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Distributed Data Filtering in Logistics Wireless Sensor Networks Based on Transmission Relevance

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***Abstract*—Energy-efficient operation is mandatory in wireless sensor networks due to the limited energy budget of sensor nodes. Considering the potential application of wireless sensor networks in logistics, cost efficiency is another major requirement due to high cost pressure. To save on data transmissions within such sensor deployments, which account for the major part of energy consumption and monetary costs, we develop a method for data filtering based on an in-network determination of transmission relevance of sensor data. Our approach explicitly incorporates interdependencies between wireless sensor nodes and their measurements and data transmissions. It contributes to efficiency in wireless sensor networks by filtering out irrelevant data and enables a subsequent reduction of unnecessary transmissions from a network-wide view, while being able to still offer real-time data provision with sufficient data fidelity to stakeholders. The benefits of our approach are indicated by preliminary evaluation results.**

I. Introduction

An essential necessity for wireless sensor networks (*WSNs*) is energy-efficient operation, because wireless sensor nodes (*motes*) rely in general on batteries as their energy sources. Besides this basic technology-inherent requirement, additional requirements are usually imposed on WSN deployments by specific application scenarios. In the work at hand, our focus is on WSN application in logistics transport processes. This application domain is characterized by a huge cost pressure. Consequently, cost-efficient operation is another main requirement for WSN deployments in such an application environment.

Despite significant research efforts to provide energy-efficient data transmission (discussed, e.g., in [1], [2]), the energy required for data transmission still exceeds the energy required for data processing in the general case [3]. In addition, data transmission is a major source for monetary costs in logistics WSNs, as usually technologies liable to fees are employed to transmit data from a WSN, e.g., on board a ship, to stakeholders [4].

Data filtering is a promising means to efficiently reduce the number of data transmissions in WSNs (cf. [5], [6]). In [7], we have already proposed a data filtering mechanism based on transmission relevance as an efficient approach to reduce communication overhead in logistics WSNs. There, we focused on a strict mote-centric view. But as motes and sensor data possess interdependencies, e.g., due to spatial proximity of deployed motes, an extended filtering approach which considers and evaluates such interdependencies provides the opportunity to further reduce the number of data transmissions. Consequently, in the work at hand, we provide such an extended filtering approach and describe a method to incorporate interdependencies and correlation in the decision about the relevance of data by employing specific discount factors. With the reduction of communication overhead possible with this approach, it contributes to the enhancement of energy and cost efficiency in logistics WSNs.

The remainder of this paper is structured as follows: Section II provides an introduction to the application scenario and briefly revisits the concept of transmission relevance. Our approach of in-network data filtering based on transmission relevance determination is presented in Section III. Section IV describes the evaluation of our approach. Section V presents conclusions and future work.

II. Background

A. Application Scenario

The application of WSN technology is particularly promising for logistics (cf., e.g., [3]). During transport processes, motes can locally monitor relevant environmental parameters and detect critical situations in real time. Subsequently, they can immediately initiate a wireless data transmission and inform responsible decision makers via gateways, so that the possibility for an early reaction is provided. Such real-time detection and notification facilities would be in particular beneficial for temperature-sensitive transports, because for example product losses of up to 35% in food transportation can be attributed to temperature mismanagement and quality decay [8]. Consequently, we focus in the following on temperature-sensitive transport processes and event detection with WSN technology in such transport scenarios.

In this context, events are understood as "essential state changes for certain addressees" [9], e.g., the violation of temperature thresholds. Thus, events can be detected by local target-performance comparisons on deployed motes. In such an application context, it is essential to take care of energy- and cost-efficient operation. Data transmission accounts for both the major part of energy consumption as well as monetary costs. Thus, we proposed to use data filtering as an efficient way to reduce communication overhead [7]. In [7], we focused on a local, mote-centric view on data aggregation, whereas we extend this view to a network-wide view, incorporating correlation between events, in the work at hand.

Jedermann et al. have already conducted research concerning WSN deployments in such application scenarios, specifically in food transports [10]. For example, they investigated communication link quality within a container packed with bananas (cf. Fig. 1) and have developed a specific communication protocol for such an application scenario. As we focus on application layer-driven data filtering in our approach, we base our work on their findings and results for the lower network layers in the considered application scenario as presented in [10]. Overall, with our focus on temperature-sensitive transports, environmental phenomena occurring locally and exhibiting no sudden, but rather gradual, changes are the phenomena we envision to be monitored.

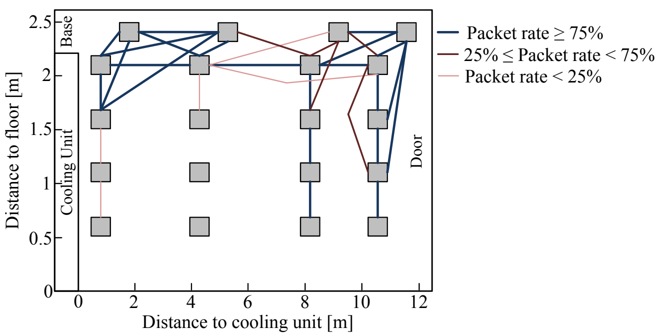

Fig. 1. Motes and communication links within a container with bananas (based on [10])

B. Transmission Relevance of Sensor Data

To reduce communication overhead by avoiding the transmission of irrelevant data, we differentiate transmission relevant and non-transmission relevant events (cf. [7]). Therefore, on the one hand, sensor data is assigned an information value, which reflects the value of benefit for the receiver of this data, e.g., the information of a temperature event transmitted to a decision maker in a logistics process. On the other hand, the transmission costs in terms of money and energy required for the corresponding data transmission are accounted for and compared to the information value. In case the information value equals or exceeds the transmission costs, sensor data is deemed transmission relevant (1) and is transmitted, otherwise the data is deemed non-transmission relevant (2) and filtered out so that no data transmission takes place.

$$\begin{aligned} &Transmission\ relevant\ event_{E_D} \Leftrightarrow \\ &\quad Information\ value_{E_D} \geq Transmission\ costs_{E_D} \end{aligned} \tag{1}$$

$$\begin{aligned} &Non\text{-}transmission\ relevant\ event_{E_D} \Leftrightarrow \\ &\quad Information\ value_{E_D} < Transmission\ costs_{E_D} \end{aligned} \tag{2}$$

An exemplary local operationalization of this concept for WSN application in logistics transport processes is also provided in [7]. In the reference, sensor data has been locally filtered by differentiating transmission relevant events and non-transmission relevant events on single motes using scoresheets.

III. In-Network Transmission Relevance Determination

With the extension of a purely local and mote-centric view on transmission relevance to a network-wide view, an essential necessity is to incorporate interdependencies between sensor measurements, respectively detected and transmitted events. Specifically, we consider spatial and temporal correlation in this context. Our basic idea is to discount the information value of an event received for forwarding by a mote from another mote with respect to such correlations. Afterwards, the transmission relevance is calculated by comparing this discounted information value to the transmission costs prevailing in the current context on the mote as described in (1) and (2). On this basis, the decision is made to either forward the data or filter it out.

Therefore we determine a spatial discount factor (*sdf*) to account for spatial interdependencies and a temporal discount factor (*tdf*) to account for temporal interdependencies between events. Additionally, as events possess different information values according to their specific properties, such an information value difference has to be considered as well with an information value difference discount factor (*ddf*). To allow for an additional fine-grained adjustment, e.g., in relation to product-specific characteristics influencing the extent of correlation between events, individual weights w_x for the different discount factors can be specified as well. Overall, we calculate our discounted information value as described in (3), with parameter notations depicted in Tab. I.

$$\begin{aligned} &IV^{'}(E_D, M_F) = \\ &\frac{IV(E_D) \cdot sdf \cdot w_{sdf} + IV(E_D) \cdot tdf \cdot w_{tdf} + IV(E_D) \cdot ddf \cdot w_{ddf}}{w_{sdf} + w_{tdf} + w_{ddf}} \end{aligned} \tag{3}$$

Our actual operationalization of equation (3) and particularly of the different discount factors has been based on our employed application view as described in Section II and is adjusted to the information gain, which a data transmission would yield in the actual context. Thus, we consider this information gain being the lower, the more spatially correlated events are. Concerning temporal correlation, the same holds true and we consider the information gain being the lower, the higher the temporal correlation of events is. In contrast, the information gain is positively correlated with the information value difference between events.

In consequence, we operationalize the spatial discount factor *sdf* dependent on the relative spatial distance between two motes as points of origin for events to be compared, using the route information in the network, e.g., gathered from IDs of forwarding motes contained in forwarded event messages (4).

$$\begin{aligned} sdf = &\frac{hc(r(M_A, M_F)) + hc(r(M_D, M_F))}{max(hc)} \\ &- \frac{2 \cdot aidh(r(M_A, M_F), r(M_D, M_F))}{max(hc)}; sdf \in [0, 1] \end{aligned} \tag{4}$$

TABLE I
TABLE OF NOTATIONS

Notation	Description
E_D	event D
M_F	mote F
$IV^{'}(E_D, M_F)$	discounted information value of E_D on M_F
$IV(E_D)$	information value of E_D, e.g., transmitted with the event
sdf	spatial discount factor
tdf	temporal discount factor
ddf	information value difference discount factor
w_x	weight of discount factor x
$r(M_A, M_F)$	route between M_A and M_F (denoted by IDs of forwarding motes)
$hc(r(M_A, M_F))$	hop count for route between M_A and M_F
$aidh(r(M_A, M_F), r(M_D, M_F))$	number of identical hops between given routes
$max(hc)$	maximum hop count in network
$ts(E_X)$	timestamp of occurrence of E_X
$max(td)$	maximal time difference between two events
z	individual shaping factor for the temporal discount
$max(IV)$	maximal information value
$TR(E_D, M_F)$	transmission relevance of E_D on M_F
$TC(E_D, M_F)$	transmission costs for E_D on M_F

The temporal discount factor *tdf* is operationalized on the basis of the relative temporal difference between events to be compared, using timestamps (5).

$$tdf = (\frac{ts(E_D) - ts(E_A)}{max(tdf)})^z;\ tdf, z \in [0, 1] \quad (5)$$

In this context, a normalization solely based on the maximal time difference between two events (e.g., interpreted as expected duration of the monitored transport at its begin) can lead to undesired small discount factors from an application view. Therefore, we employ an individual user- and time-specific scaling function. Specifically, to provide for flexible shaping in this context, we propose the usage of a power function based on [11] with power *z*, which can be individually specified by a user depending on preferences and current context.

Considering the discount factor *ddf* for the information value difference, we basically propose to set the actual information value difference in relation to the maximal achievable information value (e.g., interpreted as the maximum value achievable in the scoresheet developed in [7]). Nevertheless, depending on the different information values of events, *ddf* can exhibit a negative value. Thus, we employ a shifting of the value range by adding the maximal achievable information value to the information value difference in the nominator and subsequently considering this by doubling the maximal achievable information value in the denominator (6).

$$ddf = \frac{IV(E_D) - IV(E_A) + max(IV)}{2 \cdot max(IV)};\ ddf \in [0, 1] \quad (6)$$

With these operationalizations of the discount factors in combination with equation (3), a mote can determine the discounted information value for a received event in comparison to other events in its current context. To finally decide on the transmission relevance of an event, the minimum discounted information value in comparison to all similar events in the event history of a mote is contrasted with the actual transmission costs prevailing on the mote (7).

$$TR(E_D, M_F) = \min(IV^{'}(E_D, M_F)) - TC(E_D, M_F); \quad \forall \text{ comparable } E_A \text{ stored on } M_F \quad (7)$$

In consequence, if (7) yields a value below zero, the event is considered non-transmission relevant and thus filtered out. Otherwise, the event is considered transmission relevant and a corresponding data transmission is initiated.

IV. EVALUATION

In order to evaluate our approach, we test its behavior in the context of temperature-sensitive transports (cf. Section II). Therefore, we obtained temperature data from a major logistics company (*Trace1* in Fig. 2) and extracted temperature traces published in [4] (*Trace2* in Fig. 2) as basic input for our evaluation. Further, the temperature distributions between the different motes in the modeled container we use are based on the description in [12].

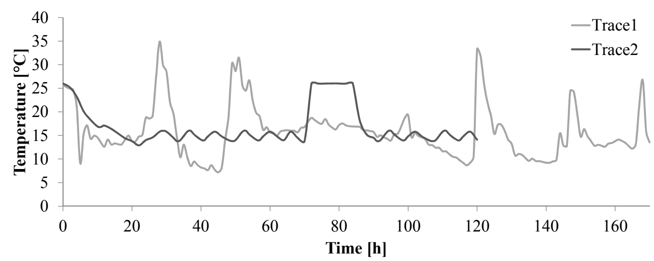

Fig. 2. Temperature traces used in simulations

Against the background of these temperature traces, our approach is evaluated within simulation experiments and compared to a periodic monitoring approach and a business rule-based monitoring approach relying on thresholds. These mechanisms represent the two currently prevalent reporting methods in logistics. With periodic monitoring, data is transmitted regularly, whereas with business rule-based reporting data is only transmitted in case it violates given thresholds.

We have conducted initial simulations with COOJA/MSPSim [13] on the basis of the TelosB mote platform [14] for the periodic monitoring approach, the business rule-based approach, and the local transmission relevance-based approach. The TelosB is widely used in WSN research and is even applied in logistics WSNs [15]. COOJA/MSPSim provides us with the ability to perform network-level simulations in combination with hardware emulation to analyze the energy consumption of different algorithm settings.

The results of our simulations are presented in Figs. 3 and 4. It can be seen that our local transmission relevance-based filtering approach [7] already achieves significant reductions of the number of transmissions and corresponding energy and network lifetime gains. For the performance of our distributed transmission relevance-based approach, we have calculated first estimations on the basis of the findings of our COOJA/MSPSim simulations and the settings employed for the local transmission-relevance based approach. In this context, we calculated as a first estimation the reduction of the number of data transmissions for low, medium, and high settings of the different discount factors and estimated the consequences for the network lifetime, interpreted as the time until the first node fails due to energy depletion. For the sake of simplicity, within this calculations the discount factors have all been weighted equally. As can be seen in Figs. 3 and 4, we expect a further reduction of data transmissions in comparison to the local transmission relevance-based approach of roughly about 15 to 20 percentage points, which would lead to an increased network lifetime of about 7%.

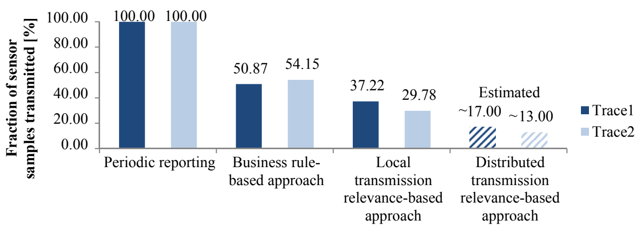

Fig. 3. Simulation results for data transmissions

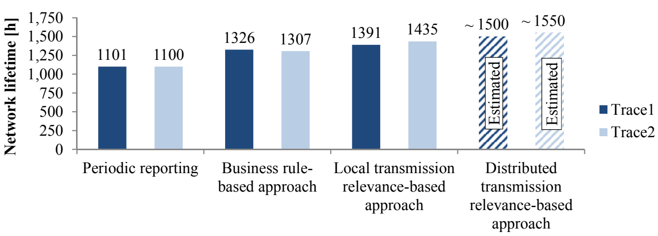

Fig. 4. Simulation results for network lifetime

V. Conclusions and Outlook

The logistics domain is a particular promising application area for WSN technology, which provides the possibility of real-time monitoring of transport processes. Energy- and cost-efficient operation is mandatory in such a context. Therefore, we proposed an in-network data filtering approach, which allows to reduce the communication overhead in logistics WSNs, while sill providing a sufficient supply of information. The presented approach is based on the transmission relevance of events and compares the information value of an event with the required transmission costs to decide whether data should be forwarded or filtered out. In particular, it provides a method to explicitly take into account the temporal and spatial correlation between events and thus adapt their information value accordingly by using specific discount factors. Overall, this allows to save on energy and monetary costs simultaneously by not transmitting irrelevant data.

We have conducted initial simulation experiments which already yielded promising results. Thus, as future work, our simulations will be extended to analyze more settings and explicitly incorporate monetary costs to account for cost efficiency effects. Additionally, deployments on real hardware will be realized and corresponding field tests conducted as a proof-of-concept.

Acknowledgment

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