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Locating Mechanical Damages Using Magnetic Flux Leakage Inspection in Gas Pipeline System

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Abstract Gas transmission pipelines are often inspected and monitored using the magnetic flux leakage method. An inspection vehicle known as a "pig" is launched into the pipeline and conveyed along the pipe by the pressure of natural gas. The pig contains a magnetizer, an array of sensors and a microprocessor-based data acquisition system for logging data. This paper describes magnetic flux leakage (MFL) signal processing used for detecting mechanical damages during an in-line inspection. The overall approach employs noise removal and clustering technique. The proposed method is computationally efficient and can easily be implemented. Results are presented and verified by field tests from an application of the signal processing.

Keywords: Edge Detection, Gas Pipeline Inspection, Mechanical Damage, Magnetic Flux Leakage Signal

1. Introduction

Magnetostatic methods are used very widely for the inspection of ferromagnetic materials such as steel billets, tank shells and automobile crank shafts (Blitz, 1991). One of the more interesting applications of magnetostatic methods is the inspection of underground natural gas pipelines. Natural gas is a very important component of a country's energy resource base in US. Unfortunately, most of times, it is produced at well sites that are far removed from consumer locations. Consequently natural gas must be transported in order to be used. The most common method of transportation is through steel pipelines that are buried under ground. The United States has over 300,000 miles of transmission gas pipelines that link pumping stations with the distribution centers.

The magnetic flux leakage (MFL) method (Weisweiler et al., 1987 and Mandayam et al., 1996) is one of the more popular methods used to detect flaws in gas and oil pipelines. MFL techniques provide a comprehensive analysis of metal loss defects, as well as other discontinuities that could have a detrimental effect on the pipeline's operation if they are not discovered and remedied in a timely manner.

Mechanical damage is one of the largest causes of failure in gas-transmission pipelines today. Mechanical forces, such as those caused by heavy third-party construction equipment, can deform the cylindrical shape of a pipeline, scrape away metal coating, introduce notches and cold work the steel. Cold work, in turn, can locally change the microstructure and mechanical properties of steel. The resultant mechanical damage often remains benign for the operational life of the pipeline. However, it can also lead to an immediate or delayed failure. Because practical pigging frequencies are of the order of years, in-line inspections can only be used to detect damage that could lead to a delayed failure. Nonetheless, having an inspection system

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that can both detect and characterize mechanical damages could provide pipe industries with an important tool in its efforts to maintain a safe and reliable pipeline infrastructure.

In this paper, edge based location approach applies detecting as possible as small damage such as mechanical damage and enhancing the signal-to-noise ratio(SNR) of MFL signals that are corrupted by several type of noises.

2. Mechanical Damage in Transmission Line

Internal pipeline inspection tools have been very successful when used to reveal loss of pipe wall thickness due to corrosion and other causes. Inspection tools employing magnetic flux leakage inspection techniques (Ivanov et al., 1998, Lee et al., 2008, and Clapham et al., 2008) have proved capable of locating pipeline irregularities such as corrosion pitting, mechanical damage, manufacturing defects, construction defects, hard spots, bends, and dents in addition to metal loss due to corrosion. Also, depending on the mass of the metal, MFL can normally detect features as circumferential welds, valves, casings, and sleeves.

Magnetic flux leakage techniques are employed as an in-line inspection method to inspect gas transmission pipelines. MFL techniques can be used to detect metal loss in pipelines due to corrosion and gouging. A schematic diagram of the inspection vehicle is shown in Fig. 1. The magnetic circuit of inspection vehicle consists of a pair of high energy permanent magnets, a backing iron plate, a pair of steel brushes that establishes contact with the pipe, and the pipewall itself. A very high field due to the neodinium-iron-boron magnets ensures that the pipewall is highly saturated. Several hall plate sensors are mounted circumferentially around the pipe to detect leakage fields that are generated due to defects. Since the signals are sampled at intervals that are fractions of an inch apart, the volume of data generated by each sensor is very large.

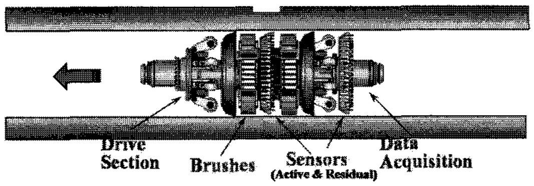


Fig. 1 Schematic diagram of a typical pig used for gas pipeline inspection

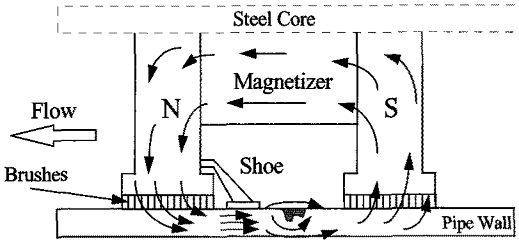
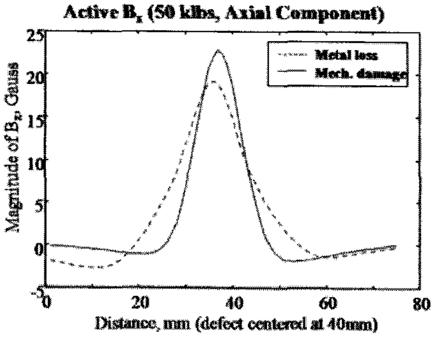
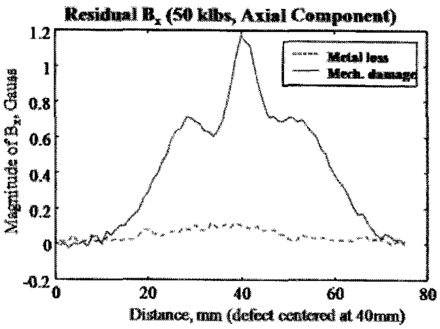


Fig. 2 Two dimensional schematic view of on MFL inspection tool

The types of defects generally in gas pipelines are classified into two broad classes; metal loss and mechanical damage. Metal loss defects usually originate due to corrosion of the pipewall, where as mechanical damage is caused mainly by third party excavations and natural forces such as earth movement etc. Mechanical damage in gas pipelines includes, denting due to deformation in the cylindrical shape of the pipeline, metal loss due to scraping away of material, and cold working of the metal which is commonly classified as gouging in pipeline industries. In many cases, mechanical damage leads to a delayed catastrophic failure of the pipeline, where the time between the event causing the mechanical damage and actual failure can be as long as months or even years. Fig. 3(a) shows the customary active measurements obtained from a conventional pig. The signals due to the two defects of metal loss and mechanical damage are not clearly distinguishable. Fig. 3(b) shows the measurement of the residual magnetic field around the defects. These plots show that the residual field MFL measurement can be used to distinguish between mechanical damage and metal loss defect. This is due to the sensitivity of the residual field to



(a)



(b)

Fig. 3 Comparison of MFL signals from mechanical damage and metal loss defects of identical dimensions (a) active field measurement (b) residual field measurement. (Afzal et al., 1999)

stress distribution around the defect in case of mechanical damage. It is also possible to observe that the signals generated by mechanical damage exhibit very small amplitudes. This is because mechanical damage causes relatively small changes in the properties of the pipeline material. In other word, the MFL signals generated by these small changes are low in amplitude.

3. MFL Signal Analysis

The edge detection scheme consists of three stages; filtering, differentiation, and detection. In the filtering stage, the signals are normalized and thresholded, in order to remove noise. In this case, this is achieved by using the Gaussian filter described in next section. Differentiation

Data Acquisition

⇩

Thresholding and Normalization

⇩

Location via edges

⇩

Clustering

⇩

Output

Fig. 4 Process flow for proposed approach

highlights the locations in the data where intensity changes are significant. Finally, in the detection stage, the defect edges highlighted by differentiation operator are extracted. In this approach, edge detection is applied to the one-dimensional signal from each individual MFL sensor. After the edge detection process is completed, a data clustering method is applied to remove any trends between the sensors in the circumferential direction. Fig. 4 depicts the overall process for locating mechanical damages.

3.1 Canny Edge Detection

The purpose of edge detection is to significantly reduce the amount of data in an image, while preserving the structural properties to be used for further data analysis. Canny's (1986) aim was to discover the optimal edge detection algorithm. On the Canny operator, the parameter definition for an optimal algorithm consists of three criteria:

1. Detection: A low error rate. Occurring image edges are not dismissed by the algorithm.
2. Localization: Well localized edges, being on the same position as the occurring edges.
3. Minimal response: One given edge is marked once, and image noise does not create false edges.

For edge detection which is a main step, we use the approach initially suggested by Shapiro

Smoothing

⇩

Finding gradients

⇩

Non-maximum supression

⇩

Double thresholding

⇩

Edge tracking

Fig. 5 Individual step of the Canny operator

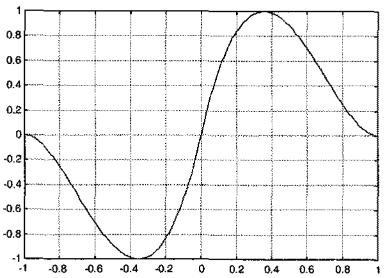


Fig. 6 First derivative filter coefficients of the Canny operator

and Stockman (2001). The edge detection algorithm runs in 5 separate steps as shown in Fig. 5.

In this approach, the edge detection is achieved by convolving the noisy input signal, $s(x)$, with a function $h(x)$ and marking the edges as the maxima of the output signal. Canny shows that the first derivative of a Gaussian in Fig. 6 forms an efficient approximation of the optimal filter $h(x)$. The impulse response of a one-dimensional derivative filter is given by

$$h(x) = -\frac{x^2}{\sigma^2}\exp(-\frac{x^2}{2\sigma^2}) \qquad (1)$$

In the edge localization, we have assumed that the values of σ in the Gaussian based edge detectors is known. Finding an optimal value of σ is not straightforward. Therefore, the important problem is how to determine the appropriate value of σ in a given signal. After convolving the input signal $s(x)$ with an impulse response $h(x)$, the process is performed to find the local maxima.

3.2 MFL Signal Enhancement

In many signal processing, we have to remove some linear trend signal. Since we process MFL signals, which are collected on one direction (axial on the pipe), the noise source can be generated linearly. This part applies to remove the trend signal with straightforward concept, which consists of two parts: clustering and calculating the difference between reference signal and a given MFL signal.

On clustering signal, the MFL signals are composed of several distinct subclasses. In our case, we assumed that there are two different classes, feature signal and background noise signal. The problem of finding subclasses in a set of MFL signals from a given class is called unsupervised learning. The problem is easiest when the feature vectors for MFL signals in a subclass are close together and form a cluster. The k-means algorithm (Tou and Gonzalez, 1974) is one of the common methods for unsupervised approaches. It can use a minimum-distance classifier to separate them. It can be viewed as a greedy algorithm for partitioning the n signals into k (in our case, k=2) clusters so as to minimize the sum of the squared distance to the cluster centers. Once we partitioned MFL signals to desired number of clusters, the background noise signal can be set as a reference signal $r(x)$. $r(x)$ represents the average of signals contained in the second cluster (noise signals). The reference signal is applied to the output $g(x)$ of the edge detector as follows,

$$y_i(x) = r(x) - g_i(x), \qquad i = 1,2,\ldots,m. \qquad (2)$$

where m is number of sensors surrounding pipe in the circumferential direction.

Three types of data sets were used for mechanical damages. The overall layout for data sets is shown in Fig. 7. Data set 1 used 96 sensors for each axial direction and data set 2 and 3 used 32 sensors for row 1 and row 2 respectively as indicated in Fig. 7. The resolution of pixel for axial direction is 100

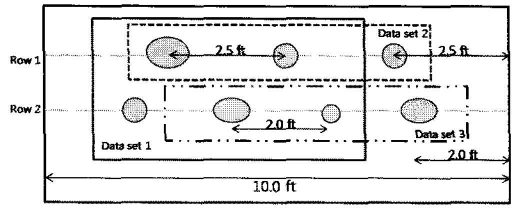


Fig. 7 Experimental data set layout

samples/ft and circumferential direction is 24" diameter and 180 degree scanning. The total length of circumference 37.6991" and 1 pixel of circumference 0.032725 ft are used. Fig. 8 shows the results from the application of the proposed method. It was observed that the performance of this technique is reliable on MFL signal of mechanical damages. For 1-D signal implementation process, Fig. 9 shows the one of sensors on data set 3.

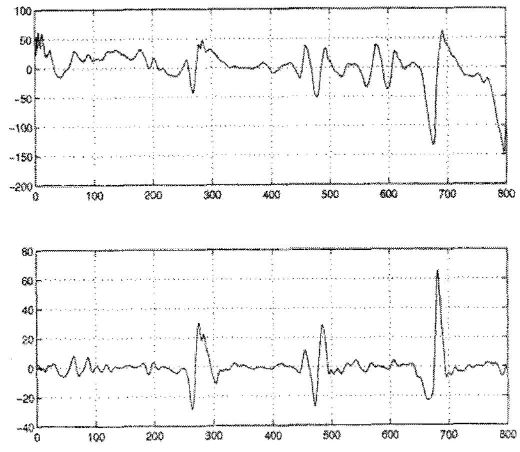


Fig. 9 1-D signal description for sensor location 20 on data set 3: normalized signal and defect location via edge detection (x-axis: samples, y-axis: magnitude)

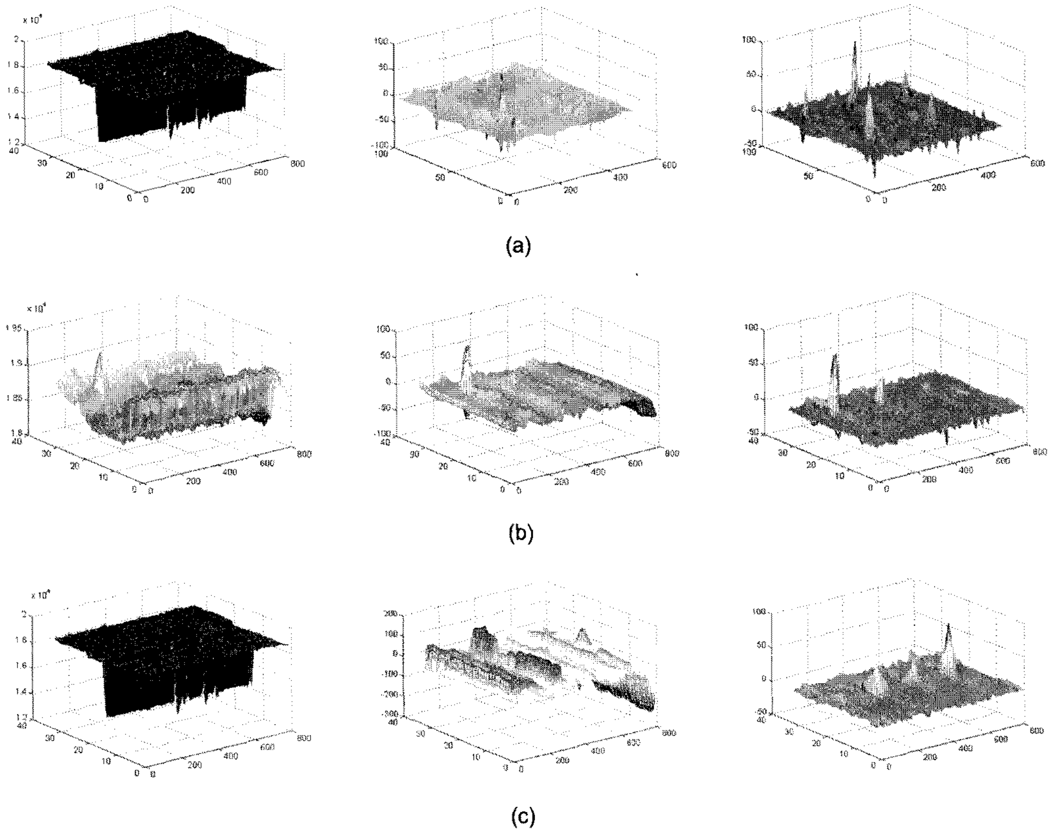


Fig. 8 Locating and filtering results of normalized signal (first column), defect location via edge detection (second column), detrended output (third column): (a) data set 1, (b) data set 2, and (c) data set 3. (From vertical line of plots, each axis means magnitude, channels and samples, respectively)

4. Conclusions

Locating and enhancing mechanical damage signals in MFL data from gas pipeline inspection has been investigated. The proposed signal processing scheme utilizes edge detection and clustering methods to extract low SNR mechanical damage signals from MFL data. The approach involves identifying factors that corrupt MFL data, and then devising techniques to suppress them. In this paper, three data sets were used for validating the edge based approach. As we can see in the results from Fig. 8 and 9, the MFL signals are incredibly enhanced. The proposed approach is simple and it is easy to implement and obtain the good performance with optimal filter coefficients. This paper can be applied to mechanical damage data from field tests and very promising results were obtained.

Acknowledgement

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