INTELLIGENT IDENTIFICATION METHOD FOR STICK-SLIP VIBRATION BASED ON DOWNHOLE DATA

by

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The stick-slip vibration problem in downhole drilling has become prominent, seriously affecting production efficiency and equipment safety. Therefore, this study proposes an intelligent stick-slip vibration recognition method based on downhole data. Utilizing downhole data aims to address the issues of strong subjectivity and low accuracy in traditional stick-slip vibration monitoring. First, time-domain preprocessing of the raw vibration signals is conducted, including outlier removal, and noise reduction filtering. Then, time-frequency analysis is performed using Fourier Transform to extract deep features from the data. A stick-slip vibration classification evaluation system is constructed using the stick-slip index method. Finally, an intelligent stick-slip vibration recognition model is established based on the long short-term memory algorithm, integrating frequency-domain and time-domain features as input features to achieve accurate monitoring of stick-slip vibration levels. Measured data from an oilfield in China were selected for comparison. The results show that the model achieves an accuracy of 85.8%, effectively identifying stick-slip vibrations and demonstrating good application potential in the field.

Key words: *drill string vibration, machine learning, Fourier transform, vibration monitoring*

Introduction

As the oil and gas drilling industry advances toward high difficulty well types such as deep wells, ultra-deep wells, and extended reach wells, the complexity of operations increases, along with greater challenges and higher costs compared to conventional drilling [1]. Consequently, higher demands are placed on the safety and efficiency of drilling operations. The drill string is subjected to complex dynamic loads, causing vibrations to occur constantly. Drill string vibrations not only reduce drilling efficiency but also significantly increase operational risks and costs. Therefore, promptly and accurately identifying drill string vibrations is crucial for safe and efficient drilling operations [2].

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With the development of downhole measurement tool technology, it has become feasible to use downhole drilling data and data-driven models to monitor drill strings. Hegde *et al.* [3] proposed a new method that classifies vibration-based metrics using drilling operation parameters, developing a stick-slip index (ISS). Baumgartner *et al.* [4] developed a simple dynamic model to study high frequency acceleration measurement outputs under rotary and stick-slip vibrations. Tang *et al.* [5] conducted time-domain and frequency-domain analyses on near-bit stick-slip data, extracted key feature vectors. Chen *et al.* [6] proposed a stick-slip vibration risk assessment method based on factor analysis (FA) and support vector machine (SVM) to evaluate the severity of drill string stick-slip vibrations.

This study aims to address the issues of high subjectivity and low accuracy in traditional stick-slip vibration monitoring that relies on surface parameters by utilizing time-frequency analysis algorithms combined with intelligent recognition models. First, a time-frequency analysis algorithm is used to reveal the dynamic response patterns between triaxial acceleration time-frequency signals and drill bit vibration states, and based on these patterns, a stick-slip vibration classification evaluation index is constructed.

Time frequency processing method for high frequency dynamic signals

Time domain signal preprocessing

Raw vibration signals acquired during data collection often contain various types of noise. Additionally, the non-linearity of measurement sensors can significantly impact the final results. To improve the reliability of vibration signal analysis, preprocessing is required before the analysis. Preprocessing tasks mainly include pre-filtering, zero-mean normalization, anomaly removal, and trend elimination. These tasks are not all mandatory, and in practical applications, different methods can be selected based on the actual measurement signals.

When signals need to be smoothed or unwanted frequency components need to be suppressed, filtering methods can be used. To avoid frequency aliasing caused by not meeting the sampling theorem, a low pass filter can be employed to limit the bandwidth of the raw signal while also reducing high frequency noise.

Anomaly removal. During signal collection, anomalies may occur due to unpredictable external factors or temporary instrument failures. These anomalies can significantly affect the analysis results, particularly for high frequency components, and must be removed. In this study, an anomaly removal method based on standard deviation is employed. This method uses the criterion of whether data values exceed three times the standard deviation. If the signal's zero-mean value falls within the confidence interval, its confidence level can reach 99.74%. Anomalies are removed by averaging the values of the two adjacent points.

Noise reduction. High frequency vibration data often contains substantial noise. This noise not only obscures the real information in the signal but can also lead to misjudgments during subsequent data analysis and fault diagnosis. Therefore, denoising is required for raw acceleration data. In this study, wavelet denoising is employed. Using three levels of wavelet decomposition and reconstruction, the db6 wavelet function is chosen with a threshold set to 0.5. A comparison of data before and after wavelet denoising is shown in fig. 1.

Time-frequency analysis method based on Fourier transform

The non-stationarity of near-bit signals leads to significant variations in their spectral characteristics, necessitating frequency-domain analysis. In the frequency domain, Fourier

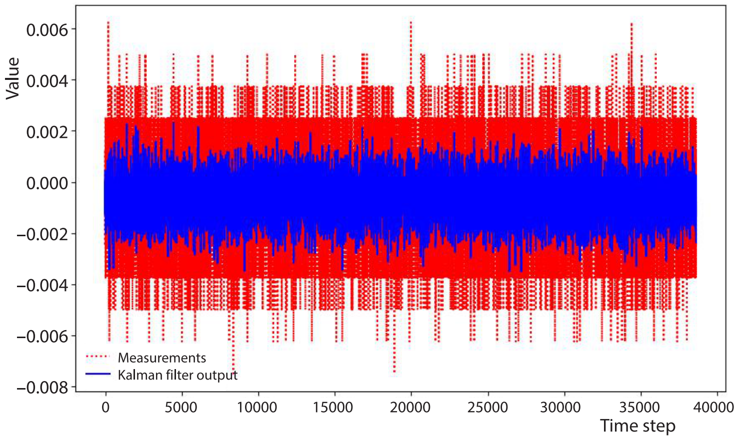

Figure 1. Comparison of data before and after wavelet noise reduction

transform (FFT) can be used to convert signals into frequency-domain representations, allowing for a better understanding of the spectral characteristics of the signals.

Fourier transform is a mathematical method for converting a time (or spatial) signal into the frequency domain, enabling the analysis of the signal's frequency components. By applying Fourier transform, a signal can be decomposed into a linear combination of sinusoidal and cosinusoidal waves of different frequencies, amplitudes, and phases, revealing the frequency characteristics of the signal.

The core concept of Fourier transform is that any complex periodic or non-periodic signal can be decomposed into multiple sinusoidal and cosinusoidal components with different frequencies, amplitudes, and phases. Through Fourier transform, a signal is converted from the *time domain* to the *frequency domain*, making it easier to analyze its frequency components.

By performing Fourier transform on the spectrum of a signal, amplitude and phase information for different frequency components can be obtained, providing a better understanding of the signal's spectral characteristics. By conducting both time-domain and frequency-domain analysis of near-bit signals, significant periodic changes in the signal can be identified. The result is shown in fig. 2. These analytical results form an important basis for subsequent modelling and evaluation.

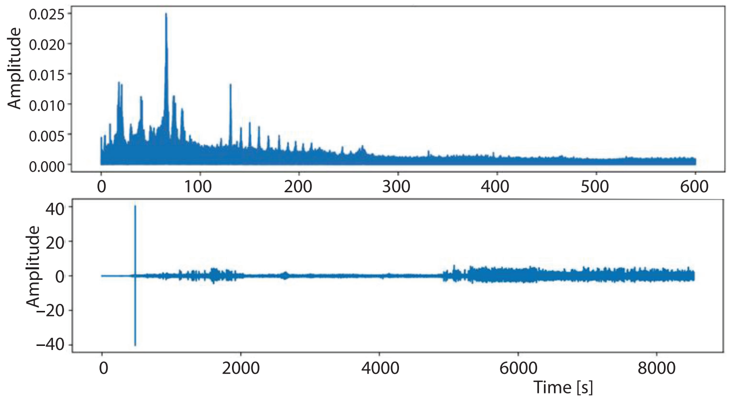

Figure 2. Comparison of signals before and after time-frequency processing

Stick-slip vibration grading evaluation system

Stick-slip vibration is one of the most severe vibration problems encountered during drilling. When stick-slip vibration occurs, the rotational speed of the downhole drill string fluctuates significantly, even reaching negative values, and the downhole rotational speed can reach 2-3 times the driving speed. This imposes significant stress on downhole drilling tools. The data used in this study includes detailed rotational speed information, enabling the grading evaluation of stick-slip vibration using the SSI. The calculation of the SSI is given:

$$SSI = \frac{\mathrm{rpm}_{\max} - \mathrm{rpm}_{\min}}{2\mathrm{rpm}_{\mathrm{avg}}} \tag{1}$$

where $\mathrm{rpm}_{\min}$ is the maximum rotational speed, $\mathrm{rpm}_{\max}$ – the minimum rotational speed, and $\mathrm{rpm}_{\mathrm{avg}}$ is – the average rotational speed.

The grading criteria for stick-slip vibration:

$$SSI = \left\{ \begin{array}{ll} 0 < SSI < 1 & \text{Torsional vibration} \\ 1 < SSI \le 3 & \text{Moderate stick-slip vibration} \\ SSI \ge 3 & \text{Severe stick-slip vibration} \end{array} \right\} \tag{2}$$

Intelligent recognition model for stick-slip vibration

Long short-term memory (LSTM) networks are a specialized form of recurrent neural networks (RNN) designed to address the common issues of gradient vanishing and gradient explosion when processing long-sequence data with traditional RNN. The LSTM can retain information over long time sequences, making it widely applicable to time-series data analysis and prediction tasks.

The key component of LSTM is its *memory cell*, which is structured around three primary *gates* – the input gate, forget gate, and output gate. Each gate is responsible for controlling the flow and storage of information. These gates allow LSTM to effectively decide which information should be retained in memory, which should be forgotten, and which should be passed to the next time step.

To improve the efficiency and accuracy of the LSTM model, selecting appropriate features is crucial. In addition frequency-domain features, time-domain features (*e.g.*, mean, variance, peak values*, etc.*) can also be incorporated as input features. Based on practical scenarios, features highly correlated with the severity of stick-slip vibration are chosen to train the LSTM.

To enhance training efficiency and accuracy, this study adopts the Adam optimization algorithm (adaptive moment estimation), which is widely used in deep learning. The algorithm dynamically adjusts learning rates to adapt to different training conditions. The intelligent recognition model for stick-slip vibration conditions is depicted in fig. 3.

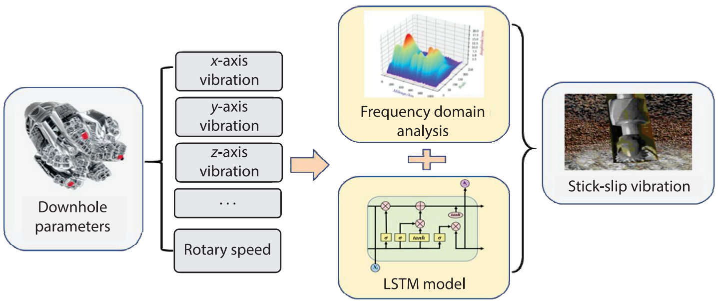

Figure 3. Intelligent recognition model for stick slip vibration working conditions

Results analysis

When training the model using real drilling data from two wells in a domestic oil field, the LSTM model demonstrated high accuracy. After training and testing the model, the confusion matrix is shown in fig. 4. The model achieved an accuracy of 85.8%, a precision of 78.7%, and a recall rate of 83.2%. These results indicate that the developed model exhibits excellent predictive performance and can effectively identify stick-slip vibrations during the drilling process.

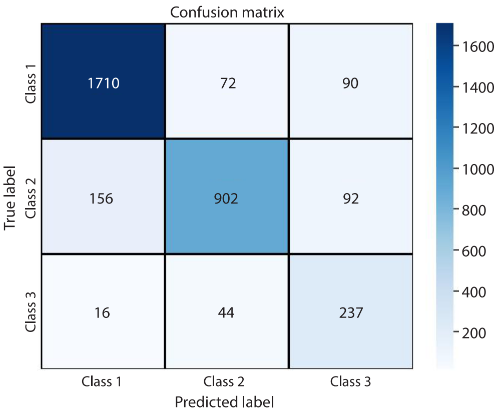

Figure 4. Classification results of stick slip vibration levels: *Class 1 – torsional vibration, Class 2 – moderate stick-slip vibration, and Class 3 – heavy stick-slip vibration*

To validate the advancement of the proposed model, this study established four machine learning models – random forest, XGBoost, BP neural network, and LSTM – for comparative experiments. The effectiveness of each algorithm was evaluated based on accuracy and recall metrics for identifying different levels of stick-slip vibration. Under identical data preprocessing conditions, the four algorithms were tested and compared, with the results shown in tab. 1.

Table 1. Comparison of model effects

Algorithm	Accuracy	Precision	Recall
Random Forest	0.749	0.624	0.715
XGBoost	0.778	0.662	0.737
BP	0.814	0.721	0.794
LSTM	0.858	0.787	0.832

The experimental results demonstrate that all these models exhibit high recognition efficiency overall. Among them, the LSTM model outperforms the others in all evaluation metrics, showcasing superior predictive performance. Compared to the conventional BP Neural Network model, the LSTM model improved accuracy by 4.4% and precision by 6.6%. This highlights the LSTM model's suitability for handling complex time-dynamic data in drilling operations and its ability to effectively extract localized data features.

Conclusion

This article constructs a monitoring method for drill string stick slip vibration based on downhole data, using Fourier transform to extract temporal and frequency domain features of downhole data and explore deep information in the data. The use of LSTM algorithm to construct the mapping relationship between stick slip vibration and downhole parameters can effectively explore the temporal characteristics of data and achieve accurate and efficient identification of stick slip vibration types. The current model has poor recognition performance for severe stick slip vibration due to class imbalance, and data augmentation methods should be considered in the future to solve this problem.

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References

[1] Popp, K., *et al*., Stick-Slip Vibrations and Chaos, Philosophical Transactions, Physical Sciences and Engineering, *332* (1990), 1624, pp. 89-105
[2] Reckmann, H., *et al*., MWD Failure Rates Due to Drilling Dynamics, *Proceedings*, IADC/SPE Drilling Conference and Exhibition, New Orleans, La., USA, 2010
[3] Hegde, C., *et al*., Classification of Drilling Stick Slip Severity Using Machine Learning, *Journal of Petroleum Science and Engineering*, *179* (2019), 8, pp. 1023-1036
[4] Baumgartner, T., *et al*., Pure and Coupled Drill String Vibration Pattern Recognition in High Frequency Downhole Data, *Proceedings*, SPE Annual Technical Conference and Exhibition, Amsterdam, The Netherlands, 2014
[5] Tang, H., *et al*., Research on Stick-slip Vibration Level Estimation of Near-bit Based on Optimized XGBoost, *Journal of System Simulation*, *33* (2021), 11, pp. 2704-2710
[6] Chen, *et al.*, Research on Stick-slip Vibration Level Estimation of Drillstring Based on SVM, *China Petroleum Machinery*, *47* (2019), 1, pp. 20-26

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