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Research on Denoising Method of Oil Well Liquid Level Resonance Signal Based on CEEMDAN-KSVD

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Abstract. Oil well liquid level resonance signal is an important indicator fo4r oil production and transportation. However, it is often contaminated by noise, which affects the accuracy of signal analysis and processing. In order to solve this problem, a denoising method based on complete ensemble empirical mode decomposition with CEEMDAN and K-SVD is proposed in this study. Firstly, the CEEMDAN algorithm is used to decompose the original signal into a number of intrinsic mode functions (IMFs). Then, the IMFs containing noise are selected according to the correlation coefficient, and the remaining IMFs are reconstructed to obtain a denoised signal. Secondly, KSVD is employed to learn a dictionary from the noisy IMFs, and sparse coding is carried out to represent the denoised signal using the learned dictionary. Finally, the denoised signal is obtained by inverse transform of the sparse coefficients. Experiments were conducted on real oil well liquid level resonance signals, and the results show that the proposed method can effectively remove noise and retain the useful components of the signal. In addition, compared with other denoising methods, the proposed method has better denoising performance.

Keywords. Oil well, liquid level resonance signal, CEEMDAN, KSVD.

1. Introduction

Oil, as the "blood" of modern industry, is an indispensable strategic resource for promoting national economic and social development and ensuring national defense security [1-2]. In order to improve oil production efficiency and ensure the secure supply of energy, it is necessary to measure various parameters of oil wells accurately, with the measurement of oil well fluid level being the most important parameter. The measurement of oil well fluid level provides the best basis for understanding oil production capacity, calculating reservoir pressure, and formulating production plans, which is also a key parameter for determining safe and efficient oil well production operations [3-5]. Accurately measuring the position of the fluid level allows for proper control of the submergence depth of the pumping unit. On one hand, this can prevent ineffective operations due to insufficient submergence depth, and on the other hand, it can avoid increasing operational burden and energy consumption due to excessive submergence depth, thus affecting equipment performance and service life [6-7].

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In recent years, various methods related to the measurement of liquid level have emerged, such as the buoyancy method, pressure gauge detection method, indicator diagram method, echo method, etc. [8]. However, the float method, pressure gauge detection method, and dynamometer method are difficult to meet the production requirements due to low measurement accuracy and large errors. The echo method has been widely used due to its simple process and convenient construction. However, there are still many problems to be solved in the measurement method based on the echo principle, such as susceptibility to mechanical noise, interference from foam and dead oil inside the casing, limited sound energy, and difficulties in identifying echo signals [8-9]. Especially when the signal-to-noise ratio is too low, the liquid level echo signal is often submerged in strong noise. It is difficult to fundamentally improve the reliability and stability of the echo method solely by improving signal processing algorithms, which to some extent limits the application and development of this method. In view of the problems with the echo method, some scholars have turned their research direction to the measurement method based on acoustic resonance principles [10-12]. Yang et al. used spread spectrum technology to emit continuous sound wave signals into the oil casing and performed correlation processing on the acquired signals to extract signals under strong noise interference, providing a new approach to improve the anti-interference ability of the measurement system [13]. In 2013, Zhou et al. proposed a new method for measuring the dynamic liquid level of oil wells based on the principle of air column resonance in the pipe field [14-15]. By studying the characteristics of the pipe field and the principle of air column resonance inside the pipe, a mathematical model for the depth of the dynamic liquid level of the oil well and the inherent frequency of the air column was established. Although the dynamic liquid level detection technology of oil wells continues to develop, the extracted air column resonance signal obtained from the wellhead of the pumping well often contains a large amount of noise, which interferes with the analysis of relevant parameters of the dynamic liquid level in the later stage. Therefore, in order to improve the accuracy of parameter analysis, it is necessary to perform noise reduction processing on the extracted raw signal.

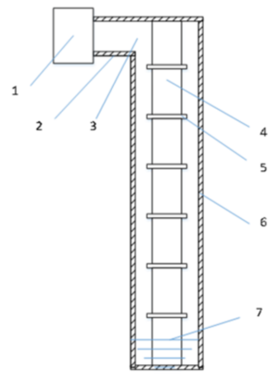
The Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) is an improved version based on EMD, while also incorporating the Gaussian noise addition and the idea of multiple iterations and averaging to cancel out the noise from the EEMD method. Therefore, CEEMDAN has significant effects on signal feature extraction, identification, and denoising. In reference [16], CEEMDAN, ED, and EE were combined to extract the energy features of ship radiation noise mixtures, and the effectiveness and high recognition rate of the method were verified. In reference [17], the CEEMDAN algorithm was used to remove noise interference and improve the prediction accuracy of Diffuse Solar Radiation (DSR).

The over-complete dictionary has an important position in the sparse representation of signals. KSVD is a dictionary learning algorithm that iteratively updates the dictionary and the coefficients of sparse representation using singular value decomposition (SVD). Noisy signals are often composed of noisy and noiseless components. However, the noisy component can be sparse, meaning it can be represented using a limited number of atoms from the dictionary, while the noise component is not sparse. By extracting the coefficients of sparse representation, the signal can be reconstructed and the noise can be removed. Therefore, denoising can be achieved through sparse decomposition. In reference [18], the combination of KLT and KSVD was used to reduce the interference of noise on seismic reflection signals. Reference [19] utilized KSVD and Bregman algorithm for denoising speckle images, and the simulation results showed a significant improvement in image signal-to-noise ratio after algorithm processing.

This article primarily focuses on the denoising processing of the resonant signals extracted from oil well column based on the principle of sonic resonance for measuring the fluid level in the well. In order to improve the signal-to-noise ratio and extraction accuracy of the resonance signals, a combined denoising algorithm based on CEEMDAN and KSVD is proposed. The remaining parts of this article are organized as follows: Section 2 describes the acoustic field model and its parameters; Section 3 introduces the CEEMDAN and KSVD algorithms; Section 4 presents the proposed combined algorithm based on CEEMDAN and KSVD and carries out simulation verification; finally, some conclusions are summarized in Section 5.

2. Sound Field Model

To accurately describe the transmission status of signals, the schematic diagram of the overall structure of an oil well given in reference [20] is shown in figure 1.



1.sound device 2. line pipe 3.well 4.oil pipe 5.hoop 6. casing pipe 7. liquid level

Figure 1 .Schematic diagram of oil well structure

The tubing string consists of casing and tubing, with the entire tubing section made up of several joints of smaller tubing connected by couplings, with each joint of tubing approximately 9.6m long. The end of the tubing string is the oil level. There is an air column between the oil pipe and the casing.

The sound emission device at the wellhead continuously emits an audio signal, which is transmitted into the tubing, exciting the resonance of the air column within the tubing and casing annulus. After reaching the oil level, a portion of the resonant signal is reflected and transmitted back to the wellhead, where it is captured by a condenser microphone and converted into digital signal through an A/D sampling card.

The input-output convolution model of the system can be represented as:

$$s(n) = \sum_{n=1}^{m} h(m-n)w(n) \tag{1}$$

$$y(n) = s(n) + u(n) \tag{2}$$

where, n represents discrete time, $s(n) \in R^n$ represents the signal sent from the transmitter to the oil level and the return signal, $h(m)$ represents the impulse response sequence, $y(n) \in R^m$ represents the signal received at the receiver, $w(n) \in R^r$ represents the reflection coefficient sequence of the oil level, which represents measurement noise, and $u(n) \in R^m$ represents observation noise.

The matrix representation of $y(n)$ is as (3).

$$Y(n) = S(n) + U(n) = \left[y_{1,}y_{2,}\cdots y_n\right] \in C^{n\times m} , \tag{3}$$

The total number of samples collected by the receiving end can be represented as follows:

$$y_n(t) = \left[y_1(t), \quad y_2(t), \quad \cdots, \quad y_n(t)\right]^T \tag{4}$$

The sampling point value of each sample $y_i(t)$ can be defined as $\upsilon_{i,j}(t)$, which can be represented as the following vector.

$$\upsilon_{i,j}(t) = \left[\upsilon_{1,1}(t) \quad \upsilon_{1,2}(t) \quad \cdots \quad \upsilon_{n,m}(t)\right] \tag{5}$$

Therefore, the received sampling signal composed of $y_i(t)$ sample values can be represented as the following matrix.

$$Y(n) = \begin{bmatrix} \upsilon_{1,1}(t) & \upsilon_{1,2}(t) & \cdots & \upsilon_{n,m}(t) \\ \upsilon_{2,1}(t) & \upsilon_{2,2}(t) & \cdots & \upsilon_{2,m}(t) \\ \vdots & \vdots & \vdots & \vdots \\ \upsilon_{n,1}(t) & \upsilon_{n,2}(t) & \cdots & \upsilon_{n,m}(t) \end{bmatrix} \tag{6}$$

3. Research Method

3.1. CEEMDAN

Mar´ıa E. Torres [21] proposed the CEEMDAN (Complementary Ensemble Empirical Mode Decomposition with Adaptive Noise) algorithm. This algorithm can effectively process nonlinear and non-stationary time series data, making the decomposed data more interpretable. This algorithm can also use decomposed modal data for prediction, which can reduce the correlation between data and improve the accuracy of prediction. The decomposition steps of the CEEMD algorithm are as follows:

Step 1. Add white noise to the original signal $y(n)$ to obtain the signal $s_1(n)$ to be decomposed.

$$s_1(n) = y(n) + r(n) \tag{7}$$

Step 2. Perform the first EMD decomposition on $s(n)$ to obtain N first order IMF components $m_i(n)$.

Step 3. Calculate the average of N IMF components to obtain the first IMF component M_1;

$$M_1(n) = \frac{1}{N}\sum_{i=1}^{N} m_i(n) \tag{8}$$

Step 4. Calculate residuals $\gamma_1(n)$;

$$\gamma_1(n) = s(n) - M_1(n) \tag{9}$$

Step 5. Add white noise to $\gamma_1(n)$, a new signal $s_2(n)$ can be obtained. Perform EMD decomposition on $s_2(n)$, then we can obtain N second-order IMF components. Average the N IMF, we can obtain the second IMF component $M_2(n)$ of CEEMDAN. Calculate the residual $\gamma_2(n)$ of $M_2(n)$.

Step 6. Repeat the above steps until the obtained residual signal is a Monotonic function and cannot be further decomposed. The total number of IMF components obtained is K. The original signal $y(n)$ is decomposed into:

$$y(n) = \frac{1}{k}\sum_{i=1}^{k} M_i(n) + \gamma(n) \tag{10}$$

3.2 Dictionary Learning Sparse Method for Denoising - KSVD

The KSVD (Singular Value Decomposition) algorithm is a widely used dictionary learning method that includes two stages: sparse encoding and dictionary update. The algorithm steps are as follows:

Step 1. Sparse encoding: Based on the training sample set y, initialize the dictionary D, use the OMP algorithm to find the best sparse representation, and obtain the sparse decomposition coefficient matrix $\sigma = \left\{\sigma_{ij}\right\}_{i=1}^{N}$. Set λ as the regularization parameter. There are the following relationships:

$$\min_{D,\sigma} \left\|\sigma_{ij}\right\|_0, s.t. \min_{D,\sigma} \left\|\tilde{y}(n) - D\sigma_{ij}\right\|_F^2 \leq \lambda \tag{11}$$

Step 2. Dictionary update: Use the KSVD algorithm to update the atoms in dictionary D column by column, $D=\begin{bmatrix} d_1 & d_2 & \cdots & d_n \end{bmatrix}$. Assuming that the coefficient matrix σ and dictionary D are both fixed, let the corresponding k-th row in coefficient matrix σ be σ_i^k. Update the j-th column atom d_j in dictionary D, then

$$\begin{aligned} \left\| y - D\sigma \right\|_F^2 &= \left\| y - \sum_{j=1}^{N} d_j \sigma_j^k \right\|_F^2 \\ &= \left\| \left(y - \sum_{j\neq n} d_j \sigma_j^k \right) - d_n \sigma_n^k \right\|_F^2 \\ &= \left\| \gamma_n - d_n \sigma_n^k \right\|_F^2 \end{aligned} \tag{12}$$

where, $\gamma_n = y - \sum_{j\neq n} d_j \sigma_j^k$ is the residual of the iteration, σ_j^k is the k-th row of σ. Therefore, the optimization problem can be described as:

$$\min_{d_j \sigma_j^k} \left\| \gamma_n - d_n \sigma_n^k \right\|_F^2 \tag{13}$$

Perform SVD decomposition on residual γ_n, where $\gamma_n = U\Lambda V^T$. Assuming $\widetilde{d_j}$ is the first column of U, then $\widetilde{d_j}$ is the update result of d_j. At the same time, update with the product χ_R^n of the first column of D and $\Lambda(1,1)$ to complete a single iteration. Repeat the above steps to obtain the optimal dictionary D. The construction of the dictionary D is to represent the original signal with the best linear combination, thereby achieving sparse decomposition of the signal, in order to better reconstruct the original signal and suppress noise.

4. Simulation Analysis

4.1 Sparse denoising method based on CEEMDAN-KSVD

Due to the residual noise of the noisy signal after CEEMDAN decomposition denoising, and the poor performance of KSVD denoising in some details, a combination of the two is considered to achieve denoising of the oil well resonance signal using CEEMDAN-KSVD.

Firstly, CEEMDAN modal decomposition is performed on the resonance signal $y(n)$ to obtain N IMF components. Then the signal $\widetilde{y(n)}$ is reconstructed based on the obtained IMF components. $\widetilde{y(n)}$ and the original signal $y(n)$ are used as training samples for the KSVD dictionary to obtain a new dictionary. Use this new dictionary and OMP algorithm to perform sparse decomposition denoising on $\widetilde{y(n)}$, and obtain the final denoising result for the original signal. The algorithm implementation steps are as follows:

Step 1. Initialize the resonance signal $y(n)$;

Step 2. Perform modal decomposition using the CEEMDAN algorithm to obtain each IMF component $m_i(n)$.

Step 3. Calculate the overall average of the obtained IMF components $m_i(n)$ to obtain the reconstructed signal $\widetilde{y(n)}$.

Step 4. Use $\widetilde{y(n)}$ and $y(n)$ as training samples to establish a KSVD learning dictionary.

Step 5. Use the OMP algorithm and KSVD dictionary to denoise the reconstructed signal $\widetilde{y(n)}$, then the final denoising result can be obtained.

4.2 Simulation Analysis

Using CEEMDAN to decompose the signal, 14 IMF components were obtained as shown in the figure 2. Calculate the arrangement entropy of each IMF component separately and perform normalization processing. The size of the normalized Hp value reflects the randomness of the time series. Select IMF sequences with Hp values greater than 0.5 for noise reduction processing. As shown in the figure 2, the instantaneous frequencies of components IMF3 to IMF14 are all smaller than the main frequency, which belongs to noise interference information and should be filtered out. That is, the first two orders of IMF should be retained. Further normalization was performed on IMF1 and IMF2, we can get Hp values of 0.738 for IMF1 and 0.412 for IMF2, as shown in table 1. Therefore, the denoised IMF1 component is obtained through SVD reconstruction.

Table 1. The correlation coefficient between each IMF component decomposed by CEEMDAN and the decomposed signal $y(n)$

IMF1	**IMF2**	**IMF3**	**IMF4**	**IMF5**	**IMF6**	**IMF7**
0.738	0.412	0.324	0.293	0.214	0.152	0.211
IMF8	**IMF9**	**IMF10**	**IMF11**	**IMF12**	**IMF13**	**IMF14**
0.237	0.149	0.098	0.102	0.083	0.041	0.027

In order to verify the effectiveness and superiority of the denoising method proposed in this paper, CEEMDAN and CEEMDAN-KSVD joint denoising methods were used to process the signal. The comparison of noise reduction effects between the two methods is shown in the figure 3.

The figure 3 shows that the CEEMDAN-KSVD joint denoising method has achieved good signal restoration, and the signal obtained is smoother compared to the CEEMDAN method.

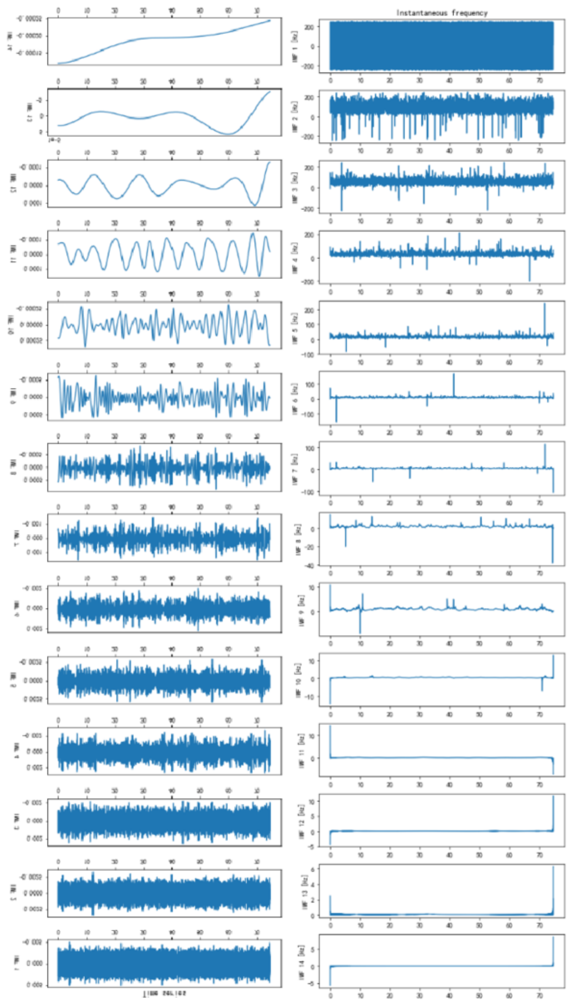


Figure 2. The decomposition results of CEEMDAN

5. Conclusion

This article combines the advantages of CEEMDAN and KSVD in signal denoising and proposes the CEEMDAN-KSVD joint denoising algorithm. And apply it to the noise reduction problem of resonance signals in the acoustic field model of oil well dynamic liquid level string containing noise. The simulation analysis results show that this method has good noise reduction ability and can provide a basis for the noise reduction of resonance signals under the sound field model of the pipe column. The main contributions of this article are as follows:

(1) This article proposes to use CEEMDAN algorithm for noise reduction of resonance signals in a dynamic liquid level pipe c

the oil well dynamic liquid level string.

(4) Compared with the CEEMDAN algorithm, the CEEMDAN-KSVD joint algorithm has better performance through simulation verification.

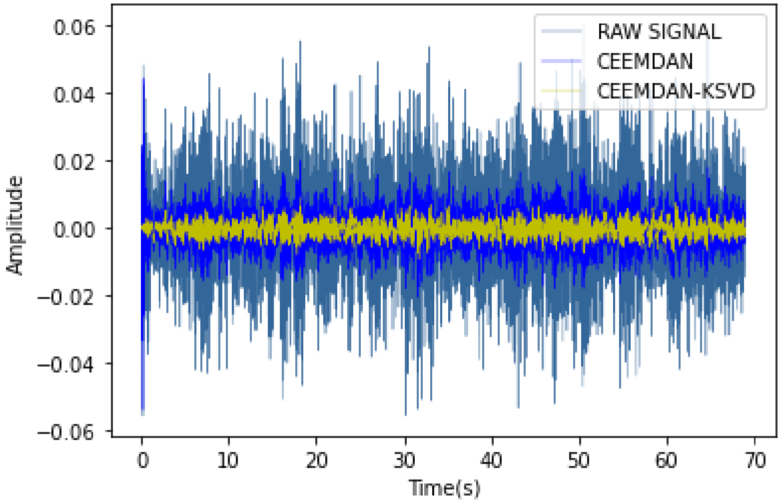


Figure 3. Performance comparison

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