Visualized Feature Extraction Method of Diesel Engine Based on Texture Enhanced Block NMF (TE-BNMF)

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Abstract—**Diesel engine is a kind of power machinery equipment and widely used in industrial and agricultural production. Aiming at the difficulty in fault feature extraction of diesel engine, a visualized method based on the texture enhanced block non-negative matrix factorization (TE-BNMF) is proposed. The method firstly performs time-frequency analysis on the collected cylinder head vibration signals; then the local binary pattern (LBP) method is used to re-encode the vibration spectrum based on the gray distribution. After that, we use block non-negative matrix factorization algorithm (BNMF) to directly extract the feature parameters of the generated local binary feature map. By using a classifier to perform pattern recognition on the above-mentioned coding matrix, the automatic diagnosis of diesel engine faults is achieved. This method was applied to the fault diagnosis of 6 typical operating conditions of diesel engines, which can get high and stable fault recognition accuracy. The experiments show that the TE-BNMF diesel engine visualized fault diagnosis method proposed in this paper can discovery rich information contained in the spectrum image of diesel engine vibration deeply and diagnose the valve clearance fault of the diesel engine adaptively.**

Keywords- diesel engine; feature extraction; local binary pattern; block non-negative matrix factorization

I. INTRODUCTION

Diesel engines are widely used in many fields such as power traction, fixed power generation, and construction machinery. Research on diesel engine condition monitoring and fault diagnosis technology is of great significance. Numerous fault diagnosis methods for diesel engines have been proposed so far, there are mainly three types: model based, signal based, and data based [1, 2]. However, signal processing is a crucial part for all of these three types. Having both rotating and reciprocating motions, diesel engine vibration response signals are complex and coupled seriously, and it has strong nonlinear and non-stationary time-varying characteristics. The time-frequency analysis method can reflect the distribution characteristics of the diesel vibration signal in both the time domain and frequency domain [3~6].

The key processes of diesel engine vibration time-frequency analysis are effective two-dimensional time-frequency characterization of vibration signals and extraction of characteristic parameters of time-frequency vibration spectrums. And time-frequency characterization is a method of transforming one-dimensional signals into two-dimensional time-frequency images for analysis, which is a powerful tool for analyzing time-varying non-stationary signals. Although many time-frequency images contain a wealth of signal failure classification information, its data dimension is too large for pattern recognition. Therefore, we need to perform further feature extraction on time-frequency images.

Non-negative matrix factorization (NMF) [7, 8] method has been applied to the characteristic extraction of the time-frequency images in many literatures [9~12]. In order to achieve better results, a number of derivative algorithms have been proposed. Among them, the typical derivative algorithm have sparse non-negative matrix factorization (SNMF), which is proposed based on the combination of sparse coding and NMF, and local non-negative matrix factorization (LNMF), which is proposed based on the objective function for divergence and adds three constraints to the basic NMF algorithm. But all these methods are solved in the one-dimensional vector space. Since the one-dimensional NMF algorithm needs to vectorize the time-frequency images before decomposition, the computational efficiency of the algorithm is very low. To get a better diesel fault diagnosis effect, we applied a new improved algorithm named Block Non-negative matrix factorization (BNMF). By improving the matrix decomposition structure, the sparsity of the coefficient matrix is increased, the dimension of the initial decomposition matrix is reduced, and the computational efficiency of the algorithm is greatly improved. Since NMF algorithm can extract local features of the image, we use Local Binary Pattern (LBP) [13] algorithm to enhance the local texture features of the original time-frequency image, which is more conducive to pattern recognition of time-frequency images [14].

Based on the above analysis, this paper focuses on the fault feature extraction in diesel engine fault diagnosis and

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effectively combines the image texture feature analysis method and the matrix algebra feature extraction method. We propose a novel diesel engine visualization feature extraction method called texture-enhanced block NMF algorithm (TE-BNMF). This method is applied to the fault diagnosis test of diesel engine cylinder head vibration acceleration signals of 6 different valve states. The fault recognition accuracy rate is very high, which fully proves the validity of this method for diesel engine automatic fault diagnosis.

II. TEXTURE ANALYSIS BASED ON LOCAL BINARY PATTERN ALGORITHM

The original LBP operator is defined in a rectangular neighborhood of size of 3×3, and the arbitrary color images should be converted to gray images with a gray scale value of 0~255. The pixels of the 3×3 rectangular area are used as sampling points, the gray value of the center pixel of the sampling window is f_0, and $f_1, f_2, \cdots, f_8$ is the gray scale value of 8 pixels around it. When $f_i \ge f_0$ the corresponding position is coded as 1, and when $f_i < f_0$ the corresponding position is encoded as 0. After all pixels within the area are coded, the encoding value of 8 pixels around the center pixel is composed of a binary number in a clockwise direction, and then we can get the LBP code of the center pixel. The LBP coding is used as a feature to reflect the texture information of the window region, and the whole extraction process is shown in Fig. 1. The coding formula of standard LBP operator can be described as follows:

$$LBP(C) = \sum_{i=1}^{8} S(f_i, f_0) \cdot 2^{i-1} \tag{1}$$

$$S(f_i, f_0) = \begin{cases} 1, & f_i - f_0 \geqslant 0 \\ 0, & f_i - f_0 < 0 \end{cases} \tag{2}$$

According to the coding rules of standard LBP, a LBP operator may have 256 kinds of binary codes at most. After LBP coding of all pixel points of the image, the corresponding LBP map is obtained. Taking Lena image as an example, the LBP map was re-encoded by the original Lena image via LBP operator, and the texture features in the original image were highlighted. The corresponding code of each pixel point is still a non-negative value, the new code values are no longer represent to pixel gray scale, but on behalf of the relations of the pixels' local texture feature.

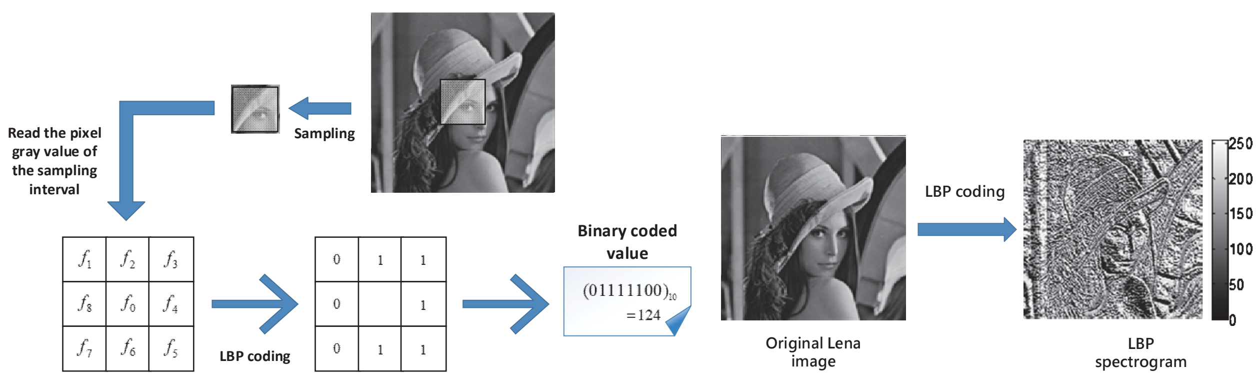


Figure 1. Schematic diagram of LBP coding process

III. IMAGE FEATURE EXTRACTION BASED ON BLOCK NON-NEGATIVE MATRIX FACTORIZATION

Non-negative Matrix Factorization (NMF) is proposed by Lee, It is essentially a linear, non-negative data representation been more and more applied to face detection, image retrieval and other fields. NMF algorithm is able to extract the multiline structure in data and can be used to extract the local characteristic information of the image.

Considering $\boldsymbol{V}_{m\times n} = \{\boldsymbol{v}_1 \quad \boldsymbol{v}_2 \quad \cdots \quad \boldsymbol{v}_n\} \in \mathbb{R}_+^{m\times n}$, where $\boldsymbol{v}_i$ donates a feature vector. Given a reduced dimension r, and then the matrix $\boldsymbol{V}_{m\times n}$ can be approximated by $\boldsymbol{W}_{m\times r}$ and $\boldsymbol{H}_{r\times n}$ by the NMF algorithm, namely [7]

$$\boldsymbol{V}_{m\times n} \approx \boldsymbol{W}_{m\times r} \cdot \boldsymbol{H}_{r\times n} \tag{3}$$

$\boldsymbol{W}$ and $\boldsymbol{H}$ should not be negative, the corresponding feature coding can be obtained by matrix projection. r is called characteristic dimension, which should be satisfied $r\cdot(m+n) < m\cdot n$. To describe the approximation effect of $\boldsymbol{V} \approx \boldsymbol{W} \cdot \boldsymbol{H}$, the *Frobenius* norm is used as the approximate error between $\boldsymbol{V}$ and $\boldsymbol{W} \cdot \boldsymbol{H}$, namely

$$E(\boldsymbol{V}\|\boldsymbol{WH}) \approx \|\boldsymbol{V} - \boldsymbol{WH}\|_F^2 \tag{4}$$

The corresponding optimization problem is

$$\min E(\boldsymbol{V}\|\boldsymbol{WH}), \quad s.t. \boldsymbol{W}, \boldsymbol{H} \ge 0 \tag{5}$$

When the matrix dimension of $\boldsymbol{V}_{m\times n}$ is high, the NMF decomposition solution will inevitably face the dimensionality disaster problem. To solve it, we propose a block non-negative matrix factorization algorithm (BNMF). Decompose observation matrices into column vectors $V_{m\times n} = [V_1 \quad V_2 \quad \cdots \quad V_b]$ where $V_i \in \mathbb{R}^{m\times n_0} (i = 1, 2, \cdots, b)$ b is number of blocks and $n_0 = n / b$. The objective function is

$$D(V\|WH) \approx \sum_{ij}(V_{ij}log\frac{V_{ij}}{(WH)_{ij}} - V_{ij} + (WH)_{ij}) \tag{6}$$

The corresponding optimization problem is

$$\min D(V\|WH), \quad s.t. W, H \geq 0 \tag{7}$$

We can solve the radical alternates of matrix and coefficient matrix by setting convergence criterion and updating law.

$$W_{ia} \leftarrow W_{ia}\frac{(VH^T)_{ia}}{(WHH^T)_{ia}} \tag{8}$$

$$H_{au} \leftarrow H_{au}\frac{(W^TV)_{ia}}{(W^TWH)_{au}} \tag{9}$$

The block matrix and the corresponding base matrix and the coefficient matrix satisfy

$$(V_i)_{m\times n_0} \approx (W_i)_{m\times r_0}(H_i)_{r_0\times n_0}, i = 1, 2, \cdots, b \tag{10}$$

Where $r_0 = r/b$ is the feature dimension. The base matrix and the coefficient matrix obtained by the decomposition are synthesized according to the following formula, and the base matrix and coefficient matrix of the original non-negative observation matrix can be obtained.

$$W_{m\times r} = [W_1 \quad W_2 \quad \cdots \quad W_b] \tag{11}$$

$$H_{r\times n} = \mathrm{diag}\left[H_1 \quad H_2 \quad \cdots \quad H_b\right] \tag{12}$$

The BNMF decomposition form of the matrix can be expressed as

$$V \overset{BNMF}{\approx} [W_1 \quad W_2 \quad \cdots \quad W_b]\cdot\begin{bmatrix} H_1 & 0 & \cdots & 0 \\ 0 & H_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & H_b \end{bmatrix} \tag{13}$$

The BNMF algorithm is used to decompose V and obtain the feature matrix W. The training image samples and the test image samples are respectively projected onto the matrix W to obtain the corresponding feature coefficients. The classifier can be used to further determine the fault mode. Since the classification vectors obtained by the block algorithm tend to have better sparsity, they can often get better classification results.

Taking the Lena image as an example, Fig. 2 shows the image reconstructed by the decomposition of the base matrix and the coefficient matrix after the image is decomposed by NMF, SNMF, LNMF and BNMF algorithms, and the number of iterations is 100 times. The feature dimension is 64 and the BNMF block number is 16. It can be seen that there are obvious noises in the NMF reconstruction graph and the SNMF reconstruction graph, and the LNMF reconstruction graph is completely blurred. In comparison, the BNMF reconstruction graph performs better on the image details. The BNMF algorithm is used to decompose the matrix, and the obtained matrix and coefficient matrix are sparse. The basic components of the image can be extracted clearly and sparsely, which can better compensate the image compression for different operating conditions of the internal combustion engine. The effect of frequency image recognition effects. The fault diagnosis model based on TE-BNMF is shown in Fig. 3.

（a）Lena （b）NMF （c）SNMF （d）LNMF （e）BNMF

Figure 2. Reconstruction of Lena images by different NMF methods

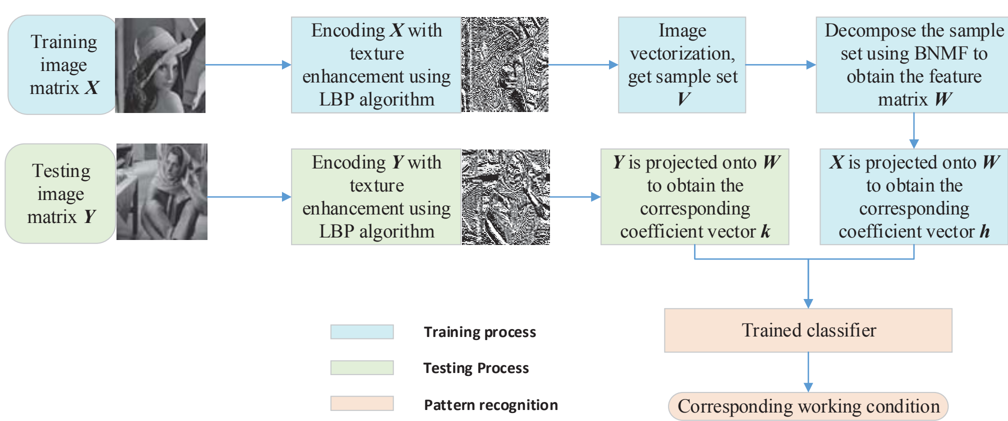


Figure 3. Fault diagnosis method model based on TE-BNMF

IV. FAULT DIAGNOSIS METHOD OF DIESEL ENGINE BASED ON TE-BNMF

A. Experiment setting

Acquisition of cylinder head vibration signal is the basis for the analysis of the running state of the diesel engine. In the process of signal acquisition, the quality of the signal is mainly affected by the precision of the measurement system, the measurement position and the sampling frequency. In this paper, BF4L1011F diesel engine is used as the research object, the rated speed of the equipment is $3000r/\min$ and the sampling frequency is $25kHz$. Fig.4 shows the location of the sensor during the test. We simulated 5 common air valve faults in comparison with the normal state of the valve, as is shown in Table 1. The normal intake valve clearance should be $0.25 \sim 0.35mm$ and exhaust valve clearance should be $0.45 \sim 0.55mm$ in the experiment, $0.3mm$ and $0.5mm$ correspond to the normal state of clearance between intake and exhaust valve, $0.06mm$ and $0.7mm$ corresponding valve clearance is too small and too large to simulate slight air leakage failure when the valve is not worn. Fig.5 illustrates the waveform and corresponding power spectrum of the normal condition vibration collected in a working cycle of the second cylinder. Lasting about 0.08 s, the waveform presents obvious non-stationary property since the transient amplitudes change sharply. The energy of vibration is concentrated in the range of [6.0, 9.0] kHz. However, it is obvious that the power spectrum cannot reveal the occurrence moment of the cyclic impulses, while the waveform cannot indicate the oscillation energy. The samples of vibration signals of 100 groups in 6 states were collected and analyzed.

TABLE I. PARAMETERS OF VALUE IN DIFFERENT CONDITIONS (UNIT: MM)

No.	Gap of the intake valve	Gap of the exhaust valve	Notes
1	0.30	0.50	Normal condition
2	0.30	0.06	Exhaust valve gap is too small
3	0.30	0.70	Exhaust valve gap is too small
4	0.06	0.06	Intake valve gap is too small
5	0.06	0.70	Intake valve gap is too small, exhaust valve gap is too large
6	0.70	0.70	Both valve gaps are too large

The most widely used time-frequency analysis methods of non-stationary signals are linear time-frequency analysis methods and nonlinear time-frequency analysis methods. In which, the typical linear time-frequency analysis method is the Short-Time Fourier Transform (STFT) and the nonlinear time-frequency analysis is represented by the Cohen class bilinear time-frequency distribution. The basis for this kind of approach is the Wigner-Ville distribution (WVD), what's more, the most widely used derivative methods of WVD are Pseudo Wigner-Ville Distribution (PWVD) and Smooth Pseudo Wigner-Ville Distribution (SPWVD). These methods can obtain the distribution of time-frequency components of different effects with different time and frequency resolution.

In order to objectively demonstrate the effectiveness and generalization performance of the TE-BNMF method, STFT, WVD, PWVD and SPWVD are selected for the time-frequency analysis of the vibration signal. Among them, the hamming window with width 25 is selected in the STFT time-frequency distribution and the hamming window with width 115 is selected in the WVD, PWVD and SPWVD time-frequency distribution. Four different time-frequency representations of the vibration signal of diesel engine are shown in Fig.6.

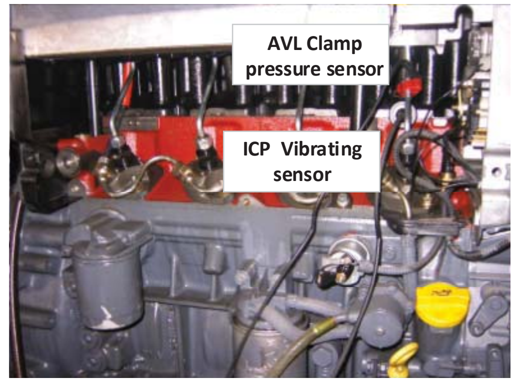
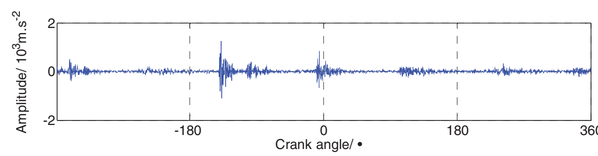
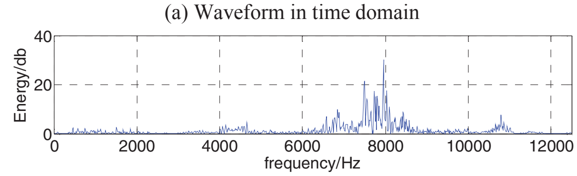


Figure 4. Experiment platform

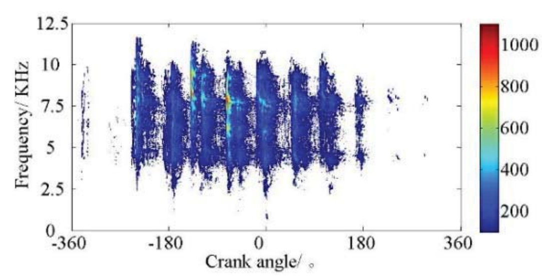


(a) Waveform in time domain

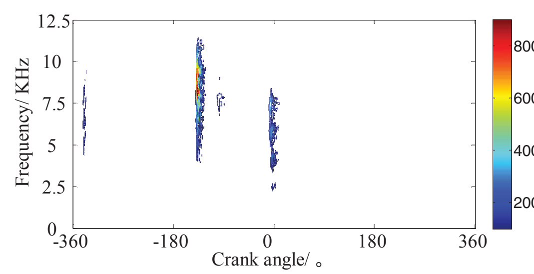


(b) Power spectrum

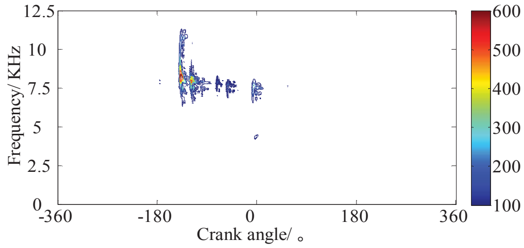
Figure 5. Waveform and power spectrum of the normal condition



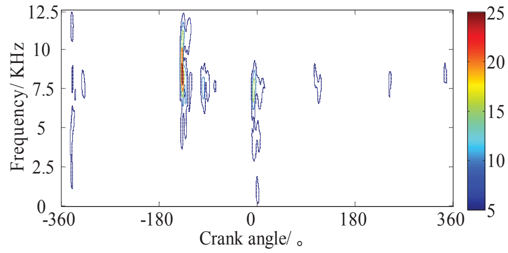
(a) WVD Distribution



(b) PWVD Distribution



(c) SPWVD Distribution



(d) STFT Distribution

Figure 6. Four different time-frequency representations of the signal

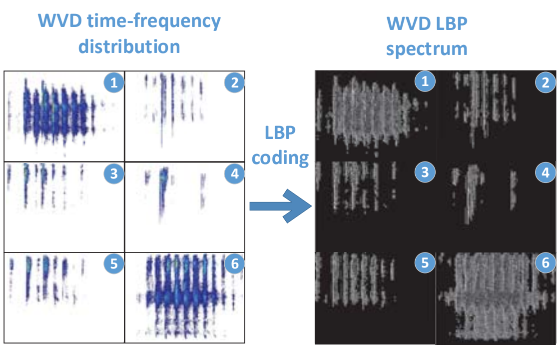


Figure 7. WVD time-frequency distribution images corresponding to diesel engine LBP spectrums

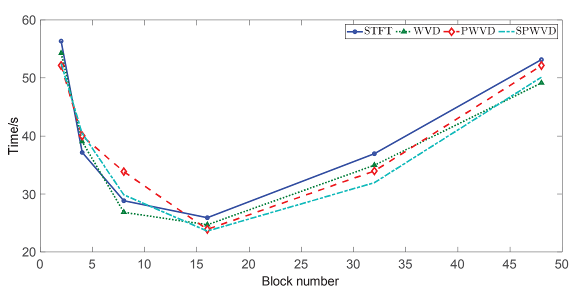
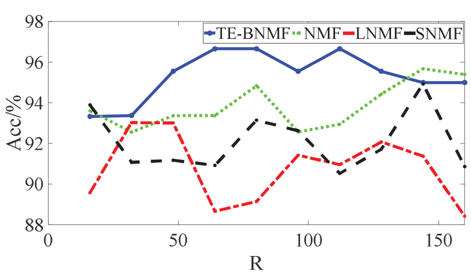
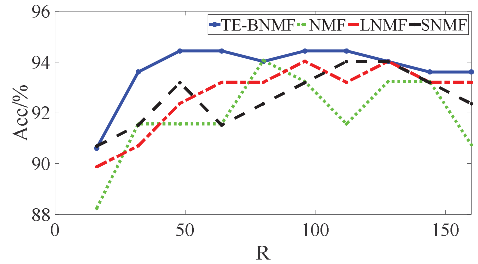


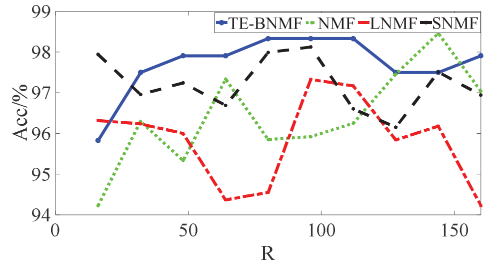
Figure 8. Time-consuming with different block numbers



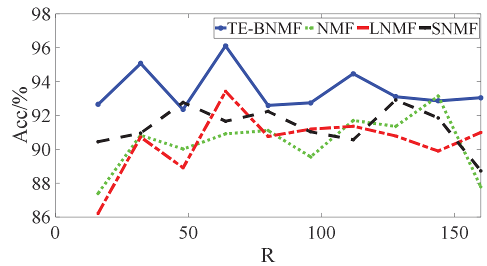
(a) WVD Distribution



(b) PWVD Distribution



(c) SPWVD Distribution



(d) STFT Distribution

Figure 9. Pattern recognition results of 8 algorithms

B. *Feature extraction and classification of time-frequency vibration spectrum of diesel engine*

Fig.7 shows a sample of WVD time-frequency distribution images corresponding to 6 working conditions of the cylinder cover vibration signal of the diesel engine, and the LBP method is used to re-code the image samples to obtain the corresponding LBP spectral image. The number in the figure is shown as the corresponding diesel engine running condition.

The influence of the number of blocks in the BSNMF algorithm on feature extraction efficiency is studied. If the number of blocks is too small, the effect of the convergence of the algorithm is not obvious. Fig. 8 shows the time it takes for the six state time-frequency image features to reach the preset error range under different block numbers. We can see highest computational efficiency is achieved when the number of blocks is 16. According to the actual matrix dimension, the step is 16 steps, R is taken from 16 to 128, and iteratively calculated under different feature dimensions, and the total number of iterations is limited to 100.

In order to compare the computational efficiency of different algorithms, we used NMF, SNMF, LNMF and the TE-BNMF algorithm in this paper to extract the characteristics of the samples of 6 working condition training sets. Algorithm unified iteration 100 times, objective function tolerance error is defined as 10^{-5}. Table 2 shows the calculation time of 6 feature extraction algorithms, which does not include the time of image loading. It can be seen from table 2, with the increase of feature dimension, the extraction time of five algorithm features is increasing.

TABLE II. TIME CONSUMING IN WVD FEATURE EXTRACTION (UNIT: 10^2S)

Characteristics dimension	NMF	SNMF	LNMF	TE-BNMF
16	7.98	6.56	10.74	2.67
32	8.30	6.83	11.08	2.68
48	8.51	7.38	11.81	2.68
64	8.64	7.68	12.47	2.69
80	8.87	8.02	14.37	3.02
96	9.64	8.83	14.83	2.70
112	9.95	9.13	15.00	3.32
128	10.17	9.41	15.29	2.73
144	11.15	10.04	16.22	3.47
160	11.53	10.49	16.91	2.74

Fig.9 shows the pattern recognition results of the 4 algorithms of NMF, SNMF, LNMF, and TE-BNMF. The test sample set and test sample set randomly selected 180 different diesel vibration time-frequency images, we selected support vector machine (SVM)[15] as the classifier and used the Libsvm toolbox with linear kernel function, and the parameter selection was automatically determined according to the optimization results of grid parameters in the toolbox. Because of the different analysis degree of four time-frequency analysis methods, the corresponding fault recognition accuracy is also different. The highest fault recognition accuracy of WVD, SPWVD, SPWVD and STFT distributions are 96.66%, 94.44%, 98.33%, 96.11%. Since WVD distribution and PWVD distributions have serious cross-interference items, the characteristic in time domain of diesel engine vibration signal cannot be fully reflected, which affected the fault pattern recognition; the STFT distribution is affected by poor resolution, meanwhile, the frequency distribution cannot accurately reflect the moment and corresponding frequency of the impact component in the vibration signal of diesel engine. Compared with the above three kinds of time-frequency analysis methods, SPWVD keeps a better time-frequency distribution of clustering and effectively curb the cross interference of WVD, it has a stronger representation ability of fault information so the fault diagnosis effect is relatively better.

V. CONCLUSIONS

In order to deal with the parameters extracting problems in fault diagnosis of diesel engine using the time-frequency images, a novel diagnosis method was proposed by the combination of the LBP and the BNMF. Firstly, by introducing the texture analysis methods into the NMF, the TE-BNMF was developed. Then, for comparison, the TE-BNMF coding matrix of WVD, PWVD, SPWVD and STFT time-frequency image sets were input to a SVM classifier to perform the classification. Finally, experiments were used to validate the efficacy of the proposed method by comparing with the methods of NMF, SNMF, and LNMF. It is shown that the proposed fault diagnosis method can efficiently classify the fault classes by using the coding matrix of TE-BNMF as the input vector of the SVM classifier, and the fault diagnosis effect is also obviously better than several traditional methods in the paper. Moreover, compared with the NMF, SNMF and LNMF, the proposed method can represent the class information more efficiently regardless of the dimensions of the image. In summary, experiments show that the proposed method has the advantage of high fault recognition accuracy and high efficiency, which explores a new approach to fault diagnosis of diesel engines and has good generalization significance.

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