Analysis and Compression of Magnetic Flux Leakage (MFL) data for defect characterization using Wavelet transform

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Abstract
All pipelines are subjected to corrosion and metal loss defects. Characterization of the defects is necessary to prevent environmental disaster due to leakage of oil or gas. Intelligent Pipeline Inspection Gauge (PIG) using MFL technique enables reliable inline inspection of pipelines. A high speed DSP based data acquisition system is designed for acquiring MFL data. An instrumented PIG acquires large amount of data from a trial run. Effective and real time compression requires fast processing of data using DSP. Only useful MFL data needs to be stored for analysis on a mass storage device. Multiresolution analysis of MFL data using discrete wavelet transform has been found most effective technique for this purpose. Compression in wavelet domain gives more compression compared to other techniques. Although the technique is lossy, using wavelets can be shown that newer techniques of compression retain complete information for characterization of defects. A very high compression ratio of order of 1:20 or higher is achievable using this technique.

1. Introduction
The basic requirement of transportation oil and gas pipeline is safety and high efficiency. However 50% of the world pipe network has been used for several decades. The pipeline defect caused by pipeline erosion, abrasion and the nature action is great hidden trouble. Meanwhile, the long transferring pipelines are buried underground or ocean floor on the whole, which make pipeline detection become more difficult.

Magnetic Flux Leakage (MFL) inspection PIG use magnetic brushes to magnetize the pipe wall and magnetic sensors to detect flux changes from fringing fields produced by any metal losses or defects. An understanding of magnetism, flux, and flux leakage is needed to understand the capabilities of MFL inspection systems.

1.1. Principle of MFL Detection
MFL test device obtains the magnitude of the defects by measuring the magnetic flux density leaked from the surface of the ferromagnetic material. If the components to be measured are not defective then all magnetic flux will pass through the components, as seen from Fig. 1(a). The presence of a defect in a magnetized ferromagnetic material results in a redistribution of magnetic field in the vicinity of the flaw, causing some of the magnetic field to "leak" out into the surrounding medium as shown in Fig. 1(b). This leakage field can be detected, using Hall element sensors to measure the axial or radial components of the magnetic flux density B.

![Fig. 1. Principle figure of MFL](image)

Typical axial components of MFL signals obtained for the geometry corresponding are shown in Fig. 2. These signals are a measure of the fields which leak out from under the defect and this makes the magnetic flux pass through the detected components, making a detour from the defects. The width of the signal is proportional to the defect length (axial dimension) and the amplitude of the signal is proportional to both the defect length and depth. The signal amplitudes, as shown, are clearly measurable.

Flux is diverted in the pipe wall, around the defect, and out of the pipe at the inner and outer diameter. The amount of flux that is diverted out of the pipe depends on the geometry of the defect. Hall sensor or mobile induced coils could detect the flux leakage. Power or weakness of the flux signal has an intensive relation to the condition...
of the pipe surveyed [1] [2]. And hence, the defects are characterized by sharp changes in flux.

The signals correspond to the axial component of the MFL field for the same depth.

1.2. Hall-Effect Sensor

A Hall-effect sensor is a device, which is affected by a magnetic field. By passing a constant amount of current through it in one direction, and by placing it in a magnetic field in another direction, we can measure a voltage across it in the third direction. This voltage is proportional to the strength of the magnetic field. This can be calibrated to provide a certain (mV) change for every Gauss of magnetic flux leakage.

MFL PIG record flux leakage at specified intervals in both the axial and circumferential directions in the pipe. The data interval in the circumferential direction is defined by the number of sensors. Measurement of either radial or axial component of leakage flux density provides sizing and contour information. The measurement system converts the leakage field into an electrical signal that can be stored and analyzed. The unit of measure when sensing an MFL signal is the Gauss or the Tesla(T) and generally speaking, the larger the change in the detected magnetic flux density level, the larger the anomaly.

The last step in an MFL inspection is analysis. Analysis is the process of estimating the geometry or severity of a defect (or imperfection) from the measured flux leakage field. The techniques and success of analyzing MFL data depend on the capabilities and limitations of the MFL tool [5], which are established by design and operational trade-offs.

1.3. MFL Process Flow

A magnetizing system applies a magnetic field along a length of pipe as the PIG moves through the line. The location of an imperfection or defect on the inside or outside surface affects the flux leakage field. Metal-loss on the inside pipe surface produce stronger signals. MFL signals for metal loss, dents, and mechanical damage are fundamentally different [3] [4]. These differences can be seen in the experimental MFL signals shown in Fig. 4.
2. Theory of Wavelet Transform

Wavelet transform is capable of providing the time and frequency information simultaneously, hence giving a time-frequency representation of the signal. In wavelet analysis the use of a fully scalable modulated window called wavelet is used to cut the signal of interest into several parts and then analyze the parts separately. The window is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter (or longer) window (obtained from a single prototype wavelet) for every new cycle. In the end the result will be a collection of time-frequency representations of the signal, all with different resolutions. It is clear that analyzing a signal this way will give more information about the when and where of different frequency components. [6][7]

Unlike the Short Time Fourier Transform (STFT), which has a constant resolution at all times and frequencies, the WT has a good time and poor frequency resolution at high frequencies, and good frequency and poor time resolution at low frequencies. The fig. below is used to explain the time and frequency resolution

![Fig. 6. Frequency and Time resolution in wavelets.](image)

It is to be noticed that area of each box is constant. At low frequencies, box is shorter but wider corresponding to better frequency resolutions and poor time resolution.

At higher frequencies the width of the boxes decreases, i.e. the time resolution gets better, and the heights of the boxes increase, i.e. the frequency resolution gets poorer. All areas are lower bounded by $1/(4\pi)$. We cannot reduce the areas of the boxes as much as we want due to the Heisenberg's uncertainty principle. [9]

On the other hand, for a given mother (prototype) wavelet the dimensions of the boxes can be changed, while keeping the area same. This is exactly what wavelet transform does. CWT is a correlation between a wavelet at different scales and the signal with the scale (or the frequency) being used as a measure of similarity.

The continuous wavelet transform is defined as follows:

$$\text{CWT}_x^y(\tau, s) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} x(t) \psi \left( \frac{t - \tau}{s} \right) dt$$  \hspace{1cm} (1)

The transformed signal is a function of two variables, $\tau$ and $s$, the translation and scale parameters, respectively. $\psi(t)$ is the transforming function, and it is called the mother wavelet. Discretisation of CWT enables the computation of the continuous wavelet transform by computers, although it is not a true discrete transform. As a matter of fact, the wavelet series is simply a sampled version of the CWT. Discrete wavelets are not continuously scalable and translatable but can only be scaled and translated in discrete steps. This is achieved by modifying the wavelet representation from

$$\psi_{s_0}(t) = \frac{1}{\sqrt{s}} \psi \left( \frac{t - \tau}{s} \right) \rightarrow \psi_{s_0^j}(t) = \frac{1}{\sqrt{s}} \psi \left( \frac{t - k \tau s_0^j}{s_0^j} \right)$$  \hspace{1cm} (2)

We usually choose $s_0 = 2$ and $\tau_0 = 1$ for dyadic sampling of the frequency and time axis respectively. A wavelet has a band-pass like spectrum and so the dilated wavelets derived from the mother wavelet for different scales will have stretched spectra. In short, if one wavelet can be seen as a band-pass filter, then a series of dilated wavelets can be seen as a band-pass filter bank. This can be used to get a good coverage of the signal spectra.

![Fig. 7. Touching wavelet spectra resulting from scaling of the mother wavelet in the time domain.](image)

Fig. 7 shows touching wavelet spectra resulting from scaling of the mother wavelet in the time domain.

It can be shown that wavelet transform is same as subband coding scheme in which a signal is analyzed by passing it through a filter bank (band-pass). [6] Therefore if we implement the wavelet transform as an iterated filter bank, we do not have to specify the wavelets explicitly.

The discrete wavelet transform (DWT), provides sufficient information both for analysis and synthesis of the original signal, with a significant reduction in the computation time. The DWT is considerably easier to
implement when compared to the CWT. The DWT analyzes the signal at different frequency bands with different resolutions by decomposing the signal into a coarse approximation and detail information. DWT employs two sets of functions, called scaling functions and wavelet functions, which are associated with low pass and high pass filters, respectively. The decomposition of the signal into different frequency bands is simply obtained by successive high pass and low pass filtering of the time domain signal. The original signal \( x[n] \) is first passed through a half band low pass filter \( g[n] \) and high pass filter \( h[n] \). After the filtering, half of the samples can be eliminated according to the Nyquist’s rule, since the signal now has a highest frequency of \( \pi/2 \) radians instead of \( \pi \). The signal can therefore be sub sampled by 2, simply by discarding every other sample. [8][9]

This constitutes one level of decomposition and can mathematically be expressed as follows:

\[
y_{\text{high}}[k] = \sum_n x[n] g[2k-n]
\]

\[
y_{\text{low}}[k] = \sum_n x[n] h[2k-n]
\]  

where \( y_{\text{high}}[k] \) and \( y_{\text{low}}[k] \) are the outputs of the high pass and low pass filters, respectively, after sub sampling by 2. The above procedure can be repeated for further decomposition. At every level, the filtering and sub sampling will result in half the number of samples (and hence half the time resolution) and half the frequency band spanned (and hence doubles the frequency resolution). Fig. 8 illustrates this procedure, where \( x[n] \) is the original signal to be decomposed, and \( g[n] \) and \( h[n] \) are low pass and high pass filters, respectively.

One important property of the discrete wavelet transform is the relationship between the impulse responses of the high pass and low pass filters. The high pass and low pass filters are not independent of each other, and they are related by

\[
g[L-1-n] = (-1)^n h[n]
\]

where \( g[n] \) is the low pass, \( h[n] \) is the high pass filter, and \( L \) is the filter length (in number of points). In our experimentation1, analysis of the MFL data using DWT, decomposition is done till the 6th scale starting from \( s = 0 \) to \( s = 5 \).

3. Wavelet Transform for Compression

MFL signals usually represent defects in terms of sharp pulses closely spaced in time. Time localization of the defect is important, hence DFT can’t be used. DFT gives the frequency components of signals without giving information about its time occurrence.

Wavelet algorithms process data at different scales or resolutions. Unlike in case of DFT, in wavelet analysis, we can use approximating functions that are contained neatly in finite domains. As a signal is passed through filter bank, frequency resolution goes on increasing and time resolution goes on decreasing i.e. better freq resolution at lower frequency and better time resolution at higher frequency. This property of wavelets makes it the best for approximating data with sharp discontinuities. [10]

More prominent frequencies in the original signal have higher amplitudes in the corresponding DWT frequency region. However, the time localization will have a resolution that depends on which level they appear. At high frequency information in signal, more no. of samples are available and time localization will be more precise. Conversely, lower frequency information will have poorer time localization. This procedure in effect offers a good time resolution at high frequencies, and good frequency resolution at low frequencies.

![Fig. 8. Implementing Wavelet using filter bank.](image-url)
Non-prominent frequency content in the original signal gives low amplitude DWT coefficients, which can be discarded, allowing data reduction without much loss of information. Fig. 9 illustrates a signal with localized high frequency component (256 samples) and its corresponding DWT coefficients. Fig. 9(b) shows the 8 level DWT of the signal in Fig. 9(a). The last 128 samples in this signal correspond to the highest frequency band in the signal; the previous 64 samples correspond to the second highest frequency band and so on. It should be noted that only the first 32 samples, which correspond to lower frequencies of the analysis, carry relevant information and the rest of this signal has virtually no information. Thus, rest of irrelevant coefficients are discarded without any loss of information. This is how DWT provides a very effective data reduction scheme. [9]

The discrete MFL signals data were transformed by using the coefficients of filter banks of orthogonal wavelets, which were found by analysis of recorded signals.

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<th>n</th>
<th>g [n]</th>
<th>h [n]</th>
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<tr>
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3.1 Compression Details

For a sample MFL signal, Wavelet analysis is done upto 6 scales, to detect any hidden transition signal. Operation is performed on a block of 256 samples at a time.

High pass filter (Wavelet) and Low pass filter (Scaling) coefficients are obtained for each scale. Thresholding is done for High-pass coefficients, to check if sample block contains transition signal. Such a block is stored onto on-board Flash memory or replaced by a 1-byte header. Header indicates details about no of such blocks skipped before a new transition block comes. Hence redundancy in data is removed and compression is achieved. In a signal of 5000 samples, not more than one or two transition signals were present. Also transition signal was present within a block of 256 samples. Hence rests of blocks were replaced by header blocks of 1-Byte each and transition part is stored in raw format itself. Hence a high compression ratio is achieved.

Fig. 9. A Signal and its DWT coefficients

Fig. 10. Low pass coefficients output for 6 scales

Fig. 11. High pass coefficients output for 6 scales
4. Conclusion and Summary

A comprehensive scheme of analysis of MFL data using wavelet transform has been discussed. Wavelet, due to its suitability for MFL data, proves to be an effective tool in identifying the original signal due to defects. A floating point DSP processor based DAS was used for faster processing of online data. Useful data is then stored on a mass storage device for offline processing for defect localization and further analysis. This scheme results in lossy compression and compression ratios of the order of 1:20 or higher is achieved. The results obtained are encouraging and newer techniques using wavelet transform can result in much higher compression ratios without losing much information.

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