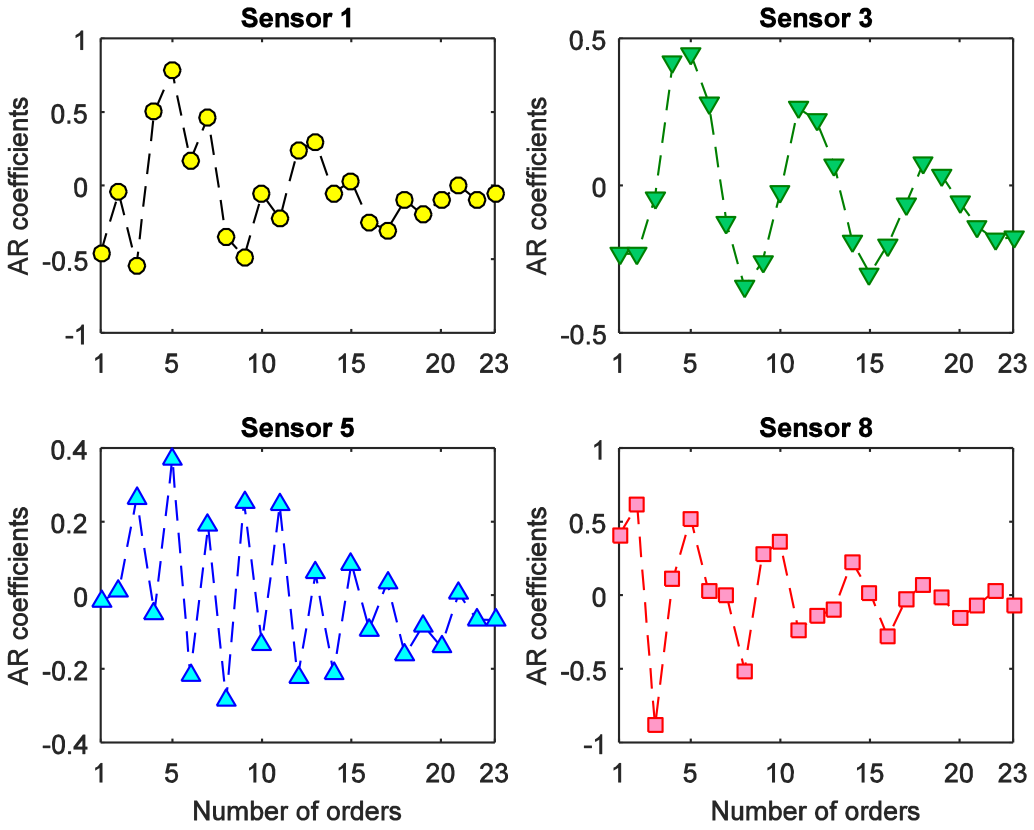
- Classifying damage sensitive features by linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), naïve Bayes (NB), and decision tree (DT) for damage diagnosis

❑ **Numerical Model :** A Supported Concrete Beam



- Nonlinear damage scenarios as simulations of breathing cracks with different severity levels
- The beam was equaipped with thirty sensors so that the fifteen sensors at the top side and the other fifteen sensors were simulated as the bottom side.
- Each of the healthy and damaged conditions consists of 20 test measurements.
- The area near to the sensor 8 is the location of damage.

Model Coefficients



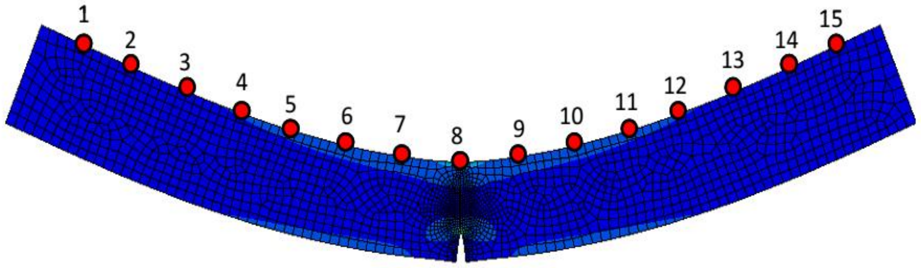


Figure 1. The coefficients of AR(23) at the sensors 1, 3, 5, and 8 in the case 1

❑ Components of PCA

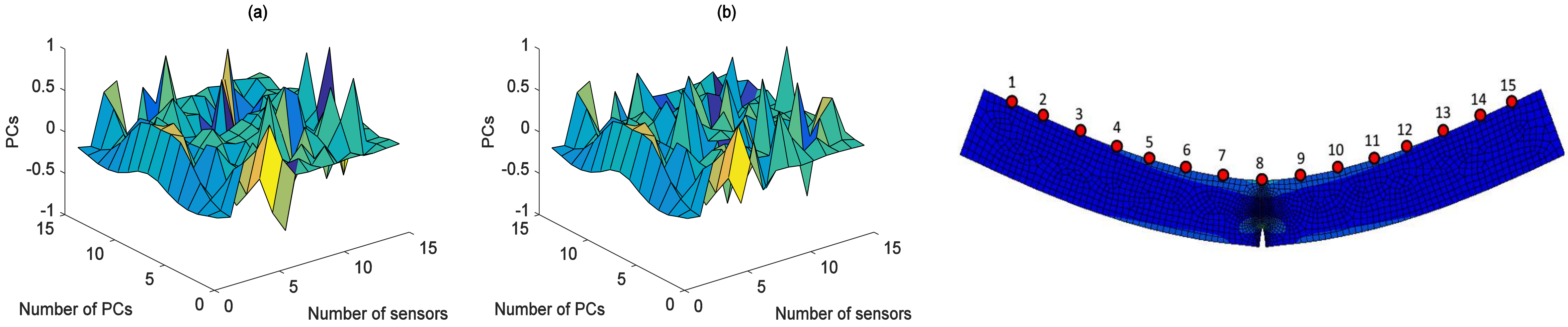
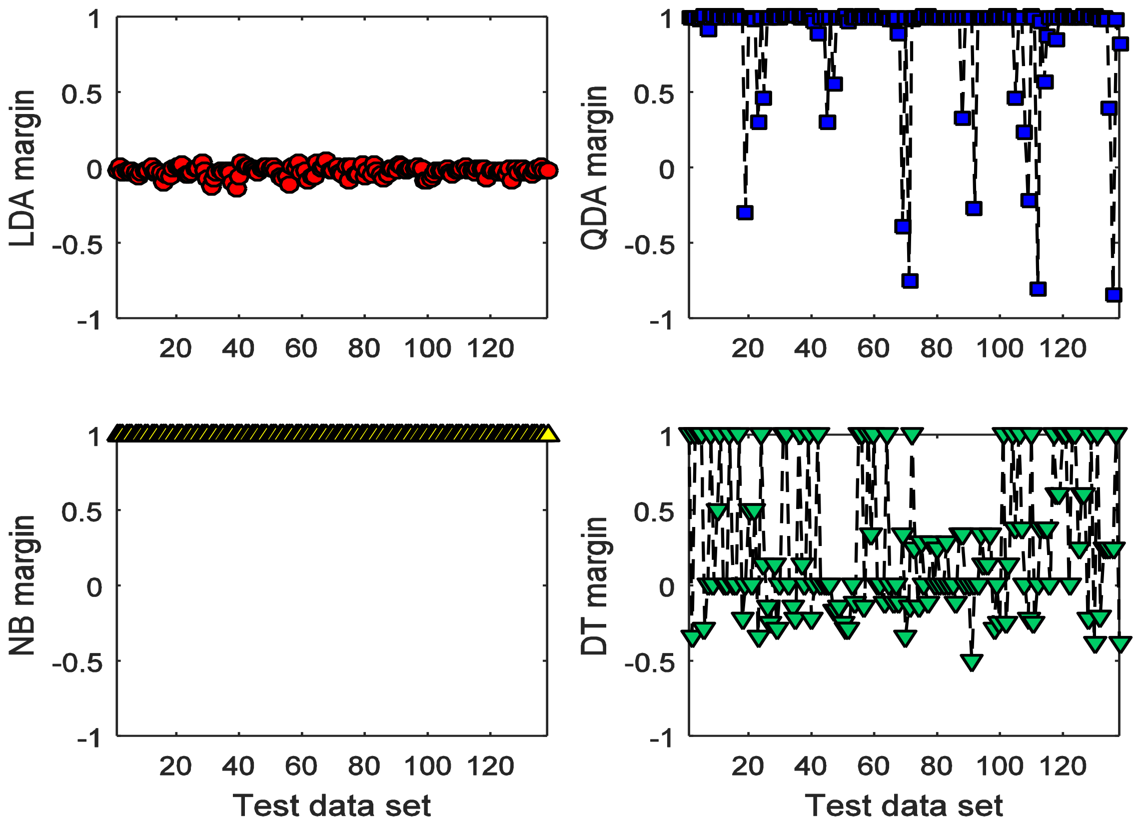


Figure 2. The principal components of acceleration time histories for the numerical beam: (a) case 1, (b) case 3

Classification Process using AR Model



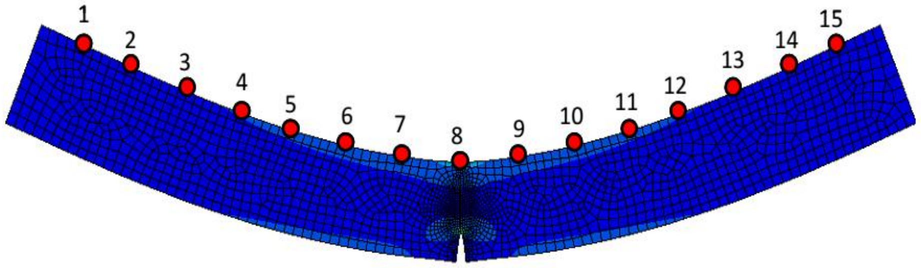
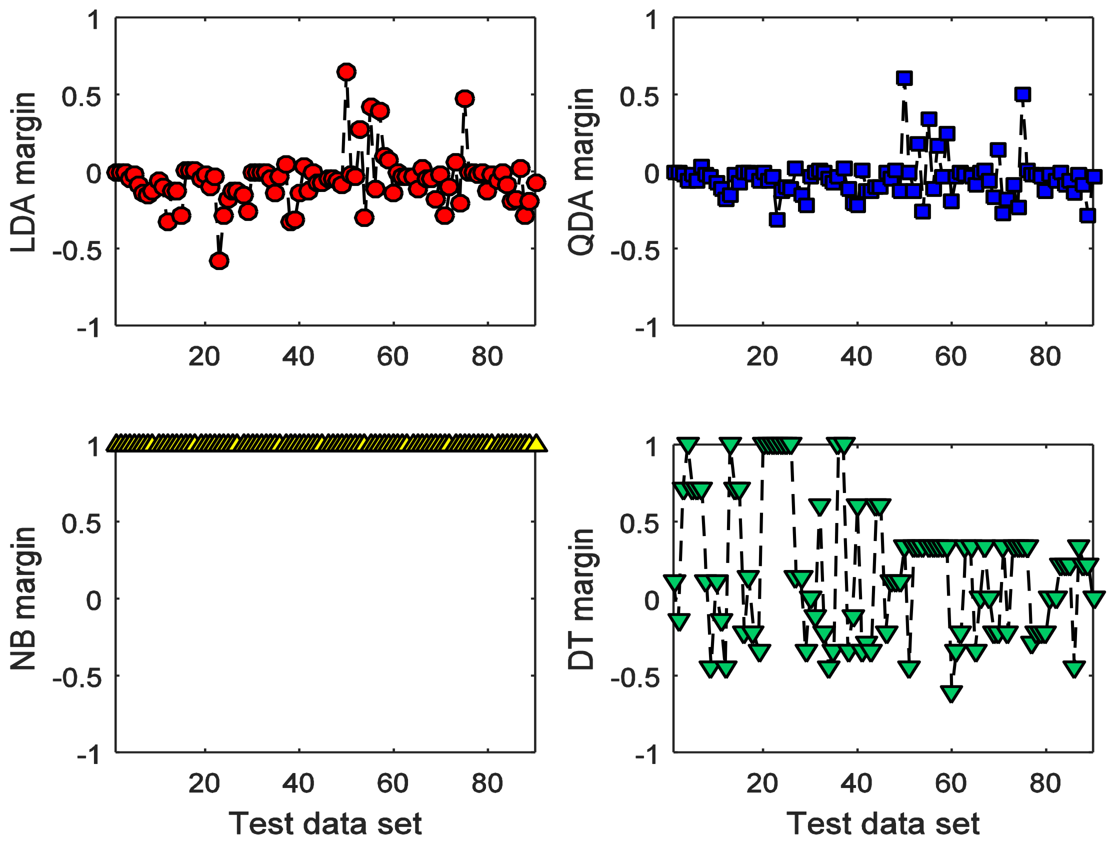


Figure 3. The process of classification using the AR feature selection technique in the numerical beam

Classification Process using PCA



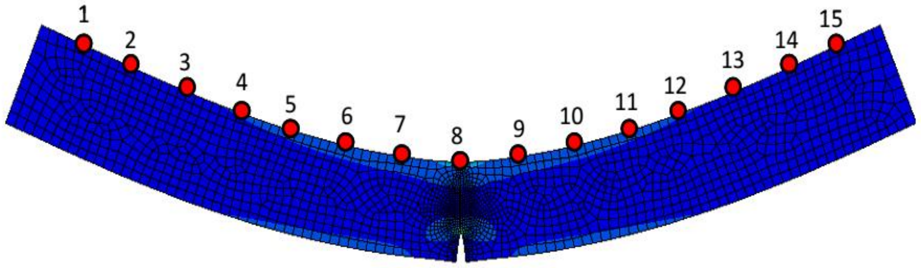


Figure 4. The process of classification using the PCA feature selection technique in the numerical beam

Classification Accuracy

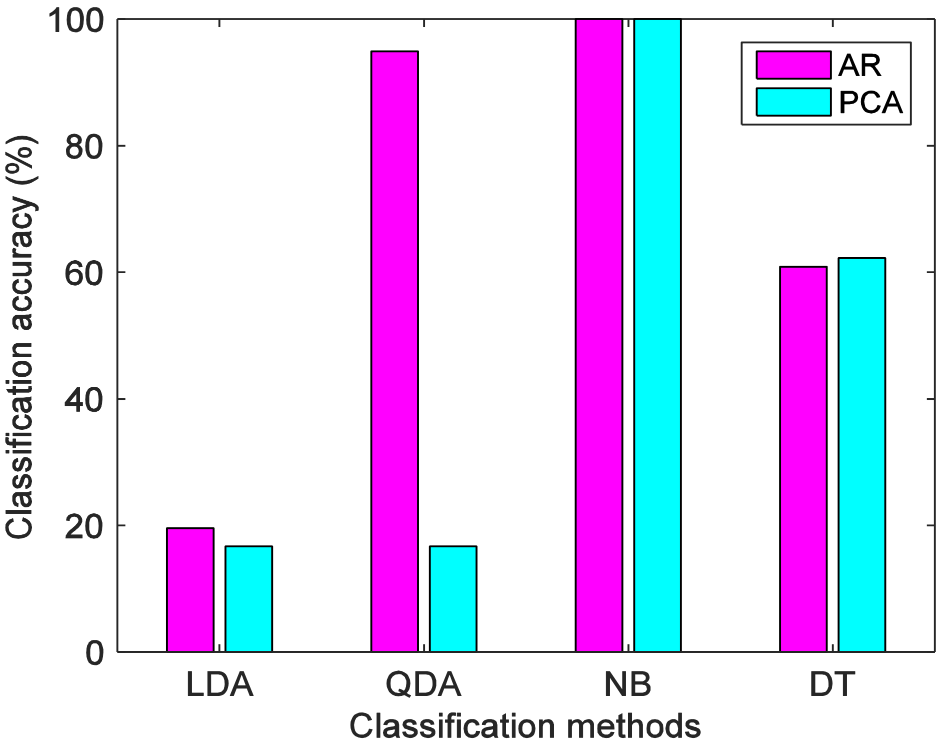
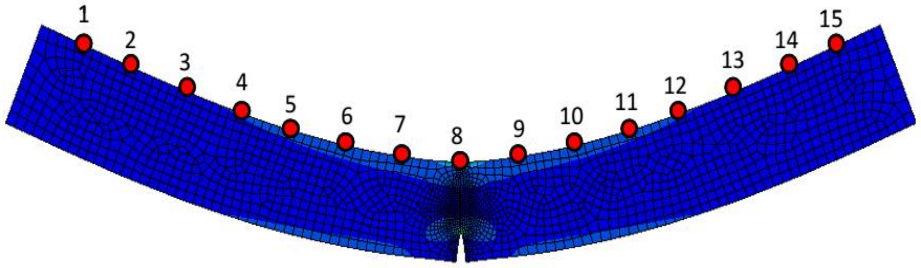


Figure 5. The classification error using AR and PCA feature selection approaches



❑ Main Conclusions of Feature Extraction

- Initial data analysis of vibration time-domain responses is a vital process before feature extraction.
- The BIC method for AR order deflection usually guarantees the accuracy of time series model order due to the extraction of uncorrelated residuals.
- Both AR time series model and PCA were succeed in extracting the damage-sensitive features from the raw vibration time-domain responses.

❑ Main Conclusions of Feature Classification

- LDA is not a reliable classification method in the context of structural health monitoring. This method cannot provide trustworthy classification results in the AR and PCA models.

- Among all of the classification methods, NB possesses the best results in both of the feature extraction technique.

Main Conclusions of Feature Classification

- QDA and DT are moderate classification methods since the results are not neither as good as NB method nor as undesirable as LDA method.

- The comparison results show that the AR and PCA models give the same classification results. Therefore, both of them are good feature extraction techniques for using in the structural health monitoring.

Thank you very much for your attention