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A framework for Resource-Aware Data Accumulation in sparse wireless sensor networks

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ABSTRACT

Wireless sensor networks (WSNs) have become an enabling technology for a wide range of applications. In contrast with traditional scenarios where static sensor nodes are densely deployed, a sparse WSN architecture can also be used in many cases. In a sparse WSN, special mobile data collectors (MDCs) are used to gather data from ordinary sensor nodes. In general, sensor nodes do not know when they will be in contact with the MDC, hence they need to discover its presence in their communication range. To this end, discovery mechanisms based on periodic listening and a duty-cycle have shown to be effective in reducing the energy consumption of sensor nodes. However, if not properly tuned, such mechanisms can hinder the data collection process. In this paper, we introduce a Resource-Aware Data Accumulation (RADA), a novel and lightweight framework which allows nodes to learn the MDC arrival pattern, and tune the discovery duty-cycle accordingly. Furthermore, RADA is able to adapt to changes in the operating conditions, and is capable of effectively supporting a number of different MDC mobility patterns. Simulation results show that our solution obtains a higher discovery efficiency and a lower energy consumption than comparable schemes.

1. Introduction

Wireless sensor networks (WSNs) have become an enabling technology for a wide range of applications [1]. Typically, a large number of sensor nodes are deployed over a geographical area. Sensors use multi-hop communication to send data acquired from the physical environment to a sink node or to an access point (AP) in the infrastructure. However, a dense WSN is not a requirement for many application scenarios, such as monitoring of weather conditions in large areas, air quality in urban scenarios, terrain conditions for precision agriculture, and so on. In this case, it is possible to exploit a *sparse wireless sensor network*, i.e., a WSN where the density of nodes is so low that they cannot communicate with each other. In order to make communication feasible, data collection in sparse WSNs can be accomplished by means of *mobile data collectors* (MDCs) [2,3]. MDCs are special mobile nodes responsible for data gathering and/or dissemination. They are assumed to be powerful in terms of data storage and processing capabilities, and are not energy constrained, in the sense that their energy source can be replaced or recharged easily. An MDC can serve either as a mobile sink (MS), a mobile node which is also the endpoint of data collection, or as a mobile relay (MR), which carries data from sensors to a sink node or an infrastructure AP. In either role, typically the MDC moves autonomously in the WSN [4].

Sparse WSNs with MDCs have many advantages over traditional dense WSNs [5]. First, costs are reduced, since fewer nodes can be deployed, as there is no need for a connected network. Second, as data is collected directly by the MDC from the sensor nodes, reliability is improved due to reduced congestion and collisions. Finally, data collection by MDC can extend the WSN lifetime, as the energy consumption is spread more uniformly in the network with respect to a static WSN, where the nodes close to the sink are usually more loaded than the others. However, data collection in sparse WSNs with MDCs also introduces several significant challenges, including energy-efficient MDC discovery and data collection.

A possible approach for energy-efficient data collection in sparse WSNs with MDCs requires that sensor nodes use a duty-cycle to discover presence of the MDCs in their communication range [4]. Moreover, the duty-cycle can be tuned according to the MDC arrivals, e.g., a sensor node can use a higher duty-cycle when there is a high probability that a MDC is in the communication range. This requires mechanisms to learn the arrival pattern of the MDC, even in the presence of uncertainty, and use that knowledge to adaptively tune the duty-cycle. To this end, solutions based

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on reinforcement learning [6] can be quite effective. In fact, reinforcement learning allows a sensor node to learn from the environment by merely interacting with it. Specifically, learning is based on the feedback from *tasks* (i.e., actions) performed by a node at any given state. A task can be selected either randomly or according to the accumulated knowledge, and the corresponding outcome is evaluated in terms of *reward*. A high reward means that the task is suitable to be executed in a given state, thus increasing the probability that the task will also be executed again in the future. As a consequence, reinforcement learning allows on-line learning and run-time adaptation by continuous interactions and feedback from the environment.

In this paper, we address the problem of data collection in sparse WSNs with MDCs, with focus on energy-efficient discovery of the mobile element. To this end, we propose the Resource-Aware Data Accumulation (RADA) framework, which exploits reinforcement learning to predict MDC arrivals and to adaptively tune a sensor node's duty-cycle for discovering the MDC. Our approach is quite simple, i.e., it demands minimal computational resources, and does not require any model of the environment. Therefore, it is very suitable for implementation on resource-constrained sensor nodes. RADA is based on discovery tasks with different duty-cycles, and on a state representation which is general enough to accommodate different MDC mobility patterns. As a consequence, RADA can be used in many sparse WSNs scenarios – including habitat monitoring and precision agriculture – without the need for application-specific strategies. We show through simulation experiments that the proposed solution can autonomously adapt to different application scenarios and diverse MDC mobility patterns, with a low energy-consumption and a high discovery efficiency.

The remainder of the paper is organized as follows. Section 2 overviews the related work, while Section 3 presents the reference network scenario and the considered mobility patterns. Section 4 describes the Distributed Independent Reinforcement Learning (DIRL) approach used for the design of RADA, which is presented in Section 5. Section 6 outlines the simulation setup, then Section 7 presents the experimental results. Finally, Section 8 concludes the paper.

2. Related work

Solutions for adaptive resource management and energy-efficient data collection in WSNs have already been considered in the literature. In the following, we provide an overview of the most relevant approaches for adaptive data collection, with particular focus on WSNs with mobile elements.

MDCs have been introduced first in opportunistic networks through the message ferrying approach [7]. In this context, a general framework for power management has been addressed by [8], and a knowledge-based approach to address the mobility pattern of the MDC has been proposed in [7]. However, as the proposed approach is devised for opportunistic networks, it cannot be used without being redesigned in the scenario considered in this paper. Many subsequent papers specifically focused on WSNs with MDCs, including [9–12,4]. However, they assume that the operating parameters are chosen prior to deployment, and do not change with time. Clearly, these approaches lack flexibility, as they require an *a priori* characterization of some network parameters (e.g., the mobility pattern of the MDC, the duration of contacts or the message generation rate). In addition, the chosen parameters cannot adapt to changing operating conditions. An adaptive data collection scheme has been considered in [13]. However, it does not address MDC discovery, but assumes that some information on the MDC mobility pattern is available prior to deployment. In this work, instead, we provide an adaptive strategy which can be used even when there is limited knowledge on the mobility pattern of the MDC.

Knowledge-based approaches for data collection in WSNs with MDCs have been proposed in [14,15]. In [14] the WSN is assumed to be rather dense, so that nodes can organize into clusters. Within each cluster, a specific node operates as a proxy, i.e., it collects data from other nodes in the cluster and relays them to the MDC. After detecting the presence of the MDC in their proximity, proxies initiate a reinforcement-based routing process so that messages are relayed to the destination while it traverses the network. Instead, in [15] reinforcement learning is exploited for discovery purposes, in the context of sparse WSNs where mobile nodes act as peers. Specifically, nodes scan for neighbors and use the number of encounters as a reward. The reward is mapped to a time-based domain. Then, sensor nodes perform discovery according to the likelihood of the other peers to be in contact, as per their energy budget. Although in [14,15] reinforcement learning is used for data collection, they do not specifically address the problem of sparse WSNs with MDCs. In fact, the approach in [14] is more focused on routing, and assumes that the network is dense enough to form cluster of nodes. Even though the solution in [15] can also be applied to sparse WSNs, it has been specifically designed for sensor nodes acting as mobile peers. Instead, we consider WSNs where ordinary sensor nodes are static and only a limited number of special nodes (i.e., the MDCs) collect data in the network. In addition, we exploit an approach based on Q-learning [16], while the proposal in [15] is based on simple reinforcement learning. Finally, we design a solution which is flexible enough to support different mobility patterns in contrast to that in [15] which is optimized for multiple MDCs obeying certain schedules.

Adaptive data collection in WSNs has also been investigated by means of middleware solutions for proactive resource adaptation [17]. Among them, many solutions such as [18–20] actually focus on dense WSNs where nodes are static (or at most have a limited mobility), and assume some coordination between nodes which is difficult to achieve in sparse WSNs. To the best of our knowledge there are only a few solutions explicitly targeted to WSNs with mobile elements. Among them, Impala [21] is a middleware architecture proposed for optimizing the energy efficiency and reliability of WSN applications. However, Impala is targeted to scenarios where all nodes are mobile and act as peers with focus on application adaptation and update, rather than on resource allocation. Instead, the TINYLIME [22] middleware has been proposed for the specific scenario of sparse WSNs. TINYLIME provides mechanisms to perform data aggregation and tune the activity of nodes in order to save energy. However, the focus of TINYLIME is on the proposed programming abstraction rather than on adaptation and resource management. In contrast, in this paper we propose an adaptive middleware approach to resource allocation for energy-efficient data collection in sparse WSNs.

In this paper, we extend the work in [23] by providing a more general solution which can be used for several different mobility patterns. Our scheme, which also supports additional features as well as multiple MDCs, is shown to be more energy-efficient than other approaches already proposed in the literature.

3. System overview

In this section, we first describe the reference scenario and the different phases involved in data collection, along with the corresponding communication protocols. Next, we provide an overview of some significant MDC mobility models which will be later exploited as a reference for the design of our framework.

3.1. Reference network scenario

The reference network scenario is illustrated in Fig. 1(a). Specifically, we assume that the network is sparse, i.e. at any time the