

Research on the Aggregation Method of Network Precision Agriculture Based on the Matching Pursuit Algorithm

BaoYuan Chen¹, Di Ma¹, YuLiang Zhuo¹, Bin Li¹,
ZhiChao Huo¹ and ZiHe Li¹

¹ The higher educational key laboratory for Measuring & Control Technology and Instrumentations of Heilongjiang Province Harbin University of Science and Technology, Harbin 150080, China
Chenbaoyuan@126.com

Abstract. This paper applies wireless sensing data collection technology to precision agriculture, and an information aggregating method of precision agriculture based on matching pursuit theory is introduced to spare the wireless sensor network measurement data. The experiments show the validity and rationality of this method with high precision reconstruction. The network data transmissions effectively lessen, the network energy consumption will decrease, the life of network will extend and the large-scale agricultural data collection comes true.

Keywords: Wireless sensor network, matching pursuit, Data sparseness

1 Introduction

In this paper, the WSN network technology is applied into precision agriculture. We can take the measures such as precision irrigation, ventilation and sun shading by the surveillance of the temperature, humidity and light intensity and the requirements for the humidity that varies with the crops. The energy can be saved and the crops growth rate will increase in this way. An aggregation algorithm based on matching pursuit data is proposed in this paper. The data collected by wireless sensor will be spared and the data aggregation transfer realizes. The network cost decreases and the life of network extends. The simulation proves that the spared data that based on the matching pursuit algorithm has the high precision reconstruction and is adaptable to the large-scale collection data supervision.

2 Wireless network data collection model using distributed nodes

It was proposed to apply WSN network into the field of agriculture environment monitor in this paragraph of the paper. As agricultural production requires large amounts of land. It's difficult to install sensor nodes in the complicated terrain, and

the high requirements for production process automation and autonomy are needed. so things can be done in collaboration sensor nodes through multiple measurements and information processing tasks to improve the performance of Things and energy effectiveness. The structure is shown in Figure 1.

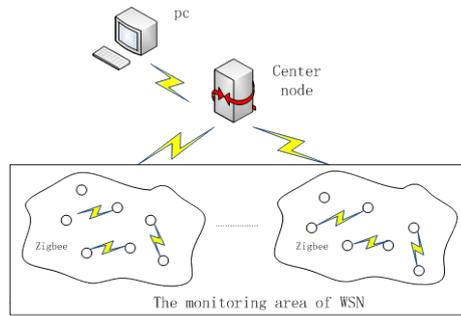


Fig. 1. The structure of WSN

3 The information aggregating algorithm based on matching pursuit

The sparse decomposition theory of the Internet of things signals is essentially the same as the image sparse decomposition theory. Moreover, as it contains the network topology information, the measuring data in Internet of things are more complicated. We can directly adopt the matching pursuit algorithm to sparser the network data. We suppose that $F=(Z,L)$ is a connection diagram corresponds to a topology of the Internet of things. $Z = [z_1, z_2, \dots, z_N]$ is the fixed points collection of this diagram and the sensor nodes collection. L means the edges collection, as well the collection of communication links. we directly give the definition to:

$$g_{\tau} = \frac{1}{\sqrt{s}} g\left(\frac{t-u}{s}\right) e^{i\tau t} \quad (1)$$

Then the time-frequency clusters shows. After a series of formula-transformation, The signal is decomposed as:

$$f = \sum_{N=0}^{\infty} \langle R^N f, g_{\tau_N} \rangle g_{\tau_N} \quad (2)$$

4 Simulation experimental

Select the greenhouse which is $300 \times 300 m^2$ as the monitoring area, at the area, we use 512 wireless network nodes to collect data.

Figure 2 is the information about the collected soil moisture data. The main program of the matching pursuit algorithm is programmed in Matlab. The number of the iterations is 80, as the reconstruction signal basically approximates the original signal after 80 times of iterations. Figure 3 shows the residual signal after 80 times of iteration. Figure 4 is the main signal, also named the reconstruction signal.

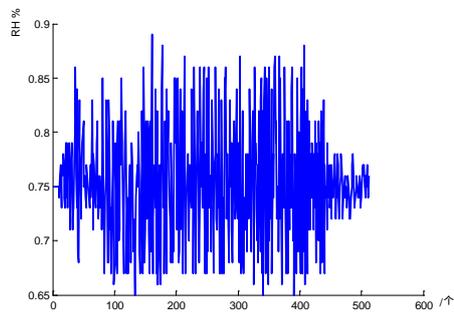


Fig. 2. Original signal

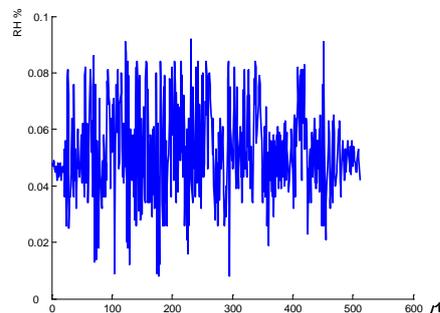


Fig. 3. Residual signal

As it can be seen from figure 2 and figure 4 that the reconstruction signal after iteration and the original signal is pretty much the same.

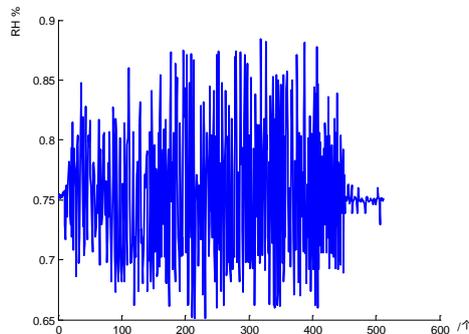


Fig. 4. Reconstruction signal

512 sensor nodes were numbered to verify the accuracy of the reconstruction signal. We did 100 times periodic measures using 5 feature nodes. The average reconstruction error of sensor network data was calculated according to the (3). In this equation, χ stands for the sensor nodes after reconstruction and γ is the measured sensor nodes. The result is shown in table 1.

$$\sqrt{\sum_{i=1}^{100} \delta_i^2 / 100} \quad (3)$$

$$\delta_i = \chi - \gamma \quad (4)$$

Table 1. The error between the measurement data and the reconstruction data

feature nodes	100	200	300	400	500
average error	0.047	0.068	0.056	0.087	0.137

5 Conclusion

As it was known from the above that the matching pursuit algorithm can realize the data aggregation transmission which greatly reduce the data traffic. In addition, the low average error of the reconstruction data can meet the demand of agriculture monitor data.

Funding. This work was supported by Heilongjiang Province College Education Engineering Projects: JG2012010282

References

1. KUSH R. VARSHNEY, MUJDAT CETI, JOHN W. FISHER, and ALAN SWILLSKY. Sparse representation in structured dictionaries with application to synthetic aperture radar [J]. IEEE Transactions on Signal Processing, 2008(8).
2. Sulaiman S, Manut A, Nur Firdaus A R. Design, fabrication and testing of fringing electric field soil moisture sensor for wireless precision agriculture applications. 2009 International Conference on Information and Multimedia Technology, 2009: 513-516.
3. Jayaashree A, G. S. Biradar, V. D. Mytri. Review of Multipath Routing Protocols in Wireless Multimedia Sensor Network. International Journal of Scientific & Engineering Research Volume 3, Issue 7, 2012(7)
4. Y. Li, X. Xu, B. Bai, Y. Zhang. An Improved Combined Multiscale Method for Image Denoising. Electronic Technology, 2008, 17(4): 618-684.
5. Emmanuel J, Candes, Michael B. Wakin. An Introduction to Compressive Sampling [J]. Signal Processing Magazine, IEEE, 2008,
6. Wang Y H. Seismic time frequency spectral decomposition by matching pursuit Geophysics, 2007, 72(1): 13-20