Environment Aware Sampling For Sensor Networks

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Abstract

This study develops an Environment AwaRe Sampling algorithm (EARS) for environment management applications. EARS is novel because it was developed for near real time, low data rate environmental applications where it adaptively controls the sampling frequency by monitoring the error derived from an autoregressive model. The approach relies on models located in each sensor to predict local parameters. The error is intermittently checked against actual readings and used to adjust the sampling frequency.

1. Introduction

Timely detection of events such as flooding is important to maximise production in farming environments. In precision agriculture, such knowledge is necessary for understanding microclimatic conditions in specialised crops. In such crops, level-driven event measurements in real time are useful for minimising loss from environmental conditions. For example in [1] King et al assert that potatoes, a water sensitive crop, need high (between 70-90%) soil moisture for optimum growth. Such levels are attained by using 30-35% of available soil moisture storage capacity, thus indicating a need for near real-time monitoring.

Wireless sensor networks are practical and cost effective solutions for near real time monitoring. A network contains battery powered communication nodes which are scattered in a remote field. The hardware of each node includes a microprocessor, data storage, sensors, an analogue-to-digital converter, a radio (transceiver), controllers and an energy source. Data are communicated from a source node to neighbouring nodes in a multi-hop fashion until they reach a given destination. Smart sensors, in spite of application specific differences, share limitations in transmission power and the radio bandwidth.

Deployments of sensor networks have varied from habitat to environmental and agricultural monitoring applications. Data collection from these remote environments imposes constraints on sensor node services and operations. Therefore any reduction in communication between sensor nodes at the expense of increased processing is desirable because communication is the most energy intensive operation.

This study proposes EARS, a sampling control algorithm for environmental applications. More specifically an adaptive autoregressive (AR) model is formulated that limits the amount of data required for processing and possibly communication thus extending battery life.

The remainder of this paper is organised as follows. In section 2 the related work is discussed. Section 3 shows an overview of the algorithm and section 4 presents some results. Finally section 5 makes concluding remarks and recommendations for future work.

2. Background and Context

Current adaptations of sensor networks have approached this sampling problem by using the sensor network as an event driven database that can be queried by a user. In such a scenario, collected data may be communicated when measurements exceed certain user defined limits . This is exemplified in work done by Rachel Cardell et al [2] where the architecture for an event driven monitoring network is presented. Cardell argues that the reactivity features reduce the amount of useless data by collecting more readings only when rain fall and soil moisture measurements change. However threshold detection based methods are highly sensitive to the particular component parameters within each node. Werner et al developed an exponentially weighted moving average (EWMA) detector to counteract sensitivity issues [3]. Detection is triggered when the ratio between a long and short term average is above some pre-specified threshold thus causing nodes to sample data continuously.

The work of Tulone et al raised the issue of reducing the communication burden using forecasting models[4]. More precisely, they developed a probability query adaptable system which used a combination of AR models located on each sensor to predict local readings. Model updates were sent to a sink whenever measured readings were outside specified bounds. In contrast, Jinboa et al proposed a scheme which dynamically adjusted the sampling frequency using a linear regression model [5]. The authors also highlighted a data compression algorithm which was incorporated into each sensor node to reduce the communication burden.

EARS is concerned with identifying the required sampling rate for control and good performance in a near real time environmental application. It “listens” to the prediction error then dynamically adjusts the sampling frequency. The algorithm is closest to work done by Tulone et al because it also uses an AR forecasting model located on each sensor. However EARS minimises the sampling frequency and communication burden at the expense of increased inaccuracy and processing.

Soil moisture was selected as the input parameter because it is a useful indicator of the soil condition under which crops are grown. Therefore information on the moisture level is a requisite in most environmental monitoring applications involving crop production. The next section discusses the novel scheme used in EARS for adapting the sampling frequency based on soil moisture readings.

3. EARS Overview

The soil moisture readings were assumed to be a discrete time signal $s(n)$. Therefore in the notation used below $s(n)$ at time unit $t = i$ to $t = i + Q$ were denoted by $s(i), \cdots, s(i+Q)$. The second order AR coefficients are calculated from the calibration data in the sensor queue (see the shaded region in Figure 1). During initialisation, the error threshold *E*, the maximum allowable number of reported outliers *max_outliercount* and the size of the prediction window *w* are defined. The algorithm is started when *Q* soil moisture readings, each separated by sampling interval τ, are loaded into a first in first out (fifo) queue on the sensor.

Next the sensor moves into the learning and monitoring phase where each of the soil moisture readings are replaced by a zero centred function using equation (1):

$$\tilde{S}(n) = S(n) - \mu \tag{1}$$

where μ is the non-zero mean of the queue.

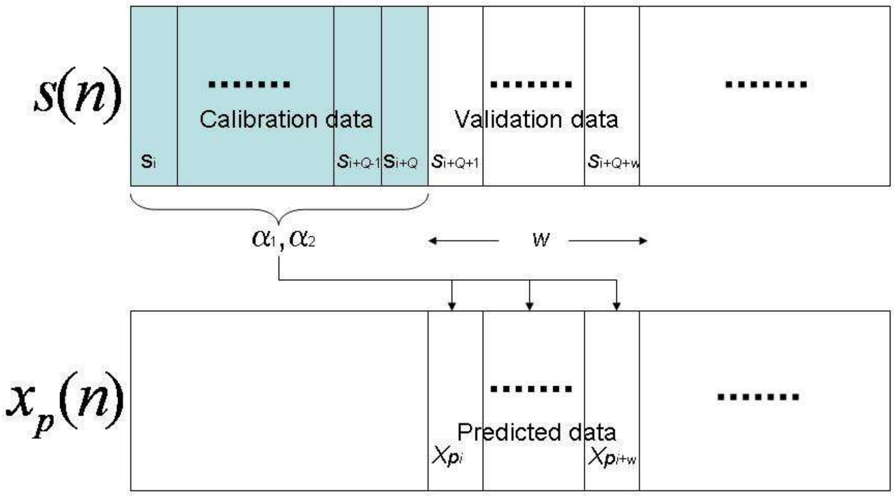

Figure 1 Calibration data in $s(n)$ are used to calculate the AR coefficients and hence the predicted samples, $x_p(n)$. Validation data are the real soil moisture measurements

The predicted samples can thus be expressed as:

$$X_p(n) = \mu + \alpha_1 \tilde{s}(1) + \alpha_2 \tilde{s}(2) \quad (2)$$

α_1 and α_2 are calculated from an approximate second order AR process:

$$\hat{\alpha}_1 \approx \rho_{xx}(1)(1-\rho_{xx}(2))/(1-\rho_{xx}{}^2(1)) \quad (3)$$

$$\hat{\alpha}_2 \approx (\rho_{xx}(2)-\rho_{xx}{}^2(1))/(1-\rho_{xx}{}^2(1)) \quad (4)$$

$\rho_{xx}(k)$ the autocorrelation of x at lag k from which the predicted readings $x_p(i),\cdots x_p(i+w)$ were calculated (see Figure 1). The error is derived from the difference between predicted samples and the actual measurements using the equation below:

$$e_i = x_p(i) - s(i) \quad (5)$$

Based on the calculated error *e* and the number of outliers *outliercount*, the algorithm has four possible outcomes (see Figure 2):

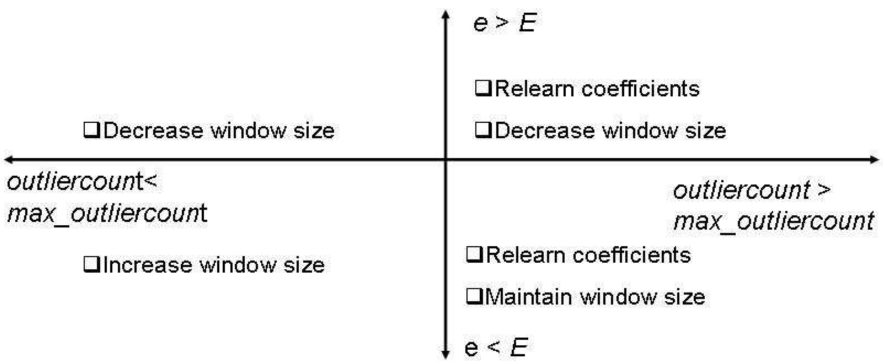

Figure 2 *outliercount* is compared against *max_outliercount* and *e* is compared against *E*. The results of the comparison place the algorithm in one of four possible quadrants which control the output of the sampling frequency. This is novel because it overcomes both the problem of inefficiency in over-sampling and inaccuracy in under-sampling.

4. Results

Assuming the number of samples was a proxy for the transmission rate and hence communication energy, performance merits of the algorithm was evaluated by the response to the question: if EARS and a periodic sample and hold strategy used the same number of samples or sampling rate, did EARS produce a closer fit to the actual data? The simulation results in Figure 3 confirms that the answer is positive since it indicates that EARS has a lower rms error than periodic sampling if the same number of prediction samples are used. For example over the duration of a week, EARS requires about 1500 samples for an rms error below 0.36 compared with over 4000 samples in the periodic case. Therefore less than half the energy is used for EARS at the same total error.

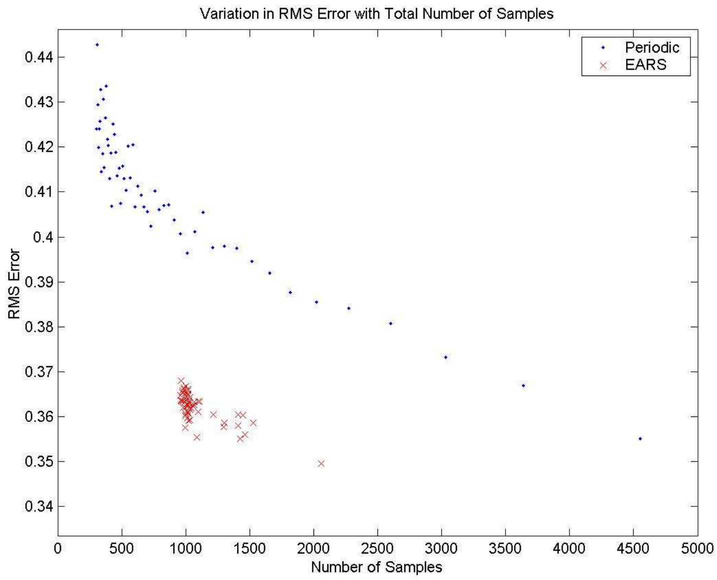

Figure 3 Simulation results showing the variation in the root mean square error against the number of samples. EARS results were obtained by varying *w*. Conversely the periodic sample and hold method was obtained varying τ.

5. Conclusions and Future Work

This study has developed an Environment AwaRe Sampling frequency control algorithm (EARS). Preliminary results have demonstrated that EARS decreases the sampling frequency required for reporting events when compared with fixed periodic sampling rates. Future considerations include enabling automated parameter selection and examining implementations in a spatio-temporal domain for thousands of sensor nodes.

References

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