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Research of Filter Processing Method of Pipeline Leak Detection Signal Based on MEMS-IMU

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Abstract

In view of the acceleration and angular velocity data obtained by MEMS-IMU, noise will inevitably be introduced, which will cause interference to the pipeline leak detection using the sensor. The pipeline leak detection experiment is carried out through the strap-down method of the sensor and the carrier, and then used median filtering method and wavelet threshold denoising method process and analyze the acceleration experimental data collected by the sensor. The experimental results of the two methods are compared, which shows that the wavelet threshold denoising effect is more ideal.

Keywords

MEMS-IMU; pipeline leak detection; wavelet threshold denoising.

1. Introduction

Pipelines are one of the important means and ways of oil, gas, and water transportation. Regular inspections of pipeline safety conditions to ensure the normal operation of the pipeline system are of great significance to industrial production and daily life. Leakage is one of the main faults in the operation of the pipeline system. The pipeline leakage will cause the loss of resources and the pollution of the surrounding environment. The timely detection of the pipeline leakage can prevent the situation from continuing to deteriorate [1].

There are many methods of pipeline leakage detection, which can be roughly divided into two types: pipeline external detection and pipeline internal detection [2]. The main methods of external detection of pipelines are: optical fiber method, capacitance method, biosensor method, optical camera method, characteristic impedance method and acoustic measurement method, etc [3]. With the development of intelligent technology, the use of robots equipped with multiple sensors to detect inside pipelines has become one of the commonly used detection methods [4].

With the development of MEMS (Micro Electrical Mechanical System) technology, this technology can be combined with IMU (Inertial Measurement Units). MEMS-IMU has the advantages of small size and low cost, and has been widely used as a sensor mounted on a robot [5-7]. The common MEMS-IMU on the market integrates a three-axis accelerometer, a gyroscope, and a magnetometer, which can measure the acceleration, angular velocity, and magnetic field strength and direction of the carrier in three mutually perpendicular directions. In the straight fluid pipeline, the suspension equipped with MEMS-IMU is used for detection, and the acceleration and angular velocity data measured by the sensor can be processed to infer whether there is leakage according to the change [8].

2. MEMS-IMU data filtering and noise reduction algorithm

Because MEMS-IMU integrates accelerometer, gyroscope and magnetometer, it can measure the three-axis acceleration, angular velocity and magnetic field strength of the moving carrier. However, since the measurement process will inevitably be interfered by noise, it is difficult to obtain more accurate carrier movement information directly using these noisy data, and it is

difficult to distinguish whether the pipeline has leaked. Therefore, it needs to be filtered and noise-reduced.

Since acceleration data and angular velocity data are generally non-linear and non-stationary when the carrier is moving, in order to better distinguish some of the sudden changes in these data, the methods of filtering them include median filtering [9], wavelet threshold denoising [10], etc.

2.1. Median filtering

Median filtering is a non-linear filtering method, which is based on sorting statistical theory and does not require statistical characteristics of data, is convenient to use and can effectively suppress noise. The basic principle of median filtering is to replace the value of a point in the data with the median value of each point in a neighborhood of the point to make the value closer to the true value, thereby eliminating isolated noise points. A one-dimensional median filter is usually a window containing an odd number of data points. After median filtering, the value of the original point is divided by the median value of all values in the odd point length window centered on that point. replace.

The process is shown in the diagram below:

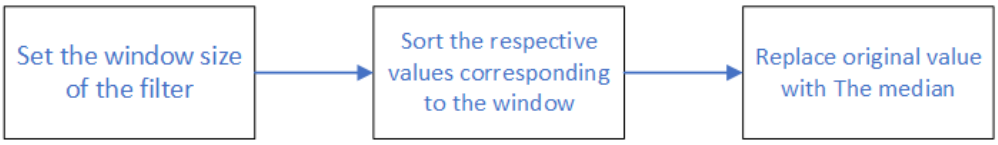


Fig. 1 Block diagram of one-dimensional median filtering

Suppose a one-dimensional sequence $x_1,x_2,\ldots,x_n$, Use a window with an odd length of p to perform median filtering on it, the median value of its window is m=(p-1)/2+1. If x_i (**m≤i≤n-m+1**) Is an element in the sequence, then median filtering is performed on the sequence, which can be expressed as:

$$x_i = median\{x_{i-v+1},\ldots,x_i,\ldots,x_{i+v-1}\} \tag{1}$$

When the median filter is used to reduce the noise of the data, the size of the window is the main factor that affects the filtering effect. The appropriate window size should be selected according to the characteristics of the object data.

2.2. Wavelet threshold denoising

2.2.1. Principle of Wavelet Threshold Denoising

The meaning of wavelet transform is to shift a certain function called basic wavelet to the displacement τ, and then at different scales α, and take the signal to be analyzed *X(t)* as the inner product, that is:

$$WT_x(\alpha,\tau) = \frac{1}{\sqrt{\alpha}}\int_{-\infty}^{+\infty} x(t)\Psi^*(\frac{t-\tau}{\alpha})dt \tag{2}$$

Wavelet transform is a local transformation of the signal in the time-frequency domain, and multi-scale analysis of the signal through operations such as scaling and translation [11]. The algorithm decomposes the signal into approximate components and detailed components at each scale. The approximate component represents the high-scale of the signal, that is, low-frequency information; the detail component represents the low-scale of the signal, that is, the high-frequency information. For the signal with noise, the main energy of the noise component is concentrated in the detail component of the wavelet decomposition. Through wavelet transform, information can be extracted from the signal effectively.

Wavelet threshold denoising is based on the theory of wavelet analysis. The signal is wavelet decomposed, and then the noise component is filtered through threshold processing, and then

wavelet reconstruction is performed according to the threshold processing denoised wavelet coefficients to obtain the denoised signal .

The essence of wavelet threshold denoising is the process of suppressing the useless part of the signal and enhancing the useful part.

The steps of wavelet threshold denoising are: (i) decomposition process, that is, selecting a wavelet to decompose the signal with n-layer wavelet; (ii) threshold processing process, that is, thresholding the decomposition coefficients of each layer to obtain estimated wavelet coefficients ; (Iii) Reconstruction process, perform wavelet reconstruction according to the wavelet coefficients after denoising, and obtain the signal after denoising. The process diagram is shown in the figure below:

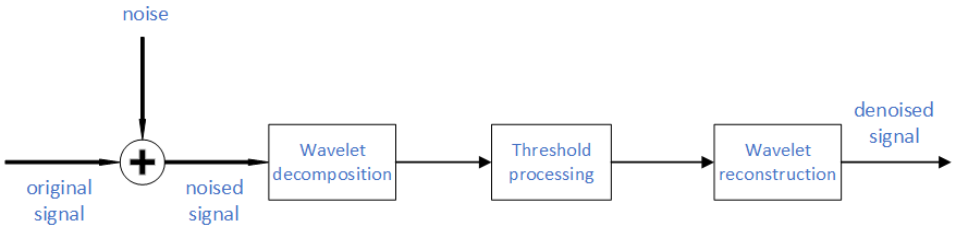


Fig. 2 Block diagram of wavelet threshold denoising

The choice of wavelet basis function, the choice of decomposition layers, the choice of threshold and the choice of threshold function are all the main factors that affect the effect of wavelet threshold denoising.

2.2.2. Selection of wavelet basis function

Appropriate wavelet basis function has an important influence on the decomposition effect of the signal [12]. When choosing the wavelet basis function, the following factors should be considered: symmetry, similarity, regularity, vanishing moment, and support length. For one-dimensional signals, db wavelet or symN wavelet is usually selected as the wavelet base.

2.2.3. Selection of the number of decomposition layers

In the wavelet decomposition of the signal, the larger the number of decomposed layers, the more obvious the different characteristics of noise and signal performance, and the more conducive to the separation of the two. However, the greater the number of decomposed layers, the more the reconstructed signal will be distorted. The larger the value is, it will have a worse effect on the denoising effect of the signal to a certain extent. Therefore, in the actual use of wavelet decomposition, the influence of the number of decomposition layers should be considered, and the appropriate number of decomposition layers should be selected.

Generally, the frequency range of wavelet decomposition is related to the sampling frequency Fs. If N-layer decomposition is performed, the size of each frequency band is (Fs/2)/2^N.

2.2.4. Selection of threshold

In the wavelet domain, the coefficient corresponding to the effective signal is large, and the coefficient corresponding to the noise is small. The coefficient of noise in the wavelet domain still satisfies the Gaussian distribution.

Threshold selection rules are model-based y = f(t) + e， e is Gaussian white noise N(0,1). 因 Therefore, the wavelet coefficients or the original signal can be used to evaluate the threshold that can eliminate noise in the wavelet domain.

The current common threshold selection methods include: unbiased risk estimation threshold, fixed threshold, heuristic threshold, maximum and minimum threshold, etc.

Unbiased risk estimation threshold

The unbiased risk estimation threshold is an adaptive threshold selection method based on Stein's unbiased likelihood estimation principle. This method first finds the risk value

corresponding to each threshold, and then selects the threshold corresponding to the minimum risk value.

The specific algorithm is:

First, take the absolute value of the wavelet coefficient vector of length n and arrange them in ascending order, and then take the square of each element to obtain the new vector N to be estimated.

For each element of the estimated vector, calculate its risk vector, as shown in the following formula:

$$Risk(k)=\frac{n-2k+\sum_{i=1}^{k}N(i)+(n-k)\cdot N(k)}{n} \tag{3}$$

If the subscript corresponding to the smallest risk vector is kmin， the threshold is:

$$Thr=\sqrt{Risk(k_{\min})} \tag{4}$$

Fixed threshold

The fixed threshold is obtained by the following formula:

$$Thr=\sigma\sqrt{2\log N} \tag{5}$$

In the formula, σ is the noise standard deviation， N is the signal length.

Heuristic threshold

The heuristic threshold rule is a compromise form of unbiased risk estimation threshold and fixed threshold. When the signal-to-noise ratio is large, the unbiased likelihood estimation rule is adopted, and when the signal-to-noise ratio is small, the fixed threshold rule is adopted.

Maximum minimum threshold

The maximum minimum threshold is also a form of fixed threshold selection. Since the denoising signal can be assumed to be the estimator of the unknown regression function, the minimax estimator is the amount that achieves the smallest mean square error under the worst conditions, which can be expressed as:

$$Thr=\begin{cases}\sigma(0.396+0.1827)\log_2 N, & N\geq 32\\ 0, & N<32\end{cases} \tag{6}$$

2.2.5. Selection of threshold function

After determining the threshold threshold of Gaussian white noise in the wavelet domain, it is necessary to filter the wavelet coefficients containing noise coefficients with a threshold function to remove the Gaussian noise coefficients. Commonly used threshold functions include hard threshold functions and soft threshold functions.

Hard threshold function

The characteristic of the hard threshold function is that when the absolute value of the wavelet coefficient is greater than a given threshold, the wavelet coefficient remains unchanged; when it is less than the threshold, the wavelet coefficient is set to zero. Its expression is as follows:

$$\overline{w_{j,k}}=\begin{cases}w_{j,k}, & |w_{j,k}|\geq Thr\\ 0 & w_{j,k}<Thr\end{cases} \tag{7}$$

In the formula, *Thr* is the threshold, $w_{j,k}$ is the wavelet coefficient before denoising, $\overline{w_{j,k}}$ is the wavelet coefficient after denoising.

The function diagram is as follows:

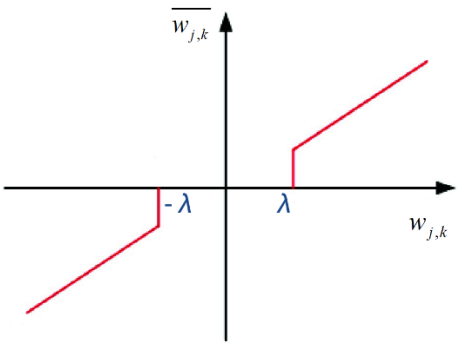


Fig. 3 Graph of hard threshold function

Soft threshold function

The characteristic of the soft threshold function is that when the absolute value of the wavelet coefficient is greater than a given threshold, the wavelet coefficient is subtracted from the threshold; when it is less than the threshold, the wavelet coefficient is set to zero. Its expression is as follows:

$$\overline{w_{j,k}} = \begin{cases} \left[\operatorname{sgn}(w_{j,k})\right](\left|w_{j,k}\right| - Thr), & \left|w_{j,k}\right| \geq Thr \\ 0 & w_{j,k} < Thr \end{cases} \tag{8}$$

In the formula， sgn() is the symbolic function， that is:

$$\operatorname{sgn}(n) = \begin{cases} 1, & n > 0 \\ -1, & n < 0 \end{cases} \tag{9}$$

The function image is as follows:

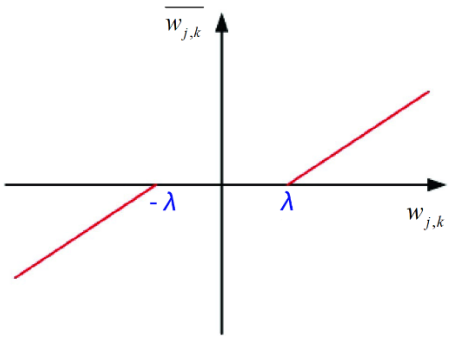
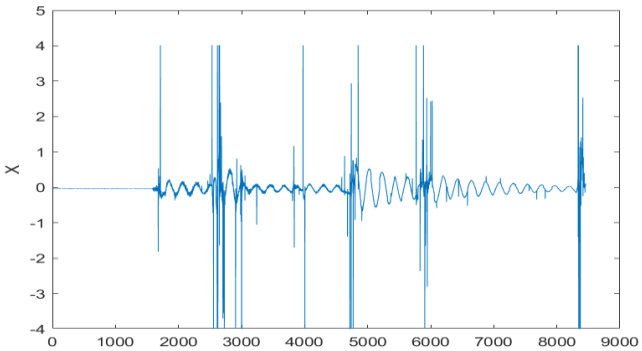


Fig. 4 Graph of soft threshold function

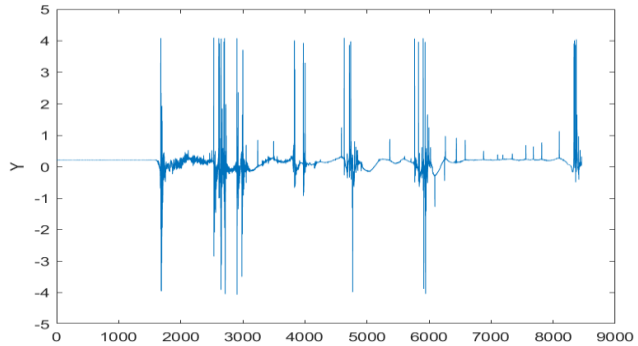
3. Experiment and result analysis

3.1. Sensor experimental data

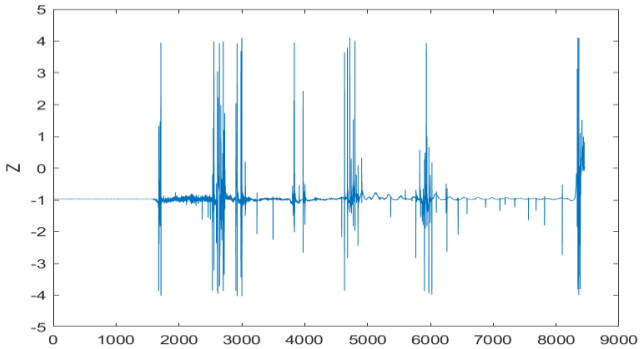
MEMS-IMU uses Bluetooth to communicate with PC, and the sampling rate is 400 Hz. Bind it with the carrier and put it into a 110 mm diameter pipeline with a 50 mm leak hole on the top to run the entire pipeline. The entire pipeline includes 4 straight pipes and 3 elbows. The sensor placement method is: Y axis is the forward direction, X and Y axes are on the same horizontal plane, and Z axis is perpendicular to the horizontal plane and upward. The acceleration data measured by the sensor is shown in the figure below:



(a)X-axis



(b)Y-axis



(c)Z-axis

Fig. 5 Graph of MEMS-IMU acceleration data

It can be seen from the figure that the acceleration data measured by the sensor includes the initial horizontal segment and the six extreme value concentrated intervals. Because the sensor was placed in the pipeline before the experiment, the front end was close to a horizontal straight line. The start of the movement will produce jitter, and then through three elbows and a leak hole, the sensor data detects fluctuations. Finally, the sensor fell from the exit, producing a steep mutation.

In addition, since there are more extreme values on the Y axis than the other two axes, further filtering of the sensor Y axis data is considered. The following uses median filtering and wavelet threshold denoising method to process it.

3.1.1. Results of median filtering

Perform one-dimensional median filtering on the sensor angular velocity X-axis data, and the results are shown in the following figure:

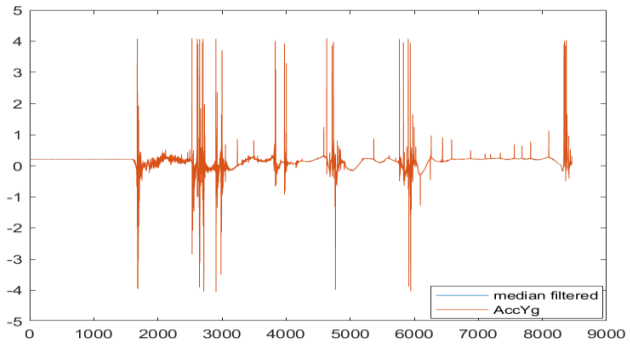


Fig. 6 Graph of median filtered Y-axis data

The figure shows that the difference in Y-axis acceleration data of the sensor before and after the median filter is not obvious, and the characteristics of the Y-axis acceleration data cannot be well distinguished from it.

3.1.2. Results of wavelet threshold denoising

The soft threshold function is used to denoise the sensor X-axis data with wavelet threshold, and the number of decomposition layers is 5 layers. After decomposition, threshold processing and reconstruction, the result is shown in the figure below:

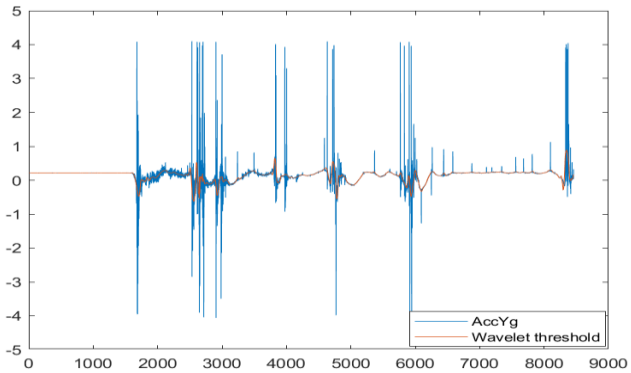


Fig. 7 Graph of wavelet threshold denoised Y-axis data

It can be seen from the figure that after wavelet threshold denoising, most of the Y-axis acceleration noise has been filtered out, and the sudden change trend is well preserved.

4. Summary

Based on the data characteristics of MEMS-IMU, this paper uses median filtering and wavelet threshold denoising methods to process the sensor data. Experiments show that compared with the median filtering method, the wavelet threshold denoising algorithm can not only filter the noise of the data well, but also retain the original characteristics of the data. The wavelet threshold denoising algorithm is used in MEMS-IMU. It has advantages in data processing.

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