Compressive sensing in wireless sensor network for poultry acoustic monitoring

Xuan Chuanzhong[1], Wu Pei[1*], Zhang Lina[1,2], Ma Yanhua[1], Liu Yanqiu[1], Maksim[1]

(1. *College of Mechanical and Electrical Engineering*, *Inner Mongolia Agricultural University*, *Hohhot 010018*, *China*;
2. *College of Physics and Electronic Information Science*, *Inner Mongolia Normal University*, *Hohhot 010022*, *China*)

Abstract: A wireless acoustic sensor network was realized using wireless sensor nodes equipped with microphone condensers, in which its sensor nodes were configured to capture poultry sound data and transmit it via the network to a collection point. A high performance computer can process these large volumes of animal audio signals under different behaviors. By performing data signal processing and analyzing the audio signal, poultry sound can be achieved and then transformed into their corresponding behavioral modes for welfare assessment. In this study, compressive sensing algorithm was developed in consideration of the balance between the power saving from compression ratio and the computational cost, and a low power consumption as well as an inexpensive sensor node was designed as the elementary unit of poultry acoustic data collecting and transmission. Then, a Zigbee-based wireless acoustic sensor network was developed to meet the challenges of short transmission range and limited resources of storage and energy. Experimental results demonstrate that the compressive sensing algorithm can improve the communication performances of the wireless acoustic sensor network with high reliability, low packet loss rate and low energy consumption.

Keywords: wireless sensor network, compressive sensing, poultry acoustic monitoring, poultry sound data, power consumption, acoustic data compression
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1 Introduction

Animal sounds produced in a variety of contexts, which are distinct and have unique acoustic structures, allowing us to interpret signals unambiguously[1-4]. Decoding the information contained in sounds can provide the key to understand the internal, affective state of animal and the external environment in intensive animal production. From the perspective of poultry welfare assessment, poultry sounds can provide us a deeper understanding of the impact of housing and management decisions on poultry[5-7]. For many applications such as intelligent agriculture, industrial control, health monitoring, environmental monitoring systems and traffic monitoring, wireless sensor network (WSN) has become a significant research area[8-12]. Thus, animal sound monitoring provides the access to poultry emotions in a non-invasive manner. Recent studies have aimed at designing sound monitoring systems which is capable of gathering animal sounds and transmitting them through wireless network to a computer. However, high-energy consumption and network unreliability have limited the applicability of those systems[13].

Traditional data gathering approaches in wireless

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Biographies: Xuan Chuanzhong, PhD, research interests: intelligent agricultural equipment and technology, Email: 282027349@qq.com; **Zhang Lina**, PhD candidate, research interests: agricultural wireless multimedia sensor networks, Email: linanazhang@126.com; **Ma Yanhua**, PhD, research interests: agricultural informatization and control technology, Email: yanhuama@126.com; **Liu Yanqiu**, PhD candidate, research interests: agricultural informatization and control technology, Email: lyq13514413846@163.com; **Maksim**, MS, research interests: agricultural wireless multimedia sensor networks, Email: mkxm2010@126.com.
***Corresponding author: Wu Pei**, PhD, Professor, research interests: intelligent agricultural equipment and technology. Mailing address: College of Mechanical and Electrical Engineering, Inner Mongolia Agricultural University, Hohhot 010018, China. Tel: +86-471-4301062, Email: jdwp@imau.edu.cn.

sensor network transmit all measurements to computer at the cost of energy and bandwidth. However, the sensor nodes in wireless sensor network are powered by very low voltage batteries, it is considered infeasible to recharge or replace the batteries of data collection nodes. Therefore, power consumption of the sensor node is a key problem to maintain the lifetime of WSNs for sound monitoring[14,15]. Some researchers put forward to reduce the radio communication to achieve enough power saving of sensor node[16]. In this research, two main approaches of duty cycle and sound data compression were introduced to reach this objective. The duty cycle scheme defines sleep and wake schedules for the sensor node, and the acoustic data compression is used to reduce the amount of data quantity communicating in the sensor network.

There are many acoustic compression techniques, such as ADPCM (Adaptive Differential Pulse Code Modulation), MP3 (Moving Picture Experts Group Audio Layer-3) and Ogg Vorbis, however, most of these techniques still obey the Nyquist criterion that the maximum sampling frequency is between 44 kHz and 48 kHz. Generally speaking, the higher the ratio of poultry acoustic compression was, the higher the percentage of power was saved. However, the processing unit of sensor node requires more power to run the compression algorithm when using these data compression algorithms, this is due to the complexity of the data compression algorithm which needs lots of memory and time[17]. So, an efficient data compression algorithm by maintaining the balance between the power saving from compression ratio and the computational cost is required. In other words, the power consumed by running additional instructions to compress sound data has to be less than the power saved from transmitting the data.

Recently, some compressive sensing and sparsity-based approaches have been taken into consideration for sound data gathering applications[18]. Compressive sensing is a concept originating from signal processing field. The strength of compressive sensing is its ability to reconstruct sparse or compressible signal from small number of measurements without requiring any a priori knowledge about the signal structure. Due to the computation at the sensor end is expensive, the compressive sensing method does not demand complex calculation at the sensor node. Moreover, the total amount of communication data can be reduced greatly[19,20]. These characteristics completely match acoustic data wireless sensor network. Compared with data compression, applying compressive sensing on poultry sound data in wireless sensor network offers promising improvements as low power sensor nodes are not generally suitable for implementing encoding of data compression techniques.

This research focused on developing a poultry acoustic monitoring system based on wireless sensor network. In the system, the sensor node will be programmed to sample the acoustic signal at high frequency and the acquired data will be transferred back to the computer for data processing. The full audio reconstruction was done using compressive sensing algorithm. This paper is organized as follows: section 2 describes the fundamental of compressive sensing; section 3 presents the WSN architecture of poultry sound gathering system and the hardware design of the end sensor node: section 4 presents the software design to reduce the energy consumption in wireless sensor network; in section 5, we demonstrate the effectiveness of this acoustic data wireless sensor network through experiments; conclusions are drawn in Section 6.

2 Fundamental of compressive sensing

Compressive sensing claims that a signal can be recovered from a small number of projections onto a second basis if it has a sparse representation in one basis. So, a signal can be reconstructed from far fewer measurements or samples than traditional methods. In other words, the number of samples can be much lower than the number of measurements required when the signal is sampled at the Nyquist rate. Such capability brings the benefits of reduced transmission bandwidth and storage space due to the compression achieved.

The critical part of the compressive sensing capability lies in two major assumptions, i.e., incoherence, which pertains to the sensing modality and sparsity, which is related to the signals of interest. Incoherence expresses the idea that objects having a sparse representation must be spread out in the domain they acquired. Sparsity on the other hand refers to the idea that the information rate of a continuous time signal may be much smaller than suggested by its bandwidth. Hence, this assumption can be extended to many natural signals that are sparse or compressible in the sense that they have concise representations when expressed in the proper basis[21,22].

Assumed that a discrete signal $X \in R^N$, which is presented by N×1 column vector, has sparse representation in some basis. Considering this sparsity concept, this signal can be expressed in term of the basis as:

$$X = \sum_{k=1}^{N} a_k \psi_k = \psi_a \tag{1}$$

where, ψ is an N×N orthonormal basis matrix $\psi = [\psi_1, \psi_2, ..., \psi_N]$, $\psi_k, k = 1,2,...,N$ is a $N \times 1$ vector, and a=[a_1,a_2,…,a_N] is the N×1 column vector of the coefficient sequence of X in ψ domain.

Signal X is compressible or sparse in ψ basis, if its coefficient vectors have a few large elements and many small or zero elements. In other words, most of the elements in a are zero. Compressive sensing theory states that if signal X is *K-sparse* on ψ basis, it can be captured and recovered from M non-adaptive, linear measurements ($K < M << N$) with a certain restriction. The sampled signal via CS is described as:

$$Y = \phi X \tag{2}$$

where, Y=[y_1, y_2, …, y_M] is M×1 measurement matrix; $\phi = [\phi_1, \phi_2, ..., \phi_M]$ represents a M×N sensing matrix and each ϕ_i, $i = 1,2,...,N$ is a N×1 vector. Each element y_i in measurement matrix is a product of vector X and a vector ϕ_i from sensing matrix. We can substitute X with ψa then y can be rewritten as:

$$Y = \phi X = \phi \psi a = \xi a \tag{3}$$

where, $\xi = \phi\psi$ is a M×N matrix.

Compressive sensing theory demonstrates that sparse signal can be recovered from M measurements if it can satisfy restricted isometric property (RIP). RIP states that ϕ and ψ must be incoherent, which means that the rows of ϕ must not sparsely represent the columns of ψ, and vice versa. Formally speaking, a matrix ξ of size M×N satisfies the RIP of order K if it can be the minimum number such that:

$$(1-\delta_k)\|a\|_2^2 \le \|\xi a\|_2^2 \le (1+\delta_k)\|a\|_2^2 \tag{4}$$

where, $\delta_k \in (0,1)$ is a restricted isometric constant. Equation (4) must be hold for all a with $\|a\|_0 \le K$, and $\|a\|_0$ is ℓ_0 norm which shows number of non-zero elements in a. ℓ_p norm of vector a is defined as:

$$\|a\|_p^p = \sum_{i=1}^{N} |a_i|^p \tag{5}$$

RIP guarantees the exact recovery of x with high probability if

$$M \ge cK \log \frac{N}{K} \tag{6}$$

However, the recovery of the signal X from Y is an NP hard problem but it can be done through optimization. To do so, ℓ_1 minimization is widely used for compressive sensing signal reconstruction, while ℓ_0 minimization is computationally intractable. We can recover the coefficients of sparse signal a by solving ℓ_1 norm minimization as follows:

$$X' = \psi a';\ a' = \arg\min_{a \in R^N} \|a\|_{\ell_1} \quad s.t.\ Y = \phi X \tag{7}$$

3 Hardware design of the end node

Architecture of poultry sound detection system is shown in Figure 1. The system consists of two separate classes of sensor nodes: the end nodes, which are responsible for recording and compress the poultry acoustic data, and the collection node which is used to receive the sound data from end nodes and transmit it to a monitor computer, which will decompress and process the poultry acoustic data. Therefore, the acoustic wireless sensor network consists of N static homogeneous end nodes deployed separately. Each end sensor node consists of three sub-modules: a sensing module used to acquire the poultry sound data; a processing module equipped with limited memory used to manage the acquired data; and a communication module, usually a radio transceiver, used to exchange information with the collection node. Since sensor nodes have very limited resources, it is essential to gather and transfer as few data as possible. To do so, the compressive sensing technology was employed to accurately reconstruct the poultry acoustic signal.

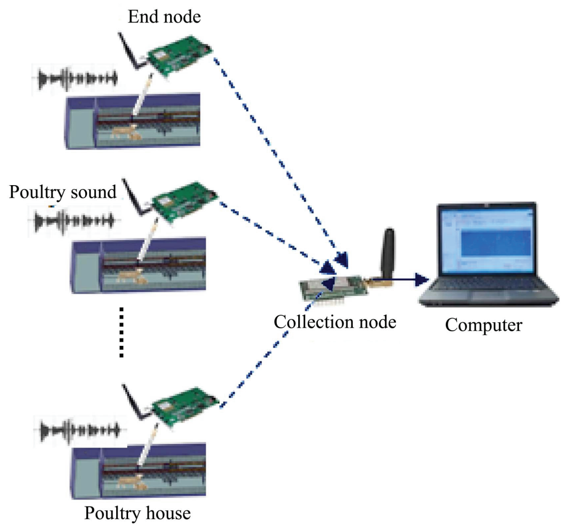


Figure 1 Architecture of poultry sound detection system

3.1 Architecture of the end node

As shown in Figure 2, the end node is consist of an acoustic data sampling sensor module, an acoustic detection trigger module, a wireless communication module, a data processing module and a power management module. In this research, a threshold was predefined for the end node such that it only triggers when the poultry sound was higher than the ambient sound level, so the acoustic detection trigger module of the end node was set a low frequency sampling rate of 1 Hz for performing a simple sensing activity. This rate was suitable to detect any distinct change in poultry vocalization activity.

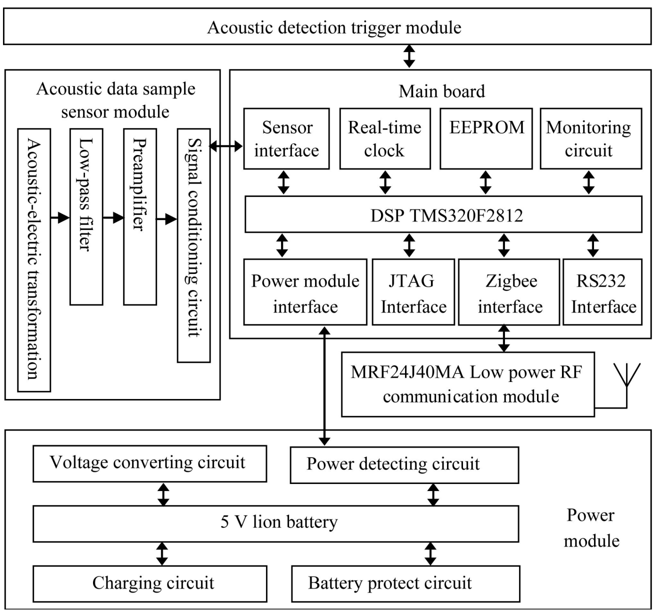


Figure 2 Hardware design of the end sensor node

3.2 Data processing and wireless communication modules

Due to many exterior connections and rich internal resources, the digital signal processor TMS320F2812 chip, whose main frequency was 150 MHz, was selected as the data processing module of our system, and it was suitable for the acoustic data compression. It can perform the sound data sampling, processing, receiving and transmitting in combination with other modules. The main part of the wireless communication module was the radio frequency chip, whose responsibility was to receive, transmit and exchange data with the coordination node. In the study, small power loss chip MRF24J40MA, made by Microchip Corporation, was selected, and it was compatible with the communication module of IEEE802.15.4 at 2.4 GHz.

3.3 Power management module

In order to extend the life cycle of the system, enough power for the end node was required, besides using the low power loss chip. Hence, the acoustic detection trigger sub-board’s power supply and the master board were separated.

Two AA batteries were used to provide the 3 V voltage for the main board, which can satisfy the power request of the main board. Due to the voltage reducing gradually, the management of battery voltage at the real-time monitoring was realized through reading the battery voltage through the AD converter output.

In order to enable the end node to sample acoustic data at low power consumption, the master board will wait for the beginning of the sampling command sent by the acoustic detection trigger module of sub-board and is in idle mode most of the time. Taking into account the energy conservation, a microcontroller port to control sub-board active status was used by sending electronic height level command.

3.4 Acoustic sensor module

The acoustic sensor module, mainly combined of the sound sensor probe and signal conditioning circuit, was used to sound-voltage signal conversion, pre-amplification, filtering and other functions. The technical parameters of the sound sensor are as following: probe diameter 30 mm, length 100 mm, a frequency response range of 10-20 kHz, input impedance more than 2000 MΩ, output impedance less than 50 Ω, the voltage gain of 60-100 dB.

4 Software design of the end node

The acoustic acquisition system consists of several end node devices and a coordinator. The end node can scan all channels to find any beacons when it is switched on, then, it checks the coordinator to justify if that is the right one by performing an association and synchronization. The end node will enter a regular circulation reading its acoustic sensor data when connection is completed, then put out the sound data to the acoustic detection trigger module, which allows the end node to put processor to sleep for long periods.

The software was designed to meet the demands of low power consumption. The poultry acoustic acquisition software integrated the real-time multitasking operating system uC/OS-II and Zigbee wireless network protocol stack. The different priority functions of uC/OS-II were responsible for acoustic signal acquisition, data compression, storage management, network communication and so on.

The application code of the end node was implemented in terms of the state machine shown in Figure 3. The end node was initially configured after power-on, and then entered State 0 of a state of minimum current consumption. The end node had a sleep time T1 to leave in state 1 after the first initialization stage. State 1 was the state where the acoustic volume was monitored by the acoustic detection trigger module. The system sampled the acoustic data with a low frequency. If the acoustic volume was higher than the predetermined volume, after the sleep time T3, the end node went to State 3 otherwise remained in State 1. Meanwhile, the end node tried to find out a nearby coordinator to connect (State 2). After the end node was switched to State 3, which represented that the poultry sound has enough volume, the sensor node would wake up and sample the acoustic data with a high frequency. All of its sampled sound data were stored in a flash memory in the form of data packets, and then the end node would send out the sound data. In state 4, the acoustic data will be compressed with compressive sensing algorithm. Because each sound packet had the limit of the size, the whole block of sound data must be divided into small packets and sent them via a queue. If successful, assuming that the end node had sufficient conditions to operate normally, after the short time T4, the end node joined the existing wireless Zigbee network and obtained and stored the network parameters for later use. The end node returned to the state 1 after the sleep time T5 if discovery or joining conditions were not met. State 5 reflected the data transmission tasks of sending the acquired data using the saved network parameters. If an acknowledgement was received from the coordinator, the sensor node entered sleep mode and returned to State 1. The sensor node would wait for the next round of sampling. On the next instance of sampling, the node would have to erase the previous acoustic data away to make space for the new. This was required as there was no use in keeping the old data once it had been successfully sent to the coordinator.

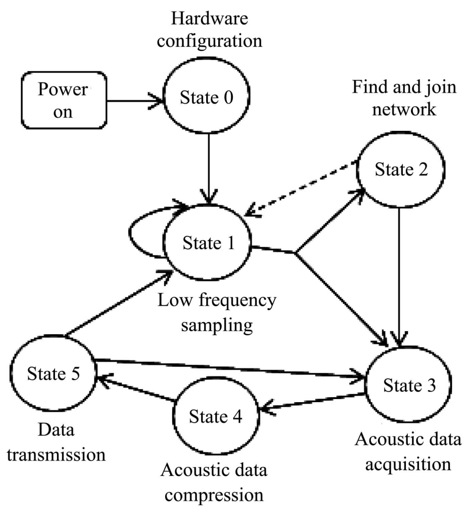


Figure 3 Finite state machine mode of sensor node

The coordinator node would be responsible for receiving incoming packets from the sensor nodes and put them into a first in first out queue and forward them through the COM port of a computer. The coordinator node possessed sufficient memory buffers for sound data transmission to accommodate simultaneously the multiple large-scale flows of incoming sound data coming from multiple end nodes. Otherwise, the bottleneck happened at this stage and slowed down the speed of data processing.

5 Simulations and evaluations

In this section, we discussed the performance of compressive sensing algorithm in terms of quality of uncompressed data and power consumption, and a number of tests had been conducted to investigate the operations of the wireless acoustic sensor network. Efforts had been concentrated on the transmission delay, packet loss rate, performance of compressive sensing algorithm, and energy consumption.

5.1 Acoustic encoding rate

In order to compare the performance of the transmission of poultry sound, three kinds of encoding rate was tested separately:

(1) Compressive sensing algorithm. The speed of coding rate was 6 kb/s. Each sound data of 20 ms were converted to a sound frame of 12 byte, and each package had five sound frames. So a 60 byte packet would be produced in every 100 ms.

(2) ADPCM coding of speed 16 kb/s. The data packet was 93 Byte in every 46.5 ms.

(3) ADPCM coding of speed 32 kb/s. The data packet was 93 Byte in every 23.25 ms.

5.2 Average packet transmission delay

Taking sheep sound for an example, a range of 40 m was obtained for the poultry acoustic monitoring. The transmission delay and packet loss rate had been conducted to determine the wireless acoustic sensor network scale between the end nodes and one coordinator node. The minimum acoustic delay that the human ear can feel is 250 ms. In Figure 4, the test results showed that a much deeper understanding on the effects of transmission delay between end nodes counts and the performance of the network. The compressive sensing algorithm was adopted to obtain the sound encoding rate of 6 kb/s, the average packet transmission delay was within 250 ms; and when an encoding rate was 16 kb/s, the maximum number of end nodes that could transmit simultaneously was six; if encoding rate was increased to 32 kb/s, only three end nodes were allowed to communicate simultaneously. The reason for this was due to all the end nodes using a single channel for communications. This channel could only provide a 250 kb/s bandwidth, which was shared by all the sensors.

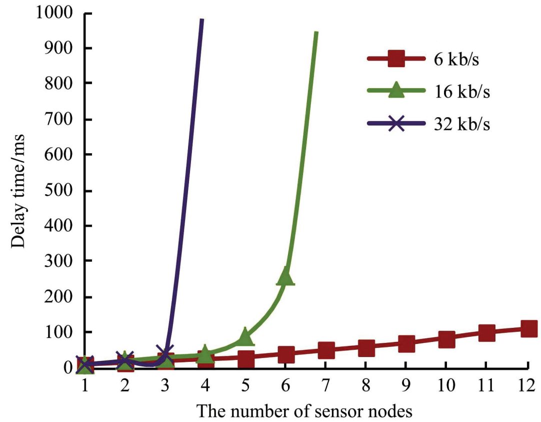


Figure 4 Average packet transmission delay of three encoding algorithm

5.3 Packet loss rate

The packet loss rate of the data transmitted as well as the volume of data communicated by the sensors was tested. In critical operating environments such as dangerous gas detection, high packet loss rate was not acceptable since packet errors can cause disastrous effects. However, certain packet loss rate was acceptable for poultry acoustic monitoring. There exist a balance between battery life and packet loss rate, because failed transmissions of the end node will result in retries. Then, transmission retries of the end node will increase the wireless network energy consumption and traffic jam. Figure 5 provides a comparison of data packet loss rate with three different acoustic encoding methods. At a transmission range of 40 m, the packet loss rate was around 10% or less, and this is considered safe and acceptable in the application. The encoding rate was 6 kb/s, the maximum of eight nodes communicated simultaneously; while encoding rate was 16 kb/s or 32 kb/s, only four or three end nodes were allowed, respectively.

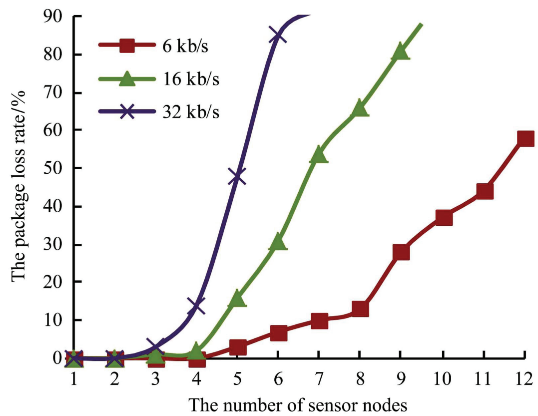
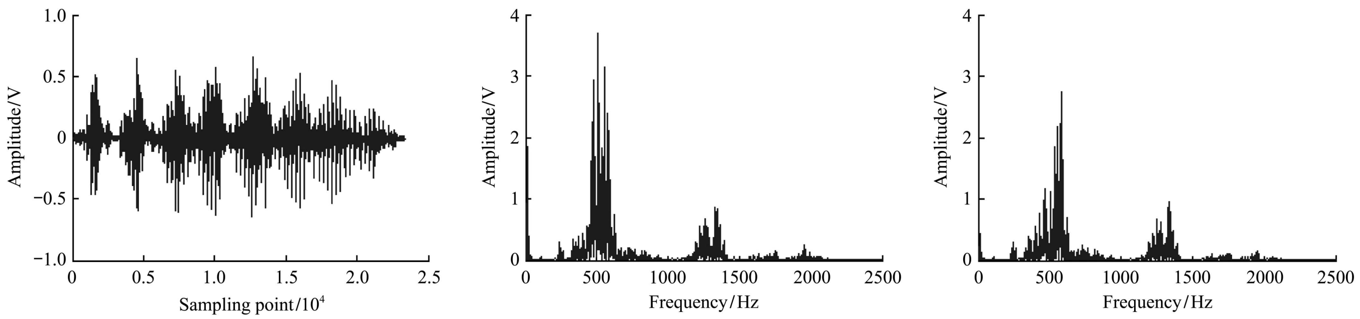


Figure 5 Package loss rate of three encoding algorithm

5.4 Performance of compressive sensing

For this example, an audio clip of 'sheep hungry' (Figure 6a) was recorded to test the performance of compressed acoustic data by compressive sensing method. The frequency bandwidth and raw data rate were 10-2100 Hz and 96 kb/s respectively. Although there are some subtle noises present in the background, it can be removed from the waveform using various digital filters the application provided in computer.

The sound data rate was decreased to 6 kb/s, so a distribution remote acoustic data acquisition and transmission would become true through wireless sensor network. The raw poultry sound of frequency domain was compared with the compressed one in Figures 6b and 6c. The spectrum analyzer shows a variety of frequency amplitudes detected over the limited spectrum. The amplitude decreased slightly in the range of 300-700 Hz and this may be due to the much lower sampling rate achieved by the end node as compared to high-quality recording. However, the overall shape of the envelope of the reconstructed waveform is still preserved.



a. Time-domain graph of the original acoustic signal b. Frequency-domain graph of the original acoustic signal c. Frequency-domain graph of the reconstruct acoustic signal

Figure 6 Comparison between the original acoustic signal and reconstruct one

The parameters for objective evaluating the performance of the sound data compression algorithm include the compression ratio (CR), the quantization signal-to-noise ratio (SNR) and correlation coefficient (R). CR is defined as the ratio of the number of original data bits and the number of compressed data bits.

$$CR = \frac{\text{the number of bits of original data}}{\text{the number of bits of compressed data}} \tag{8}$$

$$SNR = 10 \times \lg\left(\sum_{i=1}^{N} s^2(i) / \sum_{i=1}^{N} e^2(i)\right) \tag{9}$$

$$R = \sum_{i=1}^{N} \hat{s}(i) \cdot s(i) / \sqrt{\sum_{i=1}^{N} s^2(i) \cdot \sum_{i=1}^{N} \hat{s}^2(i)} \tag{10}$$

where, s represents the original signal; $\hat{s}$ is the decompressed reconstruction signal; e stands for the error between the original signal and the decompression one, i.e., quantization error.

The parameters for evaluating the acoustic data compression performance are shown in Table 1.

Table 1 Evaluation parameters of acoustic data compression results

CR	*SNR*	*R/%*
16	8.13	90.26

The test results showed that the acoustic data compression method was reasonable and feasible. By means of the compressive sensing algorithm, the SNR was more than eight and *R* more than 90%, so the acquisition and real-time reliable wireless transmission of the acoustic signal had been achieved effectively. However, low frequency poultry sounds especially 3 kHz would sound clearer and original, high frequency sounds like a bird chirping would generally appear louder and not so recognizable.

5.5 Energy consumption

To test the energy consumption of wireless network, a network of *M* end nodes and one collect node were arranged in a star topology. The collect node was located in the center and each end node had direct access to the collect node. The value of *M* increased from three to get different relative reconstruction error, which is defined as:

$$RE = \frac{\|s - \hat{s}\|_2}{\|\hat{s}\|_2} \tag{11}$$

We used relative energy consumption concept defined as the ratio of overall energy consumption of the end node to run compression algorithm over the consumed energy for sending all measurements to the collection node without applying compression algorithm. For same reconstruction error rate, energy consumption among different algorithms has been compared in Figure 7. Our approach requires fewer measurements compared to others to obtain the same reconstruction error. In addition it has less data to transmit. It therefore has the lowest energy consumption rate compared with the other two approaches.

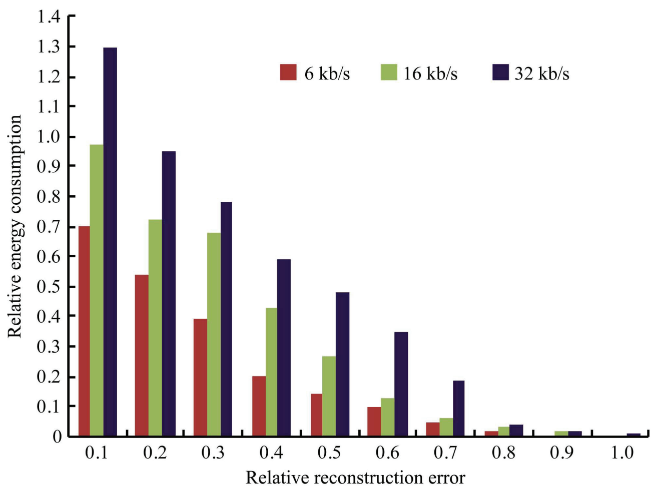


Figure 7 Relative energy consumption versus reconstruction error rate

6 Conclusions

Wireless sensor networks equipped with microphones are low-cost solutions for real-time audio data acquisition, offering numerous applications such as environmental monitoring, surveillance and bioacoustics. In this paper, the compressive sensing technique is proposed for wireless sensor networks to realize poultry acoustic monitoring. The basic elements of the acoustic data acquisition and communication were end nodes, which were low power consumption and inexpensive. In order to meet these objectives, both the hardware and software were developed to solve the challenges which include acoustic data compression, limited resources of energy and storage and short transmission range of end nodes. Tests have been carried out to evaluate the performance of the end nodes and compressive sensing algorithm for monitoring poultry sound. The results of tests show that the wireless acoustic sensor network performs high communication reliability, low packet loss rate, and low energy consumption due to end nodes and the compressive sensing algorithm.

Acknowledgments

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