Predictive Data Reduction in Wireless Sensor Networks using Selective Filtering

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Abstract: In a wireless sensor network, transmissions consume a large portion of a node's energy budget. Data reduction is generally acknowledged as an effective means to reduce the number of network transmissions, thereby increasing the overall network lifetime. This paper builds on the Spanish Inquisition Protocol, to further reduce transmissions in a single-hop wireless sensor system aimed at a gas turbine engine exhaust gas temperature (EGT) monitoring application. A new method for selective filtering of sensed data based on state identification has been devised for accurate state predictions. Low transmission rates are achieved even when significant temperature step changes occur. A simulator was implemented to generate flight temperature profiles similar to those encountered in real-life, which enabled tuning and evaluation of the algorithm. The results, summarized over 280 simulated flights of variable duration (from approximately 58 minutes to 14 hours) show an average reduction in the number of transmissions by 95%, 99.8% and 91% in the take-off, cruise and landing phases respectively, compared to transmissions encountered by a sense-and-send system sampling at the same rate. The algorithm generates an average error of 0.11 ± 0.04 °C over a 927 °C range.

1 INTRODUCTION

Research into the use of wireless instrumentation in the aerospace industry is growing, both within academia and industry. In the UK alone several large projects are currently reporting positively on wireless sensor network (WSN) based developments for this sector (Mitchell et al., 2011), (Pinto et al., 2010).

Generically, wireless measurement is considered an attractive option particularly for aircraft engines. It could reduce the complexity, weight, and cost of engine monitoring as well as provide increased sensor density, higher data rates, and enhanced sensor deployment flexibility (Yedavalli and Belapurkar, 2011).

Whilst *in-flight* engine monitoring and control based on WSN is a long term aim, in the short-to-medium term, the use of wireless instrumentation is envisaged mainly for engine design and test environments.

The research the authors have engaged with is towards *in-flight* engine monitoring. It aims to create Highly Efficient Autonomous Thermocouple (HEAT) system prototypes for EGT monitoring. A primary goal is to deliver robust, long lived wireless thermocouple systems which sample at rates of over 1 Hz. The drive towards long lived, low power wireless systems is essential to the domain, given that nodes need to run until the next service of the engine to avoid disruption of operation and need to be powered by existing energy harvesting technology (Adnan and Harb, 2011).

The HEAT hardware system developed, is composed of multiple battery powered thermocouple sensor nodes, located around the circumference of an engine casing. Each sensor node can sample at 1 Hz - 5 Hz from a Type-K thermocouple and reports the EGT data back to the sink node. Nodes use the CC2530 low powered ZigBee radio from Texas Instruments (TI) and a MAX6675 cold junction compensation chip. The nodes support Low Power Sleep.

When a HEAT sensor node's power consumption was analysed, it was found that a transmission of a single sample accounts for 75 % of the total consumption, whilst sleeping and sensing account for 24 % and 1 % of the consumption, respectively. Reducing the number of transmissions will thus provide considerable savings in power consumption and increase the

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network lifetime.

The contribution brought by this paper consists on a method for drastically reducing transmissions in EGT wireless sensing systems. The work builds on previous research in the area of dual prediction schemes (DPSs) for wireless sensor systems. In particular, we propose an application bespoke state prediction and selective filtering method to be used in conjunction with Spanish Inquisition Protocol (SIP) (Goldsmith and Brusey, 2010) (described in Section 4). The proposed method is generically suitable for applications where the data stream exhibits a combination of steady states and significant step changes. The performance of the algorithm developed is tightly correlated with the absolute values of the sensor readings. Thus in order to tune and evaluate its performance an EGT simulator was also developed.

The remainder of this paper is structured as follows, Section 2 briefly describes related work in the area of data reduction for wireless sensor systems. Section 3 describes the simulator used to evaluate the proposed algorithm. Section 4 considers the SIP as the fundamental the data reduction method within the HEAT system. Section 5 presents the selective filtering (SF) algorithm integrated with SIP. Results are given in Section 6, and concluding remarks are presented in Section 7.

2 RELATED WORK

Whist it is important to reduce the number of transmissions in a wireless networked system, it is equally important to accurately capture the phenomena being monitored. For the application at hand, transmissions reductions through sampling rate reduction can not be considered; HEAT nodes need to ensure sampling at least at 1 Hz. Data compression and reduction is however an alternative approach to long lived networks with specified requirements for data quality.

Many methods for data compression and reduction within a WSN have been proposed. Dictionary based compression algorithms such as Lossless Entropy Compression (LEC) (Marcelloni and Vecchio, 2009) provide a byte reduction on a per packet basis, although would require sensor readings to be buffered in order to reduce the number of transmissions. Schoellhammer *et al.* (2004) model the sensor readings using a liner model, by buffering the readings until the residual error of a liner fit exceeds a predefined error threshold. Due to the real-time requirement of the HEAT system, buffering approaches are not applicable.

The class of DPS algorithms solve the problem of having to buffer sensor readings. By using a model on the sensor node and the sink node, new readings can be predicted without having to transmit further data. When the error between the models exceeds a tolerable threshold, new model parameters are transmitted. Large reductions in the the numbers of transmissions can be accomplished using the DPS approach, while keeping a real-time knowledge of the system's state (Anastasi et al., 2009). A variety of implementations exist for the approach described above. Jain *et al.* (2004) use a Dual Kalman Filter (DKF) as the system model. Santini and Römer (2006) use an Least Mean-Square (LMS) filter. Le Borgne *et al.* (2007) present a general method for adaptively selecting the model using a statistical procedure termed *racing*. Such a method allows the most optimal model, from a discrete set of models stored on the sensor node, to be learned over time. Although considerable transmission reductions are reported for a variety of case studies, none of these approaches respond well to step changes in the sensed data. (A summary of the results of these algorithms can be found in (Goldsmith and Brusey, 2010) and (Borgne et al., 2007).) These works have, however inspired the authors here towards the reported developments.

3 EGT SIMULATOR

The EGT simulator attempts to produce flight like data to be used in evaluating the proposed algorithms. The simulator consists of an EGT phenomena model (PM) and a thermocouple sensor model (SM), as shown in Figure 1. For the purpose of this paper, the output from the PM, denoted s, is considered as the actual EGT. The output from the SM is taken to be the thermocouple readings, denoted y.

Flight profiles are split into three main phases: take-off, cruise and landing. At the start of the flight the EGT is relatively low. During take-off, the EGT rises sharply to around 1000 °C where it remains fairly constant for the majority of the flight. During the final landing phase, the EGT decreases to ambient temperature, with some oscillation to replicate observed practice.

For the purpose of this simulation study, the take-off and landing sequences, shown in Table 1, are considered to be consistent. The cruise sections of the flight are of variable duration, denoted d, which is regarded as an input to the simulator. To simulate a typical cruise phase of the flight, a nominal EGT of 830 °C is chosen. Furthermore, to accommodate different altitudes and weather conditions, a uniform

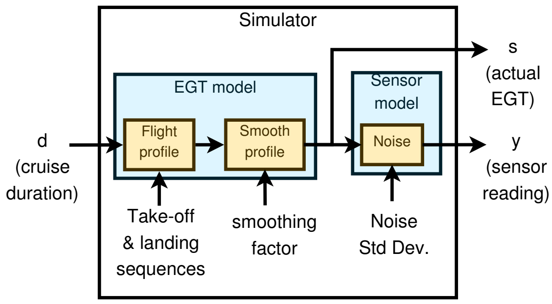


Figure 1: Simulator architecture.

distribution of the EGT about the nominal value of ± 30 °C is randomly selected at the start of each cruise section. Over the course of the cruise phase, there are additional adjustments to the flight pattern, at random times during every 90-120 minutes, i.e. in a uniformly distributed random manner. These transients consist of an increase in EGT by 25 °C for 60 seconds, followed by a further cruise section and the cycle repeats until the cruise phase is complete.

Table 1: Flight sequence for take-off and landing phases, which is identical in every simulated flight.

Phase	EGT ($°C$)	Duration (s)
Start engine	400	40
	410	5
	390	30
Taxi	430	220
Manoeuvring	390	5
	394	7
	390	4
	394	8
	395	3
Take off	950	10
	900	430
	920	10
Pull back	880	224
High idle	500	200
Landing	463	10
	442	5
	459	7
	441	4
	465	8
Reverse thrust	750	15
Engine off	20	30

Once the flight profile sequences have been generated, smoothing is applied to provide a gradual transition between flight phases. This facilitates a realistic EGT of the engine between the various steady state sections. To realise this, an exponentially weighted moving average (EWMA) filter with a value for the smoothing factor, denoted α, of 0.4 is applied to the generated time series.

It is believed that the standard deviation of the sensor noise at cruise temperature is around 0.52 °C. Consequently, Gaussian noise, with a standard deviation of 0.52 °C, is added to the PM output to simulate realistic thermocouple data.

4 SPANISH INQUISITION PROTOCOL

The Spanish Inquisition Protocol is a generic data reduction algorithm developed by Goldsmith and Brusey, designed to reduce the number of transmissions in a WSN (Goldsmith and Brusey, 2010). The underlying principle is that transmissions should only be made when sensor readings are not as expected, i.e. when some pre-defined change threshold is violated. By using a model of the system, sensor readings can be reconstructed at the sink node within a defined error tolerance.

A model state vector, denoted X_t, is calculated on the sensor node and shared with the sink. This state vector is used on both the sensor and sink to predict the future system state at every time step. As the predicted state, denoted X'_t, diverges from the actual measured state, so the reconstruction error, defined as $\varepsilon = |X'_t - X_t|$, increases. When this error exceeds a defined threshold, a new model state vector is calculated and shared.

The data reduction that SIP provides is dependent on model quality and the calculation of the predicted state, denoted X'_t. In this paper a piecewise linear model is used, as demonstrated in (Goldsmith and Brusey, 2010). The model state vector is defined as $X_t = (\bar{x}_t, \Delta\bar{x}_t)^T$. Where $\bar{x}_t$ denotes the predicted value and $\Delta\bar{x}_t$ denotes the predicted rate of change. It is then possible to predict future states between transmissions using,

$$X'_t = \begin{bmatrix} 1 & t \\ 0 & 1 \end{bmatrix} X_t$$

5 SIGNAL ESTIMATION USING SELECTIVE FILTERING

The more accurate the predicted rate of change, the longer the state prediction will remain within the allowable error range. Hence, the more predictable the signal the greater the reduction in transmissions. It is important, therefore, to remove as much noise from the signal as possible, which is done by filtering the data. Selective filtering (SF) is a rule based method of selecting between multiple filters in real time, each optimised for a different part of the signal. The signal is modelled as a sequence of states and transitions.

State transitions are identified by a predefined set of rules specific to the application. Each state has it's own filter, selected from a bank of filters and it's own predictor, which estimates the rate of change. Two states are defined in this application, steady and variable, shown in Figure 2.

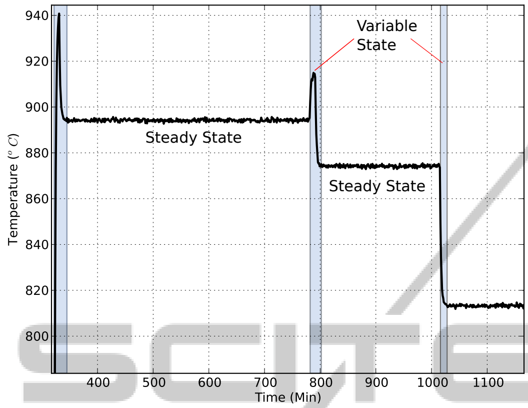


Figure 2: System states within the flight profile.

Steady states are defined as periods of low rate of change, and is the initial system state. The expected value $\bar{x}_t$ is found by filtering the sensor sample x_t with an EWMA filter having a value for α of 0.01. A transition to variable state is identified when a sample x_t deviates from $\bar{x}_t$ by more than a specified threshold, denoted b, so that $|\bar{x}_t - x_t| > b$. For this application, an appropriate value for the breakout threshold b was found to be 1.6 °C.

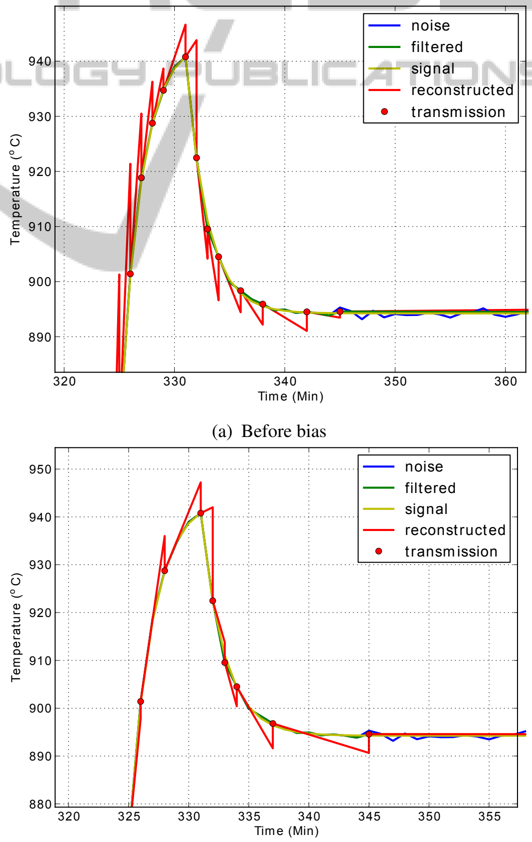
A variable state is defined as a period of large rates of change in the data. During this state a second filter can be used, or as in this application, samples can remain unfiltered. A moving window, denoted W, of the n most recent samples is stored. A steady state resumes when the range of values in the window is less than a given threshold, r, such that $\max(W) - \min(W) < r$.

Accurate state prediction depends on the calculation of the two components in the SIP model state vector. These are: the predicted value, denoted $\bar{x}_t$ and and the predicted rate of change, denoted $\Delta\bar{x}_t$. The SF method improves the quality of the prediction by reducing signal noise. When the rate of change is accurate, the model will take longer to diverge from the actual sensor readings, resulting in fewer transmissions.

In the steady state $\Delta\bar{x}_t$ is calculated using the original SIP method, $\Delta\bar{x}_t = \frac{\bar{x}_t - \bar{x}_l}{t}$, where l is the time of last transmission. Recognising that the rates of change in the variable and steady states are different, improvement can be gained by reinitialising the model state vector on each state change. In a steady state, there is, by definition, little change in the temperature. The best estimate of the initial $\Delta\bar{x}_t$ was found to be 0.

When transitioning from a steady to a variable state, the initial expected value is defined as $\bar{x}_c = x_c$, where c denotes the time of the transition to the variable state. Here the expected rate of change is calculated as $\Delta\bar{x}_c = \frac{x_c - \bar{x}_l}{c - l}$, where $\bar{x}_l$ is the last expected value from the preceding steady state at time l, and x_c is the sensor reading at the time of transitioning. Subsequent predicted values are calculated as $\bar{x}_t = x_t$ and rate of change using $\Delta\bar{x}_t = \bar{x}_t - \bar{x}_{t-1}$.

Moreover, since a variable state starts with a large change in temperature followed by a convergence to a steady state, it can be assumed that there is a high probability that future $\Delta\bar{x}_t$ will be smaller than $\Delta\bar{x}_{t-1}$. Based on this assumption, it is postulated that $\Delta\bar{x}_t$ can be better predicted with $\Delta\bar{x}_t = \gamma(\bar{x}_t - \bar{x}_{t-1})$ where $\gamma \in (0, 1]$. Where γ determines the strength of the bias of the rate of change towards a steady state. Figure 3 shows the reconstructed signal before and after bias.



(a) Before bias

(b) After bias

Figure 3: More accurate rate of change estimation after bias.

6 RESULTS

Using the simulator described in Section 3, a comparison is made between the performances of the Kalman filter, the EWMA filter, and the SF, as described in Section 5, when applied to the simulated EGT data. In particular it is of interest to assess their ability to filter the data, as well as the impact on the number of transmissions when they are used in conjunction with SIP.

SF reduces the noise while preserving the underlying signal, as observed by the reduction of the root mean squared error (RMSE) between the filtered and noise free signal, while the EWMA and Kalman filters increased the RMSE. In order to provide a fair comparison in further tests, the EWMA and Kalman filters were tuned to have a maximum error from the original signal of 3.5 °C. The simulations were run again with the new filter parameters and resulting RMSE can be seen in Figure 4.

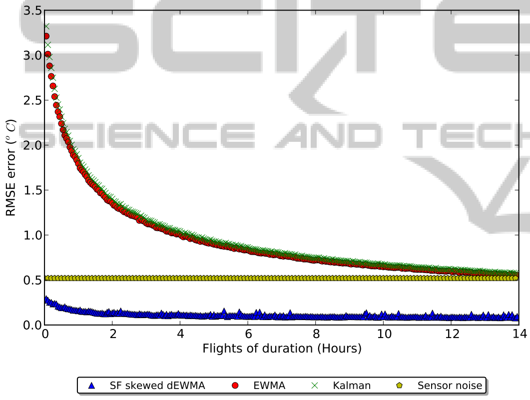


Figure 4: RMSE error between the original signal and the filtered value.

Using an error threshold of 0.5 °C, 280 random flights are generated with cruise lengths from 0 to 13 hours at 3 minute intervals, Table 2 shows the percentage number of samples that would need to be transmitted per hour for each algorithm. Figure 5 shows the expected battery lifetime of a node running each algorithm. It is important to note that the expected lifetime shown is the relative effective lifetime. Assuming the aircraft continuously serviced flights of the given duration, d. Each flight immediately following the previous flight, this would be the expected number of days the HEAT node is expected to last.

Table 2: Mean percentage of samples transmitted per hour in each phase of a flight.

Samples transmitted per Hour (%)			
Filter	Take off	Cruise	Landing
EWMA	7.9	0.4	16.4
Kalman	7.5	0.3	14.8
SF	4.8	0.2	9.5

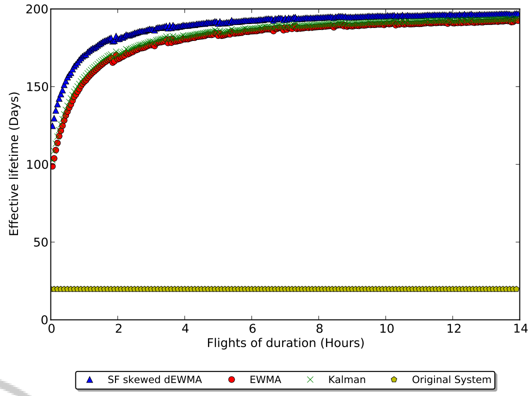


Figure 5: Comparing expected battery lifetime when using different data reduction methods.

7 CONCLUSIONS

It has been found that the new SF algorithm, comprising of SIP and SF, when applied to the HEAT system has considerably increased the battery lifetime of a sensor node. The new SF approach has be found to reduce the sensor error, as well as the overall system error. It is expected that the method could be adapted to other steady state systems with significant step changes in signal values.

There are some assumptions that have been made during the evaluation of this work, which may affect performance in a real deployment. The simulation assumes normally distributed noise, with a fixed standard deviation. However, in reality this may not be the case, and the system parameters may change over time. If this is the case then the breakout threshold values would need to be adjusted accordingly. Such an observation would lead naturally to an adaptive breakout threshold in response to the varying parameters.

A further assumption is that the temperature in the steady state is constant, i.e. no variation; in reality one could expect there would be some variation.

The encouraging results presented in this paper provide an opportunity for further exploration. For example, the algorithm presented uses a linear model and it is considered that further reductions in transmission is possible if a non-linear model were to be used.

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