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Application of Multi-sensor Signal Processing in Testing Courses

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Abstract: For illustrating the application of test technology theory in engineering practice, a multi-sensor data fusion fault diagnosis method is proposed, which uses data from flow, pressure and acceleration sensors and combines with deep learning to fuse multiple signals. Firstly, different failure modes of a certain device are simulated, and the original time series of different sensors are structured using long short-term memory. Then, the data processed by different fault modes are input into the convolutional neural network for recognition. Finally, the output of multiple networks is fused to achieve more comprehensive and accurate fault detection. This case illustrates the function of testing basic theory in solving practical engineering and the method of practical application.

1. Introduction

With the advent of Industry 4.0, industrial systems tend to be digital and intelligent. Industrial system monitoring aims to ensure the reliability, efficiency, economy and safety of industrial systems through the use of multi-sensor technology, deep learning methods. Among them, multi-sensor technology is widely used in industrial automation and control systems. Because multi-sensor signals can provide more sources of fault information, industrial monitoring using multi-sensor signals can obtain more accurate and reliable results than using only single sensor signals. Wang et al. propose a graph Transformer called DVGT former for predicting remaining useful life, which adequately learns potential degradation patterns by capturing complex correlations in multi-sensor signals [1]. Liang et al. proposed a method based on multi-sensor signal multi-scale correlation analysis for fault detection of high-speed and high-power diesel engines under complex and variable working conditions [2]. Guo et al. used sample components from multiple current sensors to construct cyclic spectral covariance matrix (ICSCM) to detect rotating machinery faults under different working conditions, and realized multi-sensor data fusion for rotating machinery fault detection [3]. Wang et al. proposed and established an action recognition model architecture based on ResNet+LSTM+D-S evidence theory [4]. In view of the application of motion recognition in industry, the characteristics of different data are fully considered to maximize the multi-sensor data value.

To sum up, multi-sensor signal processing is an important application in modern engineering technology, and its core lies in the use of multiple sensors to collect data and process these data through algorithms to achieve more accurate and reliable information fusion and decision support. In addition, multi-sensor data fusion can extract richer features and patterns, contributing to more efficient fault detection. By considering the correlations and interactions between the measurements of different sensors, hidden relationships can be discovered to derive more information-rich features for the fault diagnosis algorithm or model [5]. In the above applications, although samples under all conditions are not required, there are certain requirements for fault data. Similarly, due to complex temporal and spatial dependencies in multi-sensor signals, fusing multi-sensor information to build accurate and robust deep learn-based fault diagnosis models remains a challenge. In this paper, several data fusion methods are studied, and a robust model with strong generalization ability is designed.

2. Multi-sensor Signals Processing

2.1 Test System and Signal Acquisition

In this study, we consider data derived from flow, pressure and acceleration sensors installed on specific equipment. Because the mechanical equipment is often in a complex, noisy, and closed operating environment, the collected data tends to contain more noise, as well as the sampling rates and amplitudes of these sensors vary. In order to reduce the effect of noise as much as possible, wavelet noise reduction technology could be used to process the signal. In addition, this study uses a long short-term memory network (LSTM) to synchronize data from different time series to ensure that all data reflect uniform point-in-time information since the data collected by different sensors are often not synchronized in time. Before input to the LSTM network, the data must be standardized to improve the processing performance of the model. After data synchronization, the signal is processed into a two-dimensional image through data dimension conversion and input into the convolutional neural network (CNN) for fault identification and analysis. At the decision-making level, this study integrates information from various sensors, each model makes its own judgment, and then synthesizes these judgments through a set of decision strategies to output the final decision result. The flowchart of multi-sensor signals processing is shown in Fig 1.

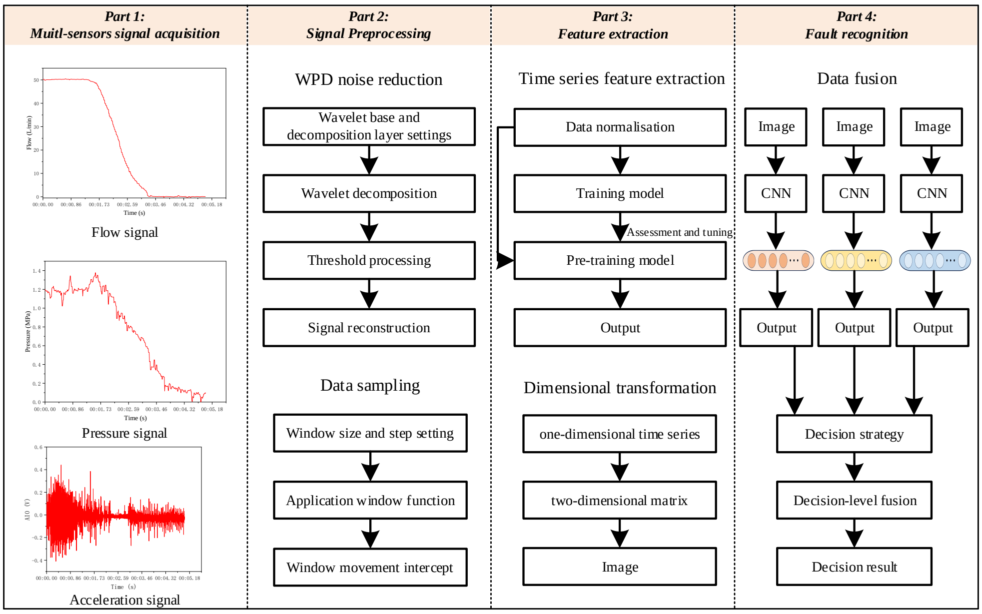

Figure 1: The flowchart of multi-sensor signals processing.

2.2 Processing and Analysis of Signal

Wavelet denoising is a signal denoising method that is particularly suitable for dealing with non-stationary signals, by splitting the signal into different frequency groups and screening for noise removal. During the signal sampling process, the original signal x(t) is decomposed into different frequency levels by discrete wavelet transform (DWT), such as formula 1.

$$W_{j,k} = \sum_t x(t) \cdot \psi_{j,k}(t) \tag{1}$$

Where $\psi_{j,k}(t)$ is the wavelet function after scaling and shifting, j is the level of decomposition, k is the location of the layer. After the wavelet transform, the wavelet coefficients of each layer $W_{j,k}$ are treated with soft thresholds (as in formula 2) to remove noise.

$$\widehat{W}_{j,k} = sign(W_{j,k}) \cdot \max(0, |W_{j,k}| - \lambda) \tag{2}$$

Where λ is threshold value. It needs to be selected based on signal characteristics and noise levels. Inverse discrete wavelet transform (IDWT) is performed on the wavelet coefficients $\widehat{W}_{j,k}$ treated with threshold values (as shown in formula 3) to reconstruct the signal.

$$\hat{x}(t) = \sum_{j,k} \widehat{W}_{j,k} \cdot \psi_{j,k}(t) \tag{3}$$

The signal after noise reduction $\hat{x}(t)$ is obtained through the above process. Fig. 2 shows the comparison between the original signal and the signal after noise reduction.

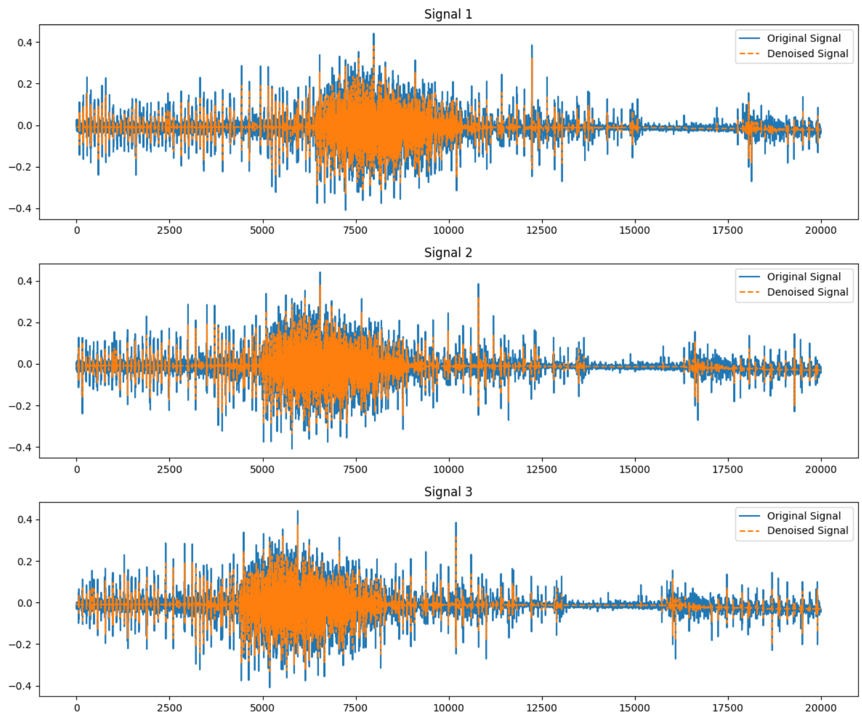

Figure 2: Original signal and noise reduction signal.

Synchronization of multi-sensor data signals refers to a method during data processing that aims to achieve the time alignment of data streams from different sensors. This technology ensures that all sensor output data reflects the same time point or event, thereby improving the accuracy and efficiency of data analysis and subsequent processing. Data synchronization can be achieved through both hardware and software. The latter often depends on algorithms to adjust data with different timestamps to ensure time consistency. In this study, LSTM is used for time alignment of multi-sensor data. In the field of time series data processing, LSTM shows significant advantages in processing series data with complex temporal properties due to its efficient processing and memory of long-term dependencies. During the signal synchronization process, the de-noised data must be standardized (see Formula 4) before it can be effectively input into the LSTM model for further analysis.

$$x_{normalisation} = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{4}$$

For missing data points, it can fill them with polynomial interpolation methods (as in Formula 5).

$$P(t) = a_0 + a_1 x + a_2 x^2 + \cdots + a_n x^n \tag{5}$$

If we have n+1 data points (x_0, y_0), (x_1, y_1), …, (x_n, y_n), coefficient a_0, a_1, …, a_n are composed of interpolation conditions $P(x_i)=y_i$ (i=0, 1, …, n). The data after noise reduction, standardization and interpolation are input into the LSTM model for time feature extraction and alignment (as shown in formula 6).

$$h_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) * tanh(f_t * C_{t-1} + i_t * tanh(W_C \cdot [h_{t-1}, x_t] + b_C)) \tag{6}$$

In time step t, the input is x_t. The hidden state of the previous time step is h_{t-1}, the cell state of the previous time step is C_{t-1}. The forgetting gate f_t determines how much of the previous cell state will be retained, and the input gate i_t determines how much of the new information will be stored in the cell state. The output gate i_t determines which part of the current cell will be output to the current hidden state h_t. b represents the offset term, and * represents the element-by-element multiplication. Formula 6 simplifies the actual operation. In the calculation process, LSTM also needs to learn and adjust various parameters, as well as the application of activation functions, to ensure that the model can effectively process and remember long-term and short-term messages.

Data dimension transformation is a data processing method that is widely used to analyze time series data using convolutional neural networks. This method can help to reveal the patterns and features in time series data and improve the accuracy of time series classification. There are two main methods to convert one-dimensional time series data into two-dimensional images. The first is time-frequency analysis method, which takes time series as signal analysis object and uses time-frequency analysis method to analyze and solve its time-frequency graph, mainly including short-time Fourier transform, wavelet transform, Hilbert-Yellow transform and so on. The second is the image coding method, which encodes the time series data by other methods, and then maps the encoded data to the two-dimensional image. There are mainly Markov transition field, recursive graph, graph difference field, relative position matrix, Gram Angle field and so on. In this paper, Markov transition field is used to construct a state transition probability matrix based on time series data. First, the time series data is discretized into a finite state. Set time series X= {x_1, x_2, …, x_n}, the discretized sequence is S= {s_1, s_2, …, s_n}. s_i is the discrete state of x_i. Then calculate the state transition matrix P:

$$P_{ij} = \frac{fre(s_k = \alpha \; and \; s_{k+1} = \beta)}{fre(s_k = \alpha)} \tag{7}$$

where P_{ij} represents the probability of moving from state α to state β. This is achieved by calculating the frequency of the transition from state α to state β, and then dividing by the total frequency of the occurrence of state α. Finally, the state sequence S and transition probability matrix P are used to construct the Markov transition field (MTF) matrix M. For each element in the Markov transition field (MTF) M_{kl}, its value is determined by the transfer probabilities of S_k and S_l (Formula 8):

$$M_{kl} = P_{sksl} \tag{8}$$

where M is an $n \times n$ matrix (See Fig.3),n is the length of the time series, and M_{kl} represents the probability of the transition from the state at position k to the state at position *l* in the time series.

Multi-sensor data fusion can be divided into data level fusion, feature level fusion and decision level fusion. Data-level fusion directly merges data from different sensors at the data level; feature-level fusion merges features extracted from each sensor; decision-level fusion merges information from each sensor at the decision level, and fuses the independent judgment of each sensor to make decision results through decision-making strategies.

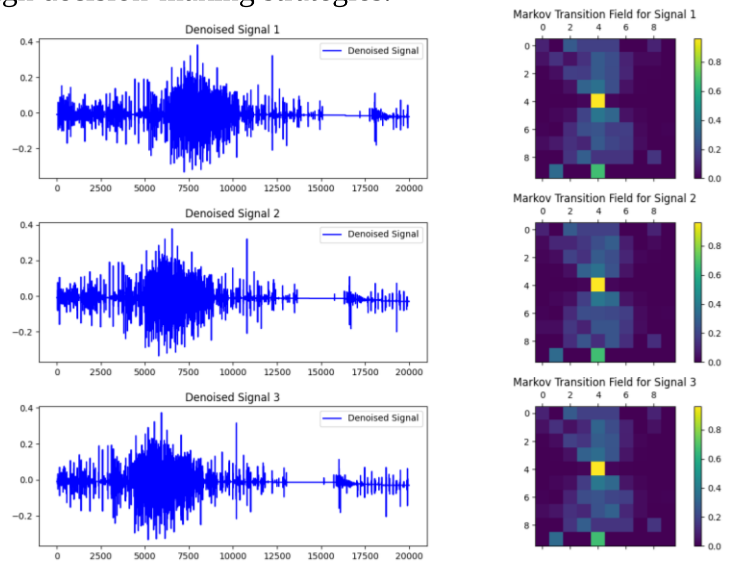

Figure 3: Markov transition field.

Dempster-Shafer evidence theory (D-S) is a mathematical framework for reasoning and decision making under conditions of uncertainty. By expressing evidence as a probability distribution, it can deal with incomplete, conflicting and uncertain information. The core of D-S theory can be simplified by the following two main formulas:

$$Bel(A) = \sum_{B \subseteq A} m(B) \tag{9}$$

Where the trust function Bel(A) is used to quantify the extent to which the evidence supports set A, and m (B) is a basic probability assignment, representing the probability directly assigned to set B. When there are two independent sources of evidence, m1 and m2, about the same proposition, their trust functions can be merged by Dempster's combination rule (formula 9):

$$m_{12}(A) = \frac{1}{1-K} \sum_{B \cap C = A} m1(B) \cdot m2(C) \tag{10}$$

K is a conflict factor that measures inconsistencies between two sets of evidence sources B and C, expressed as:

$$K = \sum_{B \cap C = \emptyset} m_1(B) \cdot m_2(C) \tag{11}$$

This combination rule is used to update trust, combine information from different sources, and finally provide a comprehensive trust assessment that considers all available evidence.

In summary, multi-sensor signals have become a very critical factor in industrial fault monitoring, and integrating data from multiple sensors makes the system more robust and reliable in distinguishing between different fault classes and accurately classifying faults. Multi-source data can be obtained by sensors in real time. After processing and analysis, information about the fault source can be mined from the data. The process of signal processing includes the steps of wavelet denoising, interpolation, LSTM signal synchronization, dimension conversion based on Markov transition field and decision fusion. Multi-sensor data fusion improves fault classification performance by reducing noise effects and minimizing false positives through wavelet noise reduction. By using standardized signal processing and polynomial interpolation methods to fill in the missing data, we further improve the consistency and integrity of data processing. Then, the non-stationary signals are effectively processed by LSTM. The key time features are extracted from the complex time series data, and the time alignment of multi-sensor signals is realized. In addition, the data dimension conversion is introduced to convert one-dimensional time series data into two-dimensional images, thus helping us to extract temporal and spatial features from multi-sensor signals. This step significantly improves the ability to recognize data patterns, and maximizes the use of each signal to help us achieve more accurate and robust fault detection. Finally, in terms of multi-sensor data fusion, we discuss the strategies of data-level fusion, feature-level fusion and decision-level fusion, and use D-S theory to deal with the uncertainty and conflict of evidence to ensure the accuracy and reliability of the fusion process.

3. Conclusion

In this study, we deeply explore the application of multi-sensor signal processing in industrial fault monitoring, and confirm its important value in improving the accuracy of fault detection and system reliability. By integrating data from multiple types of sensors, such as flow, pressure and acceleration, we are not only able to capture a more complete picture of system operation, but also effectively identify and predict potential failures through advanced signal processing technology. This study emphasizes the practical significance of implementing multi-sensor data fusion in industrial system monitoring, and provides scientific basis and technical support for intelligent manufacturing under the background of Industry 4.0. Future research can be deepened in the following aspects:

(1) Algorithm optimization: Optimize data processing and analysis algorithms to adapt to diverse industrial environments and more complex failure modes.

(2) Data fusion method: It is not limited to a single data fusion, and a variety of data fusion methods can be used for optimization.

(3) Application: Explore the application of the technologies and methods in this study to other fields, such as automotive, medical and robotics, and use more kinds of data to achieve technology integration and innovation.

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