Data detection technology of wireless sensor network based on non-stationary filtering

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Abstract. By optimizing the data detection performance of distributed wireless sensor networks, the data sensing and collecting ability of wireless sensor networks can be improved. Traditional methods adopt statistical characteristic parameter detection algorithm for distributed wireless sensor network data detection. Distributed wireless sensor network data has strong time-frequency coupling, so it is difficult to realize frequency domain spatial parameter clustering in frequency domain, and the detection performance is not good. A distributed wireless sensor network data detection algorithm based on non-stationary filtering and high-order statistical feature peak retrieval is proposed. The data model of distributed wireless sensor network is constructed under the interference of color noise. The weak vibration signal is subjected to time-frequency analysis and noise separation by non-stationary filtering, and the spectral peak of distributed wireless sensor network data is searched by the fourth-order cumulant slice post-operator to realize the optimal detection of signals. The simulation results show that the algorithm has a high probability of accurate detection, and has a good ability of suppressing noise and noise sidelobe information interference, which improves the probability of accurate detection of distributed wireless sensor network data under low signal-to-noise ratio.

1. Introduction
With the development of sensor technology, using sensors to collect signal data, so as to guide the sensor system to realize intelligent control, will have a good application prospect in navigation control, guided weapon design, flight control and other fields. Sensor gyro is a kind of high-precision sensor, and distributed wireless sensor is a kind of sensor sensitive to angular velocity and angular deviation. The output data of distributed wireless sensor has linear feature fitting. By constructing an optimized collection model of distributed wireless sensor, the signal can be collected and analyzed. Distributed wireless sensors are widely used in aircraft inertial navigation design, missile attitude sensitivity control and torpedo inertial navigation control. Distributed wireless sensors are used in complex inertial navigation control environment. By collecting data information of distributed wireless sensors as control information input, the weak detection signals in distributed wireless sensors can be optimally detected, and the ability of collecting and analyzing signals of distributed wireless sensors can be improved. People pay great attention to the research of related data detection algorithms [1-3].

At present, data detection algorithms for wireless sensor networks mainly include data detection algorithms based on fractional Fourier transform, data detection algorithms based on high-order cumulant feature extraction and data detection algorithms based on time-frequency analysis. The principle of the algorithm is to construct the data model of wireless sensor network and adopt the
corresponding signal processing algorithm to realize the data detection of wireless sensor network, and some research results have been obtained. Literature [7] proposes a data detection algorithm of wireless sensor network based on IMF component decomposition of multiple narrowband signals, which adopts instantaneous frequency filtering detection to realize signal purification, thus improving the detection probability of wireless sensor network data. However, the algorithm has high computational cost and poor real-time detection effect on wireless sensor network data. Literature [8] proposes a data detection algorithm for wireless sensor networks based on Gaussian cascade filtering and time-frequency analysis, which filters the interference generated in low frequency domain, and realizes adaptive beam focusing of wireless sensor network data combined with time-frequency analysis, and the detection effect is good. However, this method needs to accurately estimate the prior time, frequency and other parameter information of wireless sensor network data, and the detection performance is not good when the knowledge of parameter information collection is insufficient. Literature [9] proposes to use statistical feature parameter detection algorithm. Distributed wireless sensor network data has strong time-frequency coupling, so it is difficult to realize frequency domain spatial parameter clustering in frequency domain, and the detection performance is not good. To solve the above problems, this paper proposes a distributed data detection algorithm for wireless sensor networks based on fractal Fourier transform (FRFT) and fourth-order cumulant post-peak search. The data model of distributed wireless sensor network is constructed under the interference of color noise. The weak detection signal is analyzed in time-frequency and noise separation by non-stationary filtering, and the peak of distributed wireless sensor network data is searched by high-order statistical feature post-operator, so as to realize the optimal detection of signals. Finally, the performance is verified by simulation experiment, which shows the superior performance of the algorithm in weak detection data detection, and draws a conclusion of effectiveness.

2. Data Model and Noise Separation Pretreatment of Distributed Wireless Sensor Network

2.1 Data Model of Distributed Wireless Sensor Network under Color Noise Interference

Distributed wireless sensor adopts multi-turn optical fiber loop to enhance effect, and adopts strong coherent light source to enhance resonance effect of resonant cavity for signal acquisition. Micro-detection signals collected by distributed wireless sensor are interfered by strong color noise. Under the interference of color noise, the data of distributed wireless sensor network is a group of wide and stationary Gaussian narrow-band signals with time-frequency coupling performance, and the acquisition nodes of detection signals of distributed wireless sensor are distributed in the array space in the form of near-field source uniform linear array distribution[10]. The near-field source uniform linear array distribution model of wireless sensor network data is shown in Figure 1.

![Figure 1](image)

Figure 1 Distribution model of near-field source uniform linear array for wireless sensor network data

In the data distribution structure of wireless sensor network shown in fig. 1, the channel vectors between the distributed sources and array elements of wireless sensor network data have strong time-frequency coupling, the sampling time series \( s_1(t), s_2(t), \ldots s_k(t) \) of wireless sensor network data is a zero-mean, non-Gaussian, statistically independent narrow-band stationary process, the cross terms
between wireless sensor network data have non-zero peaks, and the spatial distribution distance of detection sensors in the center of the array meets the following requirements:

\[ T = F_w[v(1), v(2), ..., v(L)] \]
\[ = \left[ \frac{\sin(\lambda_d/d_i)}{2}, \frac{\sin(\lambda_d/d_j)}{2}, ..., \frac{\sin(\lambda_d/d_k)}{2} \right] \]
\[ d_i \leq 0 \]
\[ d_j > 0 \]  \hspace{1cm} (1)

In which, \( D \) represents the radiation radius of the continuous signal emitter of wireless sensor network data and the wavelength of the information source. Assuming that the detection sensor of distributed wireless sensor is a near-field source distribution model composed of array elements, and the array element coordinate at the center of the reference array element is 0, the wireless sensor network data time series model obtained by sensing the first array element is as follows:

\[ G_i = A_{F_i^{-1}} + T^H(n)RT(n) \]  \hspace{1cm} (2)

Wherein, \( s_i(t) \) is the signal complex envelope on the time-frequency coupling plane, \( n_n(t) \) is the radial phase of the wireless sensor network data, and \( g \) represents interference color noise. Through the above analysis, the analytical signal model of wireless sensor network data constructed by discrete Fourier transform is as follows:

\[ A = \begin{bmatrix} B \rho B^H & \sigma^2 I_M \\ U_{sn} A_{sn} U_{sn}^H \cos \theta \end{bmatrix} \]
\[ = \begin{bmatrix} U_{sn} A_{sn} U_{sn}^H \\ U_{sn} A_{sn} \end{bmatrix} \]  \hspace{1cm} (3)

Assuming that the vertical directivity of the signal transceiver does not change much in the distributed wireless sensor, the envelope and phase of the wireless sensor network data under the background of color noise are as follows:

\[ N(x, y) = -Cx(k) + DKx(k - \tau) + \sigma \sqrt{V} \]
\[ = -\sigma h + \int h(t)R(x, y; t) \]
\[ = -\sigma [G_i(x, y; t) + G_j(x, y; t)] \]  \hspace{1cm} (4)

Because the spectrum of sensor output resolution signal can effectively reflect the structural characteristics of wireless sensor network data, the amplitude of distributed wireless sensor network data under color noise interference is related to target characteristics, channel loss and array characteristics. By the above signal model construction, the signal source foundation is provided for realizing wireless sensor network data detection[11].

2.2 Signal noise separation preprocessing based on non-stationary filtering

On the basis of the data model construction of distributed wireless sensor networks, in order to achieve accurate detection of signals, noise separation is needed in the background interference environment of color noise with low signal-to-noise ratio. In this paper, non-stationary filtering method is used to realize signal noise separation by time-frequency analysis of signals. The order non-stationary filtering of distributed wireless sensor network data defined in the domain can be expressed as \( X_p(u) \) or \( F_p x(u) \). In the time period of continuous sampling of signals, there are:

\[ k = \sum_{i=1}^{4} S_i(t) b_i(\theta_i) \]  \hspace{1cm} (5)

The frequency spectrum characteristics of the signal in frequency domain and time domain are constructed, and the calculation formula of \( K_x(t,u) \) is obtained as follows:
Where $n$ is an integer, i.e. $n \in \mathbb{Z}$. For any non-zero distributed wireless sensor network data, in any two non-orthogonal fractional Fourier domains, the time-frequency focusing decomposition of the signal in time domain and frequency domain is adopted, and the signal order non-stationarity filtering after noise separation can be expressed as:

$$
\begin{bmatrix}
R_x(1,1), & R_x(1,2), & \ldots & R_x(1,M) \\
R_x(2,1), & R_x(2,2), & \ldots & \ldots \\
\ldots & \ldots & \ldots & \ldots \\
R_x(M,1), & R_x(M,2), \ldots & R_x(M,M) \\
\end{bmatrix}
$$

To sum up, it can be seen that the color noise in distributed wireless sensor network data can be effectively separated by using the rotational additivity and reversibility of non-stationary filtering, and the energy distribution of weak detection signals among different LFM cores has significant characteristics. Based on this, the data detection algorithm is designed[12].

3. Improve implementation of data detection algorithm

3.1 Propose the algorithm of improving the thought description spectrum peak search

On the basis of preprocessing the distributed wireless sensor network data model and noise separation, the data detection model is optimized and modeled, and the data detection algorithm is improved. By analyzing the above non-stationary filtering method, it can be seen that when the distributed wireless sensor detection signal is interfered with by strong color noise, the distributed wireless sensor network data shows strong time-frequency coupling in the time-frequency domain. The time-frequency coupling makes it difficult to realize frequency-domain spatial parameter clustering in the frequency domain and leads to poor detection performance. In order to overcome the disadvantages of traditional methods, this paper uses the insensitivity and natural blindness of high-order cumulant diagonal slices to Gaussian noise, and purifies a distributed wireless sensor network data detection algorithm based on non-stationary filtering and high-order statistical feature peak retrieval. On the basis of time-frequency analysis and noise separation of weak detection signals by non-stationary filtering, the fourth-order cumulant operator of distributed wireless sensor network data is constructed as follows:

$$
U(x) = \begin{bmatrix}
\tau(1), & \tau'(2), & \ldots & \tau'(M) \\
\tau(2), & \tau(1), & \ldots & \tau'(M-1) \\
\ldots, & \ldots, & \ldots, & \ldots \\
\tau(M), & \tau(M-1), & \ldots & \tau(1) \\
\end{bmatrix}
$$

In the formula, $x(.)$ is the input distributed wireless sensor network data, and

$$
\hat{\chi}_2(r) = \frac{1}{N} \sum_{i=0}^{N} x(i)x(i+r)
$$

represents the second-order cumulant of the signal. After the non-stationary filtering of the distributed wireless sensor network data, the spectrum peak of the signal is generated in the time-frequency domain space, and the focus analysis with obvious kurtosis value is carried out in the frequency domain.

$$
I(n_i,n_j) = \frac{1}{4} \sum_{i\Delta} \sum_{j\Delta} I_{-i}(2n_i + i, 2n_j + i)
$$

By using the insensitivity of high-order cumulant to Gaussian noise, the output weak detection signal after noise separation is matched with the kernel function of high-order cumulant at a certain
angle, which can suppress the interference of Gaussian white noise and Gaussian color noise, and realize the post-focusing of signal spectrum and the suppression of noise sidelobe information. According to this principle, in the fractional Fourier domain, the signal energy after mixed slice frequency modulation by fourth-order cumulant is:

\[
\hat{c}_e(n, \tau) = \hat{c}_e(n, \tau) + \hat{c}_w(n, \tau) = \hat{c}_e(n, \tau)
\] (10)

Wherein, \(\hat{c}_e(n, \tau)\) represents the energy of pure detection signal in distributed wireless sensor network data, \(\hat{c}_w(n, \tau)\) represents the energy of noise part in distributed wireless sensor network data, and if the interference noise is Gaussian color noise, the fourth-order mixed cumulant slice of distributed wireless sensor network data is obtained as follows:

\[
I_{(i,j)} = \begin{cases} 
0, & \text{otherwise} \\
1, & \text{mod } 2 = 1
\end{cases}
\]

(11)

On the basis of Doppler modulation processing, the signal is output by discrete non-stationary filtering, and the fourth-order mixed cumulant slice is used for post-focusing processing, then the output detection signal is:

\[
I(i, j) = \sum_{i=1}^{p} I_{(i,j)}(i, j) \times H(\nu)R^{l-1}
\]

(12)

In which \(\gamma\) represents the energy kurtosis of distributed wireless sensor network data. The kurtosis of a weak detection signal interfered by Gaussian color noise by linear integral projection. Adopting signal-to-noise kurtosis ratio (SNKR) can effectively describe the performance of data detection. To sum up the design principle, the distributed wireless sensor network data detection is carried out through the fourth-order cumulant post-peak search. The flow chart of the improved algorithm is shown in Figure 2.

Figure 2 Flow chart of improved implementation of data detection algorithm

3.2 Implementation of distributed wireless sensor network data detection

Specifically, the implementation process of the distributed wireless sensor network data detection modeling is described as follows: let the received signal \(r(t)\) of the distributed wireless sensor be:

\[
r(n,\ell) = \frac{1}{N_iN_r} \sum_{k=1}^{N_i} R(k,\kappa)e^{\frac{2\pi i \kappa_n}{N_i}} e^{\frac{2\pi i \kappa_n}{N_r}}
\]

(13)

The non-stationary filtering of the received distributed wireless sensor network data is as follows:

\[
M = \begin{bmatrix} u_{11} & u_{12} \\ u_{21} & u_{22} \end{bmatrix} = u(x, y, \sigma, \sigma_d)
\]

(14)

The non-stationary filtered distributed wireless sensor network data is subjected to post-peak search through a fourth-order cumulant post-operator, which is described as:

\[
V(u) = G(x, y; t) + w = [1 \ 0]'
\]

(15)

Based on the above algorithm design, the appropriate rotation angle is selected to match the fourth-order cumulant with the time-frequency characteristics of the processed distributed wireless sensor network data, and the time-frequency coupling is removed and the noise is effectively suppressed, thus realizing the effective signal detection.
4. Simulation experiment and detection performance analysis

In order to test the performance of this algorithm in realizing effective data detection in wireless sensor networks, a simulation experiment is carried out. Matlab 7 programming software is used to design the algorithm of wireless sensor network data detection model. Firstly, the original data of wireless sensor network data is sampled, where the sampling frequency is 23KHz, t=12ms, the number of sampling points, the input signal-to-noise ratio is 21dB, and the center frequency of colored noise is 12.35KHz the time domain waveform of wireless sensor network data under colored noise interference is obtained as shown in figure 3.

![Time domain waveform of wireless sensor network data](image)

Figure. 3 Time domain waveform of wireless sensor network data

It can be seen from the figure that the original wireless sensor network data is disturbed by large noise, which makes it difficult to realize effective detection. The method in this paper is used for non-stationary filtering noise separation, and the high-order statistical feature post-operator is used to search the spectrum peak of distributed wireless sensor network data, so as to realize the optimal detection of signals. In order to compare the algorithm performance, the spectral peak modulus of wireless sensor network data detection is obtained by using this method and the traditional method, as shown in Figure 4.

![Data detection results of wireless sensor network](image)

**Fig. 4 Data detection results of wireless sensor network**

(a) Traditional detection algorithm  
(b) The algorithm in this paper
It can be seen from the figure that the spectral peak focusing performance of wireless sensor network data detection using this method is better, and the sidelobe suppression ability is higher. However, when the traditional method is used for data detection, the waveform is completely submerged in noise, and the noise is not suppressed. In order to quantitatively analyze the performance of the algorithm, 1000 Monte Carlo tests are used to obtain the detection performance comparison results of wireless sensor network data with false alarm probability less than 0.001, and the related data are sorted and analyzed, and the detection performance curve comparison results are shown in Figure 5. From the results in Table 1, it can be seen that the accurate detection probability of this method for wireless sensor network data detection is higher than the traditional method, which shows the superiority of this algorithm in improving the detection performance.

Table 1 Detection Probability of Various Methods under Different SNR

| SNR/dB | SVM | FrFT- | This method |
|--------|-----|-------|-------------|
| 0      | 0   | 0     | 0           |
| -5     | 0.967 | 0.956 | 1           |
| -10    | 0.745 | 0.867 | 0.979       |
| -15    | 0.067 | 0.167 | 0.644       |
| -20    | 0.045 | 0.065 | 0.287       |
| -25    | 0    | 0     | 0.276       |
| -30    | 0    | 0     | 0           |

5. Conclusions
In this paper, the data detection performance of distributed wireless sensor networks is optimized to improve the data sensing and collecting ability of wireless sensor networks, this paper proposes a data detection algorithm of distributed wireless sensor networks based on non-stationary filtering and high-order statistical feature peak retrieval. The data model of distributed wireless sensor network under color noise interference is constructed, the signal noise is separated, and the high-order statistical feature post-operator is used to search the spectrum peak of distributed wireless sensor network data, so as to realize the optimal signal detection. The research shows that the accurate detection probability of distributed wireless sensor network data detection with this algorithm is higher, and the ability of suppressing noise and noise sidelobe information interference is better, and the accurate detection probability is improved at low signal-to-noise ratio.

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