

An Abnormal Breakpoint Data Positioning Method of Wireless Sensor Network Based on Signal Reconstruction

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Abstract

The existence of abnormal breakpoint data leads to poor channel balance in wireless sensor networks (WSN). To enhance the communication quality of WSNs, a method for positioning abnormal breakpoint data in WSNs on the basis of signal reconstruction is studied. The WSN signal is collected using compressed sensing theory; the common part of the associated data set is mined by exchanging common information among the cluster head nodes, and the independent parts are updated within each cluster head node. To solve the non-convergence problem in the distributed computing, the approximate term is introduced into the optimization objective function to make the sub-optimization problem strictly convex. And the decompressed sensing signal reconstruction problem is addressed by the alternating direction multiplier method to realize the distributed signal reconstruction of WSNs. Based on the reconstructed WSN signal, the abnormal breakpoint data is located according to the characteristic information of the cross-power spectrum. The proposed method can accurately acquire and reconstruct the signal, reduce the bit error rate during signal transmission, and enhance the communication quality of the experimental object.

Keywords

Abnormal breakpoint, Compressed sensing, Data positioning, Signal acquisition, Signal reconstruction, Wireless sensor

1. Introduction

WSNs have been used in monitoring of temperature, humidity, and light of the environment [1]. It usually consists of several wireless sensor nodes, and each of them perceives the environmental information, processes, and transmits it to the sink node in a wireless multi-hop manner. Wireless sensor nodes are usually arranged in unattended field areas or complex industrial control sites where replacement of battery is inconvenient. Therefore, compressing the monitoring data collected by sensor nodes and then transmitting them can effectively prolong the life cycle of wireless sensor networks (WSNs). Professional scholars in the industry have carried out a lot of research to improve the communication quality of WSNs. Jan et al. [2] found that the sensor network exposed to the environment had the risk of being eavesdropped, which was easy to be maliciously tracked to the data sending node, thus reducing the context privacy security. For this reason, the author designed a method that could effectively enhance the security of information source location in WSNs. The test results showed that, compared with other

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methods, the method designed in this study increased the security period of wireless sensor communication process by 26%, and could effectively protect the information of the signal source set node. Fotohi et al. [3] found that WSNs with a long service life were vulnerable to sleep denial attacks. Therefore, the author designed a sleep denial attack countermeasure method based on the detection accuracy of abnormal sensors. The simulation results showed that the probability of a sleep denial attack successfully attacking WSN communication was significantly reduced after this method was adopted. However, WSN was affected by abnormal breakpoints in the actual application, resulting in poor channel balance, which had a certain impact on its actual adaptability. In addition, abnormal breakpoints can also cause serious problems such as loss of communication data and increase of communication delay, therefore, it is of great importance to develop an abnormal breakpoint data positioning method for wireless communication network.

According to previous research, a method for positioning abnormal breakpoint data in WSN based on signal reconstruction is put forward. The classical compressive sensing theory only supports the compression and reconstruction of a single signal, but there is a certain correlation between multiple signals in the same area in a large-scale monitoring network. Baron et al. expanded on the basis of compressed sensing theory, realized the compressed sampling of a group of signals, and proposed the distributed compressed sensing theory that can effectively save the number of signal observations and improve the reconstruction accuracy of the signal to obtain accurate positioning results of abnormal breakpoint data in WSN.

2. Materials and Methods

2.1 Signal Collection of WSN

Usually, WSN is consisted of a great number of sensor nodes [4]. In a WSN with N nodes, $x_i (i = 1, 2, \dots)$ is the collected data and x_i is scalar, so they are in a loop. The entire data of WSN constitutes a vector, there is Eq. (1):

$$X = [x_1, x_2, \dots, x_n]^T. \quad (1)$$

For WSNs, complete samples of the signal X is required; the communication signal N can be recovered by compression sensing to obtain the transformation coefficient $\partial (\|\partial\|_0 \ll N)$ of the signal (∂ includes non-zero coefficients).

In WSNs, the data vector X is usually relatively large. This approach can reduce the data collected in the WSN. Assuming that there is a signal X and a sparse basis η , and the signal X is described by a sparse basis p , the sparse basis can be calculated using Eq. (2):

$$\eta = [\eta_1, \eta_2, \dots, \eta_p]^T. \quad (2)$$

WSN data sampling can be described by Eq. (2):

$$\begin{cases} X = \sum_{i=1}^N S_i \eta_i \\ or \\ X = S \eta \end{cases}. \quad (3)$$

In Eq. (3), S is the sparse form of X . The vector data X corresponding to N nodes in the same cycle can be represented as a vector $S = (p \ll N)$ containing p non-zero data. Through compression sampling, WSN only needs to obtain vector data with a length of $M(p < M \ll N)$ [5]. The next step is to restore the initial signal. At this time, the amount of data to be processed by the network is reduced from N to M . In addition, the matrix Φ is used to compress the sensor to sample the node data. Therefore, the relationship of Eq. (4) exists:

$$Y = \xi X = \xi S \eta. \quad (4)$$

In Eq. (4), $\xi = \{\xi_{j,i}\}$ represents the sampling matrix, in which all data are independent of each other and subject to the same distribution, and $\frac{1}{M}$ represents their variance. Therefore, Y will be significantly smaller than the original signal [6]. So Eq. (4) can be transformed into Eq. (5):

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{bmatrix} = \begin{bmatrix} \xi_{1,1} & \xi_{1,2} & \cdots & \xi_{1,N} \\ \xi_{2,1} & \xi_{2,2} & \cdots & \xi_{2,N} \\ \& \vdots & \vdots & \ddots \\ \xi_{M,1} & \xi_{M,2} & \cdots & \xi_{M,N} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix}. \quad (5)$$

For the purpose of completely recovering the compressed communication signal, the value of M here is taken as Eq. (6):

$$M \leq \frac{p \log(\frac{N}{p})}{\frac{1}{a}}, \quad (6)$$

where M is a constant. To guarantee the complete recovery of the sensing signal, four limiting conditions are given.

Firstly, in a WSN with N nodes, the sending rate v of sensor nodes is set as Eq. (7):

$$v \geq \sqrt{\frac{\log N}{\pi N}}. \quad (7)$$

Secondly, it uses ε to represent the receiving speed of the central node in the receiving communication data.

$$\varepsilon \geq \frac{4KN}{\theta M \log N}. \quad (8)$$

In Eq. (8), K and θ , respectively represent the transmission bandwidth of communication signals. A constant greater than 0, so μ represents the communication service rate as expressed in Eq. (9).

$$\mu = \frac{1+W\lambda}{W}. \quad (9)$$

For the WSN with N nodes, generally speaking, when data is transmitted between nodes n_i and n_j , the $n_i - n_j$ distance is less than θ .

$$\|n_i - n_j\| \leq v. \quad (10)$$

After the WSN signal is collected through the above process, based on this, the information reconstruction of the WSN is carried out using the compressive sensing theory.

2.2 Signal Reconstruction of WSN

In WSNs, to solve the data reconstruction of distributed compressed sensor signals, an augmented Lagrangian function is constructed firstly [7].

$$L(g_{c,i}, g_i) = \sum_{i=1}^n \left(\|g_{c,i}\|_1 + \|g_i\|_1 + \frac{\mu}{2} \|y_i - \xi_i\|_2^2 \right) + \langle \alpha, G_c B \rangle + \frac{\gamma}{2} \|G_c B\|_F^2, \quad (11)$$

where, $\alpha \in R^{m \times n}$ is the Lagrange multiplier; μ and γ are the penalty parameters; $g_{c,i}$ and g_i are the public and the individual parts of the sparse signal decomposition corresponding to the i -th node, respectively. However, related researchers have proved that in the classic multiplier alternating direction and in the distributed computing environment, when the number of nodes is $n \geq 3$, it does not necessarily

converge [8]. Aiming at this problem, an approximate term $\frac{\|g_{c,i} - g_{c,i}^{(k)}\|_{P_i}^2}{2}$ is introduced when solving the reconstruction of compressed data of distributed nodes in WSN, where P_i is a symmetric positive semi-definite matrix, and $\|g_{c,i}\|_{P_i}^2 = g_{c,i}^T P_i g_{c,i}$. When the sub-problem of the augmented Lagrangian function is not strictly convex, the introduction of this approximation term can make the corresponding sub-problem strictly convex [9], which not only makes the sub-problem easier to solve, but also the strict convexity can guarantee that the sub-problem has a unique optimal solution. In the above procedure, let $P_i = -2\gamma I$. Therefore, the distributed compressed data reconstruction problem can be solved according to the alternating direction multiplier method.

$$g_{c,i}^{(k+1)} = \underset{g_{c,i}}{\arg \min} \left\| g_{c,i} \right\|_1 + \|g_i\|_1 + \frac{\mu}{2} \|y_i - \xi_i (g_{c,i} + g_i)\|_2^2 + \frac{\gamma}{2} \left\| G_c B + \frac{\alpha}{\gamma} \right\|_F^2 + \frac{1}{2} \|g_{c,i} - g_{c,i}^{(k)}\|_{P_i}^2, \quad (12)$$

$$= \underset{g_{c,i}}{\arg \min} \left\| g_{c,i} \right\|_1 + \frac{\mu}{2} \|y_i - \xi_i (g_{c,i} + g_i)\|_2^2 + \gamma \left(\frac{2g_{c,i}^{(k)} - g_{c,i-1}^{(k)} - g_{c,i+1}^{(k)} + (\alpha_{i+1} - \alpha_i)}{\gamma} \right) g_{c,i}$$

$$g_i^{(k+1)} = \underset{g_i}{\arg \min} \|g_i\|_1 + \frac{\mu}{2} \|y_i - \xi_i (g_{c,i} + g_i)\|_2^2, \quad (13)$$

$$\alpha^{(k+1)} = \alpha^{(k)} + v\gamma(G_c B), \quad (14)$$

where v is the penalty parameter. By solving the sub-problems (i.e., Eqs. 12 and 13), the sensing data in the WSN can be reconstructed.

A distributed compressed data reconstruction algorithm on the basis of the alternating direction method of multipliers is solved by iteratively updating the common and individual parts of the data [10]. The parameters are first initialized at execution time, and the common part $g_{c,i}$ and individual part g_i are initialized to random sparse vectors. The main body of the algorithm is composed of two parts: the inner and the outer loop. After calculating the common part $g_{c,i}$, the inner loop exchanges information with the neighboring cluster head nodes to extract the common part of the signal group more accurately; the outer

loop calculates the individual part g_i on the basis of obtaining the common part $g_{c,i}$, and then obtains the perceptual data that needs to be reconstructed. When solving the sub-problems (i.e., Eqs. 12 and 13), the fixed-point continuous algorithm can be used, which is suitable for solving a minimization problem of the form $\min_x \|x\|_1 + f(x)$, where $f(x)$ is a differentiable convex function. The algorithm controls the execution of the loop by setting the inner iteration threshold k_{th} , the outer iteration threshold l_{th} and the residual threshold r .

3. Experimental Results

To demonstrate the application effect of the abnormal breakpoint data positioning method for WSN based on signal reconstruction researched in this paper, it set the sizes of all sensor nodes to 100×100 . It built WSN in this area, and took WSN as the experimental object. The target signal to be detected was randomly distributed in this area. When sensor nodes collected signals, each sensor processed and compressed signals sparsely and transmitted them to the central node. The proposed method was adopted to locate the abnormal breakpoint data in the experimental object. The results are as follows.

3.1 Signal Acquisition Test

Fig. 1 shows the node signal in the experimental object collected by the method in this paper. The information acquisition performance of the proposed method was validated by comparing the signal collected by the proposed method with the original signal.

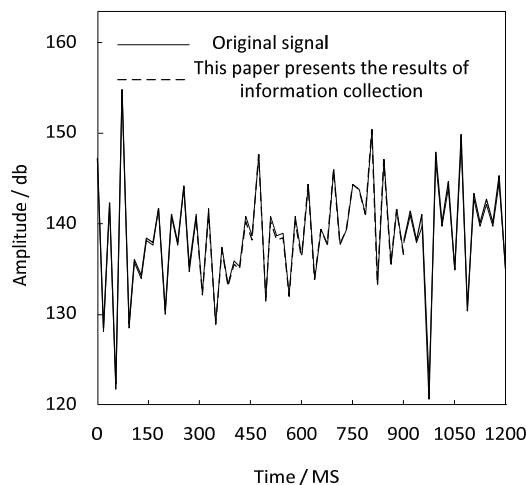


Fig. 1. Image acquisition results.

According to the analysis of Fig. 1, the signal acquisition results of the method in this paper were basically consistent with the original signal. It showed that this method could effectively suppress the noise interference and accurately collect the transmission signal of the experimental object, which was helpful to enhance the positioning accuracy of the final abnormal breakpoint data.

3.2 Abnormal Breakpoint Location Test

The proposed method was adopted to locate the abnormal breakpoint data of the signal transmission of the experimental object. The results are shown in Fig. 2.

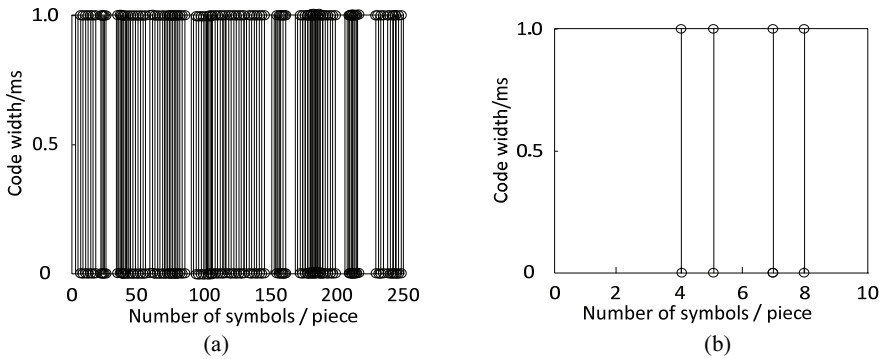


Fig. 2. Sampling location results of abnormal breakpoint location: (a) overall positioning and (b) local magnificent.

According to the judgment result in Fig. 2, the proposed method realized the abnormal breakpoint location of the communication signal of the experimental object, and the balance of the symbol output was better. The output bit error rate was tested, and the results are shown in Fig. 3. The comparison results of the two methods: the method based on the Spark parallel framework and the method based on the support vector machine (SVM) algorithm were slightly worse than the methods designed in this study. At the same time, to ensure the simplicity of the display results, the test results of the comparison method are not shown in Fig. 2.

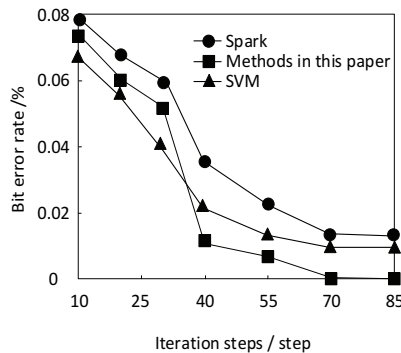


Fig. 3. Change of bit error rate.

Analysis of Fig. 3 shows that when using the method of this paper to locate the abnormal breakpoint of the communication signal of the experimental object could effectively reduce the bit error rate output, control it during the signal transmission of the experimental object in a lower range, and improve the communication quality. Specifically, after the method's bit error rate converged (that was, after the number of iterative training reached 85 times), the bit error rate of the method designed in this study and the processing method based on Spark computing platform and SVM algorithm were 0.001%, 0.017% and 0.013%, respectively, and the former was significantly lower than the latter two.

3.2 Application Effect Analysis

Before and after using the method in this paper and the two contrast methods to locate the abnormal signal breakpoint, the changes of the signal utilization rate per hour of the experimental subjects from 8:00 to 17:00 are presented in Table 1.

Table 1. Changes in signal utilization

Time	Signal utilization (%)			
	Before using abnormal breakpoint location	After adopting the proposed method	After adopting the method based on Spark parallel framework	After adopting the method based on SVM model
8:00–9:00	98.85	99.87	99.74	99.81
9:00–10:00	98.85	99.89	99.70	99.76
10:00–11:00	98.53	99.92	99.65	99.80
11:00–12:00	98.49	99.81	99.76	99.79
12:00–13:00	98.60	99.86	99.71	99.74
13:00–14:00	98.58	99.90	99.68	99.27
14:00–15:00	98.44	99.85	99.75	99.79
15:00–16:00	98.57	99.93	99.72	99.86
16:00–17:00	98.55	99.92	99.69	99.32

According to the analysis of Table 1, the average application rate of all kinds of images of the experimental objects was about 30.93% before using differential data positioning and identification. After applying the proposed method, that rate was about 39.57%. After using the two comparison methods, that rate was about 35.15% and 35.80%. Comparing the average application rates of various icons, it is found that the method in this paper has the highest improvement in the application rate of various images of the experimental subjects, indicating that the proposed method has better application effects.

4. Conclusion

In this paper, an abnormal breakpoint data positioning method of WSNs based on signal reconstruction was studied. The WSN signals were collected and reconstructed based on compressed sensing theory. For the reconstructed WSN signals, the abnormal breakpoint data positioning was realized by using the method of matched filtering and abnormal spectral peak detection. The simulation results showed that the bit error rate of the proposed method and the processing method based on Spark platform and SVM were 0.001%, 0.017% and 0.013%, respectively. And the former was significantly lower than the latter. The method designed in this study can accurately obtain and reconstruct signals, reduce the bit error rate during signal transmission, and effectively improve the communication quality of WSNs. It has good application performance. In the follow-up research and optimization work, it will focus on how to introduce edge computing technology to realize distributed compressed data reconstruction in large-scale WSNs, so as to improve the application effect of this method.

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