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Elimination of Calculable Data for Aware-Failure Networks in the WSN

K.Rajashekar
Assistant Professor,
Department of Computer Science & Engineering,
Christu Jyothi Institute of Technology & Science.

P.Avaniketh
Assistant Professor,
Department of Computer Science & Engineering,
Christu Jyothi Institute of Technology & Science.

ABSTRACT:

Wireless Energy constraints on battery-powered nodes, it is critical to minimize communication. So Wireless sensor networks are widely used to continuously collect data from the environment. Elimination has been proposed as a way to reduce communication by using predictive models to suppress reporting of predictable data. In addition cascading reduces the communication, it makes failure handling difficult, because nodes will act on incomplete or incorrect information and in turn affecting on the other nodes. However, in the presence of failuring the communication, missing data is difficult to interpret because it could have been either eliminated or lacking in transmission.

Cascading is used for handing the failure of general and spatiotemporal suppression. cascading reduces the communication and nodes will act on incorrect or incomplete information that effects on the other nodes and difficult to handle the failure. For recovering the missing data from the suppression and communication failures we propose a cascaded suppression framework that exploits both temporal and spatial data correlation to reduce communication, and applies coding theory and Bayesian inference. And the result show that cascaded suppression significantly reduces communication cost and improves missing data recovery compared to existing approaches.

INDEX TEARMS:
Security, Wireless Sensor Networks, Network, Cascading

I.INTRODUCTION:

In the natural sciences, research often relies on extensive manual investigation. Such methods can be error-prone and obviously don't scale well.

The development of autonomous data acquisition systems such as Wireless Sensor Networks (WSN) has provided a method to significantly reduce manual work and, as such, has the potential to enable researchers to address previously infeasible scientific questions. However, making the transition from WSN deployments in a laboratory to real-world deployments is still very challenging. Creating robust, error-free systems that are able to run autonomously in real-world environments without manual supervision has proven to be complex and, therefore, the number of successful collaborations between computer scientists and natural scientists is still limited. Here, we describe our successful attempt to design and deploy a WSN to monitor seabirds on Skomer Island, a UK National Nature Reserve. We summarize the evolution of the system over a period of three years, share insights on selected design decisions, and discuss both, our experience and the problems we have encountered. The wireless sensor network "macroscope " offers the potential to advance science by enabling dense temporal and spatial monitoring of large physical volumes.

This paper presents a case study of a wireless sensor network that recorded 44 days in the life of a 70-meter tall redwood tree, at a density of every 5 minutes in time and every 2 meters in space. Each node measured air temperature, relative humidity, and photosynthetically active solar radiation. The network captured a detailed picture of the complex spatial variation and temporal dynamics of the microclimate surrounding a coastal redwood tree. This paper describes the deployed network and then employs a multi-dimensional analysis methodology to reveal trends and gradients in this large and previously-unobtainable dataset. An analysis of system performance data is then performed, suggesting lessons for future deployments. Wireless sensor networks are proving to be useful in a variety of settings.

A core challenge in these networks is to minimize energy consumption. Prior database research has proposed to achieve this by pushing data-reducing operators like aggregation and selection down into the network. This approach has proven unpopular with early adopters of sensor network technology, who typically want to extract complete "dumps" of the sensor readings, i.e., to run "SELECT *" queries. Unfortunately, because these queries do no data reduction, they consume significant energy in current sensornet query processors. In this paper we attack the "SELECT " problem for sensor networks.

We propose a robust approximate technique called Ken that uses replicated dynamic probabilistic models to minimize communication from sensor nodes to the network's PC base station. In addition to data collection, we show that Ken is well suited to anomaly- and event-detection applications. A key challenge in this work is to intelligently exploit spatial correlations across sensor nodes without imposing undue sensor-to-sensor communication burdens to maintain the models. Using traces from two real-world sensor network deployments, we demonstrate that relatively simple models can provide significant communication (and hence energy) savings without undue sacrifice in result quality or frequency. Choosing optimally among even our simple models is NPhard, but our experiments show that a greedy heuristic performs nearly as well as an exhaustive algorithm.

II.IMPLEMENTATION:

Many approaches have been proposed to reduce communication in sensor networks. Tiny Aggregation (TAG) [6] utilizes in-network processing to aggregate data as it travels toward the base station. However, TAG is not suited for raw data collection. BBQ [7] proposes probabilistic model-driven data acquisition. Queries about sensor data are answered by consulting a correlation-aware statistical model. If the model cannot provide results with enough confidence, the base station acquires readings from a subset of nodes in order to reach the desired confidence level. However, the model must be trustworthy; otherwise, an answer could be wrong and there is no way of knowing it. The idea of model-based suppression has been applied in Ken [3], which uses dynamic, spatiotemporal probabilistic models. Our solution differs from Ken in three significant ways.

First, as discussed in Section 1, our cascaded suppression is more general and creates more opportunities for reducing communication. Second, Ken recovers data in the form of deterministic bounds, whereas we combine information obtained from the suppression scheme with statistical models to recover data in the form of posterior distributions. Third, Ken does not directly address the issue of transient communication failures. The Markovian nature of their models only guarantees that, once a new value for a reading arrives at the base station, the models are synchronized with respect to this reading. However, nothing can be said about the data during the time when the base station receives nothing.

This issue weakens the data quality guarantee offered by Ken. Designing a failure-aware cascaded suppression framework is challenging in many ways. How do we systematically cope with cases where a single failure has a rippling effect on other readings and nodes? What information is necessary for interpreting missing data resulted from failures and cascaded suppression? How should that information be communicated efficiently? What suppression models can we use to capture spatiotemporal correlations, without making failure handling and data analysis intractable? In this paper, we provide a holistic solution to these questions. We propose a general framework for cascaded suppression that is both communication-efficient and failure-resilient.

Inspired by prior studies on spatiotemporal suppression and on the Bayesian approach to handling failures, our work not only goes beyond them in terms of their respective strengths, but also provides a solution that unifies them for the first time. We believe our work is an important step toward making suppression a practical paradigm for data collection in wireless sensor networks More specifically, we show that cascaded suppres- sion beats previously proposed suppression techniques (namely, disjoint-cliques of Ken [3] and value-based temporal suppression in BaySail [4]) in terms of flexibility of control and the ability to exploit spatiotemporal correlations in sensor data to reduce communication. Another compelling advantage of our solution is the principled approach towards failure handling. The only existing solution with this feature works only for simple temporal suppression [4], and it deals with none of the intricacies that arise with cascading.

We show how to resolve the problem of nodes acting on inaccurate information—not by scrambling for corrective actions, but by carefully logging and forwarding information that will allow the base station to reconstruct history and interpret data later.

III.SYSTEM PRELIMINARIES:

A.SELECTING SUBSET TO TRANSMIT :

One remaining issue is how a cluster head selects a subset from the |K| current readings to transmit if transmitting nothing will make prediction go out of bounds. Selecting the "best" subset is NP-hard, so we consider greedy algorithms that can be implemented easily on sensor nodes. We present two such algorithms, both of which greedily expand the chosen subset one reading at a time until the prediction is bounded.

B.COMPUTATION COST:

Conventional wisdom is that computation costs on sensor nodes are dwarfed by communication costs. Much of the previous work on suppression provides no quantified comparison: PAQ [8] has only coarse estimation of the complexity of updating individual nodes' suppression models, while Ken completely ignores the computation cost of spatial suppression. To better understand the computation cost of suppression, we take a closer look at CS2. Computation costs of child-to-head suppression edges are negligible because value-based temporal suppression can be implemented by a handful of simple instructions. The base station is not resource constrained so computation there can also be ignored.

C.TOWARDS A BETTER SOLUTION:

For simple temporal suppression between a node and the base station, BaySail proposes that the sender attaches to every outgoing message the timestamps of its last r transmissions. Upon successfully receiving a message from this sender, the base station can (retroactively) construct the sender's transmission history, as illustrated by the following example.

IV.CONCLUSION:

Continuous data collection is a basic task in many applications of wireless sensor networks.

To reduce the energy cost of communication, we have proposed cascaded suppression. We have shown that cascaded spatiotemporal suppression is more flexible and effective than previously proposed suppression schemes. More importantly, our comprehensive solution tackles the problems of handling transient message failures, interpreting missing data, and learning from data. Failure handling is particularly challenging for cascaded suppression, because nodes can act on inaccurate information and in turn affect other nodes. We resolved this problem by logging and forwarding essential information to the base station to allow reconstruction of history and interpretation of data. We have further applied

convolutional coding techniques to the transmission of such information, using a novel decoding algorithm that does not make traditional assumptions such as the existence of good failure models. This feature, together with the fact that the correctness of suppression does not depend on the correctness of its model, make our solution especially suited for data collection tasks in unfamiliar and unpredictable environments.

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AUTHOR PROFILES:

K.Rajashekar received M.Tech from Kakatiya University Warangal. He is currently working as a Assistant. Professor in Computer Science & Engineering Department, Christu Jyothi Institute of Technology & Science ,Jangaon,Warangal,Telangana, India-506167.

P.Avaniketh received M.Tech from JNTU Hyderabad. He is currently working as a Assistant.Professor in Computer Science Engineering Department,Christu Jyothi Institute of Technology & Science ,Jangaon,Warangal,Telangana, India-506167.