2012 International Conference on Computer Technology and Science (ICCTS 2012)
IPCSIT vol. 47 (2012) © (2012) IACSIT Press, Singapore
DOI: 10.7763/IPCSIT.2012.V47.61

An Energy Effective Adaptive Spatial Sampling Algorithm for Wireless Sensor Networks

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Abstract. The objective of environmental observation with wireless sensor networks is to extract the synoptic structures (spatio-temporal sequence) of the phenomena of region of interest (ROI) in order to make effective predictive and analytical characterizations. Energy limitation is one of the main obstacles to the universal application of wireless sensor networks. Certainly, there are many researches concerned to energy efficient scheme in wireless sensor networks. In this paper, we dedicate to investigating how to schedule sensor nodes in spatial region by adaptive sampling so as to reduce energy consumption. Adaptive sampling strategy is regarded as a promising method for improving energy efficiency in recent years. 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. By adaptively sampling the 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 algorithm proposed in this literature is named as Adaptive Spatial Sampling (ASS) algorithm.

Keywords: Wireless Sensor Networks; Adaptive Sampling; Spatial Sampling; Energy Effective

1. Introduction

Wireless sensor networks [1] have received considerable academia research attention in present years. Wireless sensor networks consist of a large number of tiny sensor nodes deployed over a geographical area, each node is a low-power device that integrates computing, communication and sensing abilities. The key application of wireless sensor networks 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 the energy consumption is large. Energy limitation is one of the main obstacles to the universal application of wireless sensor networks. In recent years, several energy management schemes have been proposed for reducing the 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 conserving energy as much as possible by reducing transmission capability. Unfortunately, this assumption does not always hold in a

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number of practical applications because acquisition times are typically longer than transmission or some sophisticated acquisition process such as multimedia sensor networks.

In this paper, we dedicate to investigating how to schedule sensor nodes in spatial region by adaptive sampling so as to reduce energy consumption. 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, 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 adaptively sampling the region of interest (ROI), fewer sensors are activated at the same time. Therefore, the necessary communications are reduced, 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, and 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 wireless sensor networks, which is named as Adaptive Spatial Sampling (ASS) algorithm. The paper is organized as follows. Section 2 introduces some related works. Section 3 presents ASS algorithm in details. Simulation environment and results are finally presented in Section 4. Section 5 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 or some sophisticated acquisition process such as multimedia sensor networks. Therefore, some researchers have been investigating energy efficient sampling scheme.

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 [12-17] are discussing 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.

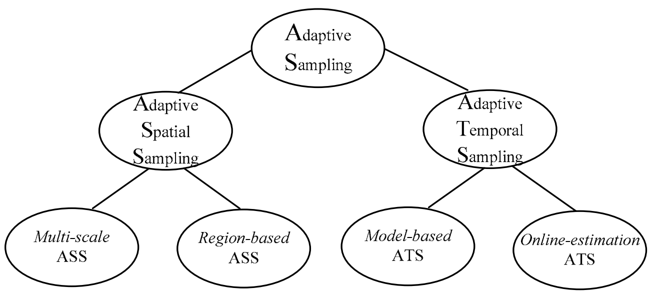

Fig.1: Sampling Category

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 region of interest (ROI) and propose a novel adaptive spatial sampling algorithm. By adaptively sampling the region of interest, fewer sensors are activated at the same time. As a result, the necessary communications are reduced and result in significant energy conservation.

3. ASS Alogorithm

Before algorithm description, system model and architecture of wireless sensor networks are assumed, where a large number of energy constrained sensor nodes are employed randomly. The topology of wireless sensor networks 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 wireless sensor networks. 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 the wireless transmission environment.

In this paper, it is assumed that a higher node density in wireless sensor networks. Therefore, the practical spatial data correlation model described in [18] 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 $d(S,\hat{S})=\|S-\hat{S}\|^2$ and with the constraint,

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

For the purpose of illustration, S is denoted as a spatially correlated random Gaussian vector in this paper.

Therefore, the main approach of ASS is described with an example in Fig.2. There are simple 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 ASS schedules the two collections one by one to save energy while guaranteeing sampling range and precision.

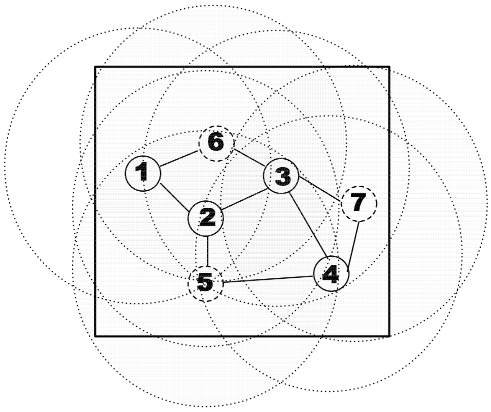

Fig.2: Over Sampling Spatial Region

There are three components that form ASS approach, which are also defined as three procedures of ASS. The first component is constructing clusters within the networks and the adaptive spatial sampling is operated within clusters 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 scheduler, which is used to collect sensory data and perform collection switching.

3.1. 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 clustering algorithm named maximum energy &

minimum distance (MEMD) clustering algorithm to establish one-hop clusters, which is described in below. First of all, the weight value of sensor node to elect CHs is defined as:

$$\omega(i) > \omega(j) \Leftrightarrow E(i) > E(j) \text{or } E(i) = E(j) \;\&\&\; id(i) > id(j) \tag{2}$$

where $E(i)$ and $E(j)$ denote the residual energy of sensor node i and j respectively, $id(i)$ and $id(j)$ denote ID number of sensor node i and j respectively. It is obvious that the defined weight is positive correlation with node residual energy, and the ID value of sensor node is the second factor. 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. 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 smaller than maximal transmission power radius $R_{\max}$. The MEMD clustering algorithm is described in Fig.3, and an example of MEMD clustering algorithm is shown in Fig.4.

 # Node i clustering procedure;
begin
Broadcast$(ID, position, E_R)$;
Receive beacon from all neighbour nodes $j \in N_i$;
Compare the weight value with ID and E_R;
if $(\omega_i \geq \omega_j \quad \forall j \in N_i)$\{
  Node i becomes Cluster Head(CH);\}
else\{
  $\omega_k > \omega_j \quad \forall k, j \in N_i$
  Vote Node k to become Cluster Head(CH);
\}
for(*each non-CH node i*)\{
Node i join in nearest Cluster Head;\}
end

Fig.3: Pseudo-code of Max Energy & Min Distance clustering algorithm

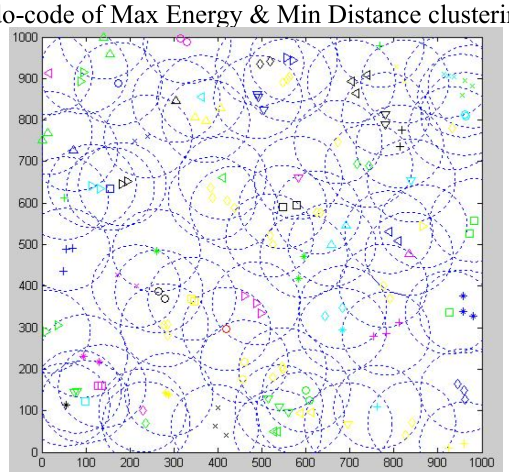

Fig.4: Clustering Results (400 sensor nodes randomly distributed in a region of 1000×1000 and Rmax=100)

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.

3.2. Sampler Collection Selection

The most important phase is to construct distinct sampling collections within each cluster. As we know, higher correlations among sensor nodes within a cluster typically lead to higher monitoring accuracy. 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. It is assumed that any two collections are completed, which means that any sensor nodes belong to one collection or the other collection.

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 ^{T} represents matrix transpose. The correlation values are always in the range [0, 1], and a value 0 implies that two series are not correlated. As a result, the objective of sampler collection selection is defined as such optimal problem in Fig.5. As we can see in the Fig.5, the key idea is to select two collections from collection set which satisfied with ROI coverage minimal correlation, thus lead to higher energy efficiency while guaranteeing monitoring accuracy. Besides, how to find coverage sets in wireless sensor networks is the coverage control problem and has been discussed in a lot of papers therefore will not be mentioned again in this paper.

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

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.5: Optimal Objective of Sampler Collection Selection

3.3. Sampler and non-Sampler Scheduler

In the section of sampler collection selection, two distinct and completed sensor nodes sequence are elected to form sampler alternative. Two sampler sets switch from one to the other following residual energy level. If the residual energy of one sampler set falls down to a certain level, then this 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. Therefore, 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 [19]. There are 54 sensor nodes deployed in the lab between February 28th and April 5th, 2004, and the location is illustrated in Fig.6. Four parameters including temperature, humidity, light and voltage are monitored.

In our performance evaluation, spatial correlation matrixes of sensor nodes and each twin collection are calculated first, and then clusters are formed by MEMD algorithm, after that adaptive spatial sampling algorithm is introduced, finally, energy efficient factor is evaluated comparing with traditional raw data transmission and traditional clustering algorithm. Considering for space limitation, the detailed results will be exploded in the full version of this paper.

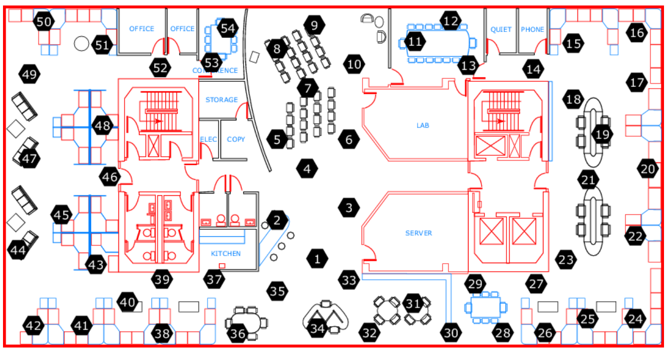

Fig.6: Intel Berkeley Research lab

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. By adaptively sampling the 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 full version paper verified the efficiency of ASS approach.

6. References

[1] F. Akyildiz, W. Su, Y. Sankarasubramaniam and E. Cayirci. "A survey on sensor networks, " IEEE communication Magazine, Aug 2002:102-114.

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

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

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

[5] G. Anastasi, M. Conti, M. Di Francesco, and A. Passarella, "Energy conservation in wireless sensor networks," Ad Hoc Networks, vol. 7, (no. 3), pp. 537-568, May 2009.

[6] R. Willett, A. Martin, and R. Nowak. Backcasting, "A new approach to energy conservation in sensor networks," Technical Report TRECE-03-4, University of Wisconsin, 2003. Available at http://www.cae.wisc.edu/willett/papers/WillettTRECE-03-4.pdf.

[7] F. Ordonez and B. Krishnamachari, "Optimal information extraction in energy-limited wireless sensor networks," IEEE J. Sel. Areas Commun. Special Issue Fundamental Performance Limits Wireless Sensor Networks, vol. 22, no. 6, pp. 1121-1129, Aug. 2004.

[8] R. Cristescu, B. Beferull-Lozano, and M. Vetterli, "On network correlated data gathering," in Proc. IEEE INFOCOM, 2004, pp. 2571-2582.

[9] C. Alippi, G. Anastasi, C. Galperti, F. Mancini, and M. Roveri, "Adaptive sampling for energy conservation in wireless sensor networks for snow monitoring applications," in Proc. IEEE MASS 2007, 2007, pp. 1-6.

[10] A. Jain and J. Y. Chang, "Adaptive sampling for sensor networks," in Proc. International DMSN 2004, 2004, pp. 10-16.

[11] J. Zhou and D. De Roure, "FloodNet: Coupling adaptive sampling with energy aware routing in a flood warning system," J. Computer Science Technology, vol. 22, (no. 6), pp. 121-130, Jan 2007.

[12] R. Willett, A. Martin, and R. Nowak, "Backcasting: Adaptive sampling for sensor networks," in Proc. IPSN 2004, 2004, pp. 124-133.

[13] M. Rahimi, M. Hansen, W. J. Kaiser, G. S. Sukhatme, and D. Estrin, "Adaptive sampling for environmental field estimation using robotic sensors," in Proc. IEEE/RSJ IROS 2005, 2005, pp. 3692-3698.

[14] C. Vigorito, D. Ganesan, and A. Barto, "Adaptive control of dutycycling in energy-harvesting wireless sensor networks," in Proc. IEEE SECON 2007, 2007, pp. 21-30.

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

[16] A. Deshpande, C. Guestrin, S. Madden, J. M. Hellerstein, and W. Hong, "Model-driven data acquisition in sensor networks," in Proc. VLDB 2004, 2004, pp. 588-599.

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

[18] M. Lotfinezhad and B. Liang, "Effect of partially correlatied data on clustering in wireless sensor networks," in Proc. IEEE Int.Conf SECON, Oct. 2004, pp.172-181.

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