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Detecting Pipe Changes via Acoustic Matched Field Processing

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Abstract

Detecting pipe irregularities such as intrusions can be challenging. However, subtle changes can be identified in the complex acoustic fields measured over a range of frequencies and over a time interval given an "array" of receivers. In particular, for two receivers one can coherently process the signals via Matched Field Processing (MFP) to infer whether or not there have been changes such as new intrusions *relative to undisturbed fields measured earlier.* There is no acoustic modelling of the fields required, only the simple linear processor is applied, and only test data (five scenarios) are used in this demonstration. A key advantage to using MFP plus two (or more) microphones is that *absolute* sound levels need *not* be carefully measured.

1 Introduction

Acoustic methods for the inspection of pipes to locate blockages and damage have been used extensively[1]-[4] with primary applications related to the quality control of pipes used in chemical engineering, the oil and gas industries, the water industry, and in the manufacturing of musical instruments. Unlike many other inspection methods, acoustic methods can be fast and non-invasive.

Many acoustic methods are based on pulse reflectometry. Such an approach injects a sound pulse into a pipe and examines the resultant reflections. Modeling is usually involved which requires constraints on the nature of the pipe or its defects. The approach of pulse reflectometry plus modeling may detect pipe *leaks* and *cross-sectional changes* after analysis of the reflections plus impedance modelling of the pipe with and without a defect[1]. This approach can also be used to determine eigenvalue shifts[2]-[3] to detect finite duct blockages for one or two sets of termination conditions. Another application has been to model a pipe "notch" and its effects on low and high frequencies via finite element modelling of the duct and its defect[4]. The results for pulse reflectometry plus modelling are usually validated by comparison with test data and usually involve the assumption of idealized acoustic conditions. Additionally, such an approach typically utilises only one microphone and thus, requires vital system calibration or some way to remove offsets in the data[1].

In practical applications to underground pipe management it is often desirable to determine the degree of change which a *long* section of a pipe has experienced over time. Such operational and structural changes are often *not localised* and occur gradually along the whole ring, resulting from the development of longitudinal cracks and continuous sedimentation. At some critical instant a small change can result in a service failure (which may then contribute to a flood event caused by a blockage or a structural pipe collapse). A small change in pipe conditions is notoriously hard to detect directly, particularly when the pipe consists of several, poorly joined sections. Thus, the pipe is not simple or "ideal". If the acoustic measurement is taken from an open end of the pipe connected to an inspection cavity of complex geometry, then it can be extremely difficult to separate the effects of the cavity from that of the pipe via the acoustic response. Thus, the impedance conditions can be difficult to model. This paper presents a novel application of the so-called matched field processing (MFP) method[5] which is able to detect changes in a continuous or non-continuous air-filled pipe and which is immune to the effect of the cavity.

The concept to be applied here is simple: compare the (new) acoustic field (measured on microphones) present in a pipe which has an *unknown* condition with that of a previously measured (old) field where the pipe condition was *known*. This comparison is done via MFP over a range of frequencies and times. MFP is a signal processing technique which derives from matched filters and which has been in use in acoustical oceanography for several decades[5]-[18]. In this paper we present the application of MPF to detect pipe changes using *two* acoustic receivers. We note that if only one receiver were used, then system calibration would be required. We note that *without* calibration, it is impossible to simply "subtract" one field from another in order to detect differences.

MFP is used in the frequency domain and is known to be sensitive to changes in the (complex) acoustic fields. This sensitivity can be a function of: frequency, range to the source, nature of the environment, array of receivers, and other characteristics[5]. Usually, MFP is applied to data versus a model prediction for the field. This allows the exact nature of the difference to be quantified via modelling. However, such an approach also assumes that the model is extremely accurate and that it is able to account for detailed and complicated modal structures in a broad frequency range and in range-dependent scenarios. Both these assumptions can be very restrictive. The approach which the authors propose herein involves no modelling - only a comparison of data with data. This approach was first suggested and successfully applied to dolphin acoustic signals for the detection and discrimination of buried mines in an ocean environment[19].

The next section (Experimental Measurements) will discuss the experimental methodology and the obtained acoustic data. Following that section, we will discuss generic MFP. Finally, we will present the results with detailed discussion of our new MFP application followed by a brief Conclusions and Future Work section.

2 Experimental Measurements

Two types of experiments were conducted in order to illustrate the versatility and general application of the proposed analysis method. For the first test, the pipe diameter is larger than the other, and the ends were terminated with inspection cavities. For the second test, the pipe is narrower and the ends are free. These two tests indicate the method usefulness for different impulse responses and different boundary conditions at the pipe ends. Moreover, the various diameter pipes will show changing emphases on the lower or higher order modes.

One type of experiment (Test 1, 2 scenarios) was on a 20m long section of a concrete pipe with a 600mm diameter. The concrete pipe was terminated with two plywood manholes at either of its ends (see Figure 1a). This pipe was not continuous but was composed of eight 2.5m long concrete sections which were joined together where the joints were connected with rubber seals. An approximately 100mm change in the internal pipe diameter was observed at each of the seven joints. These diameter changes extended approximately 50-100mm in the longitudinal direction. We note that the observed changes in the pipe diameter at the joints were comparable with the transverse dimension of the artificial blockage which was introduced in the concrete pipe in the experiment.

The other type of experiment (Test 2, 3 scenarios) was on a 8.8m long section of a PVC pipe with a 150mm diameter. This PVC pipe was continuous and did not have any joints which might have caused acoustic reflections. It was placed on the laboratory floor and its ends were open to the atmosphere.

The sources of sound for the tests were: (i) a 75mm baffled loudspeaker positioned on the right near wall of the 600mm concrete pipe; (ii) a 50mm baffled loudspeaker positioned in the middle of the 150mm PVC pipe. For both tests the speaker was connected to Rotel power amplifier, controlled by a high quality Marc-8 audio card, and it was able to emit acoustic energy in the frequency range of 50 to 18000 Hz. The stimulus was a 14-order maximum length pseudo-random sequence generated by WinMLS software[20] using the sampling frequency of 44100 Hz.

The receiver for Test1 (concrete pipe) was a two-microphone probe with the 27mm spacing between the microphones. The receiver for Test 2 (PCV pipe) was a two-microphone probe with the 12.5mm spacing between the microphones (see Figure 1b). Microphone 2 corresponds to the microphone closest to the pipe edge. The probe was inserted in each pipe and secured at the pipe soffit immediately near one of the pipe ends as shown in Figure 2. The received audio signals were digitized with a Marc-8 audio card and deconvolved using WinMLS software so that the impulse response of the pipe could be determined.

In total five scenarios were examined: (i) clean 600mm concrete pipe; (ii) 600mm concrete pipe with a 13% brick blockage (12.8cm high, 27.7cm long) placed on the bottom starting at 4.83m distance from the center of the acoustic probe (4.695m from the first microphone); (iii) clean 150mm PVC pipe; (iv) 150mm PVC pipe with a 25% heap of medium stone gravel at 5.5m from the sensor; (v) 150mm PVC pipe with a 25% heap of coarse stone gravel at 5.5m from the sensor.

Sample deconvolved impulse responses for the both audio channels from these five experiments are presented in Figures 3 and 4. We note in Fig. 3 that the data sets for the clean 600mm pipe and for the pipe with a blockage are remarkably similar so that it does not appear feasible to detect visually the blockage from the impulse response data. The long and more complicated tail in the impulse response data for the concrete pipe is due to the long range of propagation, wide range of strong frequencies, and sustained multiple reflections. We note that there was very little noise in the impulse response data because of the very high signal-to-noise ratio (ca. 84dB) provided by the 14-order MLS sequence algorithm adopted for this work [20]. Again, we note that consideration of the different types of blockages and of the different types of pipes will indicate the method versatility.

2.1 MFP

MFP is a coherent signal processing technique [5] which can be applied to an array of data at individual frequencies. This technique can use many different processors which have been developed over the years [5], but linear MFP is the simplest and most widely used processor. It is basically defined as the cross-correlation between data and model fields resulting in a scalar output indicating the agreement between data and model.

To apply standard MFP one can begin with two time domain fields $f_m(t)$ and $g_m(t)$ recorded on receivers m where $2 \leq m$ and over time t where $0 \leq t \leq t_{max}$ for some t_{max}. We will assume that the number of time domain points, K, is a multiple of 2 (this will make Fourier transforms straightforward). Typically, f_m will correspond to test data while g_m will correspond to simulated (model) data. In vector form we have $\mathbf{f} = (f_1, f_2, ...)$, $\mathbf{g} = (g_1, g_2, ...)$.

Next, these time domain fields are Fourier transformed into the frequency domain, $\mathbf{F} = \mathcal{F}(f), \mathbf{G} = \mathcal{F}(g)$, to obtain complex fields $\mathbf{F}(\omega) = (F_1(\omega), F_2(\omega), ...)$ and $\mathbf{G}(\omega) = (G_1(\omega), G_2(\omega), ...)$ at frequency ω. Additionally, the fields are normalized so that we have $\parallel \mathbf{F} \parallel = \sqrt{\parallel F_1 \parallel^2 + \parallel F_2 \parallel^2 + ...} = 1.00$, $\parallel \mathbf{G} \parallel = \sqrt{\parallel G_1 \parallel^2 + \parallel G_2 \parallel^2 + ...} = 1.00$. Finally, for the simple linear processor these complex fields are cross-correlated to obtain a scalar estimate $\mathcal{P}_{lin}$ of their similarity: a value of 0.00 indicates *no* similarity while a value of 1.00 indicates that the fields are identical. In particular,

$$\mathcal{P}_{lin} = \mid \mathbf{F}^{+} \bullet \mathbf{G} \mid^2 = \sum_{m,n=1}^{N} F_m^* F_n G_m G_n^*, \tag{1}$$

where $*$ indicates complex conjugate, $+$ indicates the conjugate transpose, and N is the number of receivers. Typically, ambiguity surfaces (AMSs) are computed and plotted as a function of two parameter values (such as source depth or range or water depth, etc.) and graphically illustrate those parameter values for which agreement is high or low. An example of a scalar estimate (1) is seen in Fig. 5 for a variation of $\mathcal{P}_{lin}$ with two arbitrary parameters P_1, P_2 (these parameters are simply variables of interest such as source range or depth from a vertical line array) where the light pixels show strong correlation (true) values while the darkest pixels show low (false) values. This example assumed a single frequency of sound ω and modelled values of $\mathbf{F}$ and $\mathbf{G}$.

Key advantages of MFP are:

1. The independence from absolute amplitude and phase levels: only the *changes* in levels *along the array* are important. Thus, we do not require knowledge of scaling or receiver calibrations as we would for single microphone data.

2. The processing is *spatially coherent* between receivers: changes in phase along the array are important. Single microphone data processing would require source spectral information for frequency coherence.

Disadvantages for MFP are *usually* considered to be:

1. A necessity for high quality modelling of the expected fields – this is *not* required here where we will be using only experimental data.

2. Sensitivity to change/error (typically data fields are compared to modelled fields looking for parameter behavior) – this sensitivity is now an advantage for us since we will be looking for changes between measured fields.

For the data considered here our array will consist of two receivers (microphones). We note that the minimum of two or more microphones is needed in order to avoid calibration issues and to take advantage of the nature of MFP, i.e., to emphasize only *relative* field changes down the "array". Next, the data will be Fourier transformed (via the FFT algorithm used in [21]) to be converted from the original time domain signals into a variety of frequency components from 0 to 22.05 kHz. In practice, the upper frequency in the acoustic response of the loudspeakers used in this work was lower than the Nyquist frequency (22.05 kHz). However, the pipe itself was acting as an acoustical filter so that the energy in the impulse response spectrum was confined largely to below: 4 kHz in the case of the concrete pipe and 18 kHz in the case of the PVC pipe. If we perform a standard Fourier transform using all (2048) points of the impulse response determined in the case of the concrete pipe of 600mm diameter (Test 1) we arrive at Fig. 6 which suggests: (i) the dominance of the low frequency components in the signal spectrum, i.e. the dominance of the first few cross-sectional modes; and (ii) the nearly identical behavior of these Fourier spectra. Thus, a simple FFT of the Test 1 data does not reveal any obvious differences for a clean pipe versus one with blockages. Similar conclusions can be made for Test 2 in the case of the impulse response spectra for the smaller PVC pipe with the 150mm diameter.

3 Results

It is a difficult task to accurately predict, i.e., model, the sound field in a open section of a pipe with arbitrary boundary conditions at the ends (such as inspection manholes of complex geometry and with wet sediment). Modelling for such conditions would require accurately describing high and low order acoustic modes in the pipe for a very difficult and range-dependent environment (the blockage and pipe itself can be non-uniform with range). With this MFP based method we can avoid modelling altogether.

Additionally, using all (2048) time domain points at one time reduces our sensitivity to change and negates potential abilities to localize obstructions. Therefore, we will generate AMSs using shorter FFTs and sliding through the time domain until all of the 2048 points have been considered. For this purpose we have experimented with a variety of $2^N = K$ FFT sizes and find that the choice of $N = 9$ ($K = 512$ points) seems to result in an AMS with sufficiently good time and frequency resolution. That is, we compute $\mathbf{F_K}$ (a vector with m components for m microphones and where each component is complex) given by

$$\mathbf{F_K} = \mathbf{F_K}(\omega, t_j) = (F_{1,K}(\omega, t_j), F_{1,K}(\omega, t_j)), \quad \text{for} \quad t \,\epsilon\, [t_j, t_j + K\Delta t], \; j = 0, 1, 2, ... \tag{2}$$

where

$$F_{m,K}(\omega, t_j) = \mathcal{F}_K(f_m(t_j)), \tag{3}$$

or

$$F_{m,K}(\omega, t_j) = \int_{t_j}^{t_j + K\Delta t} f_m(t) e^{-i\omega t} dt, \; m = 1, 2. \tag{4}$$

Here $t_j = j\Delta t$ is an instant on the sliding time scale and Δt is the sampling interval, e.g., 2.27×10^{-5} for our examples. Using the suggested value of $K = 512$ and $j \leq 1536$, we arrive at "sonograms" of the data (sliding FFTs as a function of time and frequency) as in Fig. 7 for a normalized $F_{m,K}(\omega, t_j)$ where m denotes the microphone number). In the case of our impulse response data the last initial time will be at 0.03483 s which corresponds to the 1536th impulse response point. We note that the lower frequencies for the 600mm pipe dominate the FFTs particularly at the early times.

Next, we consider the associated ambiguity surfaces $\text{AMS}(\omega, t_j)$ for the fields F_K, G_K (normalized) given by

$$\text{AMS}(\omega, t_j) = \mid \mathbf{F_K}^{+} \bullet \mathbf{G_K} \mid^2, \tag{5}$$

Ambiguity surface (5) can be used as a scalar estimate, like the earlier $\mathcal{P}_{lin}$, of the similarity between the signals received on a microphone array in two different experiments.

Fig. 8 presents an AMS using the sonograms, $F_{m,K}$ and $G_{m,K}$, obtained for the acoustical signals received on the two microphones in the concrete pipe of 600mm diameter (Test 1). Here we compare *similar* situations such as a pipe with *no* blockage with another data set for the pipe with *no* blockage. In this example, we have compared the upper subfigures of Fig. 3 with another run both for a clean pipe situation (not shown here). We notice that there are some minor differences between the data runs at some frequencies and times, but there is a relatively small number of pixels displaying low values of AMS (see the indicated scale[1]). The number of all pixels is 256x1537 = 393472 with 53 points with an AMS ≤ 0.25. Thus, the proportion of strong disagreement is well less than 0.0 %. If we compare *dissimilar* situations such as a clean pipe situation (top subfigures in Figure 3) with a blockage situation (bottom subfigures in Figure 3) we obtain the result which is presented in Fig. 9 showing significantly *more* low values of AMS (more regions of strong disagreement). In particular, for the figure shown we now have 12304 low values (more than 3 % strong disagreement).

If we compare multiple runs of Test 1 data (600mm pipe, three repeat runs of a clean pipe situation, three of a blockage situation) we can summarize the results for the 600mm diameter pipe in Table 1

[1]We recall that low values of AMS correspond to a lack of correlation between data sets.

showing the number of low value AMS pixels (npts) for each combination and the average MFP value for the indicated time window (2048 points). In particular, the clean pipe situation is represented by P_j^{600} where $j = 1, ...3$ corresponds to a data run, the blockage situation by $Bloc_j$ where $j = 1, ...3$ again corresponds to a data run. We clearly note a pattern of discrimination where for *dissimilar* situations (blockage versus clean pipe) give *many* low MFP values, e.g., npts $\geq$ 10000 and the average MFP $\leq$ 0.90, while *similar* situations (blockage versus blockage - or clean pipe versus clean pipe) give *few* low AMS values, e.g., npts $\leq$ 500 (npts) and the average MFP $\geq$ 0.95. We note that this is for a time window of $t \in [0.0, 0.035]$ sec. If the window had been moved to $t \in [0.030, 0.065]$ sec, then the results would have been even more dramatic since this later window would contain scattering from the brick obstruction throughout the window. In any case, we seem able to distinguish between changing situations by examining the number of low AMS values (npts) and average MFP values for scenarios where the concrete pipe is clean versus when a small brick blockage is present in the same pipe.

Similarly, for Test 2 (150mm pipe) if we again compare multiple sets of data (two of a non-obstruction situation, two of one obstruction situation, two of another obstruction) we can summarize the results in Table 2 showing the number of low value AMS pixels for each combination. In particular, the non-obstruction situation is represented by P_j^{150}, $j = 1, 2$ corresponding to a data set (see the top subfigure in Figure 4), the first obstruction situation by $Obs1_j$, $j = 1, 2$ for each data set (see the middle subfigure in Figure 4), and the second obstruction situation by $Obs2_j$, $j = 1, 2$ for each data set (see the bottom subfigure in Figure 4). We again note a pattern of discrimination where *similar* situations (clear pipe) give few low MFP values, e.g., npts $\leq$ 500 and average MFP $\geq$ 0.95, while *dissimilar* situations (empty vs. obstructions 1 and 2, obstruction 1 vs obstruction 2) give more low value pixels, i.e., npts $\geq$ 25000 and average MFP $\leq$ 0.80. We note that this is for a time window of $t \in [0.0, 0.035]$ sec. We again seem able to distinguish between changing situations, particularly between the types of obstructions which generated time domain fields which looked nearly identical to the eye (see middle and bottom subfigures in Figure 4).

(1) clean 600mm pipe versus 600mm clean pipe	npts (AMS ≤ 0.25)	average MFP
P_1^{600} vs. P_2^{600}	53	1.00
P_1^{600} vs. P_3^{600}	63	1.00
P_2^{600} vs. P_3^{600}	84	1.00
(2) blockage in 600mm pipe versus blockage in 600mm pipe	npts (AMS ≤ 0.25)	average MFP
$Bloc_1$ vs. $Bloc_2$	214	0.98
$Bloc_1$ vs. $Bloc_3$	314	0.97
$Bloc_2$ vs. $Bloc_3$	169	0.98
(3) clean 600mm pipe versus blockage in 600mm pipe	npts (AMS ≤ 0.25)	average MFP
P_1^{600} vs. $Bloc_1$	12304	0.86
P_1^{600} vs. $Bloc_2$	12865	0.85
P_1^{600} vs. $Bloc_3$	14154	0.85
P_2^{600} vs. $Bloc_1$	12978	0.85
P_2^{600} vs. $Bloc_2$	13528	0.85
P_2^{600} vs. $Bloc_3$	14868	0.85
P_3^{600} vs. $Bloc_1$	14331	0.85
P_3^{600} vs. $Bloc_2$	14987	0.845
P_3^{600} vs. $Bloc_3$	16161	0.84

Table 1: Table of results for the 600mm diameter pipe to show number (npts) of low AMS values (AMS < 0.25) for two types of data (the 600mm clean pipe and a brick blockage). We note that similar situations (top two categories, 6 entries) have AMSs that show great agreement, i.e., few low values (npts less than 500) while the dissimilar situations have more low AMS values (npts greater than 10,000) The total number of pixels is approximately 400K. We note that this is for a time window of $t \in [0.0, 0.035]$ sec. If the window had been moved to $t \in [0.030, 0.065]$ sec, then the results would have been even more dramatic since this later window would contain scattering from the brick obstruction throughout the window.

(1) same versus same	npts (AMS ≤ 0.25)	average MFP
P_1^{150} vs. P_2^{150}	359	0.99
$Obs1_1$ vs. $Obs1_2$	196	0.99
$Obs2_1$ vs. $Obs2_2$	70	0.99
(2) obstruction 1 versus obstruction 2	**npts (AMS ≤ 0.25)**	**average MFP**
$Obs1_1$ vs. $Obs2_1$	26809	0.80
$Obs1_1$ vs. $Obs2_2$	26768	0.80
$Obs1_2$ vs. $Obs2_1$	26777	0.80
$Obs1_2$ vs. $Obs2_2$	26803	0.80
(3) clean 150mm pipe versus 150mm pipe with obstructions	**npts (AMS ≤ 0.25)**	**average MFP**
P_1^{150} vs. $Obs1_1$	31416	0.76
P_1^{150} vs. $Obs1_2$	32040	0.76
P_1^{150} vs. $Obs2_1$	33963	0.78
P_1^{150} vs. $Obs2_2$	33964	0.78
P_2^{150} vs. $Obs1_1$	31579	0.76
P_2^{150} vs. $Obs1_2$	32240	0.76
P_2^{150} vs. $Obs2_1$	33811	0.78
P_2^{150} vs. $Obs2_2$	33845	0.79

Table 2: Table of results for the 150mm diameter pipe to show number (npts) of low AMS values (AMS < 0.25) for three types of data (clean 150mm pipe, obstruction 1, and obstruction 2). We note that similar situations (top category, 3 entries) have AMSs that show very few low values. In particular, npts is less than 500. On the other hand, dissimilar situations (middle and bottom rows) show considerable disagreement, i.e., high number of low AMS values. In particular, we see that the number of low AMS values for dissimilar situations is greater than 25000. The total number of pixels is approximately 400K. We note that this is for a time window of $t \in [0.0, 0.035]$ sec.

4 Conclusions and Future Work

We conclude that a new matched field approach can be used to discriminate between changing pipe conditions such as: (i) a clean pipe versus the pipe with a blockage; and (ii) between different types of pipe blockage. This method has been demonstrated on a collection of data sets (each using two receivers) and does *not* involve any modelling of the scenarios or of the associated propagation and scattering.

We note that the ability of this method to sense blockages is very dependent on:

- the location of the blockage (a blockage close to the source results in stronger effects and more scattering);
- the size and nature of the blockage (large, dense blockages result in stronger effects and more scattering);
- the diameter, material, and nature of the pipe (background backscatter will vary depending on the pipe);
- the time interval of the data selected for processing (if blockage effects are NOT in the processed window, MFP computations will not be affected).

Future investigations of this method may show capabilities to determine the degree of change, its extent and location. This may be achieved by varying the start time for the processing of the acoustic signals and the resolution of the FFT to determine where the low values cluster in the ambiguity surface data. We may also improve sensitivity of the method by selecting later start time segments of the data and increasing the number of the microphone channels. Finally, it may be possible to pre-compute templates (characteristic AMS features) for the defect itself in order to discriminate between types of defects, if these defects are repeatable.

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6 List of figures

there are more low values ($\mathcal{P}_{lin} \leq 0.25$, i.e., dark pixels) than for the earlier situation of Fig. 8.