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A Sparse Sensor Network Topologized for Cylindrical Wave-based Identification of Damage in Pipeline Structures

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Abstract

A sparse sensor network, based on the concept of semi-decentralized and standardized sensing, is developed, to actively excite and acquire cylindrical waves for damage identification and health monitoring of pipe structures. Differentiating itself from conventional "ring-style" transducer arrays which attempt to steer longitudinal axisymmetric cylindrical waves via transducer synchronism, this sparse sensor network shows advantages in some aspects, including the use of fewer sensors, simpler manipulation, quicker configuration, less mutual dependence among sensors, and an improved signal-to-noise ratio. The sparse network is expanded topologically, aimed at eliminating the presence of "blind zones" and the challenges associated with multi-path propagation of cylindrical waves. Theoretical analysis is implemented to comprehend propagation characteristics of waves guided by a cylindrical structure. A probability-based diagnostic imaging algorithm is introduced to visualize damage in pixelated images in an intuitive, prompt, and automatic manner. A self-contained health monitoring system is configured for experimental validation, via which quantitative identification of mono- and multi-damage in a steel cylinder is demonstrated. The results highlight an expanded sensing coverage of the sparse sensor network and its enhanced capacity of acquiring rich information, avoiding the cost of augmenting the number of sensors in a sensor network.

Keywords: sparse sensor network; cylindrical waves; nondestructive damage evaluation; pipeline structures

1. Introduction

Cylindrical structures (e.g. oil pipelines, drive shafts, bends, and hollow train axles) are ubiquitous in engineering practice, often serving as key load-bearing components. The importance of periodic inspection on these structures (broadly termed as nondestructive evaluation (NDE)), or continuous monitoring of their health/integrity (a.k.a. structural health monitoring (SHM)) could not be overemphasized. Effectual NDE and SHM warrant a reliable service of cylindrical structures, and thus the risk of structural failure can be minimized. Amongst a diversity of candidate techniques to implement NDE and SHM, those making use of the guided waves in an ultrasonic regime have proven effectiveness [1–11], as a cylindrical structure is in substance an appropriate waveguide for wave dissemination. Various modalities of wave modes along helical paths in circumferential and/or longitudinal directions of the pipe allow effective identification of damage not only on the inner or outer surface, but also within the cylinder wall. Compared to bulk waves that are three-dimensional (3-D) in nature and thus radiate energy omni-directionally, cylindrical waves possess a low rate of attenuation, because wave propagation is largely confined in the cylinder without lateral spreading, making it possible to guide the cylindrical waves to propagate over an elongated distance from a single transducer position, while retaining a reasonable signal-to-noise ratio, conducive to the inspection of long pipelines [10–12]. In addition, the short wavelengths of ultrasonic cylindrical waves enable the scrutiny of damage of small dimension. All these inherent merits have endowed cylindrical wave-based damage detection with immense prominence and potentials for real-world engineering applications.

In this backdrop, majority of prevailing techniques have been developed and implemented with handheld ultrasound transducers in an offline nature. The need to scan the entire inspection region using the bulky transducers makes them not suited for continuous monitoring, limiting their applicability. It is often a prerequisite to suspend temporarily the normal operation of the inspected system, or in some occasions to dismantle cylindrical components of interest. Moreover, pipeline structures are often lagged or coated, which needs to be removed when conducting periodic inspections. This removal process can be expensive and time consuming. Finally, success of the inspection is often achieved in a somewhat subjective manner at the discretion of the operator, thus requiring highly skilled operators. This, in addition to incurring exorbitant cost, inevitably creates vast obstacles towards real-time, automatic, and prompt inspection.

Motivated by these drawbacks, intensive research endeavors have been invested over the past two decades on the development of SHM techniques for plate-like structures including thin-walled cylinders. These SHM techniques, featuring the use of guided waves in conjunction with active sensor networks/arrays, reap the merits of miniaturized transducers (e.g. piezoelectric lead zirconate titanate (PZT) wafers) such as low power consumption, negligible footprints, low cost, and ease of integration into host structures [13–20]. Relevant approaches are in a good supply, and they can be grouped into two major categories in terms of the density of the sensors used to configure a sensor network/array: (i) dense sensing configuration (e.g. tomography), and (ii) sparse sensing configuration. The former sensing philosophy entails either the use of a relatively large number of transducers to form sensing rays densely covering the inspection region, or rotation of the inspected object by a tiny increment; while in the latter, a relatively limited number of sensors are networked, with the sensor spacing being far greater than the damage scale. In that sense, the sensors have to be prudentially distributed and strategically positioned.

With either the dense or sparse sensing configuration, waves can be generated and guided by the structures to implement NDE or SHM based on various principles. In many situations [21–23], a thin-walled cylindrical structure is usually simplified as a thin plate as if being unwrapped and laid flat, whereby conventional damage detection methods based on the theory of plate waves (Lamb waves) may be applied. For example, Leonard and Hinders [21, 22] proposed a detection algorithm for pipe-like structures based on Lamb wave tomography (LWT). LWT has demonstrated capacity of identifying corrosion and other types of flaw on the inner surface of a pipe. Bertoncini et al. [23] developed an inspection system for long pipelines based on guided waves generated by a “ring-style” transducer collar with magnetostrictive transducers clamped around the pipe, via which damage in the pipe can be located by scrutinizing the reflected longitudinal waves. A more recent study by Willey et al. [24], using a “ring-style” electromagnetic acoustic transducer (EMAT) array coupled with pipes, exploited the information carried by high-order helical modes (i.e. guided waves that wrap around a pipe multiple times before reaching sensors) in order to achieve superior imaging resolution for guided wave tomography. Sharing a similar detection philosophy to LWT and “ring-style” transducer arrays, Wavemaker™ Pipe Screening System by Guided Ultrasonics Ltd. and Teletest® by Plant Integrity Ltd. are two commercialized techniques towards pipeline SHM [4, 25, 26]. In both techniques, a circumferential transducer belt comprising a certain number of piezoelectric elements encircles the pipe at one end of a section, to generate and manoeuvre longitudinal waves propagating along the pipe axis. A few of such belts can be used to delimit different inspection sections along a long pipe. Damage can thus be characterized by calibrating the reflection coefficient of damage-echoed wave signals. They are able to detect external or internal damage in a section of a pipeline with a length up to 25 m in both directions, even when the pipeline is buried, insulated, or filled with fluid. It is relevant to stress that in a “ring-style” transducer array, it is crucial to synchronize all the transducers such that only the longitudinal wave mode is strengthened while other undesired wave modes such as the flexural wave modes are eliminated through interactions among the wave fields produced by individual transducers in the ring. This synchronism entails extra efforts in transducer collocation and excitation control. Notably, a sparse sensor network with a limited number of transducers turns out to be insufficient to accommodate such a demand.

In this study, a sparse sensor network technique is developed for damage identification and SHM of pipe structures. A concept, termed "semi-decentralized and standardized sensing", is introduced to facilitate sparse sensor network configuration in a quick and convenient manner, for active generation and acquisition of cylindrical waves. A topological expansion strategy for the sparse sensor network is further implemented, to circumvent the potential deficiencies (e.g. the presence of "blind zones") due to the use of a limited number of sensors. Theoretical analysis is first conducted to comprehend the propagation characteristics of cylindrical waves. Integrating a probability-based diagnostic imaging algorithm, a self-contained SHM system is configured for experimental validation, in which the developed approach is employed to evaluate various damage scenarios in a steel cylinder.

2. Cylindrical Waves Generated by a Sparse Sensor Network

2.1. Theory

Although there is a considerable amount of literature addressing elastic waves guided by cylindrical structures, it is incumbent to recapitulate the fundamentals and basic theory of this particular type of waves, prior to its utilization for damage identification.

Despite sharing certain similarities in propagation with their counterparts in planar structures (i.e. Lamb waves), such as the multimodal and dispersive natures, elastic waves guided by a cylindrical structure, called *cylindrical waves* or *helical waves* [27], present additional complexities due to the multi-path dissemination along the cylinder. Consider a thin-walled cylinder with an inner radius a and an outer radius b ("thin" here implies the tangential dimensions of the cylinder are much greater than its thickness), cylindrical guided wave modes can be distinguished as longitudinal, torsional and flexural modes, which are labeled as L, T and F, respectively. At lower frequencies, longitudinal, torsional and flexural modes dominate, but at higher frequencies the cylindrical waves behave more like Lamb waves. To differentiate various orders of a particular cylindrical mode, the three wave modes are denoted by L(n, m), T(n, m), and F(n, m), where n and m are two non-negative integers (n, m = 0, 1, 2, …), with the former associated with the geometric properties of the cylindrical structure and the latter denoting the wave mode's solution order. In particular, n = 0 signifies that the cylinder is axially symmetric in which the wave fields are independent of the angular coordinate θ—as is the case in most engineering applications. Axisymmetric modes include both longitudinal modes L(0, m) and torsional modes T(0, m), while non-axisymmetric modes are represented by flexural modes F(n, m) when $n \neq 0$. The field components of the three wave modes can be described generally by [28]

$$\begin{aligned} u_r &= U_r^{nm}(r)\cos(n\theta)\cos(\omega t + k^{nm}z), \\ u_\theta &= U_\theta^{nm}(r)\sin(n\theta)\cos(\omega t + k^{nm}z), \\ u_z &= U_z^{nm}(r)\cos(n\theta)\sin(\omega t + k^{nm}z), \end{aligned} \quad \textbf{(1)}$$

where u_r, u_θ, and u_z are the displacement components in the radial, circumferential, and axial directions, respectively; U_r^{nm}, U_θ^{nm}, and U_z^{nm} are the displacement amplitudes composed of the Bessel or modified Bessel functions for circumferential order n and solution order m of the wave mode of interest; ω is the angular frequency; and k^{nm} is the wavenumber. With Eq.

(1), Fig. 1 shows the dispersion curves of various cylindrical wave modes guided by an exemplary steel tube (216 mm in diameter and 4 mm in thickness). Amongst them, the longitudinal axisymmetric modes are of most interest for SHM purposes, owing to the ease and convenience in generating, capturing and extracting this sort of wave modes [29].

2.2. Sparse Sensor Network Based On Semi-Decentralized and Standardized Sensing

As opposed to ring-style sensor arrays which usually feature a dense sensor configuration (in order to deliberately eliminate undesired modes such as T(0, *m*) and F(0, *m*)) and make use of damage-echoed signals only, an active sparse sensor network is aimed at compromising "sensing cost" with "sensing effectiveness", as well as "converge" with "sensitivity"—both addressing the desire to acquire more information with fewer sensors. However, when affixed to a pipe-like structure, a sparse sensor network presents unique and intricate characteristics in exciting and acquiring cylindrical waves, some of which may impose great challenges in signal interpretation and lead to arguments on detection results if transducers are insufficient in the network.

Confronting the possible limitations of sparse sensor networks applied to pipe-like structures for SHM, a sensing concept, called "semi-decentralized and standardized sensing" in this study, is developed. Conventionally, decentralized detection requires that information retrieved by each sensor in a sensor network, which is usually geographically distributed, is independently processed before a single message/decision is transmitted to the fusion center [30]. In the semi-decentralized scheme proposed here, original wave signals acquired by individual sensors are fully transmitted to the fusion center (the central control and post-processing module, to be detailed in Section 4.1), but processed separately so that each sensor contributes one detection outcome, using all possible sensing paths associated with this sensor. Without the need to coordinate and synchronize individual sensors, the semi-decentralized and standardized sensing accentuates a three-fold feature: (i) mutual independence of individual sensors in a sensor network in perceiving signals; (ii) the establishment of detection results that are based on individual sensors, rather than direct/shortest sensing paths; and (iii) a standardized sensor formality, in order to deploy a sensor network in a quick and cost-effective manner.

The proposed sensing scheme is realized through standardized sensing elements (SSEs). An SSE is an individual sensor unit fabricated by immobilizing a circular miniaturized PZT wafer onto a polyimide film through a printed circuit, as seen in Fig. 2. Each SSE is instrumented with the signal acquisition device via a standard microdot embedded in the film as well. Enclosing PZT in polyimide isolates a fragile PZT wafer and its associated lead wires from harsh environments, providing reliable connectivity and elongated service life. A standardized manufacturing process warrants the conformance of different batches of SSEs. The PZT wafer in an SSE (0.2–0.5 mm in thickness, and 5–10 mm in diameter, depending on applications) contributes negligible weight and volume penalties to the host cylinder, conducive to the implementation of SHM with minimal impact on the overall structural integrity. To be either surface-mounted on or embedded into an inspected structure, a certain number of SSEs can configure a sensor network conveniently and promptly, capable of accommodating diverse geometric and boundary conditions of the structure. All networked SSEs perceive guided wave signals independently and communicate with the signal acquisition devices separately. Data processing-wise, an SSE is also independent of the rest in the network, as opposed to a traditional sensor network involving batch processing of measurands collected from all the sensors—a process otherwise known as “centralized sensing and processing”. The proposed data acquisition and signal processing method endows a configured sensor network with advantages over "ring-style" transducer arrays, by virtue of the following aspects:

(i) the use of fewer sensors to cover a comparable area of inspection;

(ii) a simpler manipulation and mutual independence among SSEs (contrasting a precise synchronization of all transducers in a "ring-style" array), offering enhanced robustness, error-tolerance and measurement redundancy in rugged measurement conditions, even when part of the sensor network becomes mal-functional; and

(iii) an extended sensing coverage with an enhanced signal-to-noise ratio, as SSEs are sparsely distributed along the cylindrical axis, with which both pitch-catch and pulse-echo signal acquisition modes can be implemented (contrasting a relatively limited detection resolution yielded by a "ring-style" array, as all transducers in the ring are allocated at one end of the pipe, in accordance with a pulse-echo measurement only).

2.3. Excitation and Acquisition of Cylindrical Waves with a Sparse Sensor Network

In a sparse sensor network, each SSE acts, in turn, as a wave actuator to generate a probing signal, and the propagated waves are monitored by the rest SSEs in the network, by dint of either pitch-catch or pulse-echo measurement. Fig. 3 illustrates a representative sparse sensor network based on the concept of semi-decentralized and standardized sensing, which is surface-mounted on a cylindrical structure for SHM.

Different from a "ring-style" transducer array which is able to produce a dominant wave mode (e.g. a longitudinal mode), a sparse sensor network excites all the possible wave modes guided by the cylinder, each exhibiting dispersive properties. Multiple wave modes disseminate in the cylinder, traversing not only along the cylinder wall surface but also through the thickness, making it a demanding task to distinguish damage-scattered waves, especially when the pulse-echo signals are concerned. Another complexity arising from the use of a sparse sensor network is that there can be an infinite number of helical routes between an actuator and a sensor, one of which takes the most direct path, while the others with steeper helicities are directed around the cylinder circumferentially, meaning waves may travel one or more complete loops around the pipe before reaching a sensor. Moreover, helical waves can propagate clockwise or counterclockwise with respect to the axis of the cylinder. In the presence of damage, the above complexity is increased because the damage scatters the probing waves omni-directionally as well, causing mode conversion in the meantime.

For the convenience of illustration, a cylinder is virtually anatomized along an arbitrary longitudinal line in parallel with the cylindrical axis, unwrapped, and treated as a flat plate as shown schematically in Fig. 4. Then, the imaginary line serves as two free edges of the flat plate, which are inexistent in reality. Such an ideal unwrapping process incurs an additional issue—the negligence of waves propagating across the imaginary line. This can be better interpreted using an example shown in Fig. 5, in which twelve SSEs are included in a sparse sensor network attached to an unwrapped cylinder. With the hypothesis of a flat plate upon the unwrapping process, all the direct sensing paths rendered by the sensor network are highlighted using solid, dash-dot, and dashed lines. Those paths in black solid lines are only part of the shortest sensing paths between two SSEs. The (red) dash-dotted lines do not actually represent the true wave propagation paths if first-arrival signal is concerned; the real first-arrival paths, instead, should be shorter than them due to multi-path propagation across the imaginary cutting line. Similarly, the (blue) dashed lines indicate only half of the actual paths travelled due to the same reason.

This issue could further be elucidated in Fig. 6, where the flattened geometry of the cylinder is extended in both directions perpendicular to the imaginary cutting line. Arbitrarily selecting two SSEs in the network, say S_1 and S_8 without the loss of generality, $P'_{1\text{-}8}$, the red dashed line, is the only sensing path connecting S_1 and S_8 within the inspection region if the unwrapping process is applied. Nevertheless, in reality, cylindrical waves also travel a path across the cutting line, as denoted by the black solid line $P_{1\text{-}8}$, which however would not be taken into account within the inspection region of the plate. In fact, $P_{1\text{-}8}$ is shorter in distance than $P'_{1\text{-}8}$, and should be used as the shortest propagating path if the first-arrival signals are of interest. In another instance, the S_2-generated cylindrical waves spread omni-directionally, and perceived by S_8 along not only $P'_{2\text{-}8}$, but also $P_{2\text{-}8}$ across the cutting line. If not dealt with carefully, the above-mentioned incompleteness of path coverage would contribute to the formation of some blind zones near the cutting line of the cylinder where signals are excluded for SHM.

3. Topology of Sparse Sensor Networks and Diagnostic Imaging

3.1. Topology

To tackle the above-addressed complexity and deficiency due to the unwrapping process, rectify the coverage of a sparse sensor network, and minimize blind zones, a topological expansion for the sparse sensor network is developed. In this method, the plane-like geometry of the unwrapped cylinder is virtually and continuously extended by joining its two replicas along the two free edges, as illustrated schematically in Fig. 7. In virtue of such a topological expansion, the omni-directional propagation of cylindrical waves in the sparse sensor network can be complemented to include all those traversing the imaginary cutting line. In contrast to the example demonstrated in Figs. 6 and 7 where a significant number of sensing paths are neglected inappropriately, all the candidate sensing paths yielded by the sensor network are taken into account upon the sensor network topology, to be exploited for SHM.

Another benefit of the topological expansion, though not drawn on Fig. 7 to avoid overcrowding, is the ability to visualize helical wave paths that are not the shortest between a pair of actuator and sensor. By repeatedly placing virtual SSEs vertically and joining any two of them, it is able to show helical wave routes that go around the cylinder both clockwise and counterclockwise between a actuator-sensor pair, as well as wave routes looping around the cylinder for more than one full circle. In fact, by examining cylindrical waves that travel more than one loop between an actuator and a sensor, it is able to "magnify" the difference of signals retrieved by the sensor before and after the introduction of damage [6]. In short, this topology tactically circumvents the deficiency owing to the incompleteness of partial sensing paths of a sparse sensor network in acquiring cylindrical waves, and in the meantime provides visualization of multi-path propagation of cylindrical waves between any actuator-sensor pair in the network.

In addition, aimed at enhancing the excitability and receivability of cylindrical waves associated with a sparse sensor network, *Hanning* window-modulated multi-cycle sinusoidal tone bursts are used as the probing signal. A narrowband waveform is beneficial to confining the incident wave energy at specific frequencies, so as to minimize the effect of wave dispersion. In the meantime, the excitation frequency is prudentially selected in order to minimize the multimodal and dispersive effects, which can be done by consulting the dispersion curves of cylindrical waves. As shown in Fig. 1, fewer modes co-exist in relatively low frequency bands, benefiting the identification of wave modes of interest.

3.2. Diagnostic Imaging

SHM of cylindrical structures can be implemented by exploring the changes in a variety of signal features, such as amplitude or time-of-flight, extracted from cylindrical waves acquired in accordance with either the pitch-catch or pulse-echo measurement. Driven by the incentive to "visualize" SHM results in an intuitive and prompt manner, there has been an increasing preference in projecting identification results to synthetic images, in which structural defect or damage, if any, can be highlighted and scrutinized conveniently. Approaches with such an initiative are collectively referred to as *damage diagnostic imaging* (DDI) [31–35]. In this study, a DDI approach in conjunction with the use of the topologized sparse sensor network is developed. In the synthetic images produced, SHM results are represented at the pixel level in terms of the probability of damage presence, and thus this particular approach is termed *probabilistic imaging algorithm* (PIA).

With PIA, the inspected region of an unwrapped cylinder is uniformly gridded, and projected to an image with each image pixel corresponding exclusively to a spatial point of the cylinder. The probability of damage presence in the inspection region is then defined based on the correlation of the first-arrival waves, captured in the pitch-catch mode, from the current and its corresponding reference states, respectively. This particular method derives its idea from the minimum variance distortionless response (MVDR) [36], which aims to reduce artifacts in acquired signals such as reflections that are indistinguishable from actual damage. More specifically, the non-negative correlation coefficient of the current ($\mathbf{r} = \{r_1, r_2,\ldots, r_n\}$) and reference ($\mathbf{s} = \{s_1, s_2,\ldots, s_n\}$) signals, after appropriate time windowing, can be defined in terms of their covariance, cov($\mathbf{r}$, $\mathbf{s}$), and standard deviations, σ_r and σ_s [37], as

$$\rho_{r,s} = \mathrm{cov}(\mathbf{r},\mathbf{s}) / (\sigma_r \sigma_s). \qquad \textbf{(2)}$$

As far as a single sensing path (shortest or not between two SSEs) is concerned, its associated correlation coefficient, ρ, would approach one if there is no damage on or near this particular path; on the contrary, ρ would reduce to a low value if the path is close to damage, as the damage modulates wave propagation and leads to elevated inconsistence between the current and reference signals. As the first step in developing the PIA, the correlation coefficient for each path is calculated and used to estimate a basic and relative probabilistic measure of damage presence, as $1 - \rho$, which is the perception on damage existence along that particular sensing path in the cylinder. Then, for every pixel in the inspected region, a unique weight factor is assigned to each sensing path to regulate its contribution to the probability calculation at that pixel, in terms of the relative distance between the pixel and the path. Results contributed by individual sensing paths who share a common sensor is amalgamated at the sensor level, and a source image contributed by this SSE is registered at the fusion center (a semi-decentralized detection outcome). Upon information fusion of results from all SSEs, the entire domain is then filled with accumulated probability values. Any hotspot, where the pixels feature elevated field values, can pinpoint possible damage location(s). Such a manipulation can be illuminated as follows. Consider a sparse sensor network of $N + 1$ SSEs. For a single sensor i, there are N actuator-sensor combinations and an infinite number of sensing paths or helical wave routes. If only the first-arrival wave packets in the N acquired signals are used, the estimated probability of damage presence at pixel (x, y) from the perspective of sensor i, denoted by $P_i(x,y)$, can be expressed, with a sensor-level fusion scheme based on the arithmetic mean, as

$$
\begin{aligned}
P_i(x,y) &= \frac{1}{N}\sum_{n=1}^{N} p_n(x,y) \\
&= \frac{1}{N}\sum_{n=1}^{N}(1-\rho_n)\cdot\exp\left[d_{\min}\left(x,y,x_n^a,y_n^a,x_i^s,y_i^s\right)-d_{\min}\left(x_n^a,y_n^a,x_i^s,y_i^s\right)\right],
\end{aligned} \qquad \mathbf{(3)}
$$

where $p_n(x, y)$ is the basic probabilistic measure of damage presence at pixel (x, y) determined by the n^{th} direct sensing path, and the exponential term is the weight factor of this particular path with respect to pixel (x, y), as explained in the above; the distance function $d_{\min}\left(x, y, x_n^a, y_n^a, x_i^s, y_i^s\right)$ is the sum of the shortest distances from this pixel to the actuator at (x_n^a, y_n^a), and then to sensor i at (x_i^s, y_i^s); and similarly, $d_{\min}\left(x_n^a, y_n^a, x_i^s, y_i^s\right)$ is the shortest distance on the cylinder between this pair of actuator and sensor forming the n^{th} direct sensing path. Using the information at the sensor level as obtained above, the final diagnostic result can be produced by choosing sensors of interest at the user's discretion and fusing their individual results. This feature of semi-decentralization is especially beneficial for monitoring large/long pipeline structures, or when some SSEs in the sensor network malfunction. It is also noteworthy that the idea of "probability" both in the basic measure of $1 - \rho$ defined on paths and the aggregate probability index $P_i\left(x, y\right)$ defined on pixels should be interpreted in a relative sense—they are the perceptions from the used part of the sensor network on where in the examined structure the damage is more likely to occur compared to the rest, instead of an absolute measure of frequentist probability of occurrence.

In the case where additional helical wave routes than direct paths are desired, such as those routes traveling πD more than the shortest paths (assuming D is the average diameter of the cylinder), the time window of the signals for correlation calculation can be accordingly updated using the new path lengths and wave velocity, and the two distance functions in Eq. (3) need to be adjusted as well. This new set of diagnostic results can be combined with the previous ones at the sensor level as well.

Notice that for plate structures, conventional delay and sum algorithms (e.g. time-of-flight methods) have been exclusively studied and applied, and their effectiveness in locating mono-damage as well as multi-damage have been compared with MVDR- or correlation-based imaging techniques [36, 38, 39]. In cylindrical structures, however, due to the multi-path propagation of guided waves as discussed earlier, it is generally less efficient to use features such as the time of flight for damage localization. For example, for any sensing path in a sensor network, the time of arrival at the sensor of damage-scattered waves may be associated with more than one damage locus, depending on the specific wave path assumed. However, the issue of multi-path propagation is of less concern for imaging using first-arrival waves of pitch-catch methods, such as the one proposed in this study, as the field value defined by Eq. (3) is highly inert to distant damage [38], and results from a few neighboring sensing paths can cross validate the damage's location. Thus, this study employs primarily the correlation-based algorithm of first-arrival waves (those traveling the shortest sensing paths) for damage localization in cylindrical structures.

4. Experimental Validation

4.1. System Development

For the purpose of approach validation, a self-contained SHM system, to be used with a semi-decentralized and standardized sparse sensor network, is configured. Developed via a virtual instrument technique based on the PXI (PCI eXtension for Instrumentation) platform, the system features a compact design, mobility, and expandable functional modules, with its basic frame illustrated in Fig. 8. As can be seen, the core framework of the system consists of five pivotal modules: (i) a sparse sensor network, (ii) probing wave generation (NI® PXI-5412 arbitrary waveform generator) with linear power amplification, (iii) multi-channel data acquisition (NI® PXI-5105 digitizer) with charge amplification, (iv) switch control (NI® PXI-2529 high-density matrix switch), and (v) central control and post-processing. Unlike conventional testing rigs in which isolated and incoherent measurement devices, such as function generators and oscilloscopes, are employed for probing wave generation and signal acquisition, the five modules in this system are integrated through a PXI bus (NI® PXIe-1071), for mutual communication and data synchronism via their respective interfaces. Such integration improves the overall measurement efficiency and data processing. The central control and post-processing unit is supported by an in-house software package programmed on the NI® LabVIEW® platform. The package is managed in a three-layer architecture, as displayed in Fig. 9: the man-machine interface (MMI) to deal with all system inputs and deliver diagnostic results (producing alarm if damage detected), the physical layer to drive all involved hardware in the system, and the application layer to support the interfaces of five modules.

As a key feature, the system is of an expandable and open nature, allowing it to be tailor-made towards diverse real-world applications. More modules can be integrated into the system for further development and expansion, depending on particular SHM tasks and the scale of a structure to be monitored. Benefiting from the standard data bus and compatible communication interfaces, the system can also be integrated with other commercially available measurement systems. This is especially beneficial towards the SHM of long pipeline in the real world, which requests an elongated coverage with a limited number of sensors.

4.2. Specimen Preparation and Experimental Setup

A steel thin-walled cylinder, 216 mm in outer diameter, 4 mm in thickness, and 1,000 mm in length, was prepared for validation. A sparse sensor network, comprising twelve SSEs, was surface-affixed to the cylinder. The cylinder was virtually "unwrapped", and applied with the proposed topological approach. For the convenience of discussion, the center of the unwrapped cylinder was set as the origin of coordinate system, with respect to which the coordinates of the twelve SSEs are listed in Table 1. The accordingly constructed sensor network is displayed in Fig. 7, based on which 66 monitoring paths, denoted as $P_{A\text{-}S}$, can be identified in principle, where A and S are the indices of the actuator and the sensor, respectively. Note that due to the symmetric nature of the structure, the SSEs were homogenously distributed over the unwrapped topology. This may not be the optimal strategy if there are irregularities in the geometry like radius change, which would deserve further scrutiny. The sensor network was then instrumented with the SHM system as photographed in Fig. 10.

Artificial damage was introduced to the cylinder in the form of added masses, with three scenarios considered: (i) the healthy state — with no any added masses, (ii) two mono-damage states, in which a single steel block was affixed with superglue to the cylinder outer surface at (135 mm, -10 mm), and then at (135 mm, 330 mm); and (iii) two multi-damage states, where two identical steel blocks were simultaneously affixed to the cylinder at (135 mm, -10 mm) and (-150 mm, -60 mm), and then at (135 mm, 330 mm) and (-150 mm, 280 mm). Each steel block, measuring 20 mm (length) × 30 mm (width) × 48 mm (height), was slightly curved on its bottom surface to adapt to the curvature of the cylinder. The introduction of mock-up damage in the form of added masses affects wave propagation in a similar fashion as a hole or a crack does: both of them compromise the structural integrity by introducing local discontinuities, which scatter the probing waves and incur energy dissipation as they block guided wave propagation.

A narrowband five-cycle *Hanning*-windowed signal was excited at a center frequency of 320 kHz as the probing signal, which was amplified to 60 $V_{p\text{-}p}$ after power amplification. According to the dispersion curves shown in Fig. 1, this selected frequency enables a longitudinal mode L(0,1) to stand out with a much larger group velocity (~ 5000 m/s) than the other modes available at this frequency, facilitating mode recognition. Note that, regardless of the dominance of L(0,1), all the cylindrical wave modes, L(0, *m*), T(0, *m*), and F(0, *m*), were generated at any frequency. Each SSE in the sensor network takes turns to act as the actuator, with the rest being sensors for wave acquisition concurrently. The minimum characteristic dimension of damage that is detectable at this frequency is approximately 7.5 mm, calculated as the half of the probing wavelength of the L(0,1) mode. To further improve the resolution of damage detection, one could increase the excitation frequency at the expense of possibly lower wave mode recognizability, which may require additional mode tuning and signal processing.

4.3. Results and Discussions

As representative results, Fig. 11 compares the cylindrical wave signals acquired via sensing path $P_{11\text{-}6}$, before (reference signal) and after (current signal) the damage presence, showing a significantly reduced magnitude of the first-arriving wave packet and its succeeding wave packets in the current signal with regard to the reference signal. Since $P_{11\text{-}6}$ traverses through the cylindrical area bearing the artificial damage, such an observation corroborates the previous statement that damage modulates wave propagation, leading to inconsistence between the current and reference signals.

For the healthy state (scenario i), measurements were performed in varied environments of different ambient temperatures. Fig. 12 shows the averaged results of $1 - \rho$, the basic measure of damage presence associated with each sensing path before mapping to pixels using Eq. (3), from all the paths. Although some discrepancies among various paths exist, all of the probability values remain below 0.05, which may be attributable to ambient noises and operating errors. This finding demonstrates that the basic measure is consistent across all paths when there is indeed no damage, and it can hence be assumed that changes in signal magnitude caused by environmental and operational effects are trivial to be neglected in what follows.

With the mono-damage state (scenario ii), Fig. 13 shows the updated values of $1 - \rho$ associated with all the sensing paths. It is obvious that five of them have a path probability value exceeding 0.1, namely $P_{10\text{-}4}$, $P_{10\text{-}7}$, $P_{11\text{-}1}$, $P_{11\text{-}2}$ and $P_{11\text{-}6}$, which are noted to pass through the damage spot at (135 mm, -10 mm). Another five paths, $P_{10\text{-}3}$, $P_{10\text{-}8}$, $P_{11\text{-}3}$, $P_{11\text{-}7}$ and $P_{11\text{-}10}$, close to the damage spot, are found to have a probability value over 0.05 but below 0.1 (between the two dashed lines in Fig. 13). Then, by using Eq. (3), these path probability values are mapped to each pixel in the final images, as shown in Fig. 14, for both the healthy and mono-damage states. No hotspot can be observed in Fig. 14(a) for the healthy state, while Fig. 14(b) reveals the mono-damage, in which the highlight in crimson provides an accurate diagnosis of the location and size of the simulated damage in the cylinder, as compared to the white rectangle indicating the real location and size of the added block. To take a step further to examine the effectiveness of the topologized sensor network in eliminating “blind zones”, the simulated damage was then moved to the imaginary cutting line, the area enclosed by S_8, S_{12}, S_5, and S_9. Using the same approach, the identification result is shown in Fig. 14(c), again precisely pinpointing the damage spot (both location and size). Finally, Fig. 14(d) shows the reverted 3-D cylinder in which the mono-damage is highlighted upon application of an appropriate threshold value to suppress any garbled information.

To further demonstrate advantages of the proposed sensor network topology in ameliorating detection accuracy, the results obtained using traditional unwrapping treatment with plate wave theory are presented in Fig. 15 (without the use of sensor network topology expansion). As can be seen, the damage could successfully be indicated only when it was located away from the imaginary cutting line, in the area enclosed by topologized sensing paths, as shown in Fig. 15(a). Nevertheless, provided the damage was re-located on or near the cutting line, the final image fails to indicate the damage correctly, as seen in Fig. 15(b).

For the multi-damage state (scenario iii), using the same manipulation as from the above, Fig. 16 shows the values of $1 - \rho$ of all the sensing paths. Compared to Fig. 13, the additional damage increases the values of certain paths, such as $P_{6\text{-}4}$ and $P_{11\text{-}3}$, resulting in eleven monitoring paths with damage probabilities exceeding 0.1, all of which are noticed to pass right through the two damage spots. The ultimate imaging results are exhibited in Fig. 17. It can be seen that, with the expanded topology, no matter where the two blocks were placed, either close to or far from the imaginary cutting line, two hotspots can be accurately identified in the images. The 3-D illustration of the reverted cylinder presents a more intuitive visualization results in Fig. 17(c).

In summary, the proposed technique implementing semi-decentralized SSE networks has achieved reasonably good detection results in both single- and multi-damage conditions. Specifically, this technique employs a sparse network of only 12 SSEs to cover a pipe with 1 meter in length and 216 mm in diameter; while for “ring-style” transducer arrays as mentioned in Section 1, in some instances two batches of transducers (more than 12 in each) have to be used to cover only half of this length with a similar diameter. In addition, as illustrated in the experiment, the technique proposed here does not require the synchronization of all the transducers to excite only the longitudinal modes, and therefore is more flexible in terms of sensor location and measurement mode selection due to the independence among SSEs. This is probably not viable if ring-style transducer arrays are used.

5. Concluding Remarks

In this paper, a topological improvement for a sparse sensor network is made to enable accurate damage detection and online SHM for cylinder-like engineering structures. Fundamentals of cylindrical guided waves for damage detection in cylindrical structures are first examined. A sparse sensor network composed of semi-decentralized and standardized PZT sensing elements is developed to ensure the practicality of the method. By taking into account the complicated shapes and sizes of cylinder-like structures, and the possible challenges due to the use of a fairly limited number of sensors, the topologized sparse sensor network has proven effectiveness in eliminating blind zones and creating convenient representation of multi-path wave propagation. Probability-based damage imaging is employed to show the final SHM results intuitively. A compact online damage detection and monitoring system is tailor-made to validate the proposed topology approach. The experimental validation on a steel cylinder has demonstrated the benefit of the topologized sensor network, by accurately locating mono- and multi-damage which are arbitrarily placed on the cylinder in a real-time fashion. Most significantly, the approach presented here has shown the feasibility, convenience and potential of using a sparse sensor network to cover large engineering cylindrical structures such as gas/oil pipelines, for accurate online SHM using cylindrical guided waves.

In the meantime, there is still room for improvement of the technique in future research. First, the imaging results presented here involved some noise of varying magnitudes, especially in the multi-damage case. This is probably caused by the multi-patch signal acquisition of sensors. Second, in the multi-damage case, the detection method proposed is most effective when the two added masses are well separated. In order to enhance the effectiveness of the correlation-based imaging method when the simulated masses are close to each other, one can increase the number of sensors, so as to have more sensing paths to cover the inspected area. Furthermore, to enhance the method's sensitivity to smaller damage than what was examined here, one can also increase the excitation frequency within an appropriate range.

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