Environmental Monitoring via Compressive Sensing

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ABSTRACT
Environmental monitoring aims to describe the state of the environment. It identifies environmental issues to show us how well our environmental objectives are being met. Traditional large-scale sensor networks for environmental monitoring suffers from the problems of high level of resources consumption and complex information management. In this report, we propose a novel environmental monitoring technique, called compressive sensing based monitoring, which employs only a small number of sensors to monitor target environmental signals over a region of interest. The compressive sensing technique is applied to implement our signal construction framework such that a high resolution environmental signal can be accurately reconstructed with undersampling measurements.

Categories and Subject Descriptors
C.3 [Special-purpose application-based systems]: [Signal processing systems]; C.4 [Performance of systems]: [Measurement techniques]

General Terms
Measurement

Keywords
Environmental monitoring, Compressive sensing, information management, sensor networks

1. INTRODUCTION
Anthropogenic effects on the natural environment have induced many environmental issues, including climate change, land degradation, and pollution. Some of these environmental issues seriously affect human’s life and health. Efficient and economical environmental monitoring techniques have been researched for decades for realising the environmental quality assessment, which is the precondition for enhancement of environmental quality. Large-scale sensor networks have been widely used to monitor environmental conditions so as to achieve high quality environmental signals. They deploy a large number of sensor nodes over large areas, and these sensor nodes can collaborate with each other to provide in situ, real-time data about the environmental state. On the other hand, they have the problem on both complex information analysing and high level of resources consumption due to the large number of sensor measurements. In this paper, we propose a compressive sensing based environmental monitoring technique. Our method enables a high spatial resolution of target environmental signals re-constructed with only a small number of measurements by employing the compressive sensing theory. In practice, it can highly reduce the resources cost, e.g., number of measurements. Traditional information management techniques of sensor networks minimise the amount of measurements by collecting a large number of initial sensor readings. Then, turn off some of the sensors by calculating the level of redundancy in previous sensor measurements. Our method, on the contrary, can work well with a small number of randomly measurements that exhibiting little space correlation. In addition, the number of measurements can be adapted in light of the precision requirements of the reconstructed signal.

The work presented in this paper is a part of work on our elastic sensor network framework. This framework aims to develop a novel theoretical computational model for information management in large-scale sensor networks. It combines the attention-like mechanism and model-driven mechanism to realise an optimum cost model, called elastic computation model. The idea of elastic computation aims to balance the trade-off between the cost of resources and the reconstruction accuracy, allowing user to pay per use.

The paper is organised as follows. The next section summarises the related work on environmental monitoring techniques, and section 3 provides some backgrounds on compressive sensing and introduces three standard recovery methods. In section 4, we describe our information analysis model; and experiment results of applying our model to three datasets are detailed in section 5. We make a discussion in section 6, and our conclusion and future work for improving monitoring model are explained in the last section.

2. RELATED WORK
Many environmental assessment techniques contributed to the alleviation of environmental issues. In wireless sensor networks (WSNs) [4], networks of spatially distributed au-
tonomous sensors are deployed to monitor physical or environmental conditions, such as detection of gas pollution produced by cars [10], evaluation of water quality [5], monitoring of noise pollution [8, 9], volcanic activity [13]. Environmental monitoring stations are adopted to host expensive detection sensors to analyse the target environmental substances over a monitored area. The cost of deploying and maintaining large-scale monitoring networks limits the number of environmental monitoring stations or sensors. [3] indicated the separation between stations often exceeded 10km. Take air pollution as an example, sensor-based detection techniques like [3] were introduced to overcome the limitation of monitoring stations. [2] integrated GIS system with sensor network to create a system so as to generate pollution maps in urban environments. Ghanem et al. [1, 12] used sensor grids to construct a distributed system for urban pollution monitoring and control. [1, 2, 3] concentrated on the approach of building sensor grids, and addressing the challenges like integration of distributed sensors, power consuming, or transmission protocol. However, these works also conducted direct measurements, so the solution of generated map is limited by the number of measurements. Moreover, large scale sensor networks suffer from transmission cost. It is impossible for all passive sensors to be kept awake and transmitting data to a central node all the time. For this reason, intelligent method for resource allocation has been one of the most significant challenges of environmental monitoring sensor networks. Some works tried to provide a low-cost solution by cutting physical sensor costs [6], while others tried to reduce the cost by designing sensor network simulator for WSN applications [11]. Tsujita et al. [9] developed a gas distribution analyzing system to monitoring Nitrogen Dioxide and Ozone with low-cost sensor systems. Other techniques have been proposed to improve the system performance without fully deployed sensor nodes, e.g. [7].

3. CS RECOVERY APPROACHES

The theory of compressive sensing (CS) [15] shows that under certain conditions, it is possible to reconstruct a signal from a considerably incomplete set of observations, i.e. with a number of measurements much less than required by the Nyquist-Shannon theorem. Real-world signals typically have a sparse representation in a certain transformed domain. Compressive sensing provides a framework for integrating sensing and compression of discrete-time signals, and the discrete-time signals should be sparse or compressible in a known basis or frame.

Let $x \in \mathbb{R}^N$ be the vector of signal we want to recover, and $y \in \mathbb{R}^M$ be the measurement of $x$ obtained by sensors, and $M << N$. $\Phi$ is the observation matrix. So we have:

$$y = \Phi x$$  \hspace{1cm} (1)

Clearly, solving for $x$ based on the observation set $y$ is an ill-posed problem as the system is under-determined. However, suppose that $x$ has a sparse representation in another domain, i.e. it can be represented as a linear combination of a small set of vectors:

$$x = \Psi w$$  \hspace{1cm} (2)

where $\Psi$ is an invertible matrix and $w$ is $S$-sparse, i.e. $|\text{Supp}(w)| = S << N$ where $\text{Supp}(w)$ refers to the set of indices of the non-zero elements of $w$ and $|\cdot|$ denotes its cardinality. We do not know anything about the structure of $w$ except for the fact that it is sparse. Let $\Theta = \Phi \Psi$, we would have:

$$y = \Theta w$$  \hspace{1cm} (3)

if noise $n$ exists, we would have:

$$y = \Theta w + n$$  \hspace{1cm} (4)

The CS recovery process is to find a sparse weight $w$ satisfied the equation (4) exactly or approximately with given $y$ and $\Theta$.

The theory of compressive sensing allows us to solve the recovery problem, if measurement matrix $\Theta$ satisfies the Restricted Isometry Property (RIP) for $(2S, \sqrt{2} - 1)$.

A matrix $\Theta$ is said to satisfies RIP with parameters $(S, \sigma)$ for $\sigma \in (0, 1)$, and all $S$-sparse signal $c$, it should satisfy the following:

$$(1 - \sigma)|c|_2 \leq ||\Theta c||_2 \leq (1 + \sigma)|c|_2$$  \hspace{1cm} (5)

[24] states the matrix should also holds that:

$$\sqrt{1 - \sigma} \leq \lambda_{\min}(\Theta) \leq \lambda_{\max}(\Theta) \leq \sqrt{1 + \sigma}$$  \hspace{1cm} (6)

where $\lambda_{\min}$ and $\lambda_{\max}$ refer to the minimum and maximum singular values of $\Theta$, respectively.

3.1 $\ell_1$-approach

The compressive sensing algorithms that reconstruct the signal based on $\ell_1$ optimisation in (7) are typically referred to as "Basis Pursuit (BP)".

$$\min ||w||_1 : y = \Theta w$$  \hspace{1cm} (7)

BP can be casted as a Linear programming (LP) problem and solved in polynomial time. It has the strong recovery guarantees and overcoming the NP-complete issue, which is an inherent problem of $\ell_0$ optimisation. Interior point methods were first developed for solving this LP problem by convex optimisation. Some of these interior point methods, such as primal-dual and primal log-barrier approach, are provided by the $\ell_1$ magic toolbox [25]. These algorithms offer a good performance on sparsity-undersampling trade-off that accurately reconstruction can be achieved with under-determined samples. However, they cannot be applied to implement environmental signal recovery process, because they are expensive to compute for high dimensional signals and they do not allow noise in the measurement.

Iterative thresholding algorithms [14, 23], which are fast alternative approaches, were introduce to overcome the limitations of LP by solving the Lasso equation. Lasso (8), which is a modified optimisation the BP, can be used for measurement with additive noise (4).

$$\min \frac{1}{2}||\Theta w - y||^2_2 + \mu||w||_1$$  \hspace{1cm} (8)

These iterative thresholds algorithms start from an initial signal estimate $w_0$, and iterate a gradient descent step followed by hard/soft thresholding until a convergence criterion is met. They are low cost and require only a small number of storage space in each iteration, thus is feasible to be applied to recovering high dimensional environmental signal. On the other hand, the probability of successful recovery is controlled by the choice of constant parameter $\mu$ in equation (8).
3.2 Greedy Algorithm

Greedy algorithms are another approach for solving sparse approximation problems. It iteratively refines the current estimate for the sparse weight vector \( w \) by selecting the columns of \( \Theta \). The columns are selected according to their correlation with the measurements \( y \) determined by an appropriate inner product [22]. Compared to LP approaches, it highly improves the computational speed.

Orthogonal matching pursuit (OMP) [21] is the simplest effective greedy algorithm. In each iteration, it selects sub columns of \( \Theta \) for processing by calculating the current residuals. These residuals are updated by utilising the most correlated column of \( \Theta \), which is obtained by projecting the measurements \( y \) onto a linear space. Compressive sampling matched Pursuit (CoSaMP) [17] and Subspace Pursuit (SP) [24] greedy algorithms have similar flavor to OMP, and they all need to pre-determine the sparsity parameter \( S \). The target sparsity \( S \) of an environmental signal, however, is unknown in practice so as that the performance is unpredictable.

3.3 Bayesian Compressive Sensing

Bayesian compressive sensing (BCS) [16] is a more advanced compressive sensing recovery method that utilizes the knowledge of sparse Bayesian compressive learning and Relevance Vector Machine (RVM) [19]. Different from \( \ell_1 \)-approach and greedy algorithms, there is no parameter needs to be specified. And it can empirically provide a useful sparse solution even when uses a measurement matrix without satisfying the RIP condition. Furthermore, previous recovery algorithms result in point estimate of the sparse weight \( w \). BCS, however, not only improves the accuracy over the point estimate but also formulates a posterior density function (pdf) for \( w \). With the posterior density function, “error bars” are provided. The error bars can indicate the measure of confidence of the recovery signal as well as guiding the optimal design of additional CS measurements so as to reduce the uncertainty in \( y \).

Under the common assumption of zero-mean Gaussian noise, we can get the Gaussian likelihood model:

\[
p(y|w, \sigma^2) = (2\pi \sigma^2)^{-\frac{N}{2}} \exp\left(-\frac{1}{2\sigma^2} \|y - \Theta w\|^2\right) \tag{9}
\]

Given measurement \( y \) and assume \( \Theta \) is known, the quantities to be estimated are sparse weight \( w \) and noise variance \( \sigma^2 \). Here, it seeds a full posterior density function for \( w \) and \( \sigma^2 \). BCS realises CS recovery by solving Lasso equation (8). It is straightforward to see that the solution in (8) corresponds to a maximum a posterior (MAP) estimate for \( w \), with given \( y \) and assuming the likelihood function in (9).

BCS converts the CS problem into a linear-regression problem with a constraint that \( w \) is sparse. For this purpose, a sparseness-promoting prior on \( w \) must be placed. A common choice is Laplace density function. However, as it is not conjugate to Gaussian likelihood, the associated Bayesian inference may not be performed in closed form. The hierarchical prior introduced by [19] not only has similar properties as the Laplace density function but also provide sparseness prior but is also conjugate to the likelihood.

In addition, BCS involves the fast RVM algorithm proposed in [20] to implement optimisation process which can highly improve the computational speed.

4. COMPUTATIONAL MODEL

![Figure 1: our approach](image)

In this section, we will detail the computational model of our environmental monitoring system. Figure 1 illustrates the work flow of our computational model. It mainly consists of three stages: sampling, recovery, and reconstruction.

1. Sampling

We want to generate a \( N \) dimensional environmental signal over a monitoring area. Only \( M \ll N \) sensors are randomly deployed in the monitoring area. Readings and location information of these sensors are collected and generate a sparse sample vector \( Y = [y_1, \cdots, y_M]^T \) with their coordinates \( C = [c_1, \cdots, c_M]^T \). These vectors are then used as inputs for recovery stage.

2. Recovery

The aim of this stage is to recover the sparse coefficient vector \( W \) with the under-determined samples \( Y \) as shown in equation (4) utilising compressive sensing theory. The CS measurement matrix \( \Theta \) mentioned in equation (4) should be firstly calculated by \( \Theta = \Phi \Psi \).

Based on the coordinate matrix \( C \), the sampling matrix \( \Phi = [\phi_1, \cdots, \phi_N]^T \) can be determined by

\[
\phi_i = \begin{cases} 
1 & \text{if } i = c_j \\
0 & \text{if } i \neq c_j
\end{cases} \text{ where } i = 1 \cdots N \text{ and } j = 1 \cdots M \tag{10}
\]

We make an assumption that most natural environmental signals (e.g. air pollution, temperature, humidity) could be sparsely represented by Gaussian kernels. Therefore, the sparse basis matrix \( \Psi \in \mathbb{R}^{N \times N} \) is defined as

\[
\Psi = [\psi(x_1), \cdots, \psi(x_N)]^T \tag{11}
\]

wherein \( \psi(x_n) = [K(x_n, x_1), \cdots, K(x_n, x_N)]^T \), and \( K(x_m, x_n) \) is a Gaussian kernel function

\[
K(x_m, x_n) = \exp\left(-\eta_1(x_m1 - x_n1)^2 - \eta_2(x_m2 - x_n2)^2\right) \tag{12}
\]

where \( \eta_1 \) and \( \eta_2 \) are ‘width’ parameters of the kernel function. By multiplying \( \Phi \) with \( \Psi \), the CS matrix \( \Theta \) becomes a \( M \times N \) matrix containing \( M \) rows of the
transform matrix
\[ \theta_i = \psi(x_j) \text{ if } \phi_i = 1 \text{ where } i = 1 \cdots M \text{ and } j = 1 \cdots N \]

(13)

With the sampled signals and the CS matrix determined, sparse coefficient vector \( W = [w_1, \ldots, w_N]^T \) can be recovered by proceeding with CS recovery process.

3. Reconstruction

The reconstruction is to construct the desired environmental signal \( X \), where \( X = [x_1, \ldots, x_N]^T \). After obtaining sparse vector \( W \) from the recovery stage, we can calculate the desired signal by \( X = \Psi^{-1}W \).

Our environmental monitoring system only require users to support the sparse measurements and their locations, and then generates a desired environmental signal by executing the three stages in sequence. The selection of CS recovery method in recovery stage has a great impact on the performance of our system. Hence, in section 5.1, we conduct an experiment to compare different CS recovery methods so as to find the most suitable method adopted to our system.

5. EXPERIMENT AND RESULT

We applied our methods and conducted experiments on both synthetic and real environmental data.

In the synthetic test, we reconstructed an image which represents the natural environmental signal from a small amount of measurements (sampled pixels). We used different reconstruction methods and compared their performances. The signal in the image is a mixture of Gaussian distributions. That is because most environmental signals (e.g. gas, temperature, and humidity) are produced by molecular diffusion process that amplitudes of the signals smoothly attenuates from source to tail, which has the same property as Gaussian distribution. We therefore made an assumption that most signals in natural environment could be approximated by a mixture of Gaussian distributions. For this synthetic signal, we identify the best reconstruction method, and adopt the chosen method to real environmental data.

In the real data test, we used two different types of real environmental datasets, Ozone data and surface air temperature data. Signal of the Ozone data is ideally smooth distributed, while the air temperature signal has many sudden distributions. By using these two datasets, we can achieve more comprehensive evaluation of the chosen method when adopted to implement environmental monitoring system. The real experiment showed promising result of recovery, and indicated that performance of the chosen method on environmental monitoring is guaranteed. In addition, it bore out our supposition that most smoothly natural environmental signals could be approximated by a mixture of Gaussian distributions.

5.1 Synthetic Test

In this part, we applied different reconstruction methods to recover a natural environmental signal from limited sampling. The environmental signal (as shown in Figure 2a) is simulated as the mixture of Gaussian distributions with three components. The signal, which is bell-shaped, has the resolution of 128 \( \times \) 128 (16384 pixels).

We applied three different recovery methods to construct the target signal with different amounts of samples. The number of random samples is from 40 to 10240. The recovery methods are Bayesian Compressive Sensing (BCS), Linear Programming (LP: Primal-dual interior point method), and Approximate Message Passing (AMP) [18]. We then tested the performances of different recovery algorithms when reconstructing the target environmental signal. Considering the example signal is a mixture of Gaussian distributions, we present the CS matrix by using Gaussian kernel functions (shown in equation (11)). The weights of Gaussian kernel in equation (12) is empirically set to \( \eta_1 = \eta_2 = 20 \).

As shown in Table 1, recovery error rates of LP and AMP are extremely large that both methods are fail to recover the synthetic signal. The reason for the failure of recovery is that LP and AMP rely heavily on the property of the CS matrix. These algorithms can guarantee stable recovery only if the CS matrix satisfies RIP. It has a combinatorial computational complexity to check whether our CS matrix satisfies RIP using (5). We therefore used inequality constraints (6) instead. From the inequality constraints, we can achieve the lower bound of \( \sigma \) that:

\[ \sigma \geq 1 - \lambda_{min}^2 \]

(14)

The minimum singular values of our CS matrices are so small (\(< 10^{-15}\) and approaches zero. When we put the minimum signal value in the inequality (14), we got \( \sigma \geq 1 \), which does not satisfy the RIP constrain \( \sigma \in (0, 1) \). This is a counter-example to show that the CS matrix constructed by Gaussian kernel functions does not satisfy RIP condition.

Figure 2: Recovered signal with BCS method (a)Original signal to Recover (b)Recovered signal with 320 samples (c)Recovered signal with 640 samples

On the contrary, BCS guarantees the recovery performance without requiring the CS matrix to satisfy RIP, and it has distinct advantages on both computational speed and recovery accuracy. Specifically, the recovery errors is very small (around 0.004) when using underdetermined number of samples \( M \leq 320 \times 1.95\% \). With underdetermined number of measurements, the recovered signals (shown in Fig-
Table 1: Comparison of LP, AMP and BCS recovery algorithms

<table>
<thead>
<tr>
<th>Recovery approaches</th>
<th>LP</th>
<th>AMP*</th>
<th>BCS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Computational Speed</td>
<td>69s ~ 531s</td>
<td>8s ~ 130s</td>
<td>2.7s ~ 17s</td>
</tr>
<tr>
<td>Recovery Error Rate</td>
<td>$10^3$ ~ $10^6$</td>
<td>$&lt; 10^{300}$</td>
<td>$0.02 ~ 0.09$</td>
</tr>
<tr>
<td>Adaptive Potential</td>
<td>no (only point estimate)</td>
<td>no (only point estimate)</td>
<td>yes (point and “error bars” estimate)</td>
</tr>
</tbody>
</table>

*Experiments were performed with Matlab (R2011b 7.13.0.564) on a machine with 3.20GHz processor and 8.0G RAM, with 64-bit Windows 7 OS.

ure 2) are smooth and have similar shapes to the example signal. Figure 3b shows the recovery errors of BCS decrease as the number of samples increase and start to converge after 640 measurements, while Figure 3a shows the method has a growing tendency toward computational time in the number of samples.

In addition, BCS has the potential to implement adaptive sampling technique. The estimated “error bars”, which gives the measure of confidence of recovery signal, can guide the optimal design of additional CS measurements.

![Speed (BCS)](image)

(a) Speed

![Errors (BCS)](image)

(b) Error

Figure 3: Recovery performances of BCS

5.2 Real data test

From the synthetic test above, the performance of Gaussian kernel matrix combined with BCS recovery method performs best. So we use this method to recover a real environmental signal. We also tested some other CS matrix, like Discrete Cosine transform (DCT) and wavelets. However, CS matrix constructed by Gaussian kernel has the best performance. That is because BCS treats the recovery process as a linear regression problem, and Gaussian kernel is the most common kernel function due to its good features [28].

5.2.1 Ozone Data

Here, we aim to conduct an Ozone distribution signal from a limited number of samples. The data for experiment are from NASA TOMS (http://ozoneaq.gsfc.nasa.gov). Earth Probe OMI provides near-real-time measurements of ozone in the atmosphere, and TOMS constructs Ozone distribution maps (as shown in Figure 4a) based on the measurements. We used a monthly average Ozone data from Earth Probe OMI in Feb, 2005. The data could be retrieved from ftp://toms.gsfc.nasa.gov/pub/eptoms/data/monthly_averages/ozone/L3_ozavg_epc_200502.txt

![Ozone distribution map](image)

(a) Ozone distribution map

![Signal map to recover](image)

(b) Signal map to recover

Figure 4: Ozone experiment

![Reconstructed ozone map with different numbers of samples](image)

(a) 320 samples  (b) 640 samples  (c) 1280 samples  (d) 2560 samples

Figure 5: Reconstructed ozone map with different numbers of samples

We used the Ozone data with the area from Latitudes 65.5 South to 62.5 North with 1.00 degree steps, and Longitudes
179.375 West to 19.375 West with 1.25 degree steps. The resolution of the map is $128 \times 128$.

We then applied our method on the data with different amount of sampling. Figure 5 shows the result of recovery with sampling amount from 320 to 2560. As we can see, the recovery is quite good when we just sample a few data (1.95%), and the result gets refined as more samples are added. We also compared the recovery speed and error rate under different sampling rate. As shown in Figure 6b, the error rate is quite low even with about 320 samples.

![Recovery Speed](a) Speed
![Recovery Error](b) Error

Figure 6: Recovery performances

5.2.2 Surface Air Temperature Data

In order to test the performance of our system on different type of environmental data, we applied our method to another real data, surface air temperature, published by NARCCAP (http://www.narccap.ucar.edu/).

The high resolution climate data served by NARCCAP are stored in NetCDF format and distributed through the Earth System Grid. We used a maximum daily surface air temperature data in 1st Jan, 1968, served with CRCM regional model and distributed in CCSM grid cells (Figure 7a). The data could be achieved from gsiftp://vetsman.ucar.edu:2811//datazone/narccap/DATA/CRCM/ccsm-current/table1/tasmax_CRCM_ccsm_1986010106.nc

![CRCM Gridpoints map](a) CRCM Gridpoints map
![Signal map to recover](b) Signal map to recover

Figure 7: Surface air temperature experiment

Data stored in the NetCDF file is in 2D array using projected coordinate systems because the grids are not square in lat/lon coordinates. The array dimensions are called “xc” and “yc” respectively, and the entire CCSM grid map has $114^*139$ points. We used the temperature data with the area from (xc=0 yc=0) to (xc=113 yc=113), so the resolution of the map is $114^*114$.

![320 samples](a) 320 samples
![2560 samples](b) 2560 samples

Figure 8: Reconstructed surface air temperature map with different number of samples

We then applied our method on the data with different amount of samples. Figure 8 shows the result of recovery with sampling amount 320 and 2560. The reconstructed performance is similar to the experiments above, and the results get refined when more samples are added, the error rate dropped to a small value with 320 samples.

![Speed](a) Speed
![Error](b) Error

Figure 9: Recovery performances

When comparing figures of the recovered signals with the original signal, we can see clearly that, the signals look similar. However, the original signal has sudden distribution while the recovered signals are smoothly distributed.

5.3 Summary

We showed that, both the simulation and real data experiments showed promising result of recovery, with only
limited amount of measurements. The computation performance is also guaranteed. Through our experiments, we discovered that we could use about 2% sampling to accurately reconstruct high resolution environmental distribution signals, which in practice can dynamically reduce the cost of environmental monitoring measurement.

On the other hand, by comparing the experiment results of ozone data and air temperature data, we can see that, the recovery map of ozone data is much closer to the original signal. That is because, our system approximate signals with Gaussian kernels so that it is more suited for recovering smooth signals. Even the reconstructed signal of air temperature data cannot detail the sudden events of the original signal, the overall distributions are consistent.

Overall, the chosen method offers a good performance on sparsity-sampling trade-off and is much cheaper in environmental monitoring applications than traditional large-scale information management techniques.

6. DISCUSSION

In the real environmental data experiments, our system showed great performance in signal recovery. In order to make our system more suitable for practical applications, we are currently working on the following developments:

**Randomly sampling vs. selective sampling:** In practice, randomly sampling over deployment areas is not easy to be realised due to the geography, physical equipment and other factors. Some significant features of the signal may be lost, which can result in an enormous recovery error. We therefore use selective sampling method instead. It does not only provide measurements approximate to random samples but also make the sampling more efficient and reduce the number of samples for a good quality recovery result. We consider to guide our system measurements by studying the events which have effect on the monitored environmental signal. For instance, temperature, wind, humidity and urban ontology are the factors that influence air pollution distributions. Combining information of these factors can provide a prior knowledge of the air pollution. Based on the prior knowledge, effective selective sampling can be implemented.

**Adaptive sampling:** From experiment results, we observed some elastic features of our method: in the range of low sampling, the error rate decrease as the sampling rate increase, and the inverse relationship between two is quite stable. With these features, we can propose the concept of ‘elastic computational model’ that the reconstructed signal can get refined with more samples. In practice, it is expensive to improve the signal quality by recomputing an increased number of samples. It is more efficient to refine the previous recovery results by adding some new samples. These new samples, which should reduce the uncertainty in the previous recovery signal, can be selected by adaptive sampling method. The ‘error bars’ achieved by BCS can guide the optimal design of additional CS measurements rather than random projections. Therefore, adaptive BCS approach [16] will be proposed to realise the adaptive sampling scheme.

**Localisation System:** Precise sampling locations are necessary for our system, as they have great influence on the recovery result. So we should build an accurate localisation system for estimating sampling locations. Global Positioning System (GPS) provides a lateration framework for determining geographic positions [26]. Regular GPS resolution is in the range of 10 to 15 meters that it has large error rate. In addition, it is too expensive to assemble a GPS receiver in each sensor node. For static sensor networks we will deploy a small number of seed nodes, which know their locations and protocols. And the rest of the sensors nodes can estimate their locations using the information they received. For mobile sensor network, we will utilise the sequential Mote Carlo Localisation (MCL) method [27] which can enhance the precision of the localisation and work well with low seed density.

7. CONCLUSION AND FUTURE WORK

In this paper, we used a compressive sensing method to design an efficient and economical environmental monitoring system. The compressive sensing based environmental monitoring system proposed here reduces the resources consumption (number of nodes for deploying and maintaining) for environmental issues detection, and thus reducing the cost. Also our method is non-invasive, so we can monitor the locations that could not be reached by traditional methods. Our method shows the feature of elasticity, meaning that the performance of monitoring system improves with the addition of resources. Both our synthetic and real data experiment showed good results. In practice, we only need to employ a few mobile sensors to monitor environmental signal distributions over a region of interest, then apply the compressive sensing based signal construction framework to reconstruct a high resolution environmental signal distribution.

Much work needs to be done to implement a practical environmental monitoring platform with the compressive sensing approach. First, we propose a model-driven and attention-based sensor framework which will enable a top-down selective sampling approach to detect environmental signal distribution with small cost. Second, we are going to extend our method with adaptive features, directing the measuring location where contains more information for signal recovery. Applying adaptive sensing methods would further reduce the amount of measurement needed to recover the distribution map. Third, we will design physical sensors to fit our method, and measure the performance of our system in various environment.

8. REFERENCES


