PREDICTION OF PCCP FAILURE BASED ON HYDROPHONE DETECTING

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Abstract: Prestressed Concrete Cylinder Pipe (PCCP) is a widely used water pipe all over the world. A major cause of PCCP failure is the internal wire break, which will emit acoustic signal. In this paper, a hydrophone-based PCCP real-time monitoring and failure-prediction system was proposed. By applying wavelet energy normalization analysis to signal feature extraction and Support Vector Machine (SVM) to signal recognition, a high prediction accuracy of 98.33% was achieved. The result showed that the hydrophone-based PCCP failure prediction system is much more effective and economic in real application compared with electromagnetic method and acoustic fiber optical.

Index terms: Wire break signal, acoustic, PCCP, hydrophone, wavelet analysis, SVM
Prestressed Concrete Cylinder Pipe (PCCP) is a large-diameter water pipe widely used in the world. Figure 1 illustrates the structure of PCCP, which primarily consists of five parts: the internal concrete core, a thin steel cylinder, external concrete, highly prestressed wires and external mortar layer [1][2]. Highly prestressed wire is winded on the circular surface of the concrete core by certain tensile stress. When the size of inner concrete core is fixed, the PCCP can bear different inner pressure and external loads by adjusting the prestressed wire diameter and screw pitch. Therefore, the PCCP’s bearing capacity mainly depends on the wire winded in it. Once the wire breaks due to artificial destruction or natural corrosion, the PCCP will face threat of rupture[3], which brings about not only great economic loss but also potential casualties [4][5][6]. Therefore the prediction of wire break in the PCCP is of great significance.

Conventionally PCCP is inspected manually via visual observation or sounding [7]. Recently new methods including Remote Field Eddy Current/Transformer Coupling (RFEC/TC) [8][9], Acoustic Fiber Optical (AFO), and hydrophone-based acoustic inspection are implemented in
the PCCP failure detection[10][11][12]. RFEC/TC is an off-line inspection method with rather low efficiency. In addition, the water in the PCCP has to be evacuated before the RFEC/TC inspection, which will consume large human and material resources. AFO is a real-time inspection method with quite high accuracy. However, AFO is only applicable to newly built pipelines since the interior surface of old PCCP is unavailable for AFO installation, and it is also expensive to lay fibers for AFO. Hydrophone-based inspection, an economic method compared with AFO, is not only accurate due to the high sensitivity of the hydrophone to acoustic signal but also convenient to install the hydrophone into the wells or holes that are reserved and present on the outside surface of the PCCP when constructed. Due to its distinct advantages, the hydrophone-based inspection has become a promising PCCP failure prediction method with great economic potential.

In this paper, a hydrophone-based PCCP failure prediction method is proposed and fully developed. Acoustic signal is sampled using a data acquisition device produced by the National Instruments (NI) Corporation [13]. Signal features are extracted via wavelet decomposition method. SVM is used to differentiate real wire break signal from other interfering signals. The accuracy is up to 98.33%.

II ACOUSTICAL SIGNAL PROPAGATION AND IDENTIFICATION

a. Acoustic signal propagation in PCCP

PCCP is a typical cylinder waveguide, in which three families of guided waves: longitudinal, torsional and flexural modes can propagate [14][15]. Longitudinal mode is axial-symmetric, and studies have shown that L(0,1) mode and α1 mode exist in water-filler pipes surrounded by any medium, whereas occurrence of α2 mode and α3 mode depends mainly on the surrounded medium of the pipe [16][17]. L(0,1) mode wave has been demonstrated to suffer strong attenuation due to leakage and scattering when encountering pipe joints and fittings [14-16]. The attenuation of flexural mode F(1,1) wave is also large if the mode phase velocity is greater than the longitudinal bulk velocities in the soil. Compared to L(0,1) and F(1,1)mode
wave, $\alpha$ mode wave experiences less attenuation due to its predominantly axial water-borne displacements. It is predicted that $\alpha$ mode has the most chance to be the dominant mode in the signal received over long propagation distance since $\alpha$ mode signal can propagate a long time without much energy loss into the soil or pipe wall [16]. Based on this prediction, the maximum spacing distance between sensors can be 260m within which acoustic signal still propagate[18].

b. Signal feature extraction

Wavelet analysis is a time-frequency analysis method developed by Morlet in the 1980th and it's especially suitable for instable signals[19][20]. Wavelet decomposition is widely used in signal feature extraction[21][22][23]. The results of wavelet decomposition are coefficients that include several details representing the high-frequency information and one approximation representing the low-frequency information[24]. The wavelet decomposition can be used for feature extraction by introducing the energy-mode concept. Suppose the sampling rate of signal is fs, if a j layer wavelet is used to decompose the signal, the signal can be decompose into j+i unequal frequency bands.

The jth layer wavelet coefficients can be expressed in $c_{d_k}$ ($k=1,2,3...j$), which represent the high frequency bands information, and $c_{a_j}$ which represent the low frequency energy information. The time domain energy of signal $x(t)$ can be reached by

$$\|x(t)\|^2 = \int_{-\infty}^{\infty} |x(t)|^2 dt$$

(1)

According to the Parseval energy integration theory, $x(t)$ in equation (1) can be connected with the wavelet transform coefficients $c_{d_k}$ and $c_{a_j}$, then we can get the following equation

$$E = \sum_{k=1}^{k=j} \left| c_{d_k} \right|^2 + \left| c_{a_j} \right|^2$$

(2)

According to the equation (2), the wavelet transform coefficients $c_{d_k}$ and $c_{a_j}$ have energy calculation function.

The feature vector extraction based on wavelet decomposition method can be accomplished according to the following steps:

First, decompose the signal by using wavelet analysis
Second, choose \( n \) frequency bands which are sensitive to energy and calculate each band’s energy and normalize each band. Suppose \( E_1, E_2, E_3, \ldots, E_j \) are the energy in accordance with \( c_{d_k} \) \((k=1,2,3,\ldots,j)\), and \( E_{j+1} \) is the energy in accordance with \( c_{a_j} \). Then we can get the following equations

\[
E_k = \sum_{m} |c_{d_k}^m|^2, (k=1,2,3,\ldots,j)
\]

(3)

\( m \) is the vector element number of \( c_{d_k} \)

\[
E_{j+1} = \sum_{m} |c_{a_j}^m|^2
\]

(4)

\[
E_k' = \frac{E_k}{\sum_{k=1}^{j} E_k}
\]

(5)

Third, choose the above normalized energy as the feature vector of the signal, that is

\[
E = [E_1', E_2', \ldots, E_{j+1}']
\]

(6)

c SVM method

SVM (Support Vector Machine) is a classification and regression statistical theory proposed by V. Vapnik in the AT&T Bell lab [25][26]. It’s widely used in signal recognition and classification [27][28][29][30]. The main concept of SVM lies in two notions: first, SVM is used under the condition of linear separable cases. For the linear inseparable cases, non-linear mapping algorithm is applied to transform the low-dimension input linear inseparable samples into high-dimension feature space, making it possible to use linear algorithm to analyze the non-linear characteristics of samples; second, when structural risk minimization theory is applied in constructing the optimal split hyperplane among feature space, the studying machine can get global optimization.

Given an input set \( \{x_i \in \mathbb{R}^n\}, i = 1,2,\ldots,l \) that compose of two types of modes. If \( x_i \) belongs to the first type, then \( y_i \) is 1, otherwise \( y_i \) is -1. Here \( y_i \subset [1,-1] \) is the SVM. Then the training set can be expressed by \( \{x_i, y_i\}, i = 1,2,3,\ldots,l \). The goal of SVM is to construct a target function which can separate the two modes to extremity based on the risk structure.
minimization theory. Under the linear separable condition, a hyperplane that is able to classify the samples can be expressed as below:

$$\omega \cdot x + b = 0$$  \hspace{1cm} (7)

Here “•” is dot product, $\omega$ is a normal vector of the hyperplane, b is the offset.

The hyperplane is reached by the following second-optimization

$$\min \phi(\omega) = \frac{1}{2} \| \omega \|^2$$  \hspace{1cm} (8)

which meets the constraint condition

$$y_i (\omega \cdot x + b) \geq 1, i = 1, 2, 3, ..., n.$$  \hspace{1cm} (9)

Under the condition of large feature number, the second-optimization problem can be changed into dual problem.

$$\max W(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j)$$  \hspace{1cm} (10)

$$\omega^* = \sum_{i=1}^{n} \alpha_i y_i x_i$$  \hspace{1cm} (11)

$$b^* = y_i - \omega^* \cdot x_i$$  \hspace{1cm} (12)

Which meets the following constraint condition

$$\sum_{i=1}^{n} y_i \alpha_i = 0, \alpha_i \geq 0, i = 1, 2, 3, ..., n$$  \hspace{1cm} (13)

Here the $\alpha = (\alpha_1, \alpha_2, ..., \alpha_n)$ is the Lagrange multiplier, $\omega^*$ is the normal vector of the hyperplane, $b^*$ is the offset of the hyperplane. KKT condition plays an important role in such problem solution and analysis, which is shown in the equation (14)

$$\alpha_i \{y_i (\omega \cdot x + b) - 1\} = 0, i = 1, 2, 3, ..., n$$  \hspace{1cm} (14)

According to equation (14), the samples with $\alpha_i = 0$ have no effect to the classification, while samples with $\alpha_i > 0$ are available in the classification process. The final classification function is:
\[ f(x) = \sum_{j=1}^{n} y_j \alpha_j (x \cdot x_j) + b^* \]  

(15)

III METHODOLOGIES

Since wire break is one of the primary causes of PCCP failure, precise prediction of PCCP failure depends on correct identification of PCCP wire break signal. In our approach, hydrophones were placed along the PCCP pipeline used to detect the wire break signal. However, in real monitoring system, interferential signals, such as the walking noise of human being along the pipe, external interference noise of tapping due to construction, repair, and the internal surging noise in the pipeline caused by air or unstable pressure inside the pipe, can easily disturb or mix with wire break signal since the SNR of the interfering signals itself is undesirable. Figure 2 shows the flow chart of the working process.

![Flow chart of the system working process](image)

Figure 2 Flow chart of the system working process

For the purpose of distinguishing the wire break signal from other interferential signals, frequency-based feature extraction is an option since different types of acoustical signals were dominated in different frequencies. Our research adopted wavelet analysis because wavelet
transform is good at scoping every detailed part of the original signal in both time-domain and frequency-domain. By decomposing a signal into several sub-frequency bands, the energy distribution in different bands can be utilized as eigenvectors of PCCP failure signal in feature extraction.

After feature extraction, SVM was applied to the linear inseparable interfering noise and wire break signal for classification. Since SVM is a structural-based risk minimization classification tool, cross-validation was used for parameters optimization, which will enhance the prediction accuracy tremendously. First, the original sample was divided into K average groups, with one group as testing set, while the other K-1 groups as training set each time for K times. The classification rates of the K models acquired are indicators of the property of the model.

IV EXPERIMENT

a. System introduction

Figure 3 Experiment system display

Figure 3 is a sketch of the experiment system. The diameter of PCCP in this experiment is 1.4m. Hydrophone is inserted into PCCP through the joint well in the pipelines with sealing
measures. In real PCCP, the joint wells along the pipeline can be used for hydrophone installation. The inner structure of hydrophone facilitates its high sensitivity to acoustic signal in water. In the experiment, sensitivity of the hydrophone to broadband (1Hz-100KHz) acoustic signal is -170dB. Since the aimed acoustic signal in this experiment are all within the human’s ear limitation (20Hz~20KHz), hydrophone is capable of receiving the desired signal. The signal acquisition device is USB 4431 developed by National Instrument Corporation, with a 24 bits resolution, maximum 102.4ksps simultaneous sampling rate and ±10V input range. The user interface of data acquisition is programmed using LabView. The sampling rate in this experiment is 44 kbps.

Besides the surging signal results from the instable pressure in the pipeline, and the wire break signal results from PCCP inner failure, we artificially added two interfering signals: human walking noise and hammer tapping on the pipe surface to mimic real PCCP environments.

b. Data processing

As mentioned in 1.2, \( \alpha \) mode is the dominant mode in water-filled pipeline with little energy loss into soil or scattering at joint or fitting. Therefore, acoustic signal received by hydrophone is mainly \( \alpha \) mode acoustic signal. Figure 4 shows the time-domain wave plot of the four signals, all of which can be considered as sudden event for the PCCP. The length of every signal is 6000 points.

![Figure 4 Time domain wave of four signals](image-url)
c. Feature extraction

Wavelet energy normalization method is applied to extract the feature from the four different signals. In the wavelet analysis process, the Daubechies6 wavelet is used as the wavelet basis. The signals are decomposed into 8 layers. Since the sampling rate of data collected is 44kbps, after the wavelet decomposition process, the signal is divided into 9 bands with each band characterized by a normalized energy. Figure 5 displays the four signals’ energy distributions in different bands.


Figure 5 Energy distribution of four signal base on wavelet decomposition

Figure 5 is the normalized energy distribution of the four different signals. The wire break signal has rather average distribution in each band. While the internal surging signal dominates in the low frequency band ca8(0~86HZ). The external tapping signal has concentrated energy in cd5(688~1375HZ) and cd6(344~688HZ). The walking signal dominates in the cd8(86~172HZ) and ca8(0~86HZ). From the energy distribution histogram, obvious and clear difference of the four signals can be quantified by a series feature vector which consists of 9 dimensions of elements. Since frequency is a fundamental characteristic
of acoustic signal, different types of signals may dominate in different frequencies, the
frequency-based feature extraction method is appropriate for the four acoustic signals.
d. SVM identification

In the classification process, a total number of 120 sets of data are analyzed. Set 1 to 30 are
wire break signals, sample 31 to 60 are internal surging signals and sample 61 to 90 are
external tapping signals and sample 91 to 120 are walking signals. Before the SVM
classification process, feature extraction of 120 samples is conducted based on wavelet energy
normalization method. After the feature extraction, each sample has 9 element feature vector
representing energy intensity in 9 different frequency bands. Figure 6 displays the energy
distribution of 120 samples in different frequency bands. From the figure, we can see
db3,db5,db6 and ca8 have quite good classification.
In the application of SVM, cross validation is conducted before the final classification. At first, a large step SVM parameter selection is conducted. The parameter $c$ and $g$ change...
from $2^{-10}$ to $2^{10}$ with a step of 0.5. The predicted accuracy is shown in Figure 7. The approximate range of $c$ and $g$ is achieved, where $c$ is 32 and $g$ is 32. The accuracy is 96.25%. Then a small step parameter selection is carried out. The parameter $c$ and $g$ change from $2^{-10}$ to $2^{10}$ with a step of 0.1. The result is shown in Figure 8. The best $c$ is 24.2515 and best $g$ is 73.5167. The accuracy is 97.5%.

By comparison of the results shown in Figure 7 and Figure 8, the accuracy of small step is higher than that of large step. Therefore, a final optimal parameter selection is accomplished by small step. The best $c$ is 24.2515 and the best $g$ is 73.5167.

After the determination of best $c$ and $g$, the next step is to apply the best $c$ and $g$ in the SVM model. Of the totally sampled 120 sets of data, each ten samples are chosen from the four different types as training samples. Then a classification model is built based on the training samples. A total of 120 samples are utilized to test the accuracy of the model built based on SVM method. A final accuracy of 98.33% (118/120) is shown in Figure 9. We can see that there are one internal surging signal and one walking noise signal predicted wrong. All the wire break samples are predicted right.
V CONCLUSIONS

(1) An efficient and economic PCCP failure prediction system is proposed. Hydrophone is used as the sensor due to its low cost, easy installation, and high sensitivity to acoustic signal in the PCCP. The result shows that the hydrophone is proper for PCCP failure prediction.

(2) The wavelet method is proved to be appropriate for the feature extraction of the wire break signal due to its fundamental frequency characteristics. The features of wire break signal and other three signals including human walking noise, internal surging noise and external tapping noise, show very distinct differences.

(3) SVM is proven to be an efficient and accurate method for type classification. By selecting appropriate parameters for the SVM method, high classification precision can be achieved. Wire break signal can be easily identified with reduced false prediction.

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