

Noise Feature Extraction and Analysis of Silicone Oil Fan on Diesel Engine Based on Non-negative Tensor Factorization

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Abstract: The rotate speed of the electronic-control silicone oil fan directly affects the passing-by noise of the GB 1495 requirement of the load truck in China. Especially, when the silicone oil fan is directly connected to the main shaft of diesel engine, the noise level is dramatically increases, which makes the spectrum characteristics become complex and difficult to identify for engineer, resulting in the inaccurate control of the rotate speed of the fan. It is necessary to find a high- efficiency method to analyze the frequency of the fault. In this paper, the method of non-negative tensor factorization (NTF) is used to decompose the data for fault analysis. According to the geometric model of NTF, the fixed-point alternating least squares is selected to calculate the decomposed factors after the data transmitted to a three dimensional tensor of the hyperspectral data. While all the factors are computed the sparse local bispectrum can be reconstructed with khatri-rao product between the factors, which also be named basic local feature. Experiments show that the calculation error decreases with the increase of tensor cardinal dimension, the error is still less than 9%, and the maximum proportion of the value of sparse bispectrum extracted is only 0.71%, which proves that the analysis method of non-negative tensor factorization for bispectrum extraction is a well solution.

Keywords: Silicone Oil Fan, Non-negative Tensor Factorization, Sparse, Bispectrum Feature

1. Introduction

In recent years, the regulation of noise control has further improved the requirements 83dB of pass-by noise (84dB in the second stage) to the loading trucks in China [1], which has aroused the engines and the scholars to focus on researching the diesel engine control of noise, vibration and harshness (NVH) [2, 3]. One of the key factors is the part influence. The silicon oil fan is one of the commonly used parts for cooling the diesel therein [4-6]. However, when the cooling water temperature is lower than 85° during the working, the control clutch in the silicon oil fan still maintains direct-connection between the fan and the engine shaft for excessive torque transmission, which leads to loud noise by the silicon oil fan. Then the high rotate speed of the silicon oil fan makes the pass-by noise higher than the normal value of 4~5 dB(A), which seriously block the development cycle of the load truck in performance [7, 8]. Therefore, the control of the rotate speed of silicone oil fan is an effective method to ensure the sound pressure level (SPL) meet the regulations. Take the noise into consideration, the frequency analysis of the silicon oil fan needs high sampling frequency that results in data disaster, which makes it difficult for engineers to identify fan noise correctly. Especially in the complex statuses coupling with masking effect [9]. Therefore, it is necessary to find a method that can not only decompose high-dimensional data efficiently, but also analyze its features easily.

Nonnegative tensor factorization (NTF) has the advantages of high efficiency, fast convergence and strong sparse local features extracted, which has been widely used in blind source separation, signal processing and fault diagnosis [10-14]. In order to fast and accurately identify the working characteristics of silicone oil fan on diesel engine, the noise signals are need to be acquired at the work state for the three-dimension tensor reconstruction firstly. Then, the method of non-negative tensor factorization is used to decompose the tensor and extract the bispectrum feature. Meanwhile, the iterative way of fixed-point alternating least squares (LMS) is applied to calculate the sub-factors iteratively, which meets the requirement of computation accuracy by khatri-rao product among the factors happened in the three-dimension tensor. Lastly, the local bispectrum is reconstructed by the sub-factors for the noise analysis. The sparse feature expressed by the bispectrum is extremely avoids noise interference or masking effect, which is of great significance for engineers to accurately analyze the fault types of silicone oil fans and exactly makes control-strategy.

2. Tensor Factorization Theory and Its Geometric Model

The structural noise transmission of diesel engine is complex, which is easy to produce different frequency noises in a non-stationary condition. Two or more adjacent frequency noises happen in the same time, the traditional method often gives priority to the main noise with higher sound pressure level (SPL) in the whole frequency range. When the other noise is masked by the higher one, the ignored noise will make it difficult for engineers to exactly identify the really work noise. In order to overcome this problem, NTF algorithm is used to extract the local bispectrum feature for noise analysis.

The main idea of NTF is that all substances exist in a non-negative form, including noise signal distributed in the time series. The tensor in the three-dimensional real number domain is mapped by some low-dimensional data. After completing the decomposition, the tensor $\mathcal{Y} \in \mathbb{R}^{J_1 \times J_2 \times J_3}$ is composed of its three decomposition factors and errors, that is,

$$\mathcal{Y} = U \odot V \odot W = \sum_{i=1}^{k} u^{i} \circ v^{i} \circ w^{i} + \mathbb{E}$$
(1)

Where U, V, W is the sub-factors of the decomposed tensor \mathcal{Y} , respectively, corresponding to the column u^i, v^i, w^i , $u \in U \in \mathbb{R}^{J_1 \times k}, v \in V \in \mathbb{R}^{J_2 \times k}, w \in W \in \mathbb{R}^{J_3 \times k}$, $\mathcal{B} \in \mathbb{R}^{J_1 \times J_2 \times J_3}$ is the reconstruction error between \mathcal{Y} and $U \odot V \odot W$. The symbol \odot represents the khatri-rao product. The symbol \circ represents the cross product among all the vectors. The whole geometric model of a tensor factorization is shown in figure 1.



Figure 1. Geometric model of tensor decomposition.

In the process of tensor computation, the nonnegative constraint is added to improve the computation efficiency. It can avoid dimension disaster when the sub-factors near to zero pole. NTF calculation process achieve the purpose of data decomposition through cyclic iteration, whose khatri-rao product of U, V, W approximates to \mathcal{Y} . Since the divergence of KL takes denominator fitting as the goal, the difference between the decomposed factors tends to zero, which results in difficult convergence. So the calculation of Euclidean distance is taken as the objective function,

$$D_{U}\left(\boldsymbol{\mathcal{Y}} \| U, V, W\right) = \frac{1}{2} \left\| \boldsymbol{\mathcal{Y}} - U(V \odot W) \right\|_{F}^{2}$$
(2)

Where $D_U(\bullet)$ represents the Euclidean error U direction, and $\|\bullet\|_F$ represents the Frobenius norm. When the value $D_U(\bullet)$ goes to zero, it can be approximated to U

$$U \leftarrow \operatorname{vec}_{U}(\mathcal{Y})(W\Theta V) \tag{3}$$

Where $vec_U(\mathcal{Y})$ represents the tensor \mathcal{Y} is unfolded directing to U. Similarly,

$$V \leftarrow vec_V(\mathcal{Y})(W\Theta U) \tag{4}$$

$$W \leftarrow \operatorname{vec}_{W}(\mathcal{Y})(U\Theta V) \tag{5}$$

Where $vec_V(\mathcal{Y})$ and $vec_W(\mathcal{Y})$ represent the tensor \mathcal{Y} is matrixed direct to V, W, respectively. Calculate factors with fixed alternating least squares (signed Fixed-ALS) [15], which is of fixing a matrix by nonnegative constraints, and other matrixes will iteratively compute the whole sub-factors. Assume that the optimal result of the calculation of the derivative is zero, then take this point as extreme value point, solve to the objective Eq. (3)~(5) lastly. The steps of the algorithm is shown as in table 1.

Table 1. Calculation steps of NTF.

Input: \mathcal{Y} , R, N;
Output: Decomposed factors U, V, W .
Fixed W , normalized U, V ;
For Iteration $\leq N$; % Set calculation steps
$\left\{U,V\right\}^{\dagger} \leftarrow U,V$ %The sign is a non-negative constraint \dagger
Complete W with with Eq. (3);
Compute U, V with Eq. (4)~(5);
If (Iteration>N or error \leq 10e-6) break; End End

3. Noise Problem of Electronic -Control Silicone Oil Fan on Vehicle

The electronic control clutch is one of the key parts on silicone oil fan, whose internal oil hole and the valve position controls the oil hole by opening or closing. Thus, the electronic control clutch drives the shaft coupling or decoupling. And the structure is shown as in figure 2. The torque is transmitted by the clutch in silicone oil through the speed sensor feedbacks to the ECU for speed monitoring.



1. Fan assembly 2. Lock nut 3. Flat washer 4. Silicone oil clutch 5. Drive shaft

Figure 2. Structure diagram of silicone oil fan.

When the electronic-control clutch is in a full-coupled state, which is equivalent to the fan directly connected to the diesel shaft. In this case, the noise frequency f of the fan can be directly calculated according to the rotate speed and gear transmission ratio,

$$f = \frac{R}{60} \times i \times N \tag{6}$$

Where R is the rotate speed, i is the gear transmission ratio, N is the number of fan blades. The truck is equipped with gear transmission ratio 1.27 and a 9-blade silicone oil fan.

In the initial state, the fan is directly connected to the engine. When the engine speed exceeds 1000rpm, the noise of the oil fan completely covers the engine noise, which leads to the pass-by noise out of limits.

In order to analyze the noise peculiarity, a microphones is placed at one meter outside the door of the truck door, with one meter height as well. A 12-channel B&K PULSE 3660C acquisition system and analysis software is used to the noise signal. The sample frequency is set as 25600 Hz. Data is collected for 5 times at the stable operation of the fan, each time lasts 10s. The frequency spectral are shown in figure 3



Figure 3. Noise spectrum at different rotational speeds.

As shown in Figure 3 a, b, the spectrum of the oil fan noise at 1000rpm and 1500rpm respectively, can be calculated as 190Hz and 290Hz according to Eq. (6). Take test error into

account, the results are 187.5 Hz and 300Hz. However, the spectrum is not stand out, because the unknown noise with high SPL has obvious masking effect and brings confusion to

the engineers. Therefore, the following NTF method is used to extract bispectrum feature from the oil fan.

4. Bispectrum Feature Extraction by NTF Algorithm

After data collection, 16384 points are selected at the sample rate of 2560Hz to generate matrix with the size 128×128 by bispectral transformation. In order to further verify the robustness of the algorithm, white noise signals of 0.1~6.3 are added to re-construct a three-dimensional tensor

with the size $128 \times 128 \times 64$.

4.1. Bispectrum Feature Extraction

The speed 1000rpm and 1500rpm are respectively selected for data analysis. Thus, two different tensors are generated by the white noise, respectively. According to the optimization of the basic dimension of the tensor, the core tensor is set as 32, and the error of the iterative objective is 10^{-6} [16, 17]. Part feature basis vectors are extracted and shown as in Figure 4.



Figure 4. Partial basis vectors extracted by NTF at different rotation speeds.

As shown in Figure 4, bispectrum extracted by NTF at the rotate speed of 1000 RPM and 1500 RPM respectively presents larger peak, whose sparse features distinct from other peaks. The first sixteen features are computed after all the sub-factors completed. Then, some local bispectrum by NTF are shown in Figure 5.



c. Local characteristics of 800Hz at 1500RPM



Figure 5. Partial local features of NTF extracted at different engine speeds.

The bispectrum extracted shown in Figure 5, the main frequency at 1000RPM is about 180H with the interference noise 225Hz (The frequency of intake noise), which is consistent with 187.5Hz and 237.5 Hz at the initial spectrum. At 1500RPM, the fan spectrum is about 300Hz, and 800Hz interference noise exists nearby, corresponding to the initial state as well. Thus, the frequency of the silicon oil fan can be clearly identified.

4.2. Computation Accuracy and Sparsity Analysis

When determining the rank $R \le \min\{U, V, W\}$ of NTF tensor basis, both convergence speed and computation accuracy should be taken into account. Therefore, different ranks $R = \{12, 16, 20, 24, 28, 32, 36, 42, 48\}$ are selected for performance verification, and 300 steps are set as the calculation target. The convergence is shown in Figure 6.



Figure 6. Convergence comparison of NTF under different tensor fundamental dimensions.

As shown in Figure 6, the higher rank leads to the higher convergence and accuracy. According to the algorithm of NTF described above, conjugating with Euclidean distance, the computation error is defined as:

$$Error = \sum \left\| \frac{(U \odot V \odot W) - \mathcal{Y}}{\mathcal{Y}} \right\|_{F} \times 100\%$$
(7)

Where the tensor by khatri-rao product $U \odot V \odot W$ is also called reconstructed tensor after decomposition. Here the whole

computing time is expressed as t. After all the calculations are completed, the results are recorded in table 2.

Table 2. Calculation accuracy of NTF under different tensor base dimensions.

NTF	Rank R								
	12	16	20	24	28	32	36	42	48
Calculation error %	8.22	7.18	6.36	6.11	5.95	5.83	5.75	5.68	5.63
Iteration time t/s	268	343	436	515	594	678	771	899	1029

As seen in table 2, the calculation error by NTF is all within 9%. When the input R increases, the computation error decreases, but the computation time increases. Because the length of matrix data determines the complexity of computation, especially zero matrix appears in a large data, which may enter the calculation cycle of "dimension disaster". In order to avoid the case of zero matrix, the middle value 32 is considered as the rank of the core tensor, and the main eigenvalue matrix obtained is shown in Figure 7.



b. 1500RPM working condition

Figure 7. Eigenvalue distribution of local features at different speeds.

In Figure 7, the main eigenvalues are 62 at 1000RPM and 116 at 1500RPM, respectively. Compared with the initial matrix value of 16,384, the ratio of the values number are 0.38% and 0.71%, which indicates little rank participating in the computation, meaning lower complexity and sparse bispectrum. Therefore, the bispectrum extracted by NTF has strong locality for identification.

5. Conclusion

1) For the identification problem of the silicon oil fan noise, the NTF method is proposed to decompose a three-dimension tensor and extract the feature with the form of bispectrum.

2) The bispectrum has stronger sparse for the locality feature expression, and the maximum number of eigenvalues accounting for only 0.71%.

3) Different ranks are selected for the comparison of computation performance. The error of NTF is all within 9%. When the rank R increase, the error is reduced.

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References

- [1] GB 1495-2016. Limits and measurement methods of vehicle acceleration noise outside the vehicle.
- [2] Dal H, Emiro g lu a. O, Bilge H, Et al. Experimental study of the effects of chicken and Turkey biodiesel blends on diesel engine noise emissions [J]. International Journal of Environmental Science and Technology, 2019 (9): 5147-5154.
- [3] Fei Xiong, Zhiyong Hao, Ruijun Liu, etc. Optimization of NVH performance of diesel engine based on the loudness of radiated noise [J]. Journal of central south university (natural science edition), 2016, 47 (08): 2629-2635.
- [4] Qingying Ren, LiFeng Wang, Jianqiu Huang, Et al. A Novel Capacitive Temperature Sensor for real-time Monitoring of Temperature in the Silicone Oil Fan Clutch [J]. Key Engineering Materials, 2015, 3928: 662-669.
- [5] Bangsong Li. Structural design and control analysis of electrically controlled silicone oil fan clutch [J]. Automation applications, 2018 (06): 44-46.

- [6] Xiu Xu, Zhao Ping, Liyong Zheng. Experimental analysis of an electrically controlled silicon oil clutch fan system on a heavy vehicle [J]. Practical automotive technology, 2017 (12): 217-219.
- [7] Lin Li, Xiaonan Liu, Xiaolin Feng. Heat Transfer Analysis of Silicone Oil Fan Clutch Based on Finite Element Simulation [J]. Applied Mechanics and Materials, 2015, 3744: 73-76.
- [8] feng gaoshan. Experimental study on fuel economy improvement of commercial vehicles based on cooling and heat management [J]. Equipment manufacturing technology, 2018 (04: 8-11 +22).
- [9] Tianpei Feng, Yuedong Sun, Yansong Wang, et al. An evaluation method of noise annoyance degree in non-stationary vehicles based on masking effect [J]. China mechanical engineering, 2017, 28 (24): 2919-2924+2930.
- [10] Cichocki Andrzej, Zdunek Rafal, Choi Seungjin, et al. Non-negative Tensor Factorization using Alpha and Beta divergences [C]. Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing, Part III. Honolulu, HI: 2007, 1393-1396.
- [11] H. Arahmane, Mahmoudi A, Hamzaoui, et al. Neutron-gamma discrimination based on support vector machine combined to nonnegative matrix factorization and continuous wavelet transform [J]. Measurement, 2020, 149.
- [12] Peitao Wang, Zhaoshui He, Kan Xie, et. al. A hybrid algorithm for low-rank approximation of nonnegative matrix factorization [J]. Neurocomputing, 2019, 364: 129-137.
- [13] Shan Wang. Blind separation of multichannel audio signals based on non-negative tensor decomposition [D]. Southeast university, 2015.
- [14] M. Laassiri, Hamzaoui, R. Cherkaoui. Nonnegative Tensor Factorization Approach Applied to Fission Chamber's Output Signals Blind Source Separation [J]. Journal of Physics: Conference Series, 2018966 (1): 012063.
- [15] Vesselinov Velimir V, Alexandrov Boian S, O 'Malley Daniel. The Nonnegative tensor factorization for contaminant source identification. [J]. Journal of contaminant hydrology, 2019220: 66-97.

- [16] Haijun Wang, Guo Cheng, Guoyong Deng, et al. A Fast Method of Feature Extraction for Lowering Vehicle Pass - By Noise -based on Nonnegative Tucker 3 Decomposition [J]. Journal of Archives of Acoustics, and 2017 (4): 619-629.
- [17] Yu Zhang, Guoxu Zhou, Qibin Zhao, et al. Fast nonnegative tensor factorization based on accelerated proximal gradient and low-rank approximation [J]. Neurocomputing, 2016, 198: 148-154.

Biography



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