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A Review of Signal Processing Techniques for Ultrasonic Guided Wave Testing

Ana Rita Diogo [1], Bruno Moreira [2], Carlos A. J. Gouveia [2] and João Manuel R. S. Tavares [3,*]

[1] Departamento de Física e Astronomia, Falculdade de Ciências, Universidade do Porto, 4169-007 Porto, Portugal; rita.i.diogo@gmail.com
[2] EQS Global, 4470-211 Maia, Portugal; bruno.moreira@eqsglobal.com (B.M.); carlos.gouveia@eqsglobal.com (C.A.J.G.)
[3] Instituto de Ciência e Inovação em Engenharia Mecânica e Engenharia Industrial, Departamento de Engenharia Mecânica, Faculdade de Engenharia, Universidade do Porto, 4200-465 Porto, Portugal
* Correspondence: tavares@fe.up.pt

Abstract: Ultrasonic guided wave testing (UGWT) is a non-destructive testing (NDT) technique commonly used in structural health monitoring to perform wide-range inspection from a single point, thus reducing the time and effort required for NDT. However, the multi-modal and dispersive nature of guided waves makes the extraction of essential information that leads to defect detection an extremely challenging task. The purpose of this article is to give an overview of signal processing techniques used for filtering signals, isolating modes and identifying and localising defects in UGWT. The techniques are summarised and grouped according to the geometry of the studied structures. Although the reviewed techniques have led to satisfactory results, the identification of defects through signal processing remains challenging with space for improvement, particularly by combining signal processing techniques and integrating machine learning algorithms.

Keywords: signal processing; signal filtering; defects characterisation; non-destructive testing

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1. Introduction

Tanks, pressure vessels and pipelines are omnipresent infrastructures in the industry, where they are used to store and transport products and raw materials to and from factories and, in many cases, to distribution points and end customers. Over time, due to material ageing, corrosion reduces the original wall thickness of the infrastructures, which may compromise their reliable operation and even cause the collapse of assets. In addition to representing, in many cases, a risk to the environment, health and integrity of workers and surrounding populations, this type of situation can cause high economic losses, directly due to unscheduled stops and indirectly due to supply failures. Thus, within the scope of protection and optimisation of structural resilience of critical assets, it is fundamental to carry out an inspection of structural integrity to follow the evolution of the structure condition during its ageing. In this context, ultrasonic guided waves testing (UGWT) has shown capabilities of surveying large structural components for defects, contrary to conventional ultrasonic testing (UT) based on punctual measurements, providing more comprehensive information about the integrity condition of the structure under analysis [1] (Figure 1).

Guided waves are elastic waves generated directly in the structure under analysis, which propagate along its length, confined by the geometric limits of its walls. Hence, they propagate through the structure and are reflected due to variations in the wall cross-section. The obtained findings may be related to geometric changes and variations in thickness [1]. Using the arrival time of echoes and propagation velocity in the medium, it is possible to determine the position of these changes. In turn, the amplitude of the signals allows for the estimation of defect sizes [2]. Thus, this technique makes it possible to locate internal or external defects along an in-service pipe at distances of a few tens of meters from a single excitation point. Moreover, it is possible to evaluate underground and coated or isolated structures without the need to alter them, providing more comprehensive information about their integrity condition.

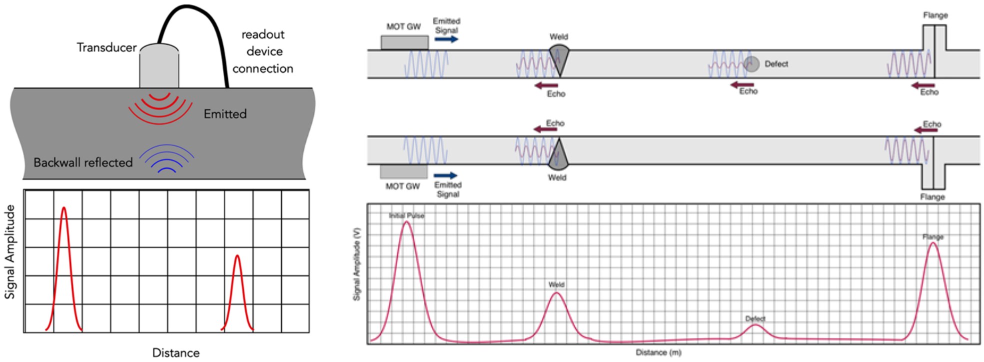

Figure 1. Representation of the conceptual difference between conventional ultrasonic testing (on the **left**) and guided wave ultrasonic testing (on the **right**).

Unlike conventional UT, there are an infinite number of guided wave modes that are supported by a structure. Depending on the geometry of the structure, these modes follow a certain classification. For plates, there are two families of modes: the Lamb waves (symmetric and asymmetric) and the Shear Horizontal waves. On the other hand, for cylindrical geometries, the modes can be grouped into three families, namely the Torsional, Longitudinal and Flexural modes. The acoustic properties of wave modes are a function of the wall thickness, the material and the frequency. Predicting the properties of the wave modes often relies on heavy mathematical modelling, which is typically presented in graphical plots, which are known as dispersion curves. Dispersion is the variation of phase and group velocities of the ultrasonic guided signal and its propagation characteristics with the frequency and the thickness of the material. Thereby, the dispersion curves represent the velocities for each mode as a function of frequency. Most wave modes are dispersive, i.e., the velocity varies with the frequency. Dispersion causes the wave packets to spread out in time as they propagate through a structure. Only Torsional and Shear Horizontal waves are non-dispersive and, therefore, are preferred for signal generation [3].

In UGWT, the generation and detection of the signals are performed using a transducer mechanically coupled to the structure under analysis. There are two main technologies for these transducers: the piezoelectric and the magnetostrictive technologies. For instance, in pipes, the transducer is a collar consisting of an array of piezoelectric elements, where the elements are excited equally and simultaneously to generate an axis-symmetric wave [2]. Alternatively, a 360° magnetostrictive ring transducer can be used, and in this case, the axis-symmetric generation is ensured due to the symmetry of the patch. In both cases, as stated before, the Torsional waves, in particular their fundamental mode, are commonly used as excitation waves due to their interesting properties. Nevertheless, even generating non-dispersive waves with axial symmetry, the non-symmetric nature of defects and some construction features of the structures will cause mode conversion and give rise to dispersive signals. The presence of dispersive waves in the signals is also seen as coherent noise. Coherent noise, as its name indicates, cannot be eliminated by averaging as it is not random. On the other hand, as it coincides in frequency with the signal of interest, it cannot be filtered using conventional filtering techniques.

The multi-modal and dispersive nature of guided waves makes the signal processing particularly challenging, which has been the subject of several studies over the years [4–6]. The used techniques are not necessary only for the interpretation of the received ultrasonic signals but also for procedure automation, which improves the non-destructive testing and evaluation, along with their reliability and replicability. Some of the issues that stem from this involve the elimination of dispersive modes, mode separation and defect identification, as well as their classification. To enhance and improve the detection and classification of defects, several techniques have been employed to process the input signal such as time–frequency representation, including the reassigned spectrogram and the Winger–Ville distribution, wavelet analysis, Hilbert–Huang transforms and cross-correlation techniques [7–11].

This review is focused on signal processing techniques that have been applied to ultrasonic guided wave testing, which has been a growing research and technological field for the last years (Figure 2) due to reasons aforementioned. There are some reviews on the topic, but to the authors' knowledge, the current review is the most recent one whose focus falls on signal processing techniques, an important factor given the growing interest and number of articles published recently [10,12–14]. Other recent reviews on ultrasonic guided wave testing seek to give a general overview of the topic, instead of looking into the techniques necessary to analyse the acquired data. Just last year, over fifteen studies have been published, introducing new approaches such as the ones based on the integration of machine learning algorithms, warranting the need for the current review.

This article is organised according to the following structure: the next section describes the search employed in the review, and then, the signal processing techniques section is divided into three sections based on the type of the structure under testing, each presenting the main achieved results, advantages and limitations of the reviewed techniques. The final section provides the main conclusions of this study.

2. Searching Method

A systematic review was performed in the SCOPUS database using the following keywords: "signal processing" and "ultrasonic guided wave testing", yielding 251 unique results. Based on an analysis of the title and abstract, 177 works were excluded for not meeting the following inclusion criteria: using signal processing techniques and being suitable for ultrasonic guided wave testing. Of the selected results, conference proceedings and book chapters were excluded, as well as 3 literature reviews. Further analysis of the body of text of the remainder articles was conducted, which led to 51 full-text original studies that propose signal processing techniques for ultrasonic guided wave testing in metallic structures. The PRISMA diagram of the performed systematic search can be seen in (Figure 3).

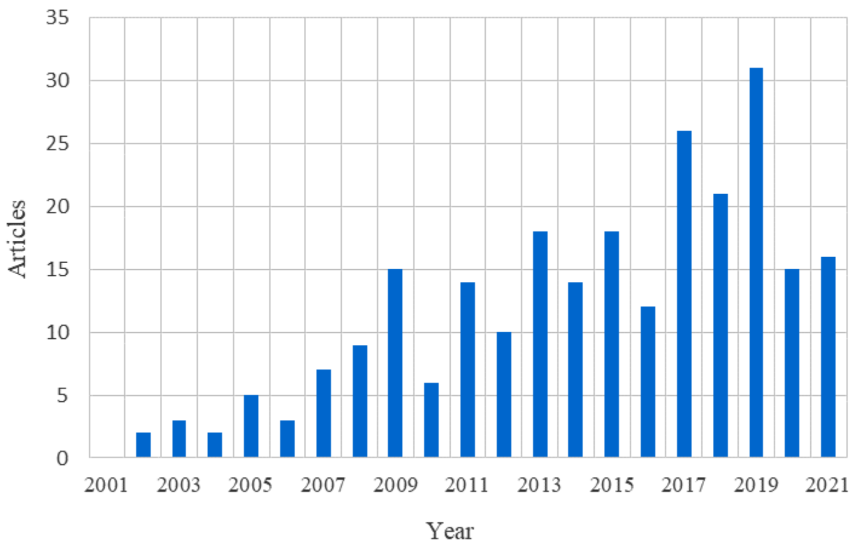

Figure 2. Articles published in the last 20 years, which were gathered using the keywords "guided wave ultrasonic testing, signal processing".

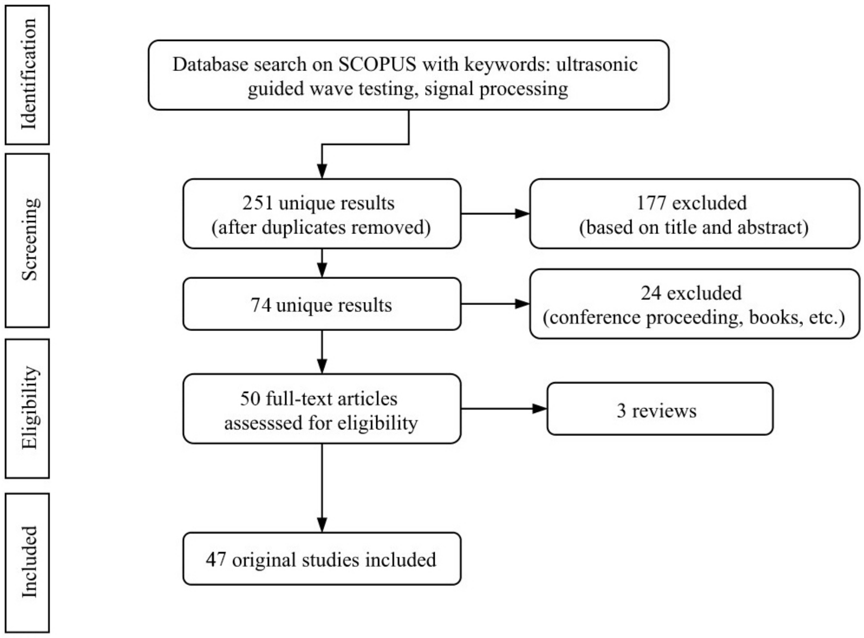

Figure 3. PRISMA study flow diagram of the performed systematic literature review.

3. Signal Processing Techniques

As aforementioned, the processing of the guided wave signals resulting from the interference of the multiple modes supported by the structure under analysis to gather information about its integrity is still an important challenge in UGWT. Over the last decade, several techniques have been developed and tested for distinct purposes. Various articles are focused on signal filtering, particularly for the removal of dispersive modes in order to improve the signal-to-noise ratio (SNR) and, consequently, increase the sensitivity for defect detection [15–18]. Furthermore, filtering dispersive modes improves the accuracy of damage localisation by increasing the spatial resolution, as Moll et al. demonstrated by employing a time-varying inverse filter to convert them into broadband high-resolution signals [19]. However, removing these modes can also imply the loss of relevant information, i.e., these modes carry relevant details regarding the nature of the defects, for example, about their angular position and if they are external or internal [20]. Thereby, the ability to separate modes rather than eliminate the dispersive ones is quite appealing [6,21]. Beyond signal enhancement and wave mode isolation, the identification and localisation of the defects are also critical factors in UGWT. Damage identification and classification have also been explored in several works [22–26], not only to roughly locate the defects, but also to assess their dimensions and to discern between their type. At last, a new tendency that has been growing is the use of machine learning algorithms, which, when combined with techniques of signal processing, allows for improved methods specifically for damage identification and classification [13,27]. It is important to note that the application of the signal processing techniques is highly dependent on the geometry of the structure under analysis as well as their advantages and limitations. An overview is presented in the next section, where the main used techniques are described. Table 1 presents an overview of the main techniques that have been commonly used, including their applications and limitations.

Table 1. Overview of the signal processing techniques that have been commonly used in ultrasonic guided wave testing.

Technique	Summary	Application	Advantages	Limitations	Ref
Adaptive filtering	Functions as a linear filter with a transfer function controlled by parameters and an optimisation technique for adjusting those parameters in each iteration.	Enhances the SNR of Torsional waves generated by defects by reducing the impact of dispersive modes.	Effectively removes noise, such as noise whose power spectrum changes over time.	For lower-order Flexural waves that have closer wave speeds to Torsional waves, the noise is not cancelled.	[28]
Split spectrum	Determines distinct interferograms for spectral sub-bands, allowing the ionospheric and non-dispersive phase terms to be separated.	Improves SNR by eliminating dispersive modes.	Enables the detection of flaws within coherent noise levels.	Accuracy is achieved when the appropriate filter bank parameters are chosen, as the technique is sensitive to their selection.	[29,30]
Wavelet transforms	Projects a signal into a set of basis functions named wavelets, which offer localisation in the frequency domain.	Pattern recognition, damage detection and classification.	Better performance than the Fourier based filters, with little to no loss of information.	Improper selection of the mother wavelet significantly affects its usefulness in extracting defect information.	[4,10,17,22,31–36]
Hilbert–Huang transform	Decomposes a signal into so-called intrinsic mode functions along with a trend with empirical mode decomposition (EMD) and obtains instantaneous frequency data using the Hilbert transform.	Defect identification.	Preserves the characteristics of the varying frequency, it is effective in extracting the low-frequency oscillations, and it can be applied to transient data without zero or mean references.	Poorly suited for separating signals when their frequencies are too close.	[4,10,11,35]

Table 1. *Cont.*

Technique	Summary	Application	Advantages	Limitations	Ref
Matching pursuit	Sparse approximation algorithm that finds a sub-optimal solution to the problem of an adaptive approximation of a signal in a redundant set, i.e., dictionary, of functions.	Damage classification.	Good results obtained for wave separation.	Construction of the dictionaries can be not straightforward, the results are highly dependent upon the quality of the dictionary used, and it has high computational complexity.	[6,19,25,26,37]
Winger-Ville distribution	Computes the Fourier transform of the ambiguity function, which provides a high-resolution representation in both time and frequency for non-stationary signals.	Time–frequency signal analysis leading to high calculation accuracy of the frequency and duration of the modes.	High spectral resolution can be achieved, and it does not suffer from leakage effects. Can be applied to pipes and plates.	Cross-term interference can make it difficult to interpret the signal properties.	[8,9,21,38]
Reconstruction algorithm for the probabilistic inspection of damage (RAPID)	By comparing the signal difference coefficient of data acquired either before and after damage, or at low and high excitation amplitude, a damage presence probability map can be obtained.	Defect imaging	Construction of an energy pattern that allows identifying the dimension of the failure.	Advanced RAPID tomographic techniques are required to improve the resolution and accuracy of the obtained images with respect to the operating surroundings. Not practical for field evaluation taking into account that two measurements are required.	[39]

3.1. Pipes

Non-destructive testing and evaluation have become crucial to reduce losses and save inspection time, specifically in pipelines, which are prevalent in many industries as part of transportation and distribution networks [40]. Pipes are usually modelled as hollow cylinders, where the axial propagation consists of Torsional and Longitudinal modes. In these structures, three types of modes are admitted: Torsional, $T(0, m)$, Longitudinal axisymmetric, $L(0, m)$, and Flexural asymmetrical, $F(n, m)$, modes, where n is the circumferential order, and m is a variable used to distinguish the modes of a given n order [41]. Some of the most prominent issues that the signal processing techniques aim to solve when it comes to the structural health of pipelines include the improvement of the signal-to-noise ratio through the cancellation of dispersive modes, isolation of modes and imaging of defects, as well as the characterisation of symmetric and asymmetric defects.

As stated before, dispersive modes decrease the SNR and the spatial resolution, thus decreasing the sensitivity of the solution to detect defects and hindering the ability to distinguish between defects close to each other or close to a construction feature of the structure under analysis, such as welding and bolts. The elimination or filtering of these specific modes is of great relevance in terms of signal processing, which can be achieved with the use of techniques such as dispersion compensation, compressed pulse analysis and split spectrum processing. Adaptive filtering was first introduced by Widrow et al. as a way to estimate signals distorted by noise or interference [42]. By making use of a primary input that contains the corrupted signal and a "reference" input that contains noise correlated to the latter, the reference input is adaptively filtered and subtracted from the primary input. Mahal et al. proposed a new method to eliminate Flexural wave modes, instead of extracting noise from the single time-domain signal by using adaptive filtering. This technique, as mentioned before, is often used as an adaptive noise canceller and increases the SNR. Different adaption techniques can be applied, but in this specific case, the authors have employed leaky normalised least mean square (NLMS), which is more suited for guided wave applications with time-varying noise because it decreases the amplification of gradient noise and also provides a fast convergence rate. The application of a leakage factor allows for a faster adaption of the filter weights to the existing noise of each iteration [28]. The optimal parameter selection is a trade-off between maximum gain and stable amplification of the SNR of smaller defects.

Furthermore, other techniques that have conventionally been explored for UT can be adapted to UGWT. Split spectrum processing was first applied to surface search radar operations [43], having later been adapted to ultrasonic testing [44]. This technique, also known as signal sub-band decomposition, consists of five major steps. First, the signal is converted from the time domain to frequency domain, which is followed by the implementation of a bank of band-pass filters that splits the signal into a set of sub-bands at different centre frequencies. The results are then converted back to the time-domain, where each element is normalised by a weighting factor and finally assembled through a recombination algorithm to yield the output filtered signal. The various frequency ultrasound signals are generated by dividing the frequency spectrum of the received signal, rather than transmitting at different frequencies, as is the case in radar applications, and are not correlated with each other. As a result, when these diverse frequency signals are composited using various techniques, the SNR can be improved. However, the success of this approach is dependent on the selection of the filter bank parameters. Good results have been previously achieved for UT testing, but the same values were not found to be appropriate for UGWT due to the existence of a combination of modes that operates in the kHz range with different velocities [29]. Using a brute force search algorithm to manage parameter definition, Pedram et al. enhance the SNR and spatial resolution of ultrasonic guided wave signals by removing dispersive wave modes, a technique that since then has been improved as a post-processing approach on coated pipes to reduce attenuation effects [30].

Mahal et al. introduced a novel statistical approach to identify defect signals corrupted by coherent noise by using the full potential of the tool-set array of conventional guided wave inspection devices. This technique demonstrates the capability of detecting defects using all of the individual transducers rather than a single signal obtained after the general process. Three different methods were tested: the first, where the threshold value is static and defined by the inspector, produced the worst results; in the second, the assigned threshold to each iteration is a percentage taken from the summation of the amplitude of all of the transducers signals as the time-domain signal generated by the normal propagation routine; and in the third one, the number of transducers with the same phase over the total number of transducers, subtracted by an offset determines the percentage value, which yielded similar results to the second method, but the threshold value can be set automatically, providing a great benefit in one-off inspections. This technique also allows the possibility of developing narrowband transducers, as opposed to the currently used wideband transducers, which have a more focused transfer function and stronger excitation power [45].

However, increasing the SNR of a signal may have a downside since dispersive modes carry important information regarding the characteristics of the existing damage. Preserving this type of information through the isolation and separation of modes, instead of its filtering, becomes then an attractive approach. This can be achieved through several techniques, such as applying a wavelet transform (WT), which decomposes a function into a set of wavelets, allowing the extraction of local spectral and temporal information simultaneously [4,22]. This concept was first developed by Haar, and since then, has been extensively studied [46]. Nevertheless, the improper selection of the mother wavelet significantly affects the usefulness of this technique in extracting defect information from the reflected signals. It has also been shown not to be suitable for the reduction in coherent noise, as it removes the smaller amplitudes regardless of whether they are signal or noise, an issue also found in the application of cross-correlation techniques. Chen J. further proposed the use of the tone-burst wavelet as the mother wavelet to denoise the signal, which was found to be effective in extracting defect-related signals and able to achieve better results than the ones based on the conventional Morlet wavelet when comparing the temporal waveforms of the normal pipe with those of the corroded pipe [34].

Matching pursuit is a technique often used to separate overlapped modes, which finds the best match for a signal from an over-complete and redundant dictionary and has the advantage of being applicable to any type of structure, given the proper dictionary. Matching pursuit decomposition is commonly used to find discrete echoes in a signal, but it can also be thought of as providing distinctive wavelets that reflect areas of the signal where energy is concentrated in complex signals [47]. The main limitation of this technique comes down to the construction of the dictionaries, as it is difficult and time-consuming to collect extensive data for that end. This technique has been combined with others to enhance damage detection. A differential evolution algorithm has been employed to improve parameter searching efficiency, and cross-term free time–frequency distribution is achieved by superimposing the Wigner–Ville distribution of each matching atom decomposed [26]. Gaussian modulated functions were chosen as matching atoms because their time–frequency characteristics match ultrasonic guided-wave signals effectively. The effectiveness of parameter searches can be considerably improved by using the differential evolution technique, and flaws can be distinguished from echo signals using time–frequency distribution characteristic comparison. The Wigner–Ville distribution function was proposed by Eugene Wigner when making calculations of the quantum corrections to classical statistical mechanics and was later derived as a quadratic representation of the local time–frequency energy of a signal by J. Ville [48]. Rostami J. et al. expanded upon it by proposing sparse representation with dispersion-based matching pursuit (SDMP), which takes dispersion into account, increasing the sparsity of the final representation [6]. This technique consists of a two-stage algorithm designed with a dictionary based on actual waves obtained from finite element simulations to represent guided wave signals with the maximum sparsity. In the first stage, a signal is approximated, and in the second, the sparsity is further increased based on the frequency components of the excitation signal. Thus, undesired components of guided wave signals are filtered, and at the end, a very clean signal with meaningfully decomposed components remains for further analysis. This method can be extended to any plate-like structure made from different materials such as plastic pipes, aluminium and composite plates, steel strands and rails, on the condition that a new dictionary is built with reference to the geometry of the structure and its material.

To detect and determine the localisation of defects, Mahal H. et al. proposed a condition-based comparison of the power spectrum achieved from a sliding moving window for the received signal. The algorithm consists of several steps, the first being its initialisation, which initialises the excitation sequence to extract the necessary features for analysis. Then, the main loop uses the advancing window and carries out the pre- and post-processing of the conditions. Finally, the spectrum of each iteration is compared with the one achieved from the excitation sequence. In each iteration, the signal is normalised, and its corresponding power spectrum is generated to detect the Torsional wave. However, due to significant changes in the excitation sequences, it is not recommended to use this algorithm with frequencies higher than 42 kHz [5].

With the growth of the machine learning field, new signal processing methods have been integrated with techniques of signal processing. Artificial neural networks, for example, are very appealing due to their ability of generalisation and for not requiring any physical fault model. Cau et al. made use of traditional feed-forward multi-layer perceptron networks to obtain information on the size and location of notches. The study employs Torsional waves as excitation waves, and the finite element method is used to model pipes and defects in order to obtain several echoes containing damage information. The obtained signals are then processed to reduce the dimension and extract relevant features. Preliminary results show that the return time of the received signals is linearly dependent on the defect position while independent of the entity of the fault, so the notch position can be, therefore, determined with accuracy [27]. On the other hand, the correlation between the variation in time–frequency spectra and the shift in predominant modes with the spread of corrosion can be obtained from the deduction in the dispersion curves. To track the mode conversions as corrosion progressed, a new time–frequency spectrum was built. By employing the k-means clustering method, indices are used to quantify the change in signal intensity with the progress of corrosion along with a modified S-transform. The subjectivity of contact type monitoring paradigms to contact pressure is a common source of uncertainty. The proposed method addressed this issue by processing time–frequency-based signals, with the key components based on propagating modes rather than signal amplitudes [49]. A summary of the techniques employed in pipes can be found in Table 2.

Table 2. Works found addressing signal processing techniques applied to pipes.

Author	Year	Technique	Summary and Results
Liu S. [4]	2021	Wavelet transform (WT) and empirical mode decomposition (EMD)	The decomposed signal in WT can better preserve defect information and reduce the interference of noise signals, but the signal processed by the EMD is better than that of the WT.
Chen J. [34]	2017	Tone-burst wavelet	Results show that the location of the corroded areas of the pipes could be accurately detected using the calculated group velocity of the guided wave. Comparing the temporal waveforms of the normal pipe with those of the corrosion, flaws were easily observed and detected.
Rostami J. [6]	2017	Sparse representation with dispersion-based matching pursuit	The SDMP with a dispersive dictionary has greatly enhanced the performance of the matching pursuit and guarantees the maximum sparsity. Although the presented SDMP for signal interpretation addresses the inspection of steel pipes, it can be applied to any plate.

Table 2. *Cont.*

Author	Year	Technique	Summary and Results
Mahal H. [5]	2019	Sliding moving window	Three different pipes with defects sizes of 4, 3 and 2% cross-sectional area (CSA) material loss were evaluated. Results demonstrate the capability of this algorithm in detecting Torsional waves with low SNR without requiring any change in the excitation sequence.
Pedram S. [29]	2018	Split-spectrum processing	Both techniques achieved the greatest SNR without distorting the relative amplitudes of the signal of interest, where an improvement of up to 38.9 dB was observed. SSP shows good potential to increase the inspection range from a single test location as it significantly reduces the level of coherent noise.
Pedram S. [30]	2020	Split-spectrum processing	SSP algorithm is shown to have great potential to decrease the background noise entirely by minimising the effect of undesired wave modes throughout the signal's trace, whereas the traditional method was not able to achieve this. Good results were obtained for coated pipes.
Mahal H. [45]	2018	Axisymmetric wave detection algorithm	An axisymmetric wave detection algorithm was designed, which was validated by laboratory trials on real-pipe data with two defects at different locations with varying CSA sizes.
Mahal H. [28]	2019	Adaptive leaky NLMS filter	The results demonstrated the capability of this algorithm for enhancing the SNR of the defect. The results proved that the model parameters can be chosen using a finite element method model, but it will not result in the maximum gain.
Majhi S. [49]	2019	Modified S-Transform	A novel time–frequency spectrum was developed to monitor the mode conversions in relation to the progress of corrosion. K-means clustering is used to quantify the variation in signal strengths with the progress of corrosion. The proposed technique was able to obtain the variation in the distribution of the spectral contribution from higher-order to lower-order modes.

3.2. Plates

The planar geometry of plates differs from cylindrical pipes, and thus, different approaches are required. Usually, planar-based ultrasonic-guided wave transducers are used for pressure vessels, tank bottom plates and wall inspection. Guided waves in plates depend on reflections from the upper and lower surfaces of the plates to travel long distances on the plate parallel to these surfaces. The profile and the velocity of each guided wave mode in plates depend uniquely on their frequency and thickness of the structure; hence, thinner plates may support guided waves with higher frequencies than thicker plates. There are two families of wave modes for plates: the Lamb Waves and the Shear Horizontal (SH) Waves. In the Lamb waves, the particle direction is parallel (longitudinal direction) to the wave propagation direction and normal to the plate, and there are two different sub-families of modes: symmetrical (S) and asymmetrical (A) modes. For the SH modes, the particle displacement is perpendicular to the wave propagation direction. The notation used for these modes is An, Sn and SHn, where *n* represents the order of the mode.

In terms of filtering dispersive modes and improving the SNR, techniques such as wavelet transform-based noise processing and compressed sensing methods can be employed.

Ianni et al. accomplished the minimisation of the number of scan point locations over the surface of an inspected structure by using compressed sensing of full wavefield data. This method asserts that thanks to sparsity: a signal can be acquired and recovered from a limited number of linear measurements without loss of information, being the reconstruction performance influenced at large by the choice of a suitable decomposition basis to exploit such sparsity [50]. Furthermore, wavelet transforms have also been previously mentioned and studied with the purpose of denoising; for example, Da et al. proposed two approaches to this issue based on time and wavenumber domains, allowing for a successful inverse reconstruction of flaws by reflected signals with a signal–noise ratio as high as −5 dB [32].

When it comes to dispersion compensation, a MUSIC-based multichannel technique was employed by Zabbal et al. to extract dispersion curves from experimental data [51]. When compared to single vector decomposition techniques, this technique enhances weak modes and displays a low noise level and a high wavenumber resolution, which allows the characterisation of multi-layered structures of different materials. Xu et al. carried out dispersion compensation as well for both single-mode and multi-mode guided waves by using the dispersion curves of the guided wave modes to sparsely decompose the recorded dispersive guided waves [52].

The use of the estimation of signal parameters via the rotation invariant technique (ESPRIT) and particle optimisation algorithm has been employed by Chen et al., resulting in root mean squared errors between the estimated and theoretical dispersion curves calculated by the inversed model parameters for simulation, steel, aluminium and composite experiments equal to 0.027, 0.032, 0.033 and 0.102 rad/m [53]. The ESPRIT-based dispersion curves extraction strategy offers a sharp objective function in the parameter space, whereas the used particle swarm optimization (PSO) algorithm can be easily implemented with few parameters to be tuned. The spatio-temporal sparse wavenumber analysis implemented by Sabeti et al. achieved good results as well for the extraction of dispersion curves, with results indicating the possibility of accurate reconstruction (correlation coefficient around 0.9) for sampling rates above 60% of the spatio-temporal Nyquist critical sampling rate. ST-SWA takes a temporally and spatially under-sampled guided wave data matrix as input and retrieves the sparse representation of the wavefield in the frequency-wavenumber domain using the two-dimensional model and two-dimensional sparse recovery technique. The generated representation can then be fed into a forward problem by the model to rebuild the original fully sampled wavefield [54]. The results indicate that as long as overfitting is avoided, minor improvements in reconstruction accuracies can be observed at greater sparsities.

Time–frequency methods allow for an analysis of acoustic signals with multiple propagation modes, as well as the measurement of group velocity dispersion. The dispersion of several Lamb modes over a wide frequency range can be calculated from a single measurement by combining a time–frequency analysis with a broadband acoustic excitation source [8]. As opposed to the Wigner–Ville distribution, the smoothed Wigner–Ville distribution offers a better representation of individual modes and can localise multiple closely-spaced modes in both time and frequency [9]. Wu et al. was able to successfully isolate guided wave modes with a signal decomposition algorithm, combining the Smoothed Pseudo Wigner–Ville distribution to obtain the time–frequency distribution and Vold–Kalman filter order tracking to isolate modes. The location of defects can be obtained from the decomposition results. First, the Smoothed Pseudo Wigner–Ville Distribution processes the signal to obtain the corresponding time–frequency distribution, followed by the extraction and separation of the different modes. The Vold–Kalman Filter Order Tracking is then applied to filter specific mode waveforms. A peak-track algorithm is then conducted in the significant areas, and finally, to minimise the error, a corresponding filter is built in the time domain [21]. This technique can also be used in analogue NDT and NDE based on ultrasonic guided waves.

As previously stated, mode separation is quite an appealing approach to signal processing since it preserves the information contained in dispersive modes. Ratassepp et al.

was able to perform this with a technique based on the guided wave mode orthogonality, which is used to separate the multi-modal signal into individual time-domain Lamb and SH mode components at the plate edge with successful results. In comparison to the standard spatial fast Fourier transform, the orthogonality-relation-based technique reduces the number of monitoring points and eliminates the need for additional mode filtering operations because obtaining the amplitudes of the modes is simple. Although the through-thickness displacements and stress field components must be measured, the orthogonality-relation at the plate edge is simplified because the stresses are null. As a result, only displacement components must be measured at a plate edge, making the method practicable [55].

Identifying distances and depth of damage is also a prevalent topic, and recent studies search to integrate machine learning to achieve better results. Rizvi et al. used an autoregressive model based on Burg's maximum entropy method to modify the kernel of the discrete Wigner–Ville distribution with an uncertainty of 5% [38]. The conventional Burg algorithm determines the reflection coefficient by minimising the backward and forward prediction error of a single sequence or segment, but the Wael and Broersen algorithm is highly efficient in estimating the prediction error of all the segments taken together; hence, a single model can be exploited for all the kernel sequences at a time. This model is more robust and stable, less biased, and more computationally efficient. The proposed technique can also be applied to pipes. It is important to mention that this study used supervised machine learning to model the other dimensions of the crack under analysis. In a realistic case, these parameters would be unknown and would significantly affect the damage signal. Artificial neural networks have also been employed, where features extracted are fed to the network, enabling the classification of defects with a success rate > 75 % [56]. Defect identification can also be performed by using baseline methods, processing the signals and extracting the time parameters of the wave packets in mode conversion signals [37,57,58]. Algortihms of deep learning have also been employed to this end [59].

Another approach commonly implemented makes use of image reconstruction to identify defects in the structure under analysis. He et al. proposed a multi-mode damage imaging technique, which combines a reverse-time migration algorithm with a 3D wave propagation simulator with the potential to simultaneously determine damage type, size and location. Even though it was not possible to obtain detailed information on different modes, good results were achieved for damage location and defect size characterisation [60]. Furthermore, a reconstruction algorithm for probabilistic inspection of damage (RAPID) was used for tomography [61], with a more accurate quantitative visualisation obtained using the dominant mode, identified through frequency shifting and short-time Fourier transform [39]. Images constructed from the correlation coefficients between the scattering signal and the atoms of the dictionary using a weighted sparse reconstruction-based anomaly imaging method yield accurate weights [62]. By using the appropriate weights applied to the objective function, the proposed method can achieve anomaly imaging with fewer artefacts, making its success limited to the selection of a suitable dictionary. Zhang et al. developed a processing technique to separate modes to effectively remove artefacts resulting from the multi-mode interference in the imaging process, which is able to properly measure multi-site faults with geometry, size, and depth information. Green's function is used to back-propagate the scattering Lamb signals in the frequency-domain, allowing the monitored area's back-propagated acoustic field information to be collected. A reverse-time migration method is then applied to reconstruct the damage, by the cross-correlation between the incident acoustic field and the back-propagated acoustic field [63]. Numerical results show that mode separation pre-processing aids in effectively removing artefacts caused by multi-mode interference in the imaging process. The full waveform inversion algorithm is also an interesting guided wave tomography method, which makes use of a numerical forward model to predict the waveform of guided waves when propagating through corrosion defects and an inverse model to reconstruct the thickness map from the ultrasonic signals acquired by transducers around the defect. The results of Rao et al. show that it is affected by the shape of the defect [64]. The abrupt change in the wall thickness was shown to decrease the reconstruction error of small defects compared to the smoothly varying thickness.

Lugovtsova Y. et al. studied several wavenumber mapping techniques applied to composite-overwrapped pressure vessels. The study proposes the pre-processing of the wavefield so that only one mode at one frequency is left before wavenumber mapping, followed by the application of instantaneous and local wavenumber techniques. This method presents an excellent defect sensitivity and suitable defect quantification performance. The main limitation of this approach is that it is not possible to quantify every delamination between CFRP plies caused by the impact, as is the case for conventional UT. Only some parts of the impact damage are visible in the wavenumber and thickness maps. Another limitation is that the relation between wavenumber and effective thickness is non-monotonous due to the complexity of the layup of the composite plate used in experiments and its anisotropy [65].

Wind turbines are often subject to guided wave testing since they are subjected to significant mechanical loads, requiring an appropriate maintenance strategy to ensure cost-effective power generation while minimising life cycle expenses. Several studies have thus been conducted where pattern recognition is carried out using techniques such as supervised learning classifiers, Wigner–Ville distribution, and filtered signal by Hilbert Transform [31,66]. The approach taken by Arcos et al. filters the dataset by wavelet transform, and the dimension of the signal is reduced by feature extraction and selection, followed by pattern recognition with supervised learning classifiers [36]. It is noteworthy that although good results have been achieved, the cost and time-consuming process of acquiring the necessary data for model training needs to be taken into consideration when employing this method. Table 3 presents a summary of the techniques employed in plate-like structures [67].

Table 3. Works found addressing signal processing techniques applied to plates.

Author	Year	Technique	Summary and Results
Da Y. [32]	2017	Wavelet transform in time and wavenumber domains	Wavenumber-domain WT operation gives a better denoising effect than direct time-domain WT denoising. Using the former, one can perform the inverse flaw reconstruction by reflected signals with an SNR as high as −5 dB.
Xu C. [67]	2018	Dispersion compensation method based on compressed sensing	The method can compensate both single-mode and multi-mode dispersive guided waves effectively, based on the accurate dispersion curves and every dispersive wave packet to the waveform of the excitation as well, and achieve better performance than the time-distance mapping method.
Wu J. [21]	2017	Smoothed Pseudo Wigner–Ville distribution and Vold–Kalman filter order tracking	The results of the simulation signal and the experimental signal reveal that the presented algorithm succeeds in decomposing the multi-component signal into mono components. Further research needs to be undertaken to validate the feasibility of locating defects by the algorithm.
Chen Q. [53]	2021	Estimation of signal parameters via rotation invariant technique (ESPRIT) and particle swarm optimisation algorithm	The root mean squared errors between the estimated and theoretical dispersion curves calculated by the inversed model parameters for simulation, steel, aluminium and composite experiments are: 0.027, 0.032, 0.033 and 0.102 rad/m.
Sabeti S. [54]	2020	Spatio-temporal sparse wavenumber analysis	The results indicate the possibility of accurate reconstruction (correlation coefficient of around 0.9) for sampling rates above 60% of the spatio-temporal Nyquist critical sampling rate.

Table 3. *Cont.*

Author	Year	Technique	Summary and Results
Rizvi S. [38]	2021	Autoregressive model based on Burg's maximum entropy method to modify the kernel of the discrete Wigner–Ville distribution	The proposed method precisely estimated the distance between two closely spaced notches in a metallic plate from different simulated noisy signals with a maximum uncertainty of 5%.
Bagheri A. [56]	2016	Artificial neural network	The non-contact inspection system and the signal processing technique enable the classification of the plate health with a success rate of > 75 %.
Wang G. [37]	2019	Matching pursuit algorithm of Gabor function	The first iterative compensation of the proposed method can achieve compensation within the temperature range greater than 7 °C, and the compensation within the temperature range greater than 18 °C can be achieved after three iterations.
Jia H. [57]	2020	Baseline-free method based on the mode conversion and the reciprocity principle	In the case of 1.0 mm depth, which performed with a strong mode conversion ability, four obvious wave packets were observed. The result shows that the method could accurately localise both defects.
Douglass A. [58]	2018	Temperature compensation method based on dynamic time warping	For frequencies above 200 kHz and temperature differences above 25 °C, the correlation coefficients were consistently greater than 0.75, while the scale transform showed correlation coefficients below 0.35. Correlation coefficients are consistent above 0.75, while the scale transform's correlation coefficient dropped to 0.45 with as little as 0.4 ms of data.
He J. [60]	2019	Reverse-time migration (RTM) imaging	A reverse-time migration (RTM) imaging algorithm was combined with a numerical simulator: the three-dimensional elastodynamic finite integration technique (EFIT), in order to provide multi-mode damage imaging. The results represent the damage location and size but do not provide detailed information on different modes.
Lee Y. [39]	2021	Reconstruction algorithm for probabilistic inspection of damage (RAPID)	Location possibility was confirmed through the application of the anti-symmetric mode, and that quantitative imaging was very difficult in the bending stress dominant mode. The more accurate quantitative visualisation of defects was achieved when imaging was performed through this mode.
Xu C. [62]	2019	Weighted sparse reconstruction-based anomaly imaging method	Results for carbon fiber-reinforced polymer (CFRP) plate with an additional mass show that the weights constructed from the correlation coefficients between the scattering signal and the atoms of the dictionary are appropriate and accurate.
Zhang H. [63]	2018	Reverse time migration method	Numerical results demonstrate that the pre-processing of mode separation helps to effectively remove the artefacts resulting from the multi-mode interference in the imaging process.
Lugovtsova Y. [65]	2021	Wavenumber mapping	The approaches used deliver an accurate estimate of the in-plane size of the large delamination at the interface but only a rough estimate of its depth. None of the wavenumber mapping techniques used in the study can quantify every delamination between CFRP plies caused by the impact, which is the case for conventional UT. This may be solved by using higher frequencies or more advanced signal processing techniques.

Table 3. *Cont.*

Author	Year	Technique	Summary and Results
Arcos Jiménez A. [36]	2019	Wavelet transform and supervised learning classifiers	Results show that the combination of the k-nearest neighbours algorithm with the principal component analysis technique provides the best results for the detection and diagnosis of mud in the developed experiments. The classifier that detects and identifies mud in all cases is the ensemble subspace discriminant model for E-1. Fuzzy k-nearest neighbours is the best classifier for E-2.
Tiwari K. [66]	2018	Wavelet transform	The discrete wavelet transform, along with the amplitude detection technique, was applied on experimental B-scans to locate and size the defects with a significant accuracy: the percentage error was less than 12%.
Gómez Muñoz C. [31]	2018	Wavelet transforms	The envelope of the filtered signal from wavelet transforms is completed based on the Hilbert Transform, and the pattern recognition is achieved by autocorrelations of the Hilbert transform. The approach detects the ISO 12494 cases of un-frozen, frozen without ice, and frozen with ice in wind turbines.
Tiwari K. [35]	2017	Wavelet transform, Hilbert–Huang transform	The size of defects having diameters of 15 and 25 mm at the −3 dB threshold level was measured as 9 mm with a percentage error of 40% and 34.5 mm with a percentage error of 38%. The location of defects at the −3 dB threshold level from the start point of scanning was also calculated as 29 mm (for the defect of 15 mm), with a percentage error of 37.5%, and 405.5 mm (for the defect of 25 mm) with an error of 2%.

3.3. Other Structures

Even though this review is focused on pipes and plate-like structures, it is important to point out certain methods that have been developed for other elements and geometries far more complex, thus, presenting new challenges. For example, seven-wire strands, when considered individually, resemble a hollow cylinder, but altogether, the structure becomes complex and presents new complications.

In steel strands, He et al. used the lowest Longitudinal mode L(0, 1) as the excitation mode so that the received signal could be denoised with multi-level discrete wavelet decomposition and a single branch reconstruction method [33]. Multi-level discrete wavelet decomposition is based on wavelet analysis, which produces a group of organised decompositions. By iterating the decomposition process, a signal is broken down into many lower-resolution components. To perform dispersion compensation, Legg et al. used dispersion curve data to characterise the wave propagation using a broadband maximum length sequence (MLS) excitation signal and spectrograms in overhead transmission cables [68]. Only the first set of echoes could be resolved without dispersion compensation, whereas with dispersion compensation and some filtering, individual echoes could be recognised for at least five sets of echoes from the end of the cable. While the study used an ACSR cable, the method can be applied to increase the inspection range for other structures, such as plates, pipes, and other types of cables. Ji et al. later applied singular value decomposition and the support vector regression model to evaluate the stress level in strands, employing the theoretical and the finite element method to solve the dispersion curves of single wire and steel strands under various boundary conditions [69]. Despite simulated and experimental results showing the effectiveness and potential of the proposed technique, it is not always the best for visualisation. On the other hand, the reliability can be enhanced by adding more samples.

Due to the intricate nature of these structures, machine learning techniques have been applied to further the interpretation of the acquired signals, for example, by using a deep convolutional neural network (DCNN) with a VGG-like architecture-based regression model for detecting and estimating the looseness in bolted joints using a laser ultrasonic technique [70]. First, the signals are measured at each impinging point and then the imaging process is performed to produce full-field ultrasonic datasets. These datasets are then submitted to signal processing techniques, and a model evaluation process is used for choosing the best performance. At last, the DCNN model is generated to estimate the looseness value of bolted joints. The ultrasonic receiver needs to be set up manually and can be applied in the straight-line area only. For beams, Liew C. introduced a multi-layer perceptron for pattern recognition, operating with one hidden layer of neurons, and progressively trained using a backpropagation algorithm with the integration of a weight-range selection (WRS) technique that was dependent on the test pattern to achieve good results for damage location and depth [71].

Attention has also been given on methods that can monitor practical structures with arbitrary complexity. Recently, Ju et al. proposed a new nonlinear guided wave technique to non-destructively determine the presence of microstructural defects in a large-area structure with complex geometry. When the multi-mode guided waves diffusely propagate through any physically-connected structure with arbitrarily complex geometry, all available guided wave modes in any interrogated zone of the structure are automatically down-selected by the medium through attenuation, dispersion, or filtering. Such remaining modes efficiently transfer energy, for example, to their second harmonic modes, when they encounter micro-cracks even in the case of irregular geometries [72]. A summary of the techniques employed in these different structures can be found in Table 4.

Table 4. Works found addressing signal processing techniques applied to other structures.

Author	Year	Technique	Summary and Results
He C. [33]	2008	Multi-level discrete wavelet decomposition and single branch reconstruction	The Daubechies wavelet of order 40 is used as the mother wavelet for the decomposition. This wavelet denoise method improves the SNR.
Legg M. [68]	2015	Dispersion curve compensation	Attenuation and dispersion compensation was then performed for a broadband maximum length sequence (MLS) excitation signal. It was found that an increase in terms of SNR between 4 and 8 dB was observed relative to the dispersed signal. The main benefit was the increased ability to resolve the individual echoes from closely spaced structures: the end of the cable and an adjacent cut.
Ji Q. [69]	2021	Singular value decomposition and support vector regression	Results show that the fundamental mode dispersion curve offset on the high-frequency part and cut-off frequency increases as the boundary constraints enhance, demonstrating the capability of the proposed support vector regression method for evaluating the stress level in the strands.
Tran D. [70]	2020	Discrete convolutional neural network	The DCNN and wave propagation imaging produced the highest R2 score and lowest MSE score: 0.91 and 1.55, respectively.
Liew C. [71]	2008	Series combined network with the integration of a weight-range selection	The system was able to achieve average predictions accurate to 2.5 and 7.8% of the original training range sizes for the damage location and depth, while the WRS provided up to 13.9% improvement compared to equivalent conventional neural networks.

Table 4. *Cont.*

Author	Year	Technique	Summary and Results
Ju. T. [72]	2022	Nonlinear response of multi-mode guided wave ultrasonic signals	Experimental results are consistent with numerical simulations, indicating that the proposed method can be implemented for semi-quantitative detection or early warning indication of microstructural defects in complex, large-area structures.

4. Conclusions

Ultrasonic guided wave testing is a dominant field in structural health monitoring and non-destructive testing, serving as an effective long-range inspection method. Nonetheless, the multi-modal and dispersive nature of guided waves makes signal processing a particularly difficult task. This review aimed to present an overview of signal processing techniques applied to guided waves. Numerical methods to improve the SNR, isolate and separate modes, and identify and classify defects were discussed in terms of effectiveness and limitations, along with machine learning techniques that can be integrated with them, which is an approach that has shown promising results in the field. New lines of research can be brought to light with the understanding of the aforementioned issues in terms of ultrasonic guided waves. The solution seeks to improve the capacity of UGWT to detect damage in all sorts of structures in a more informed and reliable manner.

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Abbreviations

The following abbreviations are used in this article:

UGWT	Ultrasonic guided wave testing
NDT	Non-destructive testing
SHM	Structural health monitoring
SNR	Signal-to-noise ratio
EMD	Empirical mode decomposition
RAPID	Reconstruction algorithm for the probabilistic inspection of damage
WT	Wavelet transform
SSP	Split spectrum
NLMS	Normalised least mean square
SDMP	Dispersion based matching pursuit
CSA	Cross-sectional area
ESPRIT	Estimation of signal parameters via rotational variant technique
CFRP	Carbon fibre reinforced polymer
MLS	Maximum length sequence
DCNN	Deep convolutional neural network
WRS	Weight-range selection

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