Adaptive Data Aggregation for Clustered Wireless Sensor Networks

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Abstract. Wireless sensor network (WSN) has emerged as an event-driven paradigm based on the collective effort of numerous sensing nodes. Due to the dynamic topology and random deployment, incorporating adaptive behavior into protocols in WSNs is important. Hence, we propose an adaptive data aggregation (ADA) scheme for the clustered WSNs. In ADA scheme, the temporal aggregation degree controlled by the reporting frequency at sensor nodes and the spatial aggregation degree controlled by the aggregation degree at Cluster Heads (CHs) are determined by the current scheme state according to the observed reliability. Furthermore, the ADA scheme is mainly performed at the sink node, with a few functions at CHs and sensor nodes. Performance results show that the scheme state converges to the desired reliability starting from any initial state.

1 Introduction

Wireless Sensor Networks (WSNs) have emerged as a new information-gathering paradigm relying on the collective effort of numerous sensor nodes. The ultimate goal of a WSN is to detect the specified interest event in a sensor field. Since the detection range of the sensor nodes often overlaps, the same event is usually reported by numerous sensor nodes, which leads to the data redundancy. In-network data aggregation has been proposed as an essential paradigm for routing in WSNs [1].

WSNs are severely energy-constrained. And replacing batteries on up to thousands of sensor nodes in possibly harsh terrain is infeasible. These necessitate devising the energy conserving solutions for some traditional wireless problems [2]. To ensure the scalability and increase the efficiency of network operations, clustering approaches have become an emerging technology for building scalable, robust, energy-efficient WSN applications [3]. Efficient data aggregation scheme is also an essential candidate for the clustered WSNs, where data aggregation is executed parallel at the Cluster Heads (CHs).

J. Indulska et al. (Eds.): UIC 2007, LNCS 4611, pp. 475–484, 2007.

Almost all of the clustering and data aggregation protocols presented in the literature aim to prolong the network lifetime. WSNs exhibit complex distributed behavior rendering the static pre-configuration useless. Therefore, it is important to incorporate adaptive behavior into the protocols in such dynamic networks. On the other hand, WSNs are envisioned to consist of many inexpensive sensor nodes, each with limited sensing, computing and wireless communicating capabilities. It is necessary to minimize the functions of the data aggregation required at sensor nodes and shift the burden to the resource-rich sink node. With these motivations, we proposed an Adaptive Data Aggregation (ADA) scheme for the clustered WSNs. In the proposed scheme, the reporting frequency at sensor nodes and the aggregation degree at CHs are configured by the current scheme state relying on the observed reliability. In addition, most functions of ADA scheme are performed at the sink node, which a little part is implemented at CHs and sensor nodes.

2 Related Work

In the last few years, many clustering and hierarchical structure schemes aiming to improve energy efficiency, such as LEACH [5], HEED [6], and so on, have been proposed for ad hoc and sensor networks. Our work does not address the clustering protocol, just utilizes the clustering architecture. Our ADA scheme can be combined with any proposed clustering protocol.

Because of its well-known energy efficiency properties, data aggregation techniques have been extensively investigated, and many data aggregation algorithms targeting different sensor network scenarios have been proposed. Directed diffusion is a data-centric architecture where sink node broadcasts interests for the relevant data [1]. Sensor nodes producing relevant information respond and data paths back to the sink node are formed. Data is aggregated when a node is part of various data paths. SPIN does not really use an explicit aggregation mechanism [7]. In [8], Xue et al. addressed the problem of maximizing lifetime routing for data aggregation in WSNs and presented a tree-based approximation algorithm. In [9], we presented a novel data aggregation scheme in clustered WSNs, which used the meta-data negotiation to improve the energy efficiency. Many other data aggregation schemes exist. Our ADA scheme, distinguishes itself from existing solutions in that the spatial and temporal aggregation degree is adaptive to the dynamic state of WSNs via the interaction between the sink node and the CHs.

Several WSN papers addressed the need for incorporating adaptive behavior into the protocols. SPIN makes adaptive decisions to participate in data dissemination based on current energy levels and the communication cost. SPEED utilizes neighborhood information to make more informed routing decisions in response to network congestion and changing traffic patterns [10]. ESRT adjusts the reporting frequency of source nodes in order to reach the target reliability level and conserve energy [11]. While many more examples of adaptive protocols exist, these solutions provide relevant example of how adaptation is beneficial in the unpredictable and dynamic WSNs. Our work is elicited by [11] and [4]. Many of these examples are orthogonal and can coexist with our work.

3 Problem Definition

In this paper, we consider a single-hop clustered WSN application involving the detection of event features based on the collective information of numerous sensor nodes. Assume an event happen at some place in the detected area, the sensor nodes in the sensing range of the event S, referred as *source nodes*, can sense it and generate the sensing information, and try to transmit the information to their corresponding CHs. On receiving the collected data from its Cluster Members (CMs), CH performs the data aggregation and sends the aggregated data to the sink node. The data aggregation process is illustrated in the Fig. 1.

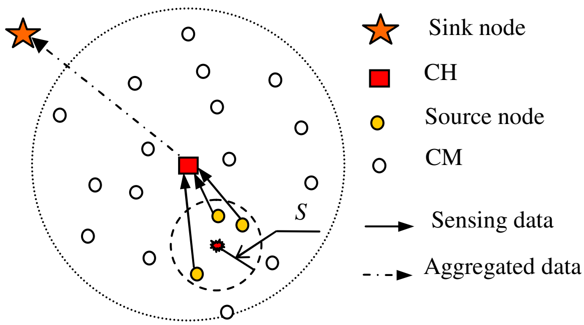

Fig. 1. Data aggregation process in single-hop clustered WSN

As mentioned above, since the detection range of the sensor nodes often overlaps, there are several source nodes for a happened event. That is the data redundancy problem. For each source node, it periodically reports the collected data, which is called as the *temporal redundancy* and can be aggregated at node-level by controlling the reporting frequency, f. For each cluster, the sensing data of the same event received by CH will be same or analogical, which is called as the *spatial redundancy* and can be aggregated at cluster-level by controlling the aggregation degree, d.

Assume the sink node make a decision on the event features every τ time units, where τ denotes the duration of a decision interval and depends on the application. At the end of each decision interval, the sink node makes a decision on reliability r based on the data received from the sensor field during that interval. Assume that r_i be calculated only using the available information at the sink node during the i^{th} decision interval, which is extracted from the received data. Therefore, the reliability of the event features is related with the number of the received data of the sink node. Fig. 2 shows the hypothetic relationship between the reliability of the event features r and the number of the received data N according to the spatial and temporal correlation model in [4]. In Fig. 2, when $N < N_1$, r increases exponentially with N; when $N_1 \leq N \leq N_2$, r increases linearly with N; and when $N > N_2$, r increases logarithmically with N.

There are two kinds of reliability, the observed one and desired one. From Fig. 2, the observed reliability r_i can be defined as the number of received data during the i^{th} decision interval at the sink node. And the desired reliability R is the number of data

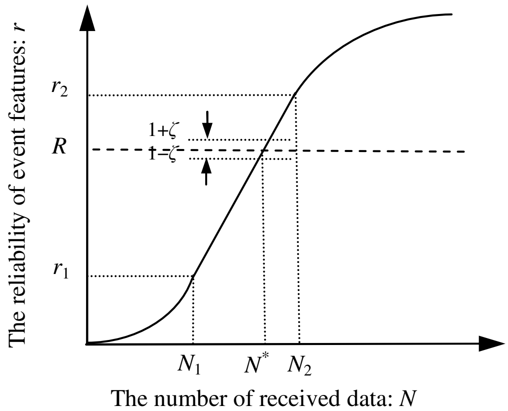

Fig. 2. Hypothetic relationship between r and N

needed for reliable event detection, which is determined by the application. If r_i is greater than R, the event can be detected reliably. Otherwise, appropriate action needs to be taken to improve the reliability until R is achieved.

When an event happens in the detected field, there are n sensor nodes in the sensing range of the event. For the sensing data are received by the sink node with the temporal redundancy and the spatial redundancy removed at node level and cluster level, the total number of received data by sink node in each decision interval is

$$N = n\tau f / d \tag{1}$$

The adaptive data aggregation problem for the clustered WSNs is to configure f of sensor nodes and d of CHs so as to achieve the desired reliability of detected event, R, at the sink node with the energy efficiency. Due to the dynamic characteristics of WSNs, it is necessary for the ADA scheme to keep track of the observed reliability in the sink node and accordingly adjust the aggregation parameters, f and d.

4 An Adaptive Data Aggregation Scheme

Without loss the generality, R can be represented as the spatial reliability R_s and the temporal reliability R_t, which are controlled by d and f, respectively. When CH receives the data from the source nodes in its cluster, it does not forward all of these data to sink node, but select a part of them. When d is configured, R_s is determined by the data from the selected source nodes. Similarly, when f is configured, R_t is determined by the data from one of the selected source nodes.

4.1 State and Region

The normalized reliability is defined as $\vec{\eta}_i = (\eta_{s,i}, \eta_{t,i})$, where $\eta_{s,i} = r_{s,i} / R_s$ $\eta_{t,i} = r_{t,i} / R_t$. $r_{s,i}$ and $r_{t,i}$ are the observed spatial reliability and the observed temporal reliability in the i^{th} decision internal, respectively. R_s and R_t are the desired spatial reliability and the desired temporal reliability. The goal of our ADA scheme is to operate with $\vec{\eta} = (1,\ 1)$ as close as possible. When $\vec{\eta} = (1,\ 1)$, the number of received data is the optimal value N^*. For practical propose, a tolerance zone with width 2ζ around $r = R$ is shown in Fig. 2, which means a tolerance zone with width $2\vec{\theta}$ around $\vec{\eta} = (1,\ 1)$, and $\vec{\theta} = (\theta_s, \theta_t) = (\zeta / R_s,\ \zeta / R_t)$.

We define nine characteristic regions using the following decision boundaries.

- **LSR/LTR** (Low Spatial Reliability, Low Temporal Reliability Region): $\eta_s < 1-\theta_s$ and $\eta_t < 1-\theta_t$
- **LSR/OTR** (Low Spatial Reliability, Optimal Temporal Reliability Region): $\eta_s < 1-\theta_s$ and $1-\theta_t \le \eta_t \le 1+\theta_t$
- **LSR/HTR** (Low Spatial Reliability, High Temporal Reliability Region): $\eta_s < 1-\theta_s$ and $\eta_t > 1+\theta_t$
- **OSR/LTR** (Optimal Spatial Reliability, Low Temporal Reliability Region): $1-\theta_s \le \eta \le 1+\theta_s$ and $\eta_t < 1-\theta_t$
- **OOR (OSR/OTR)** (Optimal Operation Region): $1-\theta_s \le \eta_s \le 1+\theta_s$ and $1-\theta_t \le \eta_t \le 1+\theta_t$
- **OSR/HTR** (Optimal Spatial Reliability, High Temporal Reliability Region): $1-\theta_s \le \eta_s \le 1+\theta_s$ and $\eta_t > 1+\theta_t$
- **HSR/LTR** (High Spatial Reliability, Low Temporal Reliability Region): $\eta_s > 1+\theta_s$ and $\eta_t < 1-\theta_t$
- **HSR/OTR** (High Spatial Reliability, Optimal Temporal Reliability Region): $\eta_s > 1+\theta_s$ and $1-\theta_t \le \eta_t \le 1+\theta_t$
- **HSR/HTR** (High Spatial Reliability, High Temporal Reliability Region): $\eta_s > 1+\theta_s$ and $\eta_t > 1+\theta_t$

Let $\mathbf{S}_i$ denote the data aggregation state variable at the end of the i^{th} decision interval. The sink node decides $\vec{\eta}_i$ at the end of the i^{th} decision interval. Then, $\mathbf{S}_i \in$ {**LSR/LTR**, **LSR/OTR, LSR/HTR, OSR/LTR, OSR/HTR, HSR/LTR, HSR/OTR, HSR/HTR, OOR**}. The primary motivation of our ADA scheme is to achieve and maintain operation in state **OOR**.

For r_s and r_t is controlled by d at CHs and f at source nodes respectively, the simplified ADA scheme state model and transitions are shown in Fig. 3, where the symbol x denotes the spatial dimension or the temporal dimension. Generally, the data aggregation state resides in one of nine states {**LSR/LTR**, **LSR/OTR, LSR/HTR, OSR/LTR, OSR/HTR, HSR/LTR, HSR/OTR, HSR/HTR, OOR**}. According to the current state $\mathbf{S}_i$, the sink node calculates f_{i+1} and/or d_{i+1} and broadcasts to CHs, and CHs broadcast f_{i+1} to the corresponding CMs.

4.2 Scheme Operation

The ADA scheme determines the current state $\mathbf{S}_i$ from $\vec{\eta}_i$ at the i^{th} decision interval. According to $\mathbf{S}_i$, d_i, f_i and $\vec{\eta}_i$, the scheme computes d_{i+1} at CHs and f_{i+1} at sensor nodes. Subsequently, at the end of the $(i+1)^{th}$ decision interval, the sink node calculates $\vec{\eta}_{i+1}$ using the data received during the $(i+1)^{th}$ decision interval using d_{i+1} at CHs and f_{i+1} at sensor nodes, and then identifies $\mathbf{S}_{i+1}$ again. Therefore, the task of our ADA scheme is mainly performed on the sink node, with a little function at the CHs and sensor nodes. This process is performed repeatedly until the scheme state is

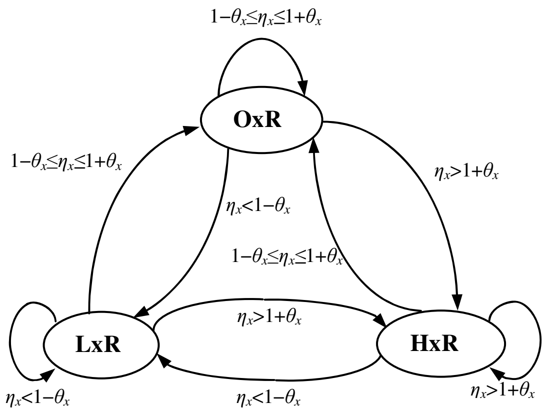

Fig. 3. Simplified state model and transitions

OOR. Because of the dynamic characteristics of WSN, the ADA scheme needs to continuously observe the state even if **OOR** is reached.

Adjusting policy of spatial aggregation degree. The detailed policies for adjusting d are related to the current state.

When the current state is **LSR**, $\eta_{s,i}<1-\theta_s$, that means d_i is so large that the received data cannot provide enough information and the observed spatial reliability is lower than the required one. In order to reach the desired spatial reliability of event features, it is necessary to decrease d. Thus, d_{i+1} can be calculated as

$$d_{i+1} = \frac{d_i}{2}(1+\eta_{s,i}) \tag{2}$$

When the current state is **HSR**, $\eta_{s,i}>1+\theta_s$, that means d_i is so small that the received data provide excessive information, and the observed spatial reliability is higher than the required one. Excessive transmitted data consume the excessive energy. In order to conserve energy, it is necessary to increase d. Thus, d_{i+1} can be calculated as

$$d_{i+1} = d_i \eta_{s,i} \tag{3}$$

When the current state is **OSR**, $1-\theta_s \le \eta_{s,i} \le 1+\theta_s$, that means the required spatial reliability is reached. Therefore, d keeps current value for the next decision interval.

$$d_{i+1} = d_i \tag{4}$$

Adjusting policy of temporal aggregation degree. When the current state is LTR, ηt,i<1−θt, that means fi is so small that the received data from a source node cannot provide enough information and the observed temporal reliability is lower than the required one. In order to reach the desired temporal reliability of event features, it is necessary to increase f. Thus, fi+1 can be calculated as

$$f_{i+1} = f_i / \eta_{t,i} \tag{5}$$

When the current state is **HTR**, $\eta_{t,i}>1+\theta_t$, that means f_i is so large that the received data from a source node provide excessive information, and the observed temporal reliability is higher than the required one. In order to conserve energy, it is necessary to decrease f. Thus, f_{i+1} can be calculated as

$$f_{i+1}=\frac{f_i(1+\eta_{t,i})}{2\eta_{t,i}} \tag{6}$$

When the current state is **OTR**, $1-\theta_t\leq\eta_{t,i}\leq1+\theta_t$, that means the required temporal reliability is achieved. Then, f maintains current value for the next decision interval.

$$f_{i+1}=f_i \tag{7}$$

If the deployed clustered WSN supports tracking different types of events, our ADA scheme is applicable in the same way. If different events have different desired reliabilities, different modules at the sink node are set up to perform the ADA scheme corresponding to the different events.

5 Performance Analysis

For an effective scheme, the data aggregation state must converge to state **OOR** stating from any initial state $\mathbf{S}_0$, where $\mathbf{S}_0\in\{$**LSR/LTR**, **LSR/OTR, LSR/HTR, OSR/LTR, OSR/HTR, HSR/LTR, HSR/OTR, HSR/HTR, OOR**$\}$. Starting from **OOR**, the scheme state converges. Here, we analyze that the scheme state converges to state **OOR** starting from any of other eight initial states.

5.1 Analytical Results

LEMMA 1. Starting from $\mathbf{S}_{s,0}$=**LSR**, with the linear reliability behavior when the number of received data is greater than N_1, the scheme state remains unchanged until it converges to state **OSR**.

PROOF: The linear reliability behavior for $N_s>N_{s,1}$ can be described as $N_s=\alpha\eta_s$, where α denotes the slope. On the other hand, N_s is reversely proportional to d, that can be expressed as $N_s=\beta/d$, where β denotes the proportion coefficient. Therefore, the relationship between d and η_s is $d=\beta/\alpha\eta_s$.

When the current state is $\mathbf{S}_{s,i}$=**LSR**, d_{i+1} is calculated as (2). Then,

$$\eta_{s,i+1}=\frac{2\eta_{s,i}}{1+\eta_{s,i}} \tag{8}$$

Since $d_{i+1}<d_i$ from (2), it follows that $\mathbf{S}_{s,i+1}\in\{$**LSR**, **HSR**, **OSR**$\}$, $\forall i\geq0$, until the scheme state converges. If possible, let $\mathbf{S}_{s,i+1}$=**HSR** when $\mathbf{S}_{s,i}$=**LSR** for some $i\geq0$ before the scheme state converges. Then,

$$\eta_{s,i+1}=\frac{2\eta_{s,i}}{1+\eta_{s,i}}>1+\theta_s \tag{9}$$

It means that $\eta_{s,i} > \frac{1+\theta_s}{1-\theta_s}$, but $\eta_{s,i} < 1-\theta_s$ since $\mathbf{S}_{s,i}$ =**LSR**. Therefore, $\mathbf{S}_{s,i+1} \neq$ **HSR** for any $i \geq 0$ until the scheme state converges. Consequently, it can be concluded that $\mathbf{S}_{s,i+1}$=**LSR** $\forall i \geq 0$, until the scheme state converges to state **OSR**. ■

LEMMA 2. Starting from $\mathbf{S}_{s,0}$=**LSR**, with the linear reliability behavior when the number of received data is greater than N_1, the scheme state converges to state **OSR** in $\tau\left\lceil \log_2\left(\frac{1-\eta_{s,0}}{(1+\eta_{s,0})\theta_s}\right)+1\right\rceil$ time units, where τ is the duration of the decision interval.

PROOF: Let the i^{th} decision interval be the first one where $\mathbf{S}_{s,i}$=**OSR**. It follows from *LAMMA 1* that i is the least suffix such that $\eta_{s,i} > 1-\theta_s$. Using (8),

$$\begin{aligned} \eta_{s,i} &= \frac{2\eta_{s,i-1}}{1+\eta_{s,i-1}} > 1-\theta_s \\ \eta_{s,i-1} &= \frac{2\eta_{s,i-2}}{1+\eta_{s,i-2}} > 1-2^1\theta_s \\ &\vdots \\ \eta_{s,1} &= \frac{2\eta_{s,0}}{1+\eta_{s,0}} > 1-2^{i-1}\theta_s \end{aligned} \tag{10}$$

Therefore, $i > \log_2\left(\frac{1-\eta_{s,0}}{(1+\eta_{s,0})\theta_s}\right)+1$ and the result follows. ■

LEMMA 3. Starting from $\mathbf{S}_{s,0}$=**HSR**, with the linear reliability behavior when the number of received data is smaller than N_2, the scheme state converges to state **OSR** aggressively.

PROOF: The linear reliability behavior for $N_s<N_{s,2}$ can be described as $N_s=\alpha\eta_s$, where α denotes the slope. On the other hand, N_s is reversely proportional to d, that can be expressed as $N_s=\beta/d$, where β denotes the proportion coefficient. Therefore, the relationship between d and η_s is $d=\beta/\alpha\eta_s$.

When the current state is $\mathbf{S}_i$=**HSR**, d_{i+1} is calculated as (3). Thus $\eta_{s,i+1}=1$, and the scheme state aggressively converges to the state **OSR**. ■

LEMMA 4. Starting from $\mathbf{S}_{t,0}$=**LTR**, with the linear reliability behavior when the number of received data is greater than N_1, the scheme state converges to state **OTR** aggressively.

LEMMA 5. Starting from $\mathbf{S}_{t,0}$=**HTR**, with the linear reliability behavior when the number of received data is smaller than N_2, the scheme state remains unchanged until it converges to state **OTR**.

LEMMA 6. Starting from $\mathbf{S}_{t,0}$=**HTR**, with the linear reliability behavior when the number of received data is smaller than N_2, the scheme state converges to state **OTR** in $\tau\left\lceil \log_2\left(\frac{\eta_{t,0}-1}{\theta_t}\right)\right\rceil$ time units, where τ is the duration of the decision interval.

The proof of the LAMMA 4, 5 ,6 is similar to that of the LAMMA 1, 2 ,3.

In order to calculate the convergence times of ADA scheme starting from $\mathbf{S}_{x,0}$=**LxR** with $N<N_1$, and $\mathbf{S}_{x,0}$=**HxR** with $N>N_2$, the nonlinear reliability behavior needs to tracked analytically. Due to the limited space, we are not including these two case.

5.2 Simulation Results

In order to validate the analytic results in section 5.1, we developed an evaluation environment using MATLAB 7.1. The cluster protocol used in simulation is LEACH, the first cluster protocol proposed for WSNs [5]. Assume that 100 sensor nodes are randomly deployed in the detected area with a size of 100m×100m. The sink node locates at outside of the detected area. The percentage of the CHs is 4, and the sensing range of an event is 40m.

The convergence results is shown in Table 1 for the initial scheme state $\mathbf{S}_0$=**LSR/LTR**, **HSR/LTR, LSR/HTR,** and **HSR/HTR**, where tolerance $\theta_s=\theta_t=5\%$.

Table 1. The corresponding (d_i, $\eta_{s,i}$, f_i, $\eta_{t,i}$) and scheme states

	i	0	1	2	3	4
1	$\mathbf{S}_i$	**LSR/LTR**	**LSR/OTR**	**LSR/OTR**	**LSR/OTR**	**OOR**
	d_i	5.4	4.3546	3.8318	3.5705	3.4345
	$\eta_{s,i}$	0.6128	0.7599	0.8636	0.9283	0.9635
	f_i	0.8	4.9261	4.9261	4.9261	4.9261
	$\eta_{t,i}$	0.1624	1.0073	1.0073	1.0073	1.0073
2	$\mathbf{S}_i$	**LSR/HTR**	**LSR/HTR**	**LSR/HTR**	**LSR/HTR**	**OOR**
	d_i	5.4	4.3546	3.8318	3.5705	3.4345
	$\eta_{s,i}$	0.6128	0.7599	0.8636	0.9283	0.9635
	f_i	7.8	6.3631	5.6446	5.2855	5.1059
	$\eta_{t,i}$	1.5834	1.2917	1.1458	1.0729	1.0423
3	$\mathbf{S}_i$	**HSR/LTR**	**OOR**			
	d_i	2.16	3.3048			
	$\eta_{s,i}$	1.532	1.0013			
	f_i	0.8	4.9261			
	$\eta_{t,i}$	0.1624	1.0073			
4	$\mathbf{S}_i$	**HSR/HTR**	**OSR/HTR**	**OSR/HTR**	**OSR/HTR**	**OOR**
	d_i	2.16	3.3048	3.3048	3.3048	3.3048
	$\eta_{s,i}$	1.532	1.0013	1.0013	1.0013	1.0013
	f_i	7.8	6.3631	5.6446	5.2855	5.1059
	$\eta_{t,i}$	1.5834	1.2917	1.1458	1.0729	1.0423

From this table, we observe that the ADA scheme for $\mathbf{S}_0$=**HSR/LTR** converges in a total of two decision intervals and the ADA scheme for $\mathbf{S}_0$=**LSR/LTR**, **LSR/HTR,** and **HSR/HTR** converges in a total of five decision intervals.

6 Conclusions

Due to the dynamic topology and random deployment, it is important to corporate the adaptive characteristic into the protocols for WSNs. Furthermore, since sensor nodes are resource-constrained, it is necessary to minimize the responsibilities required at sensor nodes and shift the burden to the resource-rich sink node. In this paper, we proposed an ADA scheme for the clustered WSNs. In this scheme, the reporting frequency at sensor nodes and the aggregation degree at CHs are determined by the current scheme state based on the observed reliability. The task of the ADA scheme is mainly performed on the sink node, with a little function at the CHs and sensor nodes. Analytical and simulation results show that the scheme state converges to the desired reliability starting from any initial state.

References

1. Intanagonwiwat, C.R., Govindan, C.R., Estrin, D.: Directed Diffusion: a Scalable and Robust Communication Paradigm for Sensor Networks. In: Proc. of MobiCom, pp. 56–67 (2000)
2. Akyildiz, I.F., Su, W., Sankarasubramaniam, Y., Cayirci, E.: Wireless Sensor Networks: A Survey. Computer Networks 38, 393–422 (2002)
3. Gober, P., Ziviani, A., Todorova, P., Amorim, M.D., Hunerberg, P., Fdida, S.: Topology Control and Localization in Wireless Ad Hoc and Sensor Networks. Ad Hoc & Sensor Networks 1, 301–322 (2005)
4. Vuran, M.C., Akyildiz, I.F.: Spatial Correlation-Based Collaborative Medium Access Control in Wireless Sensor Networks. IEEE/ACM Trans. on Networking 14(2), 316–329 (2006)
5. Heinzelman, W.R., Chandrakasan, A., Balakrishnan, H.: An Application-Specific Protocol Architecture for Wireless Microsensor Networks. IEEE Trans. on Wireless Communications. 1(4), 660–667 (2002)
6. Younis, O., Fahmy, S.: HEED A Hybrid, Energy-Efficient, Distributed Clustering Approach for Ad-hoc Sensor Networks. IEEE Trans. on Mobile Computing. 3(4), 660–669 (2004)
7. Heinzelman, W., Kulik, J., Balakrishnan, H.: Adaptive Protocols for Information Dissemination in Wireless Sensor Networks. In: Proc. of MobiCom, pp. 174–185 (1999)
8. Xue, Y., Cui, Y., Nahrstedt, K.: Maximizing Lifetime for Data Aggregation in Wireless Sensor Networks. Mobile Networks and Applications (2005)
9. Chen, H., Mineno, H., Mizuno, T.: A Meta-Data-Based Data Aggregation Scheme in Clustering Wireless Sensor Networks. In: MDM 2006 Workshop MLASN, pp. 43–49 (2006)
10. He, T., Stankovic, J., Lu, C., Abdelzaher, T.F.: SPEED: A Stateless Protocol for Real-Time Communication in Sensor Networks. In: Proc. of ICDCS (2003)
11. Sankarasubramaniam, Y., Akan, O.B., Akyildiz, I.F.: ESRT: Event-to-Sink Reliable Transport in Wireless Sensor Networks. In: Proc. of MobiHoc, pp. 177–188 (2003)