Expert Systems with Applications 38 (2011) 1650–1658

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

A hybrid immune model for unsupervised structural damage pattern recognition

Bo Chen [a,b,*], Chuanzhi Zang [a,c]

[a] Department of Mechanical Engineering – Engineering Mechanics, Michigan Technological University, 815 R.L. Smith Building, 1400 Townsend Drive, Houghton, MI 49931, USA
[b] Department of Electrical and Computer Engineering, Michigan Technological University, 1400 Townsend Drive, Houghton, MI 49931, USA
[c] Shenyang Institute of Automation, Chinese Academy of Science, Nanta Street 114, Shenyang, Liaoning 110016, PR China

ARTICLE INFO

Keywords:
Structural health monitoring
Unsupervised structural damage pattern recognition
Fuzzy clustering
Artificial immune pattern recognition

ABSTRACT

This paper presents an unsupervised structural damage pattern recognition approach based on the fuzzy clustering and the artificial immune pattern recognition (AIPR). The fuzzy clustering technique is used to initialize the pattern representative (memory cell) for each data pattern and cluster training data into a specified number of patterns. To improve the quality of memory cells, the artificial immune pattern recognition method based on immune learning mechanisms is employed to evolve memory cells. The presented hybrid immune model (combined with fuzzy clustering and the artificial immune pattern recognition) has been tested using a benchmark structure proposed by the IASC–ASCE (International Association for Structural Control–American Society of Civil Engineers) Structural Health Monitoring Task Group. The test results show the feasibility of using the hybrid AIPR (HAIPR) method for the unsupervised structural damage pattern recognition.

1. Introduction

The structural health monitoring (SHM) is a process of observing a structure's dynamic response measurements from a group of sensors, extracting damage-sensitive features from these measurements, and analyzing these features to determine the current state of the structure (Kolakowski, 2007). Due to high instrument and installation costs of wired SHM systems (Sazonov, Janoyan, & Jha, 2004), the wireless sensor-network-based SHM is emerging as a feasible approach since it allows dense sensing through many inexpensive sensor nodes and is easy for deployment and maintenance (Xu et al., 2004). While sensor network approach presents a number of advantages, SHM sensor network systems currently face a number of challenges (Farrar & Worden, 2007). Major challenges in SHM sensor networks include: (1) how can we provide sustainable monitoring and control in an autonomous manner? For complex structures, a monitoring sensor network may consist of hundreds or thousands of sensor nodes and may be deployed in environments that are difficult to access (embedded in physical structures). Given such a deployment size and environment, sensor networks are required to monitor structural changes and perform damage diagnosis autonomously; (2) can we develop adaptable approaches to SHM that are able to dynamically adapt to changing monitoring conditions? Due to resource constraints in sensor networks, a SHM sensor network that is able to manage its resources effectively under different circumstances is critical; (3) how can we detect and identify structural damages in an active way? The passive monitoring of structures by continuously gathering real-time structural data causes data transmission problem due to limited bandwidth and power available in wireless sensor networks; (4) how can we establish an unsupervised damage diagnosis methodology?

The natural immune system is an effective defense mechanism for a given host against infections (De Castro, 2006). From a pattern recognition perspective, the most appealing characteristic of the immune system is its immune cells (B-cells and T-cells) carrying surface receptors that are capable of recognizing and binding antigens. The antibodies are soluble forms of the B-cell receptors that are released from the B-cell surface to cope with the invading nonself antigen. Antibodies bind to antigens leading to their eventual elimination by other immune cells (De Castro & Timmis, 2002). When a B-cell encounters a nonself antigen that has sufficient affinity with its receptors, coupled with a stimulation signal from T-cells, the B-cell is activated. It, therefore, undergoes a clonal selection that increases the number of the activated B-cell and the diversity of the antibody set. The generated B-cells with high antigenic affinities are selected to become memory cells that remain in the immune system for months or years. The first exposure of a B-cell to a specific type of antigen triggers the *primary response* in which the pattern is recognized and the memory is developed (Castiglione, Motta, & Nicosia, 2001). The memory cell for a specific antigen that had stimulated in the primary response will respond to previously recognized antigen in a much shorter time

* Corresponding author at: Department of Mechanical Engineering – Engineering Mechanics, Michigan Technological University, 815 R.L. Smith Building, 1400 Townsend Drive, Houghton, MI 49931, USA.

E-mail address: bochen@mtu.edu (B. Chen).

0957-4174/$ - see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2010.07.087

comparing to a newly activated B-cell (Carter, 2000). The novel characteristics of the immune system have inspired the development of artificial immune systems for various applications (Dasgupta, 2006; Hart & Timmis, 2008). The major application areas include data mining (Freitas & Timmis, 2007), pattern recognition (Watkins, Timmis, & Boggess, 2004; Zhong, Zhang, Gong, & Li, 2007), fault diagnosis (Dasgupta, KrishnaKumar, Wong, & Berry, 2004; Taylor & Corne, 2003), and medical classification problems (Polat, Gunes, & Tosun, 2006).

Due to the similarities of the human immune system and the SHM systems, the artificial immune system (AIS) model could be used as the basis for SHM strategies (Chen, 2009). This approach is well suited to address SHM problems because: (1) the AIS-based SHM is autonomous. The AIS-based SHM systems can automatically manage structural monitoring tasks by dynamically generating and distributing the mobile monitoring agents; (2) the AIS-based SHM is adaptive. The amount and type of molecules of the immune system can adapt themselves to the antigenic challenges via clonal selection (Cesana et al., 2005). The adaptive mechanism of the natural immune system has great value in SHM sensor networks. The selective generation of mobile monitoring agents is essential for producing large enough amount of specialized mobile monitoring agents in resource-constrained sensor networks (Negoita, 2005); (3) the AIS-based SHM is active. The concept of active dispatching mobile monitoring agents (mimicking B-cells) helps the distribution of specialized monitoring agents to the sites where they are needed; and (4) the immune learning and memory mechanisms help the development of unsupervised damage detection and pattern recognition, which is desirable in SHM.

This paper presents a hybrid immune model for unsupervised structural damage pattern recognition based on the fuzzy clustering technique and the artificial immune pattern recognition (HAIPR). The fuzzy clustering (FC) algorithm is employed to generate initial memory cells for damage patterns. These initial memory cells are then evolved by an immune learning process to improve the quality of memory cells to represent damage patterns. The presented unsupervised structural damage pattern recognition algorithm has been tested using a benchmark structure (Structural Health Monitoring Benchmark Problem) proposed by the IASC–ASCE (International Association for Structural Control–American Society of Civil Engineers) Structural Health Monitoring Task Group. The test results show the feasibility of using the HAIPR method for the unsupervised structural damage pattern recognition. The rest of the paper is structured as follows. Section 2 presents the algorithm design of the HAIPR approach. Section 3 describes how to use the HAIPR method for the unsupervised damage pattern recognition for the IASC–ASCE benchmark structure and shows the validation results. Section 4 discusses the impact of the system's parameters on the performance of the HAIPR unsupervised pattern recognition and the comparison of the HAIPR method with conventional classification algorithms. Section 5 concludes the presented work.

2. The HAIPR approach for unsupervised structural damage pattern recognition

2.1. The HAIPR approach

In unsupervised structural damage pattern recognition, the pattern information of the training data is not available. The presented HAIPR unsupervised pattern recognition method employs fuzzy clustering algorithms to establish the initial representative for each pattern of the training data. The representative for each pattern generated by the fuzzy clustering algorithms, however, includes limited information. For example, the fuzzy clustering algorithms use one point in a multidimensional space to represent each cluster (pattern) for a compact data set. To obtain more informative pattern representative (memory cells) and provide the evolution capability, the artificial immune pattern recognition method is employed to improve the quality of memory cells for each damage pattern.

Fig. 1 shows the major components of the HAIPR algorithm. The measurement data from multiple sensors are compressed from n-dimensional space (n sensors) into one dimensional space by the Principal Component Analysis (PCA) algorithm. The features of the compressed time series sensor data are extracted from the auto regression (AR) model of the time series. The initial memory cells for sensor data patterns are generated by the fuzzy clustering algorithm. These initial memory cells are also used to classify the training data into a specified number of patterns based on the nearest neighbor criterion. The classified training data are then used to evolve memory cells in an immune learning process based on clonal selection principle. The evolved memory cells are then used for the structural damage pattern recognition.

2.2. Feature extraction from sensor data

In structural damage pattern recognition, damage patterns are represented by feature vectors extracted from dynamic response data of a structure. A feature vector consists of a number of

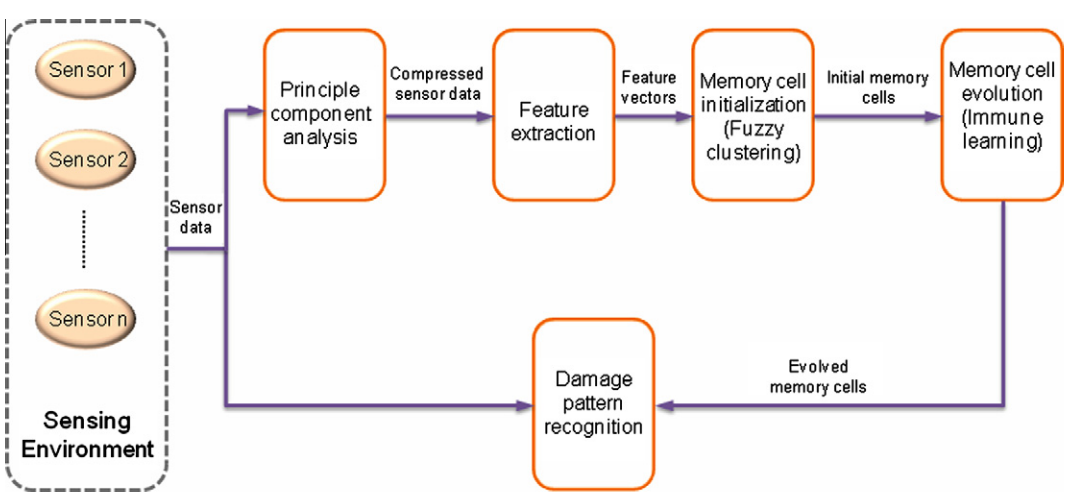

Fig. 1. Overview of the HAIPR approach.