Compressive Sensing and Reconstruction of Crop Growth Environmental Information

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ABSTRACT

The crop growth environmental information in farmland such as temperature and humidity has a gentle variation amplitude in a certain time or space domain, and is sparse in the discrete cosine transform domain. Based on compression sensing, we construct the approach to crop growth environmental information monitoring. The reconstruction error for crop growth environmental information is validated through the simulation experiment. By exploiting orthogonal matching pursuit method, it is found that the reconstructed environmental information data are consistent with the measured data.

KEYWORDS
Compression sensing, reconstruction, environmental information, orthogonal matching pursuit.

INTRODUCTION

Recently, wireless sensor network (WSN) has been widely applied in many areas, for example, environmental monitoring, health monitoring, and agriculture monitoring [1]. The modern agriculture is a new paradigm for shortening the production cycle and increasing the production. However, the crop growth is influenced by many environmental conditions, such as temperature, humidity, and carbon dioxide concentration. Thus, it is necessary to control the environmental data in real time. WSN is comprised of spatially distributed sensor nodes, where each node is capable of sensing, processing, and communicating data [2]. The sensor nodes are limited at processing power and constrained at energy resources [3]. It is known that the costs for processing and communication account for the majority of the energy consumption. Thus, to decrease the transmission data is essential to save the sensor energy and prolong the lifetime of WSN. During monitoring the environmental information of crop growth, the number of data processed by each node is huge. Therefore, it is need to reduce the redundancy of sensed data and decrease the network data traffic.

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Recently, a new data acquisition paradigm—the compressed sensing (CS) has been brought forward [4]. As long as the signal is sparse or transformation is sparse, then the signal can be reconstructed from a few measurements by solving the convex optimization problem [5]. To solve the problem of data collection and transmission in WSN with CS, considerable research has been conducted. For instance, Baron et al. [6] proposed a novel model for joint sparsity in WSN applications and illustrated the advantage of distributed CS. Bajwa et al. introduced CS for WSN in which a fusion center retrieves signal field information from an ensemble of spatially distributed sensor nodes [7].

In this paper, we investigate the environmental information of crop growth based on CS. First, a environmental information of crop growth collecting system is proposed. Then, the environmental information data collection experiment is conducted in wheat field. Next, the collected data is processed by exploiting CS technology. Finally, we perform a simulation on the environmental information of crop growth through Matlab.

**COMPRESSIVE SENSING THEORY**

For Nyquist theory, the signal must be sampled at least twice its bandwidth in order to be represented without error [8]. The arbitrary signal \( D \) in \( \mathbb{R}^N \) can be expressed as a basis of \( N \times 1 \) vectors \( \{ \psi_i \} \). The arbitrary vector in \( \mathbb{R}^N \) can be denoted as a linear combination of basis vectors \( \{ \psi_i \}^N \) as follows:

\[
D = \sum_{i=1}^{N} s_i \psi_i, \quad D = \psi_s
\]  

where \( \psi \) and \( \psi_i \) are the basis matrix and the ith column of basis matrix, respectively. S is the \( N \times 1 \) column vector of weighting coefficients. Moreover, the compressible signal \( D \) includes \( K \) nonzero coefficients and \( N-K \) zero coefficients. Furthermore, all transform coefficients can be calculated by \( s=\psi^TD \). It is worth mentioning that only the largest \( K \) coefficients and their locations are encoded and transmitted.

CS adopts nontraditional linear measurements in the form of randomized projections, which can be denoted as \( y = \Phi D \). The \( K \) sparse signal \( D \) in \( \psi \) can be reconstructed from \( M = O(K \log N) \) compressive measurements, where \( M \) is the number of required compressive measurements. For reconstruction, it is need to solve a convex optimization problem which can be represented as follows:

\[
\begin{align*}
\arg \min_{s} \|s\|_1 & \quad \text{ s.t. } y = \phi s
\end{align*}
\]  

where \( \|s\|_1 \) denotes the \( L_1 \) norm of vector \( s \).

**THE ENVIRONMENTAL INFORMATION OF CROP GROWTH COLLECTING SYSTEM**

The framework of environmental information of crop growth on the basis of CS is illustrated in Fig. 1. It can be seen that the studied parameters in each experimental field
is set as $x_i$ ($i=1, 2, ..., n$). The corresponding random observation value in each experimental field can be represented as $y_i$ ($i=1, 2, ..., n$). Moreover, the total observed matrix $Y$ can be denoted as $Y=[y_1, y_2, ..., y_n]$. The process flow for environmental information of crop growth is as follows: the observed matrix is first sent to the receiver, and then the observed signals are obtained at the receiver. The random observation values $y_i$ ($i=1, 2, ..., n$) are reconstructed, and the reconstructed values can be acted as the final output values.

**The sparse representation of the signal based on the discrete cosine transform (DCT).**

In a certain time or space domain, the environmental information of crop growth change slowly. For instance, the amplitude of temperature variation in several experimental fields at a certain period of time is small, and it has a better sparsity on the DCT domain. Thus, DCT can be acted as the base matrix of signal sparse decomposition for temperature in experimental field. Furthermore, the real coefficients can be obtained from the DCT domain. The DCT transform can be represented by:

$$X(k) = \frac{1}{\sqrt{n}} \sum_{i=0}^{n-1} x(i) \cos \left(\frac{2i+1}{2n} \pi k \right), k = 0, 1, ..., n-1$$

**The random Gaussian observation matrix.**

The measurement matrix $A=\Phi \psi$ must satisfy the constraints of restricted isometry property (RIP) as follows:
\[(1 - \delta_k)\|X\|_2^2 \leq \|A_T X\|_2^2 \leq (1 + \delta_k)\|X\|_2^2 \]  \tag{5}

where \(0 < \delta_k < 1\), and \(A_T\) is \(N \times T\) matrix, which composed of a collection of column vectors.

**Orthogonal Matching Pursuit (OMP) algorithm.**

The OMP is a basic iterative algorithm, which is analyzed by Tropp et al. [9]. The OMP can be described as follows:

1. Initialize the residual \(r^0 = v\), the index set \(\Lambda_0 = \emptyset\), and the iteration counter \(n = 0\).
2. Find the index \(\lambda_t\) that solves the easy optimization problem
   \[
   \lambda_t = \arg \max_{j=1, \ldots, d} \left| \left( r_{t-1} - \Phi_j \right) \right|
   \tag{6}
   \]
   If the maximum occurs for multiple indices, break the tie deterministically.
3. Augment the index set \(\Lambda_t = \Lambda_{t-1} \cup \{\lambda_t\}\) and the matrix of chosen atoms
   \[
   \Phi_t = [\Phi_{t-1} \Phi_{\lambda_t}]
   \tag{7}
   \]
4. Solve a least-square problem to obtain a new signal estimate:
   \[
   x_t = \arg \min_{x} \| \Phi_t x - v \|_2
   \tag{8}
   \]
5. Calculate the new approximation of the data and the new residual:
   \[
   a_t = \Phi_t x_t
   \tag{9}
   \]
   \[
   r_t = v - a_t
   \tag{10}
   \]
6. Increment \(t\), and return to step (2) if \(t < m\).
7. The estimate \(\hat{s}\) for the ideal signal has nonzero indices at the components listed in \(\Lambda_m\). The value of the estimate \(\hat{s}\) in component \(\lambda_j\) equals the \(j\)th component of \(x_t\).

**SIMULATION RESULTS AND ANALYSIS**

The experimental setup.

The experiment is performed at the wheat field in Xiaotangshan national precision agriculture research demonstration base. Each experimental field is \(3 \times 3\) m, and includes two sensor nodes. Moreover, the total number of selected experimental fields is 20. The sensor nodes are powered by voltage of 3.5 V and capacity of 1800 mAh lithium battery.
Results analysis.

The Root Mean Square Error (RMSE) can be acted as the indicator of the reconstruction precision, and it can be calculated as follows:

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n} (X_{\text{obs},i} - X_{\text{rec},i})^2}{n}}
\]  

where \( X_{\text{obs}} \) is the observed values, \( X_{\text{rec}} \) is the reconstructed values, and \( n \) is the number of samples.

The RMSE of the reconstructed temperature data in twenty experimental fields is presented in Fig. 2. It can be seen that the RMSE of temperature data in experimental fields is about 0.01 °C. The phenomenon can be ascribed to the smooth of temperature in the domain and the stronger sparsity.

Taking the number ten experimental field as an example, we perform the simulation of temperature data reconstruction. The reconstructed temperature data is shown in Fig. 3(a). It is found that the reconstructed temperature data is consistent with the measured data. The RMSE of temperature in the number ten experimental field is 0.012 °C. It is noting that the measured temperature data can have up to two digits after the decimal point. That is to say, the error of 0.012 °C has little impact on data recovery. After the compression sensing and reconstruction of the temperature in experimental fields, we find that the better the sparsity, the larger the accuracy of the recovery, and the less number of samples needed.

Moreover, the reconstructed humidity details is illustrated in Fig. 3(b). It can be seen that the reconstruction of humidity data is better than that of temperature data, since humidity changes relatively stable. The accuracy of humidity reconstruction is large which can be due to the humidity fluctuate continuously.

Figure 2. The reconstruction error of temperature information in experimental fields.
Figure 3. (a) the recovery data of temperature information in number 10 experimental field; (b) the recovery data of humidity information in number 10 experimental field.

SUMMARY

Due to the environmental information of crop growth in farmland such as temperature and humidity has a gentle variation amplitude in a certain time or space domain, it can adopt CS technology to compression and reconstruction for environmental information of crop growth. In this paper, we construct the approach to environmental information of crop growth monitoring. The reconstruction error for environmental information of crop growth is validated through the simulation experiment. By applying orthogonal matching pursuit method, it is found that the reconstructed data of temperature and humidity are consistent with the measured data.

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