The effect of corrosion induced surface morphology changes on ultrasonically monitored corrosion rates

Attila Gajdacsi and Frederic Cegla

Mechanical Engineering Department, Imperial College London, Exhibition Road, South Kensington, London SW7 2AZ, UK

Received 23 March 2016, revised 24 May 2016
Accepted for publication 15 June 2016
Published 7 October 2016

Abstract

Corrosion rates obtained by very frequent (daily) measurements with permanently installed ultrasonic sensors have been shown to be highly inaccurate when changes in surface morphology lead to ultrasonic signal distortion. In this paper the accuracy of ultrasonically estimated corrosion rates (mean wall thickness loss) by means of standard signal processing methods (peak to peak—P2P, first arrival—FA, cross correlation—XC) was investigated and a novel thickness extraction algorithm (adaptive cross-correlation—AXC) is presented. All of the algorithms were tested on simulated ultrasonic data that was obtained by modelling the surface geometry evolution coupled with a fast ultrasonic signal simulator based on the distributed point source method. The performance of each algorithm could then be determined by comparing the actual known mean thickness losses of the simulated surfaces to the values that each algorithm returned. The results showed that AXC is the best of the investigated processing algorithms. For spatially random thickness loss 90% of AXC estimated thickness trends were within $-10$ to $+25\%$ of the actual mean loss rate (e.g. 0.75–1.1 mm year$^{-1}$ would be measured for a 1 mm year$^{-1}$ actual mean loss rate). The other algorithms (P2P, FA, XC) exhibited error distributions that were 5–10 times larger. All algorithms performed worse in scenarios where wall loss was not distributed randomly in space (spatially correlated thickness loss occurred) and where the overall rms of the surface was either growing or declining. However, on these surfaces AXC also outperformed the other algorithms and showed almost an order of magnitude improvement compared to them.

Keywords: corrosion monitoring, ultrasonic monitoring, surface morphology, corrosion rate, structural health monitoring

(Some figures may appear in colour only in the online journal)
reported for some laboratory measurements [4–6], whereas the repeatability of manual ultrasonic measurements is in the range of millimetres [7]. Furthermore, very frequent measurements are possible which makes it easy to extract wall loss rates with a very good response time. The determination of a wall loss rate, or corrosion rate, with a short response time is very important when one is interested in mitigating the effects of corrosion. Accurate information can be used to fine tune production processes in many ways, e.g. by feedback variation, change of operating conditions or the addition of corrosion inhibitor chemistries [8, 9].

However, ultrasonically monitored wall thickness data acquired on real plants has shown that sudden, unrealistically rapid changes in wall thickness can be reported by online monitoring systems. An example of this is shown in the solid blue line of figure 1, where a component that loses wall thickness at a steady rate of about 0.3 mm year$^{-1}$ suddenly shows an apparent thickness increase followed by a large drop in thickness. After 2 months of large deviation the monitored wall thickness then re-joins the overall steady trend of 0.3 mm year$^{-1}$.

There is a clear physics based explanation for the effect that is observed in figure 1. The wall thickness estimate that is reported is extracted from the temporal separation of the ultrasonic wavepackets that bounce up and down in the material whose thickness is being measured. Usually a simple algorithm such as the timing between consecutive peaks (peak to peak—P2P) is used to evaluate the travel time and hence the wall thickness (see figure 2). However, if the inner wall surface of the instrumented pipe changes shape, such as during some corrosion/erosion processes, then the ultrasonic wave packets can become distorted [10, 11]. This can lead to substantial changes/errors in the estimated wall thickness.

Further evidence for this explanation of the thickness deviations in figure 1 can be found when inspecting the raw ultrasonic waveforms (A-scans) associated with thickness measurements at different stages during the thickness deviation. Figure 3 shows the A-scans that were recorded at the times corresponding to the locations marked by the letters A, B, C and D in figure 1. The A-scans clearly show a strong distortion of the wave packet that is reflected from the inner pipe surface (second wave packet) indicating strong shape changes (corrosion activity) at that location. This is clearly an ultrasonic phenomenon which is a result of the interaction of the ultrasonic wave with the non-uniform surface morphology of the component that is being monitored. There is literature that has described the effect of rough surface scattering on ultrasonic signals and thickness measurements for both shear [10, 11] and longitudinal waves [12–15].

The data of figure 1 obviously casts doubts on the accuracy of ultrasonic corrosion rate estimates that are based on P2P timing algorithms. This paper addresses this issue by suggesting a more advanced signal processing algorithm. The algorithm is called adaptive cross-correlation (AXC). Its working principle is described in detail and it is compared to standard travel time estimation techniques (P2P, first arrival —FA, cross correlation—XC). The performance of all algorithms was tested on simulated ultrasonic signals reflecting from sequences of evolving, rough surfaces.

**2. Thickness calculation and arrival time extraction**

Figure 2(b) shows a typical waveform that is measured. It also illustrates that the thickness is extracted from the arrival time
difference between different wavepackets. Once the arrival times of individual wave packets have been established and the wave path is known this is a straightforward exercise. Equation (1) describes how to calculate the wall thickness based on the arrival times for the example geometry that is shown in figure 2 (a):

\[ T = \frac{1}{2} \sqrt{c^2 \cdot \Delta t^2 + 2 \cdot D \cdot c \cdot \Delta t} \]

where \( c \) is the velocity of the ultrasonic wave, \( \Delta t \) is the time difference between \( t_1 \) and \( t_2 \) the arrival time of the first and second wave packet respectively and \( D \) is the separation between the transmitting and receiving transducer. In this paper \( D = 1.7 \text{ mm} \) and \( c = 3250 \text{ ms}^{-1} \) unless otherwise stated.

Estimation of the arrival time of the first and second wavepackets from the ultrasonic waveform is therefore the key problem. There are a number of signal processing methods commonly used for this purpose. In this study the P2P, XC and FA algorithms have been implemented and are briefly described here.

P2P methods ignore the phase information of a signal and rely on computing an envelope function for the measured waveform. One way to achieve this is via the Hilbert transform. The Hilbert transform applies a 90° phase shift to all frequency components of the signal. This allows the envelope to be calculated:

\[ E(t) = \sqrt{f(t)^2 + H(f(t))^2}, \]

where \( f(t) \) is the signal for which the envelope is calculated, \( H(f(t)) \) is the Hilbert transform of \( f(t) \) and \( E(t) \) is the computed signal envelope. Once the envelope is computed for a waveform, its maximum peaks are assumed to be the arrival times of the various wavepackets. This is illustrated in figure 4 (a).

FA is another common technique to estimate arrival times. It also relies on calculating an envelope for the waveform; FA then finds the highest peak for each wavepacket. Following this, a threshold is applied to each peak as a function of the amplitude of that peak (e.g.: \(-6 \text{ dB}\)). The first crossing of the given threshold with the envelope signal is then taken as the arrival time for the given wavepacket. This is shown in figure 4 (b).

XC is also a popular arrival time estimation method. The XC process for real valued functions is defined by equation (3):

\[ h(t) = \int_{-\infty}^{\infty} f(\tau) \cdot g(\tau + t) d\tau, \]

where \( h(t) \) is the XC of function \( f(t) \) with a kernel function \( g(t) \). The peaks of the resulting correlation function are then determined and taken as arrival times. This is because at those particular time offset values the received signal is most similar to the transmitted signal. An example signal, its XC function and the extracted arrival times are shown in figure 5.

The above commonly used arrival time extraction techniques are not expected to perform well on ultrasonic signals that are reflected from surfaces with rough and evolving surface morphology. This is most easily explained by looking at the ultrasonic signal that is reflected from a rough surface.
as shown in figure 3(c). The signal in figure 3(c) has become distorted by the rough surface reflection so that none of the techniques based on the arrival time of the maximum amplitude (P2P), the FA or the XC with an idealised toneburst will result in a reasonable estimate for the arrival time of the backwall echo wave packet. Since the standard signal processing methods are not expected to perform adequately for gradually changing rough backwall surfaces, a new method—AXC—is proposed.

AXC was conceived specifically for the purpose of accurately estimating the mean wall thickness loss rate of gradually changing backwall surfaces that lead to distortion of the backwall echo signal. The method is based on the standard XC algorithm, however it uses an alternative reference signal for the XC process. This is because the transmitted toneburst that is used in the standard XC technique is not a good model for distorted backwall echo signals. Corrosion is assumed to take place on the backwall only, this is a reasonable assumption when measuring internal corrosion in pipes with a sensor on the outside of the pipe. AXC relies on the XC function to determine arrival times, however it accounts for distortion of the backwall signal by updating the signal that is used in the XC process with the received ultrasonic waveform. The updated signal is the distorted backwall reflection that was previously recorded from the rough internal surface. Careful windowing of the backwall signal is required and then only small distortions of the signal are expected to occur between consecutive measurements and therefore the overall temporal shift of the wavepacket is extracted more reliably. Consequently, AXC is expected to provide more accurate mean wall thickness loss rate measurements. In the absence of a previous measurement, i.e. for the first measurement a standard XC measurement is required.

The signal processing protocol of AXC to determine the arrival times of a sequence of waveforms \((w_{1..n})\) can be formally summarised as follows:

\[
\begin{align*}
T_1^{SW} & \leftarrow \text{xcorr}(w_1, S^0), \\
T_1^{BW} & \leftarrow \text{xcorr}(w_1, S^0), \\
S_{n-1}^{BW} & = w_{n-1} (t_{n-1}^{BW} + \Delta_{BW}^{length}) \\
t_n^{SW} & \leftarrow \text{xcorr}(w_n, S^0) \\
t_n^{BW} & \leftarrow \text{xcorr}(w_n, S_{n-1}^{BW})
\end{align*}
\]

where \(\text{xcorr}(a, b)\) is the XC of signals \(a\) and \(b\), \(\leftarrow\) denotes the extraction of the time of the highest peak in the first wavepacket of a signal, \(\leftarrow\) denotes the extraction of the time of the highest peak in the second wavepacket of a signal, \(w_n\) is the \(n\)th waveform, \(w(t_a : t_b)\) denotes windowing a waveform between times \(t_a\) and \(t_b\), and \(S_n^{BW}\) is the windowed backwall wavepacket for the \(n\)th measurement. The superscripts SW and BW refer to surface wave and backwall respectively. The plots at the bottom of figure 5 graphically illustrate this.
AXC process and contrast it to standard cross correlation with a constant kernel function which is shown in the top plots of figure 5. In this implementation of AXC only the backwall signal is windowed and updated in order to obtain an improved estimate of the arrival time of the first wavepacket. This is because corrosion is assumed to only take place on the backwall surface (i.e. the internal surface of a pipe), the surface to which the transducer is attached is not corroding, transducer coupling is assumed to be constant and therefore surface wave signal distortions are not expected and do not need to be compensated for.

**Figure 5.** Illustration of the cross correlation (XC) algorithm (top) and adaptive cross correlation algorithm (bottom). In both cases two consecutively received raw ultrasonic signals are shown as well as the kernel functions that they are cross correlated with. In the standard XC algorithm the kernel function is not updated, whereas in AXC the backwall signal of the previous measurement is used as kernel function in order to account for potential signal distortions due to surface morphology changes.

3. **Surface morphology and a model to describe the evolution of surface morphology**

Corrosion is a very complex phenomenon and can produce very different surface morphologies. It can be spatially uniform such as in etching, or spatially non-uniform, which is commonly described as pitting. Figure 6 illustrates the difference between spatially uniform and non-uniform corrosion processes by depicting several 2D wall thickness profiles throughout a corrosion process from start to end. During spatially uniform corrosion all spatial locations along the
horizontal axis have the same probability of getting thinner, whereas in spatially non-uniform corrosion there are some sites where material is preferentially lost. In practice, even if some non-uniformity is present, most plants quote an allowable corrosion rate for engineering components in service. This inherently assumes averaging of the material lost over a larger area. Because reporting of a corrosion rate is standard for corrosion rates that are generally quoted and comparable to corrosion rates that are not readily available or varied by a controlled amount, one can argue for or against this being physical. A line of thought suggests that corrosion always requires a loss of wall thickness. However, on a microscopic level there are phenomena such as the formation of passivation films and oxide scales that can result in small thickness gains. The proposed model, allows both of these; small local thickness increases and an overall mean wall thickness loss are modelled. We do not claim that it is an accurate model of any particular corrosion process but it does roughly describe the variations in surface geometry that are to be expected.

Finally, it is important to describe the parameter $s$. This parameter was introduced because the addition of two Gaussian surfaces of the same $R_{\text{rms}}$ value will result in a third Gaussian surface with different $R_{\text{rms}}$ value. If the resulting surface is scaled by $s$, which remains constant for each backwall sequence, then the $R_{\text{rms}}$ value of all surfaces can be kept constant (for $s \approx 1$) or varied by a controlled amount, e.g. so that the initial backwall surface has an $R_{\text{rms}}$ value of $r_1 = 100 \mu m$ and the $R_{\text{rms}}$ steadily increases throughout the simulation to $R_{\text{rms}} = 300 \mu m$ for $B_{50}$.

$$s_{\text{const}} = \frac{1}{\sqrt{1 + \left(\frac{r}{R_{\text{rms}}}\right)^2}}$$

The control of $s$ enables the simulation of spatially random perturbations to the surface ($s \approx 1$) so that the $R_{\text{rms}}$ value remains roughly constant throughout the backwall sequence and all spatial locations are equally likely to be attacked. If $s$
is larger or smaller than one, the perturbation will not be spatially random and thinner parts will preferentially thin and thicker parts will preferentially stay thick (this is essentially what happens in pitting).

Based on the above, the algorithm that describes the surface evolution can be summarised by the following equations:

\[
B_1(x) = G(x, r_1, C_{li}) + T_i, \quad (12)
\]

\[
B_{n+1}(x) = \left( B_n(x) - T_i + G(x, r_p, C_{li}) \right) \cdot s + T_{n+1} \quad \text{for } n = 1 .. 49, \quad (13)
\]

where \( G(x, R_{rms}, C_{li}) \) is an array of Gaussian distributed points with zero mean, \( R_{rms} \), correlation length \( C_{li} \) and \( x \) is the horizontal coordinate or index (if discretised) and \( B_m \) is the \( m \)th backwall, \( m = 1 .. 50 \).

4. Simulation of the reflection of ultrasonic signals from rough surfaces, simulation procedure and parameters

Equations (13)–(11) describe the actual surface geometry evolution. For all simulations the wall surface changes were described by 50 discrete surfaces. In order to compare the performance of different thickness estimation algorithms an ultrasonic signal corresponding to the reflection from each surface is required. Therefore it was also necessary to simulate a sequence of realistic ultrasonic signals that are reflected from each one of those 50 rough surfaces. This then needed to be repeated many times because many surface evolution sequences need to be simulated so that a distribution of wall thickness trends can be determined. Therefore a fast simulation tool was required. The distributed point source method (DPSM) [20] was chosen as it is particularly fast and has been shown to simulate realistic ultrasonic signals reflecting from rough surfaces [10, 11]. For the particular transducer geometry and wave mode (shear horizontal SH wave) that was simulated it was also shown that the statistics of 2D simulations can be related to those of the full 3D case [21]. In this paper 2D simulations are carried out, but they are not adjusted to match the expected statistics of 3D simulations. This is because the 2D assumptions can be treated as the worst case scenario, since averaging over the orthogonal direction (as in the 3D case) in general reduces the distortion of the ultrasonic signal due to scattering from the rough surface. In addition, 2D simulations only take of the order of minutes per signal rather than several hours for 3D simulations. This makes it possible to simulate thousands of ultrasonic 2D signals that are representative of the worst case real life signals over a timeframe of weeks rather than years.

Figure 7 shows an illustration of the DPSM model geometry that was used for the simulation. 100 active point sources were used to model the transmitter transducer. These point sources were distributed with a separation of 10 \( \mu \text{m} \) and were offset from the transducer/sample interface by 5 \( \mu \text{m} \). The backwall surface was represented by 1200 passive point sources with a separation of 50 \( \mu \text{m} \) offset from the surface by 25 \( \mu \text{m} \) altogether spanning the width of the 60 mm backwall surface. The receiver transducer was simulated by a single receiver point at the centre of the coupled transducer. The implementation of DPSM used in this paper is identical to that of [11], which has been validated against Finite element simulation results and experiments and the interested reader is referred to this publication for exact details on the DPSM model implementation.

To generate a backwall sequence using equations (13)–(11), \( C_{li}, r_i, r_p \) and \( s \) need to be defined. \( C_{li} \) was chosen to be 1 mm \( \sim 0.6\lambda \) for all simulations. Initial simulations showed that this causes the largest changes in the ultrasonic signal and therefore we expect that it will lead to conservative results and conclusions. All of the remaining parameters for the simulations are shown in Table 1. It is highlighted that the remaining parameters are broken down into two separate simulation sets. The first set of simulations are intended to create backwall surfaces with constant \( R_{rms} \), no change in rms throughout the sequence of 50 backwall surfaces, \( s \) was calculated according to equation (11), so that the \( R_{rms} \) would not change throughout a backwall sequence. Three \( R_{rms} \) values, \( r_i = 100; 200; 300 \mu \text{m} \) were used for the initial surfaces. The surface profile of the high temperature sulfidation corrosion sample that was previously discussed showed that these are representative of values that can be experienced in real life plants. Perturbation values were chosen to be \( r_p = 5; 15; 30 \mu \text{m} \).

The second set of simulations was set up to create backwall surfaces with continuously changing \( R_{rms} \) values (change throughout the sequence of 50 backwall surfaces). In this set of simulations \( r_p = 5, 15, 30 \mu \text{m} \) cases are simulated. Selected \( r_i \) values are: 100 and 300 \( \mu \text{m} \). Here the scaling coefficient was chosen so that it would result in an \( R_{rms} \) increase from 100 to 300 \( \mu \text{m} \) (where \( r_i = 100 \mu \text{m} \)) and an \( R_{rms} \) decrease from 300 to 100 \( \mu \text{m} \) (where \( r_i = 300 \mu \text{m} \)). The numerical values for \( s \) to achieve the intended amount of \( R_{rms} \) change are a function of both \( r_i \) and \( r_p \) and they are summarised in Table 1.

For each parameter set, 200 backwall sequences were simulated, with 50 backwall samples each. Ultrasonic signals were simulated for all of the backwalls, which were then evaluated with each of the discussed signal processing methods. This resulted in 50 thicknesses per backwall sequence. Backwall sequences are therefore linked to a sequence of thickness estimates as produced by the signal processing techniques. For each backwall sequence and its corresponding thicknesses a thickness trend could be extracted using a linear least squares line fit. These trend lines were denoted \( m_{l,200} \), i.e. one for each backwall sequence. The linear fits were then normalised with respect to the real underlying mean wall thickness loss by: \( e_{1,200} = \frac{m_{l,200} - m_{l,200}}{m_{l}} \) where \( e_{1,200} \) were the normalised trend errors, while \( m_{l} \) was the real underlying mean wall thickness loss.

The performance of signal processing methods were then compared based on their thickness trend error distributions. In order to represent this visually for a large number of parameter sets, trend error distributions are shown as boxplots, where the boxes represent the data between the 25th and 75th
percentile, whereas the whiskers represent data between the 5th and 95th percentiles. A visual representation of the meaning of the box plots is shown in figure 8.

5. Results

5.1. Backwall evolution without rms change

The results of the mean wall thickness loss trend error distribution plots for AXC, XC, P2P and FA methods under constant \( R_{\text{rms}} \) conditions are shown in figure 9. Overall, the effects of both the initial surface \( R_{\text{rms}}(r_i) \) and the size of the \( R_{\text{rms}} \) that the surface is perturbed with \( (r_p) \) are as expected, increasing initial \( R_{\text{rms}} \) and perturbation increases the error bars of any signal processing method. This aligns with the conclusions of previous reports suggesting that in general ultrasonic thickness measurements are sensitive to changes of backwall morphology [10, 11].

In addition, it is apparent from figure 9 that on every plot the width of trend error distributions for AXC is narrowest. This is most noticeable on the right column of results on figure 9, where \( r_i = 300 \mu\text{m} \). Here the trend error distribution width of all standard methods (XC, P2P and FA) span between ±100%, while the trend error distribution width of AXC is close to an order of magnitude narrower, spanning between +25% and −10% with a mean of +7.5%. This means that AXC has a slight bias to overestimate the thickness (or underestimate thickness loss rate), but this is negligible compared to the error of other methods.

During the study it also became clear that AXC has limitations. AXC is based on XC, and so its failings can be similar to the erratic behaviour of XC. XC is sensitive to backwall roughness as shown by figure 9. The breakdown in accuracy is caused by the distortion of the backwall echo wavepackets when the backwall surface is rough. When the backwall surface is rough and the signal is distorted, the synthesised toneburst used by XC does not correlate well with the received signal. Since XC relies on determining the biggest peak in the signal, in these cases a peak that is not representative of the mean wall thickness may be the biggest. Consequently, the wrong peak is often found for the purposes of the thickness measurement. This failure mode of XC is referred to as peak jumping.

AXC avoids this problem by using the backwall echo wavepacket from the previous measurement in the XC process, as it is much more likely to correlate well with the received signal. However, when the backwall surface changes significantly between measurements (which could occur in practice if ultrasonic signals are not acquired sufficiently frequently), excessive signal distortion may occur. In this case the current signal will not correlate well with the previous backwall echo sample and AXC will be affected by peak jumping. For this reason AXC is expected to perform...
similarly to XC when applied to uncorrelated realisations of backwall surface geometries as evaluated by Jarvis et al [11].

Although peak jumping may introduce large errors, it is simple to detect, since the error it causes is an integer multiple of \(\sim \lambda/2\). It is also easily avoided by frequent measurements, as in a short time the backwall geometry is unlikely to change excessively. In addition, when measurements are carried out frequently, the thickness is not likely to change significantly and therefore the large error caused by peak jumping is even more straightforward to detect. Permanently installed monitoring is therefore well suited for AXC as it allows for frequent data acquisition.

The results of figure 9 only show trends where AXC peak jumping does not occur. The number of trends out of the 200 simulated sequences that match this criterion is shown above each of the plots on the figure. It is apparent from the figure that although the distribution of trend errors is not affected significantly by increasing perturbation, the number of peak jumps is affected. This observation is in agreement with the concept that excessive change in backwall geometry causes peak jumps. This finding therefore confirms that frequent measurements are recommended when using AXC in order to ensure reliable and accurate thickness loss trends. In contrast to this when standard XC algorithms are used increasing the measurement frequency does not improve matters because the signal shape of the kernel function remains constant and does not adapt to surface morphology introduced changes.

### 5.2. Backwall evolution with rms change

The mean wall thickness trend error distribution plots with \(R_{\text{rms}}\) scaling applied are shown in figure 10. It should be noted that the axes of the plots in figure 10 are 5 times larger than those of figure 9. This larger range was chosen as the trend error distributions are substantially larger when the \(R_{\text{rms}}\) is continuously increasing or decreasing. In order to better understand the reason for this, the behaviour of \(R_{\text{rms}}\) scaling in the backwall sequence generator model is considered.

The \(R_{\text{rms}}\) scaling was defined in the model as a factor that scaled the backwall geometry at every step. This was initially used to keep the surface rms constant, however if it is used to continuously increase or decrease the rms then it effectively introduces spatially correlated thickness changes. This means that with each step in the backwall sequence thinner parts of the component will become thinner and thicker parts will stay thicker (or the other way round) relative to the mean thickness of the component. It is important to point out that this correlated perturbation caused by \(R_{\text{rms}}\) scaling also leads to distortion in the ultrasonic signal. This distortion is in addition to that introduced by random perturbation. However, in the backwall sequence generator model, mean wall thickness loss is linked to random perturbation alone. Because of this, when random perturbation is small, the mean wall loss will still be small even if the correlated perturbation is large. The error introduced by large correlated perturbation will however be large relative to the small mean wall loss. This can be observed on the top row of figure 10, where the random perturbation \(r_p\) term is small but trend error distributions are large.

A real life example of a similar phenomenon is pitting. With pitting-type degradation mechanisms the backwall of the sample loses wall thickness in a spatially non-uniform fashion as individual pits grow (see figure 6(a). The continuous growth of a pit is a type of correlated perturbation, which may occur without significant mean wall thickness loss. Over time substantial changes in backwall geometry may occur, without much mean wall thickness loss, but still introducing large amounts of distortion in the ultrasonic signal.

The results of figure 10 show quantitatively that the trend error distributions for all standard methods (XC, P2P, FA) extend beyond the \(\pm 100\%\) mark for almost all simulated scenarios. The worst case scenario is the top row of the figure, where the correlated perturbation is most significant. AXC still performs better than any other signal processing method in all scenarios, however its performance is not as accurate as when uncorrelated backwall changes occur. The widths of normalized trend error distribution of AXC are as high as \(\pm 100\%\), where error is quantified as the width of trend error distributions between the 5th and 95th percentiles. In comparison, the width of trend error distributions for all other methods (XC, P2P and FA) are of the order of \(\pm 500\%\). It is worth noting however, that when random perturbation is applied in higher proportion compared to correlated perturbation (bottom two rows of figure 10), the error of all four methods (AXC, XC, P2P and FA) decreases significantly.

Another interesting feature of the displayed plots is that under increasing \(R_{\text{rms}}\) conditions (left column of plots on figure 10) XC, P2P and FA methods tend to overestimate the thickness. Under decreasing \(R_{\text{rms}}\) conditions however (right column of plots on figure 10) the same methods consistently underestimate thickness. This is a consequence of the interaction of the scattered wavefield from the backwall and the coherent backwall echo wavepacket: with increasing \(R_{\text{rms}}\) the relative amplitude of the scattered wavefield increases—effectively delaying energy within the received wavepacket. With decreasing \(R_{\text{rms}}\) the opposite effect is observed, as expected.
It is important to note that the model that introduces scaling of the rms of the backwall has severe limitations: (1) correlated perturbation in our model is simulated as scaling the backwall shape vertically. Consequently, no horizontal changes are introduced. A real pit would however be expected to grow both in the vertical and horizontal dimensions. Because of this, it is expected that the vertical scaling only may not be realistic to simulate pits. (2) For surface evolutions that show severely correlated backwall changes (i.e. isolated pits) the determination of a mean wall thickness does not make sense and is expected to always lead to large errors. This is because in the limit a zero width full depth pit (pin hole) does not affect the mean wall thickness but it is a critical defect. The presented results therefore only give an insight into the effect that different (non-random) backwall change scenarios might have on ultrasonic measurements.

It should also be noted that this study was carried out for a particular transducer geometry and wave mode (SH waves) that are used in practice for thickness monitoring. Results would be slightly different for other transducer geometries and other wave modes that are employed, but they are likely to show the same trends as presented here. The ultrasonic scattering phenomena and interactions with the rough backwall remain similar for other transducer geometries. For example the study by Benstock and Cegla [12] has shown that variation of thickness measurements with round transducers and compressional waves is of a similar order to that of waveguide transducers (see figure 2) [10]. Simply the size of the surface over which the wave field interacts with the surfaces will be different. Furthermore, it is expected that the relative performance differences between various signal processing methods are similar.

5.3. AXC results on field data

In addition to the wall thickness data that was processed by a P2P algorithm figure 11 also shows the same data processed by the AXC algorithm. It is clearly visible that AXC produces a trend that is not influenced by the signal distortion due to backwall surface morphology changes and gives a more representative wall thickness trend/corrosion rate. Overall results in less variability in the extracted corrosion rate and thus in improvement in the response time and confidence with which significant changes in corrosion behaviour can be picked up.

It is worth noting that this study explicitly focused on the accuracy of rate measurements, we did not analyse the overall accuracy of the wall thickness measurement (see e.g. Jarvis et al [11]). AXC enables better tracking of the arrival time of distorted wavepackets. This does not necessarily mean that
the overall wall thickness measurement has become more accurate (there might be a constant systematic error/offset). However, as the simulations in this paper show clearly, the rate of change (corrosion rate) prediction is markedly improved.

6. Conclusion

From field data it is known that surface morphology changes can introduce substantial errors into ultrasonically measured corrosion rates (thickness trends). In this paper a new signal processing method, AXC to overcome these problems was presented. The effect of continuously changing surface morphology on the accuracy of ultrasonically monitored corrosion rates was investigated. This was achieved by means of a backwall sequence generator model that simulates gradual perturbation of backwall surface geometries. This model was then used to generate Gaussian rough backwall sequences characterised by a range of parameters, including constant and changing surface $R_{\text{rms}}$ values and a varying size of perturbation between each surface in the sequence. Instances of both spatially random and spatially correlated perturbation were generated to simulate phenomena such as spatially statistically uniform corrosion and spatially non-uniform corrosion. Ultrasonic signals were simulated for all generated backwall geometries. These were then analysed using 3 standard signal processing methods: XC, P2P and FA and also with the newly developed AXC technique. Corrosion rates (wall thickness loss trends) were computed using all methods and the accuracy of estimated mean wall thickness loss trends was compared to the real simulated value.

Figure 10. Distribution of normalised trend error $e_{1, 200}$ for each backwall generator parameter set shown for each signal processing method with $R_{\text{rms}}$ scaling. The green boxes represent the results for adaptive cross-correlation (AXC), the red boxes are for cross-correlation (XC), the blue boxes are for peak-to-peak (P2P) and the black boxes are for first arrival (FA) methods. Axes on all plots are identical for comparability within the figure, however they are 5 times larger compared to figure 9. The numbers shown above each plot are the numbers of trends that have been evaluated and excludes trends that include peak jumps.

Figure 11. Ultrasonically monitored wall thickness over the period of 1 year (1 measurement every 12 hrs). A distinct deviation in monitored wall thickness is clearly visible 3 months after monitoring commenced. Thickness estimates shown by the solid blue line were calculated using a peak to peak (P2P) timing algorithm, thickness estimates shown by the dashed black line were calculated using the newly developed adaptive cross correlation algorithm (AXC) that is described in this paper.
It was found that the accuracy of trend predictions varies significantly with signal processing methods. When the backwall geometry was perturbed at random spatial locations, the trend errors of the XC, P2P and FA methods were as high as ±100%, where error is quantified as the width of trend error distributions between the 5th and 95th percentiles. For the same ultrasonic signals the worst trend error of AXC was 7.5% ± 18%, close to an order of magnitude less than other methods. A slight underestimation of the AXC estimated wall thickness loss rate was also observed, but this was small compared to the error of other methods and the width of the distribution. Based on this data it is expected that use of AXC on spatially randomly distributed corrosion with corrosion rate of 1 mm year\(^{-1}\) would result in estimates of corrosion rate of 0.75–1.1 mm year\(^{-1}\) whereas the estimates of other algorithms would record rates between 0 and 2 mm year\(^{-1}\) for the same ultrasonic information.

When a spatially correlated perturbation (i.e. continuously growing or shrinking \(R_{\text{rms}}\)) was added to a spatially random perturbation, the error of all signal processing methods increased compared to the case with a random perturbation only. AXC still performed best under these conditions. In the worst case scenario, where the spatially correlated perturbation was much larger than the spatially random perturbation AXC’s 5th to 95th percentile trend error width was ±100% compared to about ±500% of other methods. However these reduced to ±20% and ±70% respectively when the random perturbation was much larger than the spatially correlated perturbation. Therefore for corrosion mechanisms that result in correlated backwall changes (pitting-type) larger errors to the estimated mean wall loss trend are to be expected. This is because mean wall loss is not a good measure of spatially correlated (pitting-type) corrosion.

The improved capability to extract corrosion rates was verified on measurement data that was acquired by an industrial sensor in the field. It was shown that AXC greatly reduces the susceptibility of the sensor to surface morphology induced changes in ultrasonic reflected signal and therefore enhances the corrosion rate measurement capabilities of ultrasonic monitoring systems.

Acknowledgments

We would like to acknowledge that the problem statement arose out of communications with Permasense Ltd. We would also like to acknowledge useful discussions about the subject with Prof Peter Cawley, Dr Jon Allin, Dr Peter Collins and Dr Jake Davies.

Competing interest

Both authors are also affiliated with Permasense Ltd, a company producing permanently installed ultrasonic monitoring sensors. Patent protection for the AXC algorithm has been sought.

References

[1] Koch G H, Thompson N G and Payer J H 2001 Corrosion cost and preventive strategies in the United States NACE International Technical Report

[2] Haggan J 2014 Less is more Oilfield Technol. 7 43–5

[3] Cegla F B, Cawley P and Allin J 2011 High-temperature (500C) wall thickness monitoring using dry-coupled ultrasonic waveguide transducers IEEE Trans. Ultrason. Ferroelectr. Freq. Control 58 156–67

[4] Honavar F, Salehi F, Safavi V, Mokhtari A and Sinclair A N 2013 Ultrasonic monitoring of erosion/corrosion thinning rates in industrial piping systems Ultrasonics 53 1251–8

[5] Gajdacsi A and Cegla F 2013 High accuracy wall thickness loss monitoring Rev. Prog. Quant. Nondestruct. Eval. 1687–94

[6] Rommeveit T, Johansen T F and Johnsen R 2010 A combined approach for high-resolution corrosion monitoring and temperature compensation using ultrasonic IEEE Trans. Instrum. Meas. 59 2843–53

[7] Yi W-G, Lee M-R, Lee J-H and Lee S-H 2006 A study on the ultrasonic thickness measurement of wall thinned pipe in nuclear power plants 12th Asia-Pacific Conf. on NDT pp 4–10

[8] Yang L 2008 Techniques for corrosion monitoring (Boca Raton, FL: CRC Press)

[9] Dariva C G and Gallo A F 2014 Developments in Corrosion Protection, Corrosion Inhibitors—Principles, Mechanisms and Applications (InTech)

[10] Jarvis A J C and Cegla F B 2014 Scattering of near normal incidence SH waves by sinusoidal and rough surfaces in 3-D: comparison to the scalar wave approximation Ultrasons Ferroelectrics Freq. Control 1–3

[11] Jarvis A J C and Cegla F B 2012 Application of the distributed point source method to rough surface scattering and ultrasonic wall thickness measurement J. Acoust. Soc. Am. 132 1325–35

[12] Benstock D, Cegla F and Stone M 2014 The influence of surface roughness on ultrasonic thickness measurements J. Acoust. Soc. Am. 136 3028–39

[13] Nagy P B and Rose J H 1993 Surface roughness and the ultrasonic detection of subsurface scatterers J. Appl. Phys. 73 566–80

[14] Ogilvy J A 1991 Theory of Wave Scattering From Random Rough Surfaces (Boca Raton, FL: CRC Press)

[15] Ogilvy J A 1987 Wave scattering from rough surfaces Rep. Prog. Phys. 50 1553

[16] Strutt J E, Nicholls J R and Barbier B 1985 The prediction of corrosion by statistical analysis of corrosion profiles Corros. Sci. 25 305–15

[17] Meakin P, Jössang T and Feder J 1993 Simple passivation and depassivation model for pitting corrosion Phys. Rev. E 48 2906–16

[18] Meakin P 1993 The growth of rough surfaces and interfaces Phys. Rep. 235 189–289

[19] Johansen T and Hilfer R 1997 Statistical prediction of corrosion front penetration Phys. Rev. E 55 5433–42

[20] Placko D and Kundu T 2007 DPSM for Modeling Engineering Problems (New York: Wiley-Interscience)

[21] Cegla F and Jarvis A 2014 Modeling the effect of roughness on ultrasonic scattering in 2d and 3d AIP Conf. Proc. 1581 595–601