Nonlinear feature extraction methods for removing temperature effects in multi-mode guided-waves in pipes

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ABSTRACT

Ultrasonic guided-waves propagating in pipes with varying environmental and operational conditions (EOCs) are usually the results of complex superposition of multiple modes travelling in multiple paths. Among all of the components forming a complex guided-wave signal, the arrivals scattered by damage (so called scatter signal) are of importance for damage diagnosis purposes. This paper evaluates the potentials of nonlinear decomposition methods for extracting the scatter signal from a multi-modal signal recorded from a pipe under varying temperatures. Current approaches for extracting scatter signal can be categorized as (A) baseline subtraction methods, and (B) linear decomposition methods. In this paper, we first illustrate, experimentally, the challenges for applying these methods on multi-modal signals at varying temperatures. To better analyze the experimental results, the effects of temperature on multi-modal signals are simulated. The simulation results show that different wave modes may have significantly different sensitivities to temperature variations. This brings about challenges such as shape distortion and nonlinear relations between the signals recorded at different temperatures, which prevent the aforementioned methods to be extensible to wide range of temperatures. In this paper, we examine the potential of a nonlinear decomposition method, namely nonlinear principal component analysis (NLPCA), for removing the nonlinear relation between the components of a multi-modal guided-wave signal, and thus, extracting the scatter signal. Ultrasonic pitch-catch measurements from an aluminum pipe segment in a thermally controlled laboratory are used to evaluate the detection performance of the damage-sensitive features extracted by the proposed approach. It is observed that NLPCA can successfully remove nonlinear relations between the signal bases, hence extract scatter signal, for temperature variations up to 10°C, with detection accuracies above 99%.

Keywords: Pipeline Monitoring, Guided-waves, Nondestructive Evaluation, Structural Health Monitoring, Temperature Effects, Damage Detection, Nonlinear Principal Component.

1. INTRODUCTION

Pipelines are important components in several applications at different scales, ranging from building-level piping systems to inter-state transmission pipelines. Despite the advances in data acquisition technologies, these crucial energy transmission infrastructures still suffer from vast number of not/late-detected defects and their huge impacts. For example, according to the Department of Transportation, Pipeline and Hazardous Materials Safety Administration report (PHMSA1), only 28% of the incidents in the instrumented pipes have been detected by data acquisition and sensing systems during 2010-2012 years.

The advantages of guided-waves for nondestructive evaluation (NDE) of pipelines have been discussed for over half a century, since Worlton recognized their potential 2. Guided-waves are mechanical stress waves propagating along a media, guided by its boundaries. There are different types of guided-waves depending on the type of the structure and excitation conditions, but they all have one requirement in common: a well-defined boundary. If the thickness of the pipe is comparable to the wave length of the excited wave modes, guided-waves will travel along the axial,

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radial, and circumferential direction of the pipe wall. Therefore, generally, three types of modes can be excited in a pipe-like structure:

- **Longitudinal modes** $L(0,m)$, which travel throughout the axial direction of the pipe, and are identifiable with axial and compressional displacements along the radial direction. These modes are axisymmetric.
- **Torsional modes** $T(0,m)$, which travel parallel to the circumferential direction and introduce shear motions resulting in axial and radial displacements. These modes are axisymmetric.
- **Flexural modes** $F(n,m)$, which are not axisymmetric and introduce displacements in circumferential direction in addition to axial and radial displacements.

Guided-waves can travel long distances without significant energy loss, providing full coverage of the wave guide. Moreover, guided-waves are proven to be highly sensitive to different types/sizes of damage (e.g., internal and external corrosion, cracks, notches, and fouling). In addition, guided-wave based NDE system can operate with small number of low-cost, low-power, transducers. 3-7.

Despite many advantages, real-world application of guided-waves for pipeline NDE is still quite limited. 3 Guided-waves usually travel in multi-modal, multi-path and dispersive fashion resulting in complex signals whose interpretation is a challenging task. Damage diagnosis using guided-waves becomes even more challenging when environmental and operational conditions (EOCs) vary. The effects of EOCs (e.g., changes in temperature, flow rate, inner pressure, interference with coupling material, etc.) on guided-waves range from generation of additional wave modes to changes in the wave velocity and/or the attenuation rate. 8-10. Such effects degrade the performance of damage detection, by masking, or appearing as, the changes caused by structural anomalies, and introducing type I and II errors.

Among all of the components forming a complex guided-wave signal, the arrivals scattered by damage (so called scatter signal) are of importance for damage diagnosis purposes. Several researchers have worked on extracting the scatter signal while taking into account the effects of EOCs. 11-14. The objective of these studies is to separate the arrivals scattered by damage from the background, that is, the arrivals traveling through intact sections of the structure. These methods can be discussed under two main headings: (A) baseline subtraction, and (B) linear decomposition methods. Baseline subtraction is trivial, and the first method to be tried, for this purpose. The difference between a signal recorded from undamaged state of the structure and the signal recorded from damaged structure can be attributed to the existence of damage. However, baseline-subtraction methods may fail when EOCs between the baseline signal and the monitored signal vary. This is because the background signals in the monitored structure will not remain identical to the background signal in the baseline case, therefore, the subtraction of the two signals will not lead to accurate scatter signal. Researchers such as Croxford et al. 11 and Lu and Michaels 12 have suggested stretching/compressing the guided-waves to compensate for the temperature difference between baseline and monitored signals. Limited applicability of baseline-subtraction methods have encouraged researchers to apply statistical learning methods to extract scatter signals for a wider range of EOC variations. 14,15. In this paper, we investigate the effectiveness of both approaches, namely stretching methods for baseline-subtraction and linear decomposition methods, for a multi-modal signals that can be obtained from an operating pipeline with varying temperature. The experimental and simulation results reported in this paper suggest that signals recorded at different temperatures, and thus their bases, are nonlinearly related. In this paper, we examine the potential of nonlinear feature extraction methods for removing such nonlinear relations and decomposing a multi-modal signal into its bases, including scatter signal.

In the next sections of this paper, we first simulate the effects of temperature variation on multi-modal guided-waves. Then, we investigate the effectiveness of stretching methods and linear decomposition methods for extracting the scatter signals from multi-modal guided-waves propagating in pipes under varying temperatures. Pitch-catch records from a schedule-40 aluminum pipe segment in laboratory, with temperatures ranging from 24°C to 44°C, are used for the experiments in this paper. Finally, based on the findings of these analyses/experiments, a nonlinear decomposition approach is suggested for damage diagnosis of pipelines at widely varying temperatures.
2. SIMULATING TEMPERATURE EFFECTS ON MULTI-MODAL GUIDED-WAVES

The results of this section will help to better understand the challenges of two categories of methods used to date for extracting scatter signals under varying temperatures, namely (A) stretching methods for baseline subtraction, and (B) linear decomposition methods. Moreover, the findings of this section motivate the application of nonlinear feature extraction method that is proposed in this paper.

Guided-wave systems are highly vulnerable to temperature variations because several components of the system can be affected by such changes. Temperature-dependent parameters of guided-wave based NDE systems include: (i) Properties of transducers, (ii) Interactions between transducers and the media, and (iii) Physical properties of the wave guide\[^{10,12,17,18}\].

Researchers such as Raghvan and Cesnik\[^{19}\], Scalea and Salamone\[^{10}\], and Schulz et al.\[^{18}\] showed that elevating or decreasing temperature, beyond a certain range, can affect the piezoelectric properties of the transducers and/or the quality of transducer-media bounding which can lead to changes in the wave properties such as time of flight and amplitude. These studies are of high importance in applications with extreme temperature variation ranges, such as aircraft or airspace NDE. This paper; however, is not focusing on the applications with extreme temperatures. Therefore, the summation is that the effects of temperature on the first two parameters named above are negligible. For the simulations reported in this paper the temperature range is between 20°C and 60°C.

The effects of temperature on boundary conditions and physical properties of the wave guide can be in the form of a change in the length of travel path, a change in thickness of the media, and/or a change in the material properties such as Young’s modulus ($E$) or stiffness ($G$). These changes lead to variation in longitudinal and shear bulk velocities, thus, the solution of dispersion equations (i.e., equations that relate frequencies to the parameters such as wave numbers and physical properties of the media). Such effects are considered for simulations in this paper.

It is also notable that, unconstrained thermal expansion of the pipe is assumed. Constrained expansion/compression can generate additional stress, which may affect not only the propagation of guided-waves\[^{20}\], but also the temperature dependence of wave velocities\[^{21}\]. This assumption complies with the laboratory setup used in later sections of this paper, because (1) experimental pipe segment is free at both sides, (2) at each temperature, signals are recorded after the pipe reaches its steady state, and (3) the temperature control setup (see Section 3) provides uniform temperature distribution along the pipe.

Temperature dependence of physical properties of the pipe, in the temperature range considered here (20°C ≤ $T$ ≤ 60°C), can be linearly modeled as given in Equations 1-4, in which the subscript “0” and “$T$” refer to the values of the parameter at reference temperature, $T_0 = 20°C$, and at any other temperature $T$, respectively:

\[
L_T = L_0 + \alpha_L \Delta T L_0 \quad \text{(Thermal expansion of the pipe’s length)}
\]

\[
h_T = h_0 + \alpha_h \Delta T h_0 \quad \text{(Thermal expansion of the pipe’s thickness)}
\]

\[
E_T = E_0 + \alpha_E \Delta T E_0 \quad \text{(Thermal dependence of Young’s modulus)}
\]

\[
G_T = G_0 + \alpha_G \Delta T G_0 \quad \text{(Thermal dependence of Rigidity modulus)}
\]

In this equations, $\Delta T$ is the temperature difference between $T_0$ and any other $T$, and $\alpha_L$, $\alpha_E$, and $\alpha_G$ are thermal coefficients for linear expansion, Young’s modulus, and Rigidity modulus, respectively, in 1/°C units. $L_0$ and $h_0$ depend on the geometries of the pipe, and the values for $E_0$, $G_0$, $\alpha_L$, $\alpha_E$, and $\alpha_G$ can be obtained from references such as the Metal Handbook\[^{22}\].

The objective is to calculate longitudinal and shear bulk velocities at different temperatures as given in Equations 5-7, where, $\rho$ is density, and $\nu_T$ is the Poisson’s ratio at temperature $T$. 
\[ C_l_T = \frac{\lambda_T + 2G_T}{\rho} \] (Longitudinal bulk velocities) (5)

\[ C_s_T = \sqrt{\frac{G_T}{\rho}} \] (Shear bulk velocities) (6)

\[ \lambda_T = \frac{v_T E_T}{(1 + v_T)(1 - 2v_T)} \] (Lame’s constant) (7)

According to Equations 5-7, wave velocities at each temperature are related to Poisson’s ratio \((\nu_T)\) that can be obtained as follows:

\[ \nu_T = \nu_0 + \alpha_\nu \Delta T \nu_0 \] (Thermal dependence of Poisson’s ratio) (8)

To obtain thermal coefficient of Poisson’s ratio \((\alpha_\nu)\), one way is to use Equations 3-4 to first calculate \(E_T\) and \(G_T\) at different temperatures, and then use Equation 9 below to obtain \(\nu_T\). Now, the only unknown in Equation 8 is \(\alpha_\nu\).

\[ G_T = \frac{E_T}{2(1 + \nu_T)} \] (9)

Having calculated all required temperature-dependent parameters, \(C_l\) and \(C_s\) at each temperature (Equations 5-6) can be calculated, and the corresponding thermal coefficients can be obtained as follows, where, \(k_l\) and \(k_s\) are thermal coefficients of \(C_l\) and \(C_s\), respectively, in \(\text{m/s}^2\) unit:

\[ C_{l_T} = C_{l_0} + k_l \Delta T \] (10)

\[ C_{s_T} = C_{s_0} + k_s \Delta T \] (11)

Table 1 summarizes the properties of the aluminum pipe segment used in this paper. Following the process explained above, thermal coefficients of \(C_l\) and \(C_s\) are calculated as \(k_l = -0.9\) \((\text{m/s}/\text{°C})\) and \(k_s = -0.8\) \((\text{m/s}/\text{°C})\). These results are in excellent agreement with experimental thermal coefficients obtained by Augereau et al.\(^{23}\) for aluminum 6061-T6 at the temperatures between 25°C and 225°C, and by Salama and Ling\(^{21}\) for aluminum 6063-T4 at the temperatures between 27°C and 73°C. This suggests the validity of the assumptions discussed above.

<table>
<thead>
<tr>
<th>Material Type</th>
<th>6061-T6</th>
<th>(E_0(T_0 = 20^\circ\text{C}))</th>
<th>69 GPa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type of the Pipe</td>
<td>3 ½ Schedule-40</td>
<td>(\alpha_\nu(T_0 = 20^\circ\text{C}))</td>
<td>26 GPa</td>
</tr>
<tr>
<td>External Diameter</td>
<td>101.6 mm</td>
<td>(\alpha_L)</td>
<td>23.6 \times 10^{-6} \text{ 1/°C}</td>
</tr>
<tr>
<td>Internal Diameter</td>
<td>90.17 mm</td>
<td>(\alpha_F)</td>
<td>-4.8 \times 10^{-4} \text{ 1/°C}</td>
</tr>
<tr>
<td>Nominal Thickness</td>
<td>5.84 mm</td>
<td>(\alpha_G)</td>
<td>-5.2 \times 10^{-4} \text{ 1/°C}</td>
</tr>
<tr>
<td>Pipe Length (L)</td>
<td>1.219 m</td>
<td>(C_{l_0}(T_0 = 20^\circ\text{C}))</td>
<td>6120 m/s</td>
</tr>
<tr>
<td>Density ((\rho))</td>
<td>2700 kg/m(^3)</td>
<td>(C_{s_0}(T_0 = 20^\circ\text{C}))</td>
<td>3103 m/s</td>
</tr>
</tbody>
</table>

PCDisp\(^{24}\), an open source software for modeling guided-waves in cylindrical media, is used in this paper to solve the dispersion equations under each temperature \((20^\circ\text{C} \leq T \leq 60^\circ\text{C})\). In order to excite guided-waves close to lamb waves in plates, the following criteria should be met\(^{25}\): \(r \gg h, A \gg h,\) and \(r \gg \lambda,\) where \(r, h,\) and \(\lambda\) are pipe radius, pipe thickness and wavelength, respectively. Therefore, for the aluminum pipe given in Table 1, the desirable range for excitation frequency is between \(-125\) KHz and \(-1000\) KHz. In this paper, 0.1 \(ms\) Gaussian excitation signal with central frequency of 250 KHz is transmitted from one end of the pipe, and 10 \(ms\) of ultrasonic signals, with sampling frequency of 10 MHz, are recorded at the receiver in the other end.

Figure 1 shows the rates by which the phase velocities \((\nu_{ph})\) of different modes change with respect to temperature, at different frequencies. As can be seen in this figure, different wave modes may have significantly different sensitivities to temperature variations, particularly in the more practical ranges of frequency. As will be discussed
further in the following sections, different rates of velocity change can complicate the effects of temperature on multi-modal guided-waves. Such challenges motivate the method that will be proposed later in this paper.

Figure 1: The rates by which the phase velocities ($v_{ph}$) of different modes change with respect to temperature

3. EXPERIMENTAL SETUP

For controlling the temperature variations, the authors designed and built a setup in laboratory, which consists of a 1.5$m \times 1.5$ $m$ box made of insulation foam, with 50.8 $mm$ thickness, R-value of 10, and maximum operation temperature of 74$^\circ$C. Figure 2 shows this setup. Interior temperature of the box is maintained within $\pm 0.5^\circ$C of the specified setpoint, 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 (PZT) 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. As mentioned above, in order to excite guided-waves that are close to lamb waves in plates, the following criteria should be satisfied:\[^2\]: $r \gg h, \lambda \gg h$, 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 $\sim 125$ KHz and $\sim 1000$ 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 grease-coupling a mass to the outer surface of the pipe.

Figure 2: Laboratory setup for controlling temperature variation: 1) Thermally insulated box to contain the pipe segment, 2) Thermostat, 3a & 3b) PZT transducer and receiver, respectively, 4) Grease-coupled mass to simulate structural abnormality.
4. CURRENT METHODS FOR EXTRACTING SCATTER SIGNAL

In this section, the performance of two main categories of methods that are currently applied to extract scatter signals under varying EOCs is examined for a wide range of temperature variation. The experimental data explained in Section 3 is used for this purpose. The experimental findings in this section are attributed to the simulation results reported in Section 2. The findings summarized in this section motivate application of the nonlinear decomposition method that is proposed in the next section of this paper.

4.1 Stretching a multi-modal guided-wave signal for baseline subtraction

Overview:

Let \( Y_0(t) = X^0_d(t) \) be the baseline signal recorded from an undamaged pipe at temperature \( T_0 \), and \( Y_i(t) = X^i_d(t) + X^0_d(t) \) be the monitored signal from a damaged pipe at temperature \( T_i \), where \( X^i_d(t) \) is the background signal consisting of arrivals from undamaged paths, and \( X^0_d(t) \) is the scatter signal consisting of the arrivals from damaged paths. In baseline-subtraction methods for damage detection, the goal is to extract \( X^i_d(t) \) from Equation 12:

\[
\Delta Y(t) = Y_i(t) - Y_0(t) = X^i_d(t) + X^0_d(t) - X^0_d(t) \tag{12}
\]

In an ideal scenario, where the EOCs at time zero and \( i \)th are identical, the term \( X^i_d(t) - X^0_d(t) \) would be zero, and the baseline subtraction will lead to the scatter signal, i.e., \( \Delta Y(t) = X^i_d(t) \). However, if EOCs, here temperature \( T \), vary (\( T_0 \neq T_i \)), then \( X^i_d(t) \neq X^0_d(t) \). In this case, baseline subtraction will include a nonzero term \( \Delta X_T(t) = X^i_d(t) - X^0_d(t) \) because of the temperature effects, which we name *temperature noise*. Therefore, the result of baseline subtraction will look like Equation 13:

\[
\Delta Y(t) = \Delta X_T(t) + X^i_d(t) \tag{13}
\]

This *temperature noise* can be significant, and usually enough to mask the effects of the damage included in \( X^i_d(t) \). Therefore, it is desired to compensate for the effects of temperature on the baseline signal so that \( \Delta X_T(t) \) approaches zero. Current methods approximate the effect of temperature on wave velocities as stretching/compressing of the baseline signal.\(^{11,12,26}\) Let \( T_\xi(.) \) be a function that stretches/compresses the baseline signal \( X^0_d(t) \) by factor \( \xi \) which depends on the temperature difference \( \Delta T = T_i - T_0 \). Therefore, the baseline subtraction given in Equation 12 will result in the following equation in which \( \Delta X_T(t) \) is expected to be small compared to \( X^i_d(t) \):

\[
\Delta Y(t) = \left( X^i_d(t) - T_\xi(X^0_d(t)) \right) + X^i_d(t) = \Delta X_T(t) + X^i_d(t) \tag{14}
\]

The objective of this case study is to show the insufficiency of the stretching methods for characterizing the effects of temperature variations in a multi-modal signal. For this purpose, the following tasks are performed which will be elaborated more in this section:

- Stretch a baseline signal \( X^0_d(t) \), recorded at \( T_0 = 24^\circ C \), with stretching factors \( \xi \) corresponding to different \( \Delta T \)s.
- At each temperature \( T \), compare the temperature noise after stretching, \( \Delta X_T(t) = X^i_d(t) - T_\xi(X^0_d(t)) \), with scatter signal \( X^i_d(t) \).

Pitch-catch measurements recorded from the aluminum pipe shown in Figure 2 are used. Temperature varies from \( 24^\circ C \) to \( 44^\circ C \) with \( 0.5^\circ C \) increments. At each temperature, a total of 1,000 signals are recorded, consisting of 500 measurements from undamaged pipe, and 500 measurements from the pipe with structural abnormality. To estimate stretching factor \( \xi \) for different \( \Delta T \)s, we employed the experimental approach used by Lu and Michaels,\(^{27}\), which can be summarized as follows:

1) Divide both \( X^0_d(t) \) and \( X^i_d(t) \) signals into smaller windows (here, the window width is 50 \( \mu s \))
2) Apply cross-correlation between the signals at each window
3) Plot the lag (\(\tau\)) corresponding to the max correlation versus the window center (\(t_c\)).
4) The slope of this plot will be the time-shifting factor \(\xi\).

Stretching a signal with factor \(\xi\) can be expressed by Equation 15. This can be approximated by interpolating the signal with the rate \(\beta = 1 - \xi\).

\[
T_\xi(X_0^d(t)) = X_0^d(t - \xi t)
\]  

(15)

**Shape distortions at large \(\Delta T\)s:**

It is observed that the cross correlation method for estimating stretching factor \(\xi\) fails for larger values of \(\Delta T\), i.e., \(\Delta T > \sim 10^\circ C\). As shown in Figure 1, multiple wave modes traveling in a pipe have different sensitivities to temperature variations. This means that the change in temperature will affect the propagating modes differently, altering the arrival times of these modes relative to each other. The result is a change in the shape of the signal. For example, Figure 3 shows two signals recorded under two different temperatures from an undamaged pipe in the laboratory. Significant shape distortion, especially in the later arrivals, can be seen very clearly in this figure. The marked areas in the figure are some examples of the distorted parts of the signals. When shape distortion exceeds a certain level, the cross-correlation method which is based on peak-to-peak correlation at each window fails to find the lags between the corresponding peaks of the signals. Figure 4 shows an example of the lag-window center (\(\tau - t_c\)) plot generated for two signals with \(\Delta T = 15^\circ C\). It can be seen that for later arrivals, the cross correlation methods fail to find suitable match for signal peaks resulting in negative lags, while positive values are expected.

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**Temperature noise \(\Delta X_T(t)\) vs. scatter signal \(X_d(t)\)**

At each temperature \(T_i\), temperature noise \(\Delta X_T(t)\) is obtained by subtracting the stretched baseline signal \(\hat{X}_i^0(t) = T_\xi(X_0^d(t))\) from the actual signal \(X_i^0(t)\) recorded at \(T_i\), i.e., \(\Delta X_T(t) = X_i^0(t) - T_\xi(X_0^d(t))\). It is notable that both \(X_0^d(t)\) and \(X_i^0(t)\) signals are recorded from an undamaged pipe. To obtain scatter signal, at each temperature \(T_i\), the signal recorded from undamaged pipe \(X_i^0(t)\) is subtracted from the signal recorded from damaged pipe. \(Y_i(t) = \)
\( X_u^i(t) + X_d^i(t) \). This is a close approximation of scatter signal, because temperatures are kept the same, and the effects of other EOCs are sufficiently controlled by the laboratory setup.

Figure 5 shows the comparison of temperature noise and scatter signal, when the baseline signal is stretched to compensate for only \( \Delta T = 1^\circ C \). In this case, energy content of the temperature noise is 2.5 times larger than the energy content of the scatter signal. This difference increases to 6.6 times when stretching is performed to compensate for \( \Delta T = 9^\circ C \). Figure 6 shows the comparison of the average energy content of temperature noise and scatter signals at different temperatures. It can be seen that stretching a multi-modal signal fails to reduce the energy content of \( \Delta X_T(t) \) below the damage signal even for small values of \( \Delta T \).

\[
\Delta X_T = X_u^i - T \{ X_u^0 \}, \text{at } \Delta T = 1^\circ C
\]

\[
X_d^i = (X_u^i + X_d^i) - X_u^i, \text{at } T = 24^\circ C
\]

Figure 5: Comparing the scatter signal \( X_d^i \) with temperature noise \( \Delta X_T \), resulted from subtraction of the stretched baseline signal and the monitored signal with \( \Delta T = 1^\circ C \).

Figure 6: Average energy of temperature noise \( \Delta X_T \) after stretching the baseline signal for various \( \Delta T \)s, and of scatter signal \( X_d^i \).

4.2 Limitations of linear decomposition methods for temperature effects in a multi-modal signal

During the past two decades, several studies have taken advantage of statistical and signal processing techniques to decompose guided-waves into their bases, including scatter signal. These studies include, but not limited to, denoising and rectifying damage-sensitive component extracted through wavelet transform\(^{15}\), blind source separation using linear time-frequency representations\(^{27}\), and extracting scatter signal using singular value decomposition (SVD)\(^{14}\). In this paper, we investigate the SVD-based method recently proposed by Liu et al.\(^{14}\), as an example of linear decomposition method. This method is chosen because it has shown high potential for extracting the scatter signal under varying EOCs, therefore, it is a good candidate for investigating temperature effects on linear decomposition methods.
What does SVD extract?

Singular value decomposition (SVD) is a linear decomposition method for extraction of orthogonal bases of the data space. If \( Y^{m \times n} \) is the data matrix, consisting of \( m \) observations and \( n \) variables with rank \( r \) (\( r \leq m \leq n \)), its SVD will be as follows, where, \( U^{m \times m} \) is the matrix of left singular vectors (LSVs), \( S^{m \times m} \) is the matrix of singular values, and \( V^{n \times n} \) is the matrix of right singular vectors (RSVs):

\[
Y = USV^T
\]  

(16)

Each left singular vector \( u_i^{m \times 1} \) \((i = 1, ..., m)\) represents the projection of the observations in \( Y \) on the subspace represented by the corresponding right singular vector \( v_i^{n \times 1} \). SVD is closely related to PCA as the left and right singular vector matrices are eigenvectors of \( YY^T \) and \( Y^TY \), respectively, and the singular values are square roots of the eigenvalues of \( Y \).

Let us assume an ideal case of monitoring in which EOCs, here temperature, does not change for different signals recorded at times \( t_i \) to \( t_m \). In this case, the recorded signals at any time between \( t_i \) to \( t_{i-1} \) (i.e., before damage occurs) will be identical to each other, since nothing changes from one observation to another \((X_u^i = X_u^{i-1} = X_u)\).

Let damage occur at time \( t_i \). All the observations recorded from this time forward will include scatter signals, which again will be identical for all records \((X_d = X_u^m = X_d)\). Therefore, the data matrix \( Y \) will look like below:

\[
Y^{m \times n} = [\vec{Y}_1, ..., \vec{Y}_{i-1}, \vec{Y}_i, ..., \vec{Y}_n] = [\vec{X}_u, ..., \vec{X}_u, \vec{X}_u + \vec{X}_d, ..., \vec{X}_u + \vec{X}_d]
\]  

(17)

As can be seen from this data matrix, the addition of \( X_d \) at time \( t_i \) is equivalent to adding, linearly, a component to the initial, and the only, component in the data space, i.e., \( X_u \). Assuming that these two components are orthogonal to each other, they can be separated by a method decomposing the data space into orthogonal bases, such as SVD. Therefore, in this scenario, two LSVs would exist, each representing \( X_u \) and \( X_d \). The LSV corresponding to \( X_u \) will be constant for all the observations in \( Y \), because the \( X_u \) component is common among all observations. In other words, all the observations will have the same projection on \( X_u \). On the other hand, the values of the LSV corresponding to \( X_d \) will change for observations \( i \) to \( m \). That is, the projection of signals from undamaged pipe \((Y_1 \text{ to } Y_{i-1})\) on \( X_d \) will be different than the projections of the signals from damaged pipe \((Y_i \text{ to } Y_m)\). This would lead to a step-like change in the LSVs corresponding to the time that damage occurs. Liu et al.\(^{14}\) have used these step-like changes for damage detection.

**Nonlinear effects of temperature:**

The effects of temperature on wave velocities can be approximated as stretching/compressing of the signal. If stretching effects are linear, they can be removed from the stretched signals, therefore, signals can be decomposed into the same orthogonal bases before stretching, namely \( X_u \) and \( X_d \). In this section, we investigate the accuracy of this assumption for a multi-modal signal.

Usually, the stretching effects of temperature are modeled with interpolation of the signal, with a stretching factor \( \beta \) which depends on the magnitude of the temperature variation \( \Delta T \). Let \( T_\beta(\cdot) \) be stretching of a signal with stretching factor \( \beta \). For simplicity, let us assume that a multi-modal signal is only composed of two modes, \( A \) and \( B \), so \( Y = A + B \). The linearity condition for the stretching function is as follows:

\[
T_\beta(A + B) = T_\beta(A) + T_\beta(B)
\]  

(18)

Equation 18 only holds if \( \beta = \beta_A = \beta_B \), that is, mode \( A \) and \( B \), and their superposition, have the same stretching factor as a result of a particular change in temperature \((\Delta T)\). However, as we discussed in Section 2.1 (see Figure 1), different modes have different sensitivities to temperature variations, leading to different stretching effects (i.e., \( \beta_A \neq \beta_B \)). Therefore, in general, stretching effects of temperature in a multi-modal signal are not linear. This means that, at different temperatures, the signal components \((X_u, \text{ and } X_d)\) are non-linearly related to each other. Therefore, if a linear decomposition method such as SVD is applied to a dataset of signals from wide range of temperatures, the
extracted RSVs may significantly deviate from the actual $X_u$s and $X_d$s of the signals. This is because a linear method cannot remove the nonlinear dependency between the components, hence, may not extract them accurately. This can lead to inaccurate diagnosis using the extracted scatter signal.

Moreover, assume that the signals are recorded from an undamaged pipe at different temperatures. As discussed, since the $X_u$s at different temperatures are nonlinearly related, it is likely that these $X_u$s are extracted as separate components. That is, although there is no damage, we may still observe step-like changes in the LSVs (i.e., projections on different components) as temperature changes. This can increase the false positives.

Figure 7a and Figure 7b show a scenario in which the temperatures of the observations vary within only 1°C ($25^\circ C \leq T \leq 26^\circ C$). As can be seen in Figure 7b, the damage-sensitive LSV can completely separate the undamaged and damaged observations. This means that the extracted $X_d$ component in the corresponding RSV is a good representative of the scatter signal. However, if the temperatures vary within a wider range, as shown in Figure 7c ($25^\circ C \leq T \leq 31^\circ C$), the extracted components deviate from the $X_d$s and $X_u$s of different observations. Therefore, as shown in Figure 7d, the projections on the supposedly scatter component can no longer separate two classes.

Figure 8 shows the correlation between the RSV that is expected to be representative of the scatter signal $X_d$, and the average of the actual scatter signals, as the $\Delta T$ between undamaged and damaged observations in the dataset increases. It can be seen that the extracted scatter component $X_d$ substantially deviates from the actual scatter signal with the increase in temperature variation.

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**Figure 7:** Left Column: A scenario that SVD can sufficiently extract the $X_u$ and $X_d$ components. Right Column: A scenario that SVD fails to extract the $X_u$ and $X_d$ components, due to large temperature variation, therefore, the projections on the supposedly damage-sensitive RSV are not separated.

**Figure 8:** Correlation between the RSV that is expected to represent the scatter signal, and the average of the actual scatter signals, as the temperature difference between damaged and undamaged observations change.
Figure 9 shows the first eight LSVs for a dataset consisting of only undamaged observations measured under temperatures varying from around 31℃ to around 32℃. It is notable that, the data used here is continuously recorded from a pipe with no interruption during data collection process. As can be seen in this figure, slight temperature variation can cause step-like patterns in the values of the first few LSVs. This is because SVD extracts the $X_u$s at different temperatures as separate components of the data space, and projections on these components will have different values for observations with different temperatures. Such behaviors can lead to false positives, if the values of LSVs are used for damage detection.

Figure 9: Shift in the projections of undamaged observations on the different $X_u$s extracted by SVD for different temperatures.

5. NONLINEAR FEATURE EXTRACTION

In this paper, we utilize a nonlinear decomposition method, namely nonlinear principal component analysis (NLPCA), to remove nonlinear effects of temperature variation on multi-modal guided-wave signals.

Studies to date e.g., 16,28 have shown high potential of linear principal component analysis (PCA) in decomposing guided-wave signals into the components, and thus extracting scatter signal, under varying EOCs. High performance of PCA-based methods suggests that the scatter signal is orthogonal to the other signal components, since PCA decomposes a dataset into its orthogonal bases. As will be explained further in this section, NLPCA shares the same principal. That is, applying NLPCA will still lead to extraction of orthogonal bases of the signal. However, as discussed throughout the previous sections, in general, the components of a multi-modal guided-wave signal at different temperatures are nonlinearly relate. Being a linear method, PCA fails to remove such nonlinear relations, if temperature variations are large enough to make these interrelations significantly deviate from linearity. Therefore, NLPCA is selected, since it extracts the orthogonal components that may be nonlinearly related. To extract the nonlinear principal components (NLPCs), a method based on auto-associative neural network is examined. The performance is compared with the linear SVD-based damage detection method discussed in previous section.

5.1 Overview of NLPCA-based method

The auto-associative neural network approach suggested by Kramer 29 is used to extract the NLPCs. To better understand the architecture of this approach, it is helpful to first review the linear PCA method, as summarized by Kramer 29.
Linear PCA:

The objective of PCA is to map a multi-dimensional data into lower dimensions with minimal loss of information. The criterion here is to identify orthogonal linear components of a data space so that the reconstruction error (L-2 norm) of the observations in this data space is minimized. Factorization of data matrix $Y^{m \times n}$, with $m$ number of observations and $n$ variables, into a score matrix $\tilde{Y}^{m \times f}$ and a loading matrix $\tilde{P}^{m \times f}$, $f$ being the reduced new dimension ($f < m$), will be as is given below, where $\tilde{E}$ is the matrix of residuals:

$$Y = \tilde{Y} \tilde{P} + \tilde{E} \quad \text{(Linear PCA)}$$  \hfill (19)

PCA can be viewed as the linear mapping of data from $R^n$ to $R^f$. Based on Equation 19, this mapping can be expressed as below, knowing that $\tilde{P}^T \tilde{P} = I$:

$$\tilde{Y}_j = Y_j \tilde{P} \quad \text{(Linear mapping by PCA)}$$  \hfill (20)

In this equation, $Y_j$ is the $j$th observation of $Y$, and $\tilde{Y}_j$ is the corresponding row of $\tilde{Y}$. The loading matrix $\tilde{P}$ provides the coefficients for the transformation. Reconstruction of the data matrix back to $R^n$ from the extracted transformations in $R^f$, and the information lost because of this transformation, are given in Equations 21 and 22, respectively:

$$Y'_j = \tilde{Y}_j \tilde{P} \quad \text{(Reconstruction of an observation)}$$  \hfill (21)

$$\tilde{E}_j = Y_j - Y'_j \quad \text{(Residual error for an observation)}$$  \hfill (22)

Nonlinear PCA (NLPCA):

Kramer$^{29}$ follows by generalizing the mapping discussed above in order to allow for arbitrary nonlinear functions. Generalizing Equation 20, mapping in NLPCA can be expressed as below:

$$\tilde{Y}_j = \tilde{G} Y_j \quad \text{(Nonlinear mapping by NLPCA)}$$  \hfill (23)

In Equation 23, $\tilde{G}$ is a nonlinear vector function, composed of $f$ individual nonlinear functions; $\tilde{G} = \{\tilde{g}_1, ..., \tilde{g}_f\}$, analogous to the columns of $\tilde{P}$ in linear PCA. If $\tilde{Y}_{j,i}$ represents the $i$th element of $\tilde{Y}_j$, nonlinear mapping of the $j$th observation into the $i$th nonlinear factor $\tilde{G}_i$ will be represented as follows:

$$\tilde{Y}_{j,i} = \tilde{g}_i Y_j \quad \text{(Nonlinear mapping into the $i$th factor)}$$  \hfill (24)

Similar to Equation 21, the inverse transformation will be done by another nonlinear function $\tilde{H} = \{\tilde{h}_1, ..., \tilde{h}_n\}$:

$$Y'_j = \tilde{H} \tilde{Y}_j \quad \text{(Reconstruction of an observation)}$$  \hfill (25)

Two feed-forward neural networks (shown in Figure 10) can be used to estimate nonlinear vector functions $\tilde{G}$ and $\tilde{H}$. The architecture of the two ANN networks representing $\tilde{G}$ and $\tilde{H}$ can be summarized as follow:

- The network for estimating $\tilde{G}$ operates on each observation in $Y$, and has $n$ inputs.
- Hidden layer of $\tilde{G}$ (mapping layer) has $M_1$ nodes with sigmoidal transfer functions, $M_1 > f$.
- Output of $\tilde{G}$ network is the projection of input vector into feature space, thus has $f$ nodes.
- The function $\tilde{G}_i$ is defined by the weights and biases that connect inputs to the $i$th output $\tilde{Y}_{j,i}$.
- The network for representing $\tilde{H}$, or inverse mapping functions, takes the $f$ elements in $\tilde{Y}_{j,i}$ as inputs.
- Hidden layer of $\tilde{H}$ (demapping layer) has $M_2$ nodes with sigmoidal transfer functions, $M_2 > f$. 

Output of $\bar{H}$ network is the reconstructed data, $Y'_j$, thus has $n$ nodes.

In this architecture, when training the $\bar{G}$ network, the output $\bar{T}^j_{ij}$ is not known, and when training $\bar{H}$ network, the desired outputs are known ($Y_j$) but the corresponding inputs ($\bar{T}^j_{ij}$) are not known. Therefore, rather than training these two network separately, they are combined in series so that $\bar{G}$ network feeds the $\bar{H}$ network directly. This new network is trained so that the output $Y'_j$ approaches original data vector $Y_j$ (i.e., identity mapping). Training for learning identity mapping is referred to as self-supervised, auto-association or auto-encoder\textsuperscript{29,30}. Auto-encoder is a neural network that is used to learn a compressed representation of a data. In other words, auto-encoder is a simple method to convert an input data space into an output data space with least possible distortion. Figure 10 gives a schematic overview of the auto-associative NLPCA architecture used in this paper.

![Figure 10: Network architecture for determining $f$ nonlinear principal components with the method proposed by Kramer\textsuperscript{29}](image)

**Hierarchical NLPCA:**

Decomposition into principal components is usually done for two reasons: 1) pure dimensionality reduction, 2) identifying meaningful components, also called feature extraction. In the standard auto-associative NLPCA algorithm explained above, all of the components are treated equally, therefore, there is no particular order in the identified components. In other words, the algorithm does not have any feature discrimination power. As Scholz and Vigario\textsuperscript{31} discuss in their paper, an implementation of NLPCA for feature extraction should possess two properties:

- **Scalability**: The first $n$ components represent maximal variance of the data that can be represented by an $n$-dimensional subspace.
- **Stability**: the $i$th component of the $f_1$-feature solution is identical to the $i$th component in a $f_2$-feature solution.

Researchers such as Saegusa et al. and Scholz and Vigario\textsuperscript{31,32} propose a hierarchical approach for using the standard NLPCA algorithm explained above. In a hierarchical NLPCA ($h$-NLPCA), the network consists of a hierarchy of sub-networks, each being solved through standard NLPCA process. For the experiments in this paper, we have employed the $h$-NLPCA approach developed by Scholz and Vigário\textsuperscript{31}. Readers are referred to the original works for more detailed information regarding standard NLPCA and/or $h$-NLPCA.

**5.2 Experimental validation of $h$-NLPCA under varying temperatures**

In this section, we investigate the performance of the NLPCA in removing the nonlinear relations between $X_d$ and $X_u$ components; hence, separating the undamaged observations from damaged ones. Pitch-catch records from the laboratory setup explained in Section 2.2 are used.
Figure 11 shows the projections of 800 observations on the NLPC that is expected to be representative of scatter signal \(X_d\). These observations are recorded from undamaged and damaged pipe, at the same range of temperature as in Figure 7d and 7c \((25^\circ C \leq T \leq 31^\circ C)\). As can be seen in Figure 11, unlike SVD (Figure 7c), NLPCA is successful in removing the nonlinear relations between the components. That is, the scatter signal \(X_d\) is extracted with good accuracy, therefore, the projections on this component sufficiently separate the two classes.

Table 2: Detection statistics of SVD and h-NLPCA methods for different ranges of temperatures. Note: K-mean clustering is used to examine the discrimination power of the scatter component extracted by the two methods.

<table>
<thead>
<tr>
<th>Temperature Range</th>
<th>Linear Decomposition Method (SVD)</th>
<th>Nonlinear Decomposition Method (h-NLPCA)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Accuracy (%)</td>
<td>FPR (%)</td>
</tr>
<tr>
<td>23°C ≤ T ≤ 25°C</td>
<td>97.4</td>
<td>0</td>
</tr>
<tr>
<td>23°C ≤ T ≤ 27°C</td>
<td>98.8</td>
<td>0</td>
</tr>
<tr>
<td>23°C ≤ T ≤ 29°C</td>
<td>57.2</td>
<td>39.1</td>
</tr>
<tr>
<td>23°C ≤ T ≤ 31°C</td>
<td>61.7</td>
<td>30.5</td>
</tr>
<tr>
<td>23°C ≤ T ≤ 33°C</td>
<td>55.9</td>
<td>44.3</td>
</tr>
<tr>
<td>23°C ≤ T ≤ 35°C</td>
<td>57.6</td>
<td>30.4</td>
</tr>
<tr>
<td>23°C ≤ T ≤ 37°C</td>
<td>55.0</td>
<td>33.6</td>
</tr>
<tr>
<td>23°C ≤ T ≤ 39°C</td>
<td>54.3</td>
<td>39.5</td>
</tr>
</tbody>
</table>

Figure 12: Detection accuracies of SVD and h-NLPCA methods for different ranges of temperatures. Note: K-mean clustering is used to examine the discrimination power of the scatter component extracted by the two methods.

To compare the separation power of linear and nonlinear decomposition methods, both SVD and NLPCA are applied to datasets at different ranges of temperature. The observations are projected onto the component that is expected to be a good representation of scatter signal. A simple K-mean clustering method is applied to examine the
performance of this component in discriminating damaged and undamaged pipes. Three metrics are used for this evaluation: (1) detection accuracy (i.e., the ratio of the number of correctly labeled damaged and undamaged observations to the total number of test observations), (2) false negative rate (i.e., FNR, the ratio of the number of incorrectly labeled damaged observations to the total number of damaged observations), and (3) false positive rate (i.e., FPR, the ratio of the number of incorrectly labeled undamaged observations to the total number of undamaged observations). Table 2 summarizes these statistics for different ranges of temperature, for both methods. Figure 12 depicts the detection accuracies, for easier understanding of the trend in detection performance of the two methods as temperature varies. The results show that, when temperature varies between 23°C and 27°C, both SVD and NLPCA can extract the scatter signal satisfactorily, hence separate the two classes. However, as the range increases, the nonlinear relation between the multi-modal signals at different temperatures become more significant, leading to a drop in detection performance of SVD compared to NLPCA. As can be seen in Table 2, the performance of NLPCA stays high for temperatures ranging from 23°C up to 33°C, and slightly drops after. In all temperatures, however, NLPCA outperforms SVD.

6. CONCLUSION

Ultrasonic guided-waves in pipes, with varying environmental and operational conditions (EOCs), are usually the results of complex superposition of multiple modes travelling through multiple paths. Two categories of methods are currently used to extract the scatter signal while coping with the effects of EOCs (mainly, temperature): stretching of baseline signals for baseline-subtraction, and linear decomposition methods. In general, in a multi-modal guided-wave signal, signal components at different temperatures are nonlinearly related. This is because different wave modes can have significantly different sensitivities to temperature. In this paper, we utilize a nonlinear decomposition method, namely nonlinear principal component analysis (NLPCA), to remove the nonlinear relation between the signal components when temperature varies. Ultrasonic pitch-catch records, obtained from an aluminum pipe segment in a thermally controlled laboratory environment, are used. The results show that NLPCA can satisfactorily extract scatter signals for temperatures ranging from 23°C up to 33°C.

It is notable that the objective of this paper is to propose a method for extraction of damage-sensitive features, under a wide range of temperature variations, rather than methods for damage detection. Although a simple K-mean clustering method is used here to prove the concept, more sophisticated classification algorithms need to be considered since K-mean clustering is vulnerable to particular assumptions. The future work includes development of algorithms that are less computationally expensive than h-NLPCA, to enhance the applicability of the proposed approach for real-time monitoring. Moreover, the extracted sparse signals will be used for localization of the detected damages under different EOC scenarios.

7. ACKNOWLEDGEMENT

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8. REFERENCES