Application of compressed sensing in effective power consumption of WSN for landslide scenario

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Application of Compressed Sensing in Effective Power Consumption of WSN for Landslide Scenario

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***Abstract*— Wireless sensor network (WSN) is an effective facility to predict and monitor the landslide in real time. One of the problems of the WSN for landslide monitoring is the power consumption. There is a lot of work have tried to overcome this limitation. This paper focuses on a new development of compressed sensing (CS) based algorithm which can be applied for landslide monitoring. This work exploits the natural properties of the data acquired in the time domain. The transmitted data is the random set of the Fourier coefficients corresponding to the time domain data. The effective algorithm is verified by both simulated and experimental data which are sensed from multiple sensors in the wireless node.**

Keywords—landslide; wireless sensor network (WSN); power consumption; compressed sensing.

I. INTRODUCTION

Each year in the world happened hundreds of small and large landslides that cause serious damage to people and property. Especially, in Asian countries like India, China, Japan, Pakistan, Nepal, Bangladesh, some countries in the Eurozone as France, Italy, Spain, and in Southeast Asia such as Vietnam, Indonesia, and Philippines landslides occur frequently. Because of the large loss of life and property, from the 80s of the 20th century, many countries in the world were paying attention to research to find out the methods, and solutions to minimize the damage caused by landslides. One of the effective solutions for the prevention of landslides is monitoring and early warning of landslide phenomena [1]. To alert landslides, there are two types of alerts: long-term and short-time (real-time) [2][3].

The long-term monitoring is a solution that using satellite remote sensing data combined with geographic information system GIS (Geographic Information Systems), global positioning system GPS (Global Positioning System) and the mathematical model to map areas at risk of landslides. The landslide observation unit is the annual period. The short-term monitoring is an instantaneous method using the sensors to identify the signs of the landslide just before the incident landslides. In the real-time alert, the use of rain sensors, soil moisture sensor, acceleration sensor, temperature sensor is needed. It also require to build a system of wireless sensor network in which multiple sensors are integrated to each node [4]. Obviously, the power consumption is an important problem of this kind WSN.

In this paper, we applied a well-known technique called compressed sensing in order to reduce the number of transmitting data [5]. Firstly, in each node, the environment data is sensed by multiple sensors. Secondly, the data is converted from time domain to the frequency domain by using Fourier transform. Thirdly, the wireless node sends a random amount of the corresponding Fourier coefficients to the gateway and transfer to the central computer. The time domain data would be reconstructed by a suitable nonlinear algorithm.

II. WORKING PRINCIPLES

A. Sensor Integration

The components of a sensor column (namely, wireless sensor node) are integrated as shown in Fig. 1. Each sensor column includes three kinds of sensor for measuring parameters of the environment. The microprocessor Atmega328 will receive data from sensors and execute some processes such as sensor calibration and noise filtering. The Xbee module will transmit the observed data to a central computer [6]. A large capacity battery is used to supply power for each sensor node up to one year. Thus, the sensor column consists of full components to measure the environments and data transmission, which is suitable for landslide monitoring (see Fig. 2). There are three kinds of sensor used in this work:

- ✓ Soil moisture sensor: measures the water content of soil. The changing of the dielectric permittivity of the soil is a function of the water content.
- ✓ Temperature sensor: measures the temperature of the environment. The physical properties of soil and water change with temperature.
- ✓ Acceleration sensor: The acceleration play role as a tilt meter and a geophone. The acceleration sensor is used for measuring the soil layer movements as low creep movement or sudden movement and analysis of vibration cause during a landslide.

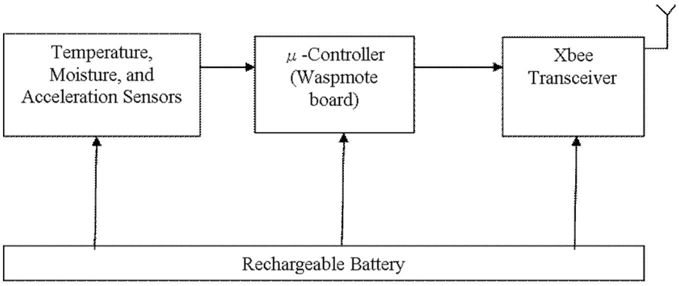

Fig. 1. Block diagram of a sensor column

The wireless data transmission module XBee PRO [6] uses the 802.15.4 standard for wireless communication. It can cover a bigger area than Bluetooth wireless transmission, but lower power consumption compared to the standard 802.11 WI-Fi wireless communications. XBee module communicates with the micro-controller via the serial port and other devices for the purpose of accessing the ZigBee network [6]. The XBee module PRO offers improvements in power consumption and transmission protocol. The maximum transmission distance is up to 7 km in outdoor conditions without obstructions. It provides the data transfer reliability with -102 dBm of the sensitivity. Data transmission speeds may be up to 250 kbps with 50mW of the transmitted power. Each module has a physical address of 16-bit only. The module has two communication modes: point-to-point and point-to-unicast network-wide broadcast using the 2.4GHz frequency band. XBee modules also provide the sleep mode to save power consumption.

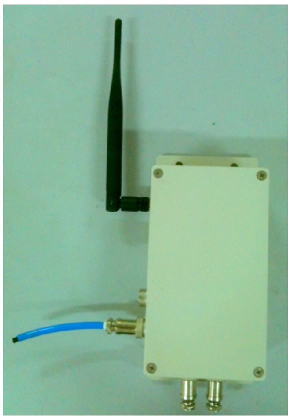

Fig. 2. Photo of a sensor node [10]

B. Power Consumption of WSN

One of important requirements for any landslide monitoring system is the efficient delivery of data in a real-time manner. The architecture of the system in this study is shown in Fig. 3. The complete architecture consists of six wireless sensor columns to measure parameters of the environment. The WSN is designed as a star topology. The observed data at each node will be sent to the gateway via Xbee. The data received from the gateway is stored in a database server. Furthermore, the data is also processed by computer via available designed program. The real-time data and the results of data analysis are then streamed on the Internet in real-time. Alert services such as the Short Message Service (SMS) is implemented to alert about the probability of landslides.

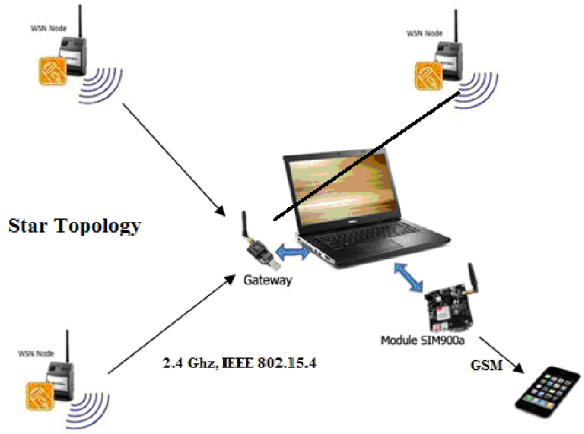

Fig. 3. WSN uses star topology and SMS alert service.

In order to to transmit data effectively, the data frame is needed to design carefully. The data frame sent from sensor columns have the following structure:

#	Node ID
#	WASPMOTE_XBEE
#	Frame index
#	Data no. 1
#	Data no. 2
#	Data no. 3
#	…

where:

Node ID: is an ID address of the node that has 9 numbers

Frame index: will increase after each post

Data no. i: is data of the i^{th} sensor that is divided into two fields: name of sensor and data value. As an example, data frame received from sensor column is: #382537687 #*Reserved*#3 #TCA:22 #HUMI1:200.5 #HUMI2:0.0 #BAT:23 #ACC1:4.0 #DATE:13-1-11 #TIME:12-30-11#

Note that the information of the battery health and the reading time index are also attached into this frame. The gateway receives the data frame at every one minute and transfer the data to the central computer.

The battery for sensor node is a Lithium one with 6600mAh capacity and the voltage is 3.7V. The power is calculated by using the following formula:

$$Power = Voltage * Current \qquad (1)$$

From Equ.1, the power consumption here is 24.420Wh. Multiplying this result with 3600s, we can get the possible energy which is 87912J. After every 1 minute, we read and transfer data that costs a time of 3 seconds. In the time remaining (i.e. 57 seconds), the sensor node switches to sleep mode and consume much lower power.

TABLE I. POWER CONSUMPTION CALCULATOR OF A SENSOR NODE

Components	**Current (mA)**		**Voltage (V)**	**Power (mW)**	
Wapsmote	15 (Active)	0.055 (Sleep)	3.3	49.5 (Active)	0.18 (Sleep)
Xbee-ZB-PRO module	3		3.3	10 (estimated with distance 100m)	
Temperature sensor (LM35)	10		3.3	33	
Acceleration sensor (ADXL345)	0.35		3.3	1.155	
Soil moisture sensor	2		3.3	6.6	
Total Average Power in active model draw $\sum(I*V)$ = 100.255mW Total Average Power in sleep model = power of Wapsmote in the sleep status = 0.18mW					

The total of the consuming energy during 3 seconds for reading and transferring data is: 100.255 mW×3 seconds= 0.08 mWh. During the sleep period, the energy consumption is: 0.18 mW×1 min = 0.003 mWh. Thus, the number of times that the node reading and transferring data is: 24420 mWh/ (0.08 mWh+0.003 mWh) = 222000 times. Consequently, the sensor node can live about: 222000 times × (1 min + 3 seconds) × (100% - 25%) = 2914 hours (or 4 months).

C. Compressed Sensing

A recent breakthrough in mathematics and signal processing under the name of compressed sensing (CS) shows that sparse or, more generally, compressible signals can be recovered from a small number of linear random measurements [1]. Exact reconstruction can be achieved by nonlinear algorithms, using such as l_1 norm or Orthogonal Matching Pursuit [7]. In the context of signal sampling, CS is seen as random undersampling. This method is important because many signals of interest, including natural images, diagnostic images, videos, speech and music, are sparse in some appropriate domain of signal representation. Among various applications of CS, it has lately been demonstrated to be successfully applied to MRI for fast acquisition by Lustig et al. in [8]. In special, random undersampling is carried out in the k-space. In other words, by acquiring the image with a smaller number of measurements as compared to normal full sampling, the speed of acquisition can be enhanced.

Let $x \in R^N$ be the signal of interest and suppose that we know x admits a *sparse* linear representation which reads x=Φs, where $s \in R^N$ is a K-sparse vector (i.e., containing exactly K nonzero values) and $\Phi \in R^{N\times N}$ is called the sparsifying matrix. Suppose also that we measure/sense x by a linear system $\Psi \in R^{M\times N}$, called the measurement matrix. Then, the measurements are given by y = Ψx, with $y \in R^M$. Suppose we want to reconstruct x from y. This is equivalent to reconstructing s from y, since we can write y = Θs, where Θ=ΨΦ.

III. PROPOSED SCHEME AND RESULTS

The natural properties of acquired data in the landslide monitoring is that is concentrated in the low frequency area. Thus, we can reduce the number of the transmitted sampled data by their corresponding Fourier coefficient. Firstly, in each node, the environment data is sensed by multiple sensors. Secondly, the data is converted from time domain to the frequency domain by using Fourier transform. Thirdly, the wireless node sends a random amount of the corresponding Fourier coefficients to the gateway and transfer to the central computer. The time domain data would be reconstructed by a suitable nonlinear algorithm.

The problem of the sparse signal reconstruction can be solved by l_1-regularized least-squares programs (LSPs) [9]. The reconstruction is obtained by solving the constrained optimization problem:

$$\begin{aligned} &\arg\min_x \left\{ \left\| F_u x - y \right\|_2^2 + \lambda \left\| \Phi x \right\|_1 \right\} \\ &subject\ \ to \quad \left\| F_u x - y \right\|_2 < \varepsilon \end{aligned} \tag{2}$$

where x is the sensed data in the time domain, y are k-space measurements, F_u is the undersampled Fourier operator associated with measurements, Φ is the sparsifying transform operator, and λ is a data consistency tuning constant.

Three kinds of sensors have been tested successfully in the laboratory and the data is acquired [10]. In the conventional scheme, the information on temperature, soil moisture, acceleration, and the status of battery health is sent frequently and directly to the central computer though the gateway. In the proposed scheme, their corresponding Fourier coefficients were sent instead. Figures 4, 5, and 6 show the original and reconstructed data from temperature, moisture, and acceleration sensors after a reconstruction process at the central computer using LSPs [9]. In these cases, the reduced number of data is 45 percentages. It can be seen that, at the compression rate r = 0.45, the reconstructed data is acceptable.

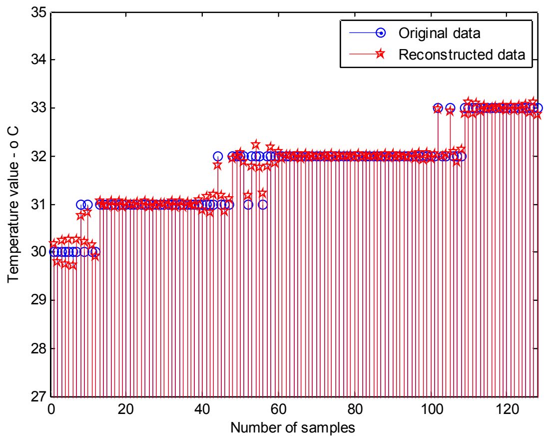

Fig. 4. The original and reconstructed data from a temperature sensor

To analyze the dependent of the reconstructed performance to the ratio of compression, we proposed to use the reconstructed error:

$$\varepsilon = \frac{1}{N}\sum_{j=1}^{N}\left|x_j - \hat{x}_j\right| \quad (3)$$

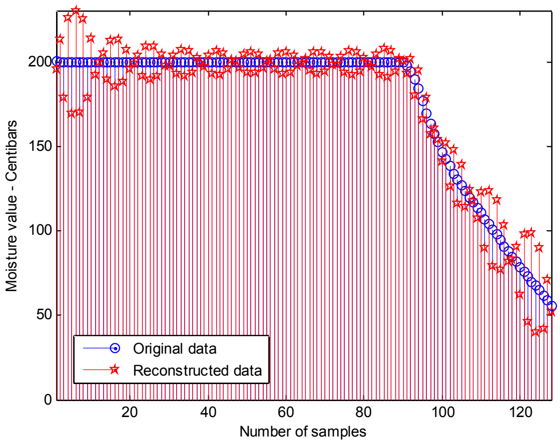

Fig. 5. The original and reconstructed data from moisture sensor

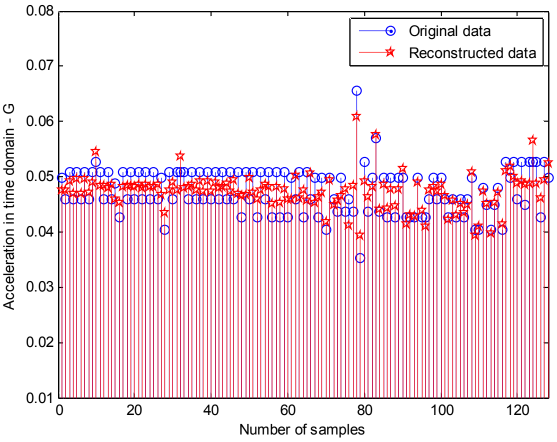

Fig. 6. The original and reconstructed data from acceleration sensor

Figure 7 shows the dependent on the relative error of the compression ratio in the case of using acceleration sensor. It is seen that the error is gradually reduced in the low range of compression ratio (0.1 to 0.5). With a higher ratio (i.e. $r > 0.55$), the relative error is closed to 0. It means that the information in k-space is good enough to offer an ideal reconstruction. From this result, we can choose the value of compression ratio of 0.55 for the further work.

IV. CONCLUSIONS

This study has successfully developed an effective scheme for transmitting the acquired data from different kinds of sensor in each node of the WSN. The data in the time domain are not sent directly from the sensor node to the gateway. We transmitted a smaller number of data which is the Fourier coefficients corresponding to the time-domain data. The amount of data can be reduced twice, hence, we can reduce the power consumption due to the transmission process. It can be seen that the whole system can be implemented in real environment.

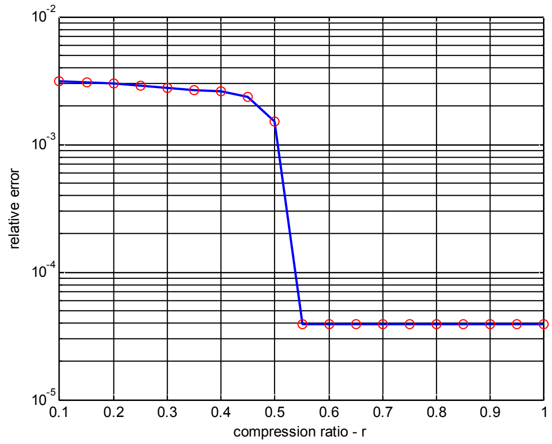

Fig. 7. The dependence of the relative error to the compression ratio.

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