Smart sensor network for efficient damage detection and tracking in oil and gas pipelines

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ABSTRACT: Sensors are frequently used in damage diagnosis for structural health monitoring (SHM) of engineering structures. This process typically requires a considerably large number of sensors. By increasing the number of sensors, the amount of data collected, though useful, becomes a burden due the required computational overhead. In this paper, a cross correlation approach is used to track damage intensity and propagation. The relative correlation between any set of randomly chosen sensors is recorded and compared over time. The randomness of the process leads to a robust detection and tracking of any arbitrary crack propagation. A case study for damage detection and tracking using 72 sensors in a steel pipeline is presented and discussed. It is shown that the proposed method can successfully allow damage tracking while limiting the data considered in the sensor network.

1 INTRODUCTION

In the last two decades, researchers used advances in communications and sensing technology to ensure infrastructure safety. The main domain of these efforts was the field of structural health monitoring (SHM). Establishing an SHM system requires overcoming four main challenges. First: a robust technology for sensing the responses of structures; Second: information sharing and communication between sensors; Third: identification of features that can represent damages in structures via receiving signals from sensors; and Fourth: processing algorithms to recognize the damage state of the structure and the severity of this damage (Chang & Markmiller 2006, Farrar et al. 2000). While advances in sensor and wireless technology have provided great means to overcome these challenges, the availability and temptation to use a large number of sensors have resulted in an overwhelmingly large amount of data. As the collected data increases, the available techniques for SHM become more and more inefficient, and at times, even fail to perform. Hence the need for smart sensor networks is evident. The importance of smart sensor networks becomes apparent when considering relatively long structure such as cross-country oil and gas pipelines where the structure is extended for hundreds of kilometers. The ability to limit data processing and enable smart damage tracking can significantly enhance monitoring system efficiency. Design of smart sensor networks requires innovative methods for selection of the number, type and location of sensors.

Research activities in sensor networks were focused on maximizing the covered area while minimizing consumption of energy (Buczak et al. 2001, Chakrabarty & Chiu 2002). Two different approaches were used: (1) maximizing the area of coverage per sensor using geometrical and physical boundary conditions (Lin & Chiu 2005), and (2) minimizing uncertainty in decision-making based on data acquired from sensor network (Field & Grogoriu

2006). An optimum sensor network for SHM under uncertainty as the sensor configuration that can maximize the probability of damage detection (POD) was introduced by Guratzsch & Mahadevan (2006). The POD approach was used in designing optimal sensor networks successfully for damage detection in a composite plate with the system optimization executed using genetic algorithms (Chang et al. 2007). Other researchers suggested finding optimal allocations of sensors in SHM sensor networks using information entropy and information functions (Papadimitriou et al. 2000, Kirkgaard & Brincker 1999). Weighted components of the mode shape matrix corresponding to the sensor locations were used (Li et al. 2006), and a probabilistic approach was shown capable of optimizing sensor networks in long cable stayed bridges (Azarbayejani et al. 2008). Research efforts showed the value added using sensor networks enabling efficient use of sensing data and reducing the overall number of sensors.

In this paper, we identify an approach for optimal data processing that minimizes the amount of data required. The proposed approach can be extended as a methodology to operate an on/off scheme over the sensors. This method will help in reducing data computation and communication overhead significantly without compromising the monitoring system's ability to detect damage. We focus our approach application to the critical field of oil and gas pipelines. The intention is to demonstrate the feasibility of the proposed approach for monitoring cross-country oil/gas pipelines serving in extreme conditions such as those in Saudi Arabia and other Arabian Gulf countries. The proposed method is shown to enable smart damage tracking. The proposed method can provide a valuable tool for identifying and tracking damage in pipelines due to corrosion, cracking, etc. This development can significantly extend the service life of such critical infrastructure.

2 METHODS

Assuming that sensory data from a healthy structure will by highly similar, and that similarity gets distorted as damage starts developing, our approach is based on observing dissimilarities between measurements by a collection of sensors. In order to define a measure of dissimilarities, a cross-correlation function is first defined. For *M* sensors installed on the structure, the cross correlation between all *M* sensors and randomly picked sensor *i*, within a window of size *N* is computed as:

$$R_{i,j}(m) = \frac{1}{N-m}\sum_{n=0}^{N-m-1} x_i(n)\, x_j(n+m) \qquad m = 0,1,\dots,N-1\ ,j = 1,2,\dots,M \tag{1}$$

After the cross correlation between the sensors is computed, dissimilarity between the cross correlation functions can be computed as:

$$d_j = \left|\frac{R_{i,j}}{max(R_{i,j})} - \frac{R_{i,i}}{max(R_{i,j})}\right| \qquad j = 1,2,\dots,M \tag{2}$$

Normalized correlation dissimilarity (*NCD*) for each set of data is computed as:

$$NCD_i = \begin{cases}\left(\frac{d_i}{max(d_i)}\right) & max(d_i) \neq 0 \\ d_i & max(d_i) = 0\end{cases} \quad i = 1,2,\dots,M \tag{3}$$

This process is repeated as the window moves over time. Using a time window means that information only within the window is analyzed. Therefore, the window width and time shift are critical parameters for ensuring method ability to identify correlation dissimilarity. The idea behind the proposed approach is that damage results in producing discontinuity in the responses of the region around it and thus increases the dissimilarity of the computed correlation of that region of the structure and all other regions. Therefore, getting a high value of normalized correlation similarity (NCD) at a sensor compared with other sensors indicates damage might have taken place around that sensor. Moreover, continuous observation of high NCD value at one location indicates the intensity (i.e. propagation) of damage at that location. Using the above approach, damage location can be identified and damage propagation can be tracked.

3 CASE STUDY

In this case study, we identify damage location and perform damage tracking in a steel pipeline. The steel pipeline is 3600 mm with clear diameter of 1000 mm and has a thickness of 10 mm. The initial crack is assumed to take place at the mid span of the pipeline with a length of 30 mm and width of 9 mm going through the plate thickness. 72 strain gauges were assumed to be installed around of the pipeline (Figure 1). The pipeline was modeled using the finite element (FE) method. The pipeline was modeled in ANSYS® FE environment. Solid 45 elements with element size of 30 mm used to model the pipeline. Other properties of the plate include modulus of elasticity of 200 GPa, Poisson's ratio 0.3 and density equal to 7.85 g/cm^3. A random and time varying internal pressure was applied to the pipeline. The magnitude of the stress is shown in Figure 2(a). The stress was applied for a total of 710 seconds. Simultaneously, the initial crack was assumed to propagate due to external environmental conditions not related to the loading. The crack was assumed to propagate following the protocol shown in Figure 2(b).

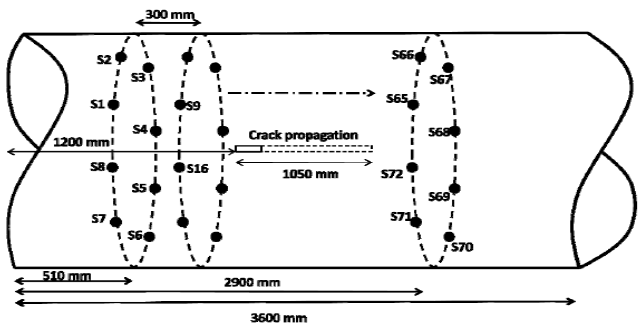

Figure 1. Pipeline with sensors and crack positions.

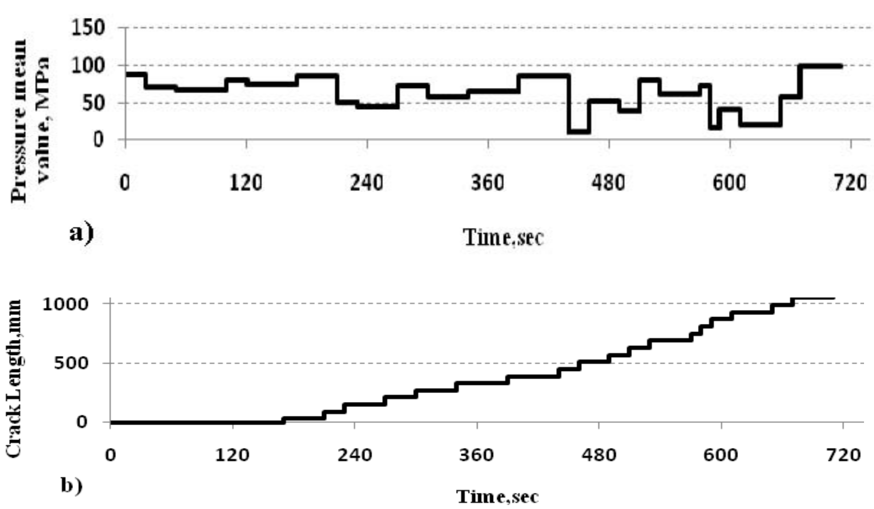

Figure 2. Load and crack propagation protocols; a) load protocol, b) crack propagation.

Crack propagation started after 170 seconds of loading. The crack propagation protocol was set independent of the loading protocol. The pipeline did not experience plastic deformation at any time. A sampling rate of 100 Hz was used to acquire the strains recorded at all the 72 sensors as predicted by the FE model. Figure 3 shows the results of FE of cracked pipeline for first principle strain contour at the last step of crack propagation and mean pressure of 99 MPa. No noise was added to data extracted from the finite element model in this study. However, if such noise exists, classical filtering methods can be used to de-noise sensing data.

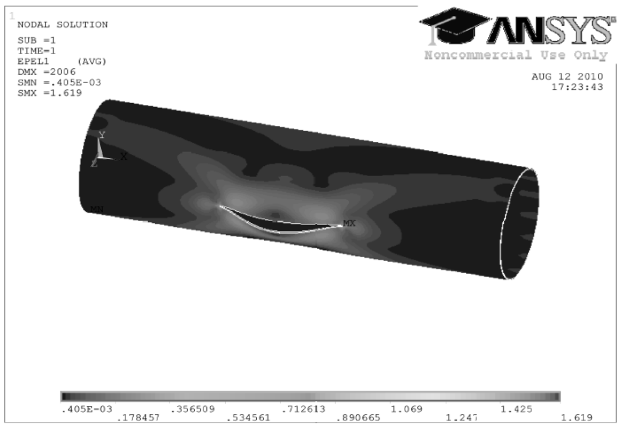

Figure 3. FE model and first principle strain at nodes at the final step of crack propagation.

4 RESULTS AND DISCUSSIONS

The strain measurements, after smoothing, for sensors S16, S24 and S70 are shown in Figure 4(a) and for sensors S32, S40 and S70 are shown in Figure 4(b). It can be observed that strains at all sensors were similar up to 170 sec. After that, the initial 30 mm crack occurred between sensors (S24) and (S32). A small jump in the strains at S24 and S32 was observed. After 270 seconds, the crack extended close to sensor S32 and sensor S32 experienced high strain.

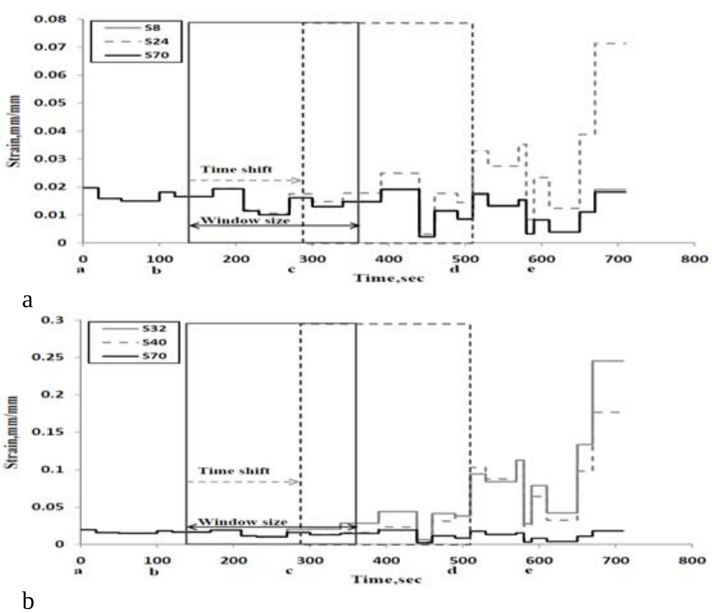

Figure 4. Strain at selected strain gauges during time, window tracking and window time shift.

The strain then increased as the crack passes the sensors. Similar effect on the strain response from sensor S40 can be observed as the crack got close to S40 with crack length reaching 510 mm. Figure 4 shows the initial crack and its propagation by tracking the strains all the time. If strains at all sensors at all locations are monitored, crack propagation can be detected. However, observing strains in all sensors and analyzing them simultaneously is expensive from computational resources and power demand points of view. Therefore, we develop a window tracking and time shifting algorithm that will reduce the required data while still enabling damage identification and tracking without analyzing all data observed.

In the following section, results from window monitoring at specific instances are presented. These specific time instances are indicated as a, b, c, d and e shown in Figure 4(a) and Figure 4(b). These time instances occur at 1, 100, 270, 490 and 590 sec respectively. These specific time instances include three important events of crack propagation as shown in Figures 4(a) and (b). Figure 5 shows the results for a window size 50 second extended from point a to point e with a time shift equal to 80% of window size. NCD of all sensors were calculated as per Equation 3 with sensor S70 at the five time instances (events) **a, b, c, d** and **e**. Sensor S70 was picked for being far from the crack location. At time instances **a** and **b**, all values of NCD at sensors S1 to S72 are equal to zero which means that the system did not experienced any damage. Such high values in event **c** at S24 and S32 indicate damage occurred near S24 and S32 but closer to S32. However, NCD values dramatically dropped as we passed sensors S17 and S33. This indicates that the damage occurred at the area in between to sensors S17 to S33. Comparing graphs of events **d** and **e** by event **c** in Figure 5 shows that the maximum NCD value moved from sensor S32 to S48 and values at sensors S17 and S56 also increased. Moreover, at other time instances **d** and **e**, some small changes at sensors S25 and S33 can be observed. Combining all the results in Figure 5 it can be observed that damage took place between 170 to 270 seconds in time at the area between S24, and S32 but it was closer to S32 around 270 sec. Afterward, the damage propagated to sensor S40 and reached S48. The region affected by damage is enclosed by sensors S24, S48, S17 and S41 up to 610 sec.

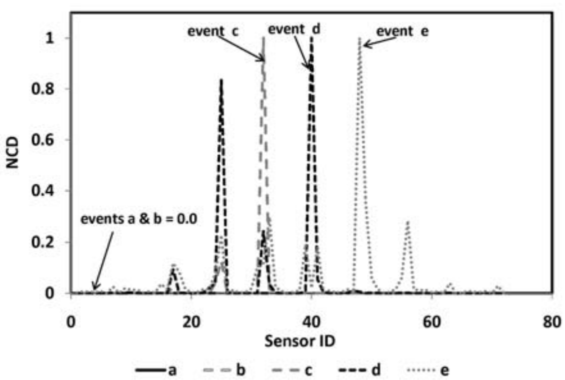

Figure 5. Results NCD for window size 50 sec and time shift 40 sec at events a, b, c, d and e.

The window size definitely affects the above results. Smaller window size reduces the amount of data processing at any given time. For example, in this case study if the window size assumed to be less than 10 sec, all the data will be well correlated to each other in each window. This is because the very small window size will enforce correlation between strain signals. On the other hand, if a relatively large window size is used, large data storage and data processing will be required. The time shift of the window is another critical parameter. It is the time that data is not processed or there is a shift in analysis. Therefore, events occurring during the time shift period will be missed. It is suggested to pick the time shift less than the window size causing an overlap between windows and hence prevent missing any event. If the time shift is picked larger than window size, some data will be definitely missed. In the following sections the significance of these two parameters (window size) and (time shift) are further examined.

4.1 Window size effect

Two different window sizes, 10 sec and 30 sec, were examined and compared to the original case of 50 sec presented above. For all of the cases, the time shift was fixed at 15 sec in order to minimize its effect for all three cases. Figure 6 and Figure 7 show the NCD metric for 10 and 30 sec window sizes. Figure 8 shows NCD metric for 50 sec window with 15 sec time shift. It is important to note that by considering a window size of 10 sec and a time shift of 15 sec, the time of correlation analysis is less than or equal to each step of load protocol and crack propagation protocol. Therefore, events **c**, **d** and **e** are missed since they are all correlated in the analysis time period. The proposed method not only will be unable to identify the correct crack occurrence location but will also be unable to provide damage tracking. It is obvious that a window size relatively small compared with the time steps of damage propagation will not be capable of realizing damage events. In addition, it is noticeable that in a time shift relatively larger compared with the window size, a considerable amount of data will be lost.

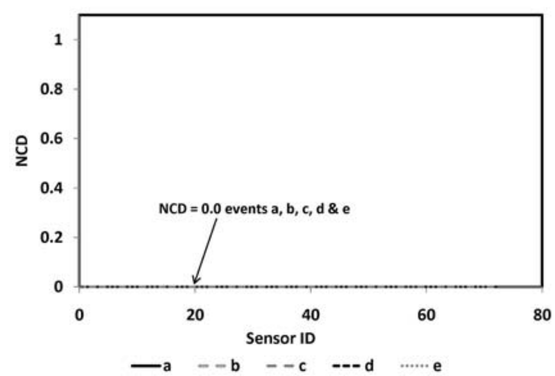

Figure 6. Results NCD for window size 10 sec and time shift 15 sec at events a, b, c, d and e.

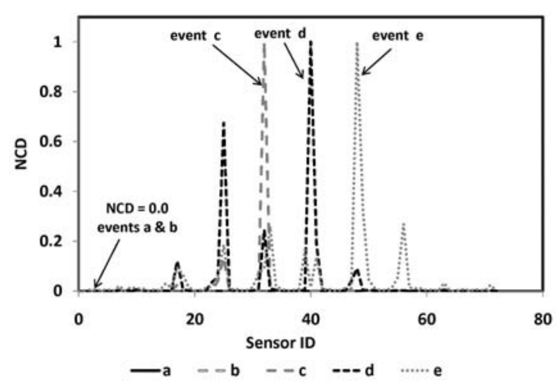

Figure 7. Results NCD for window size 30 sec and time shift 15 sec at events a, b, c, d and e.

Results for the 30 sec window size were better than the 10 sec window size. Trends similar to those observed in 50 sec window size (Figure 5) were observed. Damage can be identified to occur near S24 and S32 and propagates toward S40 and S48. Furthermore, the significance of the crack on the strain measurements above the crack location (S17, S25 and S33) can also be detected. The choice of a time shift smaller than the window size seems essential to obtain good results. Results for the 50 sec window size with 15 sec time shift (Figure 8) were similar to those observed in Figure 5. It is obvious that reducing the time shift to 15 sec will increase the computation overhead compared to the case presented in Figure 5.

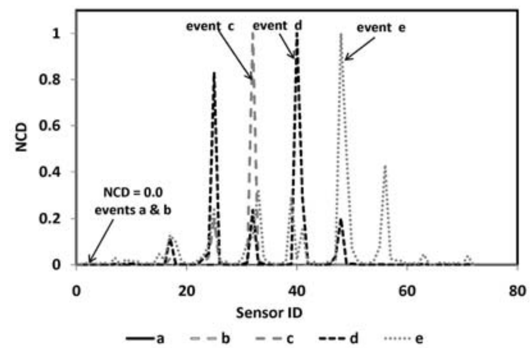

Figure 8. Results NCD for window size 50 sec and time shift 15 sec at events a, b, c, d and e.

4.2 *Window shift effect*

To further examine the effect of window shift, two time shifts of 20 and 30 sec were used with the window size of 50 sec. The two time shifts represent 40% and 60% of the window size. Figure 9 and Figure 10 show the NCD metric for 20 and 30 sec time shifts respectively. Results shown in Figure 9 are similar to results shown in Figure 5.

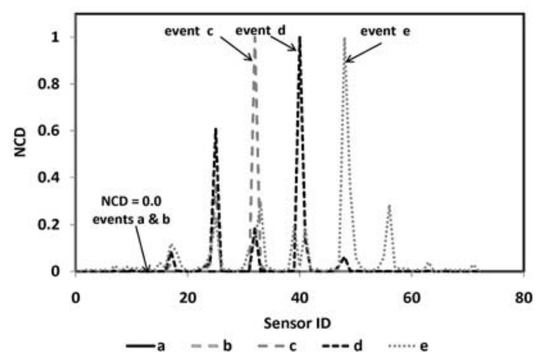

Figure 9. Results NCD for window size 50 sec and time shift 20 sec at events a, b, c, d and e.

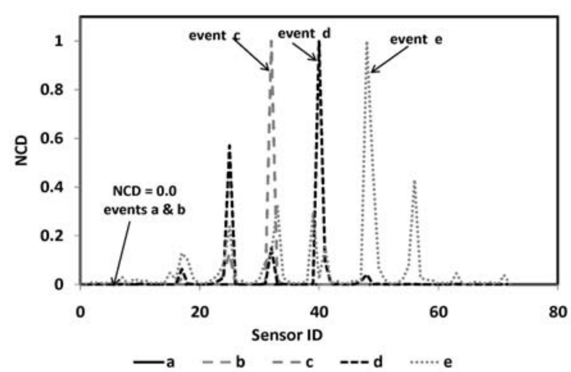

Figure 10. Results NCD for window size 50 sec and time shift 30 sec at events a, b, c, d and e.

When a time shift close to 60% of the window size is used (Figure 10), a smaller amount of computation will be needed. The results prove the fact that a time shift close to 60% of the window size shall be useful in reducing the computational overhead while ensuring the system will not miss any major events. Such time shift seems able to provide the necessary overlap to identify and track all damage events in the pipeline.

5 CONCLUSIONS

It is evident that damage can be identified and tracked by computing correlation dissimilarity between a large number of sensors forming a sensor network. In order to reduce the computation overhead and the amount of data required, the proposed method uses a time window approach. Despite this reduction in data, the method was able to robustly identify damage occurrence and region, and track damage propagation as well. Key parameters in the proposed approach are the time window size and time shift. A relatively small time window size is needed for efficient damage detection. It was demonstrated that time shift equals to 40-60% of the time window size is desirable for efficient damage tracking.

A smart sensor network can be developed using the above approach. For instance a smart sensor network can start with operating 20% of the sensors only. After correlation dissimilarity is observed, more sensors in the vicinity of the damage region shall be enabled with a narrower time window and shorter time shift. This sensor network shall be able to detect damage occurrence and track damage propagation efficiently. The proposed method can provide a valuable tool for enhancing the monitoring process of cross-country oil and gas pipelines. Successful developments of the proposed method will have a broader impact on the oil and gas pipeline industry with the ability to extend the service life of pipelines by focusing maintenance resources to areas of potential damage. Experimental investigation on using the proposed method for corrosion damage detection in oil and gas pipeline is on-going.

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