Signal Denoise Method Based on Fractal Dimension, the Higher Order Statistics and Local Tangent Space Arrangement

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Abstract— **In denoise method for nonlinear time series based on principle manifold learning, reduction targets are chosen at random, using linear method of singular value decomposition solving local tangent space coordinate, these caused efficiency and effect of denoise lower. To solve this problem, a new denoise method based on based on the fractal dimension, higher order statistics and local tangent space arrangement is proposed. The intrinsic dimension is estimated as dimension of reduction targets by fractal geometry method, the data outside intrinsic dimension space will be regarded as noise signal to be eliminated . At the same time, making use of restraining characteristic to colored noise of high-order cumulan, covariance matrix is constructed with the fourth-order cumulant function instead of second-order moment function covariance matrix ,local tangent space alignment algorithm based on fourth-order cumulan is also proposed. Noise reduction experiments on lorenz signal and fan's vibrating signal show that method proposed in this paper has better denoise effect.**

Index Terms—**fractal dimension; the higher order statostics; local tangent space arrangement; denoise**

I. INTRODUCTION

Traditional denoise methods are mainly filter technology based on linear smoothing. For status signal of complex mechanical system,signal and noise have similar wide spectral characteristic, so non-linear denoise filter is necessary. Phase space reconstruction is an important tool for nonlinear dynamic analysis. In the phase space,dynamical behavior of system is in the form of the attractor,chaotic system corresponds to strange attractor, noise is a random distribution. The denoise algorithm based on phase space reconstruction have singular spectrum method[1], local projective method[2-3] and so on,but they are iterative local neighborhood methods, not considering the global structure information of manifold. At present mainfold learning has already become the new research hot spot data on dimensionality reduction, feature extraction and the pattern recognition. The classical algorithm have Isometric Feature Mapping (ISOMAP) [4] , Local Linear Embedding (LLE) [5] algorithms, Laplace Mapping (LE) [6-7], Local Tangent Space Alignment (LTSA) [8-9] and so on [10].Manifold learning are based on the data geometry, algorithm is sensitive to noise. To reduce the impact of noise, Yin J.S. proposed neighborhood smoothing embedding (NSE) [11], Choi H proposed kernel ISOMAP noisy manifold algorithm [12], Zhang Z.Y proposed local weighted smoothing [13], Mattgias Hein proposed denoise method based on graph diffusion processes[14]. To non-linear denoise, Yang Jianhong proposed algorithm based on phase reconstruction and manifold recognition[15] which also called LTSA denoise algorithm in this paper.

But in this algorithm, the choice of target dimension is stochastic and uncertain scope, thus causes the efficiency of the dimension reduction lower. The size of the main feature space is decided by target dimension, which directly impact on the effect of denoise.Furthermore, in LTSA denoise algorithm,local tangent space coordinates are obtained from singular value decomposition to neighbors covariance matrix in the phase space, while covariance matrix is second order statistics reflecting the linear correlation, and that can not do anything for the essential characteristic extraction of nonlinear dynamic systems. In order to solve these question, signal denoise method based on fractal dimension,the fourth order cumulant and local tangent space arrangementis (The simple form is FDFOC-LTSA) is proposed. At first, the intrinsic dimension is estimate by means of fractal geometry, the high dimensional phase data in the local

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tangent space are mapped to the local intrinsic dimension of space, and then using the higher order statistics can completely inhibit gaussian colored noise in theory , construct phase point covariance matrix with the fourth order cumulant function instead of second-order moment function, finally realize denoise. Experiments on lorenz signal and blower's vibrating signal show that this method has better denoise effect.

II. The Fractal Dimension estimation method for intrinsic dimension

Intrinsic Dimension describes the minimum number of independent parameters of the data set, which determines the space distribution character of phase points in the neighborhood. Based on fractal geometry theory, fractal dimension is using to estimate the dimension of data sets. Common fractal dimension has the capacity dimension, similar dimension, correlation dimension, information dimension and so on. In this paper, we select correlation dimension to estimate the fractal dimension of the data, which may be gotten by the Grassberger and Procaccia's algorithm [16].

Let $x_i(i=1,2\cdots n)$ is Independent and identically distributed sample, given a smaller embedded value m_0, we can obtain the corresponding reconstructed phase space $Y(t_i)$,and then alculate correlation function according to Eq.1.

$$C(r)=\lim_{N\to\infty}\frac{1}{N}\sum_{i,j=1}^{n}\theta(r-|Y(t_i)-Y(t_j)|) \quad (1)$$

where, $|Y(t_i)-Y(t_j)|$ expresses the distance between $Y(t_i)$ and $Y(t_j)$, $\theta(z)$ is Heaviside function, $C(r)$ is the cumulative distribution function, which expresses the probability less than distance between two points on the attractor in the the phase space. If selecte an appropriate range for r ,it should satisfy the linear relationship between the low embedding dimension d and the cumulative distribution function $C(r)$ of the system, $d(m)=\ln C(r)/\ln r$. the estimate $d(m_0)$ of the correlation dimension corresponding to m_0 is obtained by linear fitting. Next, Increased the embedding dimension $m_1 > m_0$ and repeate the above calculation until $d(m)$ unchange within a certain error when m increase, we believe that d at this time is the correlation dimension of the system.

III. Denoise method based on local tangent space arrangement

Given time series signal $S=[s_1,s_2,\cdots s_n]$,the best embedding dimension m and delay time τ are obtained by C-C algorithm, the phase matrix after the reconstruction is as followed.

$$P\in R^{m\times[n-(m-1)t]}, \qquad P_{j,k}=s_{k+(j-1)t} \quad (2)$$

where, $j\in[1,m]$, $k\in[1,n-(m-1)t]$ .The intrinsic dimension d is regarded as reduction target dimension obtained by fractal geometry method. Select k , construct the local neighborhood matrix P_j^k of each point P_j .Then calculate d dimension loacl coordinate $\Theta_i=Q_i^T(P_j-\overline{P}_j^k 1_k^T)$ by orthogonal singular value decomposition to centralized matrix $P_j-\overline{P}_{j\ i}^k 1_k^T$, where $\overline{P}_j^k=\frac{1}{k}\sum_{j=1}^{k}P_j$ .At last, the global manifold coordinates $\{y_i\}_{i=1}^n$ may be obtained by the local affine transformation. Under the normative constraint $YY^T=I$, The global low dimensional coordinates $T=[\tau_2,\tau_3,\cdots\tau_{\hat{d}+1}]\in R^{\hat{d}\times k}$ are made of the eigenvectors $\tau_2,\tau_3,\cdots\tau_{\hat{d}+1}$ corresponding to $\hat{d}$ minimum eigenvalues of $B=SWW^TS^T$ arrange matrix.where, $S=[\mathrm{S}_1,\mathrm{S}_2,\cdots\mathrm{S}_\mathrm{i},\cdots\mathrm{S}_\mathrm{N}]$ is the neighbor selection matrix, $W_i=(I-\frac{1}{k}ee^T)(I-\Theta_i^+\Theta_i)$ .To restore the original one dimensional data, high dimensional phase data need to be reconstructed from the useful signal after denoise in the low dimensional space,reconstruction formula is as follows：

$$y_k=f(\tau_k)=\overline{P}_k+Q_jL_k^{-1}(\tau_k-\overline{\tau}_k) \quad (3)$$

where, L_k^{-1} is the inverse matrix of L_k , $L_k=T_k\Theta_k^+$ .The result $Y\in R^{m\times n}$ is the high dimensional manifold of the useful signal after denoise, reverse calculate to Y by Eq. 4 and one dimensional signal could be obtained.

$$\hat{x}_i=\frac{\sum_{t\in\{I_i(j,k)\}}Y_t}{C_i} \qquad i=1,2,\cdots,n \quad (4)$$

Where, $\{I_i(j,k)\}$ express all elements set satisfied $k+(j-1)\tau=i$, C_i is number of elements in $\{I_i(j,k)\}$, $j\in[1,m], k\in[1,N-(m-1)\tau$.

IV. Construction of the covariance matrix based on fourth order cumulant

As one kind of nonlinear signal processing tool, higher order statistic can reflect the nonlinear structure of signal and system, and also better suppress the disturbance of noise. The higher order statistics's main application in the signal processing domain are as followed: the recognition of signal nonlinear characteristics, the reduction of colored Gaussian noise, the extraction of information deviation from the gaussian distribution, the reconstruction of non-minimum phase signal and so on

[17-19]. The definition of higher order moment and higher orde cumulant to random variables are as followed.

Suppose $\{x(n)\}$ is the zero average value and k order stationary random process, the k order moment is defined as

$$m_k^x(\tau_1,\tau_2\cdots\tau_{k-1})=E\{x(n)x(n+\tau_1)\cdots x(n+\tau_{k-1})\} \quad (5)$$

$E\{\bullet\}$ expresses the operation operator striving for the mathematic expectation.

According to higher order moment and higher order cumulant transformation relation, the higher order cumulant of $\{x(n)\}$ expresses as follows

$$C_k^x(\tau_1,\tau_2,\cdots\tau_{k-1})=m_k^x(\tau_1,\tau_2,\cdots\tau_{k-1}) - m_k^G(\tau_1,\tau_2,\cdots\tau_{k-1}) \quad (6)$$

Where $m_k^G(\tau_1,\tau_2,\cdots\tau_{k-1})$ is the k order moment function of the gauss signal having the same mean and autocorrelation function as $\{x(n)\}$ .when $\{x(n)\}$ is the gauss signal and $k\geq 3$, $m_k^x(\tau_1,\tau_2,\cdots\tau_{k-1})$ = $m_k^G(\tau_1,\tau_2,\cdots\tau_{k-1})$, $C_k^x(\tau_1,\tau_2,\cdots\tau_{k-1})=0$. The first order cumulant expresses signal’s mean, the second order cumulant expresses signal’s autocorrelation function. The fourth order cumulant's expression is as follows:

$$\begin{aligned}C_4^x(\tau_1,\tau_2,\tau_3)&=m_4^x(\tau_1,\tau_2,\tau_3)-m_2^x(\tau_1)m_2^x(\tau_3-\tau_2)\\&-m_2^x(\tau_2)m_2^x(\tau_3-\tau_1)-m_2^x(\tau_3)m_2^x(\tau_2-\tau_1)]\\&-m_1^x[m_3^x(\tau_2-\tau_1,\tau_3-\tau_1)+m_3^x(\tau_2,\tau_3)+m_3^x(\tau_1,\tau_3)\\&+m_3^x(\tau_1,\tau_2)]+(m_1^x)^2[m_2^x(\tau_1)+m_2^x(\tau_2)+m_2^x(\tau_3)\\&+m_2^x(\tau_3-\tau_2)+m_2^x(\tau_2-\tau_1)-6(m_1^x)^4\end{aligned} \quad (7)$$

As can seen from Eq.8, the fourth order cumulant have three variables. When using this cumulant to construct covariance matrix, variables need reduce to two.T he conventional procedure is to carry out the angle slice method, which makes two of three variables equal. If $\tau_2=\tau_3$, the fourth order cumulant becomes binary function.

$$\begin{aligned}C_4^x(\tau_1,\tau_2,\tau_2)&=m_4^x(\tau_1,\tau_2,\tau_2)-m_2^x(\tau_1)m_2^x(0)\\&-2m_2^x(\tau_2)m_2^x(\tau_2-\tau_1)-m_1^x[m_3^x(\tau_2-\tau_1,\tau_2-\tau_1)\\&+m_3^x(\tau_2,\tau_2)+2m_3^x(\tau_1,\tau_2)]+(m_1^x)^2[m_2^x(\tau_1)\\&+2m_2^x(\tau_2)+2m_2^x(\tau_2-\tau_1)+m_2^x(0)-6(m_1^x)^4\end{aligned} \quad (8)$$

In the above equation, k order moment's estimate expression is as followed

$$m_1^x(\tau)=\frac{1}{N}\sum_{n=1}^{N}x(n) \ , m_2^x(\tau)=\frac{1}{N}\sum_{n=1}^{N}x(n)x(n+\tau),$$

$$m_3^x(\tau_1,\tau_2)=\frac{1}{N}\sum_{n=1}^{N}x(n)x(n+\tau_1)x(n+\tau_2)$$

$$m_4^x(\tau_1,\tau_2,\tau_2)=\frac{1}{N}\sum_{n=1}^{N}x(n)x(n+\tau_1)x(n+\tau_2)x(n+\tau_2) \quad (9)$$

After obtaining the fourth order cumulant of $x(n)$, covariance matrix A is constructed with diagonal slices, the elements in A are

$$(A)_{i,j}=C_4^x(i,j,j) \quad (10)$$

Where $i,j=1,2,3\cdots m$, m is embedding dimension.

Ⅴ. SIGNAL DENOISE METHOD BASED ON FDFOC -LTSA

In the singular spectrum denoise theory, by the singular value decomposition, the subspaces composed of the eigenvectors corresponding to the different eigenvalue form the ellipsoid or super- ellipsoid, eigenvalue, the eigenvalue is equal to the square of the ellipsoid half axle 's square and the eigenvector has assigned half axle's direction. In the phase space,the most substantial direction is decided by the eigenvectors corresponding to the maximum eigenvalue. If the eigenvalue is small, the corresponding eigenvectors can be considered as noise to eliminate. Here the d biggest right singular vectors of the centralized neighborhood matrix form the local manifold of the phase space and carry the system's important information,other eigenvectors corresponding to the smaller eigenvalues are considered to generate from the noise and the disturbance, and should be assigned zero.

In this paper, the covariance matrix is constructed with the fourth order cumulant function instead of second order moment function, fractal dimension inrcreases the efficiency of the dimension reduction, which has realized denoise algorithm’s optimization.

Given time series signal $S=[s_1,s_2,\cdots s_n]$,the step of LTSMR algorithm follows:

1). The best embedding dimension m and delay time τ are obtained by C-C algorithm, phase matrix after the reconstruction is $P\in R^{m\times[n-(m-1)t]}$.

2) The intrinsic dimension d is fractal dimension obtained by G-P algorithm,and also regarded as reduction target dimension.

3). Select k , construct the neighborhood matrix P_j^k of each point P_j .

4). Calculate the fourth order cumulant C_4^p to the neighborhood matrix P_j^k of P_j ,obtain the covariance matrix $(A)_{i,j}=C_4^x(i,j,j)$ with diagonal slices.

5).Run LTSA, $T=[\tau_2,\tau_3,\cdots\tau_{d+1}]\in R^{d\times k}$,we may obtain manifold.

6). Reconstruct the phase space $Y\in R^{m\times n}$ by $y_k=f(\tau_k)=\bar{P}_k+Q_jL_k^{-1}(\tau_k-\bar{\tau}_k)$.

7). reverse one dimensional signal by Eq.4 , which is the signal after denoise.

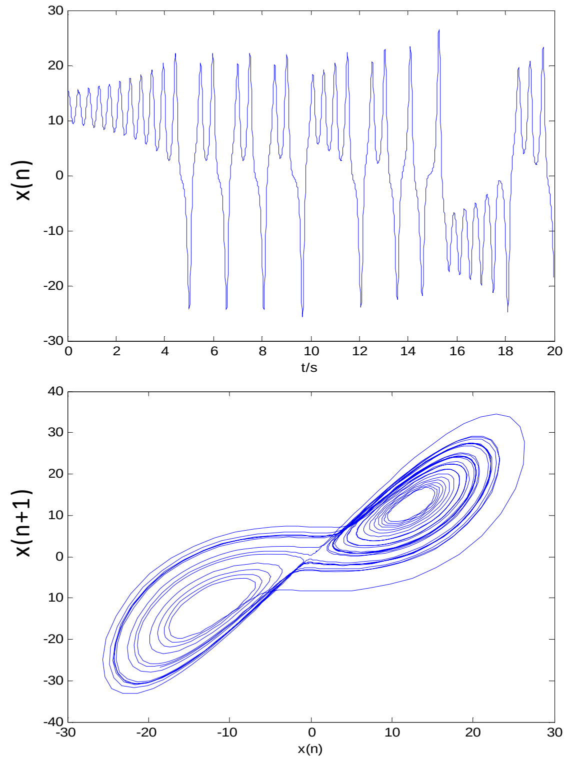

Fig.1 the time-domain waveform and phase diagram of Lorenz signal

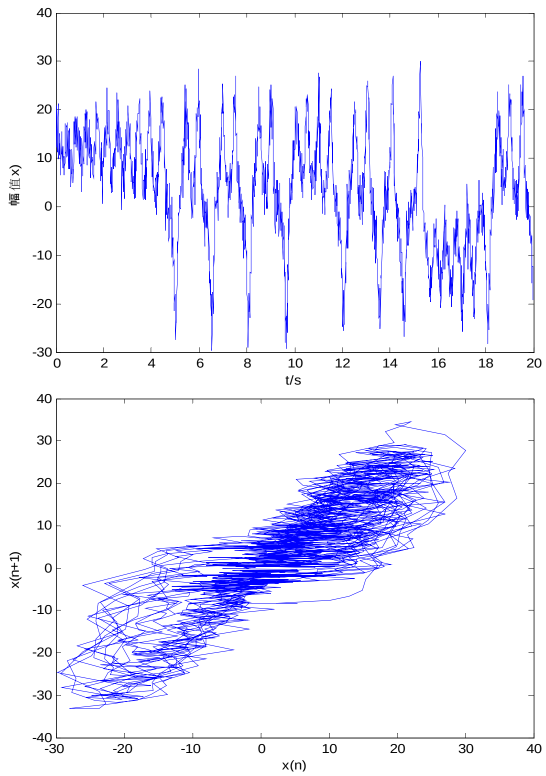

Fig.2 the time-domain waveform and phase diagram of Lorenz signal with noise

VI. DENOISE EXPERIMENT TO LORENZ SIGNAL

Lorenz system is a kind of typical chaotic non linear systems, which is brought out by lorenz in 1963 when he studied natural convection phenomenon under the action of temperature gradient of the atmosphere [20]. Lorenz system's expression is as follow:

$$\begin{cases} \dot{x} = \delta(y - x) \\ \dot{y} = rx - y - xz \\ \dot{z} = -bz + xy \end{cases} \tag{11}$$

Taking $\delta = 10, b = 8/3, r = 28$, sampling frequency 100HZ, obtain 20s test signal by fourth-order Runge-Kutta method. Fig.1 is the time-domain waveform and phase diagram of Lorenz signal. Fig.2 is the time-domain waveform and phase diagram of Lorenz signal with noise SNR 11.6 dB.

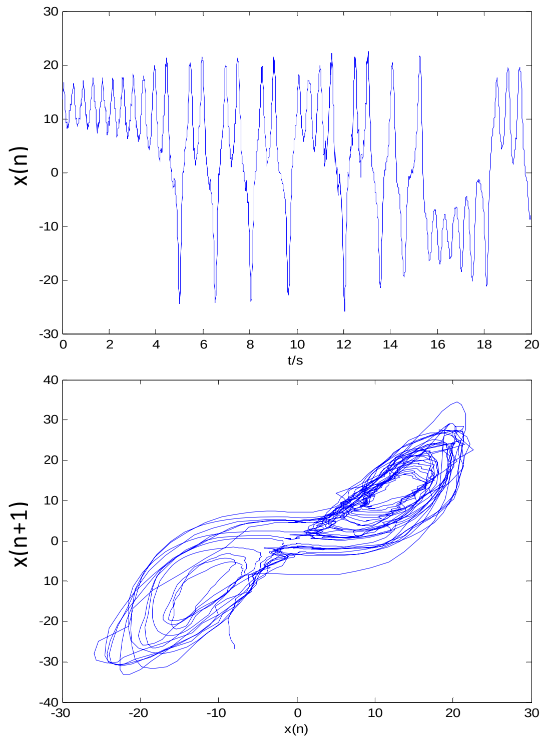

Fig.3 the time-domain waveform and phase diagram of Lorenz signal after denoise by LTSA

Tabel 1 the intrinsic dimension of Lorenz signal with different level noise

NUM	SNR	dimension
1	signal	1.9409
2	11.60dB	4.5557
3	9.30dB	4.5598
4	7.26dB	4.7292

According to the fractal theory, correlation dimension is fractional dimension; we estimate the intrinsic dimension of Lorentz signal and Lorenz signal with different level noise.

Table 1 shows that the greater the noise and the lower SNR, the intrinsic dimension becomes higher. The intrinsic dimension of Lorenz signal is close to 2,but these with noise rise to between 4～5.Therefore intrinsic dimension is not only one important index of dimension reduction, but also can be used to measure the effect of denoise algorithm.

The following is denoise experiment to Lorenz signals in Fig.2. Here embedding dimension $m = 200$, time delay $\tau = 1$, intrinsic dimensions $d = 2 \sim 4$, neighbor number $k = 10 \sim 30$. Fig.3 and Fig.4 are the time-domain waveform and phase diagram after denoise by LTSA and FDFOC-LTSA ($k = 12$, $d = 2$).

As we can see from Fig.5, the highest SNR after denoise can be close to 22dB when $d = 2$, $k = 10$, LTSA and FDFOC-LTSA have the best effect. The effect of denoise becomes lower and unstable along with the increase of k and d. In short, for white noise signal, when parameters have appropriate values, LTSA and FDFOC-LSTA methods can achieve good denoise effect.

FDFOC - LTSA denoising algorithm's advantage lies in the strong inhibition to color noise than LTSA denoising algorithm, the following chapter test this advantage by denoising experiment on fan vibration signal with color noise sampling from engineering field.

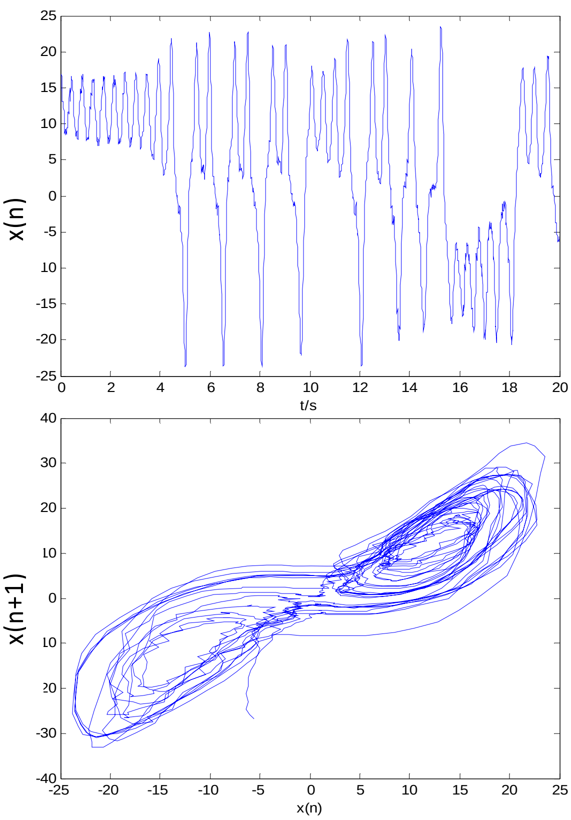

Fig.4 the time-domain waveform and phase diagram of Lorenz signal after

VII. DENOISE EXPERIMENT TO THE VIBRATION SIGNAL OF LARGE FAN

Fan is the rotating machinery that can convert mechanical energy to gas pressure and kinetic energy. Due to the large fan often run in terrible conditions, where has big dust and strong electromagnetic interference, the vibration signal sampling by sensors contains a lot of noise. In order to obtain effective condition characteristic signal of fan , fisrstly signal must be denoised.

In this experiment, vibration signal with color noise was collected from fan system simplified as Fig.6. Fan rated speed is 735 r/min, motor power is 475 KW. In Fig.8, the measuring point near the fan side in the vertical direction. In the power spectrum, 2 time and 3 time frequency are very strong (base frequency is 12.25HZ), this shows that system has severe rub fault. The purpose of denoise is to highlight 2 time and 3 time frequency components and reduce the other frequency components.

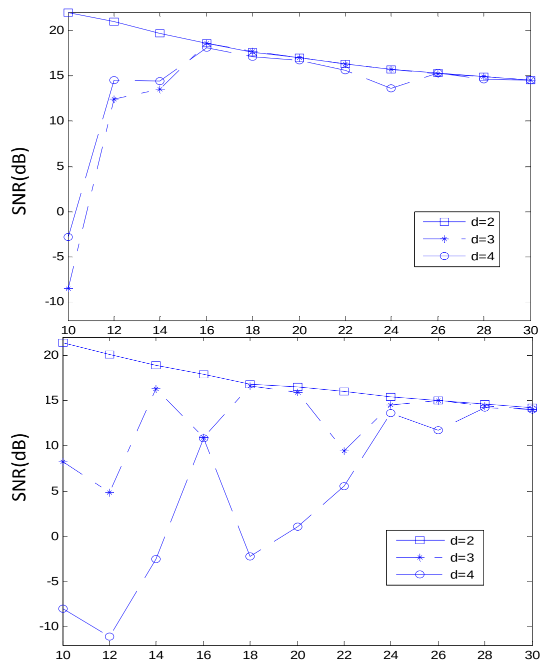

Fig.5 The relation in SNR of signal after denoise by LTSA(up) and FDFOC-LTSA(down), neighbor number, intrinsic dimension

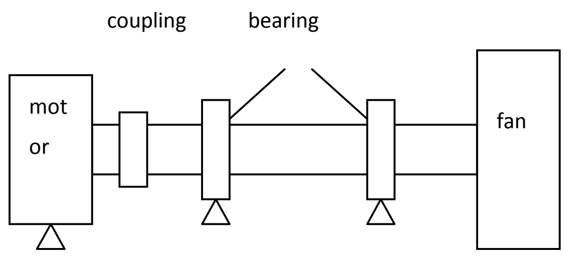

Fig.6 Simplified model of fan system

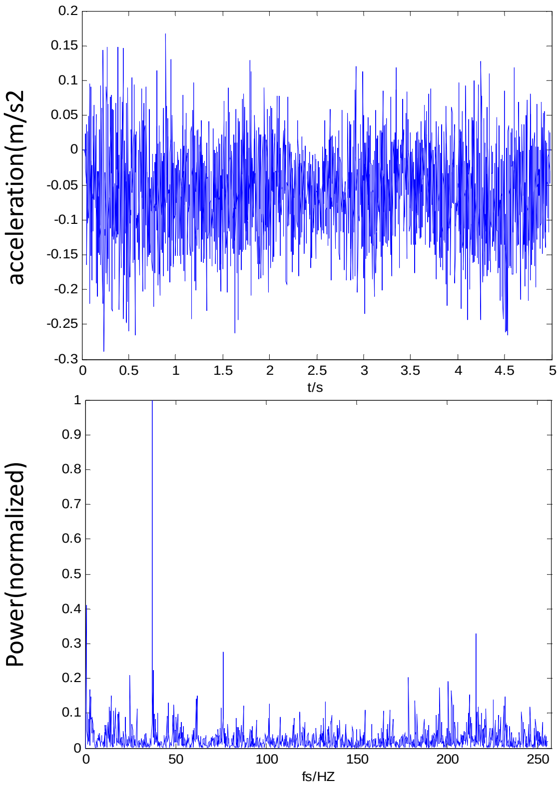

Fig.7 Time-domain waveform and power spectrum of fan vibration signal

Because we don't ascertain distribution of sinal and noise, SNR is difficult to obtain.The research [16] showed that noise level of signal becomes higher, the intrinsic dimension becomes higher, the intrinsic dimension estimated value of Lorenz signal also confirmed this point. Thus , signal's dimension can be also used as a quantitative standard of denoise effect.

In this experiment, we obtaint intrinsic dimension 8.5126 of fan signal with noise by MLE, the intrinsic dimension of the useful signal should be less than the dimension of signal with noise, here reduction target dimension d are taken 3～6, neighborhood numbers $k =$ 12～30, $m = 400$, $\tau = 1$. Fig.8 and Fig.9 are time-domain waveform and power spectrum of signal after denoise with LTSA and FDFOC-LTSA algorithms ($k = 16$, $d = 5$).Comparison with Fig.8, vibration amplitude of signal after denoise decrease , 2 time and 3 time frequency in power spectrum become more prominent. FDFOC-LTSA method has better effect on noise reduction.

We analysis the impact on two algorithms by the neighbor numbers k and the reduction target dimension d . In Fig.10, LTSA algorithm has almost no denoise effect whatever the intrinsic dimension is in most situations, these show that LTSA algorithm has been not very satisfactory with noise reduction effect on fan's vibration signal with the colored noise. In FDFOC-LTSA algorithm the intrinsic dimension d is between 3 and 6.5 when the neighborhood number k is less than 28, that process is stable and has very good denoise effect.

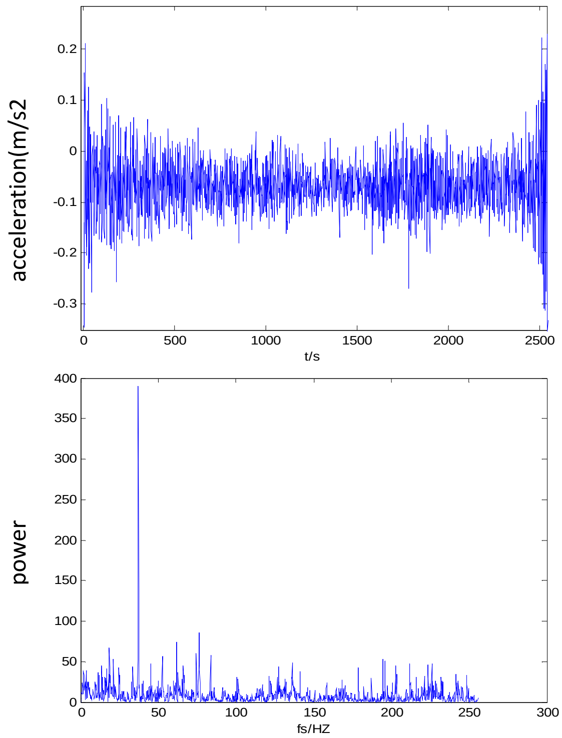

Fig.8 Time-domain waveform and power spectrum after noise reducation by LTSA

VIII. Conclusion

In the LTSA noise reduction algorithm, reduction target dimension are chosen at random and local tangent space coordinate is solved by linear method of singular value decomposition, these caused efficiency and effect of denoise lower. We propose a new denoise method based on the fractal dimension, higher order statistics and local tangent space arrangement. Firstly the intrinsic dimension was obtained by fractal geometry method, then covariance matrix is constructed with the fourth-order cumulant function instead of second-order moment, at last runs LTSA algorithm and the inverse process of phase space reconstruction, obtains the useful signal after denoise. Experiments on lorenz signal and fan vibration signal with the colored noise show that FDFOC-LTSA algorithm has better noise reduction effect than LTSA algorithm.

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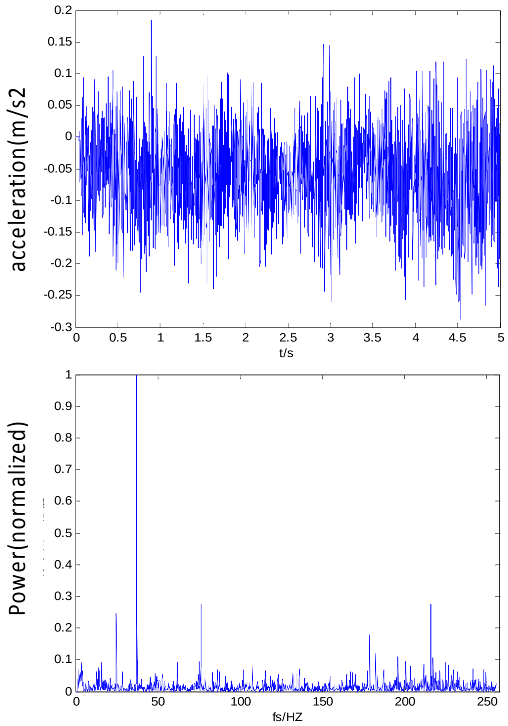

Fig.9 Time-domain waveform and power spectrum after noise reducation by FDFOC-LTSA

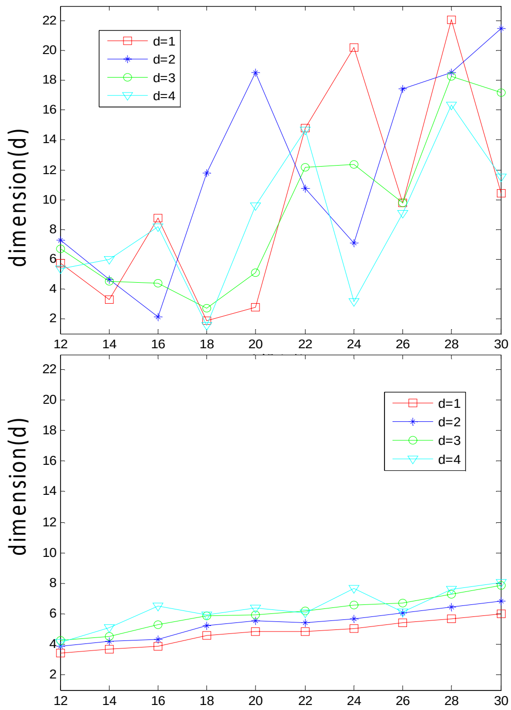

Fig.10 The relation in signal dimension after denoise by LTSA(up) and FDFOC-LTSA(down), neighbor number, intrinsic dimension

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