Sparse representation of ultrasonic guided-waves for robust damage detection in pipelines under varying environmental and operational conditions

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SUMMARY

The challenges of guided-wave based structural health monitoring can be discussed under three headings: (a) multiple modes, (b) multi-path reflections, and (c) sensitivity to environmental and operational conditions (EOCs). The objective of this paper is to develop damage detection methods that simplify guided-wave signals while retaining damage information and have low sensitivity to EOC variations. A supervised method is proposed for damage detection. The detection performance is maximized, by imposing a sparsity constraint on the signals. This paper reports a diverse set of laboratory and field experiments validating the extent to which EOC variations, as well as damage characteristics can influence the discriminatory power of the damage-sensitive features. The laboratory setup includes an aluminum pipe with temperature varying between 24 and 38 °C. The method is further validated using an operational hot water supply piping system of different size and configuration than the one used in the laboratory, which operates under noisy environment, with constantly varying flow rate, temperature, and inner pressure. Moreover, the proposed method is used to detect occurrence of consecutive actual damages, namely, a crack and a mass loss as small as 10% and 8% of the wall thickness, respectively. The validation results suggest that a simple binary-labeled training data (i.e., undamaged/damaged), obtained under a limited range of EOCs, are sufficient for the proposed method. That is, the detection method does not require prior knowledge about the characteristics of the damage (e.g., size, type, and location), and/or a training dataset that is obtained from a wide range of EOCs. Copyright © 2015 John Wiley & Sons, Ltd.

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KEY WORDS: structural health monitoring; pipeline monitoring; ultrasonic guided-waves; damage detection; sparse representation; online monitoring

1. INTRODUCTION

Reliable prediction of degradation in structural integrity of pipelines is important to ensure delivery of expected services, to decrease environmental/human safety risks associated with missed or delayed detection of damages, and to reduce cost/time of repair and handling of the impacts of incidents. According to the Department of Transportation, Pipeline and Hazardous Materials Safety Administration report [1], 10,613 incidents have been reported in the USA between 1994 and 2013, which translates to an average annual rate of 531 incidents, 19 fatalities, 71 injuries, property damage of more than $308.8 million, and more than 133,000 barrels of spilled hazardous liquid, including crude oil. Recent advances in sensing and computing, however, do not seem to have substantial impact on improving these statistics. For example, only 28% of the reported incidents in the instrumented pipes are identified by data acquisition and testing systems between 2010 and 2012 [2]. According to the study conducted

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in 2013 at the National Oceanic and Atmospheric Administration and the University of Colorado [3], the ratio of the leakage to the average hourly natural gas production can reach up to 14% in certain locations. Another example of pipeline application affected by missed or delayed detection of damages is water transmission. As reported by the American Water Works Association, 237,600 breaks per year occur in the USA, which lead to an approximate $2.8 million loss in annual revenue [4]. One of the main causes of these losses is leakage because of different types of damages in pipes [5].

Data acquisition and sensing systems, however, are valuable for continual monitoring and for cases where accessing pipeline is not feasible [2]. Therefore, research is needed to improve the reliability of these systems. Difficulties, cost, and safety risks associated with interrupting the operation and accessing different portions of pipelines make non-destructive evaluation (NDE) techniques attractive for pipeline monitoring [6]. In particular, during the past decade, ultrasonic guided-waves have been widely considered for NDE of pipelines by researchers and service providers in different applications, for example, [7–10]. This is due to many favorable characteristics of guided-waves compared with conventional NDE methods. The advantages include full coverage of the thickness and surface of the pipe, long travel distances without significant energy loss, and high sensitivity to different sizes/types of damage. In addition, guided-wave based NDE systems can operate with small number of low-cost, low-power transducers, making their implementation efficient [6,11–15].

However, despite many advantages, real-world application of guided-waves for pipeline NDE is still quite limited [6]. The challenges can be discussed under three headings: (a) multiple modes, (b) multi-path reflections, and (c) sensitivity to environmental and operational conditions (EOCs).

In this paper, we propose a method to address these challenges through simplifying guided-wave signals while retaining damage information. A supervised method is proposed to extract a sparse subset of the guided-wave signals that contain optimal damage information for detection purposes. Ideally, if the arrivals scattered from damage are completely retrieved from the recorded signals, they could be used for damage detection. However, studies have shown that variation of EOCs affects scatter signals so that damage information is suppressed by the EOC effects [16–19]. The fundamental assumption for the development of the proposed method is that, by maximizing the detection performance while imposing sparsity constraint, in the extracted signals, the effects of damage are more dominant than the EOC effects. If true, this damage-sensitive subset can be used for damage detection rather than the complete scatter signal. This assumption, as well as different aspects of the proposed method, is validated later in this paper.

In the following sections, first, an overview of the problem background is provided. Then, the proposed method is discussed. Next, the results of an extensive set of laboratory experiments are summarized, along with analytical discussions on the findings. Assumptions and damage detection performance of the proposed method are validated using data recorded from a pipeline operating under wide range of EOCs, as well as data from a pipe with a small crack. Finally, concluding remarks and future work are discussed.

2. RESEARCH BACKGROUND

This section provides an overview of the open challenges in applying guided-waves for pipeline SHM, as well as a review of the studies to date addressing these issues.

2.1. Multiple modes

Generally, three types of modes can be excited in a pipe-like structure: (a) longitudinal modes, L(0, m), (b) torsional modes, T(0, m), and (c) flexural modes, F(n, m), m and n referring to wave orders and circumferential order of modes, respectively [11]. The presence of at least two modes at any given frequency is one of the factors making the guided-wave problems complex as compared with bulk waves [14]. Another complexity arises from the dispersive nature of guided-waves [11]. That is, propagation velocities of different wave modes are themselves functions of frequency.

To address these challenges, one of the most widely considered solutions is to excite limited number of modes in a non/less dispersive range by using either an array of transducers or multi-element
transducers, for example, [13,14]. Among all, axisymmetric modes, L(0,2) and T(0,1) are mostly used in practice, mainly because they are easier to be excited, and the acoustic field is relatively simple [7,14,20]. Studies such as [10,14,20–24] have shown that different wave modes are sensitive to different characteristics of the damage. Considering the fact that the geometry of a real damage in pipes can extend in any or all of the axial, radial, and circumferential directions, damage diagnostics based on single-mode excitation may lose the benefit of multiple modes. Moreover, mode conversions can still occur when the incident mode interferes with damage or other material such as flowing fluid [25]. That is, the excited non-dispersive mode can be converted to other mode(s) that may be dispersive. In addition, even in the case of successful single-mode excitation, multi-path reflections from structural features and/or damage, as well as the EOC effects, which will be discussed in the next sections, cause the guided-waves, traveling in an operating pipe, to be the result of superposition of multiple modes [18]. Other challenges include implementation difficulties/costs compared with simple broad-band multi-mode excitation transducers [20,24].

2.2. Multi-path reflections

Reflections from the features of the structure (e.g., boundaries, pipe welding, and damage), and their superposition, add to the complexity of guided-waves. A number of studies have worked on solutions to address the challenges of multi-path reflections. Many approaches rely on baseline-subtraction, for example, [17,26]. Ideally, baseline-subtraction will remove the background complexities that are due to structural features. However, such reference signals should be recorded under similar EOCs as the new signal, or the effects of the EOC variation need to be compensated. Among all, the effects of temperature have been widely studied [18,26–28]. Temperature effects on wave velocity are approximated as stretching/compressing of the signal. However, such stretching methods may successfully approximate only small ranges of temperature variation, that is, 0.5 to 1 °C, depending on the complexity of the structure and the number of propagating modes [18,29]. Moreover, other EOCs, such as fluid flow rate and inner pressure [19,30–32], can further degrade the performance of these methods.

A number of studies have employed methods based on time-frequency analysis to cope with the complexity of guided-waves [8,33–36]. One inherent limitation of most of these methods is the uncertainty principle, which means achieving high frequency resolution requires sacrificing time resolution, and vice versa [37]. This becomes even a bigger challenge in a multi-modal signal in which multiple modes with relatively similar characteristics are excited at a given frequency. Moreover, the majority of these methods strongly depend on the selection of parameters like mother wavelet and dictionary of atoms. It is also notable that the sensitivity of such parameters to EOC variations remains to be incorporated into the methods. Recently, Harley and Moura [38] developed a method for recovering a denoised signal by removing random noise and multi-path signal interference for Lamb waves in plates, using reference signals obtained from a network of transducers. However, further developments are still needed to examine the performance of this method when the EOCs of test and reference signals are different and when different reference signals are associated with different EOCs (e.g., non-uniform temperature change in the plate). In addition, relying on a network of transducers can be a challenge for certain NDE applications because it calls for wider spatial access to the structure. Finally, yet importantly, the disregarded multi-path reflections may include information regarding damage, as will be illustrated in this paper.

2.3. Sensitivity to environmental and operational conditions

Guided-wave based damage detection of pipelines becomes even more challenging when EOCs vary over time, for example, changes in temperature, flow rate of the fluid carried by the pipe, inner pressure, and interference with coupling material [16,17,19,28,39–41]. EOC effects range from generation of modes to changes in the wave velocity, changes in attenuation rate, and so on [25,27,42]. Such effects degrade the performance of damage diagnosis by masking and/or appearing as the changes caused by damage and introducing type I and II errors.

Many studies have investigated, both theoretically and experimentally, the effects of EOCs, such as temperature and coupling material, on guided-waves [25,27,28]. However, few studies have tried to
incorporate such effects into damage diagnosis approaches. These studies mainly include stretching of the reference signals to incorporate the effects of temperature on wave velocity of guided-waves into baseline-subtraction methods, for example, [18,26]. The challenges and limitations of such methods are briefly discussed in Section 2.2 and further illustrated in the authors’ other work [16].

During the past two decades, a number of researchers have utilized data analysis techniques to overcome some of the EOC challenges and enhance the application of guided-waves for damage diagnosis, for example, [30,43–45]. Statistical and signal processing techniques have shown high potential for extracting damage-sensitive features that are less sensitive to the particular EOCs considered. However, improvements are still needed to address limitations such as dependence on a network of transducers, reliance on a dictionary of atoms, case-specific tuning parameters, and linear decomposition of multi-modal signals whose bases may be related non-linearly (for more detailed discussion on this topic, please refer to the authors’ other work [16]).

3. METHOD

This section summarizes an overview of the proposed method, the motivations, and the assumptions behind it, and the criteria for evaluating its success in achieving the objectives of this research.

The complexity of guided-waves is rooted in three features discussed in chapter 2. The objective of this work is to overcome these challenges for damage detection of pipes, while addressing the limitations of the current approaches. That is, to develop methods that (a) simplify guided-wave signals, by retrieving damage information for detection purposes, without the need for prior knowledge about the damage characteristics (e.g., type, size, and location) and (b) have low sensitivity to EOC variations so that they can be extensible to diverse operation scenarios.

Figure 1 illustrates the application of the proposed method for continuous, online damage detection of a pipeline. The process consists of an initial training stage and the continuous monitoring stage. Different components of these stages are introduced in this section and experimentally examined in the next sections of this paper.

3.1. Overview of the sparse discriminant approach

Being reflected from any scatterers in the structure (e.g., welding, geometric boundaries, and damage), guided-waves in a medium travel through multiple paths. Depending on the wave velocities, travel
path, boundary conditions, and so on, these reflections will arrive to the receiver at different ranges of time throughout the sampling period. Any point in time will include different portions of these arrivals, either individually or as superposition of multiple arrivals. However, it is important to note that not all these arrivals contain significant damage information. Intuitively, an arrival that has only illuminated the undamaged section of the medium will not contain significant information regarding the damage (note: this is true only if the damage size is small enough that the physical properties of the medium such as rigidity and Young’s modulus are not changed significantly).

For example, considering a pipe with small wall thickness to diameter ratio [46], let Figure 2 be an unrolled view of the pipe, with a two-transducer pitch-catch setup, where excitation happens at point A, and arrivals are recorded at point B. Let the small circle at point C be the damage on the pipe, and the two ends of the pipe symbolize any scatterer in the pipe, such as welding and boundaries. Note that this figure is just a simple illustration and does not include all of the possible wave propagation paths.

In this schematic depiction (Figure 2), arrivals that have traveled through paths 1 to 4 (i.e., the paths that do not include point C) are not expected to contain significant information regarding damage. On the other hand, arrivals that have illuminated the damaged section of the pipe (i.e., paths 5 and 6 that include point C) may contain damage information. Any record during sampling period that contains part of these arrivals would include information regarding damage. However, the question is that in what subset of such records this information suppresses the irrelevant information and leads to optimal damage detection under varying EOCs?

3.1.1. Training stage. In this paper, we propose a method to extract a subspace of the time-trace of the signals. The idea is to find a discriminant vector in the time space of the signals so that the signals from damaged and undamaged pipes have different projections onto this vector. That is, this vector is located in a direction that the arrivals with significant damage information have distinguishable projections onto the vector.

As discussed in Section 2, when guided-waves are interfered by damage, their propagation characteristics may change in a number of ways, such as mode conversion, change in the phase/group velocities, multi-path reflections, and energy dissipation [47–49]. However, it is notable that the proposed method does not make any assumption regarding the nature of such interactions, but rather its goal is to extract a subset of the signal with optimal damage information, regardless of the physical phenomenon leading to such a subset.

As shown in equation (1), the coefficients of the discriminant vector \( \mathbf{X}^{n \times 1} \) are trained so that the projections of training signals \( \mathbf{Z}^{m_{tr} \times n} \) on \( \mathbf{X} \) are good predictors of the state of the pipe (i.e., \( Y_j = 1 \) for intact pipe and \( Y_j = -1 \) for pipe with structural abnormality). Let \( m_{tr} \) be the number of signals in the training dataset, including signals from both intact and damaged pipes, \( n \) be the length of the time-trace of the signals, and \( Y \) be the vector of state labels.

\[
\text{argmin}_{\mathbf{X}} \frac{1}{2} \| \mathbf{Z}^{m_{tr} \times n} \mathbf{X}^{n \times 1} - \mathbf{Y}^{m_{tr} \times 1} \|^2 \tag{1}
\]

In equation (1), if the sample points in the training signals are zero-meaned and normalized by standard deviation (i.e., standardize \( \mathbf{Z} \) in column), the magnitude of the coefficients in \( \mathbf{X} \) will reflect the significance of each of the \( n \) sample points in defining the state of the pipe.

Figure 2. A schematic unrolled view of a pipe, illustrating example wave propagation paths passing through undamaged (dashed arrows) and damaged (solid arrows) sections of a pipe.
At this point, it is notable that linear discriminant analysis (LDA) is another method used in pattern recognition to find such linear subspaces that separate different classes. However, as discussed in the authors’ previous work [19], LDA fails to find such a discriminant subspace for guided-waves when using the original time-trace of the signals. It is mainly because LDA assumes that the variables are normally distributed. However, as we will further discuss in Section 5 of this paper, guided-wave signals do not satisfy this assumption.

Although the method proposed in equation (1) does not assume any particular distribution for the $n$ sample points, its performance can still be affected by the curse of dimensionality. If the number of training observations ($m_{tr}$, slow time recording duration) is smaller than the number of predictor variables, $n$ (thousands of sample points in a signal, i.e., fast time recording duration), the extracted coefficients in the $X$ vector may not be statistically significant. Satisfying the $m_{tr} > n$ condition is neither practical nor favorable. Therefore, the dimensionality of the problem needs to be reduced.

Common methods for dimensionality reduction in time domain, such as down-sampling and filtering, would be vulnerable to remove useful information, or would require prior knowledge about the propagating wave modes, wave reflection scenarios, damage properties, and so on. The method proposed in this paper assumes that a sparse subset of a guided-wave signal will contain sufficient damage information for optimal damage detection. This assumption is in line with the discussions provided earlier in this section (Figure 2) and will be verified further in the validation section of this paper (i.e., Section 5).

Therefore, our suggestion is to penalize the magnitude of the coefficients that correspond to the variables with less contribution in predicting the class labels $Y$ (using a regularization scalar $\xi$ in equation (2)). Ideally, this can be carried out by penalizing the $\ell^0$ - norm of the $X$ vector ($X_0$). That is, forcing the optimization algorithm to assign zero coefficients to the variables with insignificant contribution in reconstructing $Y$ and non-zero otherwise. However, finding the solution for such a problem is NP-hard (non-deterministic polynomial-time hard) [50]. An approximate solution to this problem can be found by penalizing $\ell^1$ - norm of the $X$ vector instead of $\ell^0$ - norm [51]. This forces a sparse solution for the $X$ vector so that variables with smaller contribution in defining the state of the pipe will be assigned close-to-zero coefficients.

$$\arg\min_{Z \in \mathbb{R}^{m_{tr} \times n \times 1}} X^{n \times 1} - Y_{m_{tr} \times 1} + \xi X^{n \times 1}$$  
\hspace{4cm} (2)

Finding a sparse discriminant (SD) vector ($X$) in the time space of the signals addresses the complexity challenges of guided-waves discussed in Section 2 (through the second part of equation (2)) while retaining damage information for detection purpose (through the first part of equation (2)). The question that remained to be answered is whether the effects of damage in the extracted sparse subset of the signals suppress the EOC effects under different scenarios.

It is notable that equation (2) is based on the Lasso optimization principle, which is different than ordinary regularization methods such as Tikhonov regularization, because Lasso minimizes $\ell^1$ - norm instead of Euclidean norm, and in this way, the sparsity is imposed to the solution. For the experiments reported in this paper, the Matlab convex optimization package (i.e., cvx [52]) is used to solve the Lasso optimization problem formulated in equation (2). The regularization scalar $\xi$ can be selected so that the sparsity is maximized, while the training error is minimized.

3.1.2. Monitoring stage. The proposed SD method can be used to extract damage-sensitive features for damage detection during the monitoring stage depicted in Figure 1. Projecting a test signal $d_j$ ($\rightarrow d_j \in \mathbb{R}^n$, $j = 1, \ldots, m_{tr}$) on the trained $X$ vector will result in a scalar $3$ representing the predicted class label for the signal (ideally, $\hat{Y}_j = 1$ for intact pipe and $\hat{Y}_j = -1$ for pipes with structural abnormalities).

$$\hat{Y}^{m_{tr} \times 1} = D^{m_{tr} \times n} X^{n \times 1}$$  
\hspace{4cm} (3)

3.2. Evaluation criteria for the sparse discriminant approach

3.2.1. Detection performance. The EOC variations, along with other parameters that may vary between training and monitoring stages (i.e., damage characteristics and location), may cause the values of $\hat{Y}$s to deviate from exact $1$ and $-1$. The first objective to be evaluated is the extent to
which the extracted SD vector and hence the damage-sensitive features (\(\hat{Y}\)'s in equation (3)) retain damage information.

In order to examine the performance of these features in discriminating damaged and undamaged pipes, three metrics are used in this paper: (a) detection accuracy (i.e., the ratio of the number of correctly labeled damaged and undamaged observations to the total number of test observations), (b) false negative rate (i.e., FNR, the ratio of the number of incorrectly labeled damaged observations to the total number of damaged observations), and (c) false positive rate (i.e., FPR, the ratio of the number of incorrectly labeled undamaged observations to the total number of undamaged observations).

At this point, it is worth emphasizing that the SD method is not a detection algorithm but a feature extraction approach for damage detection. Therefore, a number of classification methods can be used to evaluate discriminatory power of the features. A simple method is to cluster the predicted labels. In this paper, a two-class \(k\)-means clustering is used for this purpose. The \(k\)-means is a simple unsupervised partitioning method in which each observation is assigned to one of the clusters. The \(k\)-means clustering is used because it is an unsupervised method that do not need training data; therefore, its performance will be independent from training parameters. After clustering different test observations, we use some heuristic process to calculate the three aforementioned detection metrics. If more than 50% of the observations in a cluster are from the same class (e.g., intact), the cluster is considered to be representative of that particular class. Then, accuracy, FPR, and FNR can be calculated. It is also notable that \(k\)-means algorithm can be very sensitive to the initial values of cluster centroids. The results reported in this paper are the average of different folds of cross-validations. We do not optimize the initial centroid values, which suggests that the findings in this paper can be even further improved if more sophisticated classifiers are applied.

3.2.2. Sparsity. In order to quantify the simplicity of the extracted sparse signals, for different scenarios, that is, to verify the sparsity assumption of the SD method, we introduce a metric, sparsity ratio (Sr), which is the ratio of the number of zero coefficients to the total length of the signal \(n\) (equation (4)). It is notable that, using the \(l^1\) norm of the \(X\) vector in equation (2), the values of the coefficients may never be absolute zero but rather may be very small. To handle this, any coefficient whose magnitude is smaller than the largest coefficient (i.e., \(x_{\text{max}}^{\text{noise}}\)) assigned to the initial part of the signal (i.e., before the first arrivals) is considered to be zero.

\[
Sr = \frac{\left\{ i \in \{1, 2, \ldots, n\} : |x_i| \leq x_{\text{max}}^{\text{noise}} \right\}}{n} \times 100
\]

3.2.3. Sensitivity to environmental and operational conditions. The second objective to be evaluated is low sensitivity of the SD method to EOC variations. To evaluate this, we examine the following: (a) detection performance, and Sr, as the SD method is trained at different EOCs, and (b) detection performance as the EOCs between test and training data vary. It is notable that for the laboratory experiments used to evaluate the SD method, temperature is the only varying environmental factor. However, the performance of the SD method is later validated using field data recorded from a pipeline operating under dynamic conditions with wide range of varying temperature, fluid flow rate, and inner pressure, among others.

4. EXPERIMENTAL INVESTIGATION

4.1. Experimental setup

For controlling the temperature variations, the authors designed and built a setup in laboratory, which consists of a 1.5 × 1.5 m box made of insulation foam, with 50.8 mm thickness, \(R\)-value of 10, and maximum operation temperature of 74 °C. Figure 3 shows this setup. The interior temperature of the box is maintained within ±0.5 °C of the specified set point, using a thermostatically controlled electric space heater. In this paper, we use a 1.2-m, Schedule 40 aluminum pipe segment, with 101.6 mm outer diameter and 5.8 mm thickness. Pitch-catch records are obtained using two Lead Zirconate Titanate transducers that are coupled to the outer surface of the pipe. Temperature readings at three points throughout the 1.2-m length of the pipe show a uniform distribution of temperature along the pipe.
segment. In order to excite guided-waves that are close to Lamb waves in plates, the following criteria should be satisfied \([53,54]\): \(r \gg h, \lambda \gg h\), and \(r \gg \lambda\), where \(r\), \(h\), and \(\lambda\) are pipe radius, pipe thickness, and wavelength, respectively. Therefore, for the aluminum pipe segment used in the laboratory, the desirable range for excitation frequency is between \(~125\) and \(~1000\) KHz. In all the following laboratory experiments, we transmitted 0.1 ms Gaussian excitation signal with central frequency of 250 KHz and recorded 10 ms of ultrasonic signals, with sampling frequency of 10 MHz, at the receiver. Structural abnormalities are simulated by masses of different sizes, grease-coupled to the outer surface of the pipe.

Figure 4 shows the four different layouts for the aluminum pipe segment that are used in the experiments throughout this paper. In Figure 4(a) and (b), transducers are located as far as 1.0 m from each other. We refer to this transducer layout as layout #1. In Figure 4(c) and (d), on the other hand, the transducers are as close as one-third of the length of the pipe (0.4 m). We refer to this transducer layout as layout #2. The perpendicular distance of the mass to the undamaged path A-B in Figure 4(b) and (d) is two times the distance in Figure 4(a) and (c). We refer to the closer mass location (Figure 4(a) and (c)) as Loc1, and the further location (Figure 4(b) and (d)) as Loc2. For all the four layouts, data
are collected using two different sizes of mass to reflect different sizes and characteristics of structural abnormalities. The small mass is a light aluminum bar with 1.2-cm height and 1.2-cm diameter, and the bigger mass is a heavier bar with 7.6-cm height and 5.08-cm diameter. For simplicity, throughout this paper, these eight layouts will be referred to as [1 or 2]-[Loc1 or Loc2]-[sml or big], where the first number indicates the transducer layout, the second symbol refers to the location of the mass, and the third symbol indicates the size of the mass.

4.2. Temperature variation

4.2.1. Detection performance of damage-sensitive features. As shown in equation (3), the trained sparse coefficients can be used to predict class labels of new observations. In this section, we examine whether, for different temperature variation scenarios, the class labels predicted by SD method can be used as features to detect the structural abnormalities.

In order to investigate the effect of temperature difference ($\Delta T$) between training and test datasets, 5500 observations from intact and 5500 observations from the pipe with abnormality are measured, at temperatures ranging from 24 to 32 °C, from 1-Loc1-sml pipe layout (Figure 4(a)). A total of 55 datasets, each consisting of 100 intact and 100 damaged signals are created. The sparse coefficients are trained and tested with each of these datasets at a time.

As mentioned before, the focus of this paper is not to propose a particular classifier for damage detection but to propose an approach for extracting damage-sensitive features for damage detection. The discriminatory power of these features ($\hat{Y}$s) can be tested using various classification methods. In this paper, a simple $k$-means clustering method is found to be satisfactory to separate the predicted test labels.

A total of 6050 training/test scenarios are examined (55 training datasets, each tested by 55 test datasets, through two-fold cross-validation (CV)). The $ij$th pixel in Figure 5(a) is the average accuracy of two-fold CV for the $i$th testing dataset with temperature $T_i$ and the $j$th training dataset with temperature $T_j$. As can be seen in this figure, for the majority of the scenarios, two classes are perfectly separated (detection accuracy is 100%). However, expectedly, detection performance drops slightly as $\Delta T$ between training and testing increases (the lower right and upper left corners of the figure). That is, the extracted sparse vectors become less representative of testing data as $\Delta T$ increases. The FPRs and FNRs are below 10% for 97% of the scenarios. Figure 5(b) shows the ROC-curves (receiver operating characteristic) for different cases in which training and test temperatures vary between 0.0 and 8.0 °C. For almost all these cases, these curves are far from the 45° diagonal of the ROC curve, suggesting high sensitivity of the test (TPR) even with the drop in specificity (1-FPR). These results imply that, not only the predicted labels ($\hat{Y}$s) are significantly damage-sensitive, but also the separation between $\hat{Y}$s of two classes has low sensitivity to $\Delta T$ (i.e., two classes can still be separated for large ranges

Figure 5. (a) Average detection accuracy of two-fold cross-validation, for different training/test temperature combinations (24 °C ≤ $T$ ≤ 38 °C), using the class labels predicted by sparse discriminant method ($\hat{Y}$s) as the only damage-sensitive feature for clustering. (b) ROC-curves for training/test scenarios with 0 °C ≤ $T$ ≤ 8 °C. $T_{tr}$, training temperature; $T_{tst}$, test temperature.
of \( \Delta T \)ss). Table I summarizes the average detection statistics for two-fold CV of all 3025 training/test combinations with different \( \Delta T \) scenarios.

It is useful to have a closer look at the temperature effects on the predicted class labels. The distinction between intact and damaged observations is related to the distance between \( \hat{Y} \)s in two classes. For each training/test combination, Figure 6 shows the change in the distance between average predicted labels for intact and damaged test observations, as a ratio of the standard deviation of the predicted labels for intact observations \( (\text{dist} = \frac{\bar{Y}_{\text{int}} - \bar{Y}_{\text{dmg}}}{\sigma_{\hat{Y}_{\text{int}}}}) \). The brighter colors indicate larger distance between the labels and hence, clearer distinction between the two classes. These distances can become as large as 350 times the \( \sigma_{\hat{Y}_{\text{int}}} \) and for the worst training/test scenario, as low as two times the \( \sigma_{\hat{Y}_{\text{int}}} \). Expectedly, the distinction between predicted labels degrades as the \( \Delta T \) increases (i.e., moving further from diagonal of the matrix in Figure 6). The wider dark region in the lower triangle of the figure, compared with the upper side, implies that the degradation in the distinction between the class labels may also be sensitive to training temperature in addition to \( \Delta T \). Large \( \text{dist} \) values for the majority of the scenarios implies that the class labels predicted by SD method can perform reasonably even at large \( \Delta T \)s (up to 8 °C in this experiment).

4.2.2. Online damage detection. Low temperature sensitivity of the predicted class labels makes them attractive for online damage detection of pipelines. The state of a pipe operating under varying temperatures can be predicted as the new observations are streamed (equation (3)). This implementation of the SD method is illustrated with an example in Figure 7. In this example, training data include 50 intact and 50 damaged observations, all measured at 26°C, from the 1-Loc1-sml layout. Test dataset includes 550 observations from intact pipe, and 550 observations from the 1-Loc1-sml pipe, in which the abnormality is simulated by introducing a small mass. As can be seen in Figure 7(a), temperatures of the test observations can differ significantly from the training temperature \( (-4°C \leq \Delta T \leq +5°C) \). Figure 7(b) shows the correlation between each test signal and the average training intact signal. No distinguishable pattern in the correlations of intact versus damaged test signals is observed.

Table I. Average statistics of twofold CV, reflecting the detection performance of class labels predicted by SD method \((\hat{Y} \)s), for a total of 3025 training/test scenarios given in Figure 5.

<table>
<thead>
<tr>
<th>Average detection accuracy (%)</th>
<th>Average FPR (%)</th>
<th>Average FNR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>99.0</td>
<td>1.0</td>
<td>1.4</td>
</tr>
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</table>

CV, cross-validation; SD, sparse discriminant; FPR, false positive rate; FNR, false negative rate.

Figure 6. Variation of the distance between predicted labels for intact and damaged test observations at different training/test temperature scenarios. \( T_{\text{tr}} \), training temperature; \( T_{\text{test}} \), test temperature; \( \bar{Y}_{\text{int}} \), average predicted labels for intact test observations; \( \bar{Y}_{\text{dmg}} \), average predicted labels for damaged test observations; \( \sigma_{\hat{Y}_{\text{int}}} \), standard deviation of the predicted labels for intact test observations.
The online detection discussed here could be performed by updating the training dataset as the test observations are streamed. However, in this paper, in order to investigate the performance of the SD method when the EOCs are different for test and training data, the training dataset, and thus the calculated $X$ vector, are not updated. In other words, the online monitoring implementation reported in this paper is not adaptive.

To quantify the detection performance of the predicted labels ($\hat{Y}$s) for online monitoring, a simple detection algorithm is used. First, predicted labels of the test observations are averaged with a window of 20 records, which results in the values given in Figure 7(c). It is notable that the observations are recorded in 1-min intervals. When the distance between the label of the $j$th observation ($\hat{Y}_j$) and the average of the labels in the window before the $j$th observation ($\bar{\hat{Y}}_{j-20}$ to $\bar{\hat{Y}}_{j-1}$) is larger than 10 times the standard deviation of the labels in the window, occurrence of damage is detected ($\Delta \hat{Y} > 10\sigma$). This approach can be further improved by using the results given in Figure 6. That is, adjusting the standard deviation threshold based on the $\Delta T$ between the monitored signal and training data.

Table II summarizes the online monitoring results, when SD method is trained at different temperatures, ranging from 26 to 32 °C. The test dataset includes a total of 1220 intact and damaged signals at wide range of $\Delta T$s. In all these cases, occurrence of damage is detected, with an accuracy of above 99%. It is notable that the detection statistics of the simple algorithm explained earlier ($\Delta \hat{Y} > 10\sigma$) may vary depending on the selected window size and/or the $\sigma$ threshold. While the results given in Table II prove the concept, the online detection performance can be improved even further if more sophisticated approaches are used for the detection of the divergence in values of $\hat{Y}$s.

### 4.2.3. Physical interpretation of sparse coefficients.

High detection performance of the SD method for wide range of temperature variations implies that, for different temperatures, the time-location of the

<table>
<thead>
<tr>
<th>Training temperature (°C)</th>
<th>Range of $\Delta T$</th>
<th>Delay in detection (no. of observations)</th>
<th>Detection accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>26</td>
<td>$-2^\circ C \leq \Delta T \leq 13^\circ C$</td>
<td>9</td>
<td>99.2</td>
</tr>
<tr>
<td>27</td>
<td>$-3^\circ C \leq \Delta T \leq 12^\circ C$</td>
<td>2</td>
<td>99.8</td>
</tr>
<tr>
<td>28</td>
<td>$-4^\circ C \leq \Delta T \leq 11^\circ C$</td>
<td>6</td>
<td>99.5</td>
</tr>
<tr>
<td>29</td>
<td>$-5^\circ C \leq \Delta T \leq 10^\circ C$</td>
<td>2</td>
<td>99.8</td>
</tr>
<tr>
<td>30</td>
<td>$-6^\circ C \leq \Delta T \leq 9^\circ C$</td>
<td>6</td>
<td>99.5</td>
</tr>
<tr>
<td>31</td>
<td>$-7^\circ C \leq \Delta T \leq 8^\circ C$</td>
<td>3</td>
<td>99.7</td>
</tr>
<tr>
<td>32</td>
<td>$-8^\circ C \leq \Delta T \leq 7^\circ C$</td>
<td>6</td>
<td>99.5</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>4.8</td>
<td>99.5</td>
</tr>
</tbody>
</table>

1-loc1-sml layout is used.
Test data includes 610 intact and 610 damaged observations, recorded in 1-min intervals.
non-zero sparse coefficients do not vary significantly. That is, for the temperature range that is considered in this paper, and the pipe layout used in the experiments earlier (1-Loc1-sml, Figure 4(a)), the time-locations of the sample points containing dominant damage information fall around the same region of the signals’ time-trace. The change in the pipe layout, including location of transducers/damage and size of the damage, may affect the time-location of the sparse coefficients and therefore, affect the performance of the SD method. Effects of damage location and size will be discussed in detail in the next sections of this paper. In this section, however, we explain the physical meaning of the extracted sparse coefficients, for different temperatures.

Let $x_i'$ be the sparse coefficient corresponding to the $i$th sample point in time ($i \in \{1, \ldots, n\}$), when SD algorithm is trained with the $j$th dataset, at temperature $T_j$ ($j \in \{1, \ldots, N\}$). The average magnitude of the sparse coefficients at each point of time $i$ is obtained by equation (5):

$$\bar{x}_i = \frac{1}{N} \sum_{j=1}^{N} |x_i'| : i \in \{1, \ldots, n\} \land j \in \{1, \ldots, N\}$$

Next, the $\bar{x}_i$ is normalized by the standard deviation of $|x_i|$ values for all $N$ training datasets ($\sigma_i$). This results in standardized mean value of coefficients at point $i$:

$$\bar{x}_i = \frac{x_i}{\sigma_i} : i \in \{1, \ldots, n\}$$

The SD algorithm (equation (2)) is trained at temperatures ranging from 24 to 32 °C. For the experiments in this section, the 2-Loc2-big layout illustrated in Figure 4(d) is used. The transducers are located further from the two ends of the pipe segment (at one-third of the pipe length) in order to make the first arrival path significantly shorter than the end reflection paths. In this layout, the shortest end reflection path (A-D-A-B) is three times longer than the shortest undamaged path (A-B). This will help the first arrivals to be more distinguishable from end reflections. In addition, the mass is located further from the transducers, that is, on the opposite side of the pipe so that the first arrivals from the undamaged and damaged paths can be better distinguished. Considering the dispersion curve of this pipe layout, the first arrival from damaged path (A-C-B) should be received at about 50 μs after the last arrival from undamaged path (A-B).

Figure 8 depicts $\bar{x}_i$ values (equation (6)) for a total of $N=30$ training datasets ($24 °C \leq T_{tr} \leq 32 °C$), from 2-Loc2-big pipe layout. PCDisp [55], an open source software for modeling guided-waves in cylindrical media, is used in this paper to calculate the first arrival times shown in Figure 8. Expectedly, the first arrivals from undamaged path are associated with smaller magnitudes of coefficients and/or with larger variance (smaller $\bar{x}_s$). It can also be seen that the first arrivals from the shortest damaged path are associated with the largest coefficients, and/or smallest variance, for all ranges of training temperatures. These findings are in agreement with the reasoning behind development of the SD method. That is, the arrivals that have illuminated the damaged section of the pipe may include more significant damage information. Interestingly, several sample points consisting of later arrivals are also associated with large coefficients, indicating their importance in defining the state of the pipe. Denoising methods that are based on removing multi-path reflections should be applied with caution because, as can be seen in Figure 8, multi-path reflections and later arrivals can contain significant damage information.

4.2.3. Evaluating the sparsity assumption. Generally, no significant correlation could be observed between sparsity ratio (equation (4)) and the temperature of the training dataset in our experiments. Table III summarizes the statistics for the sparsity ratios of training datasets recorded from 1-Loc1-sml pipe layout at $24 °C \leq T_{tr} \leq 38 °C$. The results show that, regardless of the temperature of the

Figure 8. Mean of sparse coefficients at all sample points in time, normalized with the standard deviation of the magnitudes (equation (6)), for $24 °C \leq T_{tr} \leq 32 °C$. First arrival times are calculated for the 2-Loc2-big pipe layout using PCDisp [55].

training dataset, the solution of equation (2) is sparse, which, as shown in Sections 4.2.1 and 4.2.2, leads to high detection performances.

4.3. Damage size and temperature variations

Considering a particular type of damage positioned in a particular location, the arrival time of the waves reflected from damage boundaries is determined by the distance of the boundaries to the transducers. The size and shape of the damage define the location of damage boundaries with respect to the transducers. For example, consider a case where the structural abnormality used for training is so large that the front and back edge reflections can be separated in time. Intuitively, the trained sparse coefficients in this case will not be a good representative for a test observation in which the damage is so small that the front and back edge reflections arrive around the same time and are mostly overlapped.

Wang et al. [10] have used the distinction between the reflections from damage edges to characterize the extent of the damage. Their approach, however, require the damage size to be large enough so that the front and end reflections are separable. For example, they show that, in order for the two damage edge reflections to be separable, minimum longitudinal extent of the damage should be around 86 and 170 mm, for 175 and 200 KHz excitations, respectively. These values correspond to 2.5 and 5 times the diameter and 4% and 8% of the length of the pipe segment used in Wang et al. [10]. Obviously, real-world pipeline monitoring applications require detection of defects much smaller than these ranges. This implies that, in realistic detection scenarios, the reflections from damage edges are expected to arrive around the same time and be highly overlapped. Therefore, the time locations of the coefficients trained with different sizes of damage will not vary significantly (assuming that the damages are of the same type and are located at the same point in pipe). In light of this, the hypothesis being tested in this section (H1) is for practical sizes of damage, the difference in damage size between training and test data will not adversely affect the detection performance of $\hat{Y}$s predicted by the SD method.

4.3.1. Detection performance of damage-sensitive features. To test H1 given earlier, the first set of experiments is to investigate detection performance of $\hat{Y}$s when the size of structural abnormality in training and test data is different. Two different sizes of mass are used to simulate the variation in the size of the structural abnormalities. As explained in Section 4.1, the height and diameter of the bigger mass are about six and four times bigger than the small mass, respectively. If H1 is verified for such a large difference, the findings can be safely expanded to smaller variations in the size of damages with similar characteristics as these experiments.

A total of 25 training datasets ($24^\circ C \leq T_{tr} \leq 38^\circ C$) are created. Each training dataset consists of 100 observations from intact pipe and 100 observations from pipe with small mass (1-Loc1-sml). Similarly, a total of 25 test datasets ($24^\circ C \leq T_{tst} \leq 33^\circ C$) are created. Each test dataset consists of 100 observations from intact pipe and 100 observations from pipe with big mass (1-Loc1-big). Sparse coefficients are found for all 25 training datasets, and tested with all 25 test datasets, using $k$-means with two-fold CV. This translates to a total of 1250 training/test scenarios. Table IV summarizes the average

<table>
<thead>
<tr>
<th>Range of temperature</th>
<th>Average Sr. (%)</th>
<th>Minimum Sr. (%)</th>
<th>Maximum Sr. (%)</th>
<th>Standard deviation (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$24^\circ C \leq T_{tr} \leq 38^\circ C$</td>
<td>90.0</td>
<td>60.0</td>
<td>99.7</td>
<td>10.0</td>
</tr>
</tbody>
</table>

Table IV. Average detection statistics for a total of 1250 training/test scenarios with different damage sizes and temperatures.

<table>
<thead>
<tr>
<th>Average detection accuracy (%)</th>
<th>Average FNR (%)</th>
<th>Average FPR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>99.0</td>
<td>1.0</td>
<td>0.9</td>
</tr>
</tbody>
</table>

FNR, false negative rate; FPR, false positive rate.
1-Loc1-sml layout with $25^\circ C \leq T_{tr} \leq 33^\circ C$ is used for training, and 1-Loc2-big with $25^\circ C \leq T_{tr} \leq 33^\circ C$ is used for testing.
4.3.2. Online damage detection. Table V summarizes the performance of $\hat{y}$s for online monitoring. Sparse coefficients are found using seven different training datasets, at temperatures ranging from 26 to 32 °C (one training dataset for each temperature), using small mass (1-Loc1-sml). Test dataset includes 610 signals from intact pipe, 610 signals from pipe with small damage (1-Loc1-sm1l), and 500 signals from pipe with big damage (1-Loc1-big). The temperatures of the test observations vary randomly between 24 and 39 °C. As can be inferred from Table V, although the sparse coefficients are calculated using only the pipe with small damage, the occurrence of both small and big damages can be detected, for a wide range of $\Delta T$s. This also suggests the potential of the SD method for detecting changes in the severity of damage.

4.4. Damage location and temperature variation

Difference in the location of damage in the pipe between training and test data is the third factor that may affect the performance of the SD method. Considering a particular type and size of damage, the position of the damage, with respect to the transducers, defines the arrival times of the waves reflected from damage. If damage locations in training and test data are so different that the arrival times from damage differ significantly, then the trained sparse coefficients may not be a good representative of the subset of the test signals with significant damage information. In this section, we examine the impacts of damage location on detection performance of the SD method.

Figure 9(a) shows an unrolled view of a pipe with small wall thickness-diameter ratio [46]. Let C be the damage in the pipe. Here, we assume that the damage is located somewhere between the two transducers A and B, and both transducers are at the same elevation of the pipe. $L_u$ is the monitoring range. The solid red arrows show example helical paths from transducer to damage and from damage to the receiver.

A helical path of order $n$ between two transducers located in horizontal distance of $l$ and vertical distance of $z$ can be obtained through equation (7) [47,48]:

$$l_n = \sqrt{l^2 + (z + 2\pi nr)^2}$$

(7)

The length of any damaged path in Figure 9(a) is the sum of the path from transducer A to the damage C ($L_d$), and the helical paths of different orders ($n$) from the damage to the receiver B ($L_{dn}^{hn}$). To calculate the helical paths $L_{dn}^{hn}$, damage can be considered as a virtual transducer, with $l = L_u - y$. Therefore, damaged paths for the general case shown in Figure 9(a) are obtained as follows:

$$L_d = L_d^y + L_{dn}^{hn} = \sqrt{(\pi r - x)^2 + y^2} + \sqrt{(L_u - y)^2 + (z + 2\pi nr)^2}$$

(8)

In any damage scenario, the shortest damaged path is of particular importance, because it defines the time of the first arrivals. For any damage location, the shortest helical path is $L_d^{h0}$, that is, when $n = 0,

Table V. Detection performance of $\hat{y}$s for online monitoring of pipes, when sizes of damage, as well as the temperatures of training and test datasets are different.

<table>
<thead>
<tr>
<th>Training temperature (°C)</th>
<th>Range of $\Delta T$</th>
<th>Delay in detection of small mass (no. of observations)</th>
<th>Delay in detection of big mass (no. of observations)</th>
</tr>
</thead>
<tbody>
<tr>
<td>26</td>
<td>$-2^\circ C \leq \Delta T \leq 13^\circ C$</td>
<td>10</td>
<td>6</td>
</tr>
<tr>
<td>27</td>
<td>$-3^\circ C \leq \Delta T \leq 12^\circ C$</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>28</td>
<td>$-4^\circ C \leq \Delta T \leq 11^\circ C$</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>29</td>
<td>$-5^\circ C \leq \Delta T \leq 10^\circ C$</td>
<td>3</td>
<td>7</td>
</tr>
<tr>
<td>30</td>
<td>$-6^\circ C \leq \Delta T \leq 9^\circ C$</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>31</td>
<td>$-7^\circ C \leq \Delta T \leq 8^\circ C$</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>32</td>
<td>$-8^\circ C \leq \Delta T \leq 7^\circ C$</td>
<td>14</td>
<td>0</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>6.5</td>
<td>5.3</td>
</tr>
</tbody>
</table>

1-loc1-sml pipe layout is used for training, and both 1-loc1-sml and 1-loc1-big layouts are used for testing. Observations are recorded in 1-min intervals.
and damage is located in the same elevation as the receiver (i.e., \(z = 0\)). Therefore, in Figure 9(a), the minimum helical path would happen when the damage is located somewhere on the AB path. In this case, the \(L_{sd}\) is also minimal. For example, if \(x = \pi r, y = L_u/2\) as shown in Figure 9(b), referring to equation (8), minimum damaged path is as follows:

\[
L_{\text{min}}^d = L_u
\]  

(9)

The maximum \(L_d\) can happen when damage is located in one of the pipe edges (i.e., \(x \in \{0, \pi r\}, y \in \{0, L_u\}, z = 2r\)). An example position is shown in Figure 9(c). Based on equation (8), possible \(L_{d}^{\text{max}}\) values are as follows:

\[
L_{d}^{\text{max}} = \begin{cases} 
\pi r + \sqrt{L_u^2 + 4r^2(1 + \pi n)^2}, & x = 0, y = 0 \\
\sqrt{\pi^2 r^2 + L_u^2 + 2r(1 + \pi n)}, & x = 0, y = L_u \\
\sqrt{L_u^2 + 4r^2(1 + \pi n)^2}, & x = \pi r, y = 0 \\
L_u + 2r(1 + \pi n), & x = \pi r, y = L_u
\end{cases}
\]  

(10)

As can be seen in equation (10), \(L_{d}^{\text{max}}\) depends on the monitoring range \(L_u\), radius of the pipe \(r\), and order of helical path \(n\) as a multiplier of \(r\). In practice, guided-waves are used for long ranges (up to hundreds of meters) [6,7,13]. That is, practical monitoring ranges are significantly larger, by several orders of magnitude, than the radius of typical pipes in different applications (\(L_u \gg r\)). For example, the radius of the largest schedule 40 pipe available is only about 0.3 m. If the monitoring range of this pipe is 100 m, \(L_u^2\) is more than 110,000 times larger than \(r^2\). Therefore, terms including \(r^2\) in the first three cases shown in equation (10) can be ignored. Note that the multiplier \(n\) needs to be very large (in this example, around 53) to compensate for such a huge difference between \(L_u^2\) and \(r^2\). This number will be even larger for a smaller radius. We assume that, for damage detection purpose, the arrivals from such large orders of helical paths can be ignored, because they will either be received after the sampling period or will be highly attenuated. After approximating the terms under square root in equation (10) with \(L_u\), \(L_{d}^{\text{max}}\) can be approximated with \(L_u\). Following the same logic, assuming that monitoring range is significantly larger than the pipe radius, \(L_{d}^{\text{max}}\) can be approximated with \(L_u\) that is, \(L_{d}^{\text{max}} \approx L_u\).

From the discussion earlier, it is concluded that \(L_{d}^{\text{min}} \approx L_{d}^{\text{max}} \approx L_u\). In other words, for practical ranges of monitoring, regardless of the location of damage, the shortest damaged paths will be almost equal to the monitoring range.

The arrival times, however, depend on the velocity of the waves propagating to and from the damage. The wave velocity can be affected by the nature of the interference of the waves with damage (e.g., mode conversion, velocity change, and energy dissipation), which is mainly dictated by the type and geometry of the damage [13,14,20–22,24]. However, in this section, the type and geometry of the damage is considered to be constant, and the only varying parameter between training and monitoring stages is the location of the damage.

Figure 9. Schematic unrolled view of a pipe used in deriving equations (7) and (8) to illustrate the effects of damage location on detection performance of the sparse discriminant method.
Therefore, the hypothesis to be tested in this section (H2) is for a particular type and geometry of damage, the difference between the location of the damage in training and monitoring stages does not significantly affect the detection performance of the SD method.

### 4.4.1. Detection performance of damage-sensitive features.

To test H2 with high contingency, the 2-Loc1-big and 2-Loc2-big pipe layouts are used for training and testing, respectively. In the 2-Loc1-big layout used for training, the shortest damaged path \((L_d + L_{dh})\) is very close to \(L_u\) \((L_d = 1.07L_u)\). However, in 2-Loc2-big layout used for testing, the \(L_d/L_u\) ratio is unrealistically large \((L_d = 1.28 L_u)\). This difference in the length of \(L_d\) will cause time-location of the scattered arrivals in training and test signals to be different and hence, will adversely affect the detection performance of the trained sparse coefficients. If H2 is verified for this extreme case, the findings can be safely expanded to smaller differences in damage location for damages of the same type and geometry. A total of 30 training and 30 test datasets are created, with temperatures ranging from 25 to 33 °C. This translates to a total of 900 training/test combinations with different damage locations, and various \(\Delta Ts\). Table VI summarizes the average detection statistics for 1800 scenarios, as a result of \(k\)-means clustering with two-fold CV. As expected, the significant difference in the lengths of \(L_d\) in the training and test pipes has slightly degraded the discriminatory power of damage-sensitive features compared with when only temperature (Table I) or temperature and damage size (Table IV) vary.

### 4.4.2. Online damage detection.

Table VII summarizes the performance of \(\hat{Y}\)s for online damage detection, using sparse coefficients trained by five different datasets, each for every temperature ranging from 25 to 30 °C. Each training dataset includes 200 intact observations and 200 observations from 2-Loc1-big pipe layout. Test dataset includes signals from 2-Loc2-big pipe layout, including 620 intact and 580 damaged observations. Despite the extreme scenario considered here regarding the difference in damage location \((L_d = 1.07L_u\) versus \(L_d = 1.28 L_u\)), detection performance of the SD method remains satisfactory, which verifies H2.

### 4.5. Damage size, damage location, and temperature variations

In this section, the discriminatory power of \(\hat{Y}\)s is investigated when all three factors, namely, temperature, damage size, and damage location, vary between training and test data. Table VIII summarizes

<table>
<thead>
<tr>
<th>Training temperature</th>
<th>Range of (\Delta T)</th>
<th>Delay in detection (no. of observations)</th>
<th>Detection accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>0 °C ≤ (\Delta T) ≤ 7 °C</td>
<td>11</td>
<td>99.0</td>
</tr>
<tr>
<td>26</td>
<td>−1 °C ≤ (\Delta T) ≤ 6 °C</td>
<td>13</td>
<td>98.9</td>
</tr>
<tr>
<td>28</td>
<td>−3 °C ≤ (\Delta T) ≤ 4 °C</td>
<td>15</td>
<td>98.7</td>
</tr>
<tr>
<td>29</td>
<td>−4 °C ≤ (\Delta T) ≤ 3 °C</td>
<td>13</td>
<td>98.9</td>
</tr>
<tr>
<td>30</td>
<td>−5 °C ≤ (\Delta T) ≤ 2 °C</td>
<td>25</td>
<td>97.9</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>15.4</td>
<td>98.7</td>
</tr>
</tbody>
</table>

\(2\text{-Loc1-big}\) pipe layout is used for training, and \(2\text{-Loc2-big}\) is used for testing. Observations are recorded in 1-min intervals.
the detection performance of the SD method for online detection implementation. Here, the sparse 
coefficients are trained using data from 2-Loc2-big pipe layout (big damage and \( L_d = 1.28 L_u \)) at 
temperatures ranging from 25 to 30 °C. Test data are randomly selected from a pool of observations recorded 
from 2-Loc1-sml pipe layout (small damage and \( L_d = 0.07 L_u \)), including 575 intact and 617 damaged 
observations. As reported in Table VIII, presence of damage can be detected with high accuracies. 
However, it is notable that the change in the severity of damage could not be detected in the majority 
of the scenarios.

5. VALIDATION

5.1. Field data from an operating pipeline

For validation of the SD method, the first set of data is obtained from a fully operational large-scale 
pressurized hot water piping system in the mechanical space of a campus building [41]. The characteristics 
of this test bed are completely different from the laboratory setup, which strengthen the generality 
of the validation. The mechanical space is 706 m² and is mechanically and electrically noisy. This 
piping system is operating continuously, and unlike the laboratory pipes, it is carrying water with varying 
temperature, flow rate, and pressure. Because of the periodic pumping of hot water, the flow rate 
continuously varies between 45.5 and 102 m³/h, and water temperature fluctuates from 38 to 60 °C. 
It is notable that the temperature variation for the laboratory experiments ranges from a minimum of 
24 °C to a maximum of 38 °C. Therefore, the types/ranges of EOC variation are completely different 
from the laboratory data used in the previous sections of this paper. The size and material properties 
of this pipeline are also different from the pipe segment used in the laboratory. This is a schedule 40 
steel pipe with 254-mm inner diameter and 9.27-mm wall thickness covered by fiberglass insulation 
(as opposed to the aluminum pipe with 5.8-mm thickness). Pairs of Lead Zirconate Titanate transducers 
are permanently mounted on the pipe’s exterior surface, 3 or 6 m apart from each other. These 
distances are 2.5–15 times longer than the 1.2- and 0.4-m ranges used in the laboratory. To simulate 
damage, a small aluminum bar (1.2 cm diameter and 1.2 cm height) is acoustically coupled to the 
surface of the pipe at one-third of the monitoring range. The pipe is excited with 0.1 ms broad-band 
Sinc signals with the frequency band of 100–300kHz. This translates to frequency-thickness rate of 
927–2781 kHz-mm as opposed to 1450kHz-mm in laboratory experiments. The received 10 ms of 
ultrasonic signals are sampled with sampling frequency of 10 MHz.

5.1.1. Sparsity assumption. In this section, we verify the sparsity assumption for addressing the curse 
of dimensionality brought about in equation (2). That is, we assume that a sparse subset of a guided-
wave signal contains optimal damage information for damage detection. 

The objective is to verify whether damage detection performance increases as the signals become 
sparser. For this purpose, the feature extraction method proposed by Liu et al. [56] is used, because 
it has shown high potential for damage detection of pipes under varying EOCs. In their proposed 
approach, singular value decomposition (SVD) is applied on guided-waves, and the projections of 
the signals on one of the left singular vectors are used as the damage-sensitive feature (for more details 
please refer to Liu et al. [56]).

Table VIII. Detection performance of \( \hat{Y} \)s for online monitoring of pipes, when temperature, damage size, and 
damage location in training and test data are different.

<table>
<thead>
<tr>
<th>Training temperature (°C)</th>
<th>Range of ( \Delta T )</th>
<th>Delay in detection (no. of observations)</th>
<th>Detection accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>( 0 ^{}\text{°}C \leq \Delta T \leq 7 ^{}\text{°}C )</td>
<td>19</td>
<td>98.4</td>
</tr>
<tr>
<td>26</td>
<td>( -1 ^{}\text{°}C \leq \Delta T \leq 6 ^{}\text{°}C )</td>
<td>23</td>
<td>98.0</td>
</tr>
<tr>
<td>28</td>
<td>( -3 ^{}\text{°}C \leq \Delta T \leq 4 ^{}\text{°}C )</td>
<td>52</td>
<td>95.6</td>
</tr>
<tr>
<td>29</td>
<td>( -4 ^{}\text{°}C \leq \Delta T \leq 3 ^{}\text{°}C )</td>
<td>28</td>
<td>97.6</td>
</tr>
<tr>
<td>31</td>
<td>( -6 ^{}\text{°}C \leq \Delta T \leq 1 ^{}\text{°}C )</td>
<td>19</td>
<td>98.4</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>28.2</td>
<td>97.6</td>
</tr>
</tbody>
</table>

2-Loc2-big is used for training, and 2-Loc1-sml is used for testing. Observations are recorded in 1-min intervals.
A subset of the field data described at the beginning of Section 5.1 is used here. Theoretically, increasing the value of the regularization parameter ($\xi$) in equation (2) will increase the sparsity of the solution. The SD algorithm is trained for different values of the regularization parameter $\xi$, with 0.01 increments. Because the results do not vary significantly for very large values of $\xi$, Figure 10 only reports the findings for $0 \leq \xi \leq 1$. The solid red line in Figure 10 shows the sparsity ratios (equation (4)) at different values of $\xi$. It can be seen that for $\xi$ values of up to around 0.2, a sharp increase in the sparsity is observed. After this point, the change in the sparsity becomes more gradual. This behavior implies that, after a certain point, increasing the sparsity while retaining enough damage information for prediction of class labels becomes more difficult.

Sparse test signals are obtained using the sparse coefficients trained with different $\xi$s. At each $\xi$, sparse test signals are the subset of the signals that correspond to non-zero sparse coefficients at that $\xi$. The dashed black line in Figure 10 shows the detection accuracy of the SVD method when applied to signals with different sparsities. As can be seen in this figure, applying the SVD method to the complete time-trace of signals (i.e., zero sparsity, $\xi = 0$), leads to a detection accuracy of around 47%. As we increase the sparsity of the test signals, detection accuracies improve and reach their maximum when the sparsity ratios are around 90% to 97%. This trend verifies the sparsity assumption of this paper. That is, there is a sparse subset of the signals that can lead to optimal damage detection under varying EOCs. It is also worth noting that further increasing the sparsity leads to a decrease in detection accuracy until it again hits the accuracy range of zero-sparsity, or the case that classification is purely random. This pattern indicates that, similar to noisy non-sparse signals, too sparse solutions can degrade the performance, because of losing damage information.

5.1.2. Multiple environmental and operational conditions. In the laboratory experiments reported throughout this paper, temperature is the only EOC that is significantly varying during the data collection process. In this section, high performance of the SD method for online damage detection is validated using the signals recorded under a wide range of varying EOCs. Figure 11 illustrates an example of online monitoring implementation for a subset of field data explained at the beginning of Section 5.1. Figure 11(a) and (b) shows the abrupt variation of temperature and fluid flow rate, respectively, among other EOCs. The sharp drop in the predicted labels of the test observations (Figure 11(c)) indicates the time when damage (mass scatterer) is introduced. Table IX summarizes online detection performance of the SD method, as the average of 10-fold CV, for data recorded from four different summer days and three winter days. The simple detection algorithm explained in Section 4.2.2 is used here. This table also summarizes the average Srs for all the iterations of 10-fold CV. The SD method improves the performance of the SVD method reported in Liu et al. [57], which is applied in part of the data reported in this section.

5.2. Detection of a small crack and mass loss

It is important to evaluate the performance of the SD method for detection of damages of different type from training stage. As discussed in Section 2, arrival times can be affected by the nature of the
interference of the waves with damage (e.g., mode conversion, velocity change, and energy dissipation), which is mainly dictated by the type and geometry of the damage [13,14,20–22,24]. In this section, the proposed SD method is evaluated for detection of actual damages of different type from the mass scatterer that is used in training. A small crack is simulated by a saw cut on the surface of a steel pipe. Later, a small mass loss is introduced to the pipe in a different location than the crack. For online monitoring applications, evaluating the SD method for detection of consecutive damages is important. As discussed in Section 4.2.2, in this paper, we suggest a non-adaptive approach in which the training dataset is not updated as new signals are obtained during the monitoring stage. Therefore, failing in detecting the first damage does not affect detection of the second damage by degrading the accuracy of the trained discriminant vector. However, the question is whether the method can still distinguish between damaged and undamaged pipe when multiple damages occur at the same time, or ideally, can detect the change in the state of the pipe when the second damage occurs.

For these experiments, a schedule 40 steel pipe (Figure 12) with 33.5-mm outer diameter and 3.3-mm thickness is used. Before introducing the crack, ultrasonic pitch-catch records are obtained from the intact pipe and from the pipe with a small mass scatterer placed in a non-symmetric location shown in Figure 12, at different temperatures ranging from 25 to 27°C. These signals are used for training. Later, an oblique cut of 2.5-cm long, extended in both circumferential and longitudinal directions of the pipe (Figure 12), is imposed at the middle of the length of the pipe, using a jewelers’ saw. The maximum thickness along the length of the crack is approximately 0.34 mm (10% of the pipe thickness), and the maximum depth is approximately 0.7 mm (20% of the pipe thickness). The second damage is a small mass loss (Figure 12) with 5-mm diameter and maximum depth of 0.25 mm (~8% of the pipe thickness). The location of the second damage differs from both the crack and training mass.
scatterer location. For testing, signals from the intact pipe and the pipe with crack and with both crack and mass loss are used at $24^\circ C \leq T_{\text{test}} \leq 32^\circ C$.

In this set of experiments, in addition to the range of temperature variation, the location, size, number, and the type of the structural abnormality in the training and test data are different, which strengthens the generality of the results. Figure 13 shows that not only can the proposed SD method distinguish damaged and undamaged pipes when more than one damage are present, but it may also detect the change in the severity of the damage and/or occurrence of subsequent damages.

5.3. Non-Gaussianity of guided-waves

Linear discriminant analysis is a common method in pattern recognition for extracting a subspace of the variables that discriminates between the observations of different classes (i.e., discriminant vector). However, LDA assumes that the variables are normally distributed. Therefore, in order to apply LDA in the time-domain of guided-waves, $n$ sample points in the signals have to follow a Gaussian distribution. To evaluate Gaussianity, two common statistical tests, namely, *Chi-squared goodness-of-fit* (uses the variables' mean and variance) and *Jarque–Bera* test (without the knowledge of mean and variance) are used. These two metrics evaluate the null hypothesis that the variables (sample points in time) come from a normal distribution. The dataset includes 5500 signals from the intact pipe and 5500 signals from the damaged pipe at temperatures ranging from 24 to 38°C. Table X summarizes the percentage of the sample points in time, after the first arrivals, for which the null hypothesis is rejected at 5% significance level.

![Figure 12](image1.png)

Figure 12. The steel pipe used to examine the application of the sparse discriminant method for the detection of multiple actual damages, namely, a crack and mass loss.

![Figure 13](image2.png)

Figure 13. Online detection of a 2.5-cm-long oblique crack (with maximum thickness of 0.34 mm and maximum depth of 0.7 mm) and a subsequent small mass loss (with maximum depth of 0.25 mm) in a schedule 40 steel pipe.

![Figure 14](image3.png)

Table X. Percentage of the sample points, after the first arrivals, for which the null hypothesis of Gaussianity is rejected at 5% significance level.

<table>
<thead>
<tr>
<th>Gaussianity test</th>
<th>Signals from intact pipe (%)</th>
<th>Signals from damaged pipe (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-squared goodness-of-fit</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td>Jarque–Bera</td>
<td>99.8</td>
<td>99.7</td>
</tr>
</tbody>
</table>

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DOI: 10.1002/stc
significance level. As reported in Table X, almost none of the sample points in these signals follow a normal distribution. This means that LDA cannot be applied to guided-waves in time-domain.

6. CONCLUSION

This paper addresses some of the open challenges in real-world application of guided-waves for pipeline damage detection, which are mainly rooted in complexity of these signals, and their sensitivity to EOC variations. A method is proposed to extract a sparse subset of the arrivals in time-trace of guided-wave signals, as opposed to the original complex signals. The sparse signal is obtained while enforcing retrieval of the arrivals with larger contributions in defining the state of the pipe. If, in this sparse signal, the effects of damage suppress the EOC effects, this subset can be used for damage detection under varying EOCs. This condition is validated through a set of laboratory and field experiments, for EOCs such as temperature \(24°C \leq T \leq 60°C\), flow rate \(45.5\) and \(102\ m^3/h\), and inner pressure variation, operational noises, as well as flowing water inside the pipe. Good performance of the proposed method at wide range of varying EOCs makes it attractive for online damage detection of operating pipelines. In this paper, we also study the physical meaning of the extracted sparse coefficients at different temperatures. It is identified that, beside the first arrivals from the damaged path, later arrivals and end reflections may also have substantial contribution in defining the state of the pipe. This implies that the denoising methods that are based on removal of multi-path reflections may be vulnerable to eliminating useful information and should be applied with caution.

The proposed SD method is a supervised approach. That is, it requires a set of labeled data, from undamaged pipe, as well as from the pipe with a structural abnormality. This paper shows that obtaining such labeled training data does not require prior knowledge about the size, location, number, and type of the damage and can be obtained by simply imposing a scatterer to the pipe during the training stage. For example, the proposed method is successfully used to detect a 2.5-cm crack as wide as only 10% of the thickness and as deep as only 20% of the thickness of a steel pipe, under wide range of temperature variations, while the training data were obtained using a small mass located in a different position.

Development of damage in real life is a gradual phenomenon. Therefore, one open question is whether the SD method would be able to detect such gradual changes. Intuitively, observations from an in-progress damage can be distinguished as soon as the corresponding sparse signals deviate from those of the undamaged pipe. As shown in Section 5 of this paper, such deviations can be quite significant for a crack as small as 10% of the thickness of the pipe. Future work includes implementation of the SD method for detection of gradual development of defects. At this point, it is worth noting that the non-adaptive online detection approach that is followed in this paper can prove useful in preventing the undetected damaged test observations to adversely affect the performance of detecting gradual development of damage.

Moreover, the authors are currently investigating the potential of the SD method for characterizing the severity and type of the damage. It is important to determine the types of the defects that the proposed method can detect, as well as the damage stage, throughout its gradual development. On the other hand, the proposed SD method may not be applicable to the cases where access to the pipe (to impose the structural abnormality during the training stage) is not practical. For this reason, the authors are currently working on an unsupervised method that does not rely on labeled training data.

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