



Query-Driven Data Collection and Data Forwarding in Intermittently Connected MSN

Roja. M, Suganya.y

Department of computer science engineering,
Mookambigai college of engineering,
Pudukkottai,
India.
rojasheela06@gmail.com

Abstract— In wireless Sensor network, it is well-known that communication is the primary energy drain, which is unfortunate, given that the ability to report sensed data motivates the use of WSNs in several pervasive computing applications. The premise of applying data prediction is that communication can be significantly reduced by avoiding transmission of each raw sample to the sink. This is achieved by using a model to estimate the sensed values, and by communicating with the sink only when changes in the sampled data render the model no longer able to accurately describe them. WSNs consume energy not only when transmitting and receiving data, but also in several continuous control operations driven by the network layer protocols, e.g., when maintaining a routing tree for data collection, or probing for ongoing communication at the MAC layer. So data prediction are actually observable in practice. Data prediction is proposed in wireless sensor networks (WSNs) to extend the system lifetime by enabling the sink to determine the data sampled, within some accuracy bounds, with only minimal communication from source nodes.

Index Terms—Wireless sensor networks, data prediction, time series forecasting, energy efficiency, network protocols

1. INTRODUCTION

Wireless sensor networks (WSNs) provide the flexibility of untethered sensing, but pose the challenge of achieving long lifetime with a limited energy budget, often provided by batteries. It is well-known that communication is the primary energy drain, which is unfortunate, given that the ability to report sensed data motivates the use of WSNs in several pervasive computing applications.

An approach to reduce communication without compromising data quality is to predict the trend followed by the data being sensed, an idea at the core of many techniques [1]. This data prediction approach¹ is applicable when data is reported periodically—the common case in many pervasive computing applications. In these cases, a model of the data trend can be computed locally to a node. This model constitutes the information being reported to the data collection sink, replacing several raw samples. As long as the locally-sensed data are compatible with the model prediction, no further communication is needed: only when the sensed data deviates from the model, must the latter be updated and sent to the sink. Section 2 formulates the data prediction problem in more detail.

The aforementioned approach is well-known, and has been proposed by several works we concisely survey in Section 6. Nevertheless, to the best of our knowledge none of these works as been verified in practice, in a real-world WSN deployment. On one hand, the techniques employed are relatively complex, and their effectiveness is typically evaluated based on implementations in high-level languages (e.g., Java) on mainstream hardware platforms. Therefore, their feasibility on resource-scarce WSN devices remains unascertained. Moreover, the works in the literature typically evaluate the gains only in terms of messages suppressed w.r.t. a standard approach sending all samples. This data-centric view, however, is quite optimistic. WSNs consume energy not only when transmitting and receiving data, but also in several continuous control operations driven by the network layer protocols, e.g., when maintaining a routing tree for data collection, or probing for ongoing communication at the MAC layer.

Therefore, the true question, currently unanswered by the literature, is to what extent the theoretical savings enabled by

data prediction are actually observable in practice, i.e., i) on the resource-scarce devices typical of WSNs, and ii) when the application and network stacks are combined in a single, deployed system

We propose derivative-based prediction (DBP), a novel data prediction technique compatible with applications requiring hard guarantees on data quality. DBP, described in Section 3, predicts the trend of data measured by a sensor node, and is considerably simpler than existing methods, making it amenable for resource-scarce WSNs, as witnessed by our TinyOS implementation for the popular TelosB motes [3].

We perform an extensive experimental evaluation of DBP against state-of-the-art data prediction techniques, based on seven diverse real-world data sets with more than 13 million data points in total. The results demonstrate the effectiveness of DBP, which often performs better than the competition by sup-pressing up to 99 percent of data transmissions while maintaining data quality within the required application tolerances.

We describe the first² study of the interaction of data prediction with WSN network protocols, directly comparing the theoretical application-level gains against the practical, system-wide ones. We evaluate the performance of a staple network stack consisting of CTP [4] and Box-MAC [5], both in an indoor testbed and a real application setting, a road tunnel [6]. Our results show that the gains attained in practice lead to three- to five-fold WSN lifetime improvements, which is a significant achievement in absolute terms, but dramatically lower than those derived in theory.

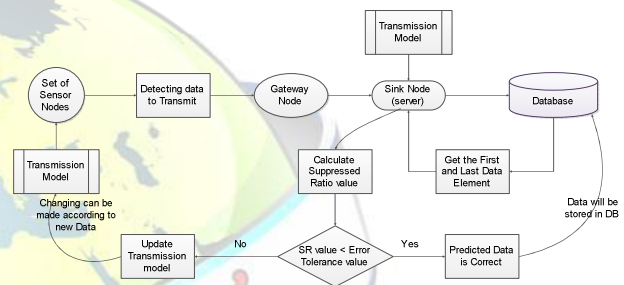
We explore the potential of cross-layer network stack optimizations to further improve the lifetime of WSN nodes running DBP. In our tunnel application, we show how a careful, yet simple, joint parameter tuning of the MAC and routing layers reduces the network control overhead considerably, without affecting the DBP operation, and yields a remarkable seven-fold lifetime improvement w.r.t. the standard periodic reporting.

The paper ends with the concluding remarks of Section 7, underlining the further lifetime improvements and enhanced reliability that can be attained by a WSN network stack expressly designed to work in conjunction with data prediction techniques.

II. PROPOSED APPROACH

Derivative-Based Prediction (DBP)

A novel data prediction technique compatible with applications requiring hard guarantees on data quality. The idea behind DBP is to use a simple model that can effectively capture the main data trends, and to compute it in a way that is resilient to the noise inherent in the data. DBP computes models capturing the trends in recently-observed data, producing models accurate with respect to future data. Suppression Ratio (SR) directly measures the fraction of application-layer messages whose reporting can be avoided the higher the value of SR, the more effectively a technique is performing.



III. SYSTEM MODEL

A. Initial Video Transaction

At first the sensor nodes in the network register their details for node authentication with the server. In wireless sensor network sink will always be the server system. Hence all the collected videos are sending to server. While transmitting the video, server identifies the sensor node information from the header of the packets and then stores the video into the database.

B. DBP Transmission Model Setup

To setup the model, need to convert the video into frames called "Learning window". Identify data points and trace the edge points of each frame. This edge point calculation helps to analyse the capturing video has the moving object or not. Based on the average value of all the frames within the video compute the value using DBP transmission.

3. Suppression Ratio value Estimation

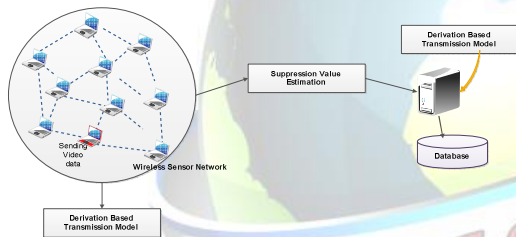
Server system also has the same DBP transmission model to compute the value. Basically server or sink compute

the DBP value based on the first video which is sent by the node initially. This value is called “value with prediction”. By getting value from the particular node with new video estimation known as “value without prediction”. Calculate the Suppression ratio value rely on the above two defined values.

4. Updating Transmission Model

At initially server fixed the error tolerance rate for all the sensor node for predicting the videos. If the calculated suppression ratio value is less than or equal to error rate, sink automatically send the feedback as predicted value is correct no need to send the video again. But if the suppression ratio is more get the video from the particular node and the n updates the new transmission model on both sides.

IV. SYSTEM ARCHITECTURE



V. EXPERIMENTS

The experiments we report are performed in our testbed for our main TUNNEL application, as results with the INDOOR data set are similar. Notably, these tests are longer than those reported earlier in this section, as CTP requires more time to reach a larger maximum beacon interval, specifically 2 hours at 8x. The 4-hour experiment duration is determined by restrictions on the testbed usage, and the need to keep the total experiment time manageable under the many combinations of parameters under consideration. Further, this set of experiments was also run at a later time w.r.t. those we presented earlier, and originally in [2]. Since then, the environment where the testbed is deployed underwent changes (e.g., a few walls were moved) that, albeit minor, affected connectivity. The experiments we present here, therefore, are also the opportunity to validate our earlier results on a slightly different WSN setup and longer experiment duration. Shows our results, with different combinations of maximum beacon intervals and MAC-level sleep intervals. A comparison with Figs. 11 and 12 can be easily seen by focusing on 1x, the

default maximum beacon interval. The trends are very similar to those observed earlier, with two major differences. First, the optimal sleep intervals without and with DBP are now 1,000 and 2,500 ms, respectively.

APPLICATION-LEVEL EVALUATION

This section analyzes the ability of our data prediction technique, DBP, to reduce the amount of data that must be transmitted to the sink. This is notably different from the system-wide energy savings enabled by such data suppression, which we analyze in Section.

$$SR = 1 - \frac{\# \text{ Messages generated with prediction}}{\# \text{ Messages generated without prediction}}$$

VI. CONCLUSION

The practical usefulness of DBP is reinforced by our system-wide evaluation, showing that with a properly tuned network stack, DBP can improve system lifetime seven-fold w.r.t. mainstream periodic reporting. The experimental results suggest that further reductions in data traffic would have little impact on lifetime, as network costs are dominated by control operations. Therefore, improvements must directly address the extremely low data rates of DBP, e.g., by considering radically different network stacks. Further, data loss in prediction-based systems has the potential to significantly increase application errors. Therefore, reliable transport mechanisms must be revisited to ensure application-level quality.

REFERENCES

- [1] T. Palpanas, “Real-time data analytics in sensor networks,” in *Managing and Mining Sensor Data*, C. Aggarwal, Ed. New York, NY, USA: Springer, 2012.
- [2] U. Raza, A. Camerra, A. Murphy, T. Palpanas, and G. Picco, “What does model-driven data acquisition really achieve in wire-less sensor networks?” in *Proc. 10th IEEE Int. Conf. Pervasive Comput. Commun.*, 2012, pp. 85–94.
- [3] J. Polastre, R. Szewczyk, and D. Culler, “Telos: Enabling ultra-low power wireless research,” in *Proc. 4th Int. Conf. Inf. Process. Sen. Netw.*, 2005, pp. 364–369.
- [4] O. Gnawali, R. Fonseca, K. Jamieson, D. Moss, and P. Levis, “The collection tree protocol,” in *Proc. 7th Int. Conf. Embedded Netw. Sen. Syst.*, 2009, pp. 1–14.
- [5] D. Moss and P. Levis, “BoX-MACs: Exploiting physical and link layer boundaries in low-power networking,” *Stanford Inf. Netw. Group, Tech. Rep. SING-08-00*, 2008.
- [6] M. Ceriotti, M. Corrao, L. D’Orazio, R. Doriguzzi, D. Facchin, S. Guna, G. P. Jesi, R. L. Cigno, L. Mottola, A. L. Murphy, M. Pescalli, G. P. Picco, D. Pregnotato, and C. Torghelle, “Is there light at the ends of the tunnel? Wireless sensor networks for adaptive lighting in road tunnels,” in *Proc. 10th Int. Conf. Inf. Process. Sen. Netw.*, 2011, pp. 187–198.



- [7] D. Tulone and S. Madden, "An energy-efficient querying frame-work in sensor networks for detecting node similarities," in *Proc. Int. Conf. Modeling, Anal. Simul. Wireless Mobile Syst.*, 2006, pp. 191–300.
- [8] *Life under your feet project* [Online]. Available: lifeunderyourfeet.org/en/src/, 2014.

