Automatic and Circumferential Oriented Detection (ACOD) for Pipeline Intelligent Inspection

Patrick DUVAUT 2, Clément FOUQUET 1, Dalila BENBOUDJEMA 2

1TRAPIL Company, 1 rue Charles Edouard Jeanneret, 78300, Poissy, France.
2ETIS-ENSEA-UCP-UMRS8051-CNRS, 6 Avenue du Ponceau, 95164, Cergy cedex, France.
Phone : + 33 1 30 73 66 66 ; Fax : + 33 1 30 73 66 27 ; email : patrick.duvaut@ensea.fr, fouclem@gmail.com, dalila.benboudjema@ensea.fr.

Abstract
This contribution introduces a highly robust and content oriented detector of circumferential weld for oil pipeline intelligent inspection, achieving close to zero-miss performance. The method, named ACOD self processes the multidimensional data collected by a pipeline inspection device equipped with many ultrasonic sensors (up to 512). ACOD can be run in a standalone mode of operation as a supplement of human expert monitoring. A compression step makes it scalable in complexity. ACOD introduces a unique “circumferential oriented” feature in the detection scheme, based on higher order statistics (HOS). This feature boosts the statistical contrast between partial circumferential events (PCE) or false alarm and full circumferential events (FCE) to be detected, such as the welds that tie together two pieces of tubes. Because of its contrast boost and its scalable complexity, ACOD outperforms an existing reference method while saving 30% of processing time.

Keywords: Circumferential weld, intelligent detection, higher order statistics, sensor clustering, abrupt change, contrast, false alarm, ambiguity function, Haar wavelets.

1. Introduction

The Pipeline Operators Forum has undertaken an initiative [1] to specify “Intelligent Pig Inspection” protocols. ACOD contributes to “smart pipeline monitoring” by automatically detecting and locating circumferential welds that bind the pieces of tubes composing the pipeline. These tubes are typically a few meters long while pipelines may be hundred kilometers long. Accurate detection of the tubes boundaries allows to segmenting the overall monitoring data into small amounts of inputs that can subsequently be processed with an acceptable numerical burden and time frame towards fault (anomalies) detection, segmentation and recognition.

The major difficulties inherent to automatic circumferential weld (CW) detection are five-fold. d1) The images to be processed can be very large, i.e. up to ~10 Giga pixels. d2) These images are highly distorted by intense noise and/or missing data. d3) Because of the need to be automatic, the joint detection-localization problem to solve is “blind”: no CW reference image exists to be searched for. d4) CWs have variable features in width and height. d5) Tube manufacturing creates irregularities of the internal surface of the pipeline that corrupts the tube geometry, even in the absence of genuine anomalies.

Classical image processing methods such as edge detection algorithms [2], Markov random fields [3] and Active Contour models [4] could not be used to detect CW, primarily because of the unacceptable complexity and processing time they would require (d1). Moreover, they would need appropriate tunings and pre-processing to handle the high level of noise and missing data (d2).

ACOD successfully addresses all these five challenges, as detailed in the remainder of the paper that is organized as follows. Section 2 is focused both on the ultrasonic inspection tools and the structure of the data it collects. In section 3, full circumferential event (FCE) detection problem is stated and key notations are introduced. Section 4 details the principles of ACOD, while its performance results are given in section 5. In particular ACOD is benchmarked with a reference CW detection method used by TRAPIL Company.
2. Pipeline Ultrasonic Inspection

2.1 Ultrasonic Inspection Tool
The most common tool for pipeline inspection is based on “conventional” ultrasonic-pulse echo techniques [5]. The tool passes through the pipeline and is driven by the flow of the medium. The ultra-sonic probes, regularly positioned at the fringe of the tool accurately measure the time it takes for the ultrasound beam to travel from the sensor to the internal surface of the pipeline. The travelling times are converted into distances that reflect the geometry of the internal surface of the pipeline, versus the sensor angular position, \( i, 1 \leq i \leq N \), and the discrete location \( n \) of the inspection tool along its path, inside the pipeline.

2.2. Ultrasonic Inspection Images
Figure 2 displays an example of “ultra-sonic image”, (USI) obtained by concatenating vertically the \( N \) distances \( y_i[n] \) between probe \( i \), and the internal surface of the pipeline, versus the tool location \( n \). A short trunk of only a few meters long (versus \( n \)) is given. Typically, \( N = 256 \) and the tool makes an ultra-sonic measurement every 3mm, or 1.5mm.

Because of the representation specifics, the vertical shape in the middle of the USI given in figure 1 represents the internal surface geometry of a “full circumferential event”(FCE), such as a CW. FCE goes across the whole periphery of the tube. It has to be differentiated with partial circumferential event (PCE) that stretches only across a limited portion of the tube circumference. PCE may stem from surface irregularities caused by the manufacturing and/or metal wrinkles due to pipe bends. The textured aspect of the USI comes from the measurement noise, failing sensors and pipe manufacturing irregularities.

3. Full Circumferential Event (FCE) Detection Problem
Detection of FCE is a three-hypothesis detection problem [6],

\[
H_0 : y_i[n] = w_i[n] \\
H_1 : y_i[n] = x_i^z[n] + w_i[n], \quad z \in \{\text{FCE, PCE}\}
\]

In equation (1), \( w_i[n] \) designates the measurement noise, while \( x_i^z[n] \) denotes the “geometry-signal” measured on probe \( i \) originating from a FCE (\( z = \text{FCE} \)) or a PCE (\( z = \text{PCE} \)) located in the vicinity of abscissa \( n \). It is recalled that, because of its automatic nature, the problem we
tackle with is blind: \( x_i[n] \) is not known and has not received any known mathematical model, in the pipeline inspection community. In the whole paper, we define the contrast operator \( C_{a,b}(. \) between two hypotheses \( H_a \) and \( H_b \) as,

\[
C_{a,b}(.) = \frac{\left| E[H_a] - E[H_b] \right|^2}{\pi \times \text{Var}[H_a] + (1 - \pi) \times \text{Var}[H_b]}
\]  

(2)

In equation (2), we have \((a,b) \in \{0,FCE,PCE\}^2\) and \(0 \leq \pi \leq 1\). The input contrast of the raw data between FCE and the noise, \( C_{FCE,0}(y_i[n]) \), has a typical value of \(-4\text{dB}\). This means that pixels pertaining to \( H_{FCE} \) and to the noise \( H_0 \) cannot be distinguished without FCE signature enhancement dedicated processing.

4. Automatic and Circumferential Oriented Detection (ACOD)

4.1 ACOD overview

ACOD goes through 3 steps displayed in Figure 2. 1) **Clustering and Circumferential “Event” (CE) Signatures per cluster.** The first step elaborates a few \((N_c = 28)\) distributed signature functions \( s_{CE}^{(k)}[n], 1 \leq k \leq N_c \) that contain “pattern-like characteristics” of circumferential “event.” Each of the signature function is obtained after processing measurements collected from a small subset (called a cluster) of all the available sensors (typically 4 sensors per cluster). Consequently, only a compressed and scalable number of sensors remain involved (here 112 instead of \(N_s = 224\)). 2) **Enhanced single FCE signature.** The second step combines the weighted distributed CE signatures functions into a single FCE one, \( s_{FCE}[n] \) with enhanced or “circumferential oriented” pattern. 3) **FCE joint Detection and localization.** The third step builds an “ambiguity-like function”[7] to detect and locate FCEs.

4.2 ACOD step One: Compression and Distributed Circumferential Event (CE) Signatures

Step One comprises three sub-steps. 1.1) First, the raw USI undergoes a circumferential (i.e. vertical in figure 1, because of the USI set up) median filtering to denoise the pixels, while preserving integrity of horizontal abrupt changes that could stem from CE. We denote \( \tilde{y}_i[n] \) the denoised data. 1.2) Second, \( N_p \) clusters \( Q_k = \{i_1^k \leq i \leq i_q^k\} \) of \( q \) probes are built. For
compression purpose, the $N_c$ clusters are populated with a reduced number of sensors, $qN_c < N_c, 1.3$) Third, in order to increase the contrast between the noise and CE events, while further reducing the dimensionality of USI from $qN_c$ to $N_c$, the cluster signals, i.e. $\tilde{y}_i[n], i \in Q_k$ undergo a so-called “abrupt-change” processing [8] that yields $N_c$ CE signatures $s^CE_k[n], 1 \leq k \leq N_c$, with,

$$s^CE_k[n] = \frac{\mu_{k,short}[n]}{\mu_{k,long}[n]}$$  \hspace{1cm} (3)

In equation (3), $\mu_{k,long}[n]$ and $\mu_{k,short}[n]$ respectively designate long-term and short-term moving averages of the denoised data, across cluster $Q_k$,

$$\mu_{k,long}[n] = \frac{1}{qT_{long}} \sum_{i \in Q_k} \sum_{l=1}^{T_{long}} \tilde{y}_i[n-l], \mu_{k,short}[n] = \frac{1}{qT_{short}} \sum_{i \in Q_k} \sum_{l=0}^{T_{short}-1} \tilde{y}_i[n+l]$$  \hspace{1cm} (4)

The average contrast $\{C^0_{FCE,0}(s^CE_k[n])\}_{1 \leq k \leq N_c}$ between FCE and the noise, of the distributed CE signatures defined by (3) is equal to 21dB, achieving thus a 25dB gain with respect to the raw USI. Consequently, as displayed in figure 3, a CE fuzzy pattern, shared by most of the distributed CE signatures (in case of FCE) shapes up. Note. It is beyond the scope of the paper to assess the impact of the compression rate on the performance.

Figure 3. Superimposed distributed CE signatures $s^CE_k[n], 1 \leq k \leq N_c$, versus $n$, with $N_c = 28$, after processing USI given in figure 1 through ACOD step 1.

### 4.3 ACOD step Two: Enhanced Single FCE Signature

The objective of step two is to combine the $N_c$ CE signatures $s^CE_k[n], 1 \leq k \leq N_c$ into a single FCE signature $s^{FCE}[n]$ (achieving thus the maximum level of compression) that is “circumferential oriented”. The latter characteristic means that the way to combine the cluster CE signatures $s^CE_k[n]$ to design $s^{FCE}[n]$ shall enhance a CE pattern only if it is present in all the clusters signatures, emphasizing thus a full circumferential event, FCE. Conversely, if there are no CE patterns in a few CE signatures (as it will happen for partial circumferential event PCE), the combining fashion shall “level out” or “marginalize” the contribution of the CE patterns present in other clusters signatures. Formally, the FCE signature $s^{FCE}[n]$ shall exhibit a large contrast between PCE and FCE. This will reduce the probability of wrongly detect FCE instead of PCE. In keeping with this base line, we have,

$$s^{FCE}[n] = \sum_{k=1}^{N_c} \alpha_k[n]s^CE_k[n]$$  \hspace{1cm} (5)
The weighting functions \( \alpha_k[n] \) are solutions of the following optimization problem,

\[
\alpha_k[n] = \text{Arg} \left\{ \min_{\alpha_k} \left( \sum_{k=1}^{N_k} (A - \alpha_k[n] \mu^L_k[n]) \right)^2 \right\} \quad \text{s.t.} \quad \sum_{k=1}^{N_k} \alpha_k[n] = 1
\]  

(6)

In equation (6), \( A \) is a constant and \( \mu^L_k[n] \) denotes the \( L \)th order moment of the CE signature \( s_k^{CE}[n] \), i.e., \( \mu^L_k[n] = \frac{1}{2M+1} \sum_{l=-M}^{M} (s_k^{CE}[n+l])^L \). The weighting functions \( \alpha_k[n] \) aims at “spatially equalizing” the \( L \)th order moments of the clusters CE signatures. Straightforward calculation leads to,

\[
\alpha_k[n] = \frac{1}{\mu^L_k[n]} \times \frac{1}{\sum_{r=1}^{N_r} \mu^L_r[n]}
\]  

(7)

It is clear from equation (7) that if the underlying CE is an FCE, all the \( L \)th order moments \( \mu^L_k[n] \) will share almost the same value and the \( \alpha_k[n] \) will be approximately identical, i.e., \( \alpha_k[n] \approx 1/N_c \). The combiner will thus be uniform. On the other hand, let us consider a PCE that spreads across half of the clusters, while the other half experiences small background signal. To better grasp the behaviour of the weighting functions in this latter case and for the sake of simplicity, we assume for instance that the background-only related \( L \)th order moments are all equal to a very small value denoted \( \varepsilon \), with \( \varepsilon \ll 1 \). Still to keep it short and simple, we consider the other half of the \( L \)th order moments inherent to the PCE are all identical and equal to a large value, \( 1/\varepsilon \) chosen as the reciprocal of \( \varepsilon \). Because of the assumptions and formula (7) the “background-only weights”, denoted \( \alpha_{\varepsilon} \), are identical. The same hold for the “PCE weights” designated by \( \alpha_{\varepsilon} \). The following relationship stems from (7) between the two weights: \( \alpha_{\varepsilon} = \varepsilon^2 \times \alpha_{\varepsilon} \). The latter relationship means that in case of PCE, all the signatures elaborated from the “PCE clusters” will be drastically attenuated through the combining process, with respect to the background-only clusters. As specified at the beginning of this section, an underlying PCE geometry will yield a FCE signature where any CE pattern would have almost vanished, drastically reducing the risk of wrongly detect a FCE instead of a PCE.

Figure 4. (a) FCE signature \( s^{FCE}[n] \) versus \( n \), obtained after processing the CE signatures given in Figure 3 through step 2 of ACOD. (b) Contrast \( C^{0}_{FCE,PCE}(s^{FCE}) \) of the FCE signature versus the order \( L \) of the moments \( \mu^L_k[n] \), see (5) (7).

Figure 4 (a) displays the FCE signature \( s^{FCE}[n] \) versus \( n \), obtained after combining the 28 distributed CE signatures \( s_k^{CE}[n] \) given in figure 3, according to the “circumferential oriented” combiner described by equations (5), and (7) with \( L=10 \). Figure 4 (b) confirms that, in (5)
and (7) higher order moments of order \( L = 10 \), achieve the largest contrast \( C_{FCE,PCE}^{0}(s_{FCE}) \) between FCE and PCE hypotheses, after combination. Through step two of ACOD the contrast between FCE and the noise continues to increase, since we have \( C_{FCE,0}^0(s_{FCE}) = 28dB \). ACOD step two thus achieves a 7 dB gain w.r.t. step one and a 32dB gain w.r.t. the raw USI!

**Note.** When \( L = 0 \), the FCE signature coincides with the arithmetic average of the CE signatures.

### 4.4. ACOD step Three: FCE joint detection and localization

The third and last step of ACOD is split into three sub-steps. 3.1) First, the FCE signature \( s_{FCE}^FCE[n] \) undergoes a low-pass or “smoothed derivative” leading to,

\[
\tilde{s}_{FCE}^FCE[n] = \sum_{l=0}^{T_l} s_{FCE}^FCE(n+l) - \sum_{l=1}^{T_l} s_{FCE}^FCE(n-l)
\]

\( \tilde{s}_{FCE}^FCE[n] \) is called the “shaped” FCE signature. The smoothed derivative is twofold. It helps to get rid of double-bumps exhibited by some FCE signatures and originating from wide circumferential weld (\( in \ the \ n\ direction, \ see\ figure\ 1 \)), with irregular geometry. Double bumps could lead to wrongly detect two FCEs. The derivative also contributes to shaping the signature to be detected (\( in\ a\ blind\ mode \)) according to Haar wavelets used in the next sub-step. 3.2) Second, an ambiguity-like [7] function \( D_{\lambda}^{FCE}[p] \) is elaborated by projecting the shaped signature \( \tilde{s}_{FCE}^FCE[n] \) onto a set of Haar wavelets \( H_{\lambda}[n] \) [9],

\[
D_{\lambda}^{FCE}[p] = \sum_{n} \tilde{s}_{FCE}^FCE[n] H_{\lambda}[n-p]
\]

The range of scale values, \( \lambda \) is chosen to fit the range of expected width of \( \tilde{s}_{FCE}^FCE[n] \).

---

**Figure 5.** Ambiguity-like function \( D_{\lambda}^{FCE}[p] \) based on the FCE signature \( s_{FCE}^FCE[n] \) given in figure 4 (a), after going through ACOD sub-steps 3.1) and 3.2).

Figure 5 displays the variation of the ambiguity-like function \( D_{\lambda}^{FCE}[p] \) versus the scale value \( \lambda \) and the location index \( p \). 3.3) The optimum scale value \( \lambda^* \) is chosen according to the following rule: \( \lambda^* = \text{Arg}\{\text{Max}_{\lambda} \{D_{\lambda}^{FCE}[p]\}\} \). Then, hypothesis \( H_{FCE} \) is decided if the detection function \( D_{\lambda}^{FCE}[p] \) crosses a threshold \( \eta \). The location index \( p^* \) of the detected FCE is finally obtained by finding the location of the maximum of the detection function, i.e. \( p^* = \text{Arg}\{\text{Max}_{p} \{D_{\lambda}^{FCE}[p]\}\} \), see figure 5.
5. ACOD Performance

5.1. FCE correct detection probability and PCE error probability

We define the correct detection probability $\beta_{FCE}$ of $H_{FCE}$ as,
$$\beta_{FCE} = 1 - \Pr[H_{FCE} | H_{FCE}]$$
where $\Pr[H_{FCE} | H_{FCE}]$ is the probability to miss $H_{FCE}$. To gauge the performance, we also introduce the error probability $\xi_{PCE}$ of wrongly deciding $H_{FCE}$ instead of $H_{PCE}$. We have
$$\xi_{PCE} = \Pr[H_{FCE} | H_{PCE}]$$
Obviously the two probabilities $\beta_{FCE}$ and $\xi_{PCE}$ depend upon the threshold $\eta$. We derive from the detection scheme introduced in section 4.4 the two following identities,
$$\Pr[D^{*} < \eta | H_{FCE}] = \beta_{FCE}$$
$$\Pr[D^{*} \geq \eta | H_{PCE}] = \xi_{PCE}$$
In the equation (10), we have $D^{*} = \max_{\lambda,p}\{D^{FCE}_{\lambda}[p]\}$.

5.2. Histograms of the ACOD detection function

Figure 6-(a) displays the histogram of the detection function $D^{FCE}_{\lambda}[p]$, conditional to the PCE hypothesis $H_{PCE}$. Figure 6-(b) gives the histogram of the maximum $D^{*}$ of the detection function, conditional to the FCE hypothesis $H_{FCE}$. Both histograms were obtained after processing the data collected from the pipeline described in section 5.3 with ACOD and $L=10$.

Because the circumferential oriented weighting functions $\alpha_{k}[n]$ (see section 4.3) maximize the contrast between $H_{FCE}$ and $H_{PCE}$, the supports of both histograms displayed in figures 6-(a) and 6-(b) do not overlap. Consequently, any threshold $\eta^{*}$ picked up in the segment $[0.2, 0.45]$ leads to the best detection performance possible, i.e. $\beta_{FCE}(\eta^{*}) = 1$ and $\xi_{PCE}(\eta^{*}) = 0$.

5.3. Detection results

The pipeline used to evaluate ACOD against the reference method provided by TRAPIL denoted REF, is 12km long. The ultrasonic inspection tool that collected the data is equipped with 256 probes and made a capture every 1.5mm along its path. Figure 7 displays the FCE
correct detection probability $\beta_{FCE}$ versus the error probability $\xi_{FCE}$ for ACOD$_{10}$ (tuned with $L=10$, i.e. the optimum weighting function) and ACOD$_{0}$ (tuned with $L=0$, i.e. the arithmetic average combiner, see § 4.3), against the reference method REF.

The performance curves displayed in figure 7 show that both ACOD$_{10}$ and ACOD$_{0}$ outperform the REF method while, according to the monitoring of the computational time, they both save 30% of processing power w.r.t. REF. Moreover ACOD$_{10}$ significantly surpasses ACOD$_{0}$ by achieving a correct detection probability $\beta_{FCE}$ of one for much smaller error probabilities $\xi_{FCE}$ (below 1%) than ACOD$_{0}$. This confirms the unique virtue of ACOD weighting functions based on HOS.

6. Conclusion
This paper unveils a method named ACOD that automatically detects circumferential welds and contributes to intelligent pipeline inspection based on ultrasonic probing. ACOD contains a unique “combination feature” based on higher order statistics that not only allows a tunable compression of the measurements collected by the ultrasonic sensors but also achieves a large contrast between partial circumferential events PCE (such as metal wrinkles due to pipe bends that can generate false alarms) and full circumferential events FCE (like bonding welds, to be detected). Relying on these assets, ACOD outperforms the reference method used by TRAPIL Company, achieving close to zero miss performance while reducing the pipeline processing time by 30%.

References