Proc. IEEE International Conference on Communications, Budapest, Hungary, June 2013

Phenomena Discovery in WSNs: A Compressive Sensing Based Approach

Dulanjalie C. Dhanapala, Vidarshana W. Bandara, Ali Pezeshki and Anura P. Jayasumana
Department of Electrical and Computer Engineering
Colorado State University, Fort Collins, CO 80523, USA
{dadcd, vwb, pezeshki, anura}@engr.colostate.edu

***Abstract*—A Compressive Sensing (CS) based solution is proposed for centralized and distributed discovery of physical phenomena in large scale Wireless Sensor Networks (WSNs). WSNs monitoring environmental phenomena over large geographic areas collect measurements from a large number of distributed sensors. Compressive Sensing provides an effective means of discovery and reconstruction of functions with only a subset of samples. Traditional CS relies on uniformly distributed samples which limits practicality of CS based recovery. To enhance the flexibility of sampling and implementation, the proposed approach uses random walk based samples. Unlike uniform sampling, random walk based sampling enables individual nodes achieve phenomenon awareness, i.e., the physical distribution of the phenomenon. We also derive a theoretical upper bound for the reconstruction failure probability. Simulation results on the number of samples required and error show that random walk based sampling is comparable to uniform sampling but with superior energy efficiency. More importantly, the proposed scheme provides a practical solution for a range of applications where uniform sampling is less economical or even infeasible.**

I. INTRODUCTION

Future Wireless Sensor Networks (WSNs) can be envisioned as large information ecosystems of millions of sensors embedded in the environment. Apart from the complexities posed by the enormous scale, factors such as lack of direct connectivity [19], coverage and delay intolerance [18], make data dissemination and fusion much challenging. Therefore, schemes for data dissemination capable of handling vast amount of data, which are also resilient to intermittent connections and lack of connectivity are in demand.

Compressive Sensing (CS) [6] is an attractive approach to estimate functions from a minimal set of samples. Employing a domain where a signal is represented with a minimal support, CS can recover a high dimensional signal with a small number of random projections or samples of the signal. The distribution of the samples has a major effect on the recovery [16]. Among the distributions identified as feasible, uniformly at random sampling is predominant in literature. However, gathering uniformly scattered samples is expensive in practice. The goal of the presented work is to investigate function recovery of natural physical phenomena using practical sampling schemes and domains providing sparse representations.

Phenomenon, in this paper, refers to a distribution or some other profile, e.g., a chemical plume, being monitored by a sensor network. Current CS based phenomena discovery approaches are implemented at a BS instead of at individual nodes [10], as they employ uniform sampling. Since collecting a set of uniformly scattered samples is costly to realize, data are only gathered at BSs, not at individual nodes. We define *phenomena awareness* as nodes being conscious of the phenomena the network is observing and call the perception process as *phenomena discovery*. Phenomena awareness ranges from a gross estimation to the exact recovery of the phenomena. This awareness at individual nodes can dramatically improve the capability of the network to efficiently track and react to the changes of the phenomenon. In this paper, we demonstrate achieving phenomenon awareness at individual nodes efficiently in a distributed manner. In the presence of a BS, phenomena awareness may be achieved at BS as well. Phenomenon awareness at the node level facilitates smarter and adaptive sensing strategies and provides localized decision making ability to sensor-actuator applications, with no involvement of a base-station. An upper bound is provided for the probability of recovery failure of CS based recovery under a given basis and a sampling scheme. This upper bound provides an estimate for the number of samples required to reconstruct a function within a desired error margin.

We present several motivating examples next. The hydrologic study by USDA-ARS Great Plains Systems Research (Fort Collins, Colorado) has 110ha of a winter wheat and fallow strip cropping system [12], where soil measurements are collected using sensors mounted on a pickup truck. A traditional CS realization needs samples scattered uniformly over the field, which is difficult to achieve with a truck. However, the truck could make random walks (RWs) to collect samples with much ease. We are interested in knowing whether CS reconstruction is possible with RW samples instead of uniform samples. Another application is Intel's Wireless Vineyard [4] which uses ubiquitous computing for agricultural monitoring. Here, the network is expected to not only collect and interpret data, but also to use such data to make decisions related to detecting parasites and using appropriate insecticides. In this delay tolerant network application [24], data collection relies on data mules [25] - small devices carried by people/dogs/robots that communicate with the nodes and collect data. Here as well the collected samples may not be uniformly scattered. The results presented in this paper are applicable under such scenarios.

Distributed phenomena discovery has many emerging applications. If the sensor nodes in Intel's Wireless Vineyard are phenomena aware, then the sensed information can be accessed via any node using a mobile phone, and alerts can be sent out via automated emails or text messages. Vehicular Ad-

This work is supported in part by the Air Force Office of Scientific Research under STTR contract FA9550-10-C-0090.

hoc Networks (VANETs) - networking vehicles with one another to build an infrastructure that provide drivers information beyond their field of vision and warn them about accidents or traffic jams [22] is another example, where it is necessary for individual nodes to be aware of phenomena being monitored.

The rest of the paper is organized as follows: Section II presents related work. Proposed novel algorithm for phenomena discovery using random walk and a mathematical bound for the reconstruction performance is discussed in Section III. Section IV delivers performance evaluation. Finally, Section V concludes the paper.

II. Related Work

Single dimension function recovery in underwater sensor networks is discussed in [9], where function is assumed to be sparse in Fourier domain and sensors send their information directly to the base station in a uniformly at random manner. Discovery of binary sparse events using Bayesian detection is addressed in [13]. However, the performance of their scheme decays as the signal to noise ratio (SNR) approaches 20dB. Minimizing the network energy consumption through joint routing and compressed aggregation is the goal in [14], with uniformly at random samples routed to a sink through a tree based structure. A scheme to efficiently exchange features in VANETs is developed in [23]. An energy efficient compressed sensing scheme for wireless sensor networks using spatially-localized sparse projections is proposed in [11] by using measurements from clusters of adjacent sensors in order to reduce transmission cost. Differing from the above, [17] proposes spatial domain sparse function recovery at a sink using RW based linear combination of the sensed values. However this scheme has scalability issues related to RW samples required in larger networks.

A CS for manifold learning protocol (CSML) is proposed in [8] for localization in wireless sensor networks. Here, each sensor transmits a subset of distance measurements to a central node. Then the central node reconstructs the full pair wise distance matrix through an L_1-minimization algorithm. A CS based approach for sparse target counting and positioning scheme is proposed in [20]. The proposed greedy matching pursuit algorithm (GMP) in [20] complements the well-known signal recovery algorithms in CS theory and proves that GMP can accurately recover a sparse signal with a high probability.

All the successful implementations discussed above share two common factors: uniformly at random sampling and recovery at a base/central station. The focus of this research is on smooth function discovery in a suitable domain, using a pragmatic sampling scheme. Uniformly sampled sensor values require many nodes to participate in propagating sensed values of a limited number of nodes to the BS. We are tempted to ask "why not make use of the sensed information lying on the paths leading to the BS?" Collecting uniformly at random samples also require sensor nodes to be placed and activated uniformly in the sensor field, which is less or even not practical in many of the applications. We propose RW based sampling, and demonstrate centralized and distributed phenomena discovery.

III. Compressive Sensing Under Random Walk based Sampling in Discrete Cosine Domain

Compressive Sensing [6] is posed as recovering an n-dimensional signal X ($\in \mathbb{R}^n$), that is k-sparse in its sparse representation x ($\in \mathbb{R}^n$), with m ($\ll$ n) number of samples y ($\in \mathbb{R}^m$) given by $y = A \cdot x$. If y is a subset of samples of X and X has a sparse representation in a domain whose inverse transform is ψ, the problem can be re-written as in [2]:

$$y = R \cdot X = R \cdot (\psi x) = (R \psi) \cdot x. \quad (1)$$

where $A = R\psi$ is called the measurement matrix and R is a subset of rows of an n×n Identity matrix selected by some probability mass function (pmf). Most of the theoretical recovery bounds in CS are derived from the Restricted Isometric Property (RIP) of the measurement matrix A. RIP requires every combination of support of x many columns of A to be well conditioned as [6]:

$$(1-\delta)||x||_2^p \leq ||A.x||_2^p \leq (1+\delta)||x||_2^p \quad (2)$$

where δ is called Restricted Isometric Constant (RIC) and is specific for the support of x. Authors of [5] provide a summary of solvers that can be used to solve the CS problem when the RIP is satisfied. The work presented in this paper uses L_1 minimization [6][15] to recover the signal vector. Given y and A, the under-determined system (1) is solved for x as:

$$\text{minimize } \|x\|_1, \quad s.t. \quad A \cdot x = y \quad (3)$$

where $\|\cdot\|_1$ is the L_1-norm and A ($\in \mathbb{R}^{m\times n}$) is the sensing/measurement matrix.

The goal is to recover the sparse transformed domain representation of the function/signal. Here, two main design criteria emerge: (1) the choice of the basis/frame, and (2) the row selection scheme. The basis/frame is chosen to provide a sparsest possible representation of the signal. The row selection scheme essentially is the sampling scheme. The probability of failure and the minimal number of samples required, when the measurement matrix is constructed by drawing rows from an orthonormal basis is derived in[16] according to an orthogonalization measure. For example, a measurement matrix constructed by uniformly sampling the Fourier basis meets the above requirements. Deviating from the traditional approach, in this paper we sample the basis based on a pragmatic sampling schemes that can be used in a sensor field. Next, we discuss the basis and the sampling scheme selected.

A. Why Discrete Cosine Basis?

According to [16], operating on a basis where the signal is sparsest, provides highest recovery probability. Therefore, in a WSN deployment to monitor real-world physical phenomena, sensing the Discrete Cosine Transform (DCT) of the phenomenon is rather promising. As reference [1] points out, the DCT of natural signals achieves nearly optimal energy compression - comparable to Karhunen-Loeve transform, yielding the fewest coefficients, i.e., the sparsest representation.

B. Why Random Walk as the Sampling Scheme?

Random routing is based on Random Walk or Brownian motion models and is the basis for a large number of routing algorithms for WSNs [3]. In random routing, each node randomly selects a neighbor and forwards the received message. Rumor routing [3] is an example RW routing protocol, in which messages such as agents and queries, also called rumors, randomly traverse the network. Even when the network is structured and deterministic routing is possible, random routing schemes play a crucial role in WSNs in discovery of resources and disseminating information, especially in the absence of a base station that acts as a global moderator. Moreover, RW motion models are applicable for the case where samples are collected by a carrier. Thus random routing is highly desirable in WSN applications. However, using RW routing to gather a set of uniformly scattered measurements from a sensor field is rather inefficient. Making the messages traverse in a RW manner, while collecting measurements along the path it traverse is more practical. But, such will not result in a uniform selection of measurements. Instead we receive a set of RW collected samples.

C. Implementation - Random Walk based Phenomena Discovery

This section discusses the proposed RW based phenomena discovery algorithm for centralized and distributed realizations.

1) Centralized Realization of Phenomena Discovery

In a centralized implementation, the network has a base station (BS) with a higher computational capacity. There are many scenarios where a centralized implementation is feasible or even preferable [4]. In this setup, we assume there is a carrier - a robot/vehicle/animal, collecting sensed information while traversing the network on a RW. At the end, the carrier either returns or transmits the collected data to the BS. Then BS will form and solve the CS problem to recover the phenomenon. Under similar conditions, forcing the carrier to collect samples uniformly at random is not pragmatic.

2) Distributed Realization of Phenomena Discovery

Nodes becoming phenomena aware with distributed schemes without the involvement of a base-station is crucial for many future ubiquitous sensor/actuator network applications. This phenomena awareness may be achieved using messages that continuously disseminate in the network for event/destination discovery or other management purposes. Let X be the vectorized 2D sensed phenomena. Then each node has a corresponding entry in X. For simplicity, we assume nodes are numbered in ascending order from the top left corner to bottom right corner (see Fig. 1), which is used as the node ID as well the index in X. In a localized network, physical position information of nodes can be used to organize X. If the network is not localized, a hash function can be used to map some identification of the node to an index in the range of X. Consider the example grid network in Fig. 1, where a message generated by node-8 traverses the network in a RW while disseminating information it gathered so far from the nodes it visited. When a node receives a message, it stores the content. Then the node piggybacks its node ID and the measurement to the message and forwards to a randomly selected neighbor. For instance, node-15 may receive the message [ID_8, T_8, ID_9, T_9] from node-9. Node-15 then stores the message and appends its node identification ID_15 and measurement T_15 and transmits to a neighbor.

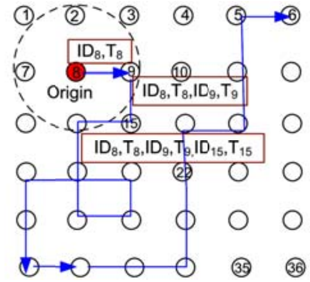


Figure 1. RW based sample collection on an example grid

INPUT: Collected samples of the phenomena
OUTPUT: Reconstructed phenomena
$\bar{m} \longleftarrow$ number of collected samples
$y \leftarrow T_i, i = 1{:}\bar{m}$
$Z \leftarrow ID_i, i = 1{:}\bar{m}$
if $\bar{m} \geq m_T$ then
  for $i = 1 \rightarrow \bar{m}$ do
    for $j = 1 \rightarrow N_T$ do
      if $j == 1$ then
        $\Psi(i,j) \leftarrow \sqrt{1/N_T}$
      else
        $k \leftarrow ID_i$
        $\Psi(i,j) \leftarrow \sqrt{2/N_T}\cos(\frac{\pi(2k+1)j}{2N_T})$
      end if
    end for
  end for
  solve $\min |x|_1$, s.t. $\Psi x = y$
  $X \leftarrow IDCT(x)$ % inverse DCT of x
else % more samples required
  for $j = 1 \rightarrow \bar{m}$ do % check whether i is a new sample
    if $ID_i == ID_j$ then
      flag $\leftarrow 1$
    end if
  end for
  flag $\leftarrow 0$
  if flag == 0 then
    $ID_{m+1} \leftarrow ID_i$
    $T_{m+1} \leftarrow T_i$
  else
    flag 1
  end if
  Forward the packet to a neighbor to which packet has not been previously forwarded
end if

Figure 2. Distributed Phenomena Discovery – Algorithm implemented at a node. A '%' symbol indicates an inline comment.

After visits from multiple packets, a node may accumulate a sufficient number of samples for recovery and construct the entire phenomena using the algorithm in Fig. 2.

In next section we evaluate the probability of recovery failure of this process. The proposed mathematical bound provides a bound on the minimum number of measurements needed to recover the function within a desired error margin.

D. Reconstruction Failure Probability

The support of the signal vector is the set of indices of non-zero elements. Let x with support S be the signal to be recovered and $|S| = s$ the number of non-zero elements, i.e., sparsity of x. Failure of recovery of a signal with support S is viewed as A being unable to satisfy RIP. In this case, RIP implies that a sub-matrix formed by columns of A over S referred as A_S being nearly orthonormal, i.e.,

$$||\widetilde{A_S}^* \widetilde{A_S} - \boldsymbol{I}||_2 \leq \delta \ . \tag{5}$$

Here $\widetilde{A_S}$ denotes column wise normalized A_S and δ is the RIC. The probability with which the above is unable to be satisfied is defined as the probability of failure ϵ.

$$\epsilon = \mathrm{P}[||\widetilde{A_S}^*\widetilde{A_S} - \boldsymbol{I}||_2 \geq \delta] \qquad (6)$$

Let $X_l = (\overline{\psi_j}(t_l))_{j\in S}$, then, expected value of $X_l X_l^*$

$$\mathbb{E}(X_l X_l^*)_{j,k} = \phi_{j,k} \qquad (7)$$

$$\mathbb{E}X_l X_l^* = \boldsymbol{I} + \square \qquad (8)$$

where $\mathbb{E}$ is expectation, ψ is an orthonormal basis, t_l is a set of arbitrary indices and I is the identity. $\square$ is the off-diagonal elements of $\mathbb{E}X_l X_l^*$. According to [16] in scenarios such as when the basis is Fourier and the sampling scheme is uniform and $\square$ is null; thus Fourier basis with uniform sampling is widely accepted to provide the optimal performance. Since we are using a different sampling scheme, recovery performance is degraded due to nonzero $\square$, thus, requiring additional number of samples to achieve similar recovery properties such as probability of failure, error in recovered function, etc., compared to those when uniform sampling is used. The general form of the RIP condition given in (2) can be re-arranged to:

$$\delta = \max_{S \subset \{1\cdots \mathrm{n}\}, |S| \leq s} ||\widetilde{A_S}^*\widetilde{A_S} - \boldsymbol{I}||_2 \qquad (9)$$

From Markov Inequality the probability of failure is bounded above by;

$$\mathrm{P}[||\widetilde{A_S}^*\widetilde{A_S} - \boldsymbol{I}||_2 \geq \delta] \leq \frac{E_p}{\delta} \qquad (10)$$

where E_p is $E_p = \mathbb{E}\left\|\widetilde{A_S}^*\widetilde{A_S} - \boldsymbol{I}\right\|_2^p$. Substituting for $\boldsymbol{I}$ from (9)

$$E_p = \mathbb{E}\left\|\frac{1}{\overline{m}}\sum_{l=1}^{\overline{m}} X_l^* X_l - \mathbb{E}X_l X_l^* + \square\right\|_2^p \leq$$

$$\mathbb{E}\left\|\frac{1}{\overline{m}}\sum_{l=1}^{\overline{m}} X_l^* X_l - \mathbb{E}X_l X_l^*\right\|_2^p + \mathbb{E}\|\square\|_2^p \qquad (11)$$

Note that $\mathbb{E}\|\square\|_2^p$ is the noise generated due to the deviation from uniform sampling. By solving for E_p

$$E_p{}^{1/p} \leq D\left[\sqrt{1 + \frac{D^2}{4} + \frac{Q}{D^2}} + \frac{D}{2}\right] \qquad (12)$$

where $D = \left(\left(\frac{2}{\sqrt{\overline{m}}}\right)^p 2^{3/4} s p^{p/2} \exp\left(-\frac{p}{2}\right)\right)^{1/\mathrm{p}}$. Let, $\bar{\kappa} = \sqrt{1 + \frac{D^2}{4} + \frac{Q}{D^2}} + \frac{D}{2}$. Substituting E_p (12) in (10) and rearranging terms we obtain the failure probability ϵ:

$$\mathrm{P}\left[\left\|\widetilde{A_S}^*\widetilde{A_S} - \boldsymbol{I}\right\|_2 \geq \delta\right] = \epsilon \leq 2^{\frac{3}{4}} s \exp\left(-\frac{\delta^2 \overline{m}}{8K^2\bar{\kappa}^2 s}\right) \qquad (13)$$

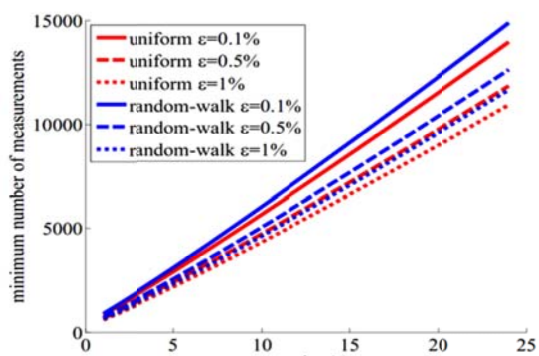


Figure 3. Variation of m and $\overline{\mathrm{m}}$ with sparsity under different failure probilities (ϵ) for a 100 x100 grid network

where $\overline{m}$ is the number of measurements needed under any sampling scheme and K is the upper bound of $\|X_l\|_2/\sqrt{s}$. Complete proof is available on [7].

The theoretical number of samples required for uniform sampling as in [11] is evaluated and shown in Fig. 3 under failure probabilities 0.1%; 0.5%; 1%, against sparsity. δ and K were set to 0.5 and 1 respectively. The number of samples required under same probabilities of failure (ϵ), by RW based sampling evaluated by simply solving (13) for $\overline{\mathrm{m}}$, which is $\overline{\mathrm{m}} \geq \frac{\mathrm{K}^2\bar{\kappa}^2\mathrm{s}}{\delta^2} . \ln\left(\frac{2^{3/4}\mathrm{s}}{\epsilon}\right)$, for the same sparsity range is also plotted in Fig. 3. Monte Carlo simulation of RW is used to estimate the probability distribution of a message visiting a node and $\bar{\kappa}$ is estimated.

IV. Performance Evaluation

Temperature distribution map of State of Alabama [21] during August averaged over 1951 - 2006 years was used to demonstrate the effectiveness of the RW based phenomena discovery (See Figure 4 (a)). There are a total of 7653 data points in a grid structure where we assume 7653 sensors are deployed. Each node is capable of communicating with its immediate four neighbors, i.e. communication range is one grid segment.

The presented experiments look into the cost of implementing centralized and distributed *phenomena awareness* with random walk sampling using a suitable basis. Experiments are carried out on MATLAB 2011a and L-1 magic [15] is used as CS solver. Performance evaluation metric is the percentage reconstruction error ($\mathrm{E_r}$) of the recovered function defined as:

$$\mathrm{E_r} = \frac{1}{\mathrm{N_T}}\sum_{\mathrm{k}=1}^{\mathrm{N_T}}(|\mathrm{X_k} - \overline{\mathrm{X}}_\mathrm{k}|/\mathrm{X_k}) \times 100 \qquad (14)$$

where $\mathrm{N_T}$ is the total number of samples in the function, which is the same as the total number of sensors in the network. $\mathrm{X_k}$ and $\overline{\mathrm{X}}_\mathrm{k}$ are the $\mathrm{k^{th}}$ sample of the original function and the reconstructed function respectively.

First, a pre analysis of temperature distribution in Fig. 4(a) was performed to identify its sparsity level. The number of significant coefficients defines the sparsity level. If the function to be reconstructed is sparse in DCT domain, we expect only a few significant DCT coefficients. It was found that to approximate the temperature function in Fig. 4(a) within a 0.1% error, 3183 DCT coefficient out of 7653 were required. This implied that even in DCT domain the selected phenomenon is not as sparse as expected.

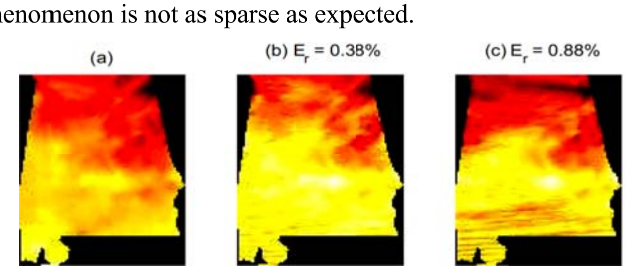
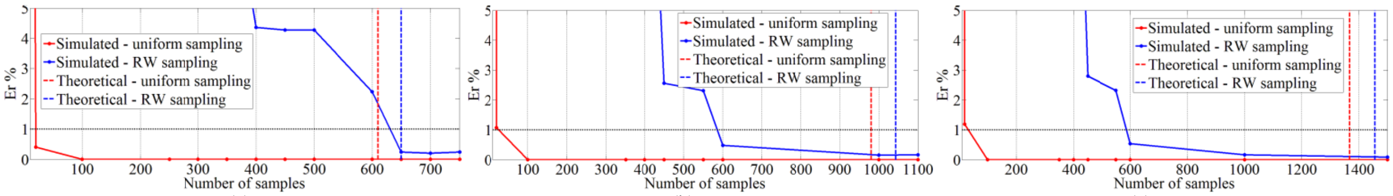


Figure 4. (a)Average temperature distribution of State of Alabama in August. 7653 sensors in total are available. (b) Reconstructed image based on 2583 samples collected at the BS by a single carrier (c) Reconstructed image at randomly selected node when 1056 samples were collected in that node



(a) (b) (c)

Figure 5. Variation of E_r with the empirical number of samples used when (a) s=2 (b) s=3 (c) s=4. Dashed lines show the theoretical number of samples needed and the dotted line show the E_r=1% level.

In order to compare the theoretical prediction with the simulated, we begin our performance evaluation by finding the number of samples needed to recover the approximated version of phenomena in Fig. 4(a) based on the most significant *s* DCT coefficients. The number of coefficients to be recovered is considered as the sparsity (*s*) of the function. Here a message with a predefined TTL (Time To Live) is disseminated into the network. Note that due to the possibility of revisiting to the same node the message will not be able to collect TTL many unique samples. Recovery error of reconstruction against the samples collected by the message is plotted as in Fig. 5, for three sparsity cases: 2, 3 and 4. As Fig. 5 indicates, the empirical values for the number of measurements needed to obtain an E_r of 1%, for sparsities 2, 3, 4 is less than 600. Dashed lines in Fig. 5 indicate the theoretical estimates for the number of samples required under each sampling scheme. The theoretical values are an over-estimate as they are based on satisfying the sufficient conditions of recovery.

Although such natural phenomena can be approximated by a sparse representation with only a few non-zero coefficients, in next simulation results, we aim to recover the original dataset - not an approximation of the original with low sparsity.

A. *Performance of Phenomena Discovery at the Base Station*

Here, the base station is assumed to be at (0,0). A carrier (robot) collects sensed information and node IDs while moving from one node to another in a RW of step size one. The maximum number of steps that the carrier will take is set to 4000 when there is a single carrier. Since revisiting to the same node twice is allowed, the carrier may collect less than 4000 samples. Fig. 4(b) shows an example recovery under RW sampling at a BS when 2583 unique samples were available. In reality, the true sparsity of the phenomenon is unknown. Therefore, the theoretical number of samples needed is undetermined. In Fig. 6 we demonstrate the variation of E_r with the number of samples used.

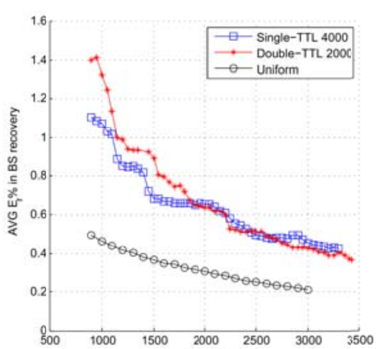


Figure 6: Variation of average error with number of samples used for reconstruction in centralized recovery. Single carrier with 4000 steps in total and two carriers with 2000 steps per each were used

The variation of error as two carriers collectively gather the same number of samples is also plotted in the same Figure. In the experiment with two carriers, each carrier has a TTL of 2000. As can be seen, performance in terms of E_r depends more on the number of samples than the number of carriers used. Even though collecting samples under uniform distribution is difficult in practice, we show the recovery error under simulated uniform sampling as a comparison. Error performance under RW sampling is only about 0.2% away that of under uniform sampling, when 2000 samples are available.

B. *Performance of Distributed Phenomena Discovery*

To the best of our knowledge, CS based distributed phenomena discovery in WSNs is proposed here for the first time. We envision that future WSNs will evolve over their lifespan and become increasingly aware of the sensed phenomena. Thus the proposed scheme will provide a cost effective infrastructure.

We use the same temperature dataset for the distributed phenomena awareness implementation and evaluation. In a WSN where there is no fixed BS, random routing is used for event and sink discovery [18]. Those messages can be used to make network learn the phenomena being observed. Note that while phenomena discovery at a BS used carriers incurring cost, the distributed implementation uses packets already disseminated in the network incurring no additional cost. In the simulation, 1000 messages with TTL 300 are generated at a randomly selected node and traversed on a RW. Messages may revisit the same node but message will carry only one sample per visited node. A view of the phenomena at a randomly selected node, which has collected 1056 samples from the messages that passed through it, is given in Fig. 4(c). Fig. 7 shows the average error E_r in the recovered phenomena at different nodes. The mean E_r is calculated over nodes with the same number of samples collected.

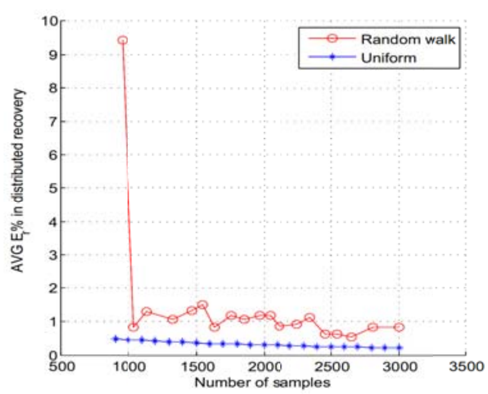


Figure 7: Variation of average error with number of samples used for reconstruction in a distributed manner. Evaluation is after 1000 messages with 300 TTL disseminated in the network.

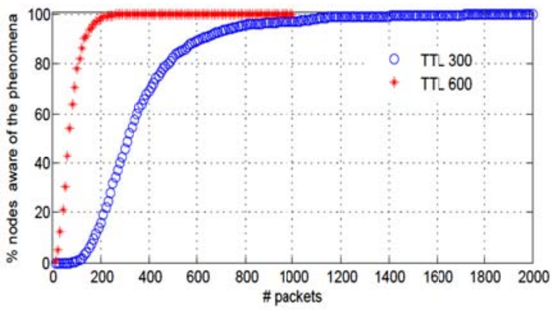


Figure 8. Convergence rate of nodes achieving phenomena awareness in a distributed implementation when messages has TTL 300 and 600

Next, we consider the convergence of the entire network achieving phenomena awareness in a distributed implementation. Fig. 8 shows the mean rate of nodes achieving phenomena awareness under two different TTL values. From Fig. 7 we deduce that a node needs at least 1000 samples to become aware of the sensed phenomena with an E_r of less than 2%. When TTL is 300, at least 1200 messages need to be disseminated in the network, while when TTL is doubled the required number of messages reduces to less than 400. Note that the network considered has 7653 nodes. If the traditional uniform sampling was used, for entire network to become aware of the phenomena, 1000 randomly selected nodes need to flood the network which leads to at least 7,653,000 transmissions. But the proposed approach achieves a map with a similar E_r with at least 240,000 transmissions with TTL 600, providing approximately 96% reduction in the number of transmissions.

V. Conclusion

A novel implementation using compressive sensing for phenomena awareness is proposed. The proposed algorithm provides nodes with network-wide knowledge of the events observed. Moving beyond the traditional approach of uniform sampling based CS for function recovery, we illustrate that RW based sampling can practically and successfully be used for phenomena awareness at base-stations and at each sensor without a BS, with minimal additional samples. An upper bound for the probability of successful recovery with a given error percentage is also derived. The derived bound provides an approximate number of samples required to recover a function under a selected basis and a sampling scheme.

We considered random walk as the mobility model due its wide spread usage in WSNs. But other mobility models as random waypoint model, Markovian model etc. can also be used in the same manner. Performance bounds for CS based phenomena discovery using a frame - an over complete basis, instead of an orthogonal basis and other practical sampling schemes that accurately captured by motion models are under investigation.

References

[1] N. Ahmed, and T. Natarajan, and K.R. Rao, “Discrete cosine transfom,” IEEE Transactions on Computers, 1974, 90 – 93.

[2] R. Baraniuk, "Compressive sensing," IEEE Signal Processing Magazine, Vol. 24, No. 4, July 2007, pp. 118-121.

[3] D. Braginsky, and D. Estrin, “Rumor routing algorithm for sensor networks”, Proc. 1st ACM int. workshop on Wireless sensor networks and applications, 2002, pp. 22-31.

[4] J. Burrell, T. Brooke, and R. Beckwith, R, “Vineyard computing: sensor networks in agricultural production,” IEEE journal of Pervasive Computing, 2004, pp.38 – 45.

[5] R. Calderbank, S. Howard, S. Jafarpour, "Construction of a large class of deterministic sensing matrices that satisfy a statistical isometry property," IEEE Journal of Selected Topics in Signal Processing, vol.4, no.2, pp.358-374, April 2010.

[6] E.J Candes, and T. Tao, “Decoding by linear programming” IEEE Transactions on Information Theory, 2005, pp.4203 – 4215.

[7] D. C. Dhanapala, "Anchor centric virtual coordinate systems in wireless sensor networks: from self-organization to network awareness," PhD Dissertation, Colorado State University, 2012.

[8] C. Feng and S. Valaee, and Z. Tan, “Localization of wireless sensors using compressive sensing for manifold learning,” 20th IEEE Int. Symp. on Personal, Indoor and Mobile Radio Communications, 2009.

[9] F. Fazel, M. Fazel, and M. Stojanovic, “Random access compressed sensing in underwater sensor networks,” 48th Annual Allerton Conf. on Communication, Control, and Computing, 2010, pp. 768 -774.

[10] J. Haupt, W.U. Bajwa, M. Rabbat, and R. Nowak, “Compressed sensing and network monitoring,” The Next Wave, vol.18, no.3, pp.16-25, 2010.

[11] S. Lee, S. Pattem, M. Sathiamoorthy, B. Krishnamachari, and A. Ortega, “Spatially-localized compressed sensing and routing in multi-hop sensor networks, Proc. 3rd Int. Conf. on GeoSensor Networks,2009.

[12] M.C. McCutcheon, H.J. Farahani, J.D. Stednick, G.W. Buchleiter and T.R. Green, "Effect of soil water on apparent soil electrical conductivity and texture relationships in a dryland field", Journal of Biosystems Engineering, pp. 19 - 32, 2006.

[13] J. Meng, H. Li and Zhu Han, “Sparse event detection in wireless sensor networks using compressive sensing,” 43rd Conf. on Information Sciences and Systems,(CISS), 2009, pp.181 -185.

[14] G. Quer, R. Masiero, D. Munaretto, M. Rossi, J. Widmer, and M. Zorzi, “On the interplay between routing and signal representation for Compressive Sensing in wireless sensor networks,” Information Theory and Applications Workshop, 2009,pp. 206 -215.

[15] J. Romberg, L1-Magic, available at: www.acm.caltech.edu/l1magic/

[16] H. Rauhut, “Compressive sensing and structured random matrices,” Journal of Theoretical Foundations and Numerical Methods for Sparse Recovery, 2010,edited by Fornasier M.,pp. 1-92.

[17] M. Sartipi, and R. Fletcher, “Energy-efficient data acquisition in wireless sensor networks using compressed sensing,” Proc. Data Compression Conference (DCC), 2011, pp223 -232.

[18] Y. Wang and H. Wu and N-F. Tzeng, “Cross-layer protocol design and optimization for delay/fault-tolerant mobile sensor networks,” IEEE journal on Selected Areas in Communications, 2008, pp. 809 -819.

[19] M. Zhang and M. C. Chan and A.L. Ananda, "Connectivity monitoring in wireless sensor networks",Journal of Pervasive and Mobile Computing,2010, pp. 112-127.

[20] B. Zhang, X. Cheng, N. Zhang, Y. Cui, Y. Li, and Q. Liang, “Sparse target counting and localization in sensor networks based on compressive sensing ,” Proc. IEEE INFOCOM, 2011,pp. 2255 -2263.

[21] ClimateWizard ,PRISM Group, Oregon State University, created 4 Feb 2007, http://www.climatewizard.org/index.html

[22] Scientific Computing, “When cars can talk,” http://www.scientificcomputing.com/news-DS-When-Cars-can-Talk-032211.aspx

[23] L. Uichin, Z. Biao, M. Gerla, E. Magistretti, P. Bellavista, A. Corradi, "Mobeyes: smart mobs for urban monitoring with a vehicular sensor network," IEEE Wireless Communications, vol.13, no.5, pp.52-57, 2006.

[24] W. Zhao, M. Ammar, and E. Zegura, "A message ferrying approach for data delivery in sparse mobile ad-hoc networks," In ACM MOBIHOC’04, Tokyo, Japan, May 2004.

[25] R. C. Shah, S. Roy, S. Jain, and W. Brunette, "Data MULEs: modeling a three-tier architecture for sparse sensor networks," Elsevier Ad Hoc Networks Journal, 1(2-3), pp.215–233, Sept. 2003.