# Pipeline Defect Detection Using Support Vector Machines

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*Abstract:* - Oil and gas pipeline condition monitoring is a potentially very challenging process due to varying temperature conditions, harshness of the flowing commodity and unpredictable terrain. Pipeline breakdown can potentially cost millions of dollars worth of loss and not to mention the serious environmental damage caused by the leaking commodity. The proposed techniques, although implemented on a lab scale experimental rig, ultimately aims at providing a continuous monitoring system using an array of sensors strategically positioned on the surface of the pipeline. Sensors used are the piezoelectric ultrasonic sensors. The raw sensor signal will be first processed using the Discrete Wavelet Transform (DWT) and then classified using the powerful learning machine called Support Vector Machines (SVM). Preliminary tests show that the sensors can detect the presence of artificially induced wall thinning in a steel pipe by classifying the attenuation and frequency changes of the propagating signals. The SVM algorithm was able to classify the signals as abnormal in the presence of wall thinning.

*Key-Words:* - Pipeline, Support Vector Machines, Discrete wavelet transform

## 1 Introduction

Currently, an established form of pipeline inspection uses smart pigs in a process called “pigging” [1, 2]. These smart pigs travel within the pipeline recording critical information like corrosion levels, cracks and structural defects using its numerous sensors. Pigs can give pinpoint information on the location of defects using techniques like magnetic flux leakage and ultrasonic detection [3]. However, using smart pigs in pipeline inspection has a few disadvantages. The cost of implementing a pigging system

can be expensive, around RM50,000 for every kilometer of pipeline [4]. More importantly, pigs measure the pipeline condition only at the instance it is deployed and does not provide continuous measurements over time. The proposed technique aims at providing a continuous monitoring system using an array of different sensors strategically positioned on the external surface of the pipeline. Sensors that are used will mainly be piezoelectric acoustic sensors. The raw sensor signal will be first processed using the Discrete Wavelet Transform (DWT) and then classified using the powerful learning algorithm called the Support Vector Machines (SVM).

The DWT is used here as a feature extraction tool in order to single out any unique features in the sensor data. A useful property of DWT is that it compresses signals and by doing so, it has the tendency to eliminate high frequency noise. The DWT is used here to eliminate noise in sensor signals and also to compress large amounts of real-time sensor data for faster processing. The compressed data or the DWT coefficients are then used as inputs to the SVM classifier, which will fuse the different sensor data together and then perform classification. SVM has been widely used lately for numerous applications due to is excellent generalization ability with small training samples. The SVM will be trained with normal and simulated defect conditions using an experimental pipeline rig in the laboratory.

The strength of the SVM classifier will then be judged on its accuracy in determining the presence of defects in the pipeline.

# 2 Background

## 2.1 Support Vector Machines

Support vector machines, founded by V. Vapnik, is increasingly being used for classification problems due to its promising empirical performance and excellent generalization ability for small sample sizes with high dimensions. The SVM formulation uses the Structural Risk Minimization (SRM) principle, which has been shown to be superior, to traditional Empirical Risk Minimization (ERM) principle, used by conventional neural networks. SRM minimizes an upper bound on the expected risk, while ERM minimizes the error on the training data. It is this difference which equips SVM with a greater ability to generalize [5].

Given a set of independent and identically distributed (iid) training samples, $S=\{(x_1, y_1), (x_2, y_2),\ldots(x_n,y_n)\}$, where $x_i \in R^N$ and $y_i \in \{-1, 1\}$ denotes the input and the output of the classification, SVM functions by creating a hyperplane that separates the dataset into two classes. According to the SRM principle, there will just be one optimal hyperplane, which has the maximum distance (called maximum margin) to the closest data points of each class as shown in Fig. 1. These points, closest to the optimal hyperplane, are called Support Vectors (SV). The hyperplane is defined by the equation $\mathbf{w}.\mathbf{x} + b = 0$ (1), and therefore the maximal margin can be found by minimizing $\frac{1}{2} \|\mathbf{w}\|^2$ (2) [5].

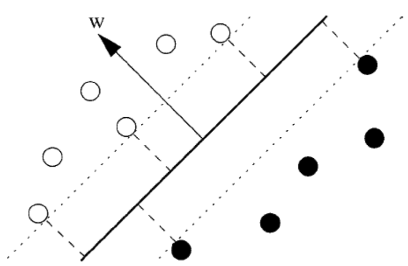


Fig. 1: Optimal Hyperplane and maximum margin for a two class data [6].

The Optimal Separating Hyperplane can thus be found by minimizing (2) under the constraint (3) that the training data is correctly separated [7].

$$y_i.(\mathbf{x}_i.\mathbf{w} + b) \geq 1 , \forall i \quad (3)$$

The concept of the Optimal Separating Hyperplane can be generalized for the non-separable case by introducing a cost for violating the separation constraints (3). This can be done by introducing positive slack variables $\xi_i$ in constraints (3), which then becomes,

$$yi.(\mathbf{x}_i.\mathbf{w} + b) \geq 1 - \xi_i , \forall i \quad (4)$$

If an error occurs, the corresponding $\xi i$ must exceed unity, so $\Sigma_i \xi_i$ is an upper bound for the number of classification errors. Hence a logical way to assign an extra cost for errors is to change the objective function (2) to be minimized into:

$$\min \{ \tfrac{1}{2} \|\mathbf{w}\|^2 + C. (\Sigma_i \xi_i ) \} \quad (5)$$

where C is a chosen parameter. A larger C corresponds to assigning a higher penalty to classification errors. Minimizing (5) under constraint (4) gives the *Generalized Optimal Separating Hyperplane*. This is a Quadratic Programming (QP) problem which can be solved here using the method of Lagrange multipliers [8].

After performing the required calculations [5, 7], the QP problem can be solved by finding the LaGrange multipliers, $\alpha_i$, that maximizes the objective function in (6),

$$W(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j \left(\mathbf{x_i^T x_j}\right) \quad (6)$$

subject to the constraints,

$$0 \leq \alpha_i \leq C, \quad i=1,\ldots,n, \quad \text{and} \quad \sum_{i=1}^{n} \alpha_i y_i = 0. \quad (7)$$

The new objective function is in terms of the Lagrange multipliers, $\alpha_i$ only. It is known as the dual problem: if we know **w**, we know all $\alpha_i$. if we know all $\alpha_i$, we know **w**. Many of the $\alpha_i$ are zero and so w is a linear combination of a small number of data points. $x_i$ with non-zero $\alpha_i$ are called the support vectors [9]. The decision boundary is determined only by the SV. Let $t_j$ ($j$=1, ..., $s$) be the indices of the $s$ support vectors. We can write,

$$w = \sum_{j=1}^{s} \alpha_{t_j} y_{t_j} x_{t_j} \quad (8)$$

So far we used a linear separating decision surface. In the case where decision function is not a linear function of the data, the data will be mapped from the input space (i.e. space in which the data lives) into a high dimensional space (feature space) through a non-linear transformation function Φ ( ). In this (high dimensional) feature space, the (Generalized) Optimal Separating Hyperplane is constructed. This is illustrated on Fig. 2 [10].

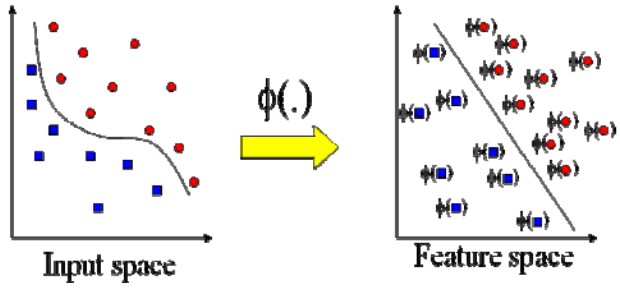


Fig. 2: Mapping onto higher dimensional feature space

By introducing the kernel function, $K(x_i, x_j) = \langle \Phi(x_i), \Phi(x_j) \rangle$, (9) it is not necessary to explicitly know Φ ( ). So that the optimization problem (6) can be translated directly to the more general kernel version [10],

$$W(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1,j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j),$$

(10)

subject to $C \geq \alpha_i \geq 0, \sum_{i=1}^{n} \alpha_i y_i = 0$.

After the $\alpha_i$ variables are calculated, the equation of the hyperplane, $d(\mathbf{x})$ is determined by,

$$d(x) = \sum_{i=1}^{l} y_i \alpha_i K(\mathbf{x}, \mathbf{x_i}) + b \qquad (11)$$

The equation for the indicator function, used to classify test data (from sensors) is given below where the new data **z** is classified as class 1 if $i>0$, and as class 2 if $i<0$ [11].

$$i_F(\mathbf{x}) = \text{sign}[d(\mathbf{x})] = \text{sign}\left[\sum_{i=1}^{l} y_i \alpha_i K(\mathbf{x}, \mathbf{x_i}) + b\right] \qquad (12)$$

Note that the summation is not actually performed over all training data but rather over the support vectors, because only for them do the Lagrange multipliers differ from zero. As such, using the support vector machine we will have good generalization and this will enable an efficient and accurate classification of the sensor signals. It is this excellent generalization that we look for when analyzing sensor signals due to the small samples of actual defect data obtainable from field studies. In this work, we simulate the abnormal condition and therefore introduce an artificial condition not found in real life applications.

## 2.2 Discrete Wavelet Transform

A discrete wavelet transform (DWT) is basically a wavelet transform for which the wavelets are sampled in discrete time. The DWT of a signal *x* is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response *g*, resulting in a convolution of the two (13). The signal is also decomposed simultaneously using a high-pass filter *h* (14).

$$y_{\text{low}}[n] = \sum_{k=-\infty}^{\infty} x[k] g[2n-k] \qquad (13)$$

$$y_{\text{high}}[n] = \sum_{k=-\infty}^{\infty} x[k] h[2n-k] \qquad (14)$$

The output of the equations 13 and 14 gives the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass). It is important that the two filters are related to each other for efficient computation and they are known as a quadrature mirror filter [12].

However, since half the frequencies of the signal have now been removed, half the samples can be discarded according to Nyquist's rule. The filter outputs are then down sampled by 2 as illustrated in Fig. 3. This decomposition has halved the time resolution since only half of each filter output characterizes the signal. However, each output has half the frequency band of the input so the frequency resolution has been doubled. The coefficients are used as inputs to the SVM [13].

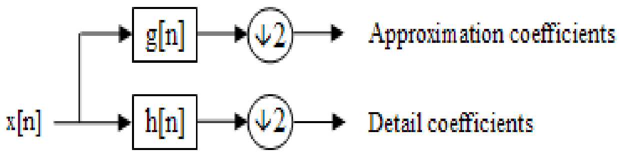


Fig. 3: DWT filter decomposition

### 2.3 Corrosion Measurement

A pipe failure and leakage of crude oil in Winchester, Kentucky on January 2000, was one of the biggest accidents that occurred and it incurred the owner Marathon Ashland Pipe Line LLC a clean up cost of $7.1 million. The crack was due to a small dent in the pipe that might have been caused by stone particles flowing along the path, in addition to the fluctuating pressure of the pipe wall [14]. An example of such a failure is shown in Fig. 4.

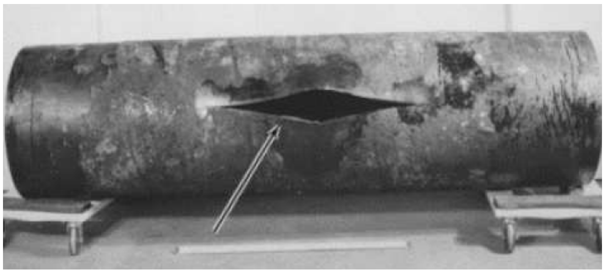

Fig. 4: The rapture pipe due to fatigue cracking [14].

Wall thinning, a common occurrence in the oil piping industry, is characterized by metal loss caused by surface erosion due to high temperature, high pressure and high flowing velocity of the flowing commodity [15]. The pipes are also subjected to combined loading by internal pressure, bending moment, and longitudinal forces.

The internal wall thinning of a pipe cannot be observed from the outside of the pipe, hence a method of condition monitoring using ultrasonic waves as a non-destructive test of the metal loss can help to determine when the pipe may be at risk for leaks or failure. Ultrasonic sensor enables detection without any contact with the object regardless of its material, nature, color and degree of transparency. They are widely use in industrial application for detecting the position of the machine parts, the flow of object on the conveyer belt and the level of measure liquid [13].
The detection technology used here lies within the concepts of nonlinear acoustics. This basically states that when sound waves travels through a material, frequency and attenuation changes occur to the sound waves. The changes in the frequency and amplitude must be detected and analyzed to give precise information on the state of the material. Ultrasonic transmitters can be used to send ultrasonic waves and ultrasonic receivers can be used to detect the propagating waves. These sensors are very accurate as they can produce and detects high frequency sound wave based on Piezoelectricity [16]. Piezoelectric transducers have solid-state pressure sensitive elements that will expand and contract in step with input signals.

Demma [17] examined the effect of defect size with frequency on the reflection from notches and was able to show the relation between the value of reflection coefficient and the defect sizing. The cylindrical ultrasonic waves propagate along the pipe and are partially reflected when met with defects thus providing a fast screening technique to determine the presence of defects. Similar results and observation are recorded by Lin [18] by using guided waves and electromagnetic acoustic transducers (EMATs) to measure the wall thickness precisely. Wave propagation is performed for a specimen with thickness of 10mm, where different artificial defects are introduced to model local wall thinning. As shown in Fig.5, when transmitted waves impinge the wall thinning, they are reflected and the intensity of the reflected waves varies.

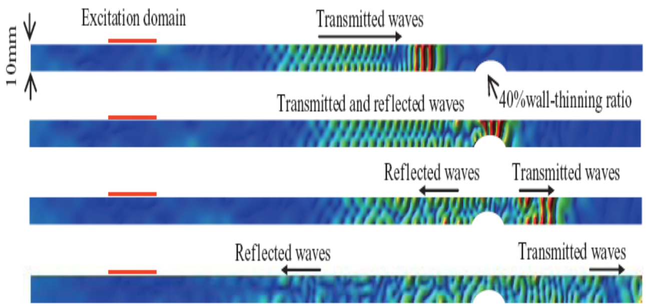


Fig. 5: The energy carried by the transmitted waves passes through the wall thinning and some reflected back as echoes. [18]

It is therefore a well known phenomenon, both theoretically and experimentally that defects in pipes can be detected by ultrasonic transducers [15]. Our aim here is to monitor the sensor signals and use SVM to predict the presence of defects.

## 3 Methodology

This section details the experimental setup that will be used to simulate pipeline conditions and also defect conditions. The aim is to create a scaled downed version of an actual section of pipeline in the laboratory using commonly available materials. Fig. 6 shows the experimental setup. A motor pump is used to pump hydraulic oil in the reservoir through the pipeline section. A flow rate of around 5 $m^3/h$ was achieved through a 1 m section of pipe (outer diameter of 48.30 mm and inner diameter of 42 mm). An electric valve is used to control the flow of oil through the pipeline section. Below are the properties of galvanize steel pipe that was used: Young's Modulus, E (GPa); 190 – 210/Density, ρ (kg / m3); 7850/Yield Strength (MPa); 340 – 1000.

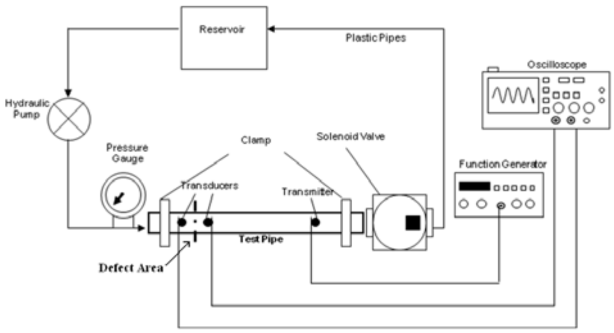


Fig. 6: Pipeline Experimental Setup.

A lathe is used to clear an area of 1mm wide and 1mm deep all around the circumference at the inner surface of the pipe as show in Fig. 7. This is to simulate a crack or corrosion at the inner surface of the pipe. An ultrasonic transmitter is used to transmit a signal across the flowing pipe and through the defect area to see changes in the ultrasound signal. Ultrasonic sensors used are Murata analogue ultrasonic transmitter which is an open structure type of sensor that has a range of up to 6 m and they will be attached to the outer surface of the pipe using epoxy. MA40B8S have the nominal frequency of 40 kHz with the maximum input voltage of 40V peak to peak. The stationary sensors can avoid any disturbance from the environment and will be able to transmit ultrasound along the length of the pipe by ringing the surface of galvanized steel pipe.

Ultrasonic receivers are placed at either side of the defect area. These receivers will be able to pick-up the waveform that is vibrating in the pipe and can be used to monitor the condition of the pipe. The changes in the ultrasound signal before and after the defect area will be used to determine the presence of any defects.

## 4 Results

The results of from the experimental rig will ultimately be used to ascertain whether SVM can detect the presence of cracks and whether DWT helps in the decision making. DWT is performed on raw time domain samples and the coefficients of the resulting DWT are inputted into the SVM for classification. Various wavelets can be tested including the Haar and Daubechies wavelets. A popular SVM algorithm called LIBSVM [19] is used to perform the SVM calculations.

LIBSVM includes a variety of kernel functions to choose from such as linear, polynomial, radial basis function (RBF), and sigmoid. To train an SVM, the user must select the proper *C* value as well as any required kernel parameters. The various kernel functions are defined as:

$$
\begin{array}{ll}
linear & k(\vec{u},\vec{v}) = \vec{u}^T \cdot \vec{v} \\
polynomial & k(\vec{u},\vec{v}) = (\gamma\vec{u}^T \cdot \vec{v} + coef0)^{degree} \\
RBF & k(\vec{u},\vec{v}) = e^{-\gamma|\vec{u}-\vec{v}|^2} \\
sigmoid & k(\vec{u},\vec{v}) = \tanh(\gamma\vec{u}^T \cdot \vec{v} + coef0)
\end{array}
$$

Time domain samples before and after the defect area are first broken down into frames where the number of samples within the frame is a variable. Each frame will represent one instance or sample needed for the SVM and the frame size is the number of attributes or dimensions. Table 1 shows the results of the SVM accuracy in percentage as frame sizes of 50 and 25 are of the same datasets are inputted into the LIBSVM algorithm. 10,000 data points before the defect and 10,000 data points after the defect are used to obtain the results.

Table 1: Classification accuracy (%) for pipeline data using LIBSVM for various kernel functions.

| Frame size | Poly | RBF | Sigmoid |
|---|---|---|---|
| 50 | 67.74 | 70.97 | 67.74 |
| 25 | 73.68 | 75.44 | 73.68 |

As can be seen from Table 1 the smaller frame size provides better classification accuracy than the bigger frame size. The radial basis function (RBF) kernel shows the highest classification rates among the kernel functions tested. Table 2 shows the results of performing DWT on the data samples before inputting into LIBSVM. The daubechies and haar wavelets were used in separate instances and the results shown.

Table 2: Classification accuracy (%) using DWT with LIBSVM for two different wavelets.

| Wavelet | Kernel | Frame Size | |
|---|---|---|---|
| | | 50 | 25 |
| DB2 | Poly | 61.11 | 83.87 |
| | RBF | 72.22 | 80.64 |
| | Sig | 61.11 | 80.64 |
| Haar | Poly | 75.00 | 89.65 |
| | RBF | 75.00 | 89.65 |
| | Sig | 75.00 | 86.21 |

As can be seen from the data in Table 2, the use of DWT increases the classification accuracy significantly. The highest accuracy is achieved is 89.65% using the Haar wavelet with a frame size of 25.

# 5 Conclusion

Monitoring hundreds of kilometers of pipelines is a difficult task due to the high number of unpredictable variables involved. Rapidly changing weather conditions, pressure changes and erosion due to gas or oil flow and ground movement are a few variables that can have direct impact on the pipelines. There variables can cause defects like corrosion, dents and cracks which will lead to loss of the valuable commodity and not to mention the serious affects on the surrounding environment.

The use of an array of sensors with help of support vector machine processing intends to solve these problems in two ways. Firstly the array of sensors provides a continuous monitoring platform along the entire distance of the pipeline. Secondly the use of artificial intelligence tools like support vector machines, makes it possible to monitor and ultimately predict the occurrence of defects. Support vector machines are ideal for applications like these where there are high number of dimensions of data (sensors) and small numbers of samples for defect scenarios. SVM has been used widely in many such applications and has provided excellent generalization performance.
An experimental miniature pipeline rig provided the setting to see the initial performance of SVM on pipeline data. Acoustic sensors were used and the corrosion defect was simulated using human manipulation. The results showed good performance by SVM using an RBF kernel function. The use of DWT further improved the performance of the SVM accuracy to 89.65%. This is due to the DWT compressing the data and filtering away unwanted noise from the high frequency acoustic signals.

This report has come to the conclusion that a combination of DWT and SVM algorithm can predict, to a high degree of accuracy, the presence of defects in pipes. This report will be used as a benchmark for testing on a higher scale pipeline rig, with more defect scenarios (types of defects) and higher number of sensors (along with different types of sensors such as Fiber Bragg Grating sensors). The ultimate aim of the research will be to predict defects before they occurs thereby conserving the precious commodity and environment. Additional experiments relating to sensor sensitivity in relation to distance from the defect will also be conducted.

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