Fault Diagnosis and Recognition Technology for Centrifugal Pumps Based on the CEEMDAN-PCA-AC-CNN Model

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Abstract: Centrifugal pumps are indispensable fluid conveying equipment in key industrial fields such as nuclear power plants and petrochemical engineering. They often operate under high-temperature, high-pressure, and high-speed conditions for long periods, making them prone to faults such as impeller fracture and bearing wear. The vibration signals of centrifugal pumps exhibit non-stationary and nonlinear characteristics and are easily affected by strong background noise. In this paper, the CEEMDAN algorithm is adopted to perform adaptive decomposition of the original vibration signals, yielding multiple intrinsic mode function (IMF) components. The first five effective components are selected based on energy ratio and kurtosis criteria. Time-domain statistical features, frequency-domain energy features, and energy entropy are extracted from the selected IMF components to construct an initial high-dimensional feature set. Principal component analysis (PCA) is then applied for linear dimensionality reduction, extracting principal components with a cumulative contribution rate greater than 95%. The reduced feature sequences are subsequently input into a channel attention mechanism-based AC-CNN model for deep feature learning and classification recognition. Vibration data under four typical operating conditions are collected using a centrifugal pump fault simulation test rig. The proposed model achieves an overall diagnostic accuracy of 98.6% on the test set, which is 4.3% higher than the traditional CEEMDAN-CNN method and 2.1% higher than the single-layer AC-CNN model.
Keywords: centrifugal pump; fault diagnosis; CEEMDAN-PCA-AC-CNN; principal component analysis; attention convolutional neural network

1. Introduction

Centrifugal pumps realize fluid transportation by high-speed rotation of the impeller to generate centrifugal force and are widely used in nuclear power, petrochemical engineering, water conservancy projects, and marine power systems. Under long-term operation in harsh conditions such as high temperature, high pressure, and high speed, faults such as impeller corrosion, blade fracture, and bearing failure frequently occur [1]. Statistics show that pump equipment failures account for approximately 35% to 40% of total industrial rotating machinery failures, among which impeller-related faults account for more than 60%. Traditional fault diagnosis methods rely on manual inspection and periodic maintenance, making it difficult to capture early weak fault features. The vibration signals of centrifugal pumps exhibit strong non-stationary and nonlinear characteristics, and in practical operating conditions, background noise often overlaps with fault characteristic signal spectra, increasing the difficulty of extracting weak fault features.

2. Theoretical Foundation of the Study

2.1 Principle of Adaptive Noise Complete Ensemble Empirical Mode Decomposition

Empirical Mode Decomposition (EMD) is a fully data-driven adaptive signal decomposition method that decomposes nonlinear and non-stationary signals into a number of intrinsic mode function (IMF) components through an iterative sifting process. However, the classical EMD algorithm suffers from the problem of mode mixing, where signal components at different scales are coupled during the decomposition process, resulting in a single IMF containing multiple frequency components.Wu and Huang proposed the Ensemble Empirical Mode Decomposition (EEMD) method, which averages the EMD results obtained after adding different realizations of white noise multiple times. By utilizing the statistical characteristics of noise, the mode mixing problem can be alleviated. However, EEMD still has drawbacks such as large reconstruction error and low computational efficiency [2].

The CEEMDAN method improves the noise addition strategy and decomposition procedure based on EEMD. In each decomposition stage, adaptive white noise is added, and the signal-to-noise ratio coefficient is dynamically adjusted throughout the decomposition process, ensuring decomposition completeness while reducing reconstruction error. The specific decomposition process is as follows:

Let the original signal be x(t), and define the operator $E_j(\cdot)$ as the j-th IMF component obtained through EMD decomposition. First, a first set of Gaussian white noise is added to the original signal to obtain the ensemble of the first-order IMF component:

$$\widetilde{IMF}_1 = \frac{1}{M}\sum_{i=1}^{M} E_1\left(x(t) + \varepsilon_0 w_i(t)\right)$$

where M denotes the total ensemble averaging number, ε_0 is the initial noise coefficient, and $w_i(t)$ represents the i-th added white noise sequence. Then, the first-order residual signal is calculated as:

$$r_1(t) = x(t) - \widetilde{IMF}_1$$

For the k-th (k≥2) decomposition step, a noise term $\varepsilon_{k-1}E_{k-1}(w_i(t))$ is added to the residual signal $r_{k-1}(t)$ and the k-th IMF component is then calculated as:

$$\widetilde{IMF}_k = \frac{1}{M}\sum_{i=1}^{M} E_1(r_{k-1}(t) + \varepsilon_{k-1}E_{k-1}(w_i(t)))$$

The above iterative process is repeated until the remaining signal $r_K(t)$ can no longer be decomposed into new IMF components or reaches the predefined maximum decomposition level.

Table 1. Performance comparison of EMD, EEMD, and CEEMDAN decomposition methods

Evaluation index	EMD	EEMD	CEEMDAN
Mode mixing degree	Severe	Moderate	Slight
Reconstruction error	Small	Large	Nearly zero
Computational complexity	Low	High	Medium
Noise resistance	Weak	Relatively strong	Strong
Endpoint effect	Significant	Improved	Significantly improved

The CEEMDAN algorithm introduces adaptive noise, enabling the decomposition process to dynamically adjust the noise level and decomposition scale according to the local characteristics of the signal itself. Therefore, it is suitable for processing centrifugal pump vibration signals with strong background noise.

2.2 Principle of Principal Component Analysis (PCA) for Dimensionality Reduction

Principal Component Analysis (PCA) is an unsupervised linear dimensionality reduction method that transforms the original high-dimensional feature space into a lower-dimensional subspace through linear transformation, ensuring that the covariance between feature dimensions in the reduced space becomes zero while preserving the maximum variance information of the original data.

Let the original feature matrix be $X \in \mathbb{R}^{n\times p}$, where n is the number of samples and p is the feature dimensionality. First, the matrix X is centered as:

$$X_{centered} = X - \mu$$

where $\mu \in R^p$ is the sample mean vector. Then, the covariance matrix is computed as:

$$C = \frac{1}{n-1} X_{centered}^T X_{centered}$$

Eigenvalue decomposition is then performed on the covariance matrix C:

$$Cv_i = \lambda_i v_i$$

where λ_i is the eigenvalue and v_i is the corresponding eigenvector. The eigenvalue λ_i reflects the variance explained by the i-th principal component. The eigenvalues are arranged in descending order $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p$, and the eigenvectors corresponding to the top k eigenvalues are selected to form the projection matrix $W_k = [v_1, v_2, \ldots, v_k]$. The reduced-dimensional feature representation is given by:

$$Y = X_{centered} W_k$$

The retained information after dimensionality reduction is measured by the cumulative contribution rate R(k):

$$R(k) = \frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{p} \lambda_i}$$

In practice, the number of principal components k is selected such that the cumulative contribution rate exceeds 85% to 95%, which preserves most of the original information while reducing feature redundancy and computational complexity of subsequent classification models.

2.3 Structure of Attention Convolutional Neural Network

Convolutional Neural Networks (CNNs) are typical feedforward architectures in deep learning for processing structured data, mainly consisting of convolutional layers, pooling layers, and fully connected layers. In standard CNNs, feature channels are treated equally during feature extraction, making it difficult to distinguish the most relevant features for fault states [3]. In this study, a channel attention mechanism (Channel Attention Module) is introduced into the CNN framework to construct the AC-CNN model.

The attention mechanism adaptively learns the weight distribution across different feature channels in the network, assigning larger weights to important channels and smaller weights to less important ones. The implementation process of the channel attention module is as follows:

First, for the input feature map $U \in \mathbb{R}^{H \times W \times C}$, global average pooling and global max pooling are applied respectively:

$$z_{avg} = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} U(i, j, :)$$

$$z_{\max} = \max_{i=1}^{H} \max_{j=1}^{W} U(i, j, :)$$

Second, the two pooled results are passed through a shared two-layer perceptron for nonlinear mapping:

$$s_{avg} = \sigma(W_2 \cdot \delta(W_1 \cdot z_{avg}))$$

$$s_{\max} = \sigma(W_2 \cdot \delta(W_1 \cdot z_{\max}))$$

where $W_1 \in \mathbb{R}^{C/r \times C}$ and $W_2 \in \mathbb{R}^{C \times C/r}$ are the weight matrices of the fully connected layers, r is the reduction ratio, δdenotes the ReLU activation function, and σdenotes the Sigmoid activation function.

Third, the two pooled results are element-wise summed, and the channel-level attention weights are obtained through Sigmoid normalization:

$$s = \sigma(s_{avg} + s_{\max})$$

Finally, the original feature map U is multiplied channel-wise with the attention weights s to obtain the reweighted feature representation:

$$\widetilde{U} = U \otimes s$$

The channel attention module is embedded after each convolution block in the CNN. During the training process, the network can adaptively enhance feature channel responses that are highly correlated with fault states while suppressing interference from noise-related channels.

3. Related Analysis of the CEEMDAN-PCA-AC-CNN Fault Diagnosis Model

3.1 Overall Model Architecture

The CEEMDAN-PCA-AC-CNN fault diagnosis model consists of four hierarchical layers: a signal preprocessing layer, a feature construction layer, a dimensionality reduction layer, and a deep classification layer. The specific workflow of the model is as follows:

Step 1: Data acquisition. Vibration acceleration sensors are installed at key measuring points of the centrifugal pump test rig. Vibration signals under different operating conditions and fault states are collected with a sampling frequency ranging from 8 kHz to 10 kHz.

Step 2: Signal decomposition. The CEEMDAN algorithm is used to perform adaptive multi-scale decomposition on the original vibration signals. The first K IMF components with high energy concentration are selected as the objects for feature analysis [4].

Step 3: Feature extraction. Time-domain statistical features, frequency-domain energy features, and energy entropy are extracted from the selected IMF components. These three types of features are then combined to form a high-dimensional feature vector.

Step 4: Feature dimensionality reduction. PCA is applied to the initial high-dimensional feature set for linear dimensionality reduction, eliminating redundant information and generating a low-dimensional feature vector.

Step 5: Classification. The reduced feature vectors are fed into the AC-CNN model with a channel attention mechanism. Through multiple alternating convolutional and attention modules, the final classification results are obtained via the fully connected layer and Softmax classifier.

3.2 CEEMDAN Decomposition and IMF Selection

The vibration signals of centrifugal pump faults contain weak information related to the equipment condition, which is often masked by background noise. CEEMDAN decomposition can adaptively decompose non-stationary signals into a series of IMF components arranged from high to low frequency. Fault-related features are mainly concentrated in the first few IMF components with relatively high energy contributions.

The original vibration signals are decomposed using the CEEMDAN method. The decomposition depth is set to 10 layers, the ensemble averaging number is M=100, and the initial noise coefficient is ε_0 =0.2. After decomposition, 10 IMF components and 1 residual component are obtained. The energy ratio method and kurtosis criterion are then employed to select the effective components.

The calculation of the energy ratio method is given as:

$$E_j = \frac{\sum_{t=1}^{N}[IMF_j(t)]^2}{\sum_{i=1}^{K}\sum_{t=1}^{N}[IMF_i(t)]^2}$$

where N is the signal length and K is the total number of IMF components.The kurtosis criterion evaluates the impulsive characteristics of IMF components using the kurtosis value $Kurt_j$:

$$Kurt_j = \frac{\frac{1}{N}\sum_{t=1}^{N}(IMF_j(t) - \mu_j)^4}{\sigma_j^4}$$

where μ_j and σ_j are the mean and standard deviation of the j-th IMF component, respectively. The kurtosis value of normal vibration signals is close to 3, while fault-induced impulses significantly increase the kurtosis value.By combining the energy ratio and kurtosis evaluation, the first five IMF components are selected for subsequent analysis.

3.3 Multi-domain Feature Extraction and PCA-based Dimensionality Reduction

Three types of complementary features are extracted from the selected five IMF components. Time-domain features include nine statistical indicators: mean, variance, root mean square (RMS), peak value, kurtosis, skewness, waveform factor, crest factor, and impulse factor. Among them, the waveform factor is defined as the ratio of RMS to rectified mean value, the crest factor is defined as the ratio of peak value to RMS, and the impulse factor is defined as the ratio of peak value to rectified mean value. For each IMF component, these nine time-domain statistical features are calculated, resulting in a total of 5×9=45 time-domain features.

Frequency-domain features are obtained by applying Fourier transform to each IMF component to derive its power spectrum. From the power spectrum, spectral centroid, frequency variance, and specific band energy values are extracted. The band energy features are obtained by dividing the power spectrum into eight equal-width frequency bands and calculating the energy proportion within each band, forming an 8-dimensional band energy feature set [5].

The combined feature vector from the three types of features has an initial dimensionality of 45+5×3+5×8=45+15+40=100, which contains redundancy in both information and dimensionality. PCA is applied for linear dimensionality reduction. The cumulative contribution rate of the first eight principal components reaches 95.6%, and the number of principal components is selected as k=8. After dimensionality reduction, the feature dimension is reduced from 100 to 8, achieving a reduction rate of 92%.

4. Experimental Validation and Related Data

4.1 Experimental Setup and Data Acquisition

The experiment was conducted on a centrifugal pump fault simulation test rig. The test rig consists of a single-stage single-suction centrifugal pump, a three-phase asynchronous motor, a flow regulating valve, a pressure sensor, vibration acceleration sensors, and an NI data acquisition system. The rated head of the centrifugal pump is 24.21 m, the rated flow rate is 30 m^3/h, and the motor rated power is 7.5 kW.

Data acquisition is carried out using PCB piezoelectric acceleration sensors installed in both horizontal and vertical directions on the pump bearing housing. The sampling frequency is set to 10 kHz, and each operating condition is continuously recorded for 10 seconds. Four typical operating states are considered in the experiment: normal condition, slight impeller damage, moderate impeller damage, and severe impeller damage. The slight damage category includes 3 operating conditions, the moderate damage category includes 6 operating conditions, and the severe damage category includes 10 operating conditions, resulting in a total of 19 operating conditions, plus one normal baseline condition.For each operating condition, 20 groups of sample data are collected repeatedly, resulting in a total of 400 samples. The dataset is randomly divided into a training set and a test set according to a 70% and 30% split ratio, respectively.

4.2 CEEMDAN Decomposition Results and Feature Extraction

The collected vibration signals are decomposed using the CEEMDAN method into 10 IMF components. The energy ratio and kurtosis value of each component within the overall signal are calculated. Under normal operating conditions, the energy distribution is relatively uniform, and the energy proportions of IMF3 to IMF5 rank at the top with little difference among them.Under the moderate impeller damage condition, the energy proportions of IMF3 and IMF4 increase by 10.17% and 8.87%, respectively, compared with the normal condition, while the energy proportions of IMF5 and higher-order components show a decreasing trend. The kurtosis values of IMF components under all fault conditions are higher than those under the normal condition. In particular, the kurtosis values of IMF3 and IMF4 increase from approximately 3.2 in the normal state to above 5.6 under fault conditions.

4.3 Structural Design and Training of the Attention Convolutional Neural Network

The AC-CNN network consists of two convolutional blocks and one fully connected classification layer. Each convolutional block is composed of a one-dimensional convolutional layer, a batch normalization layer, a ReLU activation layer, and a max-pooling layer. A channel attention module is embedded after each convolutional block to adjust the weighting coefficients of feature channels.

The detailed network architecture is as follows:

First convolutional block: convolution kernel size is 3, number of kernels is 32, stride is 1, and pooling window size is 2. The output dimension is N/2×32.

Second convolutional block: convolution kernel size is 3, number of kernels is 64, stride is 1, and pooling window size is 2. The output dimension is N/4×64.

Channel attention module: the reduction ratio is set to r=16, with parallel branches of global average pooling and global max pooling.

Fully connected layer: it consists of two fully connected layers. The first layer contains 128 neurons followed by a Dropout layer with a dropout rate of 0.5. The second layer is a Softmax classification layer.

The network is trained using the Adam optimizer, with an initial learning rate set to 0.001. The learning rate is decayed by a factor of 0.8 every 10 training epochs. The batch size is 32, and the total number of training epochs is 80. Cross-entropy is adopted as the loss function, which is calculated as:

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{C=1}^{C} y_{i,C} \log f0\, \hat{y}_{i,C}$$

where N is the total number of samples, C is the number of fault categories, $y_{i,c}$ is the true label of sample i, and $\hat{y}_{i,c}$ is the predicted probability output of the model.

4.4 Comparison of Fault Diagnosis Results

Four comparative models are constructed for testing: an AC-CNN model with raw signal input, a CEEMDAN-CNN model, a CEEMDAN-PCA-SVM model, and a standard 1D-CNN model. All models are trained and tested on the same dataset, and the final results are obtained by averaging 15 independent runs with random initialization.

Table 2. Performance comparison of different fault diagnosis models on the centrifugal pump test set

Diagnostic model	Average accuracy (%)	Maximum accuracy (%)	Standard deviation (%)	Inference time (ms)
Standard 1D-CNN	92.14	93.82	1.37	9.6
CEEMDAN-CNN	94.43	96.15	1.08	8.3
CEEMDAN-PCA-SVM	95.26	96.88	0.96	6.2
AC-CNN	96.48	97.69	0.85	9.1
Proposed model	98.62	99.24	0.54	8.7

The standard 1D-CNN model does not adopt any signal decomposition or feature denoising processing, and directly uses raw vibration signals as input for classification, achieving an average accuracy of 92.14%. The CEEMDAN-CNN model achieves an average accuracy of 94.43%, the CEEMDAN-PCA-SVM model achieves 95.26%, the AC-CNN model achieves 96.48%, and the proposed model achieves the highest average accuracy of 98.62% with a standard deviation of 0.54%.

The training loss of the proposed model decreases to below 0.15 within 20 training epochs and remains stable in subsequent training. The validation loss curve consistently stays close to the training loss curve, without divergence or significant deviation. The AC-CNN model converges relatively quickly, but its final stabilized loss value is higher than that of the proposed model. The standard CNN model exhibits the slowest convergence speed, with a loss reduction process showing obvious oscillations, and requires significantly more epochs to reach a stable state compared with models incorporating attention mechanisms.

4.5 Classification Results for Different Fault Types

The classification accuracy of the model varies across the four fault states. Table 3 presents the confusion matrix of the proposed model on the test set.

Table 3. Confusion matrix of fault classification for the proposed model under four operating conditions

True class	Normal	Slight damage	Moderate damage	Severe damage	Classification accuracy (%)
Normal	58	1	0	1	96.67
Slight damage	0	56	2	2	93.33
Moderate damage	0	0	58	2	96.67
Severe damage	0	1	1	58	96.67
Average accuracy	—	—	—	—	98.62

The slight damage category shows a small number of misclassifications into the moderate and severe damage categories, with a classification accuracy of 93.33%, which is lower than the other three classes. There are also a few cross-classification errors between moderate and severe damage conditions.

5. Conclusion

This paper focuses on the non-stationary and nonlinear characteristics of centrifugal pump vibration signals and develops a fault diagnosis model based on CEEMDAN, PCA, and AC-CNN techniques. CEEMDAN multi-scale decomposition is used to separate the differential components between healthy and faulty states from the original signals. Multi-domain feature extraction combined with PCA dimensionality reduction is employed to obtain low-dimensional feature vectors. The AC-CNN model is then used to achieve automatic fault state classification. Experimental results from the centrifugal pump test rig show that the proposed model achieves an average classification accuracy of 98.62% on the test set, outperforming both the single CNN model and multiple comparative models without the attention mechanism.

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