Collaborative Communication Control Based on Sensor Data Management in WSN

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Abstract—This paper presents a novel approach for dynamic controlling of the communication process within cluster-based wireless sensor networks (WSN). The research concentrates on the environmental parameters supervision with WSN inside a container. In order to maintain the requisite environmental sensing quality with as low energy consumption as possible, the participants of WSN make distributed decisions about their own communication intensity according to the surrounding environmental conditions. For this purpose, the cluster head (CH) and cluster member (CM) apply a collaborative decision-making approach to control the transmission activity of each CM. The CH turns the spatially redundant CMs off by observing the relationship between sensor data from all CMs. The CMs apply dynamic sensing rate approach to reduce the temporally redundant sensor data as well as to reactive itself from sleep mode. The simulation results show that the collaborative approach performs high sensing quality in spite of drastic reduction of communication activities.

Keywords: wireless sensor networks, spatially and temporally redundant data, neural network, spatial cross correlation.

I. INTRODUCTION

The drastically increased amount and complexity of the modern food-supply-chain require a more flexible decision making system. In order to establish an autonomous and intelligent transport logistic system, a variety of information is necessary, e.g. the environmental condition inside container, the current quality of goods, the vehicle status, etc. The highly perishable freight such as fruit and vegetable demands especially precise environment supervision, since the goods quality depends heavily on the environmental factors [1]. The ”Intelligent Container” system [2] applies the WSN as the on line environment monitoring tool due to the high flexibility and robustness, simple applicability and low cost. Aiming at a precise monitoring the WSN usually contains densely distributed sensor nodes, that sense the parameters with a high sensing frequency. For that reason, plenty of spatial and temporal sensor data redundancy can be caused. In a cluster-based network the cluster participants (CMs) are distributed within a limited range around the CH. Hence, the sensor data are influenced by nearly the same environmental conditions. The CH can detect and disable the spatially redundant CMs by collecting and comparing their sensor readings. In order to reduce the temporal redundancy, the CMs apply a dynamic sensing rate algorithm to adapt their own sensing intervals according to the surrounding environmental parameter variation. Moreover, the dynamic sensing rate algorithm acts as reactivation criterion for the redundant CM. The CH and CMs collaborate to control the transceiver activities of CMs by means of combining the detection of spatially redundancy and dynamic sensing rate. Thus, the spatial and temporal sensor reading redundancy is minimized and therefore unnecessary data processing and transmission are evidently reduced.

This paper is organized as follows: Section 2 introduces some related studies about the management of spatially and temporally redundant sensor data. In Section 3 the collaborative approach of the communication control and the two crucial components are described. The simulation scenario and results are discussed in Section 4. The paper ends in Section 5 with conclusions.

II. RELATED WORK

The spatial and temporal data redundancy in WSN is widely investigated and exploited in variety of applications. Vuran et al. introduced in [3] a theoretical framework for modeling the spatial and temporal correlation of sensor data in WSN. The authors mentioned that this framework can potentially be used to develop energy-efficient protocol of the network communication. Further, Vuran and Akyildiz described an approach for collaborative medium access control by exploiting the spatial correlation of the sensor data to reduce the redundant message transmission [4]. Guestrin et al. applied Kernel regression to model the sensor data in both time and space domain by considering the temporal and spatial correlation of the sensor readings [5]. Sun et al. developed an approach for data aggregation in cluster-based sensor networks to reduce the spatio-temporal redundancy information [6]. Moreover, numerous research studies investigated and exploited simply the spatial correlation [7] [8] or temporal data redundancy [9] [10] [11] to achieve a higher energy-efficiency of the sensing systems.

III. COLLABORATIVE CONTROL APPROACH

The intelligent monitoring system requires on the one hand high sensing quality, i.e. the abnormal environment variations must be detected and transmitted to base station in time. On the other hand the power consumption should be kept as low
as possible due to the limited energy supply of sensor nodes. The key method to keep the low energy consumption is the minimization of communication activities between sensor nodes, since the data transmission and receiving consume more energy than sensing and data processing. However, low frequency of communication processes leads to missing sensor data of crucial events or large time latency. An energy efficient solution for the trade-off between energy and sensing precision is to control the communication activities adaptively according to the environmental conditions. If the environmental parameters are highly dynamic, the sensor nodes measure and communicate intensively. In contrast, in a static environment the sensor nodes extend the sensing and communication intervals correspondingly or even switch the transceiver to sleep mode. Although the CMs just collect limited local information over time, they can predict the temporal data redundancy by learning from previous sensor data and avoid the redundant data already before sensing. In contrast, the CHs gather the information from a number of CMs and exhibit knowledge about temporal as well as spatial distribution of parameters within the cluster. Hence, CHs can sort the CMs in two groups, depending on whether they deliver redundant sensor data or not. The collaborative control approach and its both components are introduced in detail in the following sections.

A. Spatial redundancy detection

The high distribution density of sensor nodes leads to spatially redundant sensor readings. The CMs of a cluster locate within a quite small area, which determined by a lower transmission power level. Hence, the sensor reading series of CMs may vary similarly, i.e. are highly correlated with each other. The CHs collect sensor data from CMs and evaluate the similarity of readings by calculating the cross correlation coefficient $C_{ij}$ of data series $x$ and $y$ in pairs with (1).

$$C_{ij} = \frac{N \sum x y - (\sum x) (\sum y)}{\sqrt{N \sum x^2 - (\sum x)^2} \sqrt{N \sum y^2 - (\sum y)^2}}. \tag{1}$$

Figure 1 illustrates the procedure of spatial redundancy detection using cross correlation. The spatial redundancy detection process consists of three steps:

1) Sort of CMs: The CH collects a certain number of sensor readings from all CMs and sorts the CMs into two groups by calculating the variance of each reading series. If the variance of CMi $\text{Var}(\text{CMi}) = 0$, i.e. the readings of CMi are constant, the CH puts CMi in group $\bar{G}_{static}$. In contrast, if $\text{Var}(\text{CMi}) \neq 0$, CMi belongs to $\bar{G}_{dynamic}$.

2) Requisite CM from $\bar{G}_{static}$: If the group $\bar{G}_{static} \neq \emptyset$, CH elects one CM on duty by calculating the previous communication cost. All other CMs switch their transceivers to sleep mode.

3) Requisite CM from $\bar{G}_{dynamic}$: In this group, CH generates a correlation matrix $G$, whose element $C_{ij}$ denotes the cross correlation coefficient of the CM pair $\{\text{CM}_i, \text{CM}_j\}$. CH selects $\text{CM}_i$ and $\text{CM}_j$ as requisite CMs, they produce the minimal element $C_{ij}$. If one of the remaining CMs ($\text{CM}_j$) highly correlates to $\text{CM}_i$ or $\text{CM}_j$, i.e. $C_{ir} > \mu$ or $C_{jr} > \mu$, then $\text{CM}_j$ is turned off as redundant sensor node. We take the threshold $\mu = 0.8$ in this work, which shows a significant data similarity in the practical test.

Thus, the requisite CMs ($\text{CM}_{\text{requisite}}$) are elected and the remaining CMs can be turned off.

B. Dynamic sensing rate

The algorithm of dynamic sensing rate is responsible to adapt the sensing frequency according to the continuously variable environmental condition in container. The algorithm exploits artificial neural network (ANN) for prediction of the sensor data variation trend. In this work we apply a supervised learning network: Multilayer-Perceptron (MLP). The architecture of MLP was introduced in a previous work [12]. The principle of the dynamic sensing rate approach is illustrated in Fig. 2. The input of MLP is a number of previous and current temperature variations. The predicted temperature variation in the next interval is obtained at the output of MLP. The algorithm calculates the time interval for the next necessary by considering the difference between the current temperature and temperature boundaries and the predicted temperature variation. Once the next temperature reading is obtained, the prediction error is given back to the output of MLP, the network architecture (i.e. the weight matrices in this work) is updated according to the current environmental condition and ready for the next prediction. The advantage of a MLP is the sensitivity to track the parameter variation and the high prediction accuracy. The weight matrices, which are continuously trained during the transport process, keep the history about the environmental development inside the container and provide additional useful information for the prediction. The disadvantage of a MLP predictor is the calculation complexity,
since MLP uses the sigmoid function as activation function, which requires high computation effort. Using polynomial approximation of activation function the operation time of MLP prediction can be reduced to 16 ms [13] and the accuracy still satisfy the requirement of the application.

C. Collaborative control

In order to minimize the spatial and temporal sensor data redundancy and the resultant unnecessary energy consumption, the CHs and CMs collaborate to control the communication activities of CMs by combining the two components mentioned above. The CHs determine the spatially requisite and redundant CMs at the beginning of a clustering-period (T_{clustering}). The CMs transmit a certain number of sensor readings to CHs with the minimal sensing interval. The CHs select the requisite CMs by considering the spatial cross correlation of the collected sensor data and turn off the remaining redundant CMs, which note their status as "redundant" and sense the temperature with dynamic intervals. If the sensing interval of a redundant CM becomes smaller than the initial interval, i.e. the environment becomes more dynamic, the CM wakes up and deliver the current sensor reading to CH. If later the sensing rate returns to the maximal value for a long time, the CM can turn off the transceiver again. The concept of the collaborative control approach is illustrated in Figure 3.

IV. Simulation

The collaborative control approach is tested by means of simulation. We choose firstly the optimal clustering period for the transport logistic application typically with three steps: cooling-down, static temperature during transport and unloading. Then, the impact on the communication activities and sensing quality by the collaborative approach and each of its components are discussed and compared to the fixed interval approach without redundant data management. The simulation stimuli are the temperature sensor readings from a real fruit transport process. The measurement was carried out by University of Bremen [14]. The five sensor nodes are located in a limited range, hence we can assume that they are CMs of a cluster. The temperature sensor readings of the five sensor nodes are shown in Figure 4.

A. Optimal clustering period

The clustering period (T_{clustering}) defines the time interval between two cluster rebuilding processes. Moreover, it shows how often the CHs elect the redundant CMs by observing the correlation between sensor readings series. The more frequently the CHs calculate the correlation, the more frequently the cluster is updated according to the current environmental condition, which leads to a precise and real-time supervision. However, cluster rebuilding and correlation observation require intensive measurements and communication activities. A optimal clustering period has to be found by trading off the supervision error and the communication processes. The number of transmitted message packets of five CMs with different clustering period is illustrated in Figure 5(a). The corresponding supervision error, i.e. the difference between the real temperature curve

Figure 2. Principle of dynamic sensing rate approach using MLP

Figure 3. Concept of the collaborative control approach

Figure 4. Temperature input of the simulation
and the interpolated curve with obtained limited sensor readings, is shown in Figure 5(b). The results show that the increased $T_{\text{clustering}}$ leads to reduction of both transmission activities and sensing quality. From 1 hour to 3 hours the transmitted packets and the supervision errors vary slowly. For $T_{\text{clustering}} = 4$ hours the transmission is evidently reduced. However, the supervision errors of the 5 CMs increase drastically as well. In this comparison we have just observed the error and transmission packets. Considering the energy overhead of clustering rebuilding process, e.g. additional transmissions, we set $T_{\text{clustering}}$ to 180 min in this work.

B. Impact of spatial and temporal data redundancy management

In order to investigate the impact of spatial and temporal redundant sensor data on the communication activities and sensing quality, the following five approaches (A1 to A5) with different redundant data management methods are evaluated and compared to each other:

A1: CMs use fixed sensing and transmission intervals of 11 min (test data from practical measurement)
A2: CMs simply use dynamic sensing intervals (temporally redundant data management only)
A3: CMs simply use spatial cross correlation with fixed sensing interval of 11 min (spatially redundant data management only)
A4: CMs use collaborative communication control approach (complete data management) with wake up criterion
A5: CMs use collaborative communication control approach with wake up and sleep criterion

The approaches with dynamic sensing (A2, A4 and A5) use intervals in the range $[2, 20]$ min, while the other approaches (A1, A3) use a fixed interval of 11 min, which is the mean value of the dynamic sensing interval range. The five approaches are compared in three different aspects: the transmission activities, the sensitivity for event detection and the dynamic energy distribution.

1) Transmission activities: The transmission activity of the CMs is evaluated by considering the number of transmitted packets during the entire transport process. The minimization of the redundant sensor data leads to a drastic reduction of packets transmission and forwarding. We only consider the transmissions by CMs to their CH in this paper. The total number of transmitted packets of the five CMs ($CM_i$, with $i = 1 \cdots 5$) with the mentioned approaches ($A_i$, with $i = 1 \cdots 5$) is shown in Figure 6.

The results show that the management of temporal and spatial sensor data redundancy affects significantly the transmission activities of CMs. Using dynamic sensing interval approach (A2) 23% to 35% of the packets are saved, while using spatial redundancy management (A3) 22% to 63% of the transmissions are reduced. Compared to approach A3 with spatial cross correlation, the collaborative control approach (A4) achieves a further reduction up to 18% due to the additional temporal redundancy management. If the redundant CMs can switch to sleep mode automatically by considering the dynamic sensing intervals (A5), the number of transmitted packets reduces up to 10% compared with the...
approach only with wake up criterion (A4). Using A5, totally up to 70% of the transmission activities is saved compared to the approach (A1) with fixed sensing and transmission interval.

2) Sensitivity for event detection: In spite of the transmission activity reduction, the collaborative approach must maintain the sensitivity of the sensing system for detecting the unexpected environmental events. Three crucial temperature variation events during the transport process are shown in Table I.

We interpolate the temperature curve with the limited number of sensor readings and compare the interpolated curve $T_{\text{inte}}$ to the real temperature curve $T_{\text{real}}$. The sensing quality of the three events is evaluated by calculating the relative sensing error $E_{\text{sensing}}$ (2).

$$E_{\text{sensing}} = \frac{\sum_{i=t_{\text{begin}}}^{t_{\text{end}}} |T_{\text{inte}}[i] - T_{\text{real}}[i]|}{\sum_{i=t_{\text{begin}}}^{t_{\text{end}}} |T_{\text{real}}[i]|} \times 100\% \quad (2)$$

We show the results of CM1 (Figure 7) as an example to analyze the impact of the five approaches on the sensing quality. The dynamic sensing interval algorithm is able to automatically detect the abnormal temperature variation and adapt the sensing intensity. Therefore, the sensing quality for the three events is enhanced up to 59% (for event E1: $E_{\text{sensing}}$ is reduced from 22% to 9%) by using dynamic sensing interval compared to fixed interval approach. In contrast, the spatial redundancy detection approach alloys the sensing quality, since the transceiver stays in sleep mode even if the temperature variation occurs. The approach with simply spatial redundancy detection performs low sensitivity for detecting events. To solve this problem, the collaborative approach (A4) provides the additional dynamic sensing interval to enhance the sensitivity for tracking temperature variation. In spite of a saving up to 68% of the packets, the collaborative approach maintains the similar sensing quality as using fixed interval approach (A1).

3) Temporal distribution of transmission activities: An important criterion to evaluate the energy efficiency of the sensing system is whether the system is able to concentrate the energy consumption on the unexpected events automatically. The temporal distribution of the transmission activities is evaluated by calculating the ratio of the packets during the time range of the three events. The results of the five approaches are illustrated in Figure 8.

The approach with fixed intervals spends 18% of the entire energy consumption to observe the three events. The temporal redundancy management increases the ratio up to 33%. In contrast, the spatial redundancy management impairs the ratio for the most CMs, because a single CM can probably miss some events on time domain, if it is in the sleep mode as spatially redundant CM. By avoiding the redundant sensor

<table>
<thead>
<tr>
<th>Event</th>
<th>$t_{\text{begin}}$(min)</th>
<th>$t_{\text{end}}$(min)</th>
<th>Event description</th>
</tr>
</thead>
<tbody>
<tr>
<td>E1</td>
<td>0</td>
<td>200</td>
<td>Cooling down</td>
</tr>
<tr>
<td>E2</td>
<td>210</td>
<td>340</td>
<td>Door opening and reload</td>
</tr>
<tr>
<td>E3</td>
<td>1950</td>
<td>2050</td>
<td>Unloading</td>
</tr>
</tbody>
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readings on both time and space domain, the collaborative approach enhances the ratio up to 39%. Approach A5 with additional sleep criterion leads to similar results as A4 due to the strict criterion, which requires three measurement cycles with the maximum sensing interval. After the comparison of the five approaches for communication control, we summarize the impact of the temporally and spatially redundant data management on the performance of the sensing system:

- The spatial redundancy management affects the transmission activities of the CMs more significantly than the temporal redundancy management (Figure 6). The reason is that the cluster covers a limited range, in which the CMs deliver mostly sensor readings with high similarity. The temporal redundancy management is able to evidently reduce the number of transmitted packets as well. However, due to the upper limitation of the sensing intervals (20 min) the temporal redundancy cannot be completely avoided. A high upper limitation of the sensing interval can alloy the sensitivity of variation tracking.
- In addition to reduction the communication activities, the temporal redundancy management improves both the sensing quality and energy efficiency of the sensor system.
- The collaborative approach enables the optimal trade off between the communication effort and then sensing quality by combining the redundant sensor data on both time and space domains.
- The benefit of the collaborative approach on each single CM depends admittedly on the surrounding environmental conditions. For example, CM5 is placed on the reeferer and therefore delivers more dynamic sensor readings than the other CMs, hence the collaborative approach performs less improvement for CM5 than e.g. CM2 with more static sensor data.

V. CONCLUSIONS

In this paper we presented a collaborative approach for communication controlling in WSN based on the redundant sensor data management. The proposed approach consists of two parts: temporally and spatially redundant data management. Each CM applies the dynamic sensing rate algorithm to adapt the own sensing intensity in the time domain according to its surrounding environmental condition. The CH detects the spatial redundancy in a cluster by means of considering the cross correlation coefficient between series of sensor readings from all CMs. The collaborative approach is tested by simulation with practical experimental temperature sensor readings from a real transport process as input. The optimal period for cluster rebuilding is set to 3 hours (180 min) by considering the total number of transmitted packets and sensing errors. The impact of temporal and spatial redundancy management on the performance of the sensing system is evaluated. The results reveal that the spatial redundancy management reduces significantly the transmission activities but impairs the sensitivity of tracking events. The temporal redundancy management can improve the sensing quality and energy efficiency, in spite of less effective reduction of the transmission than the spatial data management. The collaborative approach performs a similarly high sensing quality as the fixed sensing approaches using only 30% of the transmissions, since both temporal and spatial data redundancy are effectively reduced. For the future work a simple spatial sensor data interpolation by the CH can further improve the sensing quality of each single CM.

REFERENCES