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Estimation of Robust Standard by using Compression Sensing Data in Wireless Sensor Network

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Abstract— Wireless sensor networks (WSNs) is the collection of physical measurements in a geographical area. It tracks the spatial-average of the sensor measurements in a region. Since it is highly vulnerable to sensor faults and measurement noise the average operation is not robust. In this paper the proposed computational efficient method is used to compute a weight average of sensor measurement. It takes consideration of sensor faults and sensor noise. WSN uses random projections of sensor to compress data and send the compressed data to the data fusion center. The computation efficient method uses the data fusion center for direct work with the compressed data stream. The fusion center performed decompression at the time of computed weighted average. Thus, it reduces the computational requirements. Hence the proposed method gives better accuracy and more efficient for the WSN.

Keywords- Wireless sensor network, compressive sensing, distributed compressive sensing, fault tolerance, data fusion, robust averaging.

I. INTRODUCTION

The compressive sensing consists of sampling and signal reconstruction method. The compressive sensing uses unknown signal and perform a small number of generalized measurements which is called projection. The compressive sensing in WSN reduces the required bandwidth and it also reduces the energy consumption. This paper provides the fusion of distributed compressive sensing data.

The common WSNs sensor fault is offset, stuck-at errors and variation of sensor measurement noise. WSN design chooses deploy redundant sensor because the neighboring sensor must return the same reading if they are noise-free and not fall-out. In case sensor faults the standard average is not robust. The proposed method computes a robust average sensor measurement which takes sensor faults and sensor noise in a computationally efficient manner.

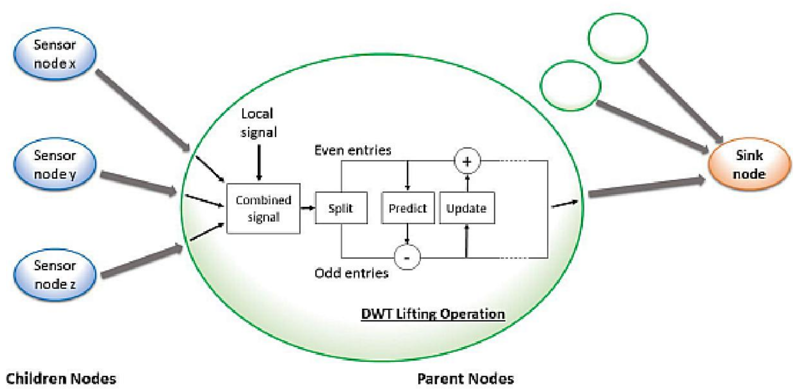

Figure 1.Wireless sensor network

Each sensor performs projection on its sensor measurements to produce low bandwidth compressed data stream. This compressed data stream is transmitted over the WSN to reach data fusion center. The data streams are decompressed to get original signal. The decompressed data stream is used to the data fusion center for signal fault. By using decompressed data stream the weight of the average operation like weight, noise signal can be calculated. The advantages of this method are that the bandwidth can be saved by sending compressed data stream to the network.

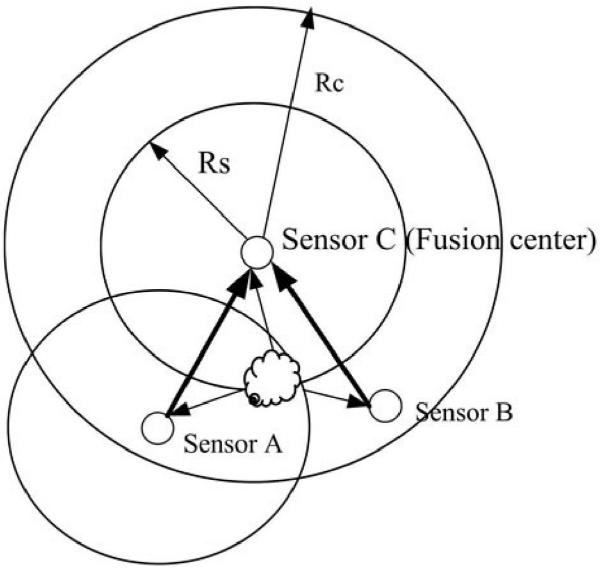

Figure 2. Fusion center

In this method the sensor once again sends compressed data stream in the data fusion center. Initially the data is decompressed from compressed data to obtain original data stream, by applying the proposed method the data can be compressed without performing decompression. The proposed method finds weight for each compressed data stream which produce a fault compressed data stream. Applying the compressive sensing reconstruction method to the data stream the robust average of the original sensor reading is obtained. The advantages of the proposed method are that it performs better reduction of computation recruitment in the data fusion center.

Initially the compressed data are directly used for whose dimension fraction of that of the original sensor is reading. Second decompression is obtained for compressive sensing reconstruction. Each decompression solves the problem of linear program which in terms save computation requirements.

Data compression reduces storage and energy consumption for resource application. The distributed source code method is used for data compression, which us entropy to encode two nodes. It is done by data individual without sharing data between them. By using a framework for distributed source code which provide prior information and knowledge of the cross correlation of sources. The framework gives highly effective and efficient compression in sensor network without using inter-node communication.

A data compression algorithm is based on energy consumption of input stream depend upon data source.

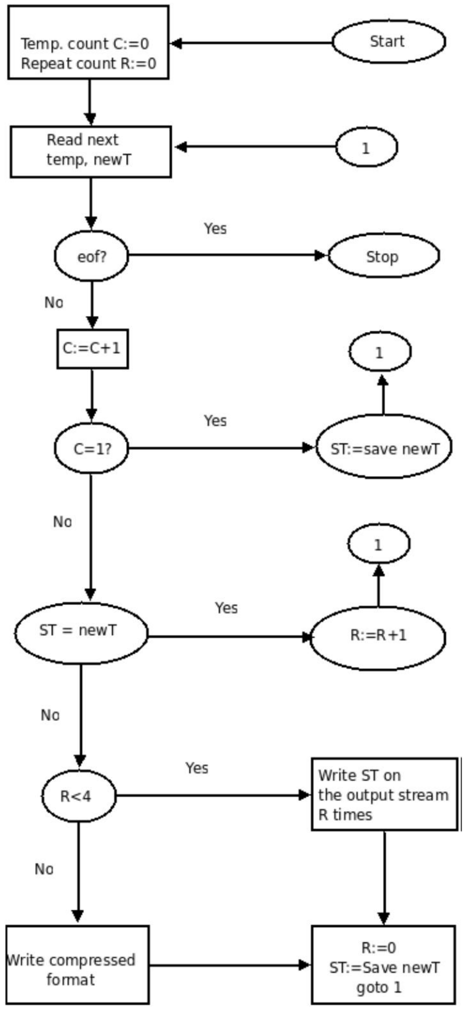

Figure 3. Data compression algorithm flow chart

II. DATA AND FAULT MODEL FOR ROBUST AVERAGING

The sensor in WSN measures some physical values at the given time, but some of it may be faulty. Bias, Stuck-at fault or measurement noise belong to fault category. All sensors have same mean reading *rt* at *t* time which finds difference in measure noise of different sensor. The ultimate aim is to recover the value of *rt* from sensor reading. The process of recovering *rt* is done by the present of faults as robust averaging. The weight can be obtained for the data compression by i) projection matrix needs to satisfy the Lemma. ii) An algorithm that determines weights from the data that has difference in IR^m, where m is the dimensional of the original data vectors.

The fault mechanism deals with fault detection and fault recovery. So it proposed the hierarchical structure disturbed fault management task among sensor node. The sensor is randomly deployed in all the sensors that have a common transmission range. Each sensor has three neighboring nodes. Fault corns occur at different level of the sensor network. Sensor nodes are capable of receiving, sending and processing when they have faults in the methods. Fault sensor detection identifies states of the node behavior.

To increase speed of computing *r* the fixed-point iteration algorithm is used. The iteration algorithm is as follows:

1. The deviation of the sensor and the weight of sensor values are found at the l-the iteration.
2. Initialize l=0
3. Where l denotes the increment in the length of the data (l+1).
4. Compute $vs = \|x_s - \sum_{i=1}^{n} \omega_i x\|_2^2$ for s=1,…,n. (1)

Since the sensor display faults at limited period of time, the weight each sensor is changed for every block of data to another for various outdoor WSN deployments the fixed point iteration is used for data collection. The fixed point iteration is faster and easier for implementation in the wireless sensor node. This provides limited power consumption.

III. DATA COMPRESSION IN MAXIMUM-LIKELIEHOOD INTERPRETATION

The fixed point iteration for robust average is used for maximum likelihood estimator, where the original sensor is measured. The maximum likelihood interpretation holds compressed data which show the variation in large. The compressed data provide the random variable for accuracy and efficiency. By applying Gaussian distributed random variable the noise is removed. The noise affected compressed data is corrupted by Gaussian noise continues to hold. The maximum likelihood holds the data even if the compressed data are used. The noise variance is larger than the affected original sensor measurement. Due to this there is an increase in the price of the robust average that derived compressed data.

The compressed data y_{sk} can be written as follows:

$$Y_{sk}=1/\sqrt{p}\sum_{t=1}^{m}\emptyset_{kt}x_{st}=\sum_{t=1}^{m}1/\sqrt{p\emptyset}_{kt}r_t+\sum_{t=1}^{m}1/\sqrt{p\emptyset}_{kt}e_{st} \quad (2)$$

The obtained fixed point iteration assumes the sensor reading that is available to find weight of data. The main goal is to compute this weight from compressed data and used Lemma. Lemma is used for the purpose of perturbation on the weight due to the use of compressed data. For the perturbation analysis purpose framework is used.

V and W denote the vector that has *s*th element is v_s and w_s. The perturbation analysis has two operations such as T_{wv} which denotes the operator that map W to V and T_{vw} which denotes the operator that maps V to W by the equation (1). The fixed point is given as follows:

$$V^0=T_{wv}(W^0) \quad (3)$$

$$W^0=T_{vw}(V^0) \quad (4)$$

IV. ACCURACY OF ROBUST AVERAGE BY COMPRESSED DATA

Bernoulli distributed projection matrix is used for the original sensor measurement and compressed data projection. The robust average algorithm is applied to the uncompressed data and compressed data. The robust average computed by applying fixed point iteration for the original data gives better sensor. Sometimes the fixed point iteration compressed data by reconstruction. The fixed point iteration always has less humidity for obtaining original sensor measurements. The compression data are followed by reconstruction. Normally the robust average is used in WSN like a stuck-at-fault, offset and variance degradation fault. The robust average always captures the trend of the working sensor which gives very low humidity. The measurement that has very low weight is represented as erroneous.

The proposed robust average method has three types of fault detection method. The first method is based on classical statistical method. It is used for detecting the outlier in a set of data. This method compute absolute standard scores for each data point in the data set, which is compared against critical value that determine outlier. The critically depend on the sample size, significant level and *t* distribution. The outlier is detected to remove from the data set for the purpose of compute the average of the data points that remains in the data set. This type is generally referred as statistical.

The second method fault detection for WSN, which use the local outlining factor (LOF). LOF gives a probability for data point at time *t* from sensor *s*. LOF has neighbor that has different number of *MinPts* parameter. MinPts is defined as number of different closest neighbor. To find the point that is outlier, the distance of the point and outside the neighborhood is compared. The Recursive Bayesian is updated on the basic of LOF. The node that has fault belief at time t we have low reputation at that time. This type of method is call as Reputation.

The third method describe about the posteriori probability that a sensor in a WSN is faulty. It used the fact that a group of working sensor shows similar trend and values. The liner regression model for a short time interval determine whether the sensor have similar trend. The weight average can be determine by using weight that is proportional to the probability that a sensor is working at a time *t*. This type of method is called as Bayes. Both Statistical and Reputation always have an independent data at the time of execution, but Bayes take temporal correlation.

Statistical, Reputation and Bayes are designed for uncompressed data. The working sensor is used for referring and computes the root mean-square (rms) error of the average find by these methods. The result obtained by this method is comparable through robust average that has a slight edge over the other methods.

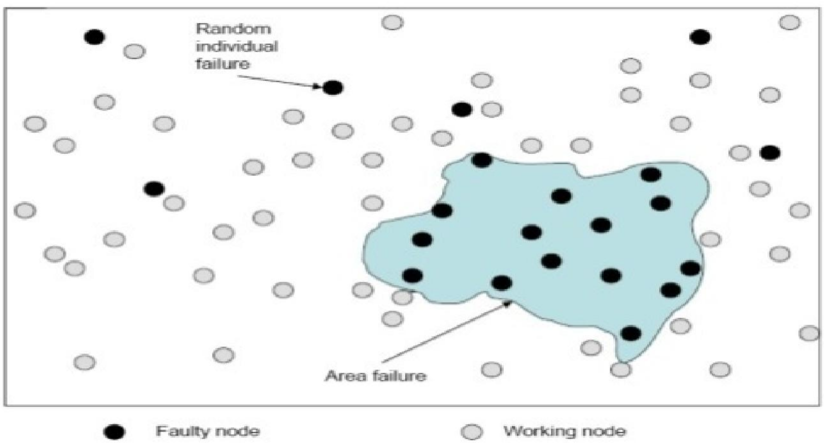

Figure 4. Fault node

All these methods are applied to the data that has four sensors (three working and one faulty) and three sensors (two working and one faulty). The robust average methods provide better result than Statistical, Reputation and Bayes. The proposed robust average, perform better and is more stable while comparing with Statistical, Reputation and Bayes algorithms which have some fluctuates with the stuck-in value. The advantages of the proposed robust average are that it reduces computation time. It also provides saving in bandwidth where compressive sensor is not used. It is applicable in multi hop topology since the bandwidth saving is more useful as and give a good percentage of results.

For obtaining projection the following four different metrics are performed:

1. The percentage reduction in computation time.
2. The percentage of bandwidth is saved.
3. Reconstruction of robust average is expressed as a percentage in the presence of relative error.
4. Relative error is estimated by the weight and is expressed as percentages.

VI. CONCLUSION

The proposed method of robust average of sensor measurement in wireless sensor network is more efficient. This method provides more efficient data transfer in compressive manner. The proposed method integrates for preserving the property that the projection metrics occur randomly. This method will make data fusion to work directly with compressed data. The proposed method makes the data fusion center to perform better in decompression of data and reduce computation requirements.

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