Designing of Environmental Information Acquisition and Reconstruction System Based on Compressed Sensing

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Abstract. At present, the collection of environmental information is mostly accomplished by sensors. In order to reduce the redundancy of sensor data collection, reduce the energy consumption of nodes, improve the service life of sensors and reduce the cost of the system, a system that combines compressed sensing reconstruction with sensors is proposed in this paper to collect and reconstruct environmental information. The designed system collects the environment information with a limited number of nodes. Compressed sensing reconstructs all the data of the required area through the optimized OMP algorithm. The final information is displayed by the software based on C# designing. The final result shows that the verification system proposed in this paper can realize the accurate reconstruction of the original environmental information, and it is effective to the collection and processing of complex environmental information.

Keywords: Compressed sensing · Reconstruction
Environmental information collection · Visualization
Orthogonal matching pursuit algorithm

1 Introduction

The rapid development of wireless communication technologies and computer networks has promoted the development of wireless sensor networks. Current wireless sensor networks consist of a large number of regularly or randomly distributed sensor nodes and aggregation nodes with advanced data processing capabilities and advanced power supply reserves. This network is characterized by a large scale, strictly limited distributed network. The sensor node can be used to detect various environmental information such as temperature, humidity, light, and pressure. However, as information collection continues to increase, the lifespan of the sensor is greatly reduced, which resulting in high cost investment. In addition, according to the Shannon-Nyquist sampling theorem, the sampling frequency must be greater than or equal to twice the signal bandwidth to recover the original signal during the information collection process. The collected information does not play a role, resulting in low efficiency, and the

L. Meng and Y. Zhang (Eds.): MLICOM 2018, LNICST 251, pp. 583–593, 2018.
https://doi.org/10.1007/978-3-030-00557-3_58

waste of resources. In addition, the cost of the equipment required for this sampling method is high. Aiming at the shortcomings of traditional sampling, Donoho, Candes and Tao et al. proposed compressed sensing [1]. Compressed sensing obtains signals directly through the transformation of space, collecting valid information in a large amount of data, which is performing certain compression while data is sampled. Then it obtains the required information through the sensing matrix. Finally some reconstruction algorithm will restore the original information. Therefore, when the amount of data is large, the number of sampling times required for compressed sensing is far lower than that of Nyquist's theory. In this paper, the design of the environment information processing system is designed by combining the sensor with the compression sensing technology, confirmation of the system is performed by adopting two information of temperature and humidity that have significant and sparse changes in environmental information, compression and transmission of information through the sensor, then the receiver reconstructs the original data through the optimized OMP algorithm. At the same time, the results are displayed on the PC side and error analysis is performed. The results show that the original data can be recovered accurately with a certain error, so the feasibility of the sensor and compressed sensing reconstruction technology cooperation system is verified.

2 Compressed Sensing

2.1 Basic Theory of Compressed Sensing

Compressive sensing technology is the combination of mathematics-based implementation and engineering applications. The premise of applying compressed sensing technology is that the information that needs to be collected must be sparse or compressible and irrelevant, so that it can realize simultaneous acquisition in information compression, so the sampling rate is lower than Nyquist sampling. Compared with traditional sampling techniques, compressed sensing technology has several differences. Compressed sensing technology is mainly applied to finite-dimensional vectors; When sampling, compressed sensing does not directly acquire information, but uses the inner product operation of the observation function and the acquired information as the value transmitted to the receiving end; The information reconstruction of the compressed sensing technology is not a simple reversible process, but a problem of mathematical optimization to find the optimal solution of the indefinite equation.

Assume that X is a $N \times 1$ dimensional column vector of R^N space, whose elements are $[n], n = 1, 2\ldots, N$ and $\{\Psi_i\}_{i=1}^{N}$ is an orthogonal set of $R^{N \times N}$ spaces. Therefore X can be expressed as $X = \Psi\,\Theta$: where $\Psi = [\Psi_1, \Psi_2, \ldots, \Psi_N]$, $\Theta = (\theta_i) = [\langle X, \Psi_i \rangle]$ is the expansion coefficient of X on Ψ. If the number of non-zero coefficients is K and $K \ll N$ is satisfied, X is sparse or compressible. Therefore, we can get the compressed signal $Y = \Phi\,\Theta = \Psi^T X$, compressed sensing technology information reconstruction process show in Fig. 1.

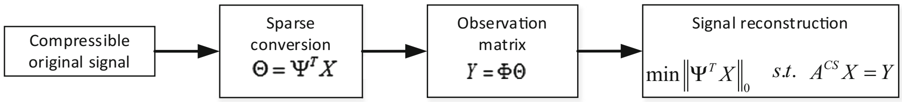

Fig. 1. Compressed sensing information reconstruction process diagram

It mainly includes three main problems: determining the sparse matrix of the signal, determining the observation matrix, and signal reconstruction, which are described in detail in the following part of this chapter.

2.2 Compressed Sensing Reconstruction Process

(1) The problem of signal sparse representation is that an orthonormal basis Ψ can be found, so that X can be sparsely represented. The conditions for the sparseness of the coefficient vector are satisfied in $0 < p < 2$ and $R > 0$:

$$\|\Theta_p\| \equiv \left(\sum_i |\theta_i|^p\right)^{1/p} \leq R \tag{1}$$

The key is to find a suitable base Ψ, which is the first step in compressing perceptual reconstruction. Pevre integrates the orthogonal basis into an orthogonal base dictionary. For a certain signal, it can be found adaptively in the orthogonal base dictionary to find the optimal one, so that the most sparse representation can be achieved.

(2) The observation matrix Φ of size $M \times N$ is designed to ensure that it is not related to the transformation base Ψ and has stability, so that the sparse vector Θ guarantees the integrity of important information in the dimension reduction process. According to the theory of compressed sensing, the observation matrix needs to meet the RIP, that is, for the signal X, ε satisfies the following formula:

$$(1-\varepsilon)\|X\|_2^2 \leq \|\Phi X\|_2^2 \leq (1+\varepsilon)\|X\|_2^2 \tag{2}$$

In the literature [2, 3], it has been proved that most random matrices satisfy RIP, but the deficiency of this criterion is that the calculation is more difficult. Therefore, the rationality of the measurement matrix can generally be judged by the correlation discriminant theory, which is the measurement matrix and Ψ is irrelevant, the literature [4] gives the calculation formula of the correlation coefficient to determine the correlation between the two:

$$\mu(\Phi, \Psi) = \max_{i \geq 1, j \leq N, i \neq j} |\langle \varphi_i \psi_j \rangle| \tag{3}$$

Therefore, the threshold of the correlation coefficient must be met when designing the measurement matrix.

(3) The signal reconstruction problem aims to solve the underdetermined equations sparsely by designing a fast and accurate reconstruction algorithm. Theoretically, the equations $Y = A^{CS}X$ have infinitely many solutions, but the equations are guaranteed due to the sparsity and compressibility of the original signal. The existence of a unique solution to the group means that the original signal can be accurately reconstructed from observational evidence. In [5] the problem was solved by l_1-norm optimization, as follows:

$$\min\left\|\Psi^T X\right\|_1 \quad s.t. A^{CS}X = \Phi\Psi^T = Y \tag{4}$$

Through this method, the linear solution is converted to a convex optimization problem. Based on this, a BP algorithm, a BPDN algorithm is proposed. However, these reconstruction algorithms have a large amount of computational deficiencies. Therefore, the matching quasi-tracking algorithm (MP) and orthogonal matching tracking algorithm (OMP) are proposed in the follow-up. The OMP algorithm has the characteristics of high computing speed and easy implementation. Therefore, in this paper the optimized OMP algorithm is used to complete the data reconstruction [6–8].

3 System Model, Reconstruction Algorithm and GUI Designing

3.1 Information Acquisition System Model

The design of environmental information acquisition and analysis system based on compressed sensing is shown in Fig. 2.

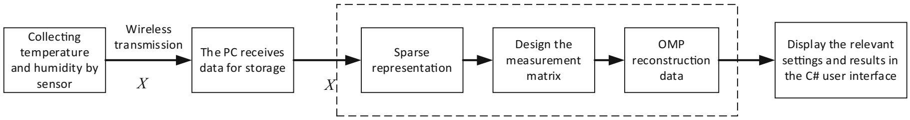

Fig. 2. Environmental information acquisition system block diagram

In the verification system designed in this paper, the temperature and humidity environment information collected by the temperature and humidity sensor has real-time and accuracy, and then the data is transmitted to the PC through the wireless serial port, which can reduce the delay and ensure the accuracy of the data in practical applications. On the PC side, through the joint design of MATLAB and C#, the user can manipulate the set parameters in the visual interface, and then use MATLAB to reconstruct the data, and finally feed the results back to the user interface.

3.2 Compressed Sensing Reconstruction Algorithm

In order to restore the original temperature and humidity accurately, the design of compressive sensing reconstruction algorithm is very important. The optimization algorithm based on the orthogonal matching pursuit algorithm adopted in this paper, because the OMP algorithm has the characteristics of high computing speed and easy to implement The strong anti-interference ability is very suitable for environmental information with complex features [9, 10]. The basic idea of the OMP algorithm is based on $K-$ sparse. The goal is to find K larger components than the absolute values of other $N - K$ components. Therefore, the algorithm needs to find the column vectors involved in the original signal measurement from the observation matrix. The OMP algorithm process is:

step1 Initialization: residual $r^0 = y$, index set $\Gamma^0 = \varnothing$, number of iterations $l = 1$;

step2 Calculate the correlation between observational evidence and residuals, and take the largest index value $i_{\max}$, that is $i_{\max} = \arg\max_i \left|\Theta_i^H r^{l-1}\right|$;

step3 Update: $\Gamma^l = \Gamma^{l-1} \cup i_{\max}$, $D^l = D^{l-1} \cup D_{i_{\max}}$;

step4 Using the Least Square Method to Solve $y = \Theta^l \theta^l$ Obtained $\hat{\theta}^l = \Theta_{\Gamma^l}^T y$;

step5 Update: $r_l = y - \Theta^l \hat{\theta}^l$;

step6 $l = l + 1$, If the judgment is satisfied or the residual is lower than the set threshold, iteratively enter step7; otherwise, return step2;

step7 $\hat{\theta}$ has non-zero elements at Γ^l, then the value is $\hat{\theta}^l$ for the last iteration.

3.3 GUI Designing

This article is mainly to develop the demonstration software based on the information reconstruction of compressed sensing environment, and complete the software design through the mixed programming of C# and MATLAB. The user interface design consists of four parts: start module, system parameter setting module, simulation analysis module, and information display module, as shown in Fig. 3.

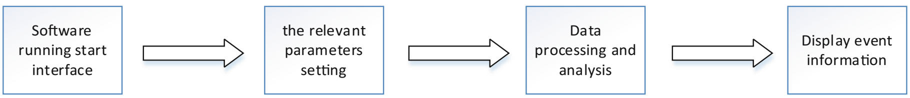

Fig. 3. Software design block diagram

Part of the parameter setting module is set by user's menu, part of which is set according to the algorithm of reconstruction and the number of data collected randomly. In the data processing part, it is mainly to realize the call of the MATLAB program, and to complete the reconstruction processing and analysis of the collection data. In the user interface, the received data and the results of the processed data can be observed in real time. Specific design is such as Fig. 4.

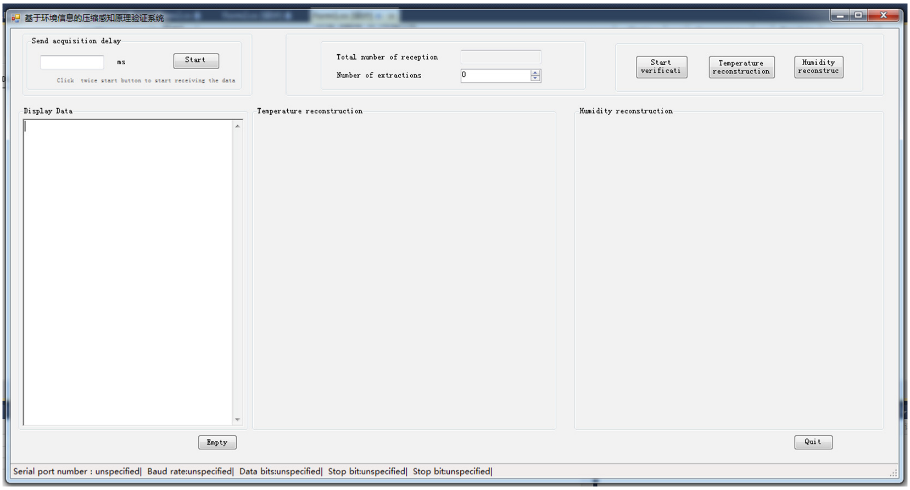

Fig. 4. User interface

4 Analysis of Results

Firstly, the influence of the sparsity and the number of measurement samples on the success probability of OMP algorithm reconstruction is verified by simulation. The original signal length is $N = 300$ and the sparsity is $s = 15$. The measurement matrix is the Gauss random measurement matrix of $M \times N$. The simulation results are shown in Figs. 5 and 6.

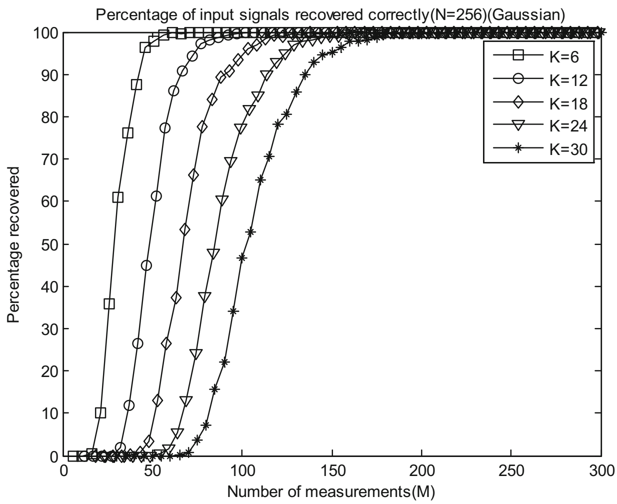

Fig. 5. Simulation diagram of the influence of sparsity on reconfiguration performance

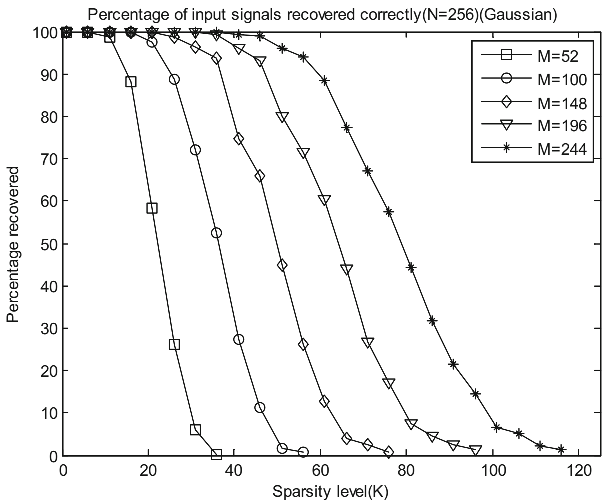

Fig. 6. Simulation diagram of the influence of observed quantity on reconfiguration performance

The simulation results show that on the one hand, with a certain degree of sparseness, the greater the number of measurement samples, the greater the probability of success of OMP reconstruction, and the probability of reconstruction success is 100% when a certain threshold is reached; on the other hand, when the measurement sample number is constant, the lower the sparseness is, the greater the probability of successful OMP reconstruction.

Secondly, we simulate the relationship between the measurement matrix and the reconstruction success probability. Let the length of the signal be $N = 256$, and the sparsity be taken as 16 and 30 respectively, for Gaussian random measurement matrix, Bernoulli random measurement matrix, partial Hadamard measurement matrix, Toplitz measurement matrix and cyclic measurement matrix have been verified, simulation results shown in Figs. 7 and 8.

Through the simulation results, we can find that in the case of low sparsity, the performance of the five measurement matrices is similar and data reconstruction can be achieved when the number of measurement samples reaches a certain value. In the case of high sparseness, the performance of some Hadamard measurement matrices outperforms the other four.

Based on the above simulation and verification of the performance of OMP algorithm, certain optimization is performed, reasonable parameters are set, the optimal situation is selected, and applied to the system designed in this paper. The collected temperature and humidity are reconstructed and verified. The results are shown in Figs. 9 and 10.

The results show that the temperature and humidity reconstruction errors are very small, and within a certain range of error, it can be demonstrated that the original temperature and humidity information is completely and accurately reconstructed

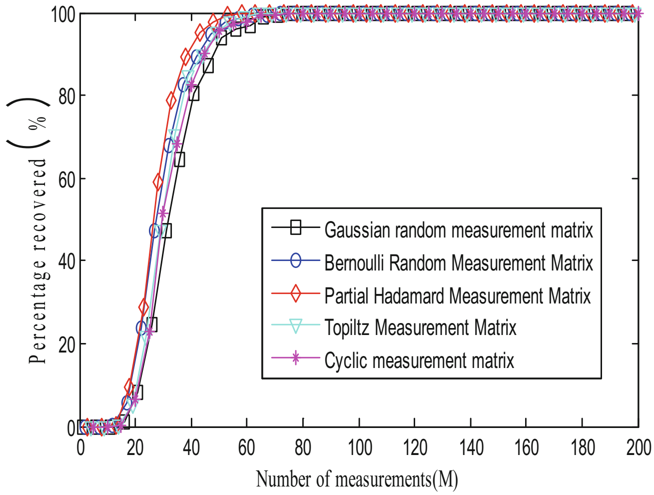

Fig. 7. Effect of five kinds of measurement matrices on the reconstruction performance when the sparsity is 16

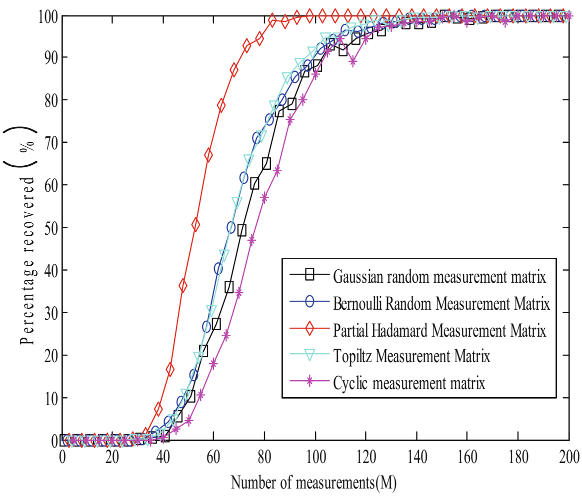

Fig. 8. Effect of five kinds of measurement matrices on the reconstruction performance when the sparsity is 30

through compressed sensing. That is compressed sensing theory is feasible in sensor data processing.

Finally, a complete design system operation test is performed. The test result is shown in Fig. 11.

The software operation interface mainly includes a user parameter setting section, which can set related parameters; the received temperature and humidity information

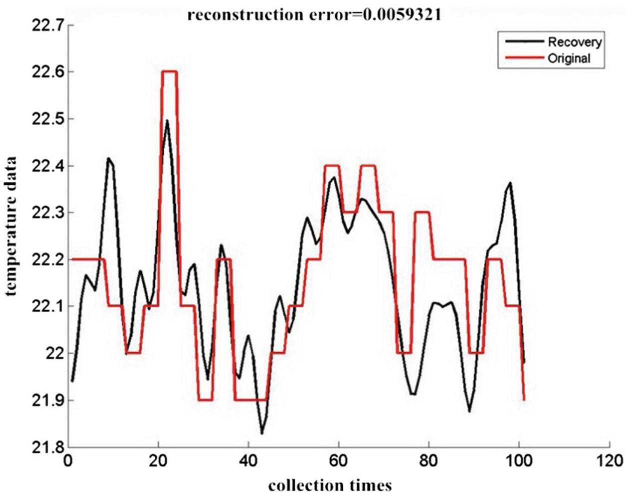

Fig. 9. Temperature reconstruction simulation based on compressed sensing

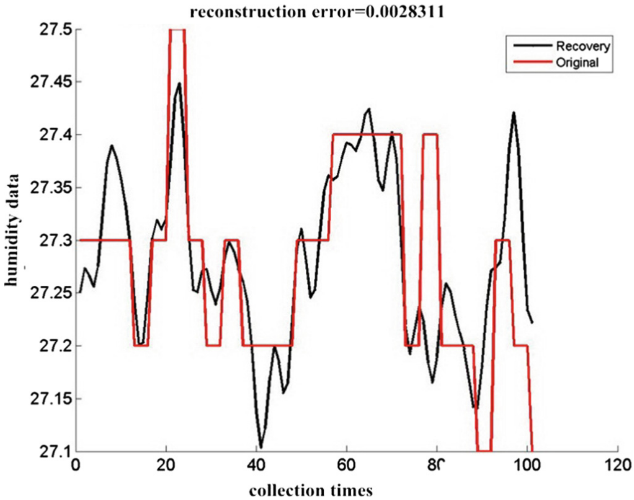

Fig. 10. Humidity reconstruction simulation based on compressed sensing

display part can be displayed in real time and stored; the other part is reconstructed based on a small number of temperature and humidity information. The reconstruction result of all the information is compared with the original data in order to verify the accuracy in this design, and the reconstruction error is calculated.

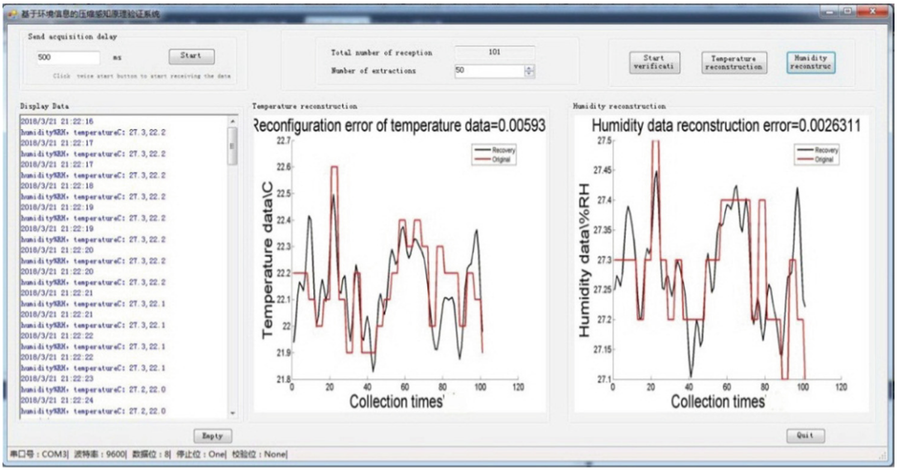

Fig. 11. Software running test interface

5 Conclusion

In the wireless sensor network of environment information collection, in order to collect data and transmit a large amount of data in real time, the energy consumption of the node is large and the service life is short. Compressed sensing technology provides a solution to this problem. This paper designs and develops an environment information reconstruction system based on compressed sensing technology, which can realize data collection in some unreachable environments, adopt compressed sensing technology to observe, then use the selected reconstruction algorithm to perform reconstruction and perform error and other performance analysis. In the process of this paper, we mainly use the random access compression sensing technology, C# and MATLAB mixed programming technology, as well as the optimization and improvement of the existing reconstruction algorithms. Finally, we verify the research results of the paper through the running test of the software.

The system designs in this paper has great significance. Firstly, Compressed Sensing technology is combined with sensors to verify the availability of compressed sensing theory in the acquisition of sensors, which can reduce the energy consumption, extend the life span, and reduce costs for the use of sensors; Secondly, through the verification of the system design, it can be found that compressed sensing technology can accurately reconstruct the original temperature and humidity data, and transmit data to the PC through wireless transmission. Therefore, for some environments where human beings cannot perform activities, such as underwater data collection and recovery can be performed through this system, then observations or analysis can be performed; In the software design of this article, a modular design is implemented through C#, and mixed programming is performed according to MATLAB's powerful data processing capabilities, so that it has a certain degree of scalability, portability, and application; Finally the design of the software has a good degree of display, simple operation, good interface, user-friendly and secondary development. Subsequent verification of changes to the software's test environment and real-time accuracy of the interface feedback have yet to be improved.

Acknowledgments. This work is supported in part by National Natural Science Foundation of China (No. 61401118, No. 61371100 and No. 61671184), Natural Science Foundation of Shandong Province (No. ZR2018PF001 and ZR2014FP016), the Fundamental Research Funds for the Central Universities (No. HIT.NSRIF.2016100 and 201720) and the Scientific Research Foundation of Harbin Institute of Technology at Weihai (No. HIT(WH)201409 and No. HIT (WH)201410).

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