A Method Based on SVM Algorithm for Wellbore Collision Monitoring: Using Vibration Signal Characteristics of Bit Drilling in Different Mediums

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***Abstract*—During well drilling operations of offshore oil and gas exploration, the progress that bit drills through rocks, steel casing and other mediums produces vibration signal with different characteristics. In this work, we presented a wellbore collision monitoring method that using vibration signal produced by bit penetrating in different drilling mediums to identify those unwanted cases that bit is colliding into adjacent wellbores in drilling operation. Firstly, experiments have been carried out to acquire vibration signal of bit drilling in sorts of rock, cement and steel casing mediums. Then, to dig out signal feature in different time scales, empirical mode decomposition (EMD) method was used to decompose every signal sample into several intrinsic mode functions (IMFs) and we extracted and analyzed characteristics in time and frequency domain of all signal IMFs. Finally, support vector machine classifiers were trained with feature vectors of a part of signal IMFs to realize the function of drilling mediums identification and classification. SVM Performance test results indicates that correct identification rate of those classifiers can basically reach 90%. The method presented in this paper proved to be feasible to provide a new approach to monitor wellbore collision risks for offshore drillings.**

***Index Terms*—offshore drilling, vibration signal, empirical mode decomposition, time and frequency domain, vector support machine**

I. Introduction

In offshore oil and gas development programs, several wells are usually drilled from the same pad on offshore platform. This way for well drilling results in well congests in shallow stratums environments. To avoid bit that is drilling a well colliding with offset wellbores, many researchers has worked on wellbore anti-collision related subjects. At present, the main current solving way to this problem is that calculating and scanning the distance between bit and adjacent well trajectory using well trajectory data measured while drilling and trajectory data of adjacent wells. Despite the popularity of this risk monitoring method, some external and inherent defects such as magnetic interference from nearby wells, low reliability of trajectory data of offset old wells and internal magnetic interference from the drill string make it difficult to provide instant and precise well collision information, see [1], [2]. And in the recent decade, a few researchers and companies have come up with some new methods using signal produced while drilling to avoid wellbore collision. Ref. [3], [4] proposed the methods using electromagnetic signal to rang the distance between the bit and adjacent well to monitor collision risk. Ref. [5] presented to use acoustic signal excited by bit which can be detected by distributed acoustic sensors deployed in adjacent wells to analyze the risky extent of bit approaching other wells. Ref. [6] proposed to detect the drilling status by signal produced during specific operation process such as on-off of mud pump and [7] used a downhole seismic source installed near bit to excite signal that contains information about bit and nearby wellbores. And our research team has presented to use feature of signal collected by sensors installed on casing head to monitor wellbore collision risk, see [8].

While the artificial intelligence technology has developed rapidly in recent years, many scholars present intelligence algorithm to analyze the signal characteristics of drill bits and drilling mediums. Ref. [9], [10] used multiple regression and artificial neural network to analyze and predict rock properties from the sound level produced during drilling. Ref. [11] analyzed the characteristic of vibration signal in time and frequency domain and [12] pointed the feasibility of recognizing rock to monitor and identify the drilling process by use of a vector quantization method processing the vibroacoustic signal. These applications show that vibration signal produced during drilling can reflect drilling conditions and the fingerprint information contained in vibration signal can be dig out by application of artificial intelligence technology. However, the difference of signal respectively produced in rock, cement and steel which are mediums with totally different physical structures has not been analyzed by previous works.

The SVM is also a hotspot in signal processing. Mostly, the topics of application of SVM to signal processing are

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fault diagnosis and mode classification of generator machines, see [13]-[15]. However, SVM applied to signal analysis of rocks or drilling mediums has been little mentioned yet.

This paper proposes a method based on SVM algorithm using vibration signal generated by PDC bit drilling in different mediums to monitor the wellbore collision risk. The vibration signal that bit drilling in cement, casing or rock features differently in time and frequency domain, which can be utilized to identify whether drill bit is in close proximity to nearby wellbore and help directional driller timely and precisely determine collision risk.

This paper consists of six sections. In Section I, the traditional and newly presented anti-wellbore collision methods and previous works on applications of artificial intelligence technology including SVM algorithm to signal analysis especially concerning drilling rock were introduced. The second section describes a series of laboratory vibration signal acquisition experiments. The third section represents signal processing using EMD and signal feature extraction. The fourth section is SVM classifiers modelling and the fifth section is the results discussion about analysis of extracted signal feature and classification results of SVM classifiers. The final section concludes the work of this paper.

II. Laboratory Experiments of Bit Approaching Wellbore Model

Laboratory experiments of bit drilling in rock-cement sheath-casing wellbore model was designed to acquire vibration signal samples. The experiment system, as shown in Fig. 1, consists of signal excitation module, signal transmission module, signal acquisition module and computer data-processing module. Vibration signal was collected by piezoelectric acceleration sensors and charge amplifier from B&K and a high-performance collector from COINV were used to transform electrical signal into digital signal data. The sampling frequency is 12800 Hz and sampling length is 1 second.

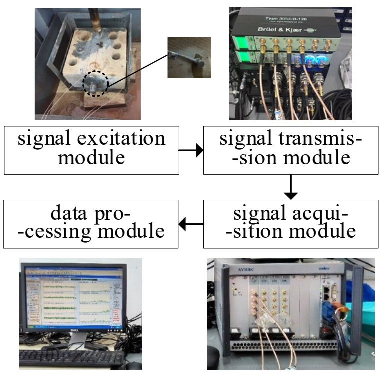


Figure 1. Schematic diagram of the laboratory experiments.

Three groups of experiments were carried out, including bit drilling in rocks of different types (red sandstone, limestone, yellow sandstone and mudstone), bit drilling in rock-cement sheath-casing wellbore model in the way bit approaching casing at a vertical angle and bit drilling in rock-cement sheath-casing wellbore model in the way bit approaching casing at an inclined angle.

III. Signal Data Processing

A. Empirical Mode Decomposition of Signal

Empirical Mode Decomposition (EMD) can decompose a complicated signal sequence into a finite number of intrinsic mode functions (IMF, for short). The feature of IMF that at every moment there only exists one single frequency component makes IMFs are meaningful to indicate local feature of signal at different time scales. The essence of the method is to empirically identify the intrinsic oscillatory modes by their characteristic time scales in signal data itself, and then decompose the data accordingly, which can be aptly called as a “sifting” process [16]. The detailed decomposition procedures are as shown in Fig. 2. Quasi Cauchy convergence criterion which is shown as the inequation (1),

$$SD=\sum_{t=0}^{T}\frac{\left[h_{i(j-1)}-h_{ij}\right]^2}{h^2_{i(j-1)}}<0.1 \tag{1}$$

was used as sifting stopping criterion. In (1), the standard deviation (*SD*, for short) of the two *h* (in Fig. 2) which are contiguously calculated out, and *T* is time length of the signal sequence.

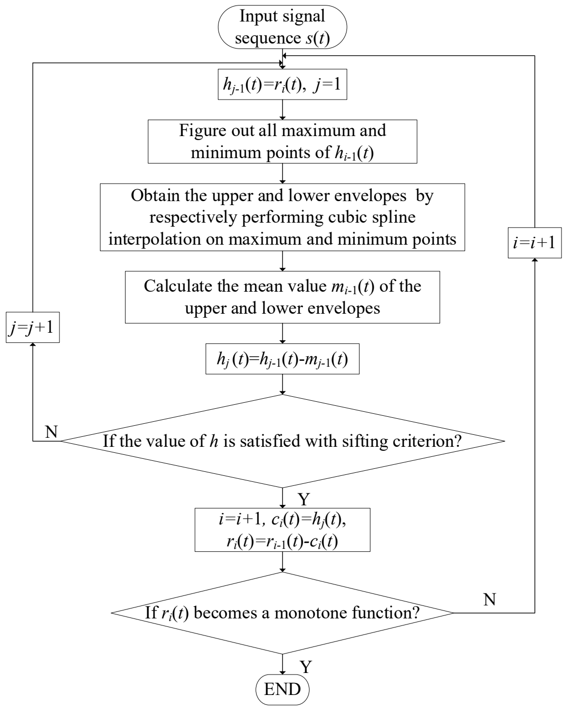


Figure 2. Schematic diagram of the laboratory experiments.

Each vibration signal $x(t)$ was denoised and decomposed into a series of IMFs $c_i(t)$ and a residual component $r(t)$ which were arranged in order of high to low frequency, as shown in (2),

$$x(t)=\sum_{i=1}^{n}c_i(t)+r(t) \tag{2}$$

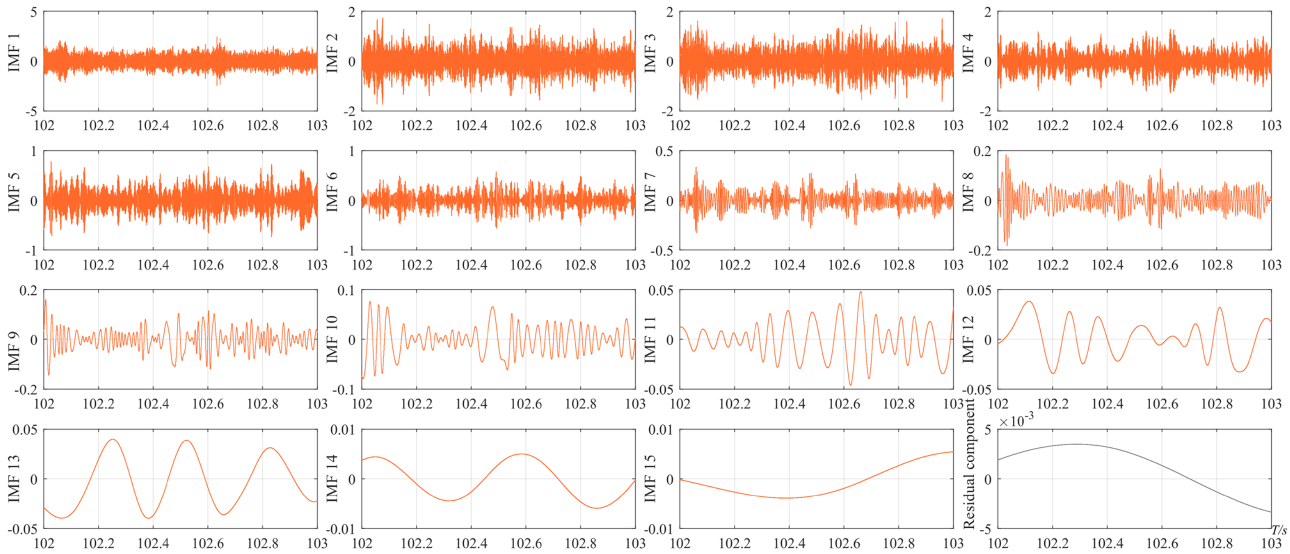


Figure 3. One example of EMD decomposition result.

An example of EMD decomposition result is shown in Fig. 3. As among almost all of signal sequences, the first six in high-to-low frequency orders of IMFs takes 98 percent of total energy which is to say that the first six orders of IMFs contain almost all characteristics of each signal, they were picked as input variables used in followed SVM modelling.

B. Extraction of Signal Feature in Time and Frequency Domain

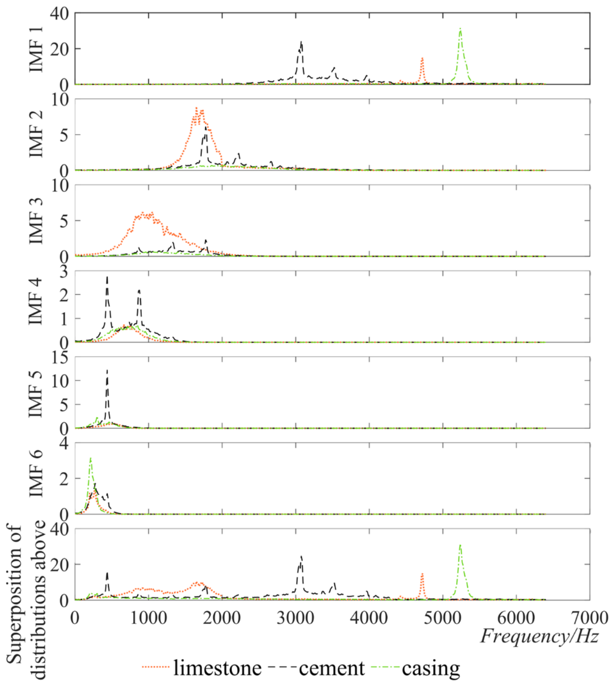


Figure 4. A power spectrum of signal after EMD decomposition produced by bit drilling in wellbore model approaching casing at vertical angle.

The power spectrums of IMFs were figured out to find out the laws of signal characteristics distributed in each IMF. Fig. 4 shows the power spectrums of IMFs of three signal. The three signal sequences were respectively produced while bit drilled in limestone, cement and casing in the group that bit approaching casing at a vertical angel. Fig. 4 illustrates that the feature frequency bands in different IMFs distribute in various ways. Feature frequency bands of signal of the three sorts of mediums are most distinguishable in IMF1. To dig out the "fingerprint information" of signal further, the feature of IMFs of each signal was extracted and analyzed.

In time domain each sample is a sequence of amplitude-time data $x_i(t)$. By using the numerical method as known as Discrete Fourier Transform (DFT), signal $x_i(t)$ can be transformed into a sequence of amplitude-frequency data $y_i(f)$ in frequency domain according to (3),

$$y(f)=\int_{-\infty}^{+\infty} x(t)e^{-j2\pi ft}dt \tag{3}$$

The signal feature in time domain can be described by feature index such as standard deviation value, root mean square value and kurtosis value and in frequency domain by centroid frequency and centroid amplitude. The feature index value in time and frequency domain of each IMF were extracted by the computational equations shown in Table I. The extracted feature indexes value was all converted to be dimensionless for clearer feature analysis work. The nondimensionalized extraction results of three group experiments are shown in Fig. 5.

Fig. 5 displays the feature indexes in time and frequency domain mentioned above as well as the energy value of the selected six IMFs of a several series of signal produced in different drilling conditions. The characteristic distribution rule of vibration signal shown in Fig. 5 indicates that it is meaningful to utilize the time-frequency-domain feature of IMFs of decomposed signal by EMD to distinguish drilling mediums. To identify vibration signal intelligently, the SVM algorithm is applied into the method using feature in time-frequency domain of signal to monitor wellbore collision risk presented in this paper.

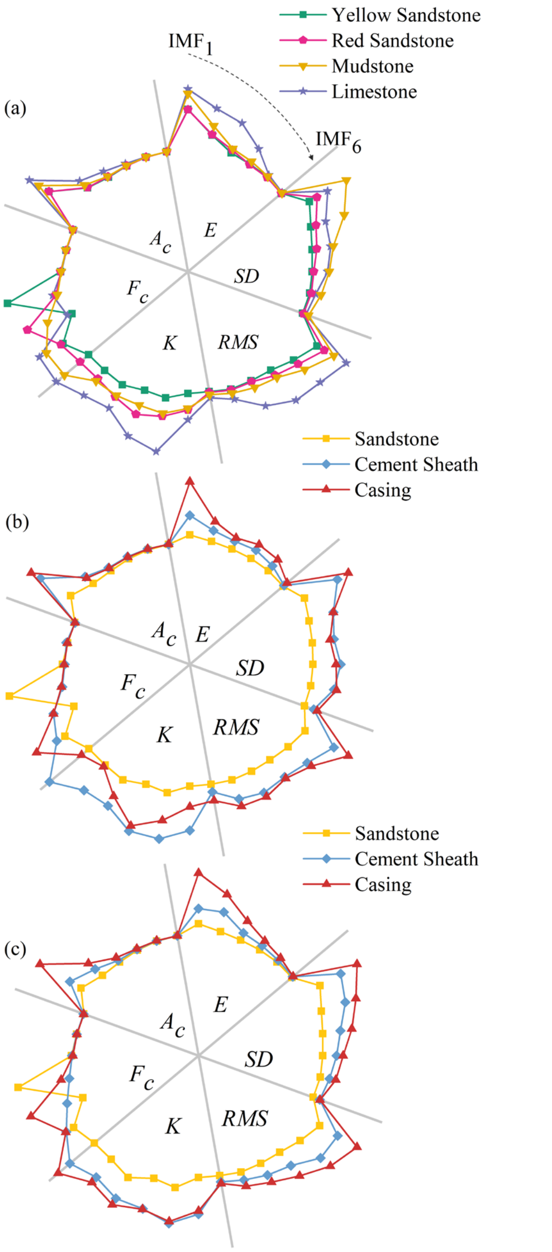


Figure 5. The feature in time and frequency domain of signal produced in three groups of drilling experiments, in which (a) is feature of signal by bit drilling into rocks of different types, (b) is features of signal by bit drilling into wellbore model in the way bit approaching casing at a vertical angle, (c) is features of signal by bit drilling into wellbore model in the way bit approaching casing at an inclined angle.

IV. Establishment of SVM Model

A. Support Vector Machine Theory

Support Vector Machine (SVM) is one of the most effective Machine Learning (ML) techniques based on statistical learning theory, see [17], which can solve the non-linear pattern classification problem. Ref. [18] proposed the idea of SVM network. Fig. 6 shows an example of a linear, binary SVM classifier. For a linear training dataset $\{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\} \in X \times Y, X \in R^n$ with expected projection outputs $Y \in \{-1, +1\}$, there exists a optimal separating hyperplane H that can classify vectors of two classes (indicated in Fig. 10 by white dots and red dots) as precisely as possible and at the same time maximizes the margin between the two classes. The margin is the distance between vectors that are from different classes and closest to the separating hyperplane, and these vectors are called support vectors. One group support vector located on $H_1 : \boldsymbol{\omega} \cdot \mathbf{x} + b = 1$ and $H_2 : \boldsymbol{\omega} \cdot \mathbf{x} + b = -1$ can determine one separating hyperplane $H : \boldsymbol{\omega} \cdot \mathbf{x} + b = 0$. For linearly inseparable problem, SVM aims at maximize the margin denoted by $2/\|\boldsymbol{\omega}\|$, which is transformed into a constrained optimization problem presented by (4),

$$f(\omega, \xi) = \frac{1}{2}\|\boldsymbol{\omega}\|^2 + C\sum_{i=1}^{n}\xi_i \tag{4}$$

Subject to:

$$y_i[(\boldsymbol{\omega} \cdot \boldsymbol{x}_i) + b] - 1 + \xi_i \geq 0, \xi_i \geq 1, i = 1, 2, \cdots, n \tag{5}$$

where ξ_i are the slack variables that soften the margin of hyperplane and C is called penalty parameter which is sufficiently large to avoid the sum of training errors, $\sum_{i=1}^{n}\xi_i$, is so large that hyperplane margin become meaningless. To solve the problem (4) which is hard to solve directly, Lagrange multiplier $\boldsymbol{\alpha} = (\alpha_1, \alpha_2, ..., \alpha_n)^T \in R_+^n$ is introduced to transform it into a dual problem as shown in (6). And according to the Karush-Kuhn–Tucker solution conditions, see [19], [20], the optimal classification function (7) can be obtained by inputting a set of training samples to figure out the unique solution of α_i^* and b^*. Then when the followed class-unknown samples are input into (7), the (7) will output the identified classes of those samples.

$$Q(\boldsymbol{\alpha}) = \sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j y_i y_j (x_i \cdot x_j) \tag{6}$$

$$f(x) = \operatorname{sgn}[\sum_{i=1}^{n} y_i\alpha_i^*(x_i \cdot x) + b^*] \tag{7}$$

$$f(x) = \operatorname{sgn}[\sum_{i=1}^{n} y_i\alpha_i^* K(\boldsymbol{x}_i \cdot \boldsymbol{x}) + b^*] \tag{8}$$

To address a non-linear problem that present in this paper, SVM introduces "kernel trick" $\Phi : X \subset R^n \to Z \subset \Lambda,\ x \to z = \Phi(x)$ to map the input vectors into a high dimensional feature space and the optimal classification function is transformed into (8) from (7). Kernel function $K(\boldsymbol{x}_i \cdot \boldsymbol{x}_j) = \Phi(\boldsymbol{x}_i) \cdot \Phi(\boldsymbol{x}_j)$ makes data are linearly separable or linearly inseparable so that the solution of (8) is simple inner product calculation in the original input space instead of complex calculation in high dimensional feature space. The most common used kernel functions include polynomial kernel function and Radial Basic Function (RBF), and the latter was used in this paper as shown in (9) where γ is the factor determining the width of RBF kernel.

$$K(\boldsymbol{x}_1, \boldsymbol{x}_2) = \exp(-\gamma \|\boldsymbol{x}_1 - \boldsymbol{x}_2\|^2) \tag{9}$$

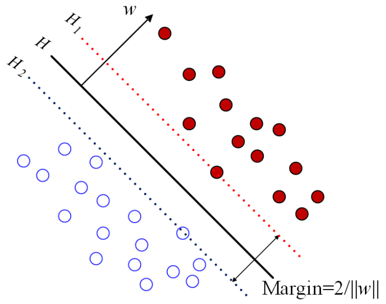


Figure 6. A linear, binary SVM classifier.

B. SVM Classifiers of Drilling Mediums Identification

Based on classification principle of SVM, once the SVM is trained by a set of input vectors, it gains the function of classification to unknown-class vectors. When vectors are then input to the SVM classifier, it can identify intelligently and output the correct class that vectors belong.

TABLE I. FEATURE INDEXES OF SIGNAL IN TIME AND FREQUENCY DOMAIN

Feature index	Computational equation	Description
Standard deviation (*SD*, for short)	$SD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \frac{1}{N}\sum_{i=1}^{N} x_i)^2}$	*SD* directly reflects the discreteness of a dataset for it is of the same dimension as raw dataset.
Root mean square (*RMS*, for short)	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$	*RMS* describes the energy magnitude of vibration signal.
Kurtosis (*K*, for short)	$K = \frac{1}{N}\sum_{i=1}^{N}(x_i - \frac{1}{N}\sum_{i=1}^{N} x_i)^4$	*K* is very sensitive to instantaneous variation of signal feature.
Centroid frequency (F_c, for short)	$F_c = \sum_{i=1}^{N} f_i y(f_i) \Big/ \sum_{i=1}^{N} y(f_i)$	F_c reflects the distribution of dominant frequency of signal sequence
Centroid amplitude (A_c, for short)	$A_c = \sum_{i=1}^{N} f_i y(f_i) \Big/ \sum_{i=1}^{N} f_i$	A_c represents the trend of energy distribution in the spectrum
Frequency band with peak value (F_p, for short)	——	F_p reflects the concentration extent of signal frequency response.

In this paper, three SVM classifiers were established for identification to drilling mediums in the three groups of experiments. For every kind of drilling medium in each experiment, 100 signal samples were continuously captured, with each of them containing 128000 sampling points with sampling time length of 1 second. Every signal sample is decomposed by EMD and the first six order of IMFs were picked up to have feature indexes value extracted. The feature indexes of each signal sample include energy percentage of each IMF taking in total energy of original signal, the energy of each of those six IMFs and the feature indexes in Table I. Thus total 48 feature indexes were extracted from each signal sample.

For the group of experiment that bit drilled in four rocks of different types, 70 of 100 signal samples for each rock type were used to train the SVM classifier and the other 30 samples were used to test performance of the SVM classifier. So, a feature vector with dimension of 280×48 were input to establish the SVM classifier and the optimal penalty parameter and the factor determining the optimal width of RBF kernel were determined to be $C_1 = 11.8$ and $\gamma_1 = 0.4964$ by the cross-validation method. Another vector with dimension of 120×48 were input to the SVM to test its performance, and classification result is shown in Fig. 7. For the other groups of experiments, the data is processed by the same procedures, and classification results are shown in Fig. 8 and Fig. 9.

V. RESULTS DISCUSSION

A. Results Analysis for Feature Indexes Extraction

As mentioned in the final paragraph of section III. B, the signal feature in time and frequency domain of different drilling mediums are all to some extent distinguishable. Except for *K* and F_c, the other feature indexes value decreases regularly as the order of IMFs lowers. From Fig. 5 (a), it can be inferred that *E*, *RMS*, *SD* and *K* vary sensitively with rock types, and among them *E* and *RMS* are positively related with the consolidation degree of rock. *K* can reflect instantaneous impact characteristic of signal, and it is well embodied in Fig. 5 which shows in (a) the *K* value of limestone is higher than sandstone, and in (b) and (c) the *K* value of every IMF order of cement and casing is much higher than that of corresponding IMF order of sandstone.

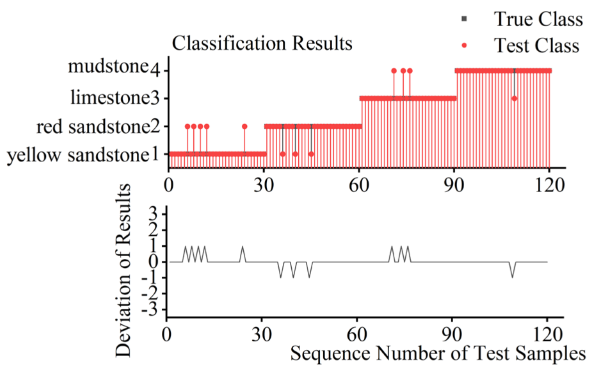


Figure 7. Classification result of the experiment that bit drilled in rocks of four types.

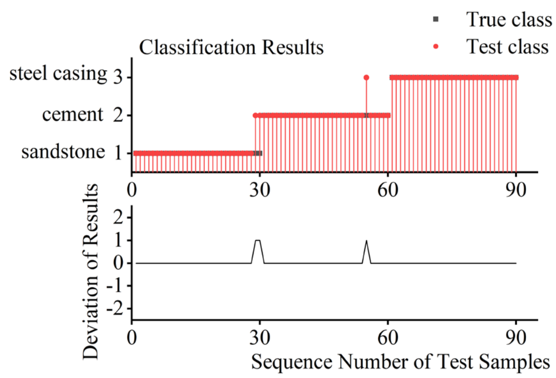


Figure 8. Classification result of the experiment that bit drilled in rock-cement sheath-casing wellbore model in the way bit approaching casing at a vertical angle.

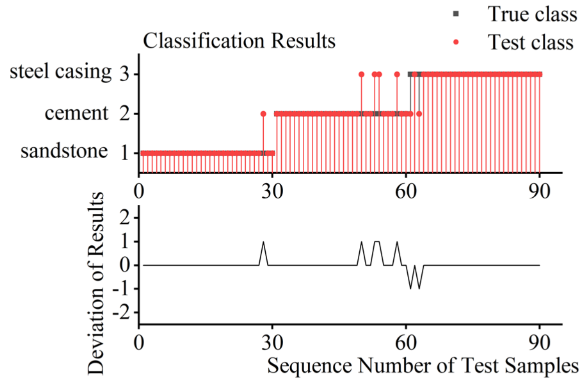
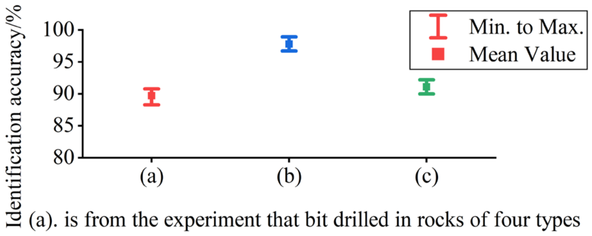


Figure 9. Classification result of the experiment that bit drilled in rock-cement sheath-casing wellbore model in the way bit approaching casing at an inclined angle.



(a). is from the experiment that bit drilled in rocks of four types (b). and (c). respectively are from the experiment that bit drilled in rock-cement sheath-casing wellbore model in the way bit approaching casing at a vertical angle and an inclined angle

Figure 10. Identification accuracy of SVM classifiers.

In Fig. 5, the distribution rule of F_c is quite different from other feature indexes, which is to say with the decrease of IMF order, F_c value does not change regularly. However, in the other hand, it reflects the rule that the signal feature of different drilling mediums distributes differently on different time scales, especially on the first three order of IMFs.

When Fig. 5 (b) compared with (c), it can be found that the distribution rules of feature indexes on each order of IMF change when the way bit approaching casing changes.

The analysis above shows that features in time-frequency domain are distinguishable among mediums with different physical properties. It is feasible to use the feature in time and frequency domain of vibration signal produced in drilling process to identify drilling medium so as to monitor wellbore collision risk.

B. *Results Analysis for SVM Classification Tests*

As shown in Fig. 7, the identification accuracy of the SVM classifier for rocks of four types reaches 90%. The greatest number of misclassifications exists in samples of yellow sandstone and red sandstone, owing to the similarity in their physical properties.

As shown in Fig. 8 and Fig. 9, the identification accuracy of the two SVM classifiers for rock, cement and steel casing are respectively up to 96.7% and 92.2%, so the trained SVM classifiers can effectively identify the drilling condition that bit drills in rocks and then approaches and collide into cement sheath and casing of adjacent well in turn. The classifier in Fig. 9 performs poorer than the classifier in Fig. 8. The misclassification in Fig. 9 mainly exists in samples of cement and steel casing, which can be explained by the reason that when bit drilled from sandstone into cement sheath in the way bit approaching casing at an inclined angle, the signal at some point contained both feature of sandstone and cement, and so it was when bit drilled from cement sheath into casing, contributing to the inaccuracy of identification. The performance tests of each SVM classifier were carried out three times to avoid accidental errors, and Fig. 10 shows the results. From Fig. 10, it can be seen that the bigger are the difference among medium properties, the better does the SVM classifier perform, and the way bit approaching casing also influences the identification accuracy of SVM classifier.

VI. Conclusion

A method based on SVM algorithm for wellbore collision risk monitoring in offshore drilling operations is presented in this paper. By laboratory experiments, the signal of bit drilling in different mediums were acquired, and the feature of those signal in time and frequency domain was extracted and analyzed, which was afterwards used to obtain SVM classifiers to realize intelligent identification to signal of different drilling mediums.

The signal acquired from laboratory experiments was decomposed into several IMFs by EMD method. It turns out that features of the picked first six orders of IMFs are relevant to the properties of drilling mediums.

The time-frequency domain feature of signal in different time scales were extracted to build up feature vectors to establish SVM classifiers which can realize intelligent identification to the difference among signal from bit drilling in rocks, cement and casing.

The results of performance tests of SVM classifiers shows that the identification accuracy of SVM classifiers for the identification to bit colliding into cement and casing is up to 92.2%, which is basically available for the wellbore collision risk monitoring in offshore drilling operations.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Gang Liu conducted the research and came up with the idea of the paper; Jialin Zhang did the experiments and a part of data analysis work; Dou Mei did a part of data analysis work and wrote the paper; all authors had approved the final version.

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