ADAPTIVE NOISE CANCELLATION SCHEMES FOR MAGNETIC FLUX LEAKAGE SIGNALS OBTAINED FROM GAS PIPELINE INSPECTION

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ABSTRACT

Nondestructive evaluation of the gas pipeline system is most commonly performed using magnetic flux leakage (MFL) techniques. A major segment of this network employs seamless pipes. The data obtained from MFL inspection of seamless pipes is contaminated by various sources of noise; including seamless pipe noise due to material properties of the pipe, lift-off variation of MFL sensor due to motion of the pipe and system noise due to on-board electronics. The noise can considerably reduce the detectability of defect signals in MFL data. This paper presents a new technique for improving the signal-to-noise-ratio in MFL data obtained from seamless pipes. The approach utilizes normalized least mean squares adaptive noise filtering coupled with wavelet shrinkage denoising to minimize the effects of various sources of noise. Results from application of the approach to data from field tests are presented. It is shown that the proposed algorithm is computationally efficient and data independent.

1. INTRODUCTION

Natural gas is transported to consumer sites through a vast network of pipelines. In order to ensure the integrity of the system, the pipelines are periodically examined using inspection tools called "pigs". The pig is a magnetizer-sensor assembly, employing the magnetic flux leakage (MFL) technique for assessing the condition of the pipe. An array of Hall-effect sensors is usually installed around the circumference of the pig to sense the leakage flux caused by anomalies in the pipe. The signal picked up by the sensor array is recorded and subsequently analyzed offline by trained analysts. The traditional method involving manual analysis of this huge volume of data is very time consuming and the performance is subject to the level of skills and training of the analyst. The gas pipeline inspection industry is therefore keenly interested in automated methods for analyzing MFL data in order to improve accuracy and decrease the turn around time between actual pigging and receipt of inspection results [1,2].

Seamless pipes are usually produced in smaller girths. Consequently, they are commonly found in the collection and distribution ends of the gas pipeline network. Since these pipes are usually located in populated areas, it is imperative that flaws are detected in a timely and accurate manner. The typical procedure for manufacturing seamless pipes consists of a sequence of piercing, rolling and milling operations. The helical nature of these operations set the grain of the seamless pipe in such a way that the data obtained from MFL inspection of these pipes contain an artifact known as the seamless pipe noise (SPN). The signals generated by SPN in MFL data are time varying in nature and appear very similar in shape and amplitude to signals due to defects. As a consequence, seamless pipe noise can in some cases completely mask MFL signals from certain type of defects, such as low SNR signals from shallow corrosion and mechanical damage. Methods for minimizing the effect of SPN and improving the detectability of defect signals in MFL data are, therefore, required. This paper presents a new technique for automated preprocessing of data gathered from MFL inspection of seamless gas pipes. In particular, a signal processing approach for removing SPN and improving the SNR of MFL signals is described.

2. APPROACH

The basic idea underlying the approach is to employ signal and image processing techniques to mitigate the sources of corruption in MFL data obtained from seamless pipes. The overall algorithm is implemented in three major steps. The first step involves data normalization where the raw data is processed to account for inaccuracies in the data introduced by the measurement system in the pig. Sources of error and noise include those contributed by variations in sensor liftoff and bad sensors. The normalized data is then passed through a normalized least mean square (NLMS) adaptive filter to remove SPN from the data. Finally, a wavelet threshold denoising technique is applied to remove the remaining random system noise in the MFL data. Since algorithms incorporated into automated analysis tools are designed for classification and characterization of large volumes of MFL data, computational efficiency and data independence are highly desirable. The technique described in this paper is designed to meet these criteria. The following sections describe the above-mentioned processing steps in greater detail.

2.1. Data Normalization

The data normalization step involves preprocessing of the MFL data to compensate for various imperfections in the data collection mechanism before denoising techniques can be applied. The effects of Hall-effect transducers that malfunction during inspection and the variations in sensor lift-off alignment are corrected for in this step. Let s_i be the signal from the i^{th} element in the circumferential sensor array on the pig and let N represent the total number of sensors in the array. The signal from a bad sensor is replaced simply by interpolating the signals from neighboring sensors. If m_i is the mean value of the signal measured by i^{th} sensor, then the lift-off variation between sensors is minimized by

$$s_i = s_i + \Delta_i, \quad i = 1,2, \quad , N. \tag{1}$$

where $\Delta_i = m_i - \overline{m}$ and $\overline{m}$ denotes the median of all signal means.

This work was carried out at Iowa State University, Ames, IA.

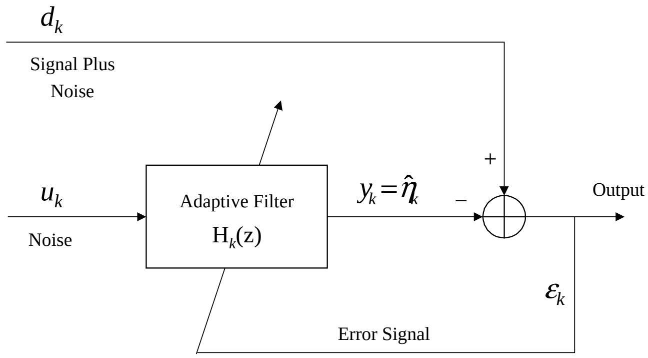

Figure 1. Schematic representation of the NLMS adaptive seamless pipe noise cancellation system.

2.2. NLMS Adaptive Filter for SPN Cancellation

The main step in the proposed algorithm employs a normalized least mean square (NLMS) adaptive filter for seamless pipe noise cancellation. SPN is a time -varying noise and thereby requires an adaptive filter to mitigate its effect. An adapti ve filter is capable of adjusting its impulse response appropriately using an algorithm that minimizes the error between the filter output and reference input. We utilize a finite impulse response (FIR) filter based on least mean square (LMS) algorithm to implement the adaptive system.

Figure 1 shows a schematic representation of the SPN rejection system. The aim of the technique is to exploit the correlation properties of the MFL signal generated by the seamless pipe and signals due to defects and other a rtifacts in the pipeline. The reference input, u_k, and the primary input, d_k, to the adaptive system are signals obtained from two MFL sensors in close proximity. Both inputs are assumed to be statistically stationary. We assume that u_k consists of the SPN signal alone, while d_k contains the desired defect signal in addition to the noise signal, that is,

$$\begin{aligned} d_k &= s_k + \eta_k \\ u_k &= \eta'_k \end{aligned} \tag{2}$$

where s_k denotes the defect signal, and η_k and η'_k represent SPN signals from the two sensors. The underlying assumption is t hat the SPN noise contained in the primary and the reference inputs, η_k and η'_k, are highly correlated with each other, and uncorrelated with the signal component, s_k. To determine the adaptive filter coefficients using the LMS algorithm, we minimize the total system output power (mean squared error) or the power in the error signal, ε_k. It can be shown [3,4,5] that the minimization term is given by,

$$E\left[\varepsilon_k^2\right] = E\left[s_k^2\right] + E\left[(\eta_k - y_k)^2\right] . \tag{3}$$

The signal power $E[s_k^2]$ is unchanged when the filter coefficients are adjusted in the error minimization algorithm. Consequently, only the term $E[(\eta_k - y_k)^2]$ is minimized in the MSE minimization. When the algorithm converges to the minimum mean square error (MMSE) solution, y_k represents the best estimate, $\hat{\eta}_k$, of the SPN contained in primary input d_k in least square sense, i.e. $y_k \approx \hat{\eta}_k$. Since $\varepsilon_k = s_k + \eta_k - y_k$, this implies $\varepsilon_k = \hat{s}_k$, where $\hat{s}_k$ is the best estimate of the defect signal s_k. This argument implies that the minimization of MSE entails cancellation of correlated components between d_k and u_k, which in this case is the seamless pipe noise. Consequently, the error signal at the output of the noise rejection system provides an estima te of the desired defect signal component in the primary input signal. Next we describe the least mean square algorithm used to obtain the MMSE solution.

2.2.1. NLMS Adaptive Algorithm

The NLMS algorithm utilizes the method of steepest decent to update the coefficients of a FIR filter. It is easy to show [3,4,5] that the filter update equation is given by,

$$\mathrm{B}_{k+1} = \mathrm{B}_k + 2\mu\varepsilon_k \mathrm{U}_k . \tag{4}$$

where B_k and U_k denote the filter coefficients and data vectors respectively. The parameter μ controls the convergence rate of the algorithm, and $\varepsilon_k = d_k - y_k$. The choice of the convergence parameter, μ, plays an important role in determining the performance of the adaptive system. It has been shown [4] that stable range of μ varies according to the input signal power. If a normalized value,

$$\mu \leftarrow \frac{\mu}{(L+1)\sigma^2} \tag{5}$$

is used, where σ^2 is input signal power and $L+1$ is the number of adaptive filter coefficients, the stable range of μ is restricted to $0<\mu<1$. In the MFL data obtained from gas pipeline inspection, the signal powe r may change due to variation in wall thickness or other artifacts in the pipe. Therefore, we replace σ^2 by a time - varying estimate,

$$\hat{\sigma}_k^2 = \alpha u_k^2 + (1-\alpha)\hat{\sigma}_{k-1}^2 \tag{6}$$

where α is called the forgetting factor with values in the range $0 < \alpha << 1$, and is selected to reduce the influence of past samples. In summary, the overall NLMS algorithm is implemented using the relations,

$$\begin{aligned} \mathrm{B}_{k+1} &= \mathrm{B}_k + \frac{2\mu\varepsilon_k \mathrm{U}_k}{(L+1)\hat{\sigma}^2}, \qquad \mu = 0.05, L = 99 \\ \hat{\sigma}_k^2 &= \alpha u_k^2 + (1-\alpha)\hat{\sigma}_{k-1}^2, \qquad \alpha = 0.001. \end{aligned} \tag{7}$$

For the adaptive noise cancellation structure shown in Figure 1, d_k is obtained from the MFL sensor passing over a defect and u_k from a sensor containing the SPN only. However, in MFL pipeline inspection, it is not known *a priori* which sensor contains only the noise data. To overcome this problem, we implement a scheme that dynamically assigns u_k and d_k from MFL sensors that are a fixed distance apart from each other. The SPN cancellation algorithm is then applied to each sensor by scanning the circumference of the pipe.

2.2.2. SPN Cancellation in the Presence of System Noise

The analysis to this point d oes not take the system noise into account. System noise includes noise generated by on -board electronics as well as sensors, and contributes to most of the high frequency noise in the data. Taking the system noise into consideration, the inputs to the a daptive noise rejection system can be described as,

$$\begin{aligned} d_k &= s_k + \eta_k + \Delta_k \\ u_k &= \eta'_k + \Delta'_k \end{aligned} \tag{8}$$

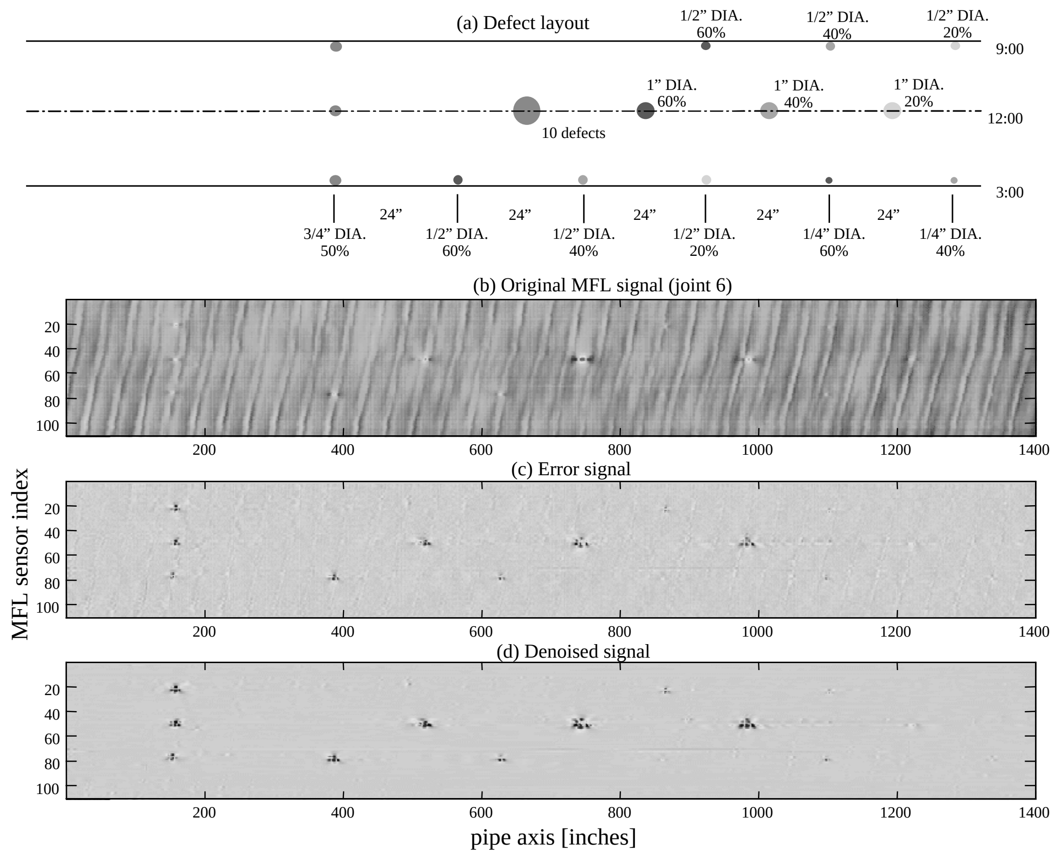

Figure 2. Results obtained from the application of the noise cancellation algorithm to field data (a) Defect layout in the test data (b) Raw MFL data (c) Output after SPN cancellation (d) Final de-noised signal.

The system noise Δ_k and Δ'_k are assumed to be uncorrelated with each other, as well as with other signal components s_k, η_k and η'_k. Both the desired and reference inputs are considered stationary processes as before. In this case, the adaptive system cancels out the correlated SPN, η'_k, and the system noise Δ_k passes through to the output ε_k.

The adaptive filter first learns the statistics of the signals and then tracks these properties if they change slowly with time. For adaptive filters operating with time-varying stationary inputs, the steady-state performance of the filter can be mathematically described using the Wiener filter theory [3]. If we assume that the adaptive noise canceling process has converged, the MMSE solution or the minimum point on the error performance surface, $H^*(k)$, is equivalent to the coefficients of the optimum Wiener filter. Thus the output of the noise canceller, ε_k, is in fact the error of the Wiener filter, which according to orthogonality principle, is uncorrelated with the filter input u_k [3,6]. This implies that all the correlated components (η_k) between primary and reference inputs will be completely eliminated at the output. However the uncorrelated system noise will not be cancelled and appears at the output, ε_k.

2.3. Wavelet Shrinkage Denoising

In the last processing step of the algorithm, the residual system noise in the adaptive noise-cancellation system output is removed from the filtered MFL data. This noise is treated as additive white Gaussian noise (AWGN), and a wavelet-based thresholding approach is utilized. The technique is known as adaptive wavelet shrinkage denoising or soft thresholding [7]. In this method, the wavelet coefficients, *w*, of the MFL data are "shrunk" towards zero using the relation,

$$\Gamma(w,\lambda) = \mathrm{sgn}(w)[|w| - \lambda]_+ . \qquad (9)$$

The threshold, λ, depends on the noise characteristics of the data and is estimated from the finest resolution level of wavelet transform of the data. Since the noise characteristics vary from transducer to transducer and from one pipe section to another, the threshold is computed adaptively for each transducer.

3. RESULTS

The proposed technique was applied to MFL data obtained from three seamless pipes of different SPN signatures. Each pipe was 20'' in diameter and had a 0.25'' wall thickness. An identical defect set, shown in Figure 2a, was machined on each pipe. Figure 2 shows processing results from application of the algorithm on MFL data obtained from one of these pipes. To further elaborate on these results, Figure 3 shows the signals obtained by processing the MFL signal acquired from an individual sensor in the data shown in Figure 2, at each step of the algorithm. Observe that the defect signals are masked by SPN in raw MFL data; however, all defect signals can be clearly identified in the processed data. When both MFL sensors that provide inputs to the adaptive system pass over a no-defect region in the pipe, d_k and u_k contain noise. The error output, ε_k, in this case would contain system noise only, which is removed by wavelet shrinkage denoising.

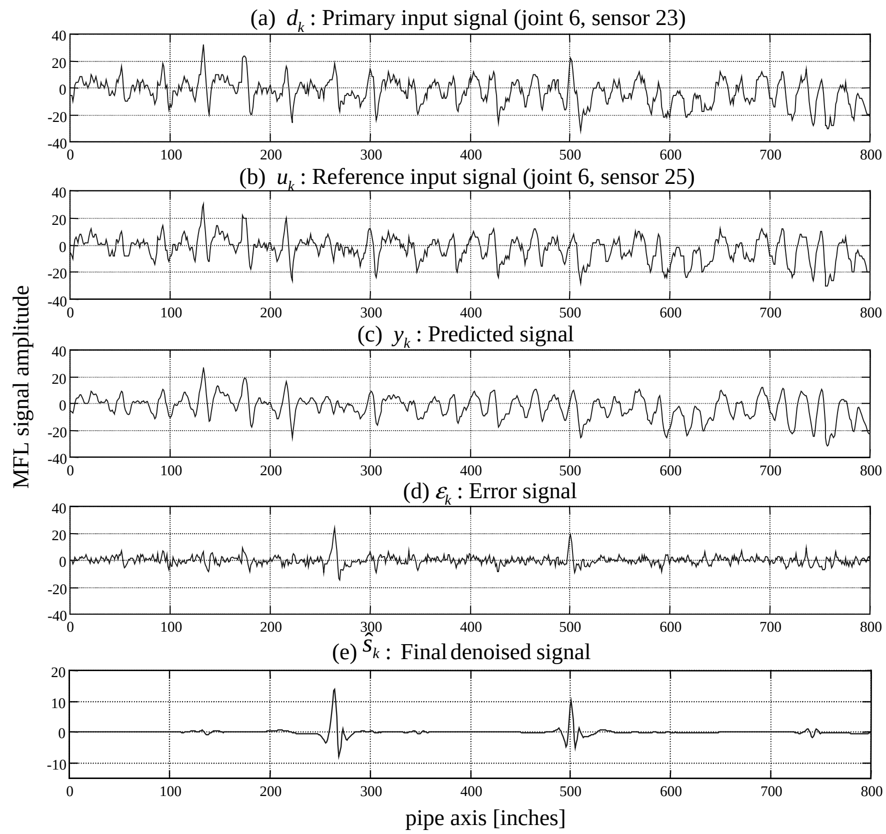

Figure 3. Line-scans corresponding to sensor 23 in the data image shown in Figure 2 (a) Primary input, d_k (b) Reference input, u_k (c) Filter output, y_k (d) Error output, ε_k (e) Final output after wavelet shrinkage denoising.

Application of the algorithm to other data sets produced results that are very similar to the ones shown in Figures 2 and 3. It should be pointed out that since the algorithm is intended for automated analysis of MFL data, it was applied blindly to all data and that none of the processing parameters were modified during its application to different data sets. Furthermore, the algorithm was also applied to blocks of incoming stream data to emulate the real world processing of large volumes of MFL data analyzed in batches. To prevent loss of time and data sections for adjusting the filter coefficients, coefficients were saved after each batch was processed, and the adaptive filters were initialized to these coefficients for processing the next batch.

4. SUMMARY AND CONCLUSIONS

A new technique for enhancing signals in MFL data from seamless gas pipeline inspection has been proposed. The approach utilizes a NLMS adaptive filter to cancel time-varying seamless pipe noise, followed by wavelet shrinkage denoising to remove the residual AWGN system noise. Signal processing results from application of the technique to MFL data obtained from different types of seamless pipes are presented. Preliminary results obtained to date show considerable enhancement in the detectability of signals in MFL data. This algorithm can be incorporated into automatic analysis tools designed for the classification and characterization of MFL data, because of its computational efficiency and data independence capabilities. In addition, the technique appears to be a strong candidate for use in systems employed for controlling quality in seamless pipe production.

5. REFERENCES

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