Energy Conservation of Sensor Nodes using LMS based Prediction Model

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Abstract: ***Energy conservation is one of the most concentrated research area in wireless sensor networks. Sensor nodes deployed on large scale in an unmanned area is used for environmental monitoring. But sensor nodes work on battery power and hence are energy constraint devices. In such scenario, energy of nodes can be conserved by reducing number of transmissions occurring from sensor nodes to base station or intermediate nodes. Applications in which environmental quantity is gradually changing over time may be transmitted only if marginal changes occur. This paper proposes a data prediction model that predict data without using a priori knowledge. Least mean square algorithm is used to implement prediction model with self-adaptive step size. This work achieves improved step size and a data reduction about 94%.This model can be used to increase lifetime of every node in the wireless sensors network.***

Keywords: energy conservation, sensor nodes, least mean square algorithm, estimation theory, data prediction

1. Introduction

Wireless sensors networks (WSN) are spatially distributed sensor nodes that monitor various parameters like temperature, humidity, air pollutants, voice activity, etc. The main aspect of every wireless sensors network is to save energy and ultimately increase the lifetime of network. Sensor nodes utilizes energy for-

1) Sensing
2) Processing
3) Radio interface

From above three, radio interface consumes more energy than other two [1]. With enhancing technology, sensor networks are expanding in size and utility. Thus, for large number of sensor nodes in a network, it is essential to minimize the energy loss due to transmission. Data reduction can be broadly classified into three categories.

1) Data compression
2) Data prediction
3) In-network processing

Data compression reduces the amount of information. Implementation of compression techniques involve encoding methods. This increases processing at sensor nodes substantially.

In-network processing performs data aggregation at the sensor nodes. Data aggregation refines the data by applying averaging functions. This yields less accurate system. Also in hierarchy based sensor networks, few sensor nodes (cluster heads) perform data aggregation while other sensor nodes transmit raw data.

Data prediction reconstructs the data within a degree of precision. Data prediction can be modeled using schemes like time-series forecasting or stochastic process approach [2]. We implemented least mean square (LMS) adaptive algorithm based time-series forecasting approach for our prediction model design. It is simple and yet can be designed without using a priori modeling. For a scenario where monitored data is increasing gradually over time, need not transmit redundant data often. This can be predicted and transmission decisions can be taken depending on prediction error. An algorithm is designed that changes step size based on the incoming sensed values so that prediction error can be minimized. LMS is implemented using adaptive filter with two filter coefficients. The energy consumed during processing is not greater than energy consumed due to radio interface [3]. Thus, this approach is suitable for reducing energy consumption of sensor nodes.

In the proposed work, a cluster based wireless sensors network is considered. Prediction model is designed for sensor nodes that transmit data in given time slot scheduled by cluster head. So, sensor nodes must be active during their transmission time slot. LMS algorithm based adaptive filter is implemented with variable step size for data transmission reduction strategy. Step size decides the convergence characteristic of the filter. If the step size is of large value, convergence is fast. If step size is small value, convergence is slow. We achieved appreciable step size. Simultaneously, stability of the filter is also maintained within a precise limit. This is done by adjusting prediction error threshold. The prediction model predicts the measured values from the previous readings. The sensor node transmits the data only when measured parameter differs from predicted one by a value greater than a threshold. The threshold value ideally is kept low as it indicates the precision of our system. Here two cases are proposed. Case 1 calculates step size that depend on samples delayed by one time period (1T). Case 2 considers samples delayed by two time periods (2T). The purpose of considering above cases is to increase the step size and ultimately fasten the convergence of the filter. Simultaneously, data transmission is reduced by significant percentage. The results obtained shows that, convergence factor is increased compared to [4] for mote 1 of [5].

The organization of the paper is given below.
Section 2: Literature review
Section 3: Implementation of prediction model
Section 4: Results

Section 5: Conclusion and future scope

2. Literature review

Energy efficiency is one of the key characteristic of wireless sensors networks. Many algorithms were proposed for energy saving and increasing network life time. A review on various methods adopted to reduce energy consumption by data reduction techniques is studied.

In the work proposed by [6], unnecessary sensing is eliminated by adjusting sampling frequency. It also reduces number of nodes that participate in sensing process assuming that sensor very close to each other can sense for alternate time intervals. For cluster based network, nodes must be always ready to transmit data in given time slots. This alternate sensing strategy might not work in the case when a node goes in idle state during its transmission time schedule given by cluster head or base station.

In [7], the data is maintained at server. This data are the readings of nodes with minimum and maximum values. This form a set of readings of previously transmitted values. Sensor nodes has to transmit only if sensed value falls outside of the set otherwise no transmission takes place for given time interval. This approach gives good results but rely on global parameters with a query session before every transmission. It checks whether the value belongs to the set or not. This increases computation at both sensor node and sink.

Author of paper [8] performed data aggregation at cluster head node. The algorithm computed average of specified values and reduced the amount of data that is to be transmitted towards base station. In network, few nodes are cluster heads compared to total number of nodes. Thus, this process is taking place only at the secondary level of transmission, from cluster-head to base station.

In [9], Kalman filter was used for data reduction. It uses model based technique. Thus, it requires prior knowledge. Overheads of sensor nodes increases along with processing cost. This is unsuitable for large WSN as sensor nodes are treated as independent devices.

Another popular approach of data reduction was introduced by [4]. The algorithm eliminated unnecessary samples. Identical predictive filters were implemented at node and sink. LMS was used with fixed value of step size (μ) to predict the readings. The length of filter used was 4.

Prediction technique was also implemented by [10] using variable step size (LMS-VSS). Step size depends on the previous values of the parameter. Here, length of filter used is kept 4. The algorithm uses first 4 data readings to calculate the initial value of μ. Next new value of μ is updated after $M^{3/2}$ readings, where M is the length of the filter. The results obtained were better than [4] for cluster based networks. Another approach [11] based on LMS is studied. The author used adaptive filter and LMS algorithm to predict the measured values. In this algorithm, μ value is set to (1/Ex) /2 for normal mode and (1/Ex)/16000 for standalone mode. Here, Ex is the mean square of the previous readings.

From the study of above research, for energy efficiency and prolong network life time, prediction model is more appropriate than other methods with respect to processing energy. It is simple to design. Comparing [4] and [10], variable step size gains faster convergence. But, leads to instability in filter prediction. This is resolved by adjusting the error threshold from 0 to 5. In [11], error threshold range is reduced to 2. But the prediction is unstable due to trade-off between step size and filter stability. This led to decrease data reduction percentage for lower values of error threshold.
In our work, an attempt was made to achieve better step size and reduce data transmission percentage. The results obtained has μ value in the range of 10^{-4} better than [4].

3. Implementation of prediction model

3.1 Adaptive filter

A filter is used to limit the output by removing undesired signal from the system. Filter can be designed to function linearly or non-linearly. The signal and its noise characteristics are often stationary and the statistical parameters are varying with time. On channels, whose frequency responses are known and are time invariant, the channel characteristics can be measured. Also the filter tap weights can be adjusted accordingly. An adaptive filter's transfer function keeps adapting new values depending on input [12]. In our work, adaptation of filter aims to adjust transfer function according to time-varying environmental input signal.

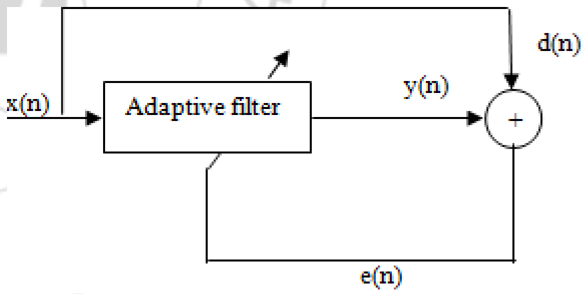

Figure 1: Adaptive filter

x(n) is the input sequence. d(n) is the desired sequence which is connected to input sequence. Thus, desired signal is the incoming signal. e(n) is the error sequence. It is the difference between filter output y(n) and desired input d(n). For slowly time-varying channel response, tap weights can be adjusted periodically or continually. Here, continual adjustment is accomplished estimating the data sequence and treating it as known measured data.

3.2 Least mean square based adaptive filter

A LMS based adaptive filter is designed where a priori modeling is not used for updating filter coefficients. It is assumed that all nodes are independent and these nodes do not use global parameters. LMS is the most robust algorithm. Each iteration of this algorithm uses a noisy estimate of the error gradient to adjust the weights in the direction to reduce the average mean square error. A new approach using estimation theory is used to vary the convergence factor of the filter. Convergence factor mainly depends on step size (μ) and filter coefficients. In our work, filter works with two coefficients (w_0 and w_1). Thus, step size is varied according to input sequence to get better prediction. An equation for step size is illustrated based on estimation theory. It is explained in 3.3. Figure 2 shows LMS based adaptive filter.

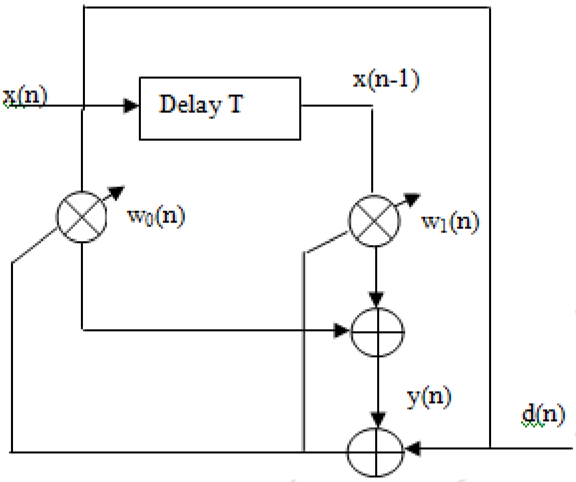

Figure 2: LMS adaptive filter

LMS undergoes a procedure in which error performance is varied with respect to randomly changing measuring parameter from iteration to iteration. Finally, settling to least or ideally zero error. The received samples in time shift manner forms a matrix of input sequence. The desired sequence of the filter is considered as the same input sequence for our experiment. The error e(n) is formed as,

$$e(n) = x(n) - y(n)$$

In above equation, x(n) is the desired sequence. y(n) is the estimate of x(n) at time instant n. The output of filter at time instant n is given by,

$$y(n) = \sum_{k=0}^{N} w_k(n) * x(n-k)$$

w(n) is the weight of the filter coefficients applied on input. w_k refers to the k^{th} tap weight at time n. The below equation show the iterative process that updates the set of weights at each time n.

$$w(n+1) = w(n) + \mu * e(n) * x(n)$$

μ is a term that limits the coefficient and thus controls the rate of convergence of the algorithm. From the above equation, if μ takes larger values, y(n) differs apparently from the input magnitude. This results instability of filter to predict correctly. Also, if μ takes smaller values, prediction is improved but filter undergoes more number of iterations to get the stability. Thus, for lower value of step size, filter gives slow convergence and stable output.

3.3 Estimate of step size

A sensor node senses environmental parameter periodically. The parameter is considered to be gradually changing over a period of time. An observation model equation based on parameter estimated is implemented. This equation is designed for parameters that slowly changes according to time. The estimated output is further used to calculate step size μ. It is calculated within the range as given below,

$$0 \le \mu \le \frac{1}{Y_{estimate}}$$

$Y_{estimate}$ is derived from set of estimates of x(n) and is calculated considering two cases. These cases are analyzed from the results given in section 4.

Case 1:
For slowly changing parameter, applying estimation theory that states as follows: true value of the measured parameter is the average of the readings taken at N instants. Sensor nodes transmit data in given time slot. For transmission, node will predict redundant data and transmit only data with high prediction error. Thus, $Y_{estimate}$ is calculated as a mean square of two input sample vectors delayed by 1T and 2T time period each. The equation is given as,

$$Y_{estimate} = \frac{(a+b)^2 * 0.1}{N}$$

'a' is the signal sequence of x(n) delayed by one time period. 'b' is the signal sequence of x(n) delayed by two time period. A constant of 0.1 yields better value of step size and thus included as constant coefficient. No other numerical constants are used in the work compared to [11].

Case 2:
In this case, $Y_{estimate}$ depends on one sample delayed by 2T time period. This assumption gave improved value of μ while maintaining the same data reduction rate. $Y_{estimate}$ is given as,

$$Y_{estimate} = \frac{b^2 * 0.1}{N}$$

The main aim of this modification is to yield faster convergence by increasing the estimated step size. The results in table 1 shows an increase in the step size of case 2 compared to case 1. This, ultimately resulted in faster convergence. If filter adapts fast convergence, prediction error is drastically minimized with less iterations. Sensor nodes have to transmit less samples, eventually increasing data reduction percentage.

4. Results

The simulated results for temperature measurement is shown below. The real time sensed values are taken from [5]. Performance metrics used are as follows:

1) Data reduction in percentage is tabulated for both cases. Readings of Mote 1 and mote 2 from [5] are taken as input.
2) Data transmitted percentage is compared graphically.
3) Relation between μ, error tolerance and data reduction percentage is shown graphically.

The experiment was carried out on two nodes. The range of error threshold is varied from 0.25 to 2 (indicates a temperature margin of 0.25°C) and observations are tabulated as below.

Case 1:

Table 1: Data reduction in percentage for node 1 and 2

	Node 1	Node 2
μ →	5.7e-004	5.8e-004
E_{th}	Data Reduction (%)	Data Reduction (%)
0.25	90	88
0.50	91	90
0.75	92	91
1.00	93	91
1.25	93	92
1.50	93	93
1.75	94	93
2.00	94	93

Case 2:

Table 2: Data reduction in percentage for node 1 and 2

	Node 1	Node 2
μ →	6.9e-004	7.0e-004
E_{th}	Data reduction (%)	Data reduction (%)
0.25	92	91
0.50	93	92
0.75	93	92
1.00	94	93
1.25	94	94
1.50	94	94
1.75	95	94
2.00	95	94

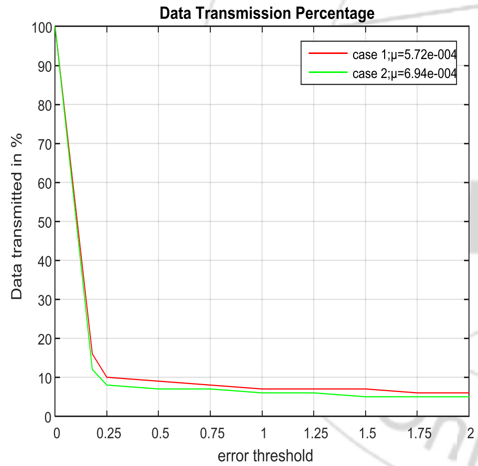

Figure 3: Data transmission from node 1

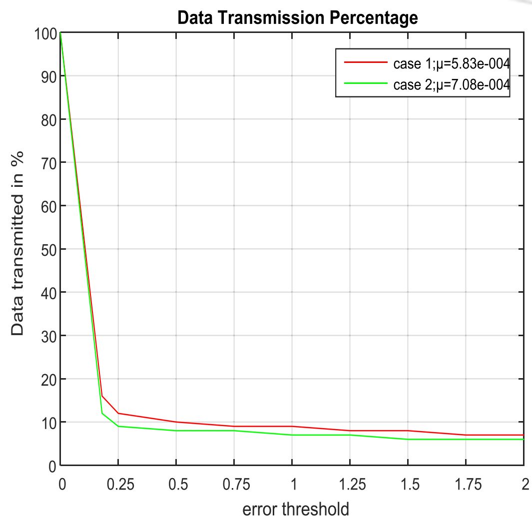

Figure 4: Data transmission from node 2

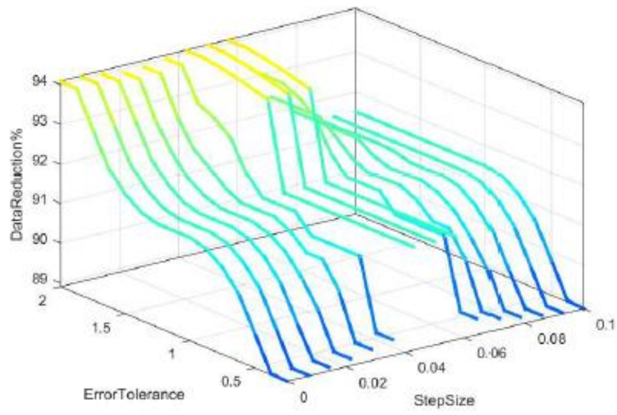

Figure 5: Relation between μ, E_{th} and data reduction %

The first inference is made from table 1 and 2. In each case μ is differently estimated. Case 2 yields better μ value. The value at 10^{-4} is realistic and practically applicable. This increases convergence rate of filter yet increasing data reduction % with maximum error threshold of 2.00.

The second inference depends on the filter performance at low error threshold. From Figure 3, at low thresholds, data reduction is increased by 2% compared with [4] for node 1. Comparing Figure 3 and 4, with increasing step size, prediction of filter becomes unstable. This leads to decrease in data reduction.

Figure 5 gives the performance of the prediction model with respect to step size and error threshold. As step size takes higher values, prediction error increases and leads to decrease in data reduction.

5. Conclusion and Future Scope

This research implemented a prediction model that can be used in each sensor node so as to reduce energy consumption. Results from section 4 implies convergence rate of the filter can be improved by using estimation theory to set proper value of step size. Simultaneously data reduction percentage is also maintained at optimal level.

In wireless sensor network, cluster heads are few compared to non-cluster head nodes. Energy consumption of sensor nodes acting as non-cluster heads can be reduced tremendously using proposed model. This will ultimately increase the network lifetime. Future work will be concentrated on effectively increasing transmission data reduction by combining prediction and data aggregation model at cluster head level of wireless sensors network.

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