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Sparse estimation based monitoring method for damage detection and localization: A case of study

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ABSTRACT

This paper suggests a Structural Health Monitoring (SHM) method for damage detection and localization in pipeline. The baseline signals, used in SHM, could change due to the variation of environmental and operational conditions (EOCs). Hence, the damage detection method could give rise to false alarm. In this study, this issue is addressed by estimating the current signal using only few reference signals with similar or very close EOCs. Such an operation can be performed by calculating a sparse estimation of the current signal. The estimation error is used as an indication of the presence of damage. Actually, a signal from the damaged pipe will be characterized by a high estimation error compared to that of a signal from the undamaged pipe. The damage location is obtained by calculating the estimation error on a sliding window over the signal from the damaged pipe. This method was tested on signals collected on a 6 m pipeline segment placed in a workshop under natural temperature variations. Results have shown that the created damage was successfully detected and localized.

1. Introduction

Structural Health Monitoring (SHM) techniques are intended to assess the integrity of structures, such as pipelines [1–3]. They are developed in order to avoid failures, which could occur as consequence of a critical damage. Some failures might give rise to considerable material, human and institutional losses. The damage could have different types and forms, where the most faced one is corrosion because of the huge use of carbon steel pipelines. SHM techniques aim at detecting the initiation of damage (i.e. at early stages) to perform thereafter the maintenance of the damaged area of the structure, without any delay. Technically speaking, early stages defect detection is ensured thanks to the monitoring, which is somewhat based on the comparison between the reference signals (i.e. baseline) obtained from the healthy structure and the current one (i.e. the structure can be damaged or still healthy). Regarding the monitoring of pipelines integrity, the signals are acquired using ultrasonic guided waves (UGW) technique [4]. UGW can travel over long distances with relatively small attenuation [5]. Hence, they can cover large areas using only small numbers of distributed sensors. These waves interact with the structures heterogeneity such as weld, flange, defect etc.

The task of comparison between the reference signal and the current signal is not easy to achieve because the healthy state of the structure could vary due to the changes in the environmental and operational conditions (EOCs)

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(e.g. temperature, humidity, vibration loads, etc.) [6]. The effects of these EOCs could be similar to those produced by damage [7,8]. This would result in false warnings. The differentiation between the aforementioned types of changes is a challenging task. In the literature, different approaches were proposed to address this issue. They can be classified into two categories: analytical and statistical methods. Clarke et al. [9] have proposed to combine two analytical methods (optimal stretch method and optimal baseline method) to compensate the effect of temperature on guided wave propagation. The first method is applied when temperature effect is dilation/compression of the received signal. However, some experimental works have demonstrated that temperature effect is not only a change of the propagation time but also a significant change in the amplitude of the signals [10,11]. The second method requires a database of reference signals acquired at different temperatures. Each time a new current signal is presented, it selects from the database of reference signals the one that gives a lower subtraction error. But, the reliability of this method depends on the temperature gap between the baselines which should be very small. This implies a huge database of reference signals. Furthermore, damage detection with these methods is based on a simple subtraction between the reference signal and current signal, which is not reliable. Concerning statistical methods, Rizzo et al. [12] applied novelty detection for defect detection in railroad using UGW. They have proposed to build a database of reference signals by adding a random noise to a baseline signal acquired from an undamaged mock up railroad. However, the added noise cannot be used to simulate the effects of EOCs. A more realistic study was developed by Chang et al. [13], they have proposed an unsupervised damage detection method using Singular Value Decomposition (SVD) of the matrix of collected signals. It was developed on the premise that the effect of damage and the effect of EOCs will be represented in different singular vectors. In this case, damage is detected by observing a jump of the mean in the right singular vectors. But the question here is in which singular vector the jump can be observed and how can we automatically detect this jump. Also, this can be only done in the case where the following hypotheses are fulfilled. Firstly, it supposes that damage occurs abruptly, which is not always true because in real cases, damage may develop progressively during a long period of time. Secondly, EOCs should be constantly changing so a jump cannot be observed in their associated singular vectors, otherwise it will be considered as an indication of the presence of damage. Here also temperature changes for example could have a clear trend, so in this case the latter hypothesis might be not verified. More recently, Eybpoosh et al. [14] have proposed a supervised method based on sparse representation of UGW signals, which can ensure discrimination between damage and variation in EOCs. However, this method requires the use of signals from the damaged pipe, which are generally not available. Indeed, in real world, when damage occurs, it progresses arbitrary. That is to say, a database collected in a given structure could not be used for others. Consequently, the aforementioned method may not be reliable in industrial context.

In this study, since signals from the undamaged pipe are the only available information which can be provided in the training step, the proposed method for damage detection is based on a novelty detection technique. To deal with variation in EOCs, we consider a method of learning in non-stationary environment. This method consists in estimating the current signal by only few signals among the reference database. Physically, if the current signal is from a healthy pipe, it will be estimated using few reference signals with similar or very close EOCs, the others being discarded. As all identification methods, the proposed approach is based on the assumption that the database of reference signal contains sufficient variation of EOCs. Otherwise, an update of the reference database is necessary to ensure viable damage detection. Such development is not implemented in the present study. Note here that the difference between the proposed method and the optimal baseline selection method is that the latter searches for only one baseline signal that matches the current signal in terms of temperature variation. While the proposed approach searches for a combination of reference signals that well estimate the current signal. The estimated signal is obtained by averaging the found reference signals with a specific weight for each one. To localize the damage, we suggest applying the sparse estimation on a sliding window over the signal from the damaged pipe. This is motivated by the fact that when dealing with UGW the effect of damage is local on the signal.

In the next section, the proposed methodology for damage detection and localization in pipeline is presented. In Section 3, the procedure for collecting the database of signals from the healthy pipe and the damaged pipe is explained. Also, the preprocessing of these signals is exposed. Section 4 is devoted to discussions on the obtained results. Finally, Section 5 concludes the paper.

2. Mathematical background and problem formulation

2.1. Overview of the sparsity problem

The monitoring process of a structure begins generally by collecting reference signals at different EOCs during a fixed period of time. Afterthat, whenever a new current signal is presented, it must be compared to these reference signals. In this paper, the proposed approach for comparing the current signal to the reference signals consists in first estimating the current signal by only a few reference signals as shown in Fig. 1. Then, we calculate the estimation error which will be used to construct a damage index. The question here is how to select from the database of reference signals those which will be used to estimate the current signal. This could be done by feature selection techniques used in machine learning. However, the problem is not only to select the suitable reference signals but also to search for the fewest number of them. Such an issue is commonly known as sparsity problem. The next section is devoted to describe the methodology that has been followed to estimate a new current signal.