

Article

Semi-Automatic Wave Mode Recognition Applied to Acoustic Emission Signals from a Spherical Storage Tank

Ruben Büch ^{1,2,*}, Benjamin Dirix ¹, Martine Wevers ²  and Joris Everaerts ² ¹ TÜV Austria Belgium, Wingepark 41, 3110 Rotselaar, Belgium; benjamin.dirix@tuv-a.com² Department of Materials Engineering, KU Leuven, De Croylaan 2, 3001 Heverlee, Belgium; martine.wevers@kuleuven.be (M.W.); joris.everaerts@kuleuven.be (J.E.)

* Correspondence: ruben.buch@pm.me

Abstract

Acoustic emission testing is a non-destructive inspection method in which ultrasonic waves emitted by defects in an object are detected and assessed based on their time of arrival and waveform, which strongly depends on the geometry of the object. Those waves appear in different modes with their own velocity and dispersion and different degrees of attenuation can occur for different wave modes. In previous work, a new method for (semi-)automatic recognition of the arrival time of wave modes was presented and validated on a dataset obtained in laboratory conditions on a flat plate. This paper builds upon the previous research and presents a modified method that can be applied to data obtained from an industrial gas storage sphere. The following two wave modes were commonly detected for this sphere: one similar to the zero-order anti-symmetrical mode (A_0) and the other similar to the zero-order symmetrical Lamb mode (S_0) in a plate. The method was adapted to solve the new challenges that were encountered for the sphere. The performance of the adapted automatic mode recognition method was assessed using a dataset with the following four different source types: Hsu–Nielsen sources, sensor pulses, impact by a metallic object and natural sources. The resulting wave mode recognition was compared to manual recognition to determine the rates of successful recognition. The resulting successful recognition rates range from 97% for A_0 and S_0 for Hsu–Nielsen sources down to 73% for A_0 in signals due to natural sources and 74% for A_0 in signals due to impact by a metallic object.

Keywords: acoustic emission; wave modes; cross-correlation; mode recognition; automated mode recognition

1. Introduction

Acoustic emission (AE) is a technique for non-destructive testing (NDT) which detects growing defects in a tested object based on ultrasonic waves emitted by the defect. The ultrasonic waves are detected using sensors attached to the surface of the tested object at fixed positions. Since acoustic emission relies entirely on naturally emitted ultrasonic waves, in contrast to waves induced by transducer pulsing, it is a passive technique. Further characterization of the source based on the detected signals can provide information regarding the location and the type of the source. Moreover, because every application of acoustic emission faces its own challenges (e.g., [1–6]), a variety of analysis techniques exist. The signals resulting from an AE test can be recorded entirely but can also be summarized in the form of signal parameters. To characterize the AE sources detected during a test, the signals are grouped into source events according to their time of arrival at the sensors.



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Subsequent analysis of the test results can be performed using the signal parameters or can also be performed using the entire signals. To extract information from entire waveforms, it is possible to use modal analysis [7], moment tensor analysis [8], advanced source localization [6] or classification according to source type or location [9].

Depending on the geometry of the tested object, the propagation of the ultrasonic waves from a source to the sensors occurs in different wave modes. In very thick structures, pressure, shear and Rayleigh waves can be distinguished. In plate-like structures, symmetrical and anti-symmetrical Lamb modes of different orders can be identified. In between those scenarios, trailing waves are expected, as plate thicknesses become too high for Lamb waves [10]. Different wave modes travelling in the same object are associated with different particle movements. Furthermore, they may also travel at a different velocity, exhibit different dispersion [11,12] and experience different frequency-dependent attenuation [13]. Of each possible wave mode in an object, AE sources can emit several with different amplitudes. For plate-like structures, the amplitude ratio between the zero-order symmetrical wave (S_0) and the zero-order anti-symmetrical wave (A_0) has been observed to depend on the depth of a source buried in the plate [14], the source mechanism [15], the crack orientation of a crack [16] and its cracking mode [17]. The wave modes can thus provide valuable clues regarding the source of detected acoustic emissions.

Since sensors used for acoustic emission only measure out-of-plane vibrations, the resulting signals are the combination of all wave modes in the wave. The wave modes can be separated manually by comparing a time-frequency representation of the signal to the dispersion curves predicted or approximated for the tested object. Since a dispersive wave mode propagates at different velocities depending on the frequency, different frequency components arrive at the sensor at different times. It is therefore possible to recognize the dispersion curves in the time-frequency representation of the signal [18,19]. Dispersion curves for different wave modes can be predicted using Vallen Dispersion [12] for plate-like structures or using GUIGUW [20] or DISPERSE [21] for more complex geometries.

Because acoustic emission tests can lead to large numbers of signals, manual mode recognition becomes very tedious. Therefore, methods are needed for automating wave mode recognition. Specifically for acoustic emission, the challenge of wave mode recognition has been approached in different ways in the past. When the acoustic emissions are measured using arrays of closely spaced sensors, the wave modes can be recognized from a 2D-FFT (two-dimensional fast Fourier transform) [22–24]. Alternatively, a frequency filter can be used to separate wave modes, if the modes tend to occupy separate frequency ranges throughout the considered dataset. For example, in ref. [25] a frequency filter was used to separate the flexural (anti-symmetric) mode below 200 kHz from the extensional (symmetric) mode between 400 kHz and 800 kHz. When this is not possible, the similar approach was proposed in [26] to decrease the temporal overlap between wave modes by applying an empirical mode decomposition to a signal and selecting one intrinsic mode function. This was, however, found “not sufficiently accurate” in [27], where the variational mode decomposition was proposed to replace the empirical mode decomposition.

In many datasets, the wave modes do have overlapping frequency ranges. For such datasets, other solutions are needed. A method that can handle some overlap of frequency ranges of different wave modes was proposed in [28]. It is a combined approach using frequency ranges while also relying on the amplitudes of different modes in different frequency ranges. The S_0 mode was identified by specifically looking for the first “non-negligible” component at 300 kHz and the A_0 by finding the highest amplitude arrival in a “low frequency range”. A set of proposed methods exist that do not rely on any separation of the frequency ranges of the considered wave modes. Those methods infer the arrival time of different plate waves based on the evolution of a function that is applied to the separate

signals similar to those used for onset detection (e.g., [29,30]). By comparing different onset detection criteria, the zero-order Lamb modes could be identified in a dataset consisting of Hsu–Nielsen sources and signals obtained by finite element modelling (FEM) [31]. Using a single onset-detection method, both zero-order Lamb modes could be identified relying on a positive versus negative changes in cumulative Shannon entropy for a low-amplitude S_0 mode and a high amplitude A_0 mode, respectively [32]. Although not strictly an onset-detection method, the use of the instantaneous phase and derived instantaneous frequency can offer a similar solution, as was shown in [33].

Alternatively, mode-dependent parameters such as the amplitude ratio between two modes can be estimated directly by comparing measured signals to a database with signals of known amplitude ratio [14]. In this case, the database was established by FEM.

In previous work [34], a new method was proposed for automatically determining the onset of different Lamb modes based on cross-correlating signals with one of a limited number of manually selected reference wavelets. The performance of this method applied to a dataset recorded on a stainless-steel plate in a laboratory environment was promising. However, its applicability in an industrial setting was not investigated. Therefore, in this study, the results of using a similar method for automatic determination of the arrival times of wave modes are presented for an industrial gas storage sphere. The application of the method to a sphere introduces additional challenges. Firstly, larger propagation distances are possible and the distances between sensors are considerably larger than on a lab plate. Secondly, some of the sensors of which the signals are considered are placed above the liquid phase level in the sphere whereas others are below. Finally, for natural sources, the exact source positions are unknown. To account for these challenges, the method was adapted in order to enable analysis of a dataset collected on site from an industrial spherical gas storage tank.

2. Materials and Methods

In this section, first the test setup and the dataset recorded from a gas storage sphere are described. Secondly, the semi-automatic mode recognition method from [34] is summarized to allow better understanding of the current work. Finally, the changes made to the abovementioned method to adapt it to the dataset from the gas storage tank are discussed.

2.1. Acoustic Emission Dataset

The acoustic emission data subjected to (semi-)automized mode recognition were recorded on a gas storage sphere with a radius of 6.3 m and carbon steel walls 2 cm thick, insulated with polyurethane foam. The sphere was filled until a liquid level of 7.5 m. The data were acquired during and after a pressure test from 10.3 to 12.5 bar, in accordance with EN14584 [35]. The pressure test was performed using 36 sensors of type Vallen VS75-SIC (Vallen Systeme GMBH, Wolfratshausen, Germany) with a 34 dB integrated preamplifier and a Vallen AMSY-6 acquisition system. The signals were sampled with a sample rate of 1.667 MHz and subjected to a 50–300 kHz band-pass filter. The Vallen VS75-SIC sensor's frequency response is shown in Figure 1a. Due to the sensor's frequency response, the effectively available frequency range is limited to 50–150 kHz. Within this frequency range, wavelengths of ultrasonic waves in the wall of the sphere are in the order of centimetres compared to the radius of the sphere of 6.3 m. As a simplification when considering the wave modes that may propagate in the wall of the sphere, the wave modes are labelled as if they were plate waves. Thus, the terms “anti-symmetric” and “symmetric” mode (of a given order), as well as “ A_0 ” and “ S_0 ”, refer to the pseudo- A_0 and pseudo- S_0 , the approximate equivalents of those plate modes in the wall of the considered sphere. Figure 1b shows the dispersion curves predicted for a 2 cm thick steel plate using Vallen Dispersion [12]. Nearly

all sampled signals in the dataset contained both a zero-order symmetric wave mode (S_0) and a zero-order anti-symmetric wave mode (A_0), with very few exceptions. Occasionally, a first-order anti-symmetric mode (A_1) or other higher-order modes are observed. In the frequency range between 50 and 150 kHz, there is an overlap between A_0 and S_0 modes. This overlap occurs at the triple point at a frequency of approximately 100 kHz. At the triple point, the S_0 , A_0 and A_1 modes have the same group velocity. Figure 1c,d show the wavelet transform of two signals recorded at different propagation distances where the S_0 and A_0 modes are indicated.

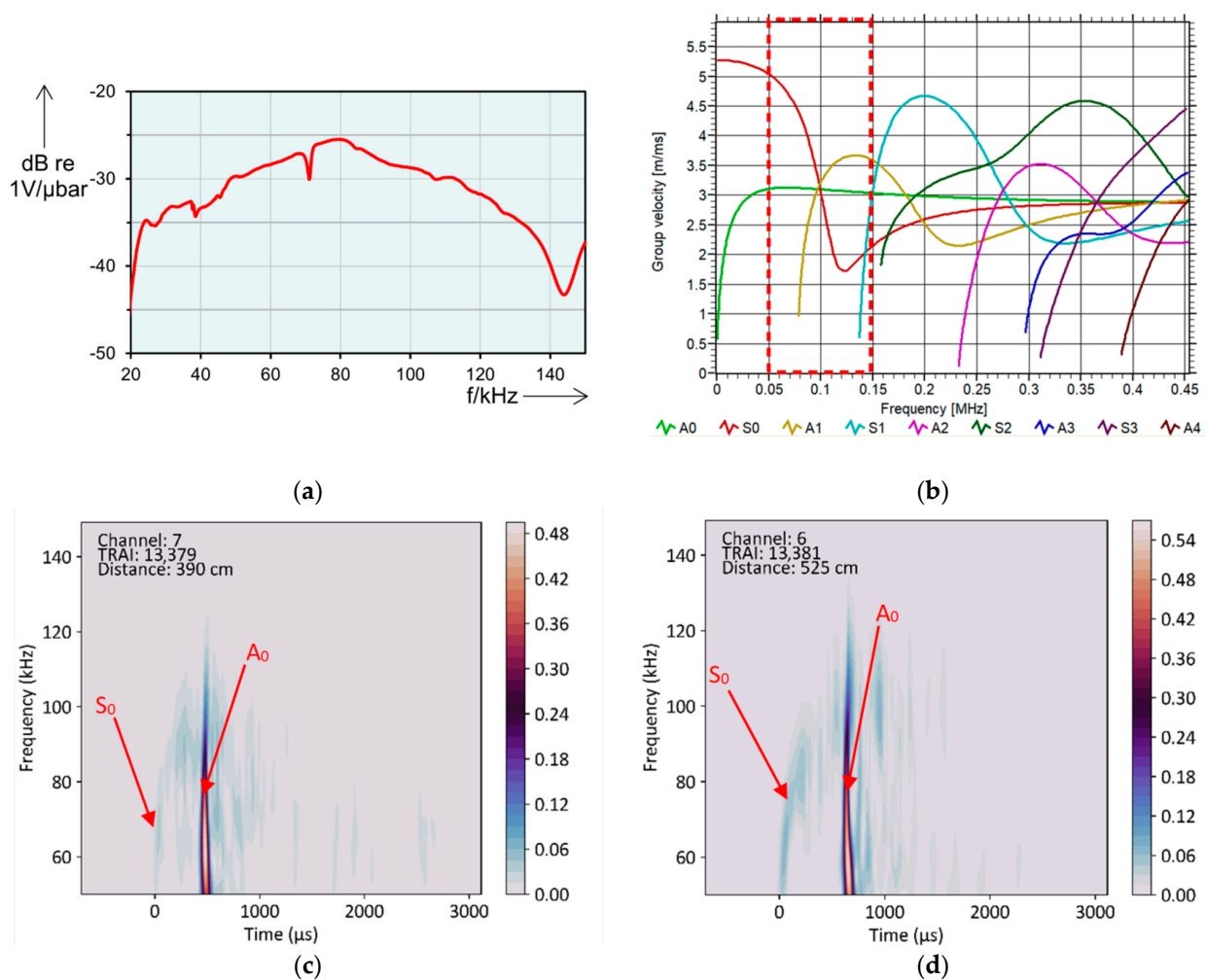


Figure 1. (a) Frequency response of Vallen VS75-SIC-34dB [36] and (b) dispersion curves for a 2 cm thick steel plate by Vallen Dispersion [12], (c,d) wavelet transform of signals from the dataset at a distance of 3.9 and 5.25 m, respectively.

In addition to the sources observed during pressure test, the following different types of artificial sources were applied to the surface of the sphere: Hsu–Nielsen sources with a pencil lead diameter of 0.5 mm, sensor pulses and mechanical impact by a metallic object. For sensor verification, Hsu–Nielsen sources and sensor pulses were applied at all sensors. Of most detected signals due to Hsu–Nielsen sources and sensor pulses, only parameterized data are available. The source locations from which Hsu–Nielsen sources and sensor pulses were included in the dataset are shown in Figure 2. The impacts by a metallic object were all applied within 8 cm from sensor nr. 2. All artificial sources were applied to the sphere at an internal pressure in the sphere of 12.5 bar.

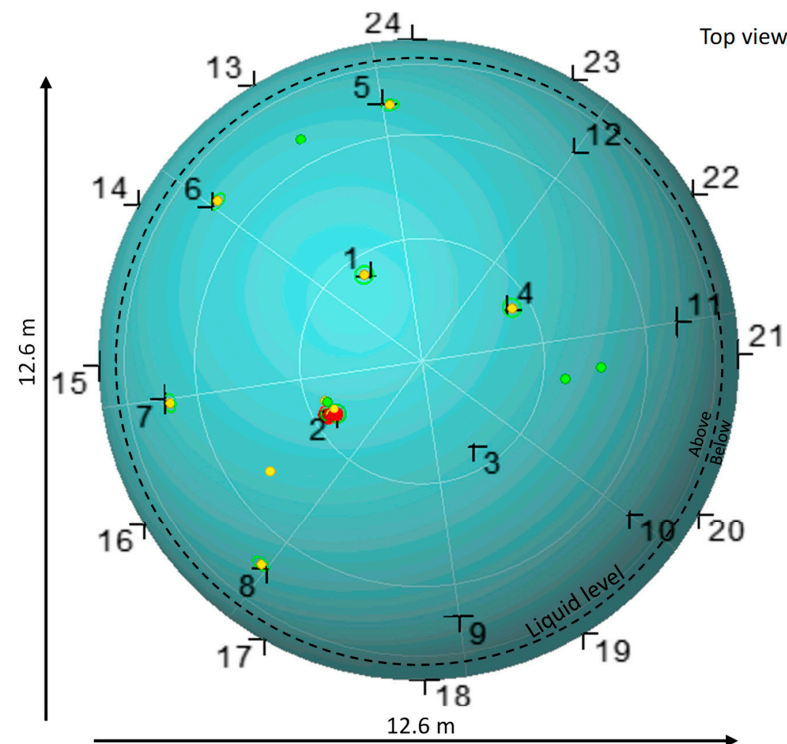


Figure 2. Localization of artificial sources on the gas storage sphere (top view) in the dataset relative to sensor placement (numbered markers). Sensor pulses are indicated yellow; Hsu-Nielsen sources and impact are indicated red.

The sources observed during the pressure test were graded according to EN14584 [35]. For two clusters of those sources, the severity grading of the sources localized nearby resulted in a recommendation to perform further NDT. No further inspections have been undertaken to identify the source mechanism. The sources observed during the pressure test are in this work referred to as “natural sources”, as opposite of “artificial sources”. The natural sources were detected predominantly during pressure increase. Amplitudes of most signals due to natural sources ranged from the threshold of 34 dB up to 75 dB, with a single outlier hit reaching 85 dB. The natural sources were localized near the supports of the sphere, as shown in Figure 3. Those natural sources were localized near the joints of the supports of the wall of the sphere. Those joints were located near the equator of the sphere, which was approximately 120 cm below the liquid level. Propagation of Lamb waves in the sphere wall in contact with the liquid phase is expected to influence the attenuation due to “leakage” into the liquid phase. The dispersion of those waves, however, is expected to remain largely unaffected [37].

For the purpose of this paper, a limited set of hits were selected to form the test dataset. Only signals for which it was possible to manually recognize the A_0 and S_0 mode were included. The exclusion of hits for which manual mode recognition is impossible is motivated by the need to have a basis of comparison for the automated mode recognition technique. This inherently excluded all signals with a propagation distance of less than 10 cm, where insufficient dispersion occurred to distinguish wave modes. This minimum distance was important for artificial sources, since they were systematically applied in the immediate vicinity of a sensor. Eight signals, all due to “natural” sources, were excluded due to failed manual mode recognition despite propagation distances longer than 10 cm. Furthermore, only the signals from source events for which at least three sampled signals were available were included. A total of 108 hits due to artificial sources were selected for the application and assessment of (semi-)automated mode recognition. Of those hits,

29 hits are due to Hsu–Nielsen sources, 40 are due to sensor pulses and 39 hits are due to impact on the surface by a metallic object. The amplitudes due to impact by a metallic object ranged from 92 dB to 97 dB, measured at a distance of less than 20 cm. In addition to the 108 signals from artificial sources, a total of 103 signals due to natural sources are included in the dataset. The dataset thereby does not contain any confirmed in-plane or dipole sources and most signals in this dataset have higher amplitudes for A_0 than for S_0 . According to [38], natural sources are mostly dipoles for which considerably higher amplitudes can occur for the S_0 mode.

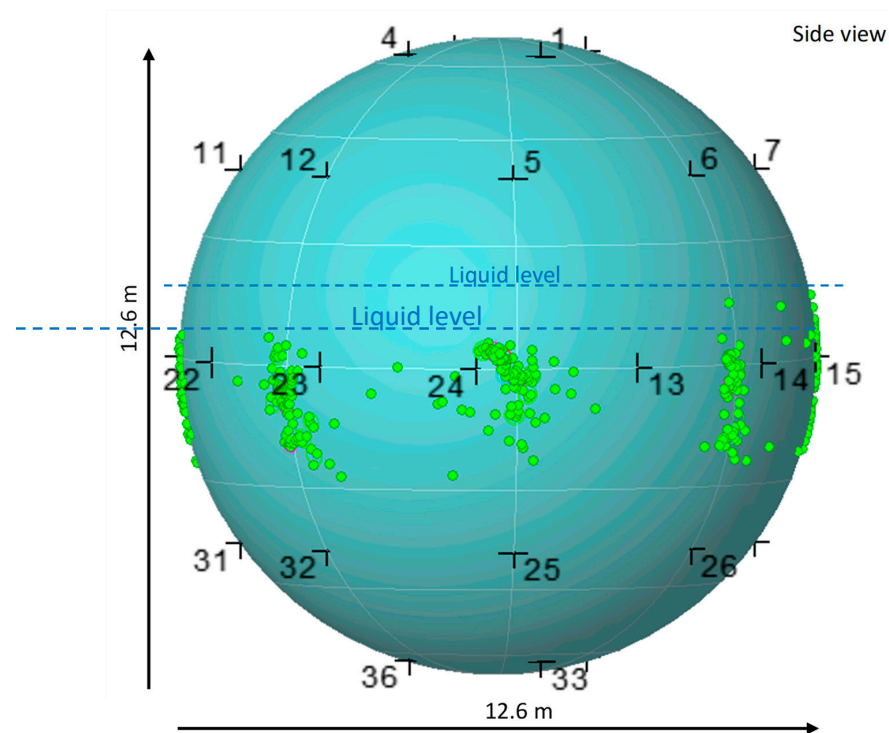


Figure 3. Localization of the natural sources on the gas storage sphere (side view). The same pattern is visible on the other side of the sphere.

The velocities of the A_0 mode and the S_0 mode were also determined based on the arrival times of waves from a Hsu–Nielsen source at different sensors above the liquid level. The resulting velocities ranged from 3000 m/s to 3200 m/s for the A_0 mode and from 4590 m/s to 5200 m/s for the S_0 mode. The exact source locations of the artificial sources are known. However, the locations of natural sources need to be determined based on triangulation. The time differences used for localization of the natural sources are calculated from the trigger times with rise-time offset using Vallen VisualAE [39]. A propagation velocity of 3000 m/s was assumed for this localization and only hits of which a sampled signal was available were taken into account. This velocity is slightly lower than the predicted velocity of 3200 m/s for the A_0 mode in a steel plate of 2 cm thick and at the lower edge of the experimentally determined range, as shown in Figure 1b. The use of a rise-time offset implicitly assumes that the peak amplitude is consistently reached by the same portion of the wave, in this case, the A_0 mode and the triple point. Since even the A_0 mode exhibits some limited dispersion, the maximum amplitude of the signal is expected to travel slightly slower than the start of the A_0 mode. For automatic wave mode recognition, the onset of the wave mode is of primary interest. For this purpose, expected velocity values of 3200 m/s and 4600 m/s were used for the A_0 mode and the S_0 mode, respectively.

2.2. Automatic Mode Recognition Method

This section summarizes the method used for (semi-)automatic mode recognition for the case of a plate in laboratory conditions, as reported in previous work [34]. In [34], this method is used to automatically find the S_0 and A_0 modes in signals recorded on a plate. The method requires a number of reference wavelets to be selected for each mode. The reference wavelets are pieces of signals in which this mode is present, chosen from signals recorded at different distances from a reference source. The reference wavelet should contain the targeted wave mode or at least the start of it. The first step in automatically recognizing wave modes in a new signal is to determine the cross-correlation of a reference wavelet with the signal as:

$$R_{s-w}[n] = \sum_{i=0}^{i=i_{max}} w[i]s[i+n] \quad (1)$$

where $R_{s-w}[n]$ is the cross-correlation between the signal $s[i]$ and the reference wavelet $w[i]$, shifted by n samples relative to the signal. i_{max} corresponds to the length of the wavelet. From the available set of reference wavelets, the reference wavelet with the propagation distance the closest to the propagation distance determined for the signal is used. The result of Equation (1) is a series of cross-correlations as a function of the time shift between the signal and the reference wavelet. High cross-correlations indicate moments when the reference wavelet shows high similarity to the signal. The values of the cross-correlations also depend on the amplitudes in the corresponding time ranges in the signal. Therefore, the cross-correlations are rescaled by the autocorrelation of the signal within the time range that has been cross-correlated with the reference wavelet to obtain the considered cross-correlation value. To avoid excessive noise amplification, a regularization term is added to the denominator that is a fraction λ of the highest autocorrelation of the signal within any time window of the length of the reference wavelet $\max(R_{s-s,window})$: [34]

$$R_{s-w,scaled}[n] = \frac{R_{s-w}[n]}{R_{s-s,window}[n] + \lambda \max(R_{s-s,window})} \quad (2)$$

where $R_{s-s,window}$ denotes the autocorrelation of the signal within the time window of the wavelet starting at sample nr. n . Subsequently, envelopes are taken of the resulting series to identify peaks. The envelope of the result from Equation (2) is normalized to allow identical filter criteria for signals of different amplitude. The peaks are filtered based on prominence and using a threshold. The final selection of the peak that represents the start of the mode is based on its propagation speed. The propagation speed of each of the peaks is determined based on the time difference in arrival with peaks from signals from the same source event at different sensors. Since it is unknown which peaks in each signal correspond, propagation speeds are calculated for each possible pair within a set of peaks using the hypothesis that the set of peaks corresponds to the same signal feature [34]:

$$v = \frac{d_{hit2} - d_{hit1}}{t_{peak,hit2} - t_{peak,hit1}} \quad (3)$$

where v denotes the hypothetical velocity at which a wave feature would have travelled to give rise to the considered combination of peaks. $d_{hit,i}$ is the distance from the source to the sensor where the signal numbered i was recorded. $t_{peak,hit i}$ denotes the arrival time of the peak found in the signal numbered i .

The hypothesis that each of the peaks is related to the same wave feature is tested based on the values of the resulting propagation speeds. The calculated hypothetical propagation speeds are at the basis of the loss function used to select a set of peaks to

represent the considered wave mode. Ideally, if all peaks correspond to the same wave feature, the propagation speed v for each combination of peaks within the set equals the propagation speed of this wave feature. If in turn this wave feature corresponds to the targeted wave mode, its propagation speed should approximate the expected velocity of the considered wave mode. The set of peaks yielding the propagation speed that best approximates the expected velocity is selected. The peaks in this set indicate the arrival of the considered wave mode in each of the signals [34].

2.3. Adaptation of the Automatic Recognition Method

The method presented in [34] requires adaptation to apply it to the dataset from an industrial gas storage sphere. Firstly, a maximum of ten cross-correlation peaks after filtering is imposed. For signals for which this maximum is exceeded, the considered mode will not be recognized. In some instances, a large number of cross-correlation peaks after normalization of the cross-correlations may be related to the absence of a mode. However, the main benefit is to decrease the calculation load, especially for events with many hits. This limitation may also strengthen the peak selection based on hypothetical velocities since a hit with too many cross-correlation peaks increases the probability of coincidental peak combinations yielding a hypothetical velocity close to the expected velocity.

Secondly, the penalty in the loss function for a difference between the obtained hypothetical velocity and the expected velocity is capped. This adaptation is motivated by the need to limit the impact of outliers, for example, in case the start of the mode in one of the signals is outside of the sampled time range. Modes are recognized by selecting a combination of cross-correlation peaks for an event. As described in [34], a loss function is minimized to select the combination of cross-correlation peaks related to the best match between the hypothetical velocities and the expected velocity. However, if the hypothetical velocity for one pair of cross-correlation peaks turns out to differ significantly from the expected velocity, the exact value of this difference should ideally not significantly affect the final value of the loss function. If it does, this may lead to poor results for events where every possible combination of peaks leads to at least one strongly deviating hypothetical velocity. In such cases, the value of the loss function may depend more strongly on the value of those outliers than on the number and values of the hypothetical velocities that are closer to the expected velocity. The cap of the loss function is implemented by taking the arctangent of the abovementioned penalty for each hypothetical velocity such that the penalty asymptotically approaches the cap with increasing velocity difference. The abovementioned adaptations give rise to changes in the loss function reported in [34]. The updated loss function is shown in Equation (4).

$$loss = \sum_{i=1}^{i=n_h} \sum_{j=1}^{j=n_h} \operatorname{atan}\left(\frac{v_{ij}-v_{expected}}{v_{expected}}\right)^2 \Delta d_{ij} + \alpha \left(t_{peak,hit\ i} + t_{peak,hit\ j}\right) \quad (4)$$

Where $i \leq 10$ and $j \leq 10$ and $i \neq j$

In Equation (4), $v_{expected}$ denotes the expected velocity for the considered wave mode. v_{ij} is the hypothetical velocity obtained combining the i^{th} peak from one hit with the j^{th} peak of the other considered hit. n_h is the total number of hits in the event for which a sampled signal is available. Δd_{ij} denotes the difference in distance from source to sensor for each hit. $t_{peak,hit\ i}$ denotes the time at which the considered peak arrives at the sensor, relative to the trigger time. α is a coefficient that determines the relative importance of the velocity term and the peak arrival time.

As can be seen in Figure 1, the group velocity of the A_0 mode is almost constant in the considered frequency range. Due to the near-nondispersive nature of the A_0 mode, the entire A_0 mode overlaps timewise with the triple point. As a consequence, the varying

presence and amplitude of the S_0 and occasionally A_1 mode can lower the cross-correlation of the A_0 mode with its wavelet. Therefore, the third and final adaptation of the method consists of applying a band-stop filter for the recognition of the A_0 mode to suppress the frequency range in which the A_0 mode overlaps with the S_0 . A band-stop filter between 90 kHz and 105 kHz is applied for the recognition of the A_0 mode. This band-stop filter is applied prior to determining cross-correlations to both the A_0 wavelet and the signals.

2.4. Reference Wavelets

In analogy to [34], the first step in this work is to select reference wavelets from reference signals containing at least the start of the mode to be targeted. The reference wavelets for A_0 and S_0 were selected from signals caused by the same Hsu–Nielsen source. For the S_0 mode, multiple reference wavelets are selected to reduce the difference in dispersion that occurs if the propagation distance of the wavelet strongly differs from the propagation distance of the wave to be analyzed. The reference wavelets for S_0 are shown in Figure 4a–c. Figure 4d shows the reference wavelet that was used for A_0 . The choice of propagation distances at which the S_0 wavelets are selected is given by the circumstance that all Hsu–Nielsen sources for which sampled signals are available are applied at one sensor. In combination with the regular sensor placement, propagation distances were clustered around 2.8 m, 4 m, 5.3 m and longer. Among the reference wavelets, each of the three closest distance groups is represented.

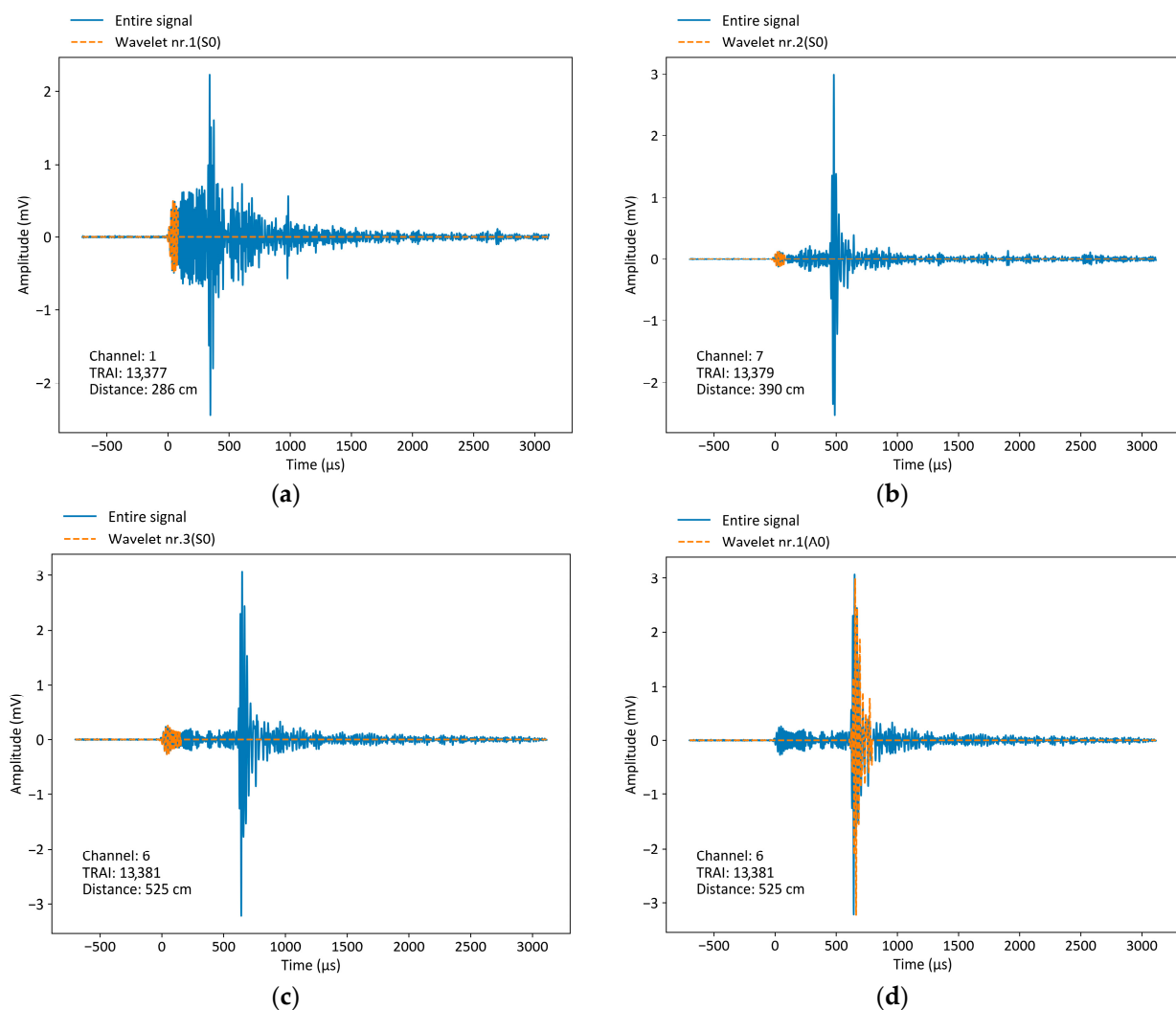


Figure 4. Reference wavelets (orange) and the signals they are selected from (blue) for S_0 (a–c) and A_0 (d).

For S_0 wavelets in particular, not the entire length of the mode in the reference signal is selected as reference wavelet. Due to its extensive dispersion, the duration of the S_0 mode strongly increases with propagation distance, until it covers more than 500 μ s at a distance of 5 m. Using the entire wave mode as reference wavelet would result in wavelets that, if used to cross-correlate with signals with lower propagation distance, overlap with the A_0 mode. This would weaken the correct cross-correlation peaks. A similar effect would be expected in signals where an A_1 mode is visible. Therefore, since the aim in the presented work is to identify the start of the mode, the S_0 wavelets only contain the start of the S_0 mode. Since the A_0 reference wavelet shows little variation in group velocity, only one A_0 wavelet was selected. Note that the A_0 reference wavelet does not perfectly match the signal it has been selected from due to the band-stop filter it has been subjected to. The liquid in contact with the wall of the sphere is expected to impact the propagating waves. As a consequence, the match between the reference wavelet and the targeted mode in a signal may weaken depending on the portion of the propagation path of the wave that took place above or below the liquid level. However, this was not considered for the selection of the current reference wavelets.

3. Results

As mentioned before, the mode recognition technique was tested on a dataset consisting of 211 hits in total. Of those hits, 29 were due to a Hsu–Nielsen source, 40 due to a sensor pulse, 39 due to impact by a metallic object and 103 due to natural sources. The result was assessed for each hit and each mode by comparison to manual mode recognition. Manual mode recognition was performed as described in the introduction, with calculating the expected travel times for each mode as verification, in analogy to [34]. A result was considered successful if manual and (semi-)automatic mode recognition found the same arrival time for a mode in a signal.

Ambiguity may arise when assessing results for signals in which the waves from two separate source events occurred within the sampled time range. Each mode can then occur twice, excluding reflections. For those cases, an automatic recognition result was assessed as successful if the first appearance of a mode in a signal was found. An overview of the observed success rates for recognition of the start of a mode for each source type is shown in Table 1. In brackets, there is a 95% confidence interval (Wilson score interval) obtained based on the number of signals and the observed success rates. The use of the Wilson score interval is motivated by the observed success rates close to 100%. It does, however, assume that the different observations are independent, which is uncertain for signals from the same event.

Table 1. Success rates for recognition of the start of a mode using the adapted method.

	A_0	S_0
Hsu–Nielsen source	97% (83–99%)	97% (83–99%)
Pulse	88% (74–95%)	95% (83–99%)
Impact	74% (59–85%)	90% (77–96%)
Natural sources	73% (64–81%)	85% (77–91%)

Figure 5a,b provide examples of successful mode recognition for a natural source for S_0 and A_0 , respectively. Figure 5c,d show the cross-correlations with the respective reference

wavelets. In analogy, Figure 5e,f show examples of recognized S_0 and A_0 , respectively, for a signal due to a sensor pulse, and Figure 5g,h show the corresponding cross-correlations. Note that the resulting A_0 is not identical to the corresponding part of the entire wave; see Figure 5b,f. This difference is caused by the band-stop filter that is applied to limit the influence of other modes on the recognition of the A_0 mode. However, since the main outcome of the mode recognition method is (the start of) the time range that the mode covers, whether to apply the same band-stop filter to present the resulting recognized mode is a matter of preference. The pulse signal in Figure 5e–h was emitted above the liquid level and detected below the liquid level, which may have contributed to the relatively high amplitude of the S_0 mode.

Although the success rates are high for all source types, the method did not provide correct mode recognition for all signals. Every signal and mode for which there was disagreement between manual and automatic mode recognition is considered as unsuccessful. Four categories of errors that prevented successful automatic mode recognition were observed. The first type of error, which accounts for 43% of all errors, is related to the selection of the wrong cross-correlation peak. The second type, accounting for 31% of all errors, is caused by a too low cross-correlation for the correct peak. The third error category, which caused 18% of all errors, occurred due to the number of peaks being too high. Finally, 9% of all errors were related to the absence of the targeted mode in the sampled signal. In one case, the error did not fit into any of the above categories. This error was due to inaccurate positioning of the correct peak, as it was reported in [34]. The contribution of different error types to the error count is similar for A_0 versus S_0 . For S_0 , errors related to absence of the mode are slightly more frequent. This distribution of errors across these four categories is similar for natural sources. Natural sources are the main contributors to the overall error count.

The first error category is illustrated in Figure 6, which shows an example signal from a natural source in Figure 6 (left) and the corresponding cross-correlations in Figure 6 (right). It can be observed that the start of the S_0 mode is recognized too late due to the selection of the wrong cross-correlation peak. In this case, the wrong peak is a second peak that occurs a very short time after the first (correct) peak. The automatic mode recognition method selected this second peak because it leads to a better match with the expected velocity.

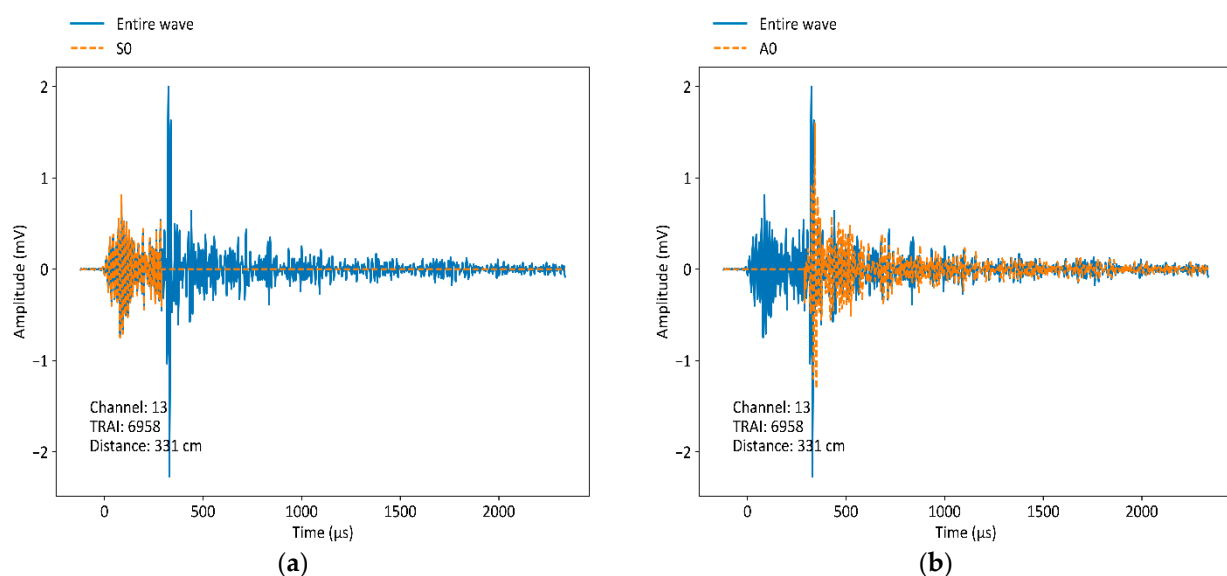


Figure 5. Cont.

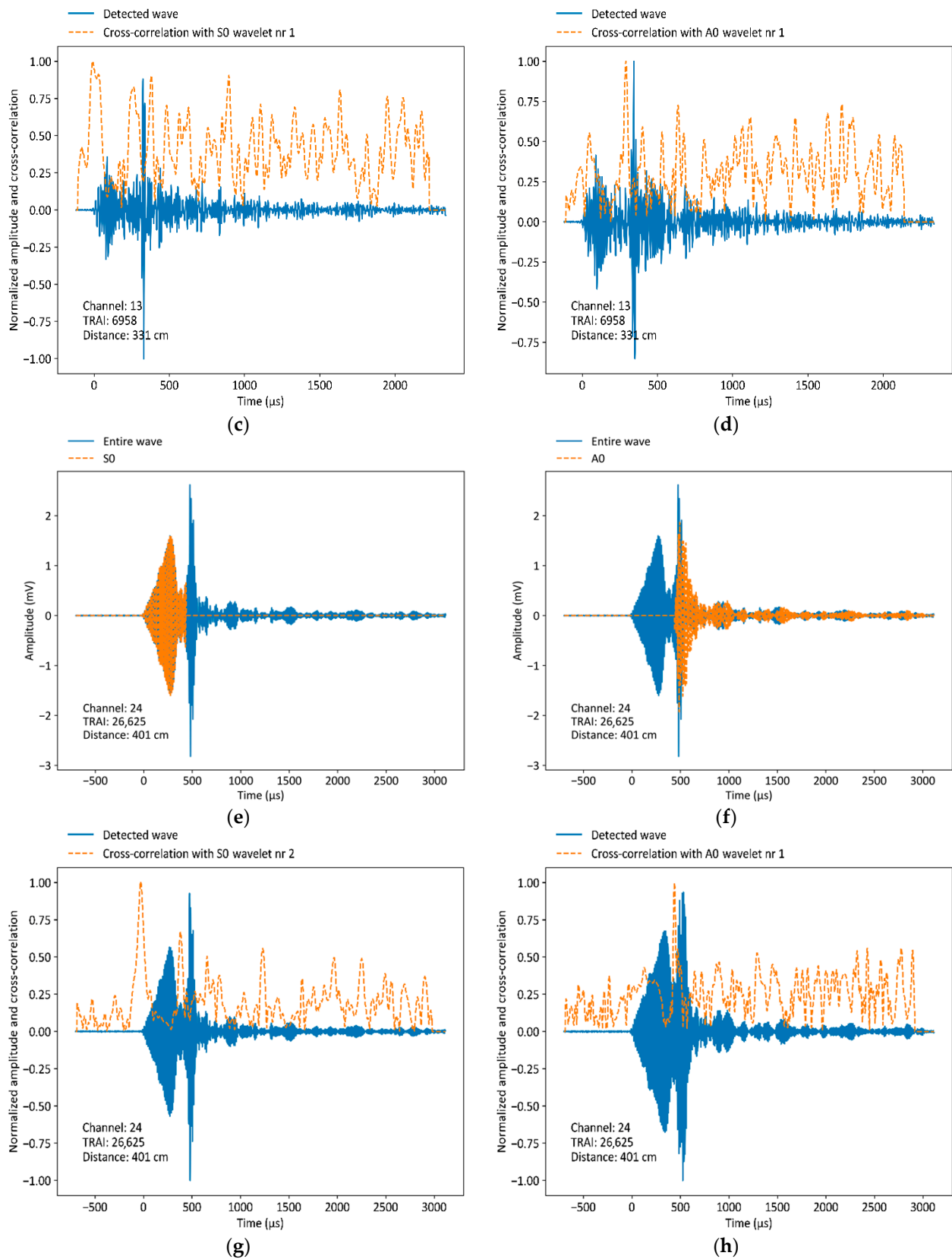


Figure 5. Examples of successful recognition and corresponding cross-correlations for a natural source (a–d) and for a sensor pulse (e–h).

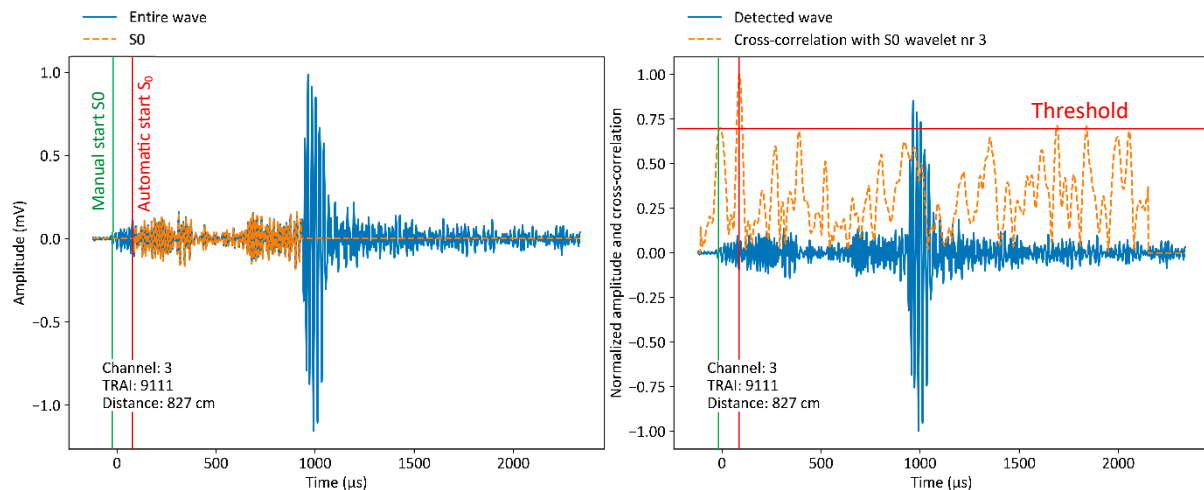


Figure 6. Inaccurate detection of S_0 (left) due to selection of the wrong one of a pair of cross-correlation peaks (right) near or at the start of S_0 .

The second type of error is related to the low cross-correlation value of the desired cross-correlation peak. For such cases, the filtering applied to limit the number of considered cross-correlation peaks can be too aggressive. An example of this type of error is shown in Figure 7, in this case for a signal from a natural source shown with the recognition result in Figure 7 (left) and with the corresponding cross-correlations in Figure 7 (right). Errors of this type are a direct consequence of an insufficient match between the reference wavelet and the targeted mode. It commonly coincides with an overlapping of competing modes or interference with the second arrival of the same mode.

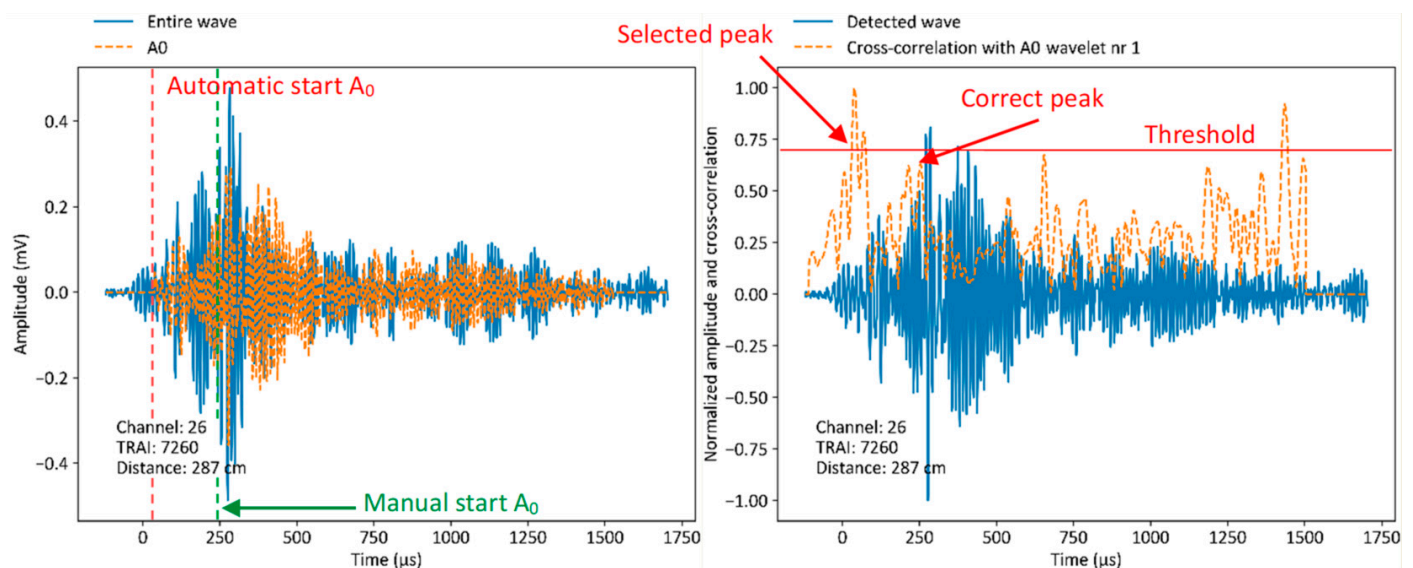


Figure 7. (Left): Example of unsuccessful detection of A_0 . (Right): Cross-correlations with the A_0 wavelet shown along with the signal after the application of the band-stop filter.

The third type of error is related to the maximum limit imposed on the number of cross-correlation peaks after filtering. If the number of peaks exceeds ten for a certain hit, the considered mode is not detected. An example is illustrated in Figure 8 for a signal due to impact by a metallic object. The automatic recognition result (no recognition) is shown in Figure 8 (left) and the corresponding cross-correlations in Figure 8 (right).

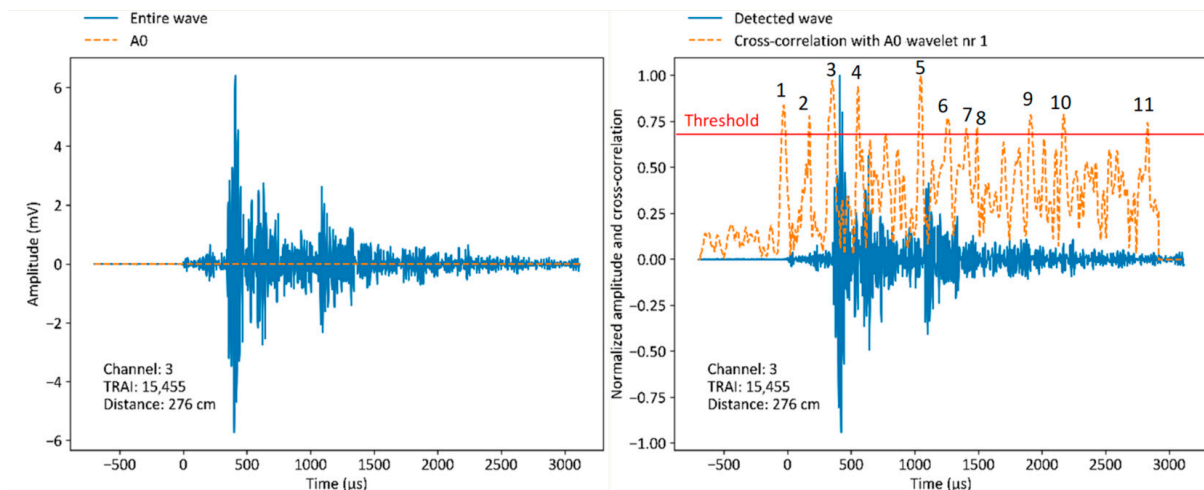


Figure 8. (Left): Failure to detect A_0 . (Right): Excessive number of cross-correlation peaks shown along with the signal after the application of the band-stop filter.

Finally, Figure 9 (left) shows an example of the fourth error type, which is related to a mode being invisible in the sampled signal, in this case from a natural source. This type of error, just as the previous two, was also observed in previous work [34]. As is visible from Figure 9 (right), the S_0 mode in this case is dominant and eclipses any possible A_0 mode that may be present. The desired result would have been not to indicate any A_0 . However, for this to occur, cross-correlation with the A_0 reference wavelet would have needed to give rise to at least 10 peaks. As described previously, for signals for which this maximum of 10 peaks is exceeded, the considered mode will not be recognized. This is not the case for the example in Figure 9.

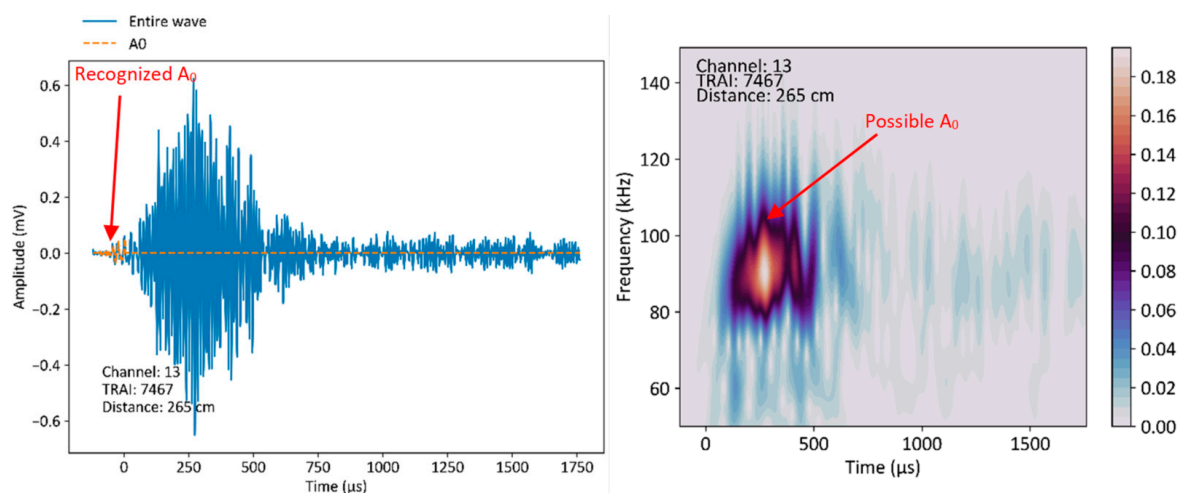


Figure 9. Signal for which A_0 is hidden behind a dominant S_0 , if present at all. (Left): Automatically recognized A_0 . (Right): Wavelet transform of the considered signal.

4. Discussion

When combined, the errors due to a too low magnitude of the best cross-correlation peak and those due to too many peaks represent 49% of the overall error count. Although different in effect, they both have a poor match between the wavelet and the targeted mode as the root cause. In the case of too many cross-correlation peaks, an alternative cause could be a high number of repetitions of the same mode in the signal. However, more than two repetitions were not observed in any signal in the studied dataset. Errors due to too many cross-correlation peaks may be further limited by reducing the considered

time range. This, however, may come at the cost of an increased probability to partially or entirely exclude one mode from the considered time range, depending on the possible propagation distances.

Wrong peak selection also stands for a considerable share (43%) of the overall error count. An improved peak selection would increase the effectiveness of the overall method. A possible improvement can be provided by taking into consideration the time difference between different wave modes in the same signal. This information is not used in the method currently presented. Using the time difference between different wave modes in the same signal would explicitly rely on both modes to be present in the signal. The currently presented method does not include a systematic strategy to handle signals where one of the wave modes is entirely absent. If explicitly assuming the presence of both Lamb modes strongly improves the performance of the automated mode recognition, the limitation to only signals with both modes present may therefore be acceptable.

Finally, the choice of using Hsu–Nielsen sources as a source of reference wavelets for mode recognition of other source types is not obvious. However, a practical benefit of using Hsu–Nielsen sources as a basis for automatic mode recognition would arise when applying mode recognition in real time, since the type of natural source is not known beforehand. For automatic mode recognition during post-analysis, one could expect a benefit from selecting reference wavelets from the same source type as the signals to be analyzed. The highest cross-correlations between a reference wavelet and the targeted mode are expected when the reference signal is more similar to the analyzed signal. Whereas artificial sources are commonly selected due to their reproducibility, considerable variation between different sources is possible, especially for natural signals. This means that one natural source does not necessarily produce suitable reference wavelets for mode recognition for a different natural source, even if both the reference wavelet and the analyzed signal are caused by the same source type. One possible type of variation between signals from different source types is the frequency content. Hsu–Nielsen sources, however, are broad-band sources and therefore at least have a frequency overlap with each of the natural sources. Nevertheless, for natural sources with sufficient reproducibility, the selection of reference wavelets from the natural sources can be an alternative. A future improvement could be to select reference wavelets from different narrow-band sources and to use the frequency overlap between signal and reference wavelet to select a suitable reference wavelet.

5. Conclusions and Future Work

Analysis of wave modes can yield valuable information regarding the source of acoustic emissions. When closely spaced sensor arrays for recognition with 2D-FFT are unavailable, the choice of automatic mode recognition method depends on the dataset. Each of the methods mentioned in the literature review as well as the method applied in this publication relies on assumptions to recognize wave modes. The most common assumptions concern systematic differences in amplitudes or frequency range. In this paper, the recently developed method for (semi-) automatic mode recognition has been adapted and applied to a dataset obtained from a gas storage sphere. The assumption at the basis of the method in this work requires wave modes to resemble reference wavelets selected from the same dataset. This assumption is more general and should allow broader applicability. As a drawback, this method requires source localization as input, whereas other mode recognition methods have been proposed as a basis for source localization.

Compared to the initial method, three further adaptations have been added to this method. The reference wavelet for the A_0 mode was subjected to a band-stop filter to suppress possible overlap with the S_0 mode. Furthermore, the loss function for selection of a set of cross-correlation peaks has been adapted to limit the influence of strongly deviating

hypothetical velocities. Additionally, a maximum number of cross-correlation peaks after filtering has been set to limit the number of possible combinations and thereby also to limit the probability of coincidentally matching hypothetical velocities.

The performance of the adapted method was assessed by comparison of the automatic results to manual mode recognition. This assessment was performed for a total of 211 signals. Signals caused by the following four types of sources were considered: Hsu–Nielsen sources, pulsing sensors, impact by a metallic object and “natural sources”. Compared to the other artificial sources, the impact by a metallic object gives rise to more complex signals and is therefore expected to be more difficult to analyze. The “natural sources” occurred during a pressure test on the gas storage sphere and are localized near the legs of the sphere. The success rate, which is the percentages of cases for which manual and automatic recognition come to the same conclusion regarding the start of a mode, was determined for each source type. The success rates range from 97% for both modes for Hsu–Nielsen sources to 74% and 90%, respectively, for the recognition of A_0 and S_0 due to impact by a metallic object. For natural sources, the A_0 was identified correctly in 73% of the signals and the S_0 for 85%. Errors leading to unsuccessful mode recognition were classified into four categories. Close to 43% of the errors were related to selection of the wrong cross-correlation peak, where a different cross-correlation peak would have led to a correct result. Further analysis of these errors and potential correlations with the propagation distance above and below the liquid level will enable possible improvements to the method. Nonetheless, the currently presented success rates show the application of the present method to a gas storage sphere as a first step in enabling the exploitation of the possibilities of modal analysis on a systematic basis, in a first instance for analyzing test results for spherical storage tanks.

Future work on the method applied in this work should focus both on its performance and its applicability to a broader range of tested objects. Currently, the wave modes are recognized independently from each other. An aspect that is currently not used is the time difference between different modes in the same signal. Taking the time difference between different modes into account might improve performance whenever both modes are reliably visible in the signals. The method applied in this work takes the increasing effect of dispersion into account based on different reference wavelets. For each signal, a distance estimate is used to select a reference wavelet. Application of this method to anisotropic materials might therefore require an extended set of reference wavelets and a more elaborated criterion for wavelet selection. Similar challenges may arise when applying this method to objects with more complex geometries since the propagation distance may no longer be sufficient to determine the dispersion expected for each signal.

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