

CLUSTERING FOR ENERGY EFFICIENT TRANSMISSION IN WIRELESS SENSOR NETWORK USING COMPRESSIVE SENSING

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Abstract— Compressive Sensing (CS) can reduce the number of data transmissions and balance the traffic load throughout networks. The sensors nodes are organized into clusters. In this paper we propose a clustering method where in the transmission range of the cluster head (CH) is the area of a cluster. Thus to avoid coverage hole problem. Within a cluster, node transmits data to the CH in a round robin fashion. CH use CS to transmit data to the sink. Thus reducing the energy consumption of a sensor node.

Keywords— wireless sensor networks, energy efficient, clustering , data compression, compressive sensing

I. INTRODUCTION

In recent years wireless sensor networks (WSN) have attracted much interest in the wireless research community as a fundamentally new tool for a wide range of monitoring and data gathering applications. A typical sensor networks is as shown in the figure1. The sensor node which is vital component of this network in battery operated and hence is significantly constrained in energy. Several applications like, habitat monitoring, battlefield surveillance, environmental monitoring, equipment diagnostics, disaster management etc. require only an aggregate value of the data to be reported to the base stations. In these cases, sensors in different regions of the field can provide more accurate report about their local region. The collected data is routed to the sink via routing tree or clustering. Clustering is a standard approach for achieving efficient and scalable performance in sensor networks [2]. Thus aggregation and clustering improves the fidelity of the reported measurement and reduce the communication overhead in the network, leading to significant energy saving. Each cluster has a coordinator referred as a cluster head (CH), and number of member nodes. These member nodes report their data to the respective CH in a scheduled manner. In many situations, it is inefficient for sensors to transmit all the raw data to the sink, especially when sensed data exhibits high correlation [3]. To reduce transport load, conventional data compression techniques are usually used to exploit the correlation among sensor data so that less data can be delivered to the sink without sacrificing the salient information. In particular, Compressive sensing (CS) is a new technique based on in-network data processing to compress sensory data and accurately recover it in the sink. In CS the

data projections generated at each CH are forwarded to the sink in 'M' rounds along the backbone tree. CS is a collection of recently proposed sampling and signal reconstruction method. A promise of CS is that obtain a good approximation of the unknown signal by performing small number of generalized measurements, called projections, provided that the unknown signal is compressible. For wireless sensor networks it means that CS can be used to reduce the bandwidth requirement and lower the energy consumption [4]. In this paper, we first detail the importance of clustering for energy efficient transmission and then apply compressive sensing for data transmission between cluster heads in wireless sensor networks to achieve less energy expenditure.

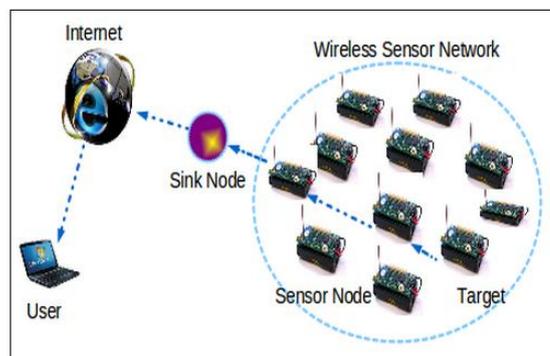


Fig 1. Wireless sensor network [1]

The paper is organized as follows in section II we discuss the advantage of clustering, data compression schemes and the compressive sensing techniques used in wireless sensor networks are discussed in section III. Related work is discussed in section IV. In section V radio propagation model of sensors is studied and finally we conclude in section VI.

II. CLUSTERING

Scalability to a large scale WSN is provided by the classical method of clustering. One of the first and most popular clustering protocol proposed for WSN was LEACH (Low Energy Adaptive Clustering Hierarchy) [5]. By

clustering different goals are sought viz. load balance, fault tolerance, network connectivity and so on. The important parameter with regard to the whole clustering procedure are: Number of clusters (cluster count), Intra cluster communication, Inter cluster communication, Node types and roles, Node and Cluster Head mobility, Cluster formed methodology, Cluster Head selection and so on [6]. Various shapes of cluster are present in literature e.g. Circle, hexagon square etc. we from the cluster based on the transmission range of the cluster head. Thus herein, clustering aims to reduce the energy expenditure of each sensor node, by transmitting data to the cluster head that is within the transmission range of the cluster head.

III. DATA COMPRESSION

Sending data is more power consuming than computation, and thus minimize data size before transmitting in wireless medium is effective to reduce total power consumption. Therefore, it is beneficial for WSNs to employ a data compression algorithm

1 Coding by Ordering

The Coding by Ordering data compression scheme is a part of Data Funneling Routing. One difficulty of utilizing this scheme is that since there is no efficient algorithm mapping permutation to data value, it requires a mapping table. As the number of sensor nodes aggregated increases, the size of table increases exponentially

2 Pipelined In-Network Compression

The basic idea is trading high data transmission latency for low transmission energy consumption. Collected sensor data is stored in an aggregation node's buffer for some duration of time. During that time, data packets are combined into one packet, and redundancies in data packets, will be removed to minimize data transmission

3 Low-Complexity Video Compression

The low complexity video compression scheme is the recently designed are mostly designed on utilizing the motion estimation and compensation, it will require a high computation power, which sensor nodes are not usually equipped with. Thus, this proposed method is based on block changing detection algorithm and JPEG data compression methods.

4 Distributed Compression

The basic idea behind the Distributed Compression scheme, is using a side information to encode a source information .Distributed Compression scheme can be applied to not only discrete sources but also continuous sources [7]

A. Compressive Sensing

The Compressive sensing theory asserts that we can recover certain signals from fewer samples than required in Nyquist paradigm. This recovery is exact if signal being sensed has a low information rate (means it is sparse in original or some transform domain). Number of samples needed for exact recovery depends on particular reconstruction algorithm being used. If signal is not sparse, then recovered signal is best reconstruction obtainable from s largest coefficients of signal. CS handles noise gracefully and reconstruction error is bounded for bounded perturbations in data.

CS relies on two principles: *sparsity*, which pertains to the signals of interest, and *incoherence*, which pertains to the sensing modality

B. The Sensing Problems

We discuss sensing mechanisms in which information about a signal $f(t)$ is obtained by linear functional recording the values

$$y_k = \langle f, \phi_k \rangle, k = 1, \dots, m. \quad (1)$$

That is, we simply correlate the object we wish to acquire with the waveforms $\phi_k(t)$. This is a standard setup. If the sensing waveforms are Dirac delta functions (spikes), for example, then y is a vector of sampled values of f in the time or space domain. If the sensing waveforms are indicator functions of pixels, then y is the image data typically collected by sensors in a digital camera. If the sensing waveforms are sinusoids, then y is a vector of Fourier coefficients; this is the sensing modality used in magnetic resonance imaging (MRI).

Although one could develop a CS theory of continuous time/space signals, we restrict our attention to discrete signals $f \in \mathbb{R}^n$. The reason is essentially twofold: first, this is conceptually simpler and second, the available discrete CS theory is far more developed (yet clearly paves the way for a continuous theory—see also “Applications”). Having said this, we are then interested in *undersampled* situations in which the number m of available measurements is much smaller than the dimension n of the signal f . Such problems are extremely common for a variety of reasons. For instance, the number of sensors may be limited. Or the measurements may be extremely expensive as in certain imaging processes via neutron scattering. Or the sensing process may be slow so that one can only measure the object a few times as in MRI. And so on. These circumstances raise important questions. Is accurate reconstruction possible from $m \ll n$ measurements only? Is it possible to design $m \ll n$ sensing waveforms to capture almost all the information about f ? And how can one approximate f from this information? Admittedly, this state of affairs looks rather daunting, as one would need to solve an underdetermined linear system of equations.

Letting A denote the $m \times n$ sensing matrix with the vectors $\phi^*_1, \dots, \phi^*_m$ as rows (a^* is the complex transpose of a), the process of recovering $f \in \mathbb{R}^n$ from $y = Af \in \mathbb{R}^m$ is ill-posed in general when $m < n$: there are infinitely many candidate signals \tilde{f} for which $A\tilde{f} = y$. But one could perhaps imagine a way out by relying on realistic models of

objects f which naturally exist. The Shannon theory tells us that, $\text{iff}(t)$ actually has very low bandwidth, then a small number of (uniform) samples will suffice for recovery [8]. Fig 2. shows the compressive sensing reconstruction algorithms and their classifications

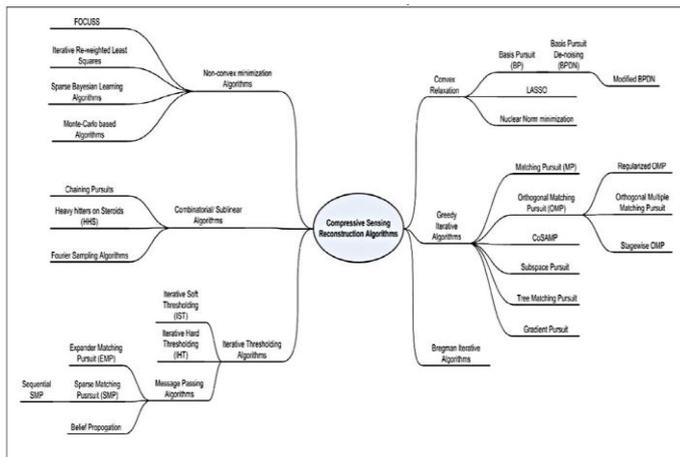


Fig 2 Compressive Sensing reconstruction algorithm

IV. RELATED WORK

Ruitao Xie et.al. used hybrid compressive sensing to design a clustering based data collection method, to reduce the data transmission in wireless sensor network. Sensor nodes are organized into cluster. Within a cluster, the data is collected by using the shortest path routing, at the cluster head, data are compressed to the projections using the CS technique. The projections are forwarded to the sink following a backbone tree. But, the field is partitioned into square grid where as the communication field of a sensor is circular in shape, so gaps will be left and coverage hole and connectivity problem can arise [9].

Giorgio Quer et.al. investigated the effectiveness of data recovery through joint Compressive Sensing (CS) and Principal Component Analysis (PCA) in actual WSN deployments. They proposed a novel framework, called *SCoRel*, for the accurate approximation of large real world WSN signals through the collection of a small fraction of data points. The author did not mention the need of clustering the data, since clustering or sensing data through a structural tree will change the effectiveness of the system.[10].

Wei Chen et.al. proposed a Fréchet mean enhanced CS approach to efficiently monitor the environmental physical parameters by WSNs. The proposed approach leads to a considerable reduction in the number of samples required by the conventional CS framework by exploiting the intra-signal and inter-signal correlation of the sensor signals. As the number of samples is approximately proportional to the total energy consumed by a SN in the processes of sampling, processing and transmission, this translates directly into

savings in energy consumption and so prolong the life time for a network having battery powered SNs [11]. Thus much of the emphasis is given on recovery of the data, but since wireless sensor networks are energy constraint, power saving should be given priority along with accuracy.

V. RADIO PROPAGATION MODEL

We use the following radio propagation model shown in fig 3. According to radio energy dissipation model, the energy expended by transmitting L bet message over distance d is given as

$$E_{TX}(L,d) = \begin{cases} LE_{elec} + LE_{fs}d^2 & \text{if } d < d_0 \\ LE_{elec} + LE_{mp}d^4 & \text{if } d \geq d_0 \end{cases} \quad (1)$$

Where,

E_{elec} is the energy dissipated per bit to run transmitter E_{TX} or receiver circuit E_{RX} .

E_{elec} depends on many factors such as digital coding, modulation, filtering and spreading of signal. E_{fs} and E_{mp} depend on transmitter amplifier model used, depending on distance between transmitter and receiver. If distance is less than a threshold, free space (fs) model is used. d is distance between transmitter and receiver. We have fixed value of d_0 [1 2]

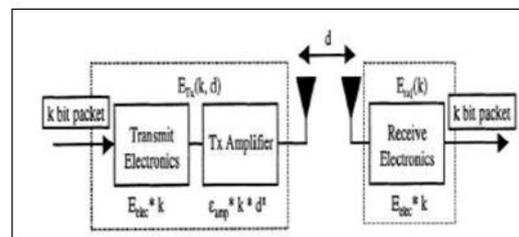


Fig 3 Radio propagation model

V. CONCLUSION

Thus we can summarized as that clustering of the sensor nodes with the size of the cluster equal to the transmission range 'r' of the cluster head is essential so that no connectivity and energy hole problem arises. For intra cluster communication we should sensor nodes transmit their data to the CH in a Round Robin fashion instead of using shortest path. For communication with the sink or base station we can use TDMA slot. Since sink being more power efficient know the location of the cluster heads.

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