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Distributed Compressed Sensing of Microseismic Signals Through First Break Time Extraction and Signal Alignment

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ABSTRACT Microseismic monitoring is widely applied in dams, mines, and various fields of underground engineering. The number of sensors in microseismic monitoring systems is usually very large, which will result in a huge amount of data being produced if the Nyquist sampling theorem is used to acquire microseismic signals. To reduce the data storage costs and accelerate the transmission speed, we propose a distributed compressed sensing (CS) scheme for microseismic monitoring signals in this paper. The distributed compressed sensing scheme begins when it detects the first break time in the microseismic signal. The data recoding of the first break time is coded and transmitted together with the measured values of CS. Depending on the correlations between the microseismic signals, the first break time of the signals are aligned to that of the reference signal. Furthermore, we make use of the distributed CS to reduce the amount of data to be transmitted and to increase the reconstruction accuracy. Simulation results show that, compared with the sampling scheme based on the Nyquist sampling theorem, the independent CS scheme or the traditional distributed CS scheme, our proposed scheme improves the accuracy in the first break time detection and the reconstruction accuracy, and the scheme reduces the energy consumption at the same time.

INDEX TERMS Compressed sensing, first break time, microseismic signal, signal sampling, signal reconstruction.

I. INTRODUCTION

The monitoring of microseismic signals, which enables people to master the structure of buildings and the stability of strata in a timely, accurate and comprehensive manner, helps to reduce the chance of disasters caused by the structural damage or wrecks. It is important for ensuring the stability and security of structures and avoiding major catastrophic disasters. Despite the necessity of microseismic monitoring, the arrangement of a large number of sensors will produce vast data when the Nyquist sampling theorem is used to acquire microseismic signals, thus exerting tremendous pressure on the transmission and storage of the system is a major bottleneck in the field of signal acquisition [1]. The compressed sensing (CS) theory proposed by Donoho, Candès and Tao in 2006 can solve this problem properly. According to the CS theory, as long as signals are sparse or compressible in a certain domain, they can be observed at a rate far lower than that of the Nyquist sampling frequency; meanwhile, the original signals can be accurately reconstructed based on a construction algorithm [2]–[5].

In the area of microseismic monitoring, relevant research on signal denoising and reduction of the communication load are guided by the CS theory. Song *et al.* [6] proposed a promising CS technique to mitigate the load of wireless communication on nodes and the complexity of data processing and caching. Gholami [7] presented a non-convex CS scheme for the reconstruction and denoising of seismic data. Rodriguez et al. [8] developed a source location algorithm based on CS to improve the accuracy of detection of a microseismic event. Vera *et al.* [9] put forth a segmentation compression algorithm according to the characteristics of microseismic signals and the CS theory used in the transmission process to achieve a high compression ratio. Furthermore, the utilization of correlation between signals can more effectively reduce the redundant information, compress signals and decrease the resource consumption.

However, there is very little research on CS using the correlation between microseismic signals. Based on the CS and network coding theories, Yang et al. [10] put forward a universal distributed data storage scheme characterized by compressed network coding by exploiting the correlation between sensor readings. However, the scheme is mainly conducted mathematically and theoretically, and microseismic signals is not mentioned.

Microseismic signals collected by two physically close microseismic sensors usually have a certain correlation, and their first break moments show a certain time shift due to their different distances from the microseismic source. Therefore, the use of the correlation between signals to realize CS and a better reconstruction effect is a key issue in this field. In 2009, the concept of distributed CS was proposed by the American scholar Baron, who put forward three kinds of joint sparsity models in his research [11].

The CS scheme proposed in this paper is based on the distributed CS scheme and the joint sparse models, but it is different in the following aspects: (1) The proposed scheme first obtains the time offset for the first break moment of microseismic signals via an algorithm for microseismic signal first break time extraction and signal alignment. (2) Then the scheme aligns the other microseismic signals to the reference microseismic signal, and subsequently conducts the distributed CS and encodes them together with the first break moment. (3) At the decoding end, this scheme first extracts the first break time, then conducts the multi-sensor data joint reconstruction. (4) Finally it adds the first break time to the recovered microseismic signal, thus recovering the microseismic signal containing accurate time information. It can be concluded that the proposed scheme based on the first break time extraction and signal alignment can achieve better effects of distributed CS and joint reconstruction, as it not only ensures the accuracy of first break time extraction but also makes effective use of the correlation between microseismic signals collected by physically close sensors.

This paper is organized as follows. In Section II, the problem description is presented. In Section III, the mathematical foundations of CS and distributed CS are introduced. In Section IV, the distributed CS scheme for microseismic signal monitoring based on first break extraction and signal alignment is proposed. In Sections V, the relevant theoretical basis of the reconstruction error and outcome assessment are given. Furthermore, simulation results and performance evaluation are provided to validate the proposed algorithm. In Section VI, the conclusions are drawn.

II. PROBLEM DESCRIPTION

The area to be monitored is considered as a three-dimensional area. The monitoring sensors are arranged in the area (illustrated in Fig.1) uniformly, randomly or in light of an optimization algorithm. The monitoring sensors comprise four types of nodes, namely, a terminal node, a cluster-head node, a transmission node and a sink node. The terminal node is responsible for sensing the environment, collecting data and uploading the collected data to the cluster-head node. The cluster-head node receives data collected by nodes in the cluster and then spreads the data to the transmission node after fusing them. The transmission node is only used for the transparent transmission of data. After a hop or hops, the data reach the sink node which finally uploads the data to the server or the host computer for processing or operation. In a microseismic monitoring system, the traditional method is that the signal terminal nodes of the same cluster are acquired at the Nyquist sampling rate before they are uploaded to the cluster-head nodes; after that, the nodes are uploaded to the sink node through one hop or several hops of the transmission nodes; and finally, the nodes are uniformly decoded, processed and analyzed by the sink node. A point at the edge of the monitoring area is determined as the origin point, and the coordinates of certain sensors i and j are set as (x_i, y_i, z_i) and (x_j, y_j, z_j), respectively; then, the distance between sensors i and j can be expressed as

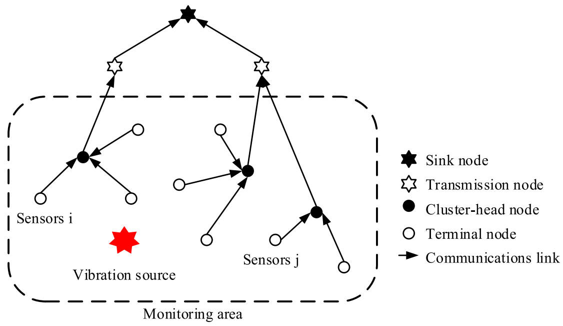

FIGURE 1. Diagram of distributed microseismic monitoring.

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2} \tag{1}$$

Given the moment of the microseismic source as t_0, the position as (x_0, y_0, z_0), and the transmission speed of the microseismic signal as $v \in [v_{min}, v_{max}]$, where v_{min} and v_{max} are the minimum and maximum speeds, respectively, the first break moment of this microseismic sensor i is

$$t_i = \int_{v_{min}}^{v_{max}} \frac{\sqrt{(x_i - x_0)^2 + (y_i - y_0)^2 + (z_i - z_0)^2}}{v} \mathrm{d}v + t_0 \tag{2}$$

where x_i, y_i and z_i are all functions of v.

III. MATHEMATICAL FOUNDATIONS

A. MATHEMATICAL FOUNDATION OF CS

Assuming a discrete signal x with length N to be K sparse, then a matrix Φ of $M \times N (K < M \ll N)$ is built as the observation matrix, and matrix Φ should also meet the condition of restricted isometry property (RIP). Then the inner product y of the observation matrix and the signal is acquired, that is [12],

$$y = \Phi x \tag{3}$$

Accordingly, the number of inner products of signal acquisition is M, which is far smaller than the number of samples acquired using the Nyquist sampling theorem. Since the number of unknown numbers is far greater than that of equations, equation (3) is an underdetermined equation with infinitely many solutions. The reconstruction algorithm aims to find the sparsest set among the solutions of equation (3) to set it as the estimation of the original signal. Its mathematical model is used to solve an l_0 norm optimization problem, i.e.,

$$\begin{aligned} &\underset{x}{\text{minimize}}\ \|x\|_0 \\ &\text{s.t. } y = \Phi x \end{aligned} \tag{4}$$

In reality, however, most of the signals in the time domain are not sparse. If the projection vectors on the $N \times P$ basic matrix Ψ are sparse, i.e.,

$$x = \Psi s = \sum_{i=1}^{N} s_i \psi_i \tag{5}$$

where s is a $P \times 1$ dimensional sparse vector. In this case, then the observed value is

$$y = \Phi x = \Phi \Psi s = \Theta s \tag{6}$$

where Θ is the product of observation matrix Φ and sparse basis Ψ. At this point, the mathematical model of signal reconstruction becomes

$$\begin{aligned} &\underset{s}{\text{minimize}}\ \|s\|_0 \\ &\text{s.t. } y = \Theta s \end{aligned} \tag{7}$$

In the condition with the existence of noise, the mathematical model can be expressed as

$$\begin{aligned} &\underset{s}{\text{minimize}}\ \|s\|_0 \\ &\text{s.t. } \|\Theta s - y\|_2 \le \epsilon \end{aligned} \tag{8}$$

where ϵ is an arbitrary small positive number.

B. DISTRIBUTED CS

The traditional CS algorithm only takes the structural characteristics of the signal itself into consideration and ignores the correlation between signals. Thus, the application of large-scale sensors faces problems of large reconstruction error and data transmission amount. Different from the traditional CS, the distributed CS proposed by Baron makes full use of the correlation between signals measured by different sensor nodes [13]. The whole process of distributed CS contains three factors, namely, sparse representation, measurement and joint reconstruction of the signal. Each sensor node encodes the signal by independently projecting it onto an unrelated observation base and then sends the encoded observation data to the decoding side. Under optimal conditions, the decoding end can accurately reconstruct each signal [14]–[16].

In a microseismic monitoring system, because microseismic information collected by each sensor is affected by both the global impact factor and the partial impact factor, the collected information fits in with the distributed CS JSM-1 model, which deems that a related information source consists of both common and unique parts.

In the JSM-1 model, the original signal can be abstracted as an N dimensional vector, and it can be presented as [17] and [18]

$$x_j = z_c + z_j, \quad j \in \{1, 2, \ldots, J\} \tag{9}$$

where the common part z_c and the unique part z_j both show sparse features on a certain signal basis, that is [19]

$$z_c = \Psi s_c, \quad \|s_c\|_0 = K_c \tag{10}$$

$$z_j = \Psi s_j, \quad \|s_j\|_0 = K_j \tag{11}$$

Among these variables, $K_c \ll N$, and $K_j \ll N$. Using an $M \times N (K < M \ll N)$ matrix Φ as the observation matrix to obtain the linear projection of the signal, the measured value is then

$$\begin{aligned} y_j &= \Phi x_j \\ &= \Phi(z_c + z_j) \\ &= \Phi\Psi(s_c + s_j), \quad j \in \{1, 2, \ldots, J\} \end{aligned} \tag{12}$$

For the joint reconstruction of two related signals x_1 and x_2 (namely, $J = 2$), $(K_c + K_1)c$ and $(K_c + K_2)c$ measurements are needed, respectively, where c is the oversampling factor defined as

$$c = M/K \tag{13}$$

There is a common part z_c between two signals, while the common part of x_2 that has already been reconstructed during the construction of signal x_1 does not need to be reconstructed repeatedly. Therefore, the joint reconstruction of signals x_1 and x_2 only requires $(K_c + K_1 + K_2)c$ measurements. It is thus evident that distributed CS can sharply lower the measurements requirements. In addition, distributed CS shifts the computational complexity from the encoding end to the decoding end, making it especially appropriate for the application scenarios with limited terminal node ability, such as the microseismic monitoring system mentioned in this paper.

IV. PROPOSED ALGORITHM

The time and space of microseismic signals are usually correlated. A certain time offset exists for the moments first break moments due to their different distances from the microseismic source. In view of these microseismic signal characteristics, the method presented in this paper uses the first break pickup and signal alignment (FBP-SA) algorithm to extract the offset time and then aligns the microseismic signals. After the sparse transformation and observation, this method encodes the measurement and the first break moment together and conducts the distributed CS on multiple signals. At the receiving end, the first break moment is first decoded and extracted, and the microseismic signals are then jointly reconstructed; finally, the microseismic signals are obtained with time information by adding the first break moment. The overall scheme is shown in Fig.2.

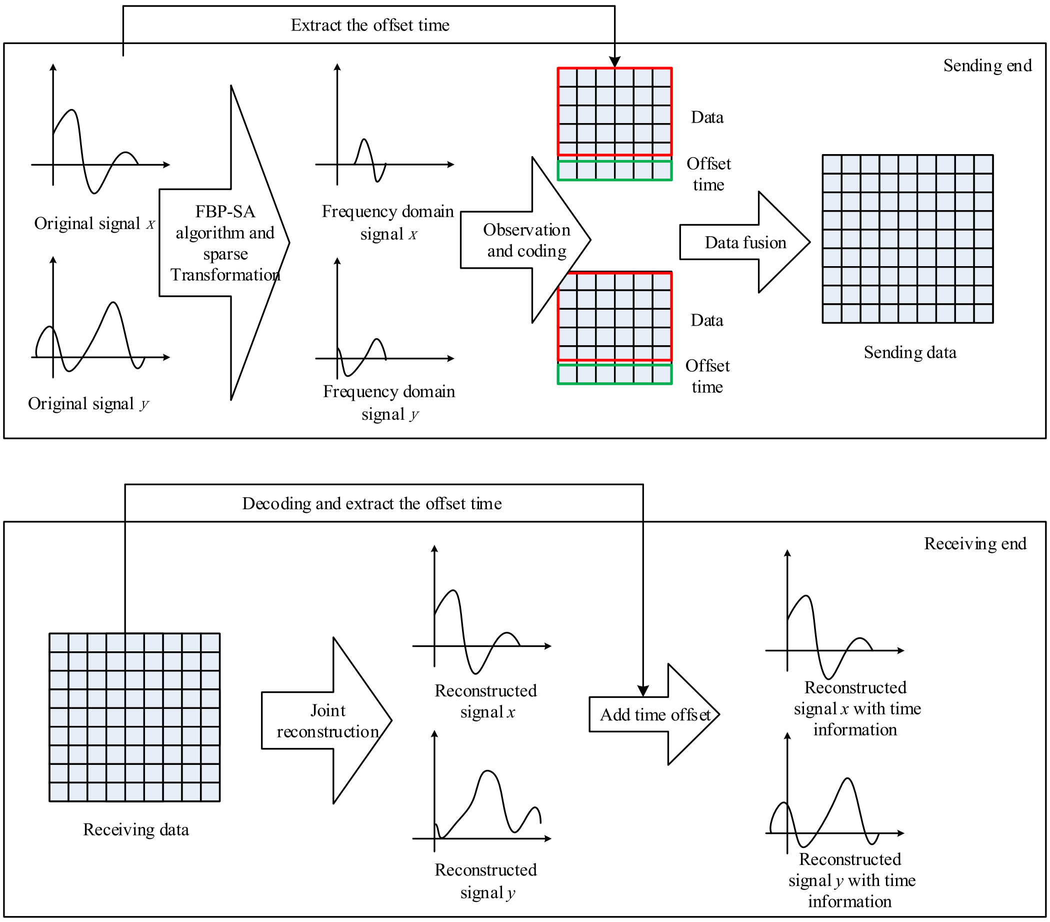

FIGURE 2. Distributed CS scheme for microseismic signal monitoring based on first break pickup and signal alignment.

A. THE FBP-SA ALGORITHM

In microseismic signal monitoring, the accuracy of first break moment extraction plays an important role in calculating and analyzing the source location and mastering the structure of buildings and the stability of strata. The proposed FBP-SA algorithm is used when terminal nodes collect microseismic signals and send them to cluster-head nodes. First, a sampling signal of a certain terminal node is randomly selected as the reference signal. Subsequently, the signals of other terminal nodes acquired within the same cluster are compared with the reference signal one by one. After the first break moments have been extracted, they are aligned to that of the reference signal. The algorithm flow is shown in Algorithm 1.

The reference signal and another random signal are assumed to be x_n and y_n, respectively. The sampling frequency is f_s. Then, the correlation function of the two signals is

$$R_{xy}(m) = \sum_{n=1}^{\infty} x(n)y(n+m) \tag{14}$$

The time offset at the maximum correlation is calculated according to the correlation function, sampling points and sampling rate; then, the maximum value of the correlation function is obtained as

$$R_{max} = \max\{|R_{xy}(m)|\} \tag{15}$$

Algorithm 1 First Break Pickup and Signal Alignment (FBP-SA)

Input: signal x_n, signal y_n, sampling frequency f_s, sequence length N

Output: offset time T_{offset}

for $n = 1$ to N **do**
  for $m = 1$ to N **do**
    $corr_{xy}(n) \leftarrow \sum_{n=1}^{N} x(n)y(n+m)$
  end for
end for
for $i = 1$ to N **do**
  $R_{xy}(m) \leftarrow \sum corr_{xy}(i)$
end for
$R_{max} \leftarrow \max\{|R_{xy}(m)|\}$
Obtain the sample number from the initial time to R_{max} time, record it as N
$T_{offset} \leftarrow N/f_s$
return T_{offset}

The number of sampling points from the initial time to time R_{max} is obtained and recorded as N. Then, the time offset is

$$T_{offset} = \frac{N}{f_s} \tag{16}$$

According to the T_{offset} calculated in the previous step, the first break moment of a random signal y_n is aligned with that of the reference signal x_n. Meanwhile, the correlation coefficient between x_n and y_n is calculated. In this paper, the algorithm is referred to as the FBP-SA algorithm.

B. SPARSE TRANSFORMATION

CS is carried out after the first break pickup and signal alignment. In CS, the sparser the signal is, the more accurate the reconstructed signal. Therefore, it is necessary to select a suitable sparse basis to realize accurate signal reconstruction. Microseismic signals are usually sparse in the frequency domain, so the Fourier transformation basis is chosen.

For a finite length sequence $x_n, n = 1, 2, \ldots, N$, its discrete Fourier transform (DFT) is defined as

$$X(k) = DFT[x(n)] = \sum_{n=1}^{N} x(n)e^{-2\pi knj/N}, \quad 1 \le k \le N \tag{17}$$

During signal reconstruction, the inverse discrete Fourier transform (IDFT) is required to transform the signal to the time domain for the convenience of analysis and feature extraction. IDFT is defined as

$$x(n) = IDFT[X(k)] = \frac{1}{N}\sum_{k=1}^{N} X(k)e^{2\pi knj/N}, \quad 1 \le n \le N \tag{18}$$

Using the experimental setup of Fig.3, an experiment was also performed to obtain the real microseismic signal and evaluate the performance of the proposed algorithm, where the two-dimensional positioning space is a 12 m×8 m flat surface. Sensors A, B and C are ADXL362 3-axis MEMS accelerometer sensors. In this paper, we only use the results from the X-axis of Sensors A, B and C.

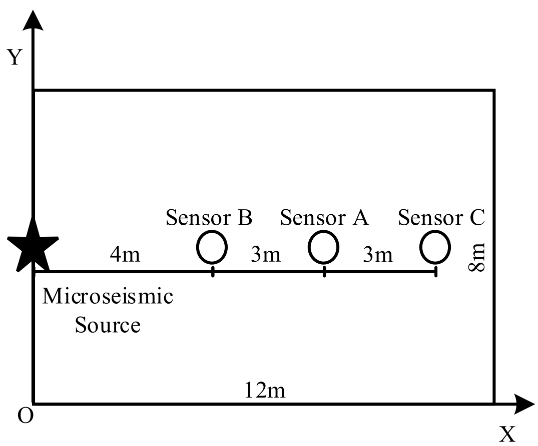

FIGURE 3. Experiment environment scheme.

As exhibited in Fig.4(a), the real microseismic signal obtained from Sensor A is 2048 points in total length. Fig.4(b) presents its signal in the frequency domain after the discrete Fourier transformation. It can be seen that there are still relatively few zero values of the real microseismic signal in the frequency domain, so the signal needs to be processed. In this paper, a threshold in the frequency domain is set, and the amplitude of the signal smaller than the proposed threshold is set to 0. Experiments show that the reconstruction results are related to the ratio of the threshold value to the largest amplitude. Table 1 is a comparison of the reconstruction error and the number of nonzero elements after IDFT in cases of different ratios of the threshold value to the largest amplitude. In the table, η is the ratio of the threshold value to the largest amplitude; $\bar{d}$ is the average reconstruction error of the original signal and the reconstruction signal; and $\|x\|_0$ is the zero norm of x, which means the number of nonzero elements of signal x.

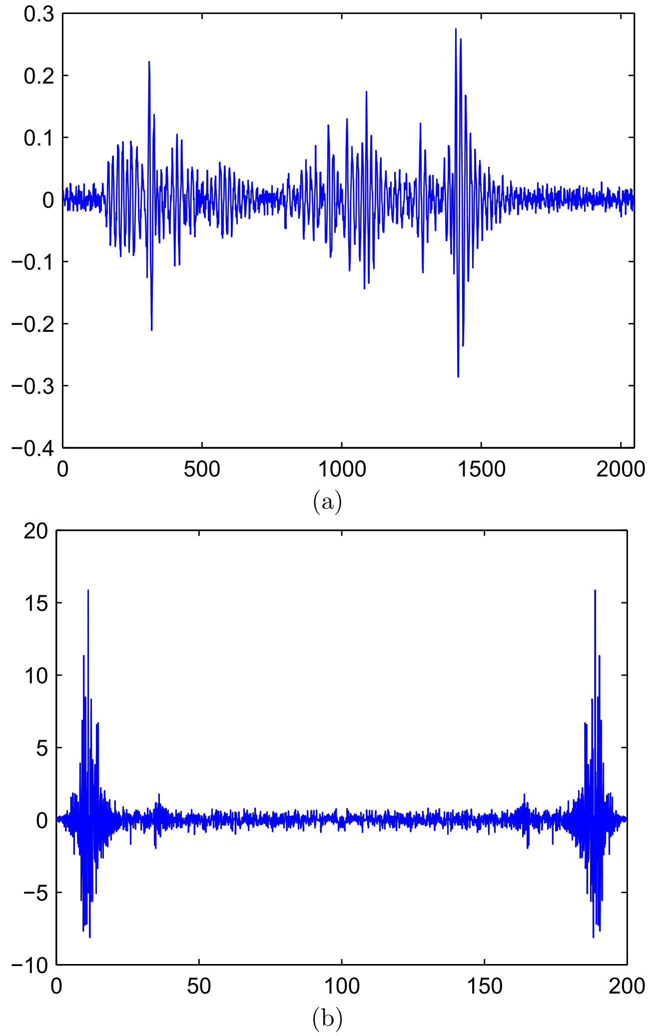

FIGURE 4. Microseismic signal x in the time domain and frequency domain.

In the following section, a 10% threshold relative to the largest amplitude is taken as the line, and the frequency domain amplitudes with values smaller than this value are all set to 0. The aim is to ensure that under the condition of

TABLE 1. Comparison of reconstruction error and number of nonzero elements in cases of different ratios of the threshold value to the largest amplitude.

η	d	$\|x\|_0$
1%	0.001	1871
2%	0.002	1416
3%	0.004	978
4%	0.005	648
5%	0.007	426
10%	0.009	216
15%	0.010	144
20%	0.012	116
30%	0.015	82
40%	0.018	56
50%	0.021	40
60%	0.023	24
70%	0.024	18
80%	0.026	12
90%	0.028	6
100%	0.029	4

a small recovery error, the signal can become as sparse as possible, that is, as many 0 values as possible can be obtained for the convenience of CS.

C. DISTRIBUTED CS FOR MICROSEISMIC SIGNALS

In this section, a method of distributed CS for microseismic signals is proposed to effectively reduce the total amount of data transmission. Similarly, this method divides the signal into a sparse common part and a sparse unique part. For N correlated microseismic signals, their time domain signals are still represented by $f_1, f_2, \ldots, f_n, n \in (1, N)$ and their frequency domain signals by $s_1, s_2, \ldots, s_n, n \in (1, N)$. The sparse common part C is set to

$$C = 1/N \sum_{n=1}^{N} s_n \tag{19}$$

The sparse unique part U_n of signal s_n is set to be

$$U_n = s_n - 1/N \sum_{n=1}^{N} s_n \tag{20}$$

After the distributed CS is conducted on multiple signals in accordance with the above method, the signals are observed through the observation matrix, which satisfies the restricted isometry property (RIP) in the CS theory.

D. JOINT CODE AND RECONSTRUCTION

The data collected by multiple sensors need to be encoded and fused before signal transmission, and the matrix after data coding and fusion is called a transmission matrix. This matrix is composed of three parts, namely, the matrix head part, the data part and the check part. The role of the matrix head part is to plan the number of total matrix rows and data rows. The data part, which includes the measurements after CS, consists of the sparse common part, the sparse unique part and the first break moment. Among them, the first break moment of the reference signal equals zero, while the offsets of other signals relative to the first break moment of the reference signal are represented by floating point numbers. The check part can adopt a CRC check to ensure the accuracy and integrity of data transmission.

The decoding and joint reconstruction can be implemented at the receiving end or the decoding end. This process includes the following steps. First, the offset time is extracted, and then the common part and the unique part are reconstructed using the orthogonal matching pursuit (OMP) algorithm [20]. After the superposition of these two parts, the complete reconstructed signal of each sensor is obtained, after which the first break offset time of the corresponding signal is superimposed on the reconstructed signal.

V. PERFORMANCE EVALUATION AND DISCUSSION

A. EVALUATION INDEXES

1) RELATIVE RECONSTRUCTION ERROR

The overall performance of CS depends on the relative reconstruction error (the smaller the better). The relative reconstruction error $Err(p)$ is defined as follows:

$$Err(p) = \|\tilde{x} - x_0\|^2 / \|x_0\|^2 \tag{21}$$

where $p = q/Q \times 100\%$ represents the percentage of the first q maximum coefficients in the total coefficient Q after ranking the original signal x_0 in descending order; $\tilde{x}$ stands for the approximation of the approximate value of x_0 obtained by reconstructing Q maximum coefficients.

The relative reconstruction error is also related to the signal length and number of CS measurements, which should not be too small. Otherwise, the performance of the CS scheme cannot be evaluated objectively. The number of measurements M usually satisfies [21]

$$M \geq K \log_2(N/K) \tag{22}$$

where K is the sparseness; N is the length of the signal.

2) RESOURCE REQUIREMENTS

The decoding end is generally a server or wired nodes, so its energy consumption is generally not taken into consideration; therefore, this paper only takes the energy consumption of the sending end (sensors in the monitoring area) into consideration. Assuming that the average energy consumption of each sensor for the proposed CS is E_{CS} [22], the average energy consumption for transmission is E_t per bit, the quantity of data transmission is D bits, and the total number of sensors is n, then the total energy consumption of the monitoring area can be expressed as

$$E = n \times (E_{CS} + D \times E_t) \tag{23}$$

To evaluate the performance of the proposed method for microseismic signals CS and reconstruction, experiments are conducted in this section. Microseismic signals are collected from the real acceleration sensors, and the simulation parameters are listed in Table 2.

TABLE 2. Simulation parameters.

Parameters	Value
Sampling frequency F_s	200Hz
Ratio of threshold value to the large amplitude η	10%
Length of signal N	2048
Measurement M	760
Average energy cost for CS E_{CS}	1000 nJ
Average energy cost for transmission E_t	1000 nJ

B. PERFORMANCE OF THE FBP-SA ALGORITHM AND THE PROPOSED DISTRIBUTED CS

1) PERFORMANCE OF THE FBP-SA ALGORITHM

As shown in Fig.5, acquired by Sensors A, B and C in Fig.3, respectively, Signals A, B and C are related to a certain degree. The abscissa represents the signal length, whereas the ordinate represents the signal amplitude. With Signal A as the reference signal, the correlation functions between Signals A and B and Signals A and C are illustrated in Fig.6. The performance after using the FBP-SA algorithm is presented in Fig.7, from which it be seen that a good alignment result can be obtained; meanwhile, the first break moment can be exactly extracted, which is later conducive to the use of distributed CS steps.

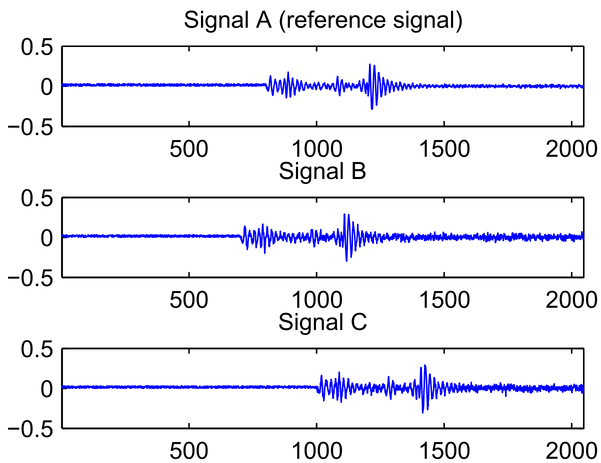

FIGURE 5. Three microseismic signals of the same source.

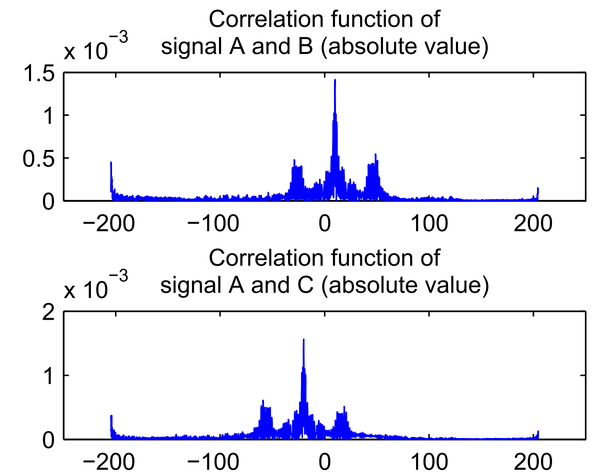

FIGURE 6. The correlation function between the reference signal and other signals.

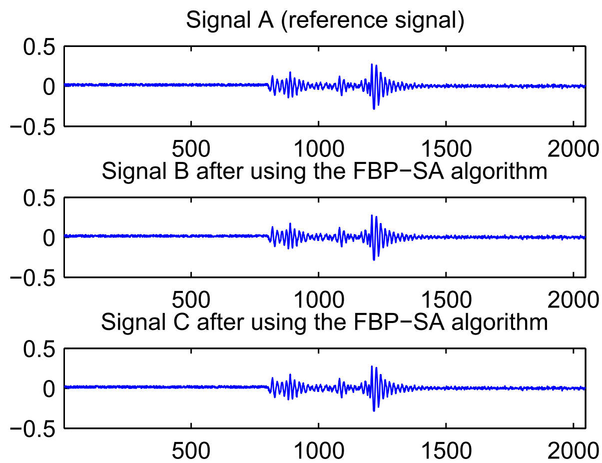

FIGURE 7. The microseismic signals after using the FBP-SA algorithm.

2) PERFORMANCE OF THE PROPOSED DISTRIBUTED CS

The aforementioned improved distributed CS for microseismic signals is applied to the three microseismic signals shown in Fig.7, and the sparse common parts and the sparse unique parts of each signal are presented in Fig.8. At the receiving end, signal a, b and c can be reconstructed based on the sparse common parts and the sparse unique parts of signal a, b and c. The comparison of the extraction error, measurement and energy consumption of proposed distributed CS and distributed CS is shown in Fig.9, Fig.10 and Fig.11. The three figures will be explained and analyzed in detail below.

C. THE RELATIONSHIP BETWEEN THE EXTRACTION ERROR OF THE FIRST BREAK TIME AND SIGNAL VARIANCE

The signal reconstruction after CS will cause errors, lowering the accuracy of first break moment extraction. As a result, the proposed scheme extracts the first break moment before CS and transmits the measurements of CS together with the first break moment, which can reduce the error of the first break moment extraction. Furthermore, because there is a proportional relationship between the error of first break moment extraction and the complexity of the signal, the complexity can be reflected by the standard deviation of the signal. Hence, we further simulate the relationship between the standard deviation of the signal and the relative error of the first break moment extraction to demonstrate the performance of various schemes. Fig.9 shows the relationship between the standard deviation of signal and the error of the first break moment extraction during sampling according to application of the Nyquist sampling theorem, independent CS (called ICS), distributed CS (called DCS) and the proposed

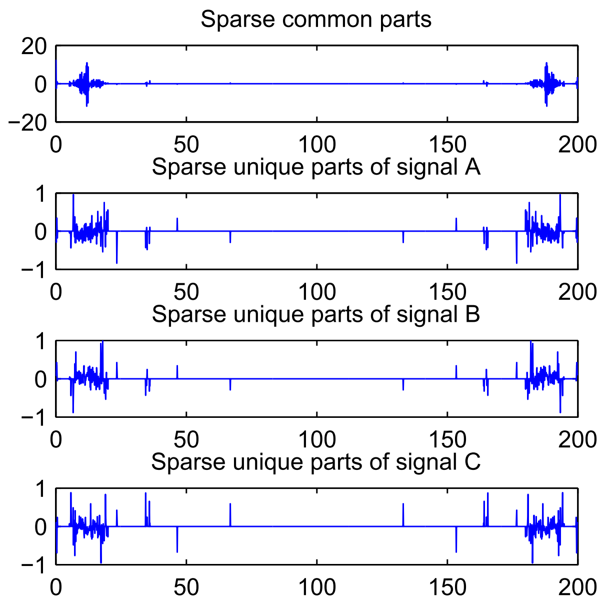

FIGURE 8. Sparse common parts and sparse unique parts.

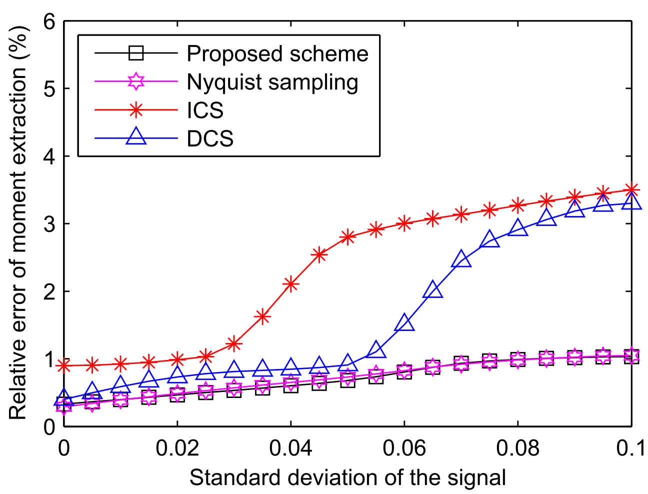

FIGURE 9. Relationship between the relative error of moment extraction and standard deviation of the signal.

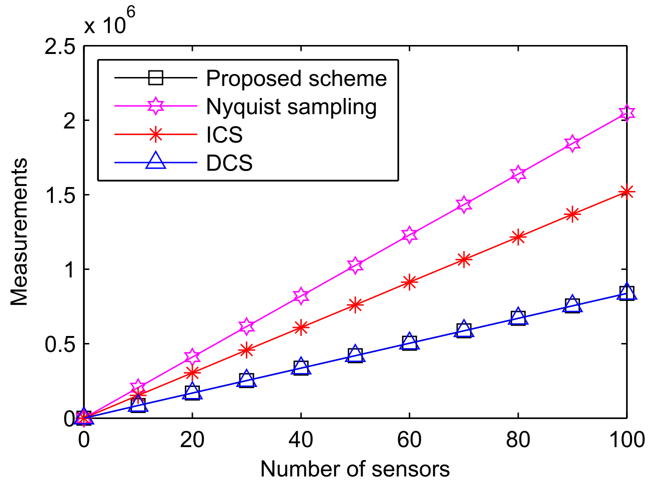

FIGURE 10. Relationship between the number of measurements and the number of sensors.

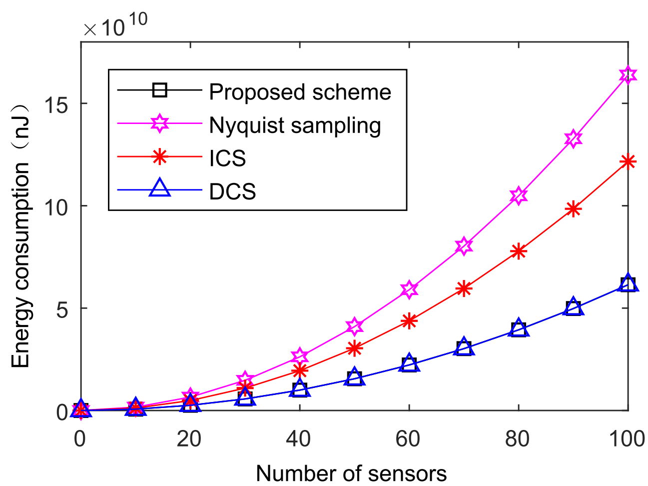

FIGURE 11. Relationship between energy consumption and number of sensors.

scheme to signals. Fig.9 illustrates that with the increase of the standard deviation of the signal, the errors of the first break moment extractions of the three schemes increase; the proposed scheme and the Nyquist sampling scheme have smaller errors. The performance of the proposed scheme increases by 69% and 54% on average compared with those of Schemes 2 and 3, respectively.

D. MEASUREMENT COMPARISON

The number of measurements can reflect the data compression performance of a CS scheme, so the performances of ICS, DCS and the proposed scheme are compared with the control measurements obtained according to the Nyquist sampling theorem. As shown in Fig.10, the number of measurements increases with the growing number of sensors; DCS and the proposed CS scheme have minimum measurements. Their performances increase by 59% and 45% on average compared with those of the Nyquist sampling scheme and ICS, respectively.

E. ENERGY CONSUMPTION

According to (23), the energy consumption of the Nyquist sampling scheme, ICS, DCS and the proposed scheme are simulated. Fig.11 shows the energy consumption increases with the growing number of sensors; DCS and the proposed CS scheme have the minimum energy consumption. Their performances increase by 61% and 48% on average compared with those of the Nyquist sampling scheme and ICS.

F. RECONSTRUCTION ERROR

Fig.12 shows the relationship among the reconstruction error, the length of the signal and the number of measurements of the three microseismic signals shown in Fig.7 after they are

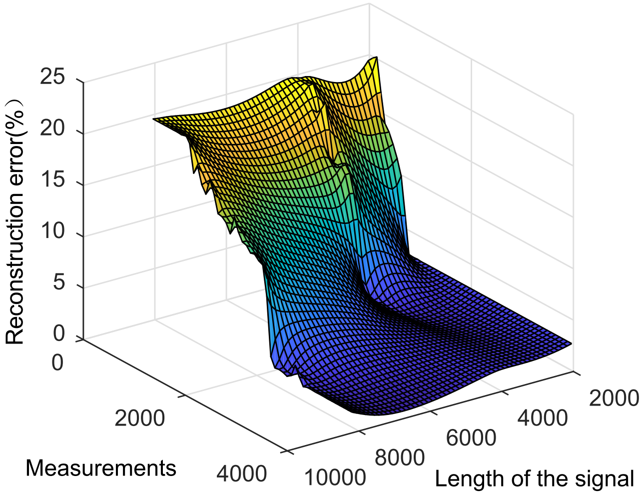

FIGURE 12. Relationship among the reconstruction error, the length of the signal and its number of measurements.

processed with the proposed distributed CS scheme. Fig.12 shows the reconstruction error of the proposed scheme when the length of the signal and the number of measurements range from 0-10000 and 0-4000, respectively. It can be seen that the reconstruction error is always maintained at lower levels; when the length of the signal is constant, the reconstruction error decreases as the number of measurements increases; when the number of measurements of the signal is constant, the reconstruction error remains unchanged; the overall trend is in conformity with (22).

VI. CONCLUSION

In this paper, we have proposed a distributed CS scheme for microseismic monitoring based on first break pickup and signal alignment, which is different from the traditional distributed CS in the following aspects. Firstly, the proposed scheme obtains the first break time offset of reference signal and other signals via an algorithm. Then it aligns the other signals to the reference signal. Subsequently it conducts the distributed CS and encodes them together with the first break moment. At the decoding end, this scheme first extracts the first break moment. Then it conducts multi-sensor data joint reconstruction. Finally it adds the first break time to the recovered microseismic signal. Thus the microseismic signals containing accurate time information are obtained. The scheme can effectively reduce transmitted data and avoid the problem of inaccurate first break time caused by CS reconstruction. Experimental results have been conducted using real microseismic signals. The simulation shows that the proposed scheme is superior to previous schemes in terms of accuracy, energy consumption and reconstruction accuracy.

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