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GENERALIZED LIKELIHOOD RATIO TESTS FOR DEFECT DETECTION IN SHM OF PIPES

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ABSTRACT

Recently, there has been a move toward the use of ultrasonic-based permanently installed systems to monitor the health status of a number of structures, such as pipes. A big advantage of this approach compared to the typical one-off inspection configuration is the potential for detection of damage at earlier stages. This is enabled by the frequent collection and analysis of data. Once the signals are corrected for the effects of temperature, the trends of the measurements taken at each structural location can be monitored, and deviations from the expected behavior can be related to the occurrence of damage. In this setting, fault-detection methods such as the ones widely used in the field of statistical process control can be used to detect those deviations. In this work, two methods based on the Generalized Likelihood Ratio are investigated and are applied to a set of T(0,1) guided wave signals collected by a pipe monitoring system. Receiver operating characteristics curves are used to identify a suitable threshold for the method to operate based on the desired levels of probabilities of false alarm and of true detection at given defect sizes. The method promises a substantial improvement in the detectability of small defects, while minimizing the human workload needed to actually inspect the signals.

Keywords: defect detection, generalized likelihood ratio, guided waves, pipe inspection, statistical methods.

1. INTRODUCTION

Inspection systems based on guided waves are widely used to detect damage in numerous applications, such as the testing of pipes for the oil & gas industry by means of the T(0,1) torsional wave mode using a pulse-echo configuration at frequencies in the order of tens of kHz [1]. In this setting, the sensor is deployed on the structure and it is then removed after taking one (or a few) measurements.

Recently, there has been strong interest in moving from the standard one-off inspection configuration to a permanently installed monitoring system (PIMS), which allows for frequent collection and interpretation of data [2], hence potentially enabling the detection of damage at earlier stages. Recent publications presented examples of such systems based on piezoelectric transducers [3, 4], Lorentz force–based EMAT transducers [5] and magnetostrictive-based EMATs [6].

In a PIMS setting, the data analysis typically involves comparing new measurements with a baseline record, where any change in the signal could represent a defect signature, in a procedure termed baseline subtraction [7]. Unfortunately, changing environmental and operational conditions (EOCs), primarily temperature, also cause changes in the signals, so degrading the damage detection performance. A number of temperature compensation methods have been proposed in the last 15 years [8-10]. A novel procedure was recently developed by the authors and is the object of a patent application [11]. One of the advantages of the new method is that the residuals obtained at each structural location appear to follow a normal distribution.

This enables the application of a number of fault-detection methods such as those used in statistical process control [12, 13], which can be used to analyze the trends of data acquired at each structural location. In this work, two methods based on the Generalized Likelihood Ratio (GLR) [14, 15] are investigated and applied to a set of T(0,1) guided wave signals collected by a pipe monitoring system. The two methods fundamentally differ on the assumptions about the statistical distribution of the analyzed trends of signals when the structure is undamaged. The most important operating parameter to set when using either of these two methods is the call-threshold. Receiver operating characteristics curves can be used to both compare the performance given by each method, and to identify suitable threshold values to guarantee some desired levels of probabilities of false alarm and of true detection at given defect sizes.

2. EXAMPLE OF GLR FAULT-DETECTION TESTS

Figure 1 shows the capability of the GLR tests originally introduced in [14, 15] for detecting a change in the mean of a sequence of data-points. Figure 1(a) plots a sequence that was

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randomly generated using MATLAB®, where points 1 to 50 are drawn from a normal distribution with zero-mean and unity standard deviation, while points 51 to 100 have the same standard deviation, but a mean of 1, hence simulating the occurrence of some damage which is captured by the measurement system. The method in [14] requires knowledge (in practice, an assumption) of the distribution of the data before the (potential) occurrence of a fault. Figure 1(b) plots the test score computed at each point (specifically, computed using the sequence of data from point 1 to each point being analyzed) when using the known parameters of the distribution followed by points 1 to 50. The test score grows past the point of change, until eventually crossing the set threshold (10 in figure) and so giving the alarm. It can be appreciated how a simple visual-inspection on the sequence in Figure 1(a) might easily miss the identification of the change. In practical cases, worse results would be achieved if the wrong parameters are used to run the test. The method in [15] completely eliminates this issue, as the test automatically estimates the parameters before the (potential) change, at the expense of a diminished sensitivity. For example, Figure 1(c) plots the test scores computed using [15] on the data of Figure 1(a), also showing the efficacy of the method.

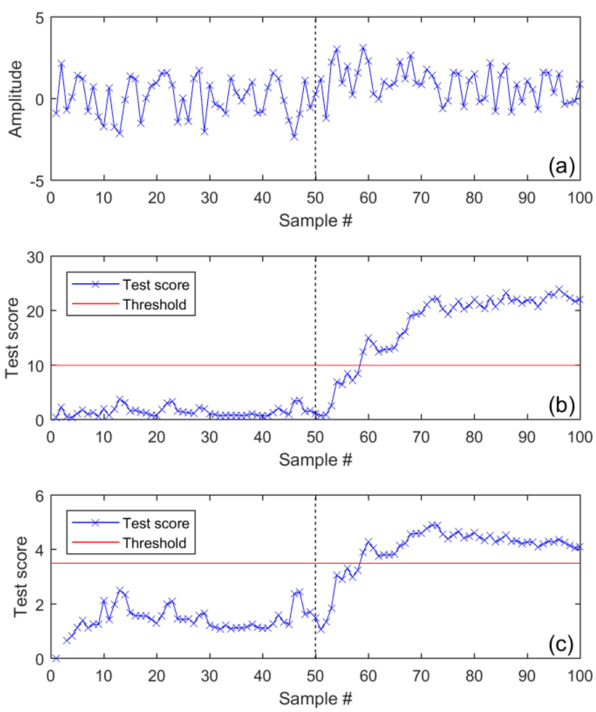

FIGURE 1: (A) SEQUENCE OF 100 NORMALLY DISTRIBUTED AND RANDOMLY GENERATED DATA-POINTS, WITH STANDARD DEVIATION OF 1, MEAN OF 0 FROM POINTS 1 TO 50, AND MEAN OF 1 FROM POINTS 51 TO 100. (B) TEST SCORE FROM THE METHOD IN [14]. (C) TEST SCORE FROM THE METHOD IN [15]. (B-C) THE RED LINES INDICATE POSSIBLE THRESHOLDS.

3. CONCLUSION

A temperature compensation procedure for ultrasonic signals that was recently developed by the authors [11] produces residuals at each structural location which appear to follow a normal distribution. This enables the application of a number of fault-detection methods that can automatically flag the occurrence of damage in the tested structure. Following extensive literature review, two methods based on the Generalized Likelihood Ratio [14, 15] have been selected as most promising for this SHM application. Receiver operating characteristics curves will be used to assess the performance offered by each method, and ultimately to identify what probabilities of false alarm and of detection at given defect sizes they would enable when applied to actual signals collected by a pipe monitoring system.

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