Sensors & Transducers, Vol. 158, Issue 11, November 2013, pp. 332-337

www.sensorsportal.com

Sensors & Transducers

http://www.sensorsportal.com

A Sparse Optimization Method for Distributed Hydrology Information Monitoring System

[1] Huang LIJUN, [1] Zhang SHUFANG, [2] Yao HAN, [1] Hu XUEQING, [3] Zhang JIAHUA

[1] College of Mechanical and Electronic Engineering, Suzhou University, 234000, China

[2] Suzhou Construction Investment Co., Ltd, 234000, China

[3] School of Mathematics and Information Technology, Nanjing Xiaozhuang University, 211171, China

[1] Tel.: 15705577979, fax: 05573048275

[1] E-mail: ljhuang@mail.ustc.edu.cn

Received: 3 September 2013 /Accepted: 25 October 2013 /Published: 30 November 2013

Abstract: The sparse optimization method is an effective technological approach to solve information detection and spectrum sensing in hydrology information monitoring sensor network and it is at the frontier domain of water data collection and transmission field in home and abroad. By combining sparse optimization with distributed hydrology information monitoring and based on the theoretical framework of sparse optimization of distributed water level monitoring, the paper puts forward the distributed sparse optimization monitoring method of water environment information, which expands the new application of sparse optimization in distributed network on one hand. On the other hand, it points out the reconstruction method of joint sparse signals based on the block coordinate descent method. Simulation experiment shows that the proposed method can converge quickly to the approximate optimal solution and has a good robustness for calculation error caused by inaccurate average and other uncertain factors in the network. *Copyright © 2013 IFSA.*

Keywords: Hydrology information, Sparse representation, Distributed data collection, Optimization algorithm, Wireless sensor networks.

1. Introduction

Hydrology information monitoring is to measure and analyze surface water, groundwater, atmospheric precipitation, water deposits, water pollution and so on, including their level, flow, temperature, precipitation, ice regime, evaporation, pollution source, pollutants and other monitoring contents. At present, water regime monitoring has become an important technological support to predicate natural water disaster, control pollution and to govern hydrology information.

In recent years, China has established various monitoring points, monitoring stations, monitoring networks and other infrastructures, forming a monitoring system oriented by monitoring station – telemetry communication network – center station. At the same time, wireless sensors network (WSN) have also been applied to hydrology information monitoring gradually. On the basis to establish

Article number P_1506

sparse optimization theory of hydrology information, people have also conducted analysis of distributed hydrology information collection and transmission. Due to the range of hydrological monitoring area is usually large and wide, and there are a large number of the sensor nodes. The sensor nodes are deployed intensive, the energy of each node is limited, and the work environment is complex and changeable, the monitoring area is irregular. All of these will bring a certain impact on acquiring and transmitting information for wireless sensor networks. Therefore, current technology and method are facing with two main problems that need to be solved:

1) Difficult to detect, express and restore regional hydrology information comprehensively and accurately.

2) Difficult to make efficient use of limited transmission spectrum resources.

These two problems on one hand show the complexity of acquisition of water information [1-2]. On the other hand they also reflect that there still exists great gap in monitoring accuracy, coverage, real-time performance and continuity. Therefore, new technology and method are needed to improve and perfect the overall performance of hydrology information monitoring system.

Due to the great need of robustness and real-time performance for multi-source information acquisition, distributed network, which is similar to hydrology information monitoring network, also faces sparse optimization problems. For example, event detection in wireless sensor network and fault location in multi-source sensor network can be molded as recovering a sparse vector in distributed network [3-8]; Spectrum sensing in cognitive radio system can be molded as recovering a set of joint sparse vectors or a low-rank matrix in distributed network [9-10]; Abnormality monitoring system in the Internet can be molded as recovering simultaneously a sparse matrix and a low-rank matrix in distributed network [11-12]; Data mining in computer network, however, involves more complex sparse optimization problems. Therefore, distributed sparse optimization problems attract more and more researchers of different fields [13-21]. Based on distributed monitoring characteristics of water data, the paper studies sparse optimization problems of data collection and transmission in distributed network.

In section 2, the paper establishes the theoretical framework of sparse optimization problems of distributed hydrology information monitoring system. Based on this theoretical framework, the section 3 points out monitoring method of distributed sparse optimization; The section 4, based on block coordinate descent method, discusses reconstruction of cognitive radio joint sparse signals, and expand the new application of sparse optimization in distributed network. The section 5 is the conclusion part.

2. Theoretical Framework of Distributed Hydrology Information Monitoring

The combination of distributed optimization algorithm and sparse optimization algorithm is the result of practical application requirements. With the rapid development of compression sensing and sparse signal processing, there appear more and more new sparse optimization algorithms and theories. For distributed network, the analysis of distributed implementation of current centralized sparse optimization algorithm can not only expand the new application of sparse optimization, but also enrich sparse optimization algorithm and theory. Physical framework of distributed hydrology information monitoring system is shown in Fig. 1.

Because the system is mainly based on telemetry system, collection and transmission of hydrology information can be divided into five levels:

The main center station – remote communication network formed by sub-center stations that is wide area network (WAN);

Data transmission between main center station and remote sensing satellite;

Telemetry network between sub-center stations or message switching relaying stations and monitoring stations;

Interconnection of instruments and equipments at monitoring station level (including sensors);

Wireless sensor network under monitoring station level.

In physical framework of distributed hydrology information monitoring system, wireless sensor network, as the front sensing end of monitoring station, forms hydrology information telemetry wireless sensor network (HITWSN). HITWSN consists of several sensor nodes and a sink-node. Sensor node is configured with many hydrology information sensors with different accuracy, including heterogeneous sensors (such as water level, rainfall precipitation, and flow), water quality sensors (such as PH sensor, dissolved oxygen sensor, chlorophyll a sensor, blue algae sensor, conductivity sensor and so on) and other meteorological sensors (such as wind speed sensor, temperature and humidity sensor, light sensor and so on).

Sensor nodes are deployed in the target hydrology information. Each node forms wireless network in self-organizing and multi-hop way to sense, collect and transmit water environment information which is in the geographical area covered by network. Sink-node is responsible for collecting this water environment information and transmitting the information to telemetry station. Then the telemetry station will store and transmit the information to sub-center stations after the pretreatment. In addition, a sink-node is also responsible for telemetry station's parsing and release of command given by WETWSN. In some areas where infrastructures are relatively weak, nodes can use battery or other environment energy, such as solar energy, to supply power.

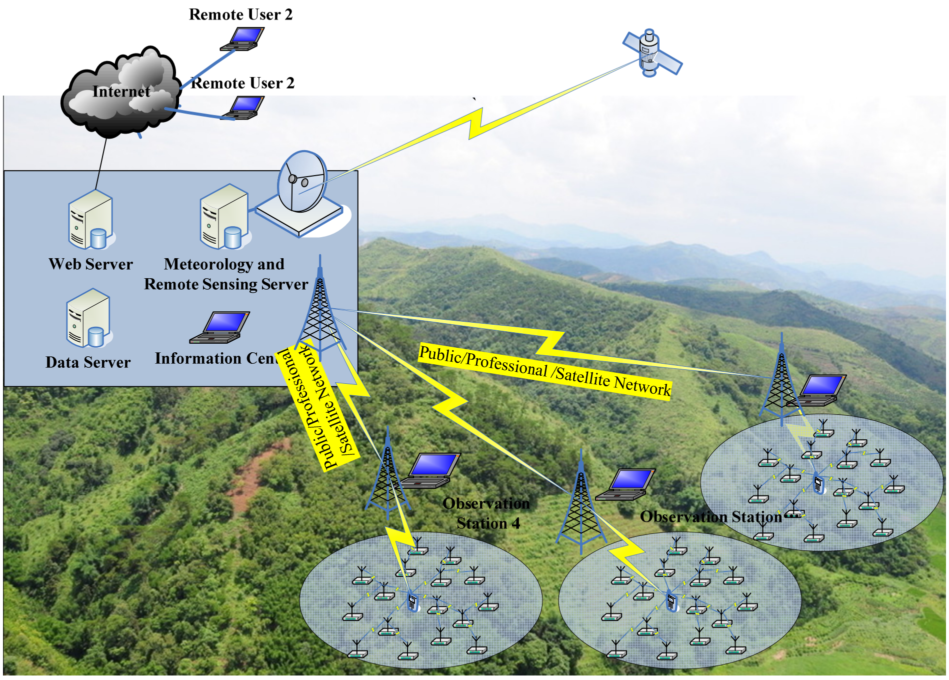

Fig. 1. Physical framework of distributed hydrology information monitoring system.

In this way, a wide range of hydrology information monitoring can be achieved without constructing and extending a lot of permanent fixed telemetry stations and other infrastructures. Sensors with different accuracy deployed at each sensor node can help collect information and improve anti-destroying ability of the system.

Moreover, due to the wireless deployment of sensor equipment, a lot of labor and infrastructure costs can be saved, thus making it is easy to maintain and deploy. At the same time, with the development and performance improvement of sensor technology, sensors of the system can be updated timely and deployed in large numbers.

But in practical application, nodes in WETWSN must depend on information exchange between neighbor nodes and use local data to independently calculate the solution, resulting in optimization variables with sparse structure. However, the current distributed optimization algorithm usually does not consider the sparse structure of optimization variables and is with low calculation efficiency. A lot of efficient sparse optimization algorithms rely on centralized center to do centralized calculations. Then this kind of algorithm is not suitable for distributed network.

Therefore, based on hydrology information monitoring characteristics, the paper points out sparse optimization algorithm aimed at solving sparse optimization problems of data collecting and transmitting in WETWSN, including recovery algorithm of sparse signals in wireless sensor network and recovery algorithm of joint sparse signals in cognitive radio network.

3. Reconstruction of Sparse Signals Based on Distributed Linear Bregman Method

Consider the application of event monitoring of wireless sensor network. Assume there are L sensor nodes in monitoring area we want to monitor the positions and intensity of abnormal events. In order to overcome the difficulties caused by the unknown quantity of abnormal events, one common method is to select N nodes in monitoring area as the candidate positions of abnormal positions.

Define a $N\times 1$ vector x, in which the jth elements is x_j, which presents the events intensity of the j candidate position. If there is no abnormal event in this position, then $x_j = 0$. The measurement result bi of the ith sensor node is affected by all events, which can be usually approximate to a linear equation $b_i = A_i x$.

Measurement results of all sensors constitute a measurement vector $b = Ax$, in which $A = \left[A_1; A_2; \ldots; A_L\right]$ is a measurement equation. If the practical events number K is far less than the candidate position number N, then x is sparse.

Therefore, events monitoring problem can be converted into a problem of solving normalized least squares.

$$\min \frac{1}{2}\left\|Ax-b\right\|^2 + \rho\left\|x\right\|_1, \tag{1}$$

where ρ is the weighting factor. The most common distributed solving method of the above normalized least squares is alternating direction multiplier method. In alternating direction multiplier method, each node I only needs local measurement matrix and results to estimate x through the information exchange with the neighbor node. In each iteration, however, each node must be accurate to solve a normalized least square problem with the same size, which, therefore, is not suitable for application in wireless sensor network.

The paper discusses the application of efficient centralized sparse signal recovery algorithm of linear Bregman method in events monitoring of wireless sensor network. An equivalent problem of solving normalized least squares for Linear Bregman method is as follows:

$$\min \|x\|_1 + \frac{1}{2a}\|x\|^2 \quad st.Ax = b, \tag{2}$$

where α is the weighting factor. The duality of the equivalent problem is smooth, therefore, the dual gradient method can be used efficiently to solve the problem. Define dual variables as P, dual gradient y, step length of k time *h(k),* and contracting operation Shrink, the updated expression of dual variables and original variables of linear Bregman method can be expressed as:

$$\begin{aligned} y(k+1) &= aAShrink(A^T p(k),1) - b \\ p(k+1) &= p(k) - h(k)y(k+1) \\ x(k+1) &= aShrink(A^T p(k+1),1) \end{aligned} \tag{3}$$

In fact, linearization Bregman method can do parallel computing. Set the corresponding dual variable of the ith node as p_i, the dual gradient y_i, the estimation of *x(i)*, then we can get the following parallel computing:

$$\begin{aligned} y_i(k+1) &= aA_i Shrink(\sum_{i=1}^{L} A_i^T p_i(k),1) - b_i \\ p_i(k+1) &= p_i(k) - h(k)y_i(k+1) \\ x^{(i)}(k+1) &= aShrink(\sum_{i=1}^{L} A_i^T p_i(k),1) \end{aligned} \tag{4}$$

When calculating the estimation of the dual gradient and original variables, each node needs to use the sum of $A_i^T P_i$ owned by all local nodes. So the high-efficient computing can not be achieved in distributed network.

Based on communication with neighbor nodes, the paper tends to calculate imprecise sum of $A_i^T P_i$, which can be converted into an imprecise average problem in network. Fig. 2 shows the comparison between centralized linear Bregman and distributed linear Bregman when L=40 nodes, N=100 candidate positions, and K=2 events, in which longitudinal axis represents the number of iterations and horizontal axis represents the error between the calculation result and optimal solution. Due to the robustness of the gradient method, distributed linear Bregman can overcome the error caused by imprecise average problem effectively and converge to the approximate optimal solution.

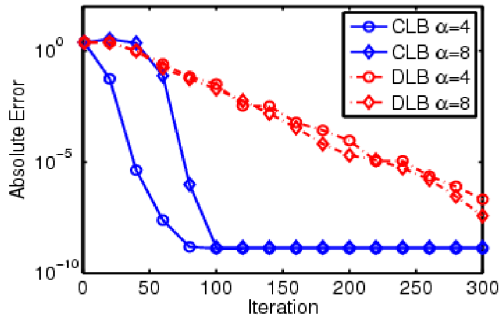

Fig. 2. Comparison between centralized linear Bregman (CLB) and distributed linear Bregman (DLB).

Distributed linear Bregman method is very simple. In this method, each node needs only the simple arithmetic without the need of solving normalized least square problems in alternating direction method. Therefore, this kind of method is very suitable for practical application of wireless sensor networks (WSNs).

4. Reconstruction of Joint Sparse Signal Based on Distributed Block Coordinate Descent Method

In cognitive radio network, cognitive radio nodes help to sense surrounding spectrum occupancy situation so as to determine the current available frequencies and improve spectrum utilization rate. Suppose that there are L cognitive radio nodes and the sensed spectrum can be divided into N bands. Define the spectrum occupancy situation of the ith node as a $N\times1$ vector, the jth element of $x(i)$, in which $x(i)$ represents the strength of the band j of the position where the ith node locates. Spectrum occupancy vectors of all nodes form a spectrum occupancy matrix $x = [x(1), x(2), ..., x(L)]$. Due to the current low spectrum occupancy rate, the non-zero line number K is far less than the total number N. In addition, spectrum occupancy situation of all nodes are similar. Therefore, if there are non-zero elements in certain line, other elements in this line are also non-zero ones. So spectrum occupancy situation is jointly sparse. Spectrum occupancy vector of node i can be measured with linear measurement equation $b(i)$=$A(i)x(i)$, in which $A(i)$ is a measurement matrix and $b(i)$ are measurement results. Cognitive radio network helps to recovery this matrix with the knowledge that the spectrum occupancy matrix is jointly sparse. This problem can be molded as L_{21} model minimization problem.

$$\min \frac{1}{2}\sum_{i=1}^{L}\left\|A(i)x(i)-b(i)\right\|^2+\rho\sum_{j=1}^{N}\sqrt{\sum_{i=1}^{L}(x_j(i))^2} \qquad (5)$$

where ρ is the weighting factor and takes compromise between least squares (the first item) and model items (the second item). L_{21} model in spectrum occupancy matrix X is defined as the sum of 2-norms in its line.

In minimization problem of L_{21} model, smooth least squares for each column of X are separable, while unsmooth items for each column of X are separable. In order to solve this problem efficiently, block coordinate descent method is approximate to least squares so as to make approximate L_{21} minimization problems for each line are separable and have simple explicit solutions. The approximate problem of the kth time is:

$$X(k+1)=$$
$$\arg\min \frac{1}{2\beta}\sum_{i=1}^{L}\left\|x(i)-p(i)(k)\right\|^2+\rho\sum_{j=1}^{N}\sqrt{\sum_{i=1}^{L}(x_j(i))^2} \qquad (6)$$

where β is the weighting factor and $p(i)(k)$ neighbor node, which can be calculated with $A(i)$ and $x(i)(k)$. Define neighbor node matrix as $p=\left[p(1),p(2),...,p(L)\right]$ and the jth line of X and P respectively x_i and p_i. Explicit solution of the above problem can be:

$$x_j(k+1)=\frac{p_j(k)}{\left\|p_j(k)\right\|}Shrink(\left\|p_j(k)\right\|,\rho\beta) \qquad (7)$$

The above centralized block coordinate descent method needs all nodes only in calculating 2-norm in each line of neighbor node matrix $P(k)$. All other steps can be done in local nodes.

The paper discusses the implementation of block coordinate descent in distributed cognitive radio network. The main idea is to calculate imprecisely 2-norms in each line of neighbor matrix $P(k)$. Because 2-norm refers to square calculation and root calculation, this problem can also be converted into an imprecise average problem. Fig. 3 shows the comparison between centralized block coordinate descent and distributed block coordinate descent when L=50 nodes, N=20 frequencies and occupied frequency K=2, in which longitudinal axis represents the number of iteration and horizontal axis represents the error between the calculation result and optimal solution. We can see that distributed block coordinate descent method can converge quickly to the approximate optimal solution and has a similar speed with centralized block coordinate descent method. Block coordinate descent method always solves an approximate problem in each iteration. Therefore, it has great robustness for calculating error caused by imprecise average and other uncertain factors in the network.

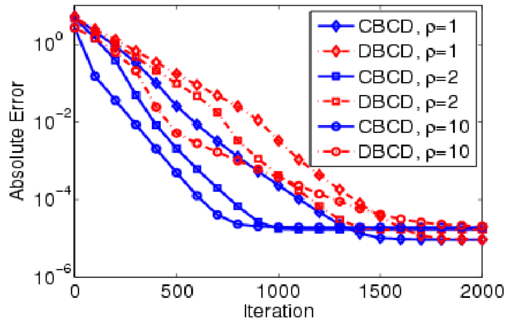

Fig. 3. Comparison between centralized block coordinate descent (CBCD) and distributed block coordinate descent (DBCD).

5. Conclusions

In the hydrology information acquisition technology, traditional manual observations as well as the conventional sensing technology has been widely applied. For example, the water level measurement technology, hydrological information involved in water science, water temperature in the flow, water quality and other hydrological elements, by observation, measurement, test, circuit automatic hydrographic survey and other conventional method of quantitative observation and analysis and published. However, if the arrival in the harsh environment or human should not be regions, especially in some unexpected event region to obtain flood information, means to obtain the hydrological information has some disadvantages, such as equipment deployment is not convenient, difficult maintenance etc. Wireless sensor network technology developed in recent years which can meet the environmental monitoring and information acquisition requirements. Hydrological wireless sensor network is a kind of advanced hydrologic real-time data collection, transmission, analysis and processing system, it application of sensor technology, modern communication technology and computer technology, real-time acquisition of rainfall, water level, flow to complete various hydrological parameters, and analyzed the processing, flood control, water supply, power generation to achieve optimal scheduling, improve the utilization of water resources, with significant economic and social benefits.

Combining sparse optimization with distributed hydrology information monitoring, the paper analyzes deeply the problem of reconstruction of sparse signals in distributed monitoring system. At the beginning, it puts forward the theoretical framework of distributed hydrology information sparse optimization. Based on this framework, the paper on one hand points out sparse optimization monitoring method of hydrology information and expand the new application of sparse optimization in distributed network. On the other hand it puts forward the reconstruction method of joint sparse signals based on distributed block coordinate descent. Simulation experiment shows that when the scope and number of node data of distributed network increases, distributed optimization will face the problem of heavy communication burden and weak robustness. Distributed network structure is more suitable for networking collection and processing of hydrology information. The method put forward in the paper can converge quickly to the approximate optimal solutions and has great robustness for calculating errors caused by imprecise average and other uncertain factors in the network, which not only provides theoretical basis for design and analysis of distributed sparse optimization algorithm of hydrology information, but also has guiding significance for general distributed optimization problems.

Acknowledgements

This work is supported by the Anhui Provincial Natural Science Research Project (No.KJ2013Z319, No.KJ2013B282), and the Suzhou University Laboratory of intelligent information processing project (No.2011YKF15).

References

[1]. C. Young, A. Bradley, W. Krajewski, Evaluating NEXRAD multisensor precipitation estimates for operational hydrologic forecasting, *Journal of Hydrometeorology*, Vol. 1, Issue 3, 2000, pp. 241-254.

[2]. L. Xu, J. Zhang, H. Li, An improved MAC protocol for marine-environment monitoring WSN system, *Journal of Networks*, Vol. 7, Issue 11, 2012, pp. 1900–1907.

[3]. M. Cetin, L. Chen, J. Fisher, A. Ihler, R. Moses, M. Wainwright, A. Willsky, Distributed fusion in sensor networks, *IEEE Signal Processing Magazine*, Vol. 23, No. 4, 2006, pp. 42-55.

[4]. N. Nguyen, N. Nasrabadi, T. Tran, Robust multi-sensor classification via joint sparse representation, *Journal of Advance in Information Fusion*, Submitted.

[5]. Q. Ling, Z. Tian, Decentralized sparse signal recovery for compressive sleeping wireless sensor networks, *IEEE Transactions on Signal Processing*, Vol. 58, No. 7, 2010, pp. 3816-3827.

[6]. K. Zhou, S. Roumeliotis, Multirobot active target tracking with combinations of relative observations, *IEEE Transactions on Robotics*, Vol. 27, No. 4, 2010, pp. 678-695.

[7]. Y. Cao, W. Yu, W. Ren, G. Chen, An overview of recent progress in the study of distributed multi-agent coordination, *IEEE Transactions on Industrial Informatics*, Vol. 9, No. 1, 2013, pp. 427-438.

[8]. H. Zhu, G. Giannakis, Sparse overcomplete representations for efficient identification of power line outages, *IEEE Transactions on Power Systems*, Vol. 27, No. 4, 2012, pp. 2215-2224.

[9]. J. Bazerque, G. Giannakis, Distributed spectrum sensing for cognitive radio networks by exploiting sparsity, *IEEE Transactions on Signal Processing*, Vol. 58, No. 3, 2010, pp. 1847-1862.

[10]. J. Meng, W. Yin, H. Li, E. Houssain, Z. Han, Collaborative spectrum sensing from sparse observations for cognitive radio networks, *IEEE Journal on Selected Areas in Communications*, Vol. 29, No. 2, 2011, pp. 327-337.

[11]. M. Mardani, G. Mateos, G. B. Giannakis, Dynamic anomalography: Tracking network anomalies via sparsity and low rank, *IEEE Journal of Selected Topics in Signal Processing*, Vol. 7, No. 1, 2013, pp. 50-66.

[12]. A. Rajaraman, J. Ullman, Mining of massive datasets, *Cambridge University Press*, 2012

[13]. G. Mateos, J. Bazerque, G. Giannakis, Distributed sparse linear regression, *IEEE Transactions on Signal Processing*, Vol. 58, No. 10, 2010, pp. 5262-5276.

[14]. J. Mota, J. Xavier, P. Aguiar, M. Puschel, Distributed basis pursuit, *IEEE Transactions Signal Processing*, Vol. 60, No. 4, 2012, pp. 1942-1956.

[15]. Q. Ling, Z. Wen, W. Yin, Decentralized jointly sparse signal recovery by reweighted lq minimization, *IEEE Transactions on Signal Processing*, Vol. 61, Issue 5, 2013, pp. 1165-1170.

[16]. Q. Ling, Y. Xu, W. Yin, Z. Wen, Decentralized low-rank matrix completion, in *Proceedings of the International Conference on Acoustics, Speech, and Signal Processing (ICASSP 2012)*, China, 10-13 March 2012, pp. 213-219.

[17]. M. Julien, Y. Bin, Supervised feature selection in graphs with path coding penalties and network flows, Journal of Machine Learning Research, Vol. 14, August 2013, pp. 2449-2485.

[18]. J. H. Zhang, A. Y. Shi, X. Wang, L. J. Bian, F. C. Huang, L. Z Xu, Self-adaptive image reconstruction inspired by insect compound eye mechanism, *Computational and Mathematical Methods in Medicine*, Vol. 2012, 2012, pp. 101-108.

[19]. J. H. Zhang, C. Zhang, Numerical simulation of flash floods routing based on improved leap-frog method, *Applied Mechanics and Materials*, Vol. 347, Issue 350, 2013, pp. 2173-2177.

[20]. L. Z. Xu, J. H Zhang, J. Y. Wu, X. F. Li, A heterogeneous hybrid tree topology structure of wireless sensor networks for marine environment monitoring, *International Journal of Electronics, Electrical and Communication Engineering*, Vol. 2, Issue 2, 2010, pp. 137-144.

[21]. J. H Zhang, X. Wang, Y. Gu, L. Z. Xu, T. H. Fan, An data correction method for hydrological monitoring based on improved BP neural network, *Applied Mechanics and Materials*, Vol. 380, Issue 384, 2013, pp. 879-883.