Adaptive Sampling Mechanisms in Sensor Networks

A Djafari Marbini, L. E. Sacks

University College London

Abstract: More and more sensor networks are being suggested as alternatives to single sensor packages as a means of measuring and recording environmental variations. The rate at which the sensors make readings from the environment is both important in terms of presenting an accurate picture of environmental changes to the users and resource usage in the network. This paper is looking at means of making an adaptive control mechanism to change the frequency of measurements by each node, as an alternative to non-adaptive fixed sampling rates.

1. Introduction

With the advances in wireless technology increasingly it is becoming apparent that ad-hoc sensor networks are suitable to satisfy requirements of environmental monitoring. The development of small, low cost network of microcontrollers is providing both cost and scientific advantages to the large sensor packages which are expensive to build, maintain and deploy [1]. The small size and cheapness of the devices will allow these self-organising, wireless Ad-hoc networks to be rapidly deployed in large numbers over an environment for the purpose of various sensing tasks [2]. One of the greatest advantages that sensor networks offer oceanographers is that the network of sensors will measure environmental phenomenon in various physical locations at the same time, as oppose to the traditional sensors which only measure at one location at a time. This allows the sensors to build a wide spatiotemporal picture of the environment and allows the measurements to be made in dangerous and inaccessible areas [3].

In sensor networks the positions of individual nodes do not need to be engineered previously. The protocols in sensor networks posses self-organising capabilities. The adaptive behaviour and management of sensornets will allow additional benefits in terms of making measurements when and where they are needed most, to present the users with an accurate picture of the environment. As examined by [4] high precision measurements which current sensors are capable of are often not necessary. The uncertainty in measurement of suspended sediment concentration by an optical backscatter sensor (OBS) resulting from the effects of time-varying sediment size was examined by [4] and concluded that ±10% was the best that could be achieved.

2. Application Context and Motivation

Using low cost devices results in limited functionality and performance. Target environments are by their nature turbulent and therefore the sensors will need to continuously adjust to extremely dynamic systems. Both the large number of the devices and the expected dynamics of the environment present challenges in the design of autonomous sensor networks. One of the most important challenges is the issue of presenting an accurate picture of the changes in the environmental variables. This can only be achieved if the physical phenomenon is sensed or sampled from the environment at an accurate rate. There is always the option over sampling, however over sampling has a resource cost. The aim is to produce an accurate spatial picture of the environment, while making an efficient use of resources e.g. CPU, memory and energy. Fixed sampling rates are not easily adaptable, and in turbulent surroundings the data collected will not produce an accurate representation of change in the environment. If a user requirement for the network is to measure environmental variations, e.g. changes in temperature and pressure, it is important that the rate at which the device makes readings from the environment is as close as possible to the rate of change. If the temperature of a particular area in the sensor networks environment is changing linearly for the time period which is of an interest to the users of the network then after a couple of readings the sensor, using an internal control loop mechanism should recognize this, and reduce from the rate at which the measurements are taken from the environment. This would be one step towards an efficient task sharing, so that resources of all the nodes are used effectively.

The writers are proposing that a feedback control mechanism will be adopted in each individual node, in order to make the rate of sensing dynamic and adaptable. Traditionally control mechanisms have been used in order to manipulate highly dynamic systems. More recently feedback control mechanisms have been suggested as a means of controlling scheduling mechanisms in distributed real-time systems [5]. The writers are therefore proposing the use of control mechanisms in order to manipulate the rate at which each individual sensor collects readings from the environment. It is important to recognize that task delegation is an important part of a community of sensors. The Figure 1 presents the feedback mechanism proposed. The sampled data will get compared to a model representing the environment. An error value will be calculated on the basis of the comparison. If the error value is more than the predefined margin of error, then the node will collect the data at higher sampling rate, and if it is lower, the sampling rate will be decreased. This will be a step towards developing locally intelligent sensors capable of dynamic self-configuration.

In designing the control mechanism in the sensors network a compromise needs to be reached between the three elements which will be called the complexity triangle. They are a) Complexity of the Control loop, b) Sampling rate and c) Complexity of the model. With an increased complexity in the control loop, a higher accuracy in the sampling rate required can be achieved. Similarly a more complex internal model would possibly help to increase the accuracy of the optimum sampling rate required for a relatively accurate representation of the environment. However, in a sensor extra complexity would mean, extra energy required for the computation. A balance needs to be achieved between knowing the best possible sampling rate and the complexity of the internal model and the control loop. The turbulent and dynamic environment that it is being measured makes it hard, if not impossible to use classical control systems to track sampling rates. The fixed point arithmetic devices will also struggle with floating point computation. Therefore it is more likely that adaptive control algorithms will be used.

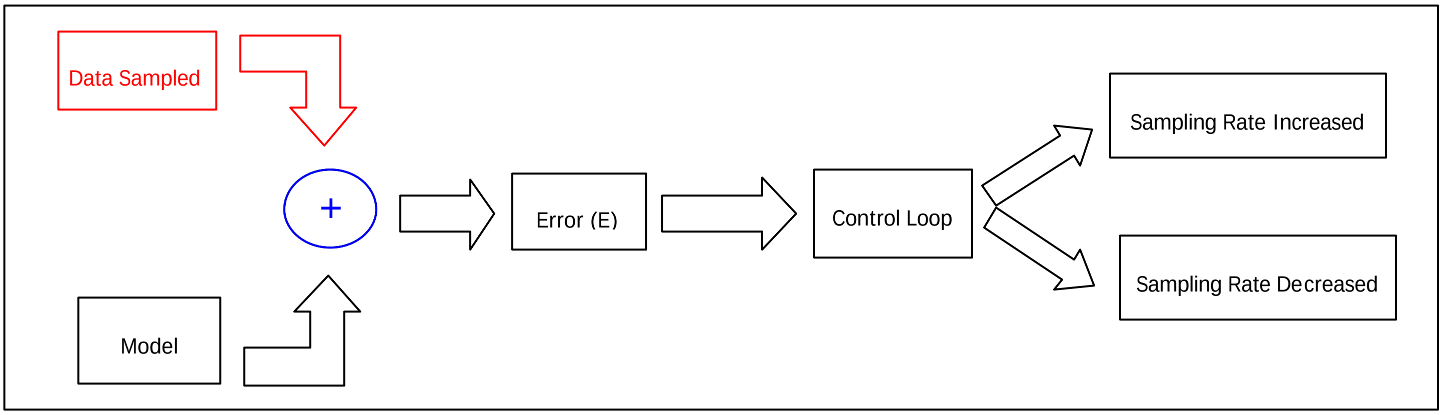

Figure 1. Control mechanism used internally within the nodes to control the sampling rate.

3. Experiments and Preliminary Results

An agent-based simulator was used to test the proposals, and the following experiment was set up. An individual sensor was placed in an environment where the temperature is varying by a constant sinusoidal. In this case the physical phenomenon that the sensor was interested in tracking was temperature. The node has an internal model which is a straight line. The node measures the temperature of the environment every so many units of time (epochs). As soon as two values (measured from the environment) are available to the sensor, it uses the model equation, to calculate the temperature of the environment until the next time the sensor makes a reading from the environment. In which case the temperature at times t+1 and t follow the model equation, and the temperature at time t-1 gets deleted from the system. The equation for the model is the straight line equation, $y_p = ax + b$, where y_p is the predicted temperature and x is the time at which the temperature occurs. The temperature then gets compared to the actual temperature collected from the environment and error will be calculated by comparing the two values, $E = y_p - y_a$. The experiment was repeated several times with different sinusoidal frequencies and sampling rates. Figures 3 and 4 depict the results of one of these experiments in which case the period of the wave is 3 epochs and the sampling rate is every 2 epochs.

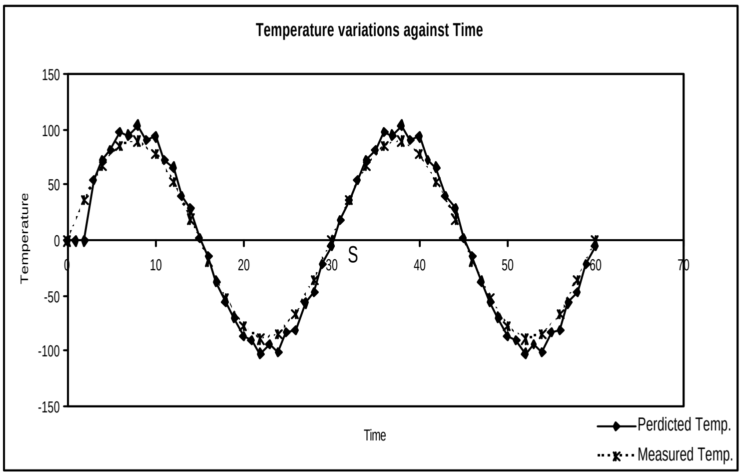

Figure 2. Temperature variations against time, Period =3 and Sampling rate = ½ (Sample/epoch)

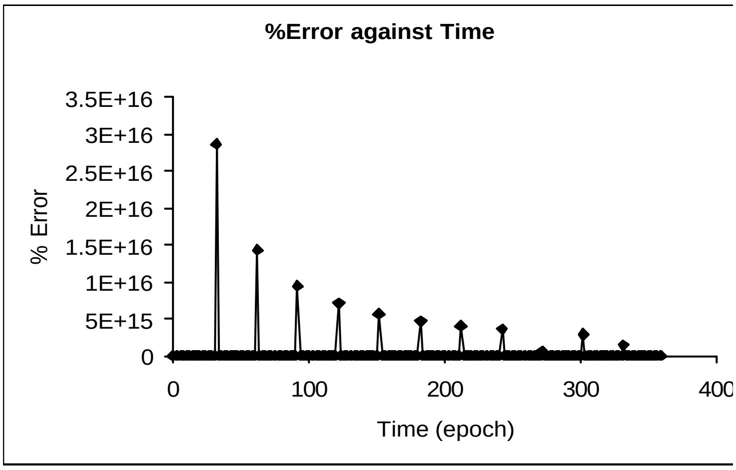

Figure 3. Error calculated between predicted and measured temperature, Period =3 and Sampling rate = ½ (Sample/epoch)

The algorithm for calculating error was then developed further to get rid of the large anomalies observed in Figure 3, so that the general trend of the error could be seen. The same experiment was repeated for different sampling rates and sinusoidal frequencies. As it was predicted the error was behaving in a sinusoidal manner. The value of the error peaks for each frequency and sampling rates were plotted. The Figure 4 depicts the results of the experiments. It is apparent that for the same error to be achieved a higher sampling rate is required the higher the frequency of the sinusoid.

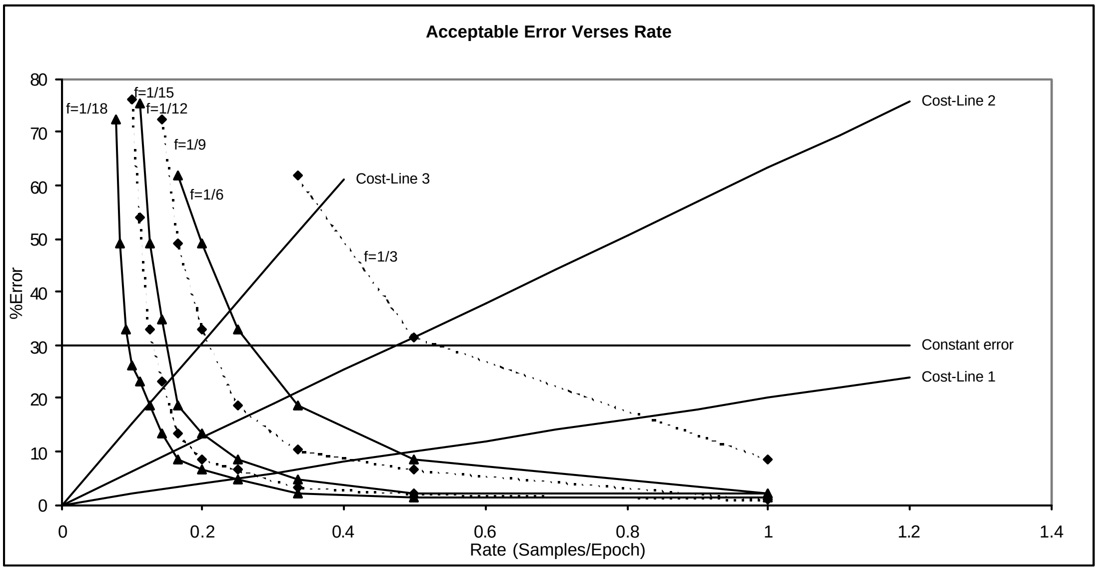

Figure 4. Error against sampling rate, for different sinusoidal frequencies, f=frequency of the sinusoid.

In addition it can be seen that in some instances a large increase in the sampling rate, achieves a small improvement in error. Therefore it is important to consider the costs and importance of realising a smaller error. To better understand the relationship between cost and error Figure 5 was plotted using the crossing between the cost lines and the frequency lines on Figure 4. A compromise between sampling rate and error needs to be achieved. Along Cost-line 1 the sampling rate is higher than Cost-line 3, however the error is also substantially lower. Cost-line 2 is a compromise between sampling rate and required error.

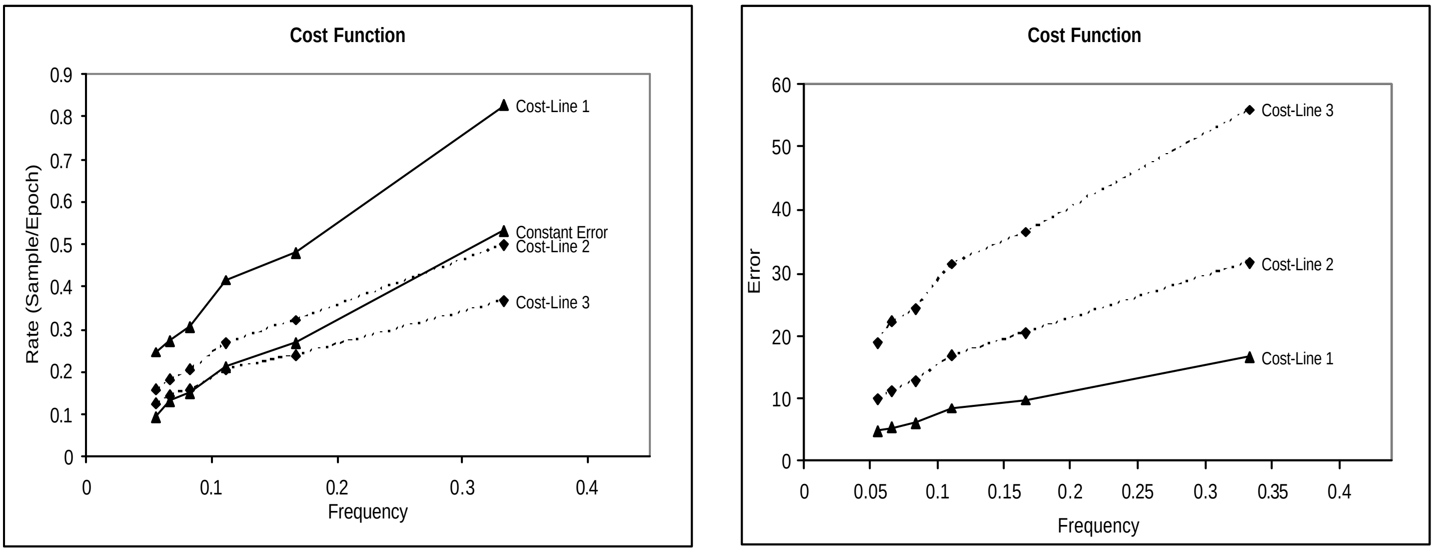

Figure 5. The cost function graphs.

4. Conclusions and Future Work

It is conclusive that a compromise between sampling rate which will influence the resource usage, and accuracy needs to be achieved. The degree of complexity of the model will also influence both the accuracy of the estimated model and resource usage. It is the intention of the writer to test more complicated environments which show some fractal behaviour against different prediction models. Addition of nodes and the result of information sharing between the nodes will also be tested.

References.

[1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, E. Cayirci, "A survey on sensor networks", IEEE Communications Magazine, Vol. 40, No. 8, pp. 102-116, August '02.

[2] S. Goel, T. Imielinski "Precision based monitoring in sensor networks: Taking lessons form MPEG ", Computer Communication Review, Number 5, pp.82-95 '01.

[3] SECOAS project web site. www.adastral.ucl.ac.uk/sensornets/SECOAS

[4] C. E. Vincent, S. J. Bass, J. M. Rees, "Uncertainties in the estimation of suspended sediment concentration due to variations in sediment size", Proceedings of Costal Sediments '03, Clearwater, Florida.

[5] C. Lu, J. A. Stankovic, G. Tao, S. H. Son, "Design and evaluation of a feedback control EDF scheduling algorithm", 20th IEEE Real-Time Systems Symposium (RTSS), Phoenix, December '99.