An LMS Based Data Reduction Technique for Energy Conservation in Wireless Sensor Network (WSN)

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ABSTRACT:

In preceding existence, Wireless Sensor Networks (WSNs) have gained an amplified attention from the research community and extended its boundaries in commercial, industrial and medical domains. The tailback in WSN based application development is the inadequate energy source. As sensor nodes are generally battery-powered devices, the critical aspect is to lessen the energy consumption of nodes, so that the network lifetime can be extended over a reasonable time span. The energy of a node is consumed by sensor, processor and radio interface, of which the radio interface is the principal consumer of nodal energy. Thus reduction of data to be transmitted can effectively lessen the energy consumption, bandwidth requirement and network congestions. Data reduction strategies aim at reducing the sum of data sent by each node by predicting the measured values both at the source and the sink node, thus only requiring nodes to send the readings that depart from the prediction. While effectively plunging power consumption, such techniques so far needed to rely on a prior knowledge to properly model the estimated values. In this paper, an adaptive filter based on Least Mean Square (LMS) algorithm is employed that requires no prior modeling, allowing nodes to work independently and without using global model parameters. In this method, the data loss and node failures are also taken in to deliberation and appropriate techniques are included to reduce the prediction error. This work also involves dynamic adaptation of step size during different modes of adaptive filter.

Keywords: Wireless Sensor Network, Data Reduction Strategies, Adaptive filter, Least Mean Square

I) INTRODUCTION:

Typically a WSN is a spatially distributed autonomous sensor nodes deployed for monitoring the temperature, pressure, humidity, sound, vibration, seismic events etc [1] and it is reported to the base station through the network architecture. In general sensor node is a miniature device with some essential components like a) Sensing unit –for data Acquisition from the surrounding environment. b) Processor – for data processing and for transitory storage purpose. c) RF transceiver-for transmitting the processed data [2]. In a wireless subsystem, a power source often has a battery with the partial energy budget. The wireless sensor nodes are highly resource-constrained unit. It has some criteria's like i) Low processing capabilities, ii) Low security level, iii) restricted coverage and iv) Short life time.

It is impossible to recharge the battery when the node is deployed in an unfriendly environment [3]. In general, sensor network have a long lifetime to accomplish the application requirements [3]. Energy is a predominant restraint when compare to other restraint, so it becomes a significant issue for the researchers. The sensor nodes are deployed over a region of interest and it represents a spatial sampling grid and for each time instant, the information residing in the network are observed and are reported as snapshots. This leads to significant communication and energy consumption.

The problem of WSN lifetime maximization, in general, has been addressed in several other works. Hnin Yu, et al [4], listed multiple approaches for saving energy. Network coding is a lifetime maximization technique in which the collected data are mixed at intermediate node then encoding packets are sent instead of sending individual packets, consequently reducing the traffic. This is relevant in a deterministic networks and broadcasting based networks. In-network processing, where intermediate nodes aggregate several events into a single event to reduce transmissions. Duty cycling is a network level approach where the nodes are alternated between the sleep and active periods depend on the network activity. By using distributed algorithm the nodes are coordinated to ensure least amount of wakeup time. Sensor scheduling is a method by which the sensor switches between sleep and wake. During sleep, the sensor shuns the listening and overhearing and during wake, the sensor senses the events in the surrounding. There are Medium Access Control(MAC) level approaches in which data collisions are shunned by reducing the packets re-transmission. There is a basic plan to avoid interference by scheduling nodes onto different sub-channels that are divided either by time, frequency or orthogonal codes.

The other approaches like dynamic voltage and frequency scaling[5], energy aware routing[6], asynchronous processors[7], nodes partitioning (clustering)[8], the use of ultra wideband for radio communication[9] and the use of CMOS low voltage and low power wireless IC[10]. The following are the energy conservation techniques like duty cycling, data-driven, mobility based approaches.

Since radio communication is the governing power consuming activity in WSN, by minimizing the amount of data transmission, a noteworthy level of energy conservation can be achieved. There are various methods to lessen the data transmission.

Data driven approaches can be segregated according to the problem addressed. Energy-efficient data acquisition schemes are mainly designed to reduce the energy spent by the sensing subsystem. Energy can be conserved through eliminating the unnecessary sensing by adjusting the sampling frequency and reducing the number of sensor nodes which participate in sensing [11].

In-network processing consists of performing data aggregation (e.g., computing average of some values) at intermediate nodes between the sources and the sink. In this way, the amount of data is reduced while traversing the network towards the sink. It minimize the data rate among all the sensor nodes [12] .This is the way the amount of data get reduced while traversing towards the sink. Again, this technique is perfect only when sensor's readings are static and readings accuracy is not that important.

Data compression can be applied to reduce the amount of information sent by source nodes. This scheme involves encoding information at nodes which generate data, and decoding it at the sink. There are two models in network like source nodes and sink nodes. The model at the sink can be used to answer queries without requiring any communication, thus reducing the energy consumption[13].

 Data reduction scheme addresses the case of unnecessary samples, which reduces communication overhead by selecting, among all data produced by the sensor network, a subset of sensor readings that is delivered to the user such that the original observation data can be reconstructed within some user-defined accuracy. The success of such prediction depends on the quality of the functional relationship and the underlying prediction algorithms [14]. Data reduction method aims to reduce the data and by saving the energy and bandwidth. Data prediction model can be used to predict the data sensed nodes with certain error bounds and resides at both source and sinks. The very purpose of data prediction is to reduce the number of information sent by the source nodes and energy necessary for communication purpose. The data reduction is achieved through predicting data using adaptive filters. The prediction is done both at source node and sink node. Data prediction techniques can be divided into three subclasses: stochastic approaches, time series forecasting and algorithmic approaches.

To conserve network resources like energy, network bandwidth, and CPU usage – a series of recent works propose different approaches to reduce the amount of data that need to be delivered to the user [2], [11-14]. Radio communication is one of the dominant power consuming activities in WSN. Here by reducing the amount of data can be transmitted, a significant level of energy conservation can be achieved. There are various methods to reduce the data transmission like data driven approach in which it can be separated according to the problem addressed.

In [15] and a series of later works, the data maintained at the central server are guaranteed to be within certain interval of the actual sensor readings, since nodes are required to report their readings to the server if the value falls outside this interval.

To reduce energy consumption, some works [16-18], propose to exploit spatio-temporal correlation among data to identify a subset of sensor readings from which the remaining measurements can be predicted within a given minimal accuracy. Readings that can be predicted from already delivered data do not need to be reported to the central server, thus reducing communication. Prediction can be performed in both time and space for example on the basis of some pre-defined model, whose parameters can be either learnt from historical data [16] or assigned by virtue of a-prior knowledge [18]. There are a huge number of adaptive algorithms which have been developed in the literature [17]. The choice of one algorithm over another is determined by the trade-off among different factors, like rate of convergence, robustness, computational complexity, and numerical properties. Many different approaches to reach the goal of accurate and fast, yet robust, prediction are currently investigated. The most significant of those make use of kalman filtering [18]. Extended kalman filtering [20], LMS adaptive filtering [14], linear adaptive filters [21], spline approximation and prediction based on Fuzzy Logic/Fuzzy Control [22], neural networks in different varieties [23], interacting multiple models [24] and sinusoidal models [25]. In general, these methods can be divided into two classes: model-based, like the multi-frequency approach of the Extended kalman Filter presented in [20], or model-free, like LMS-based algorithms for modeling autoregressive processes. Recursive least square algorithms can be applied for faster prediction but at the cost of increased computational complexity. One of the most successfully applied adaptive algorithms is the so-called LMS algorithm. Despite of its simplicity, this algorithm provides very good performances in a wide spectrum of applications [14].Typically the type of samples in nodes are exhibited using temporal correlation [21]. LMS adaptive algorithm as a data-reduction strategy in WSN has been firstly proposed by Santini and Römer [14]. LMS algorithm is an adaptive algorithm, which uses a gradient-based method of steepest decent. LMS algorithm uses the estimates of the gradient vector from the available data. In the work by Stojkoska et al[26], the time-series forecasting technique for WSN based on LMS algorithm with a variable step size (LMS-VSS) is developed.

LMS is low computation technique and it suits well for the tiny sensor nodes. The convergence of the LMS filter largely depends on the step size and filter length. In this paper, an algorithm that dynamically computes the step size based on the input values is proposed. The step size adapts itself with the changes in input values. This method is said to be LMS with Step Size

Adaptation (LMS-SSA). The step size computation varies for different modes of adaptive filter, which leads to faster convergence in normal and lesser deviation in standalone mode. Step size computation adds some overhead but is compensated by the faster convergence. Consideration has been given to data losses and node failure through applying a counter based technique. A counter increment on every prediction and reset itself if there is a transmission, if it overflows a desired data will be transmitted to ensure that node is alive. A counter data will be transmitted along with the desired value, which is then compared with another counter in the reception end. If there is an inequality, an alert message issued by the receiver and both the ends switched to initialization mode. In LMS the prediction engine changes from normal mode to standalone mode after a specific number of predictions having error less than E_{max}, here another error level E_{set} is defined that is lesser than E_{max}. The mode is switched from normal to standalone only when the error is below E_{set}. In future work, this data reduction by using spatio-temporal correlation will be analyzed.

II) **METHODOLOGY:**

The following are the components used for data reduction and energy conservation technique in wireless sensor networks using LMS based adaptive filter methodology.

A) **Dual Prediction Frame work:**

In most of the sensor network low entropy data is measured and sent to the sink node. In periodic sensor measurement the change over time and prediction methods are estimated. In this dual prediction approach, the sink node instead of direct communication exploits a time series model to predict the local reading of the sensor nodes with certain accuracy. Hence the number of communication between nodes and sink is reduced and energy expensive periodic radio transmission can be avoided. The main objective of this approach is to transmit the subset of all samples. In this model, each sensor nodes have a prediction model that is trained from the history of sensor measurement.
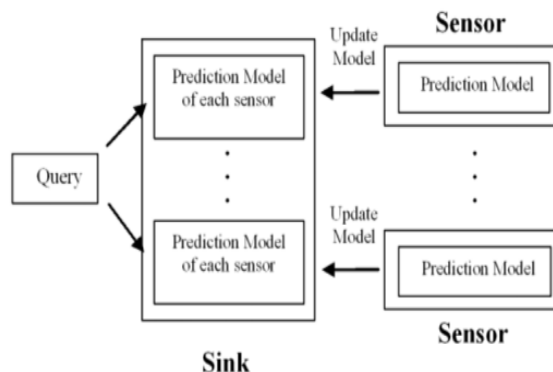
Fig 1.Dual prediction frame work

B) **Adaptive Filter:**

A filter is a device or process that removes some unwanted component or feature from a signal. Generally filters are two types linear and non-linear. The signal and its noise characteristics are often stationary and the statistical parameters are varying with time. An adaptive filter has an adaption algorithm that is meant to monitor the environment and vary the filters transfer function. It has two environments i.e. stationary and non-stationary. For stationary, the filters are converge according to the wiener filter and for non-stationary, the filters is expected to track the time variation and varies its filter coefficient.
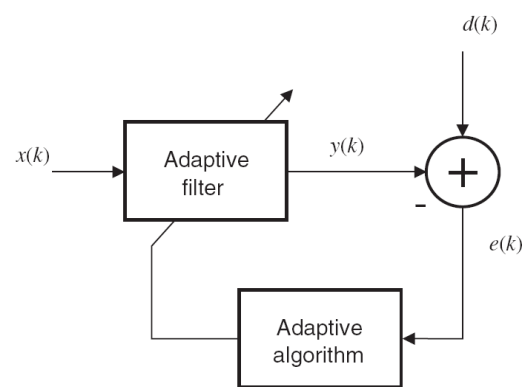

Fig.2. Adaptive Filter

An adaptation process, which aims to adjust the filter parameters (filter transfer functions) to the possibly time-varying environment, often the average square value of the error signal is used as an optimization criterion. Due to the complexity of the optimizing algorithms most adaptive filters are digital filters that perform digital signal processing. When processing analog signals, the adaptive filter is preceded by A/D converter and followed by D/A converter. Most of the adaption algorithm is based on the LMS, which can define as a cost function of a mean squared error.

C) **LMS Adaptive filter:**

Sampled data generally has strong spatial and/or temporal correlation, so there is no need to communicate the redundant information to the sink is unnecessary samples. Data reduction strategies aim at reducing the amount of data sent by each node, for example by predicting the measured values both at the source and the sink node, thus only requiring nodes to send the readings that deviate from the prediction[23]. While effectively reducing power consumption, such techniques so far needed to rely on a priori knowledge to correctly model the expected values. The proposed approach instead employs an algorithm that

requires no prior modeling, allowing nodes to work independently and without using global model parameters. In this paper, an alternative data-reduction strategy that exploits the LMS adaptive algorithm is presented.
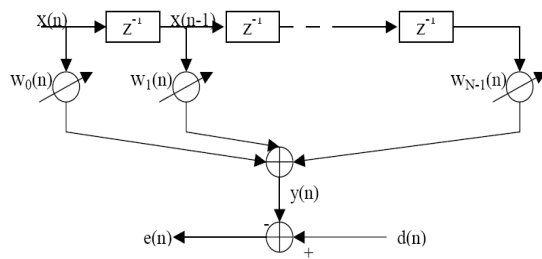

Fig.3.LMS weight calculation

LMS algorithm uses the estimates of the gradient vector from the available data. LMS incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector, which eventually leads to the minimum mean square error. LMS algorithm, compared to other algorithms is relatively simple. It does not require correlation function calculation nor does it require matrix inversions. The LMS algorithm has established itself as the workhorse of adaptive signal processing for its simplicity of implementation and a computational efficiency that is linear in the number of adjustable parameters and robust performance.

Basically, the LMS algorithm is a stochastic gradient algorithm, which means that the gradient of the error performance surface with respect to the free parameter vector changes randomly from one iteration to the next. This stochastic property combined with the presence of nonlinear feedback, is responsible for making a detailed convergence analysis of the LMS algorithm, which otherwise a difficult mathematical task.
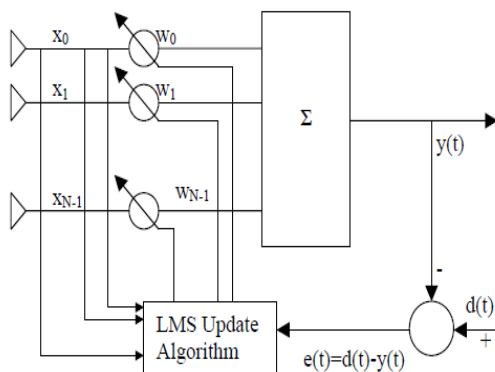

Fig.4. LMS Adaptive Filter

The LMS is an adaptive algorithm with very low computational overhead and memory footprint that despite its simplicity provides excellent performance. More importantly, unlike previous work, the proposed approach does not require a priori knowledge or modeling of the statistical properties of the observed signals. Hence, this scheme can be applied to a variety of real-world phenomena without restrictions. Moreover, the proposed algorithm does not require nodes to be assisted by a central entity for performing prediction, since no global model parameters need to be defined. Due to these characteristics, the proposed approach can be easily integrated with a variety of existing data collection approaches including schemes that support in-network data aggregation.

$$y[k]=\underline{w}^{t}[k]\underline{x}[k] \quad \ldots\ldots\ldots\ldots..(1)$$

where $y[k]$ is the predicted output at the instant of k. The output is a linear combination of last N samples of input signal x. Each input signal is weighted by the respective filter coefficient w.

$$e[k]=d[k]-y[k]\ldots\ldots\ldots\ldots\ldots(2)$$

$e[k]$ is the error between predicted and desired value $d[k]$ at the instant of k.

$$\underline{w}[k+1]=\underline{w}[k]+\mu\underline{x}[k]e[k]\ldots\ldots..(3)$$

The new weight value is constructed from the previous values, where μ is the step size. Larger values of μ lead to faster convergence, but unstable filter prediction, where smaller values of μ lead to stable filter prediction and slower convergence.

In the proposed method, the step size is calculated on every new prediction, with the input values. During normal mode, maximum value of step size is selected. The step size is selected in such a way, there is least instability in prediction. During the standalone mode, in order to avoid larger deviations the step size is set for the minimum possible value.

$$0 \leq \mu \leq \frac{1}{Ex} \quad \ldots\ldots..(4)$$

$$Ex = \frac{1}{M}\sum_{k=1}^{M} x[k]^{2} \quad \ldots\ldots.(5)$$

Here the step size μ can be set between 0 to $1/Ex$. The value of μ decides the speed of convergence at the same time in other aspect may lead to faster deviations. During normal mode the value of μ is set as $(1/Ex)/2$, which enables faster convergence. During standalone mode the value of μ is set as $(1/Ex)/16000$, which leads to lesser deviations. In LMS, the change from normal mode to standalone mode is made after continuous N no. of predictions having error less than E_{max}. Here another error level E_{set} is identified. If the error is less than E_{set}, then the mode is changed from normal mode to standalone mode. Moreover, no significant changes in the performances are observed when varying the number of filter weights from N= 4 to N = 10.

As the number of operations to be performed at each time step grows proportionally with N, this value should be kept as small as possible. In this work, it is kept as N=2, which can yield better results for dynamically varying signals. The tested values of N provides extremely low computational overhead and memory footprint of the algorithm. With N = 4, for example, the node must perform at most 17 operations each 31 seconds and needs to store in addition to the 4 filter coefficients and the filter parameters, only the last 4 sensor readings. In earlier works it is assumed that there is a loss-free communication links between sink and source to implement the dual prediction scheme. However, this is not a realistic assumption in real-world deployments. Hence, it is needed to provide appropriate mechanisms to make the proposed scheme robust to message loss. If a message is lost, the sink will use its filter to predict a value, which is not within the error budget E_{max}. Secondly, the filters in source and sink will get out of synchronization, they will output different predictions. Even when the sink receives a message eventually, the sink's filter will produce wrong predictions. Hence, it is important to provide a mechanism whereby the sink can detect lost messages and resynchronize its filter with the source. This can be achieved, by including a sequence number in each message. If the sink detects a jump in the sequence number, message loss is assumed and the source is forced into initialization mode. Here it is used, an incremental counter for generating sequence number. If the sequence number reaches its maximum value then it will be reset. The drawback in this system is the data loss can be identified, only during the subsequent transmissions. During this span the prediction may lead to deterioration. In typical sensor network deployments, sensor nodes are subject to frequent crashes, battery depletion and other temporary or permanent failures. If the source node fails due to these reasons, the sink would continue to output predictions. To limit the impact of such failures, the sink needs a mechanism to detect source failure. This can be easily achieved by forcing the source node transmit at least one sensor reading every K instants, even though this would not be necessary otherwise. If after K an instant from the last transmission the sink does not receive this message, source failure is assumed. A counter is used for the purpose. The counter increments on every prediction, it is reset to zero if there is a

transmission. If the counter value reaches K then a single transmission is initiated.

III) **RESULTS AND DISCUSSION:**

The LMS based technique with adaptive step size calculation has yield encouraging results for the given data set. The data are acquired at intel berkely lab and is publicly available [27]. The work done by saintini et al[14] has achieved up to 93% reduction in data transmission. In the proposed, adaptive step size filter, upto 95% data reduction is achieved.
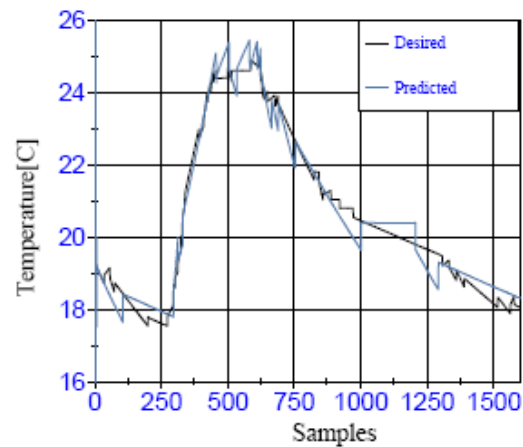

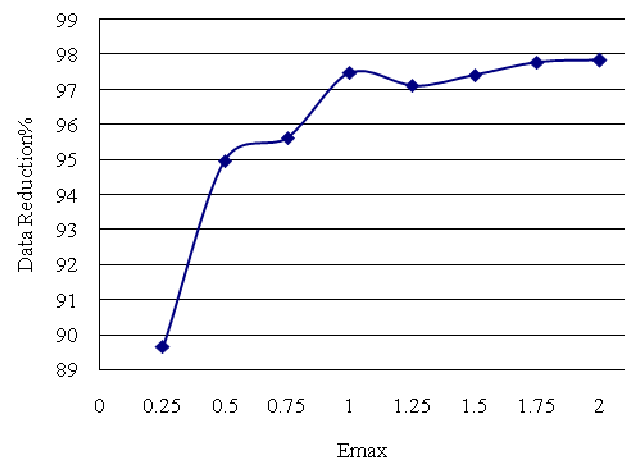Fig.5.Prediction without Data loss Model

Fig.6. Emax Vs Data reduction

Issues identified by saintini also considered and data loss models are also included in the work. Addition of data loss model can able to identify the data loss on successive data transmissions and the deviation also is corrected, in few steps at the cost of few transmissions. The node

failure model is also has the same issue of little sufferings in data prediction efficiency.
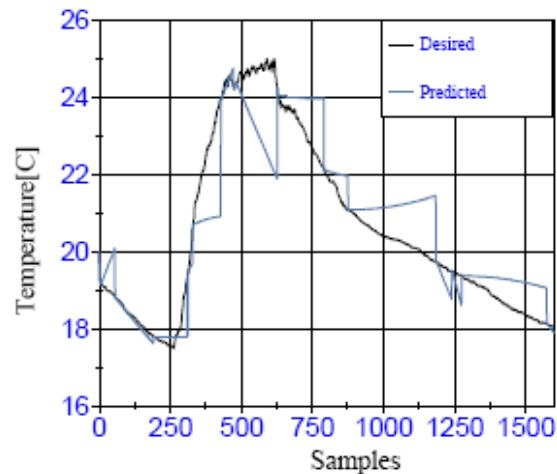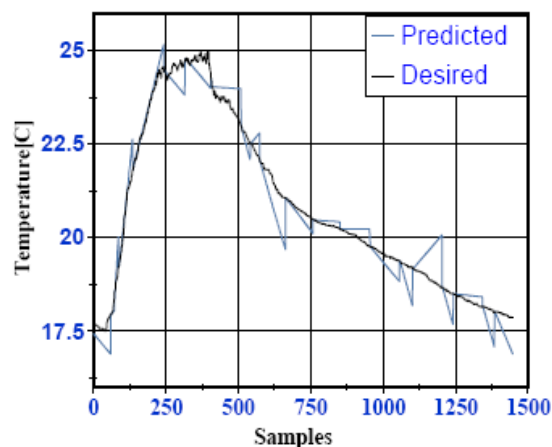

Fig.7.Prediction with data loss model

Fig.8. Prediction with node failure model

The prediction frame work is also evaluated using mean deviation of the predicted output and the desired output. Here RMSE (Root Mean Square Error), method is used for identifying the mean deviation of the predicted output from the sensor output. RSME increases with the increase in error tolerance value Emax.
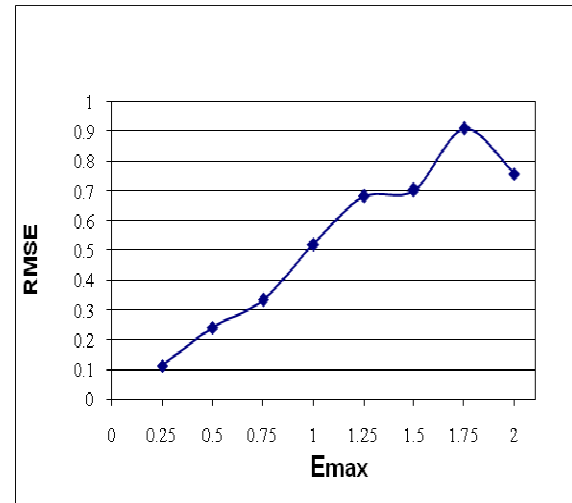

Fig 9. Emax Vs RMSE

IV) **CONCLUSION AND FUTURE WORK:**

The paper proposes an LMS algorithm for wireless sensor networks, which is capable of dynamically predicting the next temporal value at both transmitter and receiver. It is considered wireless sensor network applications that require a continuous delivery of sensor readings at regular time intervals k. This work presents an adaptive approach that allows significant drop in the amount of data that needs to be transmitted, while ensuring that the original observation data can be reconstructed within a pre-specified accuracy E_{max}. This approach is based on an efficient prediction technique using the LMS adaptive algorithm at both the source and sink of a data stream. Tests on real-world data demonstrated the effectiveness of this approach. Unlike previous work, the proposed approach is lightweight and does not assume a-priori knowledge about statistical properties of the observed phenomena and thus lends itself well to many practical applications. This approach also considers the data losses and has a solution with sequence numbers. The solution also involves node failure identification and periodical transmission of heart beat messages along with the data. The dynamic identification of filter length N is reserved for future work. Future work will be to implement spatial correlation based clustering which can be used to schedule the sensor nodes in each cluster to transfer the data. This way the sensor nodes inside the cluster periodically put into sleep mode which will further increase the lifetime of sensor networks.

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