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Application of wavelet analysis and machine learning on vibration data from gas pipelines for structural health monitoring

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Abstract

Defects due to corrosion and fatigue in pipelines may create significant hazards in the transportation of natural gas. To detect such damages, traditionally, pigging equipment like pipeline inspection gauge (PIG) are inserted into the pipeline. However, the performance of such devices may be enhanced by embedding vibration sensors externally. Such sensors equipped with machine learning capability could be used for damage detection and verification of the PIG data. This study investigates the applicability of Support Vector Machine (a supervised machine learning classifier) and wavelet analysis on vibration response in the detection of various kinds of defects present in gas pipelines. Both ends fixed and simply supported boundary conditions are incorporated on a pipe with outer diameter 200*mm* pipe with 25*mm* pipe thickness, made of structural steel to simulate the real transportation pipeline laying conditions above the ground. In this study, the pigging process is simulated in ANSYS by considering inspection gauge as moving load inside the pipeline with a constant velocity. The velocity and acceleration time history data at a fixed point on the pipe for gauge moving from one end to the other is obtained from ANSYS corresponding to different loading conditions and load moving velocities of the inspection gauge. These data are then post-processed in MATLAB environment. Wavelet analysis has been carried out on this data, to obtain spectral components of frequency contained in the data. Further, Support Vector Machine classifier is used to separate the segment of data corresponding to defect region, which can be mapped back to identify the physical location of the defect on the pipeline. The obtained results show good accuracy of defect identification and its location prediction, which can be integrated with intelligent PIG devices and pipe crawling robots.

Keywords:Pipeline; crack ; structural health monitoring; pipe inspection gauge (PIG); wavelet analysis; machine learning; support vector machine

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1. Introduction

Gas pipeline networks are massive work of technology, which require extensive level of maintenance in order to operate them safely with a long life. The failure of the pipelines during operation leads to unplanned stoppage and large expenses. The damage/corrosion/metal loss in pipelines are generally detected by visual inspection, conventional ultrasonic testing, radiography, thermography, acoustic emission and using in-line inspection tool (Bickerstaff et al. (2002)). These processes of inspection are usually very slow and time taking. Novel approaches in Structural Health Monitoring (SHM) are needed with the help of which condition based maintenance can be performed efficiently.

One of the most common and well-researched techniques for damage detection are based on modal analysis of structure (Schultz and Warwick (1971), Adams et al. (1975), Narkis (1994), Banks et al.(1996)). These techniques require response of structure in healthy condition as well as in damaged condition in order to identify the location and severity of damage. Wavelet analysis is a recent research area in structural health monitoring used for detection of damage (Wangand Deng (1999), Wang and McFadden (1996), Stubbs and Osegueda (1990)). Structural health monitoring methods based on wavelet techniques do not require prior stress condition and the material properties of the structure. In this study, a technique of pipeline health monitoring model is developed based on wavelet analysis of vibration response of pipeline structure. It involves the use of moving pipeline inspection gauge (PIG) (Ogai and Bhattacharya (2018), Bickerstaff et al. (2002)) and highly sensitive accelerometer (seismic sensor). The accelerometer being permanently integrated to each pipe in the pipeline network. In this model, the role of this PIG is just a moving load inside pipeline and an accelerometer, which is integrated at the midpoint of the pipe at the external surface. The over ground gas transportation pipelines usually extend hundreds of kilometers and are mounted on supports, which are at some interval of distance. The pipe network can be considered as continuous beam with multiple supports. However, for simplicity, the system is considered piece-wise, i.e. one beam on two simple or fixed supports. In later sections, it is shown that alternation in dynamics caused by the type of supports (i.e. simple supports or fixed supports) will not affect the structural health monitoring.

1.1 Analytical approach

This section discusses the analytical solution for healthy pipe for moving load, which will be used to verify our FEA formulation of the pipe with moving load. The PIG travelling inside the healthy pipe is treated as moving force inside the pipeline. Since the weight of the gauge is very less as compared to the weight of pipe and produces very small deflections. Hence, pipe is considered as *Euler-Bernoulli beam.* The pipe taken for analysis is of mild steel ($E=2\times 10^{11}\ N/m^2$, $v=0.33$ and $\rho=7850\ kg/m^3$) has outer diameter of *200mm*, thickness of *25mm* thickness and *2m* length.

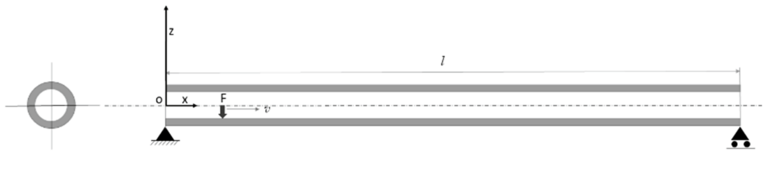


Figure 1: Schematic of pipe with a traveling force

The equation of motion of such a system can be written as follows:

$$\rho A w_{,tt} + EI w_{,xxxx} = F\ \delta\left(x - vt\right) \tag{1}$$

where, ρ is density of pipe material, A is area of cross-section of the pipe, w is deflection of pipe in z-direction at distance 'x' from origin and at any time instant 't' on pipe, F is downward moving force acting on pipe, v is velocity with which force F is moving, δ is Dirac-delta function and ω_j is j^{th} natural frequency of pipe system. The equation (1) is second-order partial differential equation in time and fourth-order in space. The boundary conditions for such system are:

$$w(0,\ t) = 0 \tag{2}$$
$$w(l,\ t) = 0 \tag{3}$$
$$w_{,xx}(0,\ t) = 0 \tag{4}$$
$$w_{,xx}(l,t) = 0 \tag{5}$$

Boundary conditions (2) and (3) corresponds to zero transverse displacement at both ends, and boundary conditions (4) and (5) corresponds to zero moment at both ends. Here, we also have two initial conditions:

$$w(x,0) = 0 \tag{6}$$
$$w_{,t}(x,0) = 0 \tag{7}$$

Initial condition (6) implies that there no initial deflection at any section of pipe, and initial condition (7) signifies that there is no initial velocity in transverse direction at any section of pipe. The solution of this equation gives response of the system. The detailed solution is presented by Hagedorn and DasGupta (2007) as follows:

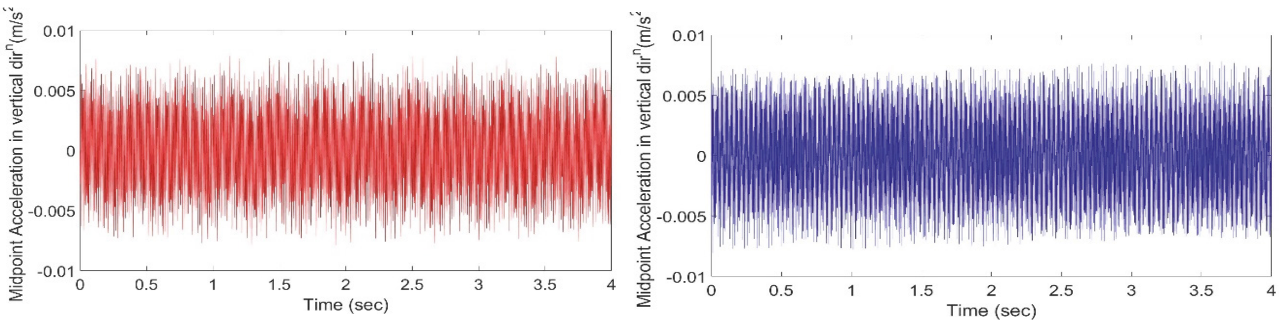
$$\ddot{w}(x,t) = \frac{2Fl^3}{\pi^4 EI} \sum_{j=1}^{\infty} \frac{1}{j^2\left(j^2 - \dfrac{\rho A l^2 v^2}{\pi^2 EI}\right)} \left(\frac{j\pi v \omega_j}{l} \sin \omega_j t - \left(\frac{j\pi v}{l}\right)^2 \sin \frac{j\pi v t}{l} \right) \sin \frac{j\pi x}{l} \tag{8}$$

1.2 Finite Element Approach

The Finite Element model of the healthy pipe with moving load is developed in ANSYS 17 workbench to obtain the acceleration response of the system. The model is setup by coupling modal analysis module and transient structural analysis module in ANSYS. Since the damping in steel is very less (damping coefficient less than 0.01), structural damping is neglected while solving analytically as well as in ANSYS model. Simply supported ends and fixed ends are used in future analysis. Eight nodded linear hexahedron solid elements are used for meshing pipe.

1.3 Comparison of transient acceleration obtained from analytical and FEM approach

The midpoint acceleration for moving load of 500N with velocity of 0.5 *m/s* is shown in figure 2. The FEM results are consistent with the analytical results for healthy pipe system. Hence, we can use this FEM model for damaged pipe system too.



(a) Analytical solution for 0.5 m/s (b) FEM solution (ANSYS) for 0.5 m/s

Figure 2: Acceleration of midpoint of pipe in vertical direction obtained analytically and by FE (ANSYS) for 500N load moving

2. Wavelet Analysis of Acceleration Response of damaged pipe system

2.1 Wavelet Transform

Wavelet transform, presented by Daubechies (1990), can provide the time and frequency information of a signal simultaneously with required accuracy. A wavelet function ψ(x), is a wave-like oscillation that has zero mean, i.e, the wavelet function has equal area above and below zero. It is a decaying function of finite duration (unlike sinusoids, which are infinite duration).

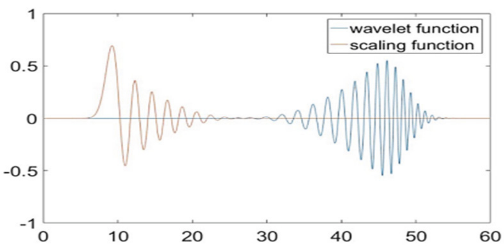


Figure 3: Daubechies 45 wavelet function and scaling function

Wavelet transforms use wavelets of different scales and translations as basis functions and a signal is represented by a linear combination of these basis functions. Discontinuous and smooth components in a signal can be extracted by analyzing the signal with basis function with different scales and shifts. In this work, discrete wavelet transform (DWT) is used to decompose acceleration signal. In discrete wavelet transform, scales and translations used obey some defined rules. The wavelet is constructed using scaling function, which demonstrates its scaling properties. There is a restriction on scaling functions that they must be orthogonal to their discrete translations. The base scale of DWT is 2 and different scales can be obtained by raising the base scale to the power the integer values. The discrete scaling function ϕ *(n)* and discrete wavelet function φ *(n)* are defined as:

$$\phi_{j,k}\left(n\right)=2^{j/2}\phi(2^{j}n-k) \tag{9}$$

$$\varphi_{j,k}\left(n\right)=2^{j/2}\varphi(2^{j}n-k) \tag{10}$$

where, j is dilation/scaling parameter, k is shifting/translation parameter and $j,k\in$ Z. A signal ***S(n)*** is decomposed by DWT into scaling function coefficients (or Approximations) and wavelet coefficients (or Details) as follow:

$$W_{\phi}(j_{o},k)=\frac{1}{M}\sum_{n}S(n)\phi_{j_{o},k}(n) \tag{11}$$

$$W_{\varphi}(j_{o},k)=\frac{1}{M}\sum_{n}S(n)\varphi_{j,k}(n) \tag{12}$$

Where W_{φ} (j_o, k) are scaling function coefficients (Approximations), and W_{ψ} (j, k) are wavelet coefficients (Details).

2.2. Discrete wavelet decomposition of response acceleration signal from damaged pipe system

In this model, Daubechies 45 (db 45) wavelet is selected for analysis because of its highly oscillating nature matches the acceleration signal. The decomposition is done up to scale 5 which results in approximation coefficients (A1, A2,.., A5) and detail coefficients (D1, D2,.., D5). The acceleration signal *S(n)* decomposition is written as *S(n)* = A5 + D5 + D4 + D3 + D2 + D1. These approximation and detail coefficients are having peaks or perturbance at certain time location, which represents the presence of damage or notch in the pipe.

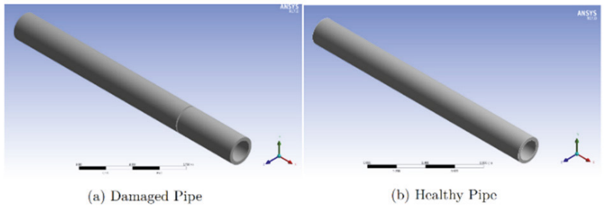
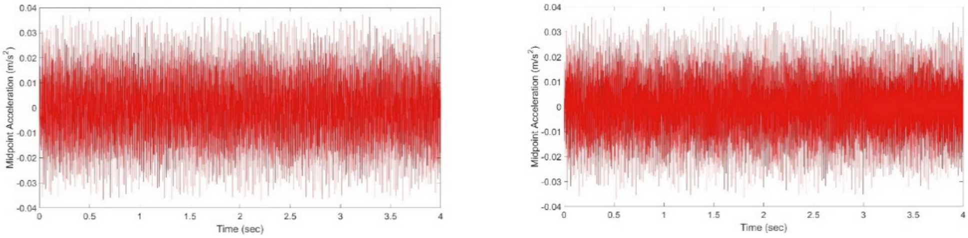


Figure 4: Damaged and healthy pipe

Healthy and damaged mild steel pipe (7850 kg/m^3 density and Young's modulus of $2\times10^{11} N/m^2$) were modeled in ANSYS for the study having 200 *mm* outer diameter, 25 *mm* wall thickness (t) and 2 *meter* length. Figure 4(a) shows of damaged pipe with a notch of depth 0.8t, width 0.4t and throughout circumference(360^{o}) at a distance of 0.5 *meters* from right end of the pipe, and figure 4(b) shows a healthy pipe. A force of 500N moving inside pipe from left end to right end with velocity of 0.5 *m/sec* and the corresponding response at midpoint is obtained. The presence of damage (or notch) causes the reduction in local bending stiffness, which introduces some transients (abrupt changes) in the response signal at the instant when moving load crosses damage.



(a) Healthy pipe (b) Notched pipe

Figure 5: Acceleration of midpoint of healthy pipe and notched pipe due to moving load (500 N) at 0.5 *m/s*

However, it is impossible to distinguish the acceleration response of damaged pipe (figure 5b) and healthy pipe (figure 5a). Therefore, wavelet transform is performed on these response signals to extract the useful information. Figure 6 and figure 7 show the wavelet coefficients of acceleration response of healthy pipe and damaged pipe respectively.

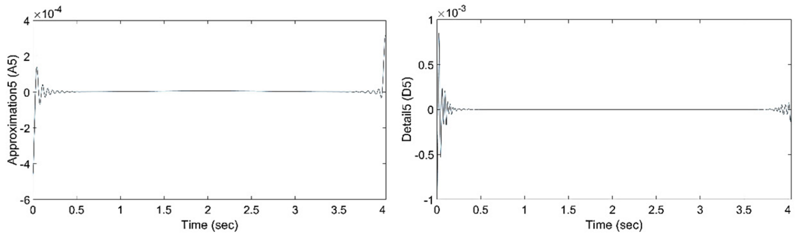


Figure 6: Wavelet coefficients, A5 and D5 of acceleration signal of healthy pipe

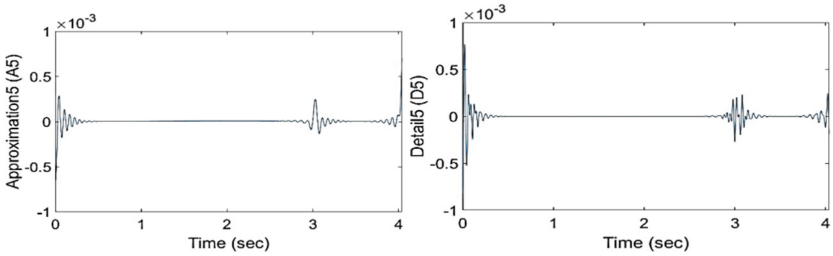


Figure 7: Wavelet coefficients, A5 and D5 of acceleration signal of notched pipe with notch of 0.5t depth, 0.5t axial extent and throughout circumferential extent located at 3/4L distance from left end.

From figure 7, it can be seen that there is disturbance in A5 and D5 coefficients at 3 seconds of time. This indicates that there is defect at location when the load is at distance 3 seconds away from its starting location. i.e. at 1.5 m from left end, which is true (see figure 4a). Peaks and disturbance at starting and end region represents the presence of supports. Same analysis for healthy pipe (figure 6) depict that there are no peaks in the A5 and D5 coefficients except at ends (due to supports). Similar results were obtained for pipe with fixed ends, suggesting that the boundary conditions do not affect the defect detection in this model. Hence, this model can be used in real scenarios with any supports. Different combination of parameters were checked and found that the notch as small as 10^o circumferential extent, $0.2t$ deep and $0.5t$ wide can be have disturbed wavelet coefficients at defect location.

The study aimed at finding whether there is any relation between reduction in local stiffness (due to erosion of material) and the disturbance in wavelet coefficients of response due to the reduction of local bending stiffness. Generally, there is no relation between peak amplitude of wavelet coefficients at defect location and notch dimensions. Hence, the severity of defect cannot be determined by this approach. The explanation for this is that this technique picks up defects based on sudden change in frequencies present in vibration response at the time when the load moves over the defect location. The peak amplitude of wavelet coefficient of particular scale at defect location tell the level of the disturbance in frequency spectrum associated with wavelet of that scale. The dimension of notch on pipe cannot be directly related to amount of change in frequencies of some specific range present in the vibration response at the time when moving load crosses notch location. This is why we cannot find the severity of defect by this approach.

However, the location of defect can be found except for the defects, which are laying at supports. Defects laying closer to the midpoint of pipe can be easily predicted as they produce large amplitude of peak of wavelet coefficients. The PIG should be designed carefully considering its weight as an important factor, as its velocity and downward force depends on it. This sensitivity analysis depends upon the wavelet and the scale for analysis selected.

3. Machine Learning technique to classify signal belonging to damaged region

3.1. Machine learning

Machine learning is a field of computer science which is evolved from the study of computational learning and pattern recognition in artificial intelligence(Russell and Norvig (2016)) and enables computer to act without being explicitly programmed (Nasrabadi (2007)). Support vector machine (SVM) are supervised learning algorithms that analyze data for classification and regression analysis, as described by Wang (2005), in his work. It builds a model that is used to assign new examples to one out of two categories by constructing a hyperplane in an infinite dimensional space that divides data into two classes. The critical data points nearest to the hyperplane supports the hyperplane and are called support vectors. New examples are then projected into the same space categorized based on the side they fall. The gap between the nearest data point from either side and the hyperplane is known as margin and the goal here is to set the hyperplane with greatest margin possible.

3.2. Application of Support Vector Machine (SVM) in this model

Machine learning is used here to incorporate automation and digitization the designed Structural Health Monitoring (SHM) system for pipeline network. Interpreting signal for pipelines of 100-200 *km* is impossible to do manually. Hence, SVM is used to locate defects automatically. The system performs wavelet analysis on the acceleration signal and SVM is used to identify peaks. In the first step, SVM model is trained as a classifier with known data set. In the second step, the classifier trained in the first step is use to classify the rest of the data in the data set.

3.2.1. Training of Model

95 different cases of defective pipe are simulated with different kinds of notches placed at random positions and their decomposed acceleration signal is used for training SVM. Trained SVM assigns *1* as defect and *0* as non-defect region. It takes a *feature matrix* and a *label vector* as input for training.

Feature matrix, m: Feature matrix is a matrix constructed from sample signals obtained from sample cases used for training. Sample signal is discrete acceleration data points (a_1, a_2, a_3,...) in time. Each rows of feature matrix is constructed such that it contains a data point $\boldsymbol{x}$ represented in a form $[W_{L_i}, W_{R_i}]$. So, the nth row of feature matrix contains data point ${}^{n}x$ and is represented by $[{}^{n}W_{L_i}, {}^{n}W_{R_i}]$, where,

$${}^{n}W_{L_i} = |a_n - a_{L_i}| \text{and} \; |a_n - a_{R_i}|$$

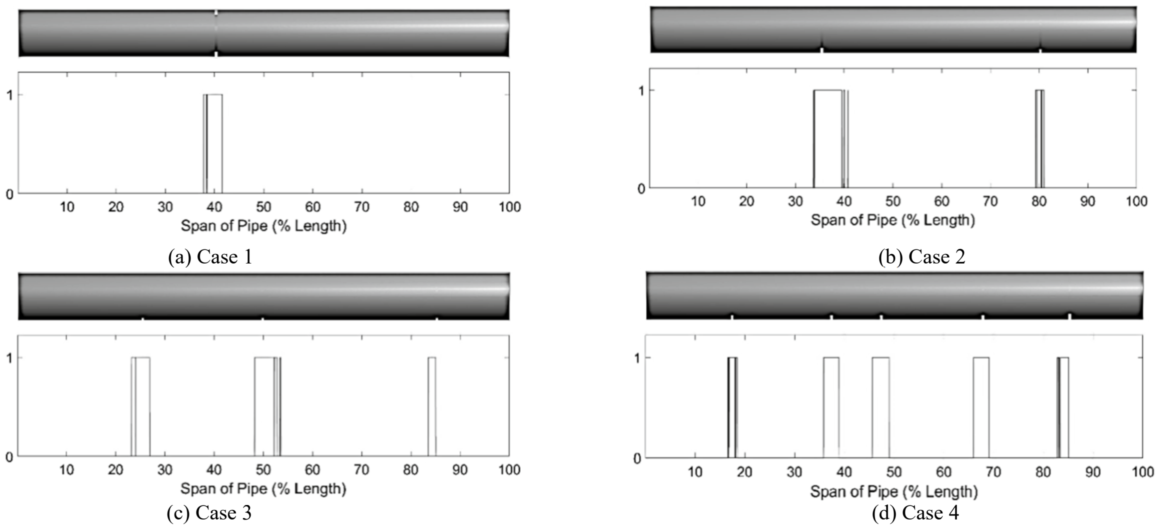
a_{L_i} is the i^{th} data point from left of a_n, a_{R_i} is the i^{th} data point from right of a_n, and i =1, 2, 3. . . 37. i was taken up to 37 as it was observed in wavelet coefficients that all the peaks were spanning approx. 74 data points. So, 37 points at each side from center of peak can cover whole peak. The number of rows of feature matrix is equal to number of data points in signal times number of sample signal taken for training. In this model, 95 sample signals, each signal containing 4040 data points were taken.

Label vector, y: Label vector is used to label the class to the rows of feature matrix. The label vector is constructed from *0s* and *1s*. *1s* are placed in rows corresponding to which the feature matrix rows have data points of notched region, and *0s* of healthy region. The training accuracy of 86.2% was obtained after training of our SVM model.

3.2.2. Testing of the trained SVM model

Defects are modeled in pipe with different conditions. Decomposed acceleration signal is given as input in the trained SVM model. The output given by SVM is a vector of same length as of input signal and contains 0s and 1s corresponding to healthy and damaged region. The output vector is mapped to the span of pipe and damaged location specified by SVM is compared to the actual known locations of damage.

Four different cases with single and multiple defects as presented in figure 8 are tested. For all the cases, pipe of 2 *meter* length is used with 500 *N* load moving from left to right end at a velocity of 0.5 *m/s*. In case 1, pipe contains notch extending whole circumference at 0.8 meters from left end. Both ends are fixed for this case. In case 2, pipe contains two notches- one at 0.7 meter and other at 1.6 meters from left end. Both notches are extending 180^o circumference and both end supports are simple. In case 3, pipe contains three notches extending 45^o circumference at 0.5, 1 and 1.7 meter from left end. Both end supports are simple. In case 4, pipe contains five notches at 0.35, 0.75, 0.95, 1.35 and 1.7 meters from left end. All three notches are extending 45^o circumference. Both ends are considered to be simply supported. Figure 8 shows plot of SVM classifier output vector for all the cases after mapping it with length of pipe. It can be seen from the figures that the SVM output vector shows 1 wherever there is a damage (or notch). The SVM marks some extra region around the notch as damaged in addition to the actual notch location. However, the actual notch locations are completely covered damaged region specified by the output vector given by trained SVM classifier.



(a) Case 1 (b) Case 2 (c) Case 3 (d) Case 4

Figure 8: SVM output for four different test cases

4. Concluding remarks

An intelligent pipeline health monitoring technique is developed based on vibration, wavelet analysis and machine learning techniques, which can predict real time health condition of pipeline without hindering the operation. This SHM system involves the use of permanently integrated accelerometer on the outer surface of pipes. The model uses vibration response of pipe under moving PIG at constant velocity. The acceleration of midpoint of the pipe in vertical direction for this moving PIG is obtained by accelerometer. The response is then post processed and wavelet transform is performed on the acceleration response. If the pipe contains defects, the wavelet transform of acceleration response is shown to produce features or disturbance in the obtained wavelet coefficients. Further, support vector machine classifier in machine learning is used to predict these disturbances in the signal. The location of the defect can be identified by mapping the location of disturbance in wavelet coefficients to the coordinates of the pipe. This tells the exact location of defects in pipe. This SHM model requires some initial training for identifying defects. That can be done initially done by using some already corroded or defective pipe and performing pigging process inside it and take decomposed acceleration data and training the SVM model with it. This SHM concept can be used for bridges, Hyperloop (Ross (2016)), railway tracks, flyovers etc. However, there are some shortcomings of this SHM model. These are:

1. This model is unable to provide information about the severity of defects.
2. This model is unable to locate defects, which are present at the supports.
3. This model is dependent on the pigging process, and the health can be checked number of times the pigging is done.

Further work can be done with respect to the locating cracks in pipe in support region, bend region, pipes with non-homogeneous medium and varying load-moving velocity.

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