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INTELLECTUAL DECISIONS TO COMPRESSIVE SENSING FOR EFFICIENT DATA ACQUISITION IN WIRELESS SENSOR NETWORKS

This paper considers the application of linear algebra methods to Compressive Sensing technology for wireless sensor networks (WSNs) specialized in temperature monitoring in "smart" greenhouses. It is shown that the traditional approach, which involves the transmission of full data streams from each individual sensor, leads to high energy consumption and generates information redundancy, which is a problematic factor for autonomous battery-powered systems. As an alternative, a special architecture of compressive sensing is proposed, within which not the original data are transmitted, but their compressed linear combinations. This radically reduces traffic, but, thanks to mathematical transformations, retains the possibility of full and accurate restoration of the entire temperature field on the receiver side.

The methodological basis is the use of the fundamental property of sparsity of temperature signals when they are presented in certain bases, in particular, the basis of the discrete cosine transform. Modern optimization and iterative linear-algebraic algorithms are used to reconstruct the original data from compressive sensing. The practical effectiveness is illustrated by a model example of a network with six sensors, where compressing sensing allowed to reduce the amount of transmitted information by 50 % and simultaneously detect anomalies in the operation of a faulty sensor, confirming the stability of the system.

The proposed architecture provides comprehensive energy efficiency, reliability and scalability of the monitoring system, supports the dynamic addition of new sensors and can be successfully integrated into modern Internet of Things systems, industrial complexes and «smart» cities. Thus, the work clearly demonstrates the powerful synergy between mathematical rigor and practical efficiency of compressing sensing for creating intelligent agricultural systems of the next generation.

Key words: *modeling, optimization methods, wireless sensor networks, compressing sensing, linear algebra, intellectual system, Internet of Things; data compression and reconstruction.*

Шишканова Г. А., Зайцева Т. А., Жир С. І., Коротунова О. В. Інтелектуальні рішення щодо компресійних вимірювань для ефективного збору даних у бездротових сенсорних мережах

У даній роботі розглянуто застосування методів лінійної алгебри в технологію компресійних вимірювань (Compressive Sensing) для бездротових сенсорних мереж, спеціалізованих на моніторингу температури в «розумних» теплицях. Показано, що традиційний підхід, що передбачає передачу повних потоків даних від кожного окремого датчика, призводить до високого енергоспоживання та генерує інформаційну надмірність, що є проблемним фактором для автономних систем із батарейним живленням. Як альтернатива запропонована спеціальна архітектура компре-

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сійного вимірювання, в рамках якої передаються не початкові дані, а їх стислі лінійні комбінації. Це радикально скорочує трафік, але, завдяки математичним перетворенням, зберігає можливість повноцінного та точного відновлення всього температурного поля на стороні приймача.

Методологічну основу становить використання фундаментальної властивості розрідженості температурних сигналів при їх поданні в певних базисах, зокрема, базисі дискретного косинусного перетворення. Для реконструкції вихідних даних із стиснених вимірів застосовано сучасні оптимізаційні та ітераційні лінійно-алгебраїчні алгоритми. Практичну ефективність ілюструє модельний приклад мережі з шістьма датчиками, де компресійне вимірювання дозволило зменшити обсяг переданої інформації на 50 % і одночасно виявити аномалії в роботі несправного сенсора, підтвердивши стійкість системи.

Запропонована архітектура забезпечує комплексну енергоефективність, надійність та масштабованість системи моніторингу, підтримує динамічне додавання нових сенсорів та може бути успішно інтегрована в сучасні системи Інтернету речей, промислові комплекси та «розумні» міста. Таким чином, робота наочно демонструє потужну синергію між математичною строгістю та практичною ефективністю компресійного вимірювання для створення інтелектуальних аграрних систем нового покоління.

Ключові слова: *моделювання, оптимізаційні методи, бездротові сенсорні мережі, компресійне вимірювання, лінійна алгебра, інтелектуальна система, Інтернет речей; стиснення та реконструкція даних.*

Problem Statement. Modern wireless sensor networks (WSNs) are increasingly used for automated monitoring and control in agricultural systems, in particular in “smart” greenhouses, where it is necessary to constantly monitor temperature, humidity and lighting to ensure optimal plant growth conditions. However, with an increase in the number of sensors, problems of data redundancy and high energy consumption arise, especially in cases where sensors are powered by batteries and most of the energy is spent on information transmission. The traditional approach with constant transmission of complete measurements does not meet the requirements of energy efficiency and reliability, which creates a need for new mathematical and algorithmic solutions. One of the promising areas is compressing sensing (CS), which is based on linear algebra methods and sparse signal representation. It allows you to reduce the amount of transmitted information without losing the accuracy of temperature field reconstruction, as well as detect anomalies in the operation of individual sensors. Thus, the problem arises of developing and researching a linear-algebraic CS model for WSNs, which will provide energy-efficient, reliable, and intelligent monitoring in greenhouses and will become the basis for creating modern agricultural Internet of Things systems.

Analysis of recent research and publications. WSNs are ideal platforms for automatic control in various areas, including modern agriculture. For example, greenhouses require constant monitoring of conditions (temperature, humidity, lighting) for optimal yield and efficient resource management. However, with increasing sensor density, problems arise: high power consumption (especially for communication) and data redundancy [1]. These limitations are especially critical for battery-powered WSNs, where communication usually accounts for a large part of the total energy consumption. Therefore, reducing the amount of transmitted data without compromising measurement accuracy has become a key research goal in the development of energy-efficient smart greenhouse systems.

A good solution is CS, whose powerful mathematical basis allows reconstructing high-dimensional data (e.g., a temperature field) from a small number of linear measurements [2]. This is possible by exploiting the sparsity or compressibility of signals. From a linear algebra perspective, CS models data acquisition as an uncertain system of equations, where the reconstruction of the full field is performed through a sparse reconstruction problem, which is usually solved using optimization or iterative linear algebraic methods. For example, optimization methods for finding the most sparse representation of a signal (basis search or basis pursuit) [3]; an iterative algorithm that selects the best basis vectors for approximating the signal (orthogonal greedy pursuit or orthogonal selection method) [4, 5]; and methods for solving the problem of Lasse regression or sparse encoding through thresholding (iterative compression-threshold algorithm) [6]. The listed methods fundamentally rely on vector and matrix operations, emphasizing the central role of linear algebra in both theory and implementation.

A review of recent publications shows [1, 7] that WSN is one of the most promising and practically significant areas of CS application, especially in scenarios characterized by limited energy resources and high data redundancy.

Research purpose of the paper is to theoretically substantiate and demonstrate the effectiveness of CS as an alternative to the traditional approach to data transmission in WSNs for environmental monitoring.

The research aims to identify practical advantages of the proposed architecture, such as reducing the amount of transmitted information, extending battery life, and increasing system reliability by detecting anomalies in sensor operation.

Within the framework of the set goal, it is envisaged to use sparse signal processing methods and linear algebraic optimization algorithms that allow to restore the full temperature field from a minimum number of measurements, while maintaining the possibility of diagnosing the state of the network itself. In addition, methods of computer modeling of the sensor network are used to quantitatively assess the achieved level of compression and reconstruction accuracy.

Basic material presentation. The temperature inside the greenhouse is monitored using a grid of sensor locations in space and at discrete points in time. Let us introduce the following notations: N is the number of sensor locations (spatial nodes); T is the number of time points that we consider (time snapshots); the vector $x \in R^N$ is the complete space-time temperature field (one snapshot).

The objective of this study is to reduce the number of transmitted samples while reconstructing x (or a sequence $\{x^{(t)}\}$) with acceptable accuracy.

Consider a linear compression measurement model. The sensors transmit scalar values to a fusion center, which forms linear combinations, which can be expressed in the following formulas:

$$y = \Phi x + e,\ y \in R^M,\ \Phi \in R^{M \times N},\ M \ll N, \tag{1}$$

with y are CS, Φ is the sensing (measurement) matrix implemented by the network, and e denotes measurement noise.

CS assumes x is (approximately) sparse in some basis $\Psi \in R^{N \times N}$: there exists $s \in R^N$ with few nonzeros such that

$$x = \Psi s, \quad \|s\|_0 = k \ll N. \tag{2}$$

For temperature fields, good choices sparsifying basis Ψ include discrete cosine transform (DCT) [8] or low-order spatial eigenvectors (PCA) because temperature varies smoothly and has dominant low-frequency components – i.e., s is compressible (rapidly decaying coefficients).

Hence, the measurement equation becomes

$$y = As + e, \quad A := \Phi\Psi, \tag{4}$$

with $A \in R^{M \times N}$. A successful recovery typically requires matrix A has the restricted isometry property (RIP) or low mutual coherence between columns. Informally, A should preserve lengths of sparse vectors [9, 10].

Next follows the recovery procedure of s from underdetermined linear system using sparsity priors.

Reconstruction of a sparse signal in CS can be formulated directly in terms of linear algebra and convex optimization. A standard approach is basis pursuit, in which the unknown sparse coefficient vector $s \in R^N$ is estimated by solving the convex program

$$\hat{s} = \arg\min_s \|s\|_1 \quad \text{s.t.} \quad \|y - As\|_2 \le \varepsilon. \tag{5}$$

Once the sparse representation $\hat{s}$ is recovered, the original signal can be reconstructed

$$\hat{x} = \Psi\hat{s}. \tag{6}$$

In scenarios where measurement noise must be explicitly accounted for, the reconstruction is often posed as a LASSO-type problem [11],

$$\hat{s} = \arg\min_s \left(\frac{1}{2}\|y - As\|_2^2 + \lambda\|s\|_1 \right), \tag{7}$$

which balances measurement fidelity with sparsity through the regularization parameter λ.

A computationally appealing alternative, especially for energy-limited wireless sensor networks, is the greedy algorithm Orthogonal Matching Pursuit (OMP) [4], iterative correlation and least squares on selected columns. Here the procedure begins with residual $r_0 = y$ and an empty set of selected indices $S = \varnothing$. At each iteration, the algorithm identifies the column of A most correlated with the current residual by selecting

$$i_t = \arg\max_j \left|\left\langle a_j, r_{t-1} \right\rangle\right|, \tag{8}$$

where a_j denotes the j-th column of the sensing matrix. The selected index is added to the support set, $S \leftarrow S \cup \{i_t\}$, and the coefficients associated with the chosen columns are updated by solving the least-squares problem

$$s_S = \arg\min_z \|y - A_S z\|_2, \tag{9}$$

where s_S is a partial vector containing only the coefficients on the currently selected support set S; z is the temporary vector we optimize to compute the best values of s_S; A_S is the submatrix of A containing only the columns indexed by S. When the Gram matrix $A_S^T A_S$ is invertible, this step has the closed-form linear-algebraic solution

$$s_S = \left(A_S^T A_S\right)^{-1} A_S^T y. \tag{10}$$

The residual is then updated according to

$$r_t = y - A_S s_S, \tag{11}$$

and the procedure continues until the residual norm is sufficiently small or the desired sparsity level is reached. Because OMP uses only inner products and small least-squares solves, it is highly suitable for lightweight fusion centers in sensor networks.

When temperature fields exhibit correlations not only in space but also in time, CS can be extended to a spatio-temporal model. Spatio-temporal models often use separable bases to exploit both spatial and temporal correlations:

$$\Psi = \Psi_s \otimes \Psi_t, \tag{12}$$

where Ψ_s and Ψ_t are spatial and temporal bases, respectively; ⊗ denots the Kronecker product [12].

Suppose T consecutive temperature fields are stacked into a matrix $X \in R^{N \times T}$. If the data admit a separable sparse or low-rank structure, they can be approximated as

$$X \approx \Psi_s S \Psi_t^T. \tag{13}$$

In vectorized form, this becomes

$$vec(X) \approx (\Psi \otimes \Psi_s) vec(S), \tag{14}$$

This structure naturally leads to Kronecker-factored sensing operators of the form

$$\Phi = \Phi_t \otimes \Phi_s, \tag{15}$$

which drastically reduce the number of degrees of freedom and computational cost [12]. Such separable models are particularly advantageous in greenhouse monitoring, where temperature fields evolve smoothly over both dimensions.

Let us consider a specific simplified case, due to the need for conciseness. Let us rewrite formula (1) in a simplified form, neglecting noise:

$$y = \Phi_x, \tag{16}$$

We have $N = 6$ temperature sensors located in a greenhouse. The readings of all 6 sensors at a certain point in time form a signal x:

$$x = [x_1, x_2, x_3, x_4, x_5, x_6]^T = [22, 23, 22.5, 60, 21, 22]^T \,°\mathrm{C}. \tag{17}$$

The temperature in the greenhouse should be more or less uniform, but in this example there is the following observation: sensor #4 is broken and shows an absurd 60 °C. This means that in the natural basis our signal is not sparse. But if we imagine that the real signal is a uniform temperature + one fault, then in another basis (for example, in the difference basis or in the frequency domain) it will be sparse.

Let us assume that our signal x is sparse in the DCT basis [3]. This means that it can be represented with only a few significant coefficients according to formula (2), where Ψ is the 6x6 DCT basis matrix, x is the sparse vector of DCT coefficients. Most of the elements of s are zero or close to zero. For simplicity, let us take the standard DCT matrix [8]. Its elements are defined as:

$$\Psi_{k,n} = \cos \frac{\pi k \cdot (2n+1)}{2N}, \tag{18}$$

approximately, up to normalization:

$$\Psi = \begin{bmatrix} 0.41 & 0.41 & 0.41 & 0.41 & 0.41 & 0.41 \\ 0.56 & 0.31 & -0.31 & -0.56 & -0.31 & 0.31 \\ 0.56 & -0.31 & -0.56 & 0.31 & 0.31 & -0.56 \\ 0.41 & -0.41 & -0.41 & 0.41 & 0.41 & -0.41 \\ 0.31 & -0.56 & 0.56 & -0.31 & -0.31 & 0.56 \\ 0.31 & -0.41 & 0.41 & -0.31 & 0.31 & -0.41 \end{bmatrix}. \tag{19}$$

The signal x in this basis will have coefficients

$$s = \Psi^{-1} x. \tag{20}$$

Due to the presence of a sharp outlier (sensor #4), the vector s will not be perfectly sparse, but several of its coefficients will be significantly larger than the others. We assume that s has only $K = 2$ significant components ($K \ll N$).

We will use the simplified formula CS (15), where y is a vector of compressed measurements of size 3 × 1, Φ is a measurement matrix of size 3 × 6. Its elements are often generated randomly (for example, from a normal distribution). An example of a measurement matrix Φ (3 × 6):

$$\Phi = \begin{bmatrix} 1 & 0 & -1 & 0 & 1 & 0 \\ 0 & 1 & 0 & -1 & 0 & 1 \\ 1 & -1 & 1 & -1 & 1 & -1 \end{bmatrix}. \tag{21}$$

Let us move on to CS and calculate the vector using formula (16):

$$y = [20.5, -15, -39.5]. \tag{22}$$

Instead of transmitting all 6 values (17), we transmit only $M = 3$ numbers (22) over the radio channel. The energy saving was 50 %. M is chosen so that $M < N$, but $M > K$ (ideally $M \approx 2K$).

Now let us move on to restoring the signal on the server.

The server receives the vector y and knows the matrices Φ and Ψ. It must solve problem (4), which we present in a simplified form, similar to (16), neglecting noise:

$$y = As. \tag{23}$$

This is a system of linear equations with 6 unknowns s and only 3 equations y. This is an indeterminate system that has many solutions.

We apply the sparsity condition, that is, we look for the solution s that has the smallest number of non-zero elements. This is the so-called L0-norm – the number of non-zero elements. However, the problem of minimizing the L0-norm is NP-hard.

Therefore, we decide to minimize the L1-norm, which corresponds to the sum of the absolute values of the elements s, which is a convex optimization problem often leads to a sparse solution.

The formal formulation of the BP optimization problem [4] is to minimize the sum of the absolute values of the coefficients s, provided that the compressed measurements exactly match the model given in formula (5).

To obtain an estimate of the sparse vector $\hat{s}$, the server applies the OMP reconstruction algorithm, which iteratively identifies the support of the signal and solves a sequence of small linear least-squares problems, using (8)–(11).

Finally, the server constructs the full sparse estimate $\hat{s}$

$$\hat{s} = \text{embed } (s_S \text{ into an } N\text{-dimensional vector with zeroes elsewhere}). \tag{24}$$

After that, it calculates the estimate of the original signal using formula (6). Expected result:

$$\hat{x} \approx [22,\ 23,\ 22.5,\ 23,\ 21,\ 22]. \tag{25}$$

Although sensor #4 reported an absurd value of 60 °C, the recovery algorithm, based on the assumption of rarefaction (temperature uniformity), correctly estimated the true temperature of ~23 °C (25) at this point and detected the anomaly.

The process diagram is shown in Fig. 1, which depicts the two-way data compression and recovery process in a distributed monitoring system.

The process begins with data collection from 6 temperature sensors, formation of a measurement vector and its compression by linear transformation using a measurement matrix. The compressed data is transmitted via a wireless communication channel to the server, where an optimization procedure is performed to restore the original signal based on the known measurement matrices and the transformation basis. Let us note the key stages:

1. Data generation and compression on the transmitter side.
2. Wireless transmission of reduced data.
3. Signal recovery by optimization on the server.
4. Anomaly detection and further data processing.

The proposed architecture demonstrates an effective approach to energy saving in WSNs by transmitting CS instead of the full data set. The use of the mathematical apparatus of compressive measurement allows not only to reduce the amount of transmitted information by 50 %, but also to effectively detect anomalies in the operation of sensors. This is achieved due to the property of signal sparsity in a certain basis and the use of optimization methods for accurate information recovery at the receiving end.

The recovery algorithm on the server uses knowledge of the data structure (sparseness) to extract complete information from incomplete measurements. This is a vivid example of the synergy of a mathematical model and computational intelligence.

Conclusions. The linear algebraic model of WSN is fundamental for CS applications, especially for temperature monitoring in greenhouses. The temperature field is spatially correlated and exhibits a low-dimensional structure, which is ideal for a sparse representation. This paper explores a linear algebraic model structure that clearly formulates the compression process for greenhouse WSNs. The architecture of a CS system for WSN is presented, thanks to which the system functions effectively under conditions of variable communication quality and failure of individual sensors. Built-in machine learning algorithms ensure continuous improvement of the quality of service. The architecture supports the dynamic addition of new sensors without changing the basic structure. The proposed extended architecture significantly increases the efficiency of modern Internet of Things systems, industrial monitoring systems, and smart cities, ensuring reliability, energy efficiency, and high quality of service at minimal data transmission costs. By describing measurement, rarefaction, and reconstruction as transformations

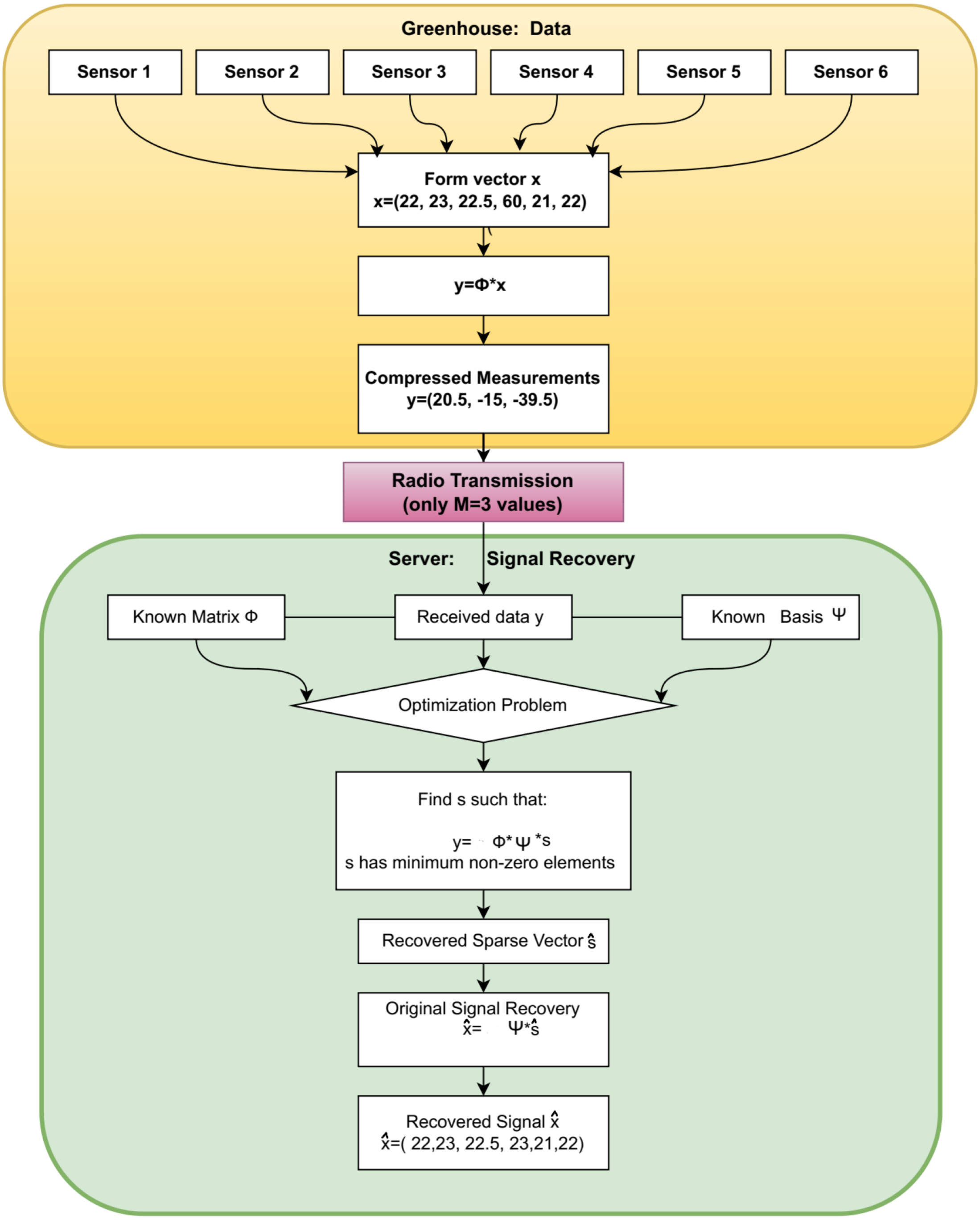

Fig. 1. Architecture of a compression measurement system for wireless sensor networks

in linear vector spaces, we emphasize both the mathematical rigor and practical effectiveness of this approach for creating energy-efficient intelligent agricultural systems. Energy savings in sensor data transmission are achieved by transmitting not all data.

Future research may investigate adaptive sensing matrices that update based on earlier measurements, enabling even more efficient data collection. Smarter sampling patterns could further reduce sensor energy consumption, while hybrid methods that combine OMP with other reconstruction techniques may improve accuracy at low computational cost. More advanced spatio-temporal or tensor-based models could better capture complex temperature variations inside real greenhouses. Distributed reconstruction approaches would allow sensors to cooperate locally, increasing robustness and reducing the workload on the central server. Additional work is also needed to handle sensor faults, noise, and missing readings. Integrating machine-learned priors or physics-based models, such as heat diffusion equations, may provide more realistic and stable sparse representations. Finally, large-scale experiments in real greenhouse environments will be essential for validating and improving the proposed framework.

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