An Improved Compressive Sensing Data Gathering in Wireless Sensor Networks Data Gathering in Wireless Sensor Networks

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Abstract— In wireless sensor networks (WSNs) the sampling rate of the sensors determines the pace of its energy use since most of the energy is used in sampling and transmission. In wireless sensor network (WSN) there are two main problems in employing conventional compression techniques. Recent advances in technologies have increased the use of wireless sensor networks in different applications like chemical and physical monitoring, healthcare, tracking and soon. The compression performance depends on the organization of the routes for a larger extent. The efficiency of an in-network data compression scheme is not solely determined by the compression ratio, but also depends on the computational and communication overheads. Propose a sparser analysis that depends on modified diffusion wavelets, which exploit sensor readings' spatial correlation in WSNs. In particular, a novel data-gathering scheme with combine routing and CS is presented. A modified ant colony algorithm-based diffusion wavelets (ACBDW), where next hop node selection takes a node's residual energy and path length into consideration simultaneously. The simulation results, show that our proposed technique improves the delivery ratio while reducing the energy and delay.

Key words: Wireless Sensor Networks, Compressive Sensing, Data Gathering, Diffusion Wavelets, Ant Colony Algorithm

I. INTRODUCTION

Wireless sensor networks include the emerging technologies which have received major attention from the research community. The sensor network which is self-organizing ad hoc system comprises of several small and low-cost devices. It observes the physical environment, collect the information and transmit it to one or more sink nodes[1]. Generally, the radio transmission range of the sensor nodes are in the orders of magnitude which is smaller than the geographical extent of the entire network. Therefore, data should be transmitted towards the sink node hop-by-hop in a multi-hop manner. By reducing the amount of data which is to be transmitted, the energy consumption of the network can also be reduced. A large number of small electromechanical devices with sensing, computing and communication capabilities are included in the wireless sensor networks[2]. It can be used for collecting sensory information, such as temperature measurements, from an extended geographic area. One of the basic distributed data processing procedures in the wireless sensor networks is data aggregation. It is used to save the energy and to reduce the medium access layer contention. The idea is to combine the data coming from different sources, eliminating the redundancy and reduce the number of transmissions, thus saving the energy. By using the in-network data aggregation, the natural redundancy in the raw data collected from the sensors can be eliminated. Moreover, such operations are useful for extracting the specific information from the data. Supporting high frequency of in-network data aggregation is severe for the network in order to conserve energy for a longer network lifetime.

The traditional approach of reconstructing signals orimages from measured data follows the well-known Shannon sampling theorem which says that the sampling rate must be twice the highest frequency. Likewise, the fundamental theorem of linear algebra suggests that then number of collected samples (measurements) of a discrete finite-dimensional signal should be at least equally great its length (its dimension) in order to ensure construction. This principle underlies most devices of current technology, such as analog to digital transition, medical imagery or audio and video electronics[3]. The novel theory of compressive sensing (CS) also recognized under the terminology of compressed sensing, compressive sampling or sparse recovery provides a fundamentally new approach to data acquisition which overcomes this common wisdom.

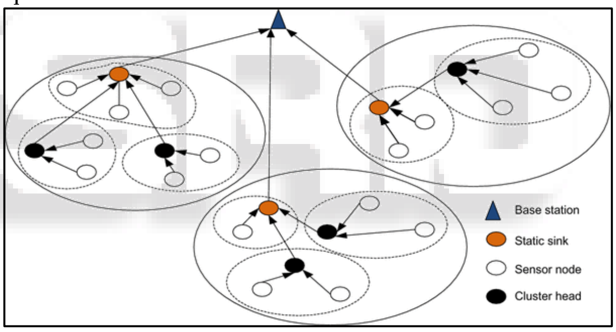

Fig. 1: Compressive Data Gathering Wireless Sensor Networks

Wireless sensor network operates based on the three fundamental operations: sensing, data processing, and data communication. These are the major power-hungry parameters in WSNs. Generally, energy consumption for data communication operation is more compared to that of sensing and data processing. In WSN, there is a possibility of node failures due to the limited battery power so that the lifetime of wireless sensor network will decrease[4]. The lifetime of wireless sensor network can be increased if we can reduce the number of transmissions in the network. Thus, reducing the total energy consumption is very important in the design of WSNs. Many researchers have addressed the challenges of energy efficiency in WSN to increase its lifetime through different methods like sleep scheduling of nodes, topology control, and data aggregation[5]. To increase the network's life time and energy efficiency implementation of proper data aggregation and touting techniques are needed in WSNs. In a real-world WSN, the sensed data has spatial correlation properties; hence the compression techniques can be used to reduce the number of data transmissions with high recovery accuracy in the sink node.

This spatial correlation property leads to an incoherent sparsity of sensed data in a known basis such as wavelet domain or discrete cosine transform. Compressive sensing claims that a signal can be recovered from a small number of projections onto a second basis if it has a sparse representation in one basis[6]. So, a sparse signal can be recovered from a very few samples. Such capability of compressive sensing brings the benefits of reduced transmission bandwidth and storage requirement due to the compression achieved. Compressive sensing can be used tore construct the sparse signal which is compressible from a small number of linear measurements without having knowledge about the signal structure in priori which is the major strength of the CS algorithm. Compressive sensing is needed in WSN applications where the measurements are expensive, and computations at the receiver end are cheap. Compared with data compression, implementation of compressive sensing in WSN brings a promising improvement because the low powered sensor nodes are not capable of handling encoding of data compression methods.

II. COMPRESSIVE DATA GATHERING

The data compression process can be performed based on the spatial or transform domain. The spatial domain algorithms are simpler than the others in transform domain and they use the correlation of the nodes to construct a new data set. However, algorithms in transform domain use some transformation to get the new type of the collected data. Then discover the redundancy of the data. That is to say, these algorithms find the correlation of data, not the nodes, in the transform domain, because the correlation of data is not obvious in spatial to temporal domain sometimes.

Advances in computing and communication technologies have led to intensive research effort on wireless sensor networks (WSNs). WSNs have found extensive applications in urban traffic monitoring and environmental surveillance. Typically, a WSN consists of a number of sensor nodes, which are randomly distributed in the field under surveillance, and a sink node. Generally, sensor nodes are required to collect data periodically and transmit them to the sink through multi-hop routing, and then the information aggregation and extraction tasks are performed at the sink. Considering that sensor nodes usually have limited energy supply and that replacing or recharging the batteries of sensor nodes is difficult in practical WSN deployments, a primary objective of data gathering in WSNs is to obtain an accurate approximation of the signal field with as little energy expenditure as possible.

One of the practical applications of a WSN is to gather all sensors readings at the sink. In its simplest way, and without using compressed sensing (Non-CS), a data collection is built using tree representation where the circular nodes represent the sensor nodes with their number as sensor ID and the black square S represents the sink node[7]. The routing tree can be constructed using different strategies such as shortest-path or minimum power-greedy algorithm. After constructing the routing tree, all nodes in the network know their corresponding parent and child nodes by sending notification messages to each other. Now, in Non-CS, leaf nodes send their data readings to their parent nodes using one packet each. Subsequently, parent nodes send their readings plus the readings from their children in separate packets to their higher parents in the tree. Here, we observe that, the nodes closer to the sink carry out many more transmission sin contrast to the leaf nodes which perform only fewer transmissions. Hence, the load in the network is greatly unbalanced.

Compressed sensing can resolve the problem of unbalanced load in the network through the so-called Compressed Data Gathering (CDG) [8]. Here, the sink node receives m coded packets instead of n packets of original data from nodes and by using CS technique, the sink recovers the original n data readings .In order to do this using CDG, each node in the network multiplies its reading (x_j) into a j column vector of basis matrix$\Phi\left(\phi_{1j}, \phi_{2j}, \phi_{3j} \ldots\ldots \phi_{mj}\right)$ andmake a vector of size m. Then, the node waits to receive all same size vectors from its child nodes and adds them to its own vector and transmits the resulting vector to its parent node using m packets. Since in matrix Φ there are ncolumns and m rows, each column is assigned to one node in the network and each row to one weighted sum.

III. PROPOSE APPROACH

Wireless Sensor Networks (WSNs) generally consist of a large number of sensor nodes and a sink node deployed in the detected environment to monitor various physical characteristics of the real world, such as temperature, voltage, wind direction, and so on. Furthermore, WSNs should have a long enough lifetime to successfully fulfill the monitoring task. However, sensor nodes are limited in terms of computational ability, communication bandwidth, and energy availability[9]. The intuition behind CDG is that higher efficiency can be achieved if correlated sensor readings are transmitted jointly rather than separately. Showing how sensor readings are combined while being relayed along a chain-type topology to the sink. In practice, sensors usually spread in a two-dimensional area, and the ensemble of routing paths presents a tree structure[10]. Routing protocol in which the sink has four children. Each of them leads a sub tree delimited by the dotted lines. Data gathering and reconstruction of CDG are performed on the sub tree basis.

It can leverage the spatial characteristics in sensor node readings from real deployments, which is an essential technique to decrease data transmission costs while preserving relatively high recovery accuracy in the sink node. In other words, the spatial correlation property of a sensor node leads to inherent data sparsity in some areas, such as wavelet domain and DCT domain[11]. In order to solve the sparsity of such signals, compressive sensing (CS) is exploited as a novel signal-processing paradigm that provides an efficient compressive method and recovers sparse or compressible signals. large number of CS-based techniques have been investigated to gather data on WSNs. However, most of the current CS-based methods neglect the topology structure or property of sensor node readings, such as spatial characteristics. Therefore, the performance of the algorithm is limited. In this paper, the spatial property of sensor node readings is exploited to strengthen the performance of networks, considering the topology structure and sensor nodes' distance[12]. Thus, we take advantage of spatial correlations of sensor node readings to further promote the efficiency of the data-gathering algorithm.

A. Modified Diffusion Wavelets

Diffusion Wavelets introduce a multire solution geometric construction for the efficient computation of high powers of local operators. Let us consider a matrix T representing a Markov transition matrix, which is a square matrix describing the probabilities of moving from one state to another in a dynamic system[13]. This matrix T enables the fast computation of functions of the operator, notably the associated Green's function, in compressed form. Their construction can be viewed as an extension of Fast Multiple Methods, and the non-standard wavelet form for the Claderon-Zygmund integral operators as well as for the pseudo-differential operators[14]. Unlike the integral equation approach, these start from the generator T of semi groups associated to a differential operator rather than from Green's operators. T was applied to a space of test functions at the nest scale, for compressing this range via local orthogonalization procedure representing T in the compressed range, computeT^2, compress and again orthogonalize and so on. At scale j obtain a compressed representation of $T^{2^{j+1}}$, acting on the range of $T^{2^{j+1}-1}$, for which we have a compressed form of orthonormal bases, then apply $T^{2^{j+1}}$, locally orthogonalize and compress the result, thus getting the next coarser subspace. The computation of the inverse Laplacian $(I-T)^{-1}$ in order to get the compressed form is done via the Schultz method.

$$(I-T)^{-1}f=\sum_{k=1}^{+\infty}T^k f \tag{1}$$

And considering

$$S_K=\sum_{k=1}^{2^K}T^k \tag{2}$$

In above equation

$$S_{K+1}=S_K+T^{2^K}S_K=\prod_{k=0}^{K}\left(I+T^{2^k}\right)f \tag{3}$$

From the above, can calculate quickly $T^{2^k}$to any function f and hence the product S_{K+1}can apply $(I-T)^{-1}$to any function f fast, with the computational complexity of$o(nlog^2n)$. This construction considers the columns of a matrix representing T as data points in the Euclidean space which are viewed as lying on a manifold.

The interplay between geometry of sets, function spaces on sets, and operators on sets is classical in Harmonic Analysis. Our construction views the columns of a matrix representing T as data points in Euclidean (or Hilbert) space, for which the first few eigenvectors of T provide coordinates. The spectral theory of T provides a Fourier Analysis on this set relating our approach to multi scale geometric analysis, Fourier analysis and wavelet analysis[15]. The action of a given diffusion semi group on the space of functions on the set is analyzed in a multire solution fashion, where dyadic powers of the diffusion operator correspond to dilations, and projections correspond to down sampling. The localization of the scaling functions we construct allows to reinterpret these operations in function space in a geometric fashion. This mathematical construction has a numerical implementation which is fast and stable[16]. The framework we consider in this work includes at once large classes of manifolds, graphs, spaces of homogeneous type, and can be extended even further.

B. Modified Ant Colony Algorithm

In ACO (Ant colony optimization) a colony of artificial ants is used to construct solutions guided by the pheromone trails and heuristic information. ACO was inspired by the foraging behavior of real ants[17]. This behavior enables ants to find shortest paths between food sources and their nest. Initially, ants explore the area surrounding their nest in a random manner. As soon as an ant finds a source of food, it evaluates quantity and quality of the food and carries some of this food to the nest. During the return trip, the ant deposits a pheromone trail on the ground[18]. The quantity of pheromone deposited, which may depend on the quantity and quality of the food, will guide other ants to the food source. The indirect communication between the ants via the pheromone trails allows them to find the shortest path between their nest and food sources. This functionality of real ant colonies is exploited in artificial ant colonies in order to solve Optimization problems.

In ACO algorithms the pheromone trails are simulated via a parameterized probabilistic model that is called the pheromone model. The pheromone model consists of a set of model parameters whose values are called the pheromone values. The basic ingredient of ACO algorithm is a constructive heuristic that is used for probabilistically constructing solutions using the pheromone values. In general, the ACO approach attempts to solve a CO problem by iterating the following two steps (1) Solutions are constructed using a pheromone model, that is, a parameterized probability distribution over the solution space. (2) The solutions that were constructed in earlier iterations are used to modify the pheromone values in a way that is deemed to bias the search toward high quality solutions.

The Algorithm is runs in two passes. In forward of the algorithm, the route is constructed by one of the ants in which other ants search the nearest point of previous discovered route. The points where multiple ants join are aggregation nodes. In the backward pass nodes of the discovered path are given weight in form of node potential which indicates heuristics for reaching to destination (for the first ant or other nodes) or nearest aggregation point (for other ants) and pheromone trails is the heuristics to communicate other ants of the route discovered. Ants tries to follow the route to get pheromone eventually converges to the optimal route. Non-optimal route pheromone gets evaporated with time. The aggregation points on the optimal tree identify data aggregation. The indicator in data aggregation points gives estimate of number of paths aggregates in it.

C. Minimum Spanning Tree

The new technology of CS motivates the investigations on data gathering with CS. where CS is only applied in the nodes whose incoming traffic is beyond the threshold, the traffic when CS is applied. The authors stated that application of CS in the simple scheme may bring no obvious throughput improvement, but application of CS in hybrid scheme can achieve significant throughput improvement. Designed the data gathering scheme, where in each round of projection m furthest nodes away from the sink send their original data directly to one of the remaining nodes which apply the CS.

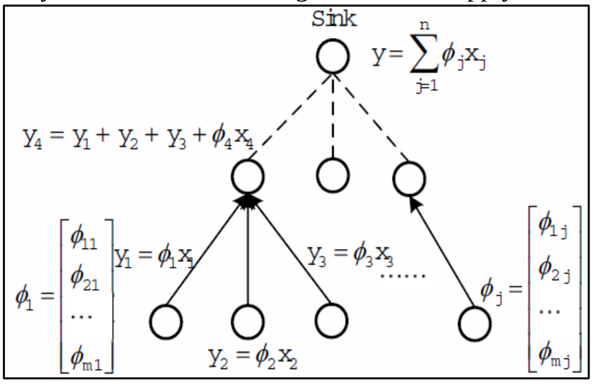

Fig. 2: Data gathering with CS in the tree Structure

The data gathering with CS in the two-dimensional area is conducted along the tree structure. In the i^{th}round of projection, each node generates a random measurement coefficient $\phi_{i,j}$ and computes the data term $\phi_{i,j}x_j$for node v_j. Each leaf node transmits its term to the parent node. Once the parent node receives data from all its descendant nodes, it can add its own data term and all received data terms together and then send it to its upper parent node or the sink node. When the sink node receives data from all its descendant nodes, it adds them to form the i^{th}projection. When the sink nodes collect m projections in the above way, it can use ℓ_1-norm minimization to recover the n original data.

The network capacity when CS is utilized in data gathering and proved that the capacity gain is proportional to the sparsity level of sensor data. Although researchers stated that the total transmission number can be reduced when the number of projections is low enough. However, if the required number of projections increases, then the total number of transmissions may be larger than the case without CS. Large throughput can be achieved with or without CS, or with the hybrid scheme, where CS is only applied in the nodes whose incoming traffic is beyond the threshold, the traffic when CS is applied[19]. The authors stated that application of CS in the simple scheme may bring no obvious throughput improvement, but application of CS in hybrid scheme can achieve significant throughput improvement. Designed the data gathering scheme, where in each round of projection m furthest nodes away from the sink send their original data directly to one of the remaining nodes which apply the CS. They proved that this scheme can reduce the transmission cost.

$$\phi_{ij} = \sqrt{3} \times \begin{cases} +1 \; with probability \; 1/6 \\ 0 \; \dots\dots\dots\dots\dots\dots \; \frac{2}{3} \\ -1 \; \dots\dots\dots\dots\dots\dots. \; 1/6 \end{cases} \quad (4)$$

Considered the number of transmissions, but they missed the fact that measurement matrix Φ is possible to have many zero elements, such as the one made from the following distribution.

IV. CONCLUSION

Therefore, in this mechanism, diffusion wavelets based on sensor nodes' degree and different nodes' distance considering the above factors are proposed. Additionally, to further reduce the transport costs in WSNs, a sparse measurement matrix is utilized and MST and modified ant colony routing are jointly applied to mitigate energy consumption and balance the network load, especially lowering the transmission costs for those nodes nearest the sink node. Experimental results have shown that our sparse basis can sparsity the signal well. This method can also accurately reconstruct the original signal. Moreover, the reconstruction error of our scheme is less than DFT. Compared with existing data-gathering approaches, our proposed algorithm not only minimizes the energy consumption of the network, but prolongs the network lifetime. Future work should consider the following aspects: On the one hand, sensor node readings have not only spatial correlation, but temporal correlation, so our future work will extend the spatial–temporal filed[20]. On the other hand, demonstrates that optimization projection will generate better recovery performance than random projection, so a possible extension to this work will consider how to design the optimization projection so as to reduce the energy consumption.

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