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An Energy Effective Adaptive Spatial Sampling Algorithm for WSNs

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Abstract: The objective of environmental observation with WSNs (wireless sensor networks) is to extract the synoptic structures (spatio-temporal sequence) of the phenomena of ROI (region of interest) in order to make effective predictive and analytical characterizations. Energy limitation is one of the main obstacles to the universal application of WSNs and therefore there are a large mass of researches on energy conservation for WSNs. Among them, adaptive sampling strategy is regarded as a promising method to improve energy efficiency in recent years, therefore, many researches are concerning to different kinds of energy efficient sampling scheme for WSNs. In this paper, we dedicate to investigating how to schedule sensor nodes in the spatial region domain by our adaptive sampling scheme so as to reduce energy consumption of sensor nodes. The key idea of this paper is to schedule sensor nodes to achieve the desired level of accuracy by activating sensor system only when necessary to acquire a new set of samples and then prepare to power it off immediately afterwards. By adaptively sampling the region of interest, fewer sensors are activated at the same time. Moreover, only the necessary communications are remaining with this algorithm, so as to achieve significant energy conservation than before. The algorithm proposed in this literature is named as Adaptive Spatial Sampling (ASS) algorithm in short. The simulation results verified that ASS algorithm can outperform traditional fixed sampling strategy. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: WSNs (Wireless Sensor Networks), Adaptive Sampling, Spatial Sampling, Energy Effective.

1. Introduction

WSNs [1] have received considerable academia research attention in present years. WSNs consist of a large number of tiny sensor nodes deployed in a geographical area, and each node is a low-power device that integrates computing, communication and sensing abilities. The key application of WSNs is monitoring physical phenomena and acquiring environment information. With the advancements in hardware miniaturization and integration, it is possible to produce tiny cheap sensor devices that combine sensing with computation, storage, and communication. Availability of such devices has made it possible to deploy them in a networked setting for applications, such as wildlife habitat monitoring [2], wild-fire prevention [3], and environmental monitoring [4], and so on.

Typically, each sensor node collects raw sensory data from phenomenon which is needed to be delivered to the users through network interconnection for further analysis. The simplest way is to permit each sensor node to deliver its raw sensory data to the base station periodically, where the data can be assembled for subsequent analysis. However, this approach results in excessive communication and therefore the energy consumption of certain sensor nodes is very large.

Energy limitation is one of the main obstacles to the universal application of WSNs. In recent years, several energy management schemes have been proposed to reduce network power consumption in the literatures. A detailed survey can be found in [5], which assumes that data acquisition and processing have an energy consumption which is significantly lower than that of communication.

Generally, data acquisition and processing consume energy that is significantly lower than that of communication. Therefore, traditional researches are concerned with how to conserve energy as much as possible by reducing transmission capability. Unfortunately, this assumption does not always hold in a number of practical applications because acquisition times are typically longer than transmission, and moreover there is unusual sophisticated signal process in some particular acquisition process such as multimedia sensor networks.

In this paper, we dedicate to investigating how to schedule sensor nodes in spatial domain by adaptive sampling algorithm so as to reduce energy consumption of sensor nodes. The key idea of this paper is to schedule sensor nodes to achieve the desired level of accuracy by activating sensor system only for the time needed to acquire a new set of samples and then powering it off immediately afterwards, this is also called periodic sensing in some literals. In addition, with the proposed algorithm, we can activate more sensors in non-smooth regions and fewer sensors in the smooth regions to improve accuracy, the same concepts named smooth and non-smooth regions are defined in [6]. By sampling the ROI adaptively, fewer sensors are activated at the same time than usually. Therefore, only necessary communications are remained, so as to achieve significant energy conservation. These fields where there are too many awaking sensor nodes than necessary are called as over-sampled region, while there are fewer awaking sensor nodes than necessary are called as under-sampled regions. However, how to move sensor node from over-sampled regions to the under-sampled regions is another research topic and doesn't mention in this paper. In this paper, we propose an energy effective adaptive sampling algorithm considering spatial correlation in each cluster for WSNs, which is named as Adaptive Spatial Sampling (ASS) algorithm.

The following paper is organized as follows. Section II introduces some related works. Section III presents ASS algorithm in details. Simulation environment and results are finally presented in Section IV. Section V is the conclusion of this paper.

2. Related Works

The problem of energy efficient transmission has been investigated with certain technology such as mathematical optimization in the current literatures [7-8]. However, most researches are concerned with energy efficient transmission, not energy efficient sampling. Unfortunately, data acquisition or sampling will consume much more energy than data transmission in a number of practical applications because acquisition times are typically longer than transmission, especially in some sophisticated acquisition process such as multimedia sensor networks. Therefore, some researchers have being investigated in energy efficient sampling scheme for WSNs.

Temporal correlation was used in an adaptive sampling algorithm for minimizing the energy consumption of a snow sensor [9]. A similar approach has been suggested in [10], where the sampling rate is adapted based on the outcome of a Kalman filter. Adaptive sampling is also proposed in [11], in which a flood alerting system is presented. The system includes a flood predictor that is used to adjust the reporting rate of individual node. Other researches illustrated in [12-19] are discussed on how to perform energy efficient sensory data sampling.

All the above energy efficient sampling algorithms are dedicated to conserving energy of sensor nodes. As a result, these schemes are named as adaptive sampling algorithms. Fig. 1 illustrates categories of current adaptive sampling algorithms, which are concluded in a lot of literatures by us.

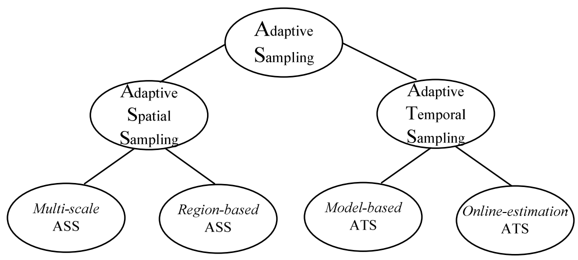


Fig. 1. Sampling category.

Generally, adaptive sampling schemes can be divided in two categories: one is adaptive spatial sampling scheme and the other is adaptive temporal sampling scheme. Adaptive spatial sampling schemes assure monitor accuracy using region location adjustment or wake-up state scheduling. Adaptive temporal sampling schemes assure monitoring accuracy using sampling frequency adjustment or online model estimation of signal tendency. Certainly, there are a few mutational adaptive sampling schemes such as multi-scale adaptive sampling, which provides multi-resolution sensory information as possible as required.

In this paper, we dedicate to studying adaptive spatial sampling by adaptively sampling ROI and propose a novel adaptive spatial sampling algorithm. By adaptively sampling the ROI, fewer sensors are activated at the same time. As a result, the total communication quantities are reduced and therefore it results in significant energy conservation for whole networks.

3. ASS Algorithm

3.1 Network Model and Algorithm Overview

It is assumed that a large number of energy constrained sensor nodes are employed in a rectangle area randomly in our network model of WSNs. Therefore, the discussed network topology of WSNs can be represented by an undirected simple graph $G=(V(G),E(G))$ in the plane, where $V(G)=\{v_1,v_2,...,v_n\}$ denotes the set of nodes and $E(G)$ denotes the set of edge links in WSNs. A unique ID is assigned to each sensor node, moreover, the area that each node covered is assumed to be a disk centered at the transmitter. The power needed to support a link uv is assumed to be $\|uv\|^{\beta}$, where $\|uv\|$ denotes the Euclidean distance between u and v, and β denotes a real constant between 2 and 5 depending on transmission environment.

In this paper, it is assumed that a higher node density in WSNs and the sensory data sets between sensor nodes close to each other are always strong correlative. Therefore, the practical spatial data correlation model described in [20] can be introduced into this paper, where sensor nodes can achieve various amounts of data aggregation based on their distance of separation. Let S be a vector of n samples of the measured random field returned by n sensor nodes. Let $\hat{S}$ be a representation of S and $d(S,\hat{S})$ be a distortion measure. With the mean square error as the distortion measure $d(S,\hat{S})=\left\|S-\hat{S}\right\|^2$ and with the constraint,

$$E(\left\|S-\hat{S}\right\|^2)<D \tag{1}$$

For the purpose of illustration, S is denoted as a spatially correlated random Gaussian vector in this paper. In general case for traditional WSNs, $\hat{S}$ and S denote sensory data of neighbor sensor nodes respectively. Because of strong relevance of sensory data, the distortion measure between neighbor sensor nodes is very small. Therefore, there is a lot of data redundancy with traditional sampling scheme. For this reason the proposed ASS algorithm is investigated. The preliminary approach of adaptive spatial sampling is described with an example in Fig. 2. There are only 7 sensor nodes with ID 1 to 7 in the square ROI. There are two unique and independent collections {Node 1, Node 2, Node 3, Node 4} and {Node 5, Node 6, Node7}, which can cover the whole square ROI. The preliminary approach schedules the two collections one by one to conserve energy while guaranteeing sampling range and precision. In the proposed ASS approach, we use a different selection criterion to decide sampler and non-sampler.

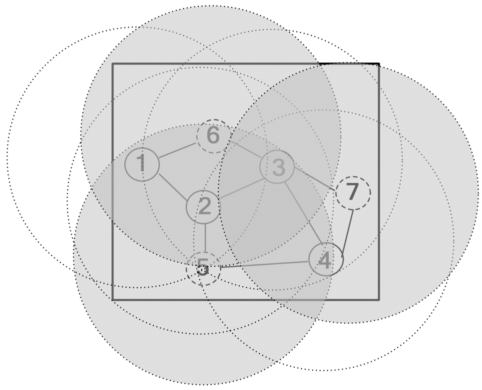


Fig. 2. Over sampling in spatial region.

There are three major procedures that form our ASS approach. The first component is in charge of constructing clusters within the networks and the adaptive spatial sampling is operated within each cluster and thus leads to a distributed manner. The second component of ASS is facilitating the selection of the nodes to serve as distinct sampler which is defined as spatial-correlation based sampler collection selection. The final component of ASS is sampler and non-sampler scheduling, which is used to collect sensory data and perform collection switching.

3.2. Cluster Construction

In the first phase, sensor nodes establish different clusters autonomously and elect CH in a fully distributed fashion. Our design proposes a simple distributed sensory correlated clustering algorithm to establish one-hop clusters, which is described in below. First of all, the probability value of sensor node to elect CHs is defined as:

$$\omega_i = p\frac{E(i)\times|N_i|}{\sum_{j\in N_i}E(j)}, \tag{2}$$

where $E(i)$ and $E(j)$ denote the residual energy of sensor node i and j respectively, $|N_i|$ denotes its one-hop sensor node degree including itself and $p\in(0,1]$ denotes the percent of cluster heads. It is obvious that the probability value is positive correlation with node residual energy. More specially, sensor nodes with more residual energy within all the neighbor nodes should be chosen to be cluster heads with higher probability, thus implementing maximum energy first principle. Each sensor node is elected randomly to be cluster head by itself with probability ω_i. After cluster heads election, each cluster member sensor node will select the nearest CH and join in that cluster. It is required that the distance between each cluster member and its nearest CH must be smaller than maximal transmission power radius $R_{\max}$. The detailed clustering algorithm is described in Fig. 3.

$\# Node\ i\ clustering\ procedure;$
$begin$
$Broadcast(ID, position, E(i));$
$Receive\ beacon\ from\ all\ neighbour\ nodes\ j \in N_i;$
$Calculate\ probability\ value\ to\ be\ Cluster\ Head;$

$$\omega_i = p \frac{E(i) \times |N_i|}{\sum_{j \in N_i} E(j)};$$

$if\ (rand(0,1) \geq \omega_i)\{$
$\quad Node\ i\ becomes\ Cluster\ Head(CH);\}$
$for(each\ non\text{-}CH\ node\ i)\{$
$Node\ i\ join\ in\ nearest\ Cluster\ Head;\}$
end

Fig. 3. Pseudo-code of sensory correlated clustering algorithm.

The first system-wide parameter p is the percent value of cluster heads and the practical value in the range (0, 0.2] and defines the average probability to be elected as cluster heads. Generally, any region-based clustering algorithms are appropriate for ASS approach, the above cluster construction is a typical one of them. The detailed constitutions of these interactive messages are omitted for simpleness.

3.3. Sampler Collection Selection

The above cluster formation follows two metrics: sensor nodes that are similar to each other in terms of sensory data should be clustered into together and sensor nodes that are close to each other should be clustered into together. Moreover, the remaining important phase is to construct distinct sampling collections within each cluster. The goal of further dividing each cluster into sub-clusters is to facilitate the election strategy of the sensor nodes to serve as samplers and non-samplers. As we known, higher correlations among sensor nodes within a cluster typically lead to higher sampling accuracy and quality. However, this will lead to low efficiency at aspect of energy at the same time. In this paper, we assume the spatial region is almost over-sampling and the ROI is covered by at least two distinct collections, therefore, sampler collection selection algorithm will be introduced in ASS.

First of all, we create a correlation matrix for each twin collection i and collection j such that, for any two nodes u and v in the collection, C_{ij} is equal to the correlation between the series D_u and D_v. Formally,

$$C_{ij} = \left| \frac{[D_u - E(D_u)] \times [D_v - E(D_v)]^T}{L \times \sqrt{Var(D_u)} \times \sqrt{Var(D_v)}} \right|, \tag{3}$$

where L denotes the length of the series and the symbol ^{T} represents matrix transpose. The correlation values are always in the range [0, 1]. Therefore, $C_{ij} = 1$ implies that two series are strong correlated and $C_{ij} = 0$ implies that two series are not correlated. Each cluster head uses sampled sensory data for all the nodes within its cluster to capture the temporal and spatial correlations using the above correlation matrix and calculate sub-clusters so that the nodes whose sensory data highly correlated are put into different sub-clusters. Therefore, the sensory data of two sub-clusters are strong similar so as to can be reconstruct with each other. The objective of sampler collection selection is defined as such optimal problem in Fig. 4. As we can see in the Fig. 4, the key idea is to elect two collections from collection set which is satisfied with ROI coverage minimal correlation, thus lead to higher energy efficiency while guaranteeing monitor accuracy.

Given a set of Collections $\{i, j | i, j \in 1,2,...,N\}$

Correlation Matrix C:

$$C_{ij} = \left| \frac{[D_u - E(D_u)] \times [D_v - E(D_v)]^T}{L \times \sqrt{Var(D_u)} \times \sqrt{Var(D_v)}} \right|$$

Minimize (C_{ij})

Subject to:

Collection i and Collection j Statisfied ROI Coverage

Fig. 4. Optimal objective of sampler collection selection.

Once the sampler nodes are determined, only these nodes delivery sensory reading to the base node and the values of the non-sampler nodes will be predicted at the cluster head by using numerical prediction model such as AR model. Two-stage AR prediction model of sensory data is illustrated:

$$X_{i+1} = \alpha(X_i - \overline{X}) + \beta(X_{i-1} - \overline{X}) + e_{i+1}, \tag{4}$$

where α and β denote coefficients of AR prediction model respectively, e_{i+1} denotes predictive error value, $\overline{X}$ denotes the mean value of historical sensory data. The coefficients of AR prediction model can be calculated with such formulations:

$$\alpha = \frac{\rho_1(1-\rho_2)}{1-\rho_1^2} \quad \beta = \frac{\rho_2 - \rho_1^2}{1-\rho_1^2} \tag{5}$$

$$\rho_k = \frac{\sum_{i=1}^{N-k} (X_i - \overline{X})(X_{i+1} - \overline{X})}{\sum_{i=1}^{N} (X_i - \overline{X})^2} \tag{6}$$

In fact, these above operations are executed within each cluster in a distributed manner. The CH maintains AR prediction model and divides non-CH nodes into sampler nodes and non-sampler nodes.

Besides, the above two distinct sub-clusters can extend to multiple sub-clusters with sub-cluster granularity. Therefore, the second system-wide γ parameter is sub-cluster granularity which defines the average size of the sub-clusters. Intuitively, larger values of γ may decrease the prediction quality because it will result in larger sub-cluster with potentially low overall correlation between its members. On the other hand, values that are too small will decrease the prediction quality since the opportunity to exploit the spatial correlations fully will the missed with very small γ. In this paper, we defined γ as half nodes of each cluster, that is to say, each cluster is divided into two sub-clusters. Therefore, the key idea is to select optimal sub-clusters by each CH, thus lead to higher energy efficiency while guaranteeing sampling accuracy.

3.4 Sampler and Non-sampler Scheduling

In the section of sampler collection scheduling, two distinct and completed sensor node sets are elected to establish sampling nodes alternative. Two sampler sets switch from one to the other following with the traditional TDM (Time Division Multiplexing) scheme. The paper divides the whole working process into different rounds. One set of sampler nodes transmit sensory data to the sensor head and afterwards turn off to the idle state, and the other set of sampler nodes wake up to perform monitoring at each round. The sensory data of sleeping nodes set are approach by awaking nodes set with CH by the proposed AR prediction model. The error between measured value and predictive value can be controlled because of minimal relevance between two sub-clusters. In a word, the monitoring coverage and accuracy can be guaranteed at the same time.

4. Performance Evaluation

The sensory data used in this paper is derived from Intel Berkeley Research lab [21]. There are 54 sensor nodes deployed in the lab between February 28th and April 5th, 2004, and each location labeled sensor ID value is illustrated in Fig. 5. Four parameters including temperature, humidity, light and voltage are monitored. Nevertheless, only single temperature value is used in our simulations because there are similar trends between different properties including temperature, humidity and light. The Fig. 6 describes the clear correlations between three properties.

We assumed that each sensor node has the same initial energy 10J and energy consumption model is described in Ref. [21]:

$$E_i^{tx} = (e_i^t + \varepsilon_{amp} \times d^2) \times m;\ E_i^{rx} = e_i^r \times m \tag{7}$$

$$e_i^t = e_i^r = 50 \text{ nJ/bit} \quad \varepsilon_{amp} = 100 \text{ pJ/(bit} \cdot \text{m}^2) \tag{8}$$

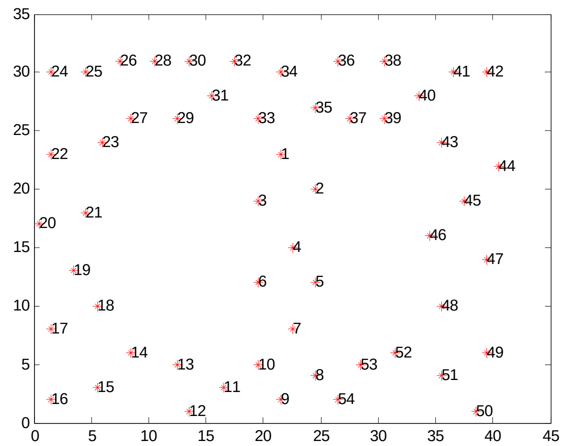


Fig. 5. Sensor locations of Intel Berkeley research lab.

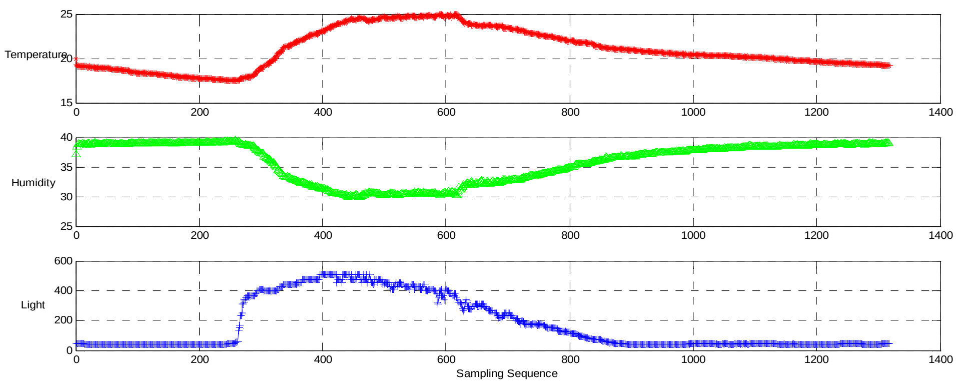


Fig. 6. The correlations between different properties.

Simulation parameters are listed in below: percent value of cluster heads p value in the range {0.05, 0.1, 0.15, 0.2}, and the sub-cluster granularity γ is the integer value of such equation $(54 \times p / 2)$, thus ensure at least two sub-clusters in each cluster. The simulation process will operate on 100 rounds to obtain the average results.

The simulation results are illustrated in below: the clustering results of different cluster head percent are described in Fig. 7. Moreover, similarity comparison of sensory tendency between different days is illustrated in Fig. 8, and we can find that they have almost same tendency, thus verify the temporal correlation. In the spatial correlation domain, the correlation values between Sensor 1 and Sensor 2 (strong correlation coefficient is 0.9393 at *W*=100), Sensor 1 and Sensor 16 (weak correlation coefficient is 0.7199 at *W*=100) at different window size are described in Fig. 9. It is obvious that the strong spatial and temporal correlation of sensory data from these results.

Moreover, considering spatial correlation between sensor nodes, the energy conservation rate improves with our proposed algorithm because fewer sampler nodes are selected. The energy conservation ratio approaches to 0.5 because only half sensor nodes are working at same time approximately. However, this result does not take additional costs into account, such as extra communication cost when clustering, extra AR model processing cost by each CH and etc. The sensory data of non-sampler nodes will be substituted and reconstruct with that of sampler nodes, and the prediction error of mote 17 at Feb. 28 can be guaranteed with the proposed ASS algorithm in Fig. 10.

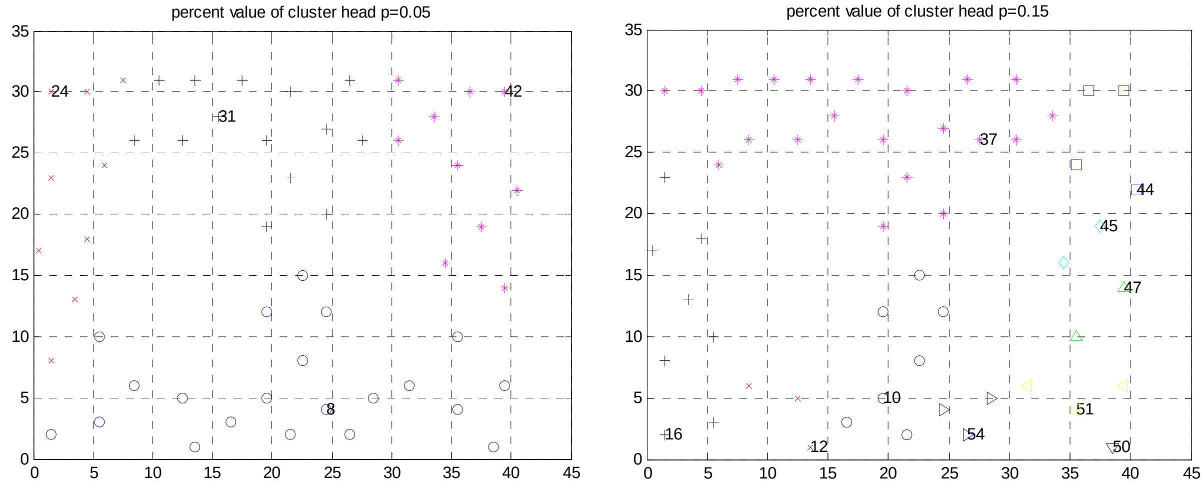


Fig. 7. Clustering results of different cluster head percents.

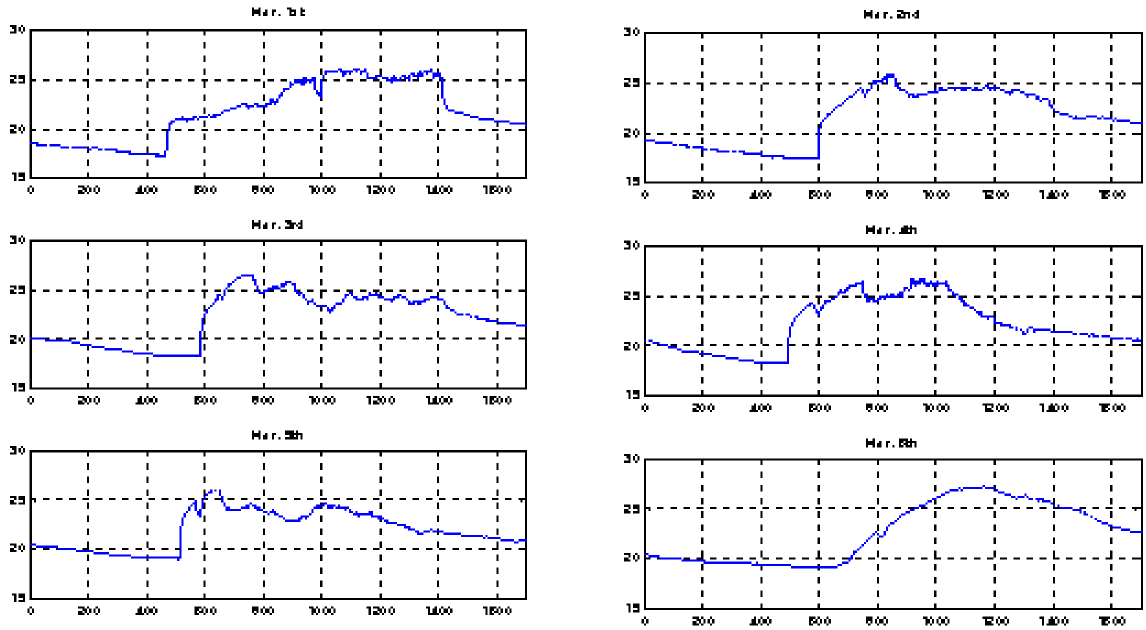
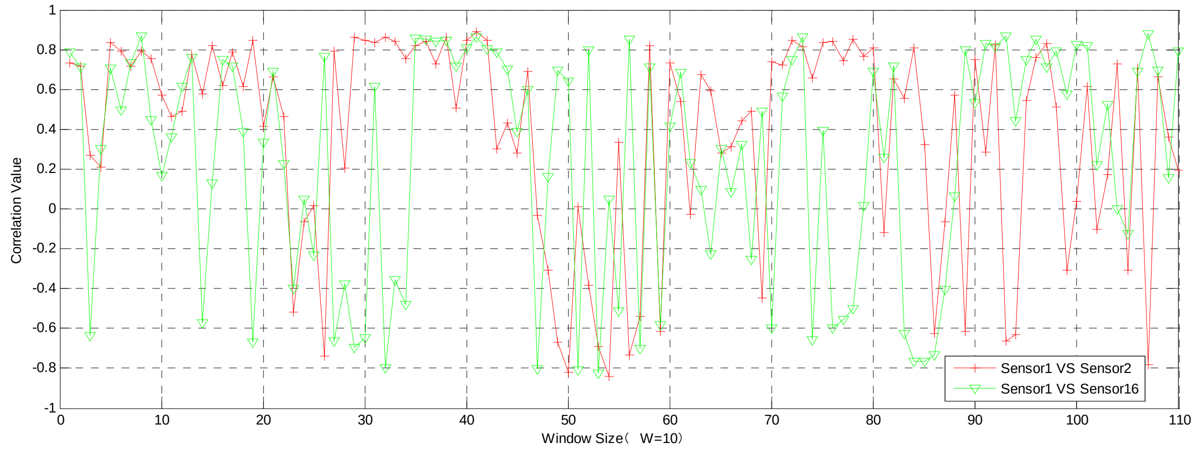
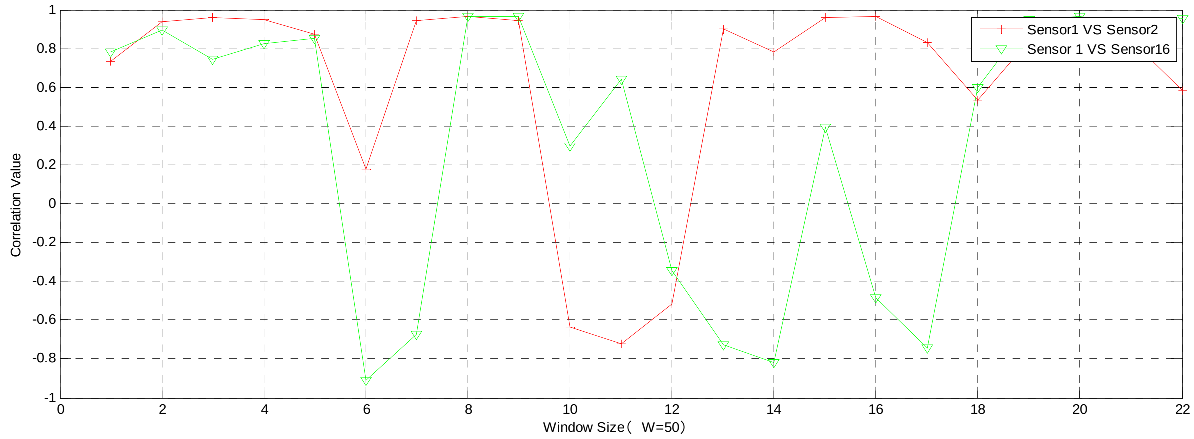


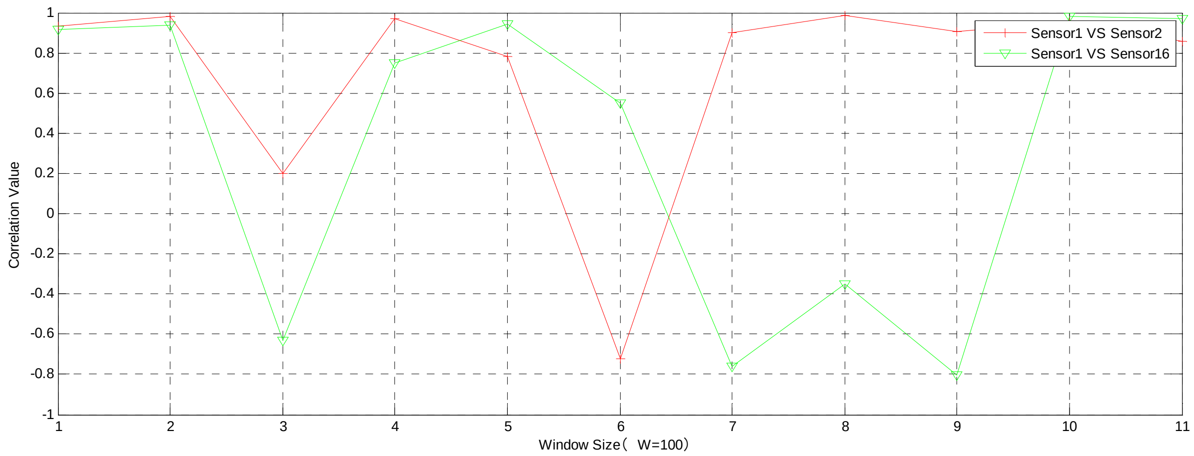
Fig. 8. Similarity comparison of tendency between different days.



(a) Window Size *W*=10



(b) Window Size *W*=50



(c) Window Size *W*=100

Fig. 9. Correlation values between Sensor 1 and Sensor 2, Sensor 1 and Sensor 16 at different window size.

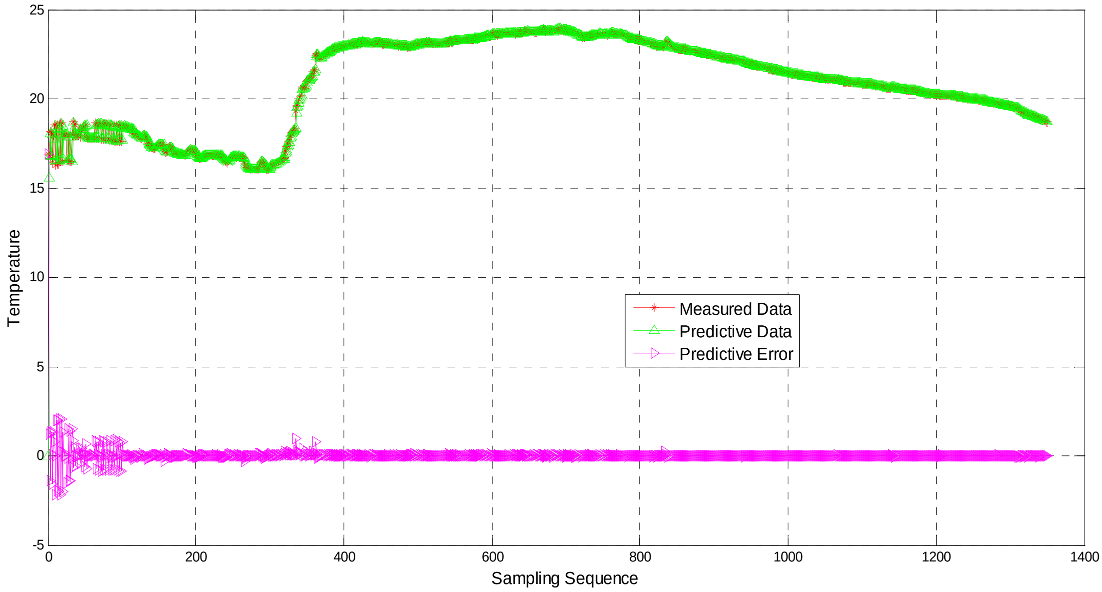


Fig. 10. Prediction error.

5. Conclusions

In this paper, we proposed an energy efficient adaptive sampling algorithm which schedules sensor nodes in spatial region so as to reduce energy consumption. With adaptive spatial sampling in each cluster of region of interest (ROI), fewer sensors are activated at the same time. Moreover, the required communications are reduced, so as to achieve significant energy conservation. The simulation results of this paper verified the efficiency of ASS approach. As we known, this is a novel trail for energy conservation for WSNs. In our future work, we will discuss multi-dimensional adaptive spatial sampling scheme.

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References

[1]. F. Akyildiz, W. Su, Y. Sankarasubramaniam, E. Cayirci, A survey on sensor networks, *IEEE Communication Magazine*, Aug. 2002, pp. 102-114.

[2]. Habitat Monitoring on Great Duck Island [CP/OL], http://www.greatduckisland.net/, 2014.

[3]. The Firebug Project [CP/OL]. http://firebug.sourceforge.net, 2014.

[4]. James Reserve Microclimate and Video Remote Sensing [CP/OL]. http://www.cens.ucla.edu, 2014.

[5]. G. Anastasi, M. Conti, M. Di Francesco, *et al.*, Energy conservation in wireless sensor networks, *Ad Hoc Networks*, Vol. 7, No. 3, May 2009, pp. 537-568.

[6]. Cai Wen-Yu, Zhang Mei-Yan, Jiang Yi-Bo, Coverage sampling technology based on spatial temporal joint union for wireless sensor networks, *Chinese Journal of Sensors and Actuators*, Vol. 26, No. 2, 2013, pp. 260-265.

[7]. A. Masoum, N. Meratnia, P. J. M. Havinga, An energy-efficient adaptive sampling scheme for wireless sensor networks, in *Proceedings of the 8th IEEE International Conference on Intelligent Sensors, Sensor Networks and Information Processing*, Melbourne, 2013, pp. 231-236.

[8]. R. Cristescu, B. Beferull-Lozano, M. Vetterli, On network correlated data gathering, in *Proceedings of the IEEE INFOCOM*, 2004, pp. 2571-2582.

[9]. C. Alippi, G. Anastasi, C. Galperti, *et al.*, Adaptive sampling for energy conservation in wireless sensor networks for snow monitoring applications, in *Proceedings of the IEEE MASS*, 2007, pp. 1-6.

[10]. Xin Qi, Keally M, Gang Zhou, *et al.*, AdaSense: Adapting sampling rates for activity recognition in Body Sensor Networks, in *Proceedings of the IEEE 19th Real-Time and Embedded Technology and Applications Symposium (RTAS)*, Philadelphia, 2013, pp. 163-172.

[11]. J. Zhou, D. De Roure, FloodNet: Coupling adaptive sampling with energy aware routing in a flood warning system, *Computer Science Technology*, Vol. 22, No. 6, Jan. 2007, pp. 121-130.

[12]. C. Aplippi, G. Anastasi, M. D. Francesco, *et al.*, An adaptive sampling algorithm for effective energy management in wireless sensor networks with energy-hungry sensors, *IEEE Transactions on Instrumentation and Measurement*, Milan, Vol. 59, No. 2, 2010, pp. 335-344.

[13]. M. Rahimi, M. Hansen, W. J. Kaiser, *et al.*, Adaptive sampling for environmental field estimation using robotic sensors, in *Proceedings of the IEEE/RSJ IROS*, 2005, pp. 3692-3698.

[14]. C. Vigorito, D. Ganesan, A. Barto, Adaptive control of duty cycling in energy-harvesting wireless sensor

networks, in *Proceedings of the IEEE SECON*, 2007, pp. 21-30.

[15]. J. Kho, A. Rogers, N. R. Jennings, Decentralised adaptive sampling of wireless sensor networks, in *Proceedings of the ATSN*, 2007, pp. 1-8.

[16]. V. Sachidananda, A. Khelil, D. Noack, *et al*., Information quality aware co-design of sampling and transport in wireless sensor networks, in *Proceedings of the 6th Joint IFIP Wireless and Mobile Networking Conference (WMNC'13)*, USA, 2013, pp. 1-8.

[17]. B. Gedik, L. Liu, P. S. Yu, ASSP: An adaptive sampling approach to data collection in sensor networks, *IEEE Trans. Parallel Distributed Systems*, Vol. 18, No. 12, Dec. 2007, pp. 1766-1783.

[18]. Rajeev Ranjan, Shirshu Varma, Collision-Free Time Synchronization for Multi-Hop Wireless Sensor Networks, *Journal of Computational Intelligence and Electronic Systems*, Vol. 1, Issue 2, 2012, pp. 200-206.

[19]. Divya Lohani, Shirshu Varma, Distributed Computing Paradigms for CSIP in Wireless Sensor Networks: A Comparative Review, *Journal of Computational Intelligence and Electronic Systems*, Vol. 1, Issue 2, 2012, pp. 207-212.

[20]. M. Lotfinezhad, B. Liang, Effect of partially correlated data on clustering in wireless sensor networks, in *Proceedings of the IEEE Int. Conf. SECON*, Oct. 2004, pp. 172-181.

[21]. Intel Berkeley Research Lab [CP/OL]. http://www.intel-research.net/berkeley/index.asp, 2014.

[22]. G. Anastasi, M. Conti, M. Di Francesco, *et al*., Energy conservation in wireless sensor networks, *Ad Hoc Networks*, Vol. 7, No. 3, May 2009, pp. 537-568.
