Compressive Sensing For Lidar and Cognitive Radio Applications

Presented by: Zhu Han
Wireless Networking, Signal Processing & Security Lab
University of Houston, USA

CR work is supported by NSF ECCS-1028782
Agenda

- Part I: Introduction to Compressive Sensing
- Part II: Applications
  - Collaborative Spectrum Sensing in Cognitive Radio
  - Multi-spectrum Lidar
  - Other Works
- Part III: Other work in the Lab
  - Security
  - Cooperative via Coalition
  - Smartgridcomm
Part I
Introduction to Compressive Sensing

- Motivation
- CS Concepts
Traditional Signal Acquisition Approach

The Typical Signal Acquisition Approach

Sample a signal very densely (at least twice the highest frequency), and then compress the information for storage or transmission.

- This 18.1 Mega-Pixels digital camera senses 18.1e+6 samples to construct an image.
- The image is then compressed using JPEG to an average size smaller than 3MB – a compression ratio of ~12.
A natural question to ask is

Could the two processes (sensing & compression) be combined

Move the burden from sampling to reconstruction

The answer is YES!

This is what Compressive Sensing (CS) is about.
CS Concept

- Sparse X
- Random linear projection
- Dimension reduction from X to Y
  \[ M > K \log(N/K) \]
- Recovery algorithm for ill-posed problem
Compressed Samples $Y = \phi \times X$

Exact Recovery

$\hat{X} = \arg\min_{\|X\|_1 \leq m} \|X - \phi Y\|_2$

K-Sparse Signal

Random Linear Projection (RIP)

$m \times n$

$\phi$

$Y = \phi \times X$

$K \ll m \ll n$
What is Compressive Sensing (CS) About?

- An emerging field of research (ICASSP)
- Beat Nyquist sampling theorem
- Explore sparsity & redundancy of signals
- Construct the combination of sensing & compression
- Offers algorithms of overwhelming probability for signal recovery
Part II

First Example: Compressive Collaborative Spectrum Sensing for Cognitive Radio Networks

- ICASSP 2010
- JSAC 2011
- NSF IHCS
Collaborative Spectrum Sensing from Sparse Observations for Cognitive Radio Networks

Outline

- Introduction CR Networks and CSS
- Proposed System Model
- Joint Sparsity Model
  - Proposed Joint Sparsity Recovery Algorithm
- The Art of Matrix Completion
  - Proposed Matrix Completion Algorithm
- Simulations
- Comparison Between the Two Algorithms
Cognitive Radio & Spectrum Sensing

- The idea of CR is based on the observation that at certain times, most of the licensed spectrum is not used by the licensed users.

- How Cognitive Radio Works
  - Secondary (unlicensed) users detect the spectrum holes (unoccupied spectrum) and utilize the spectrum at the absence of the primary (licensed) users.

- Advantage of Cognitive Radio
  - Improve radio spectrum utilization

- Key Enabler
  - Spectrum sensing

- HOWEVER …..
Limitations of Current CSS Scheme

- **Time Consuming**
  - Spectrum /channel scan performed by each CR

- **Limited Local Observation, CSS Needed**
  - Single CR node has only limited local observation to the whole spectrum due to power constraints;
  - Collaborations among CR nodes (CSS) are necessary for acquiring the complete spectrum information.

- **Incomplete Sensing Information**
  - Power limitation and channel fading limited the available channel sensing information;
  - Missing and erroneous reports due to random transmission loss are inevitable.
We Propose

- Equip each CR with a set of **frequency selective filters**, with **random coefficients**
  - Blended data
- Each CR **sense** as many channels as possible **simultaneously**
  - Save time
Signal Model

- $n$ is the number of channels in the network
- $m$ is the number of CR involved in CSS
- $p$ is the number of filter set for each CR
- Measurement at the fusion center $M = F \cdot R \cdot G$
- Due to loss or distortion, $M$ is incomplete, matrix completion is needed

Question is with incomplete $M$, how to reconstruct $R$
Joint Sparsity Problem Formulation

- Non-zero rows of $X = R \cdot G$ denote the occupied channels
- Each column vector in $X$ is sparse
- All column vectors have the same sparsity pattern
- The $i$th column of $M$ is related only to the $i$th column of $X$
- $F$ is designed, and known exactly at the fusion center
- Reduced to multiple CS recovery problems
- What’s better, each recovered column of $X$ acts as cross check for the others, increase probability of detection
Limitations of Joint Sparsity

- Preliminary simulations show that:
  - When the spectrum sparsity level is high
  - Or when the channels from CR to the fusion center are too bad (large number of missing reports)
  - Joint Sparsity won’t work well

- Can we predict the lost information first?
- Yes, with matrix completion
The Art of Matrix Completion

- Latest development in mathematics claims that if a matrix satisfies the following conditions, we can fulfill it with confidence from a small number of its uniformly random revealed entries.
  - **Low Rank**: Only a small number of non-zero singular values;
  - **Incoherent Property**: Singular vectors well spread across all coordinate.

![Singular vector](image)

- a) spiky
- b) Spread across all coordinates
- c) Sparse singular value
Matrix Completion Algorithm

- Resemble the $l_1$ norm minimization for finding the sparse solution to compressive sensing problem. Low rank matrix can be reconstructed through **nuclear norm minimization** follow a two steps algorithm:
  - Rank prediction (how many none zeros in the singular values);
  - Nuclear norm (sum of the singular value) minimization.

**System model:**

\[
M_{p \times m} = F_{p \times n} R_{n \times n} (G_{m \times n})^T.
\]

**Incomplete measurement matrix:**

\[
M_{ij}^E = \begin{cases} 
M_{ij}, & \text{if } (i, j) \in E, \\
0, & \text{otherwise}.
\end{cases}
\]

**Matrix completion:**

Lasso

\[
\min_{M \in \mathbb{R}^{p \times n}} \tau \|M\|_* + \frac{1}{2} \sum_{(i, j) \in E} |M_{i,j} - M_{ij}^E|^2
\]
Simulation Settings – Parameters

- Due to the different properties each algorithm holds, we choose different parameters to test their performance and carry out comparison between the two algorithms.

- We chose to test the Joint sparsity algorithm for CSS with such settings:
  - A set of 500 channels;
  - 20 (Maximum) CR nodes collaboratively detecting the occupied channels;
  - The number of occupied channels is 1 to 15

- We chose to test the Matrix completion algorithm for CSS with such settings:
  - A set of 35 channels;
  - 20 (Maximum) CR nodes collaboratively detecting the occupied channels;
  - The number of occupied channels is 1 to 4
Simulation Results – Joint Sparsity Noisy

Prob. Of Detection (POD), False Alarm Rate (FAR), and Missing Detection Rate (MDR) performance vs. Noise Level for Different Number of PU.
Simulation Results – Matrix Completion

FAR and MDR vs. Sampling rate.
For different # PU

POD vs. sampling rate
For different # PU
Compare the Two Algorithms

- **Joint sparsity** recovery algorithm has the advantage of low computational complexity which enables fast computation in large scale networks, with relatively low spectrum utilization;

- **Matrix completion** algorithm is good for small scale networks, with relatively high spectrum utilization.

- What if we have a large scale network with relatively high spectrum utilization?
  - Divide it into several small networks.
Part II
Multispectrum Lidar

NCALM – National Center for Airborne Laser Mapping (www.ncalm.org)

Funded by:
- NSF Division of Earth Sciences
- Instrumentation and Facilities

- 2003: Funded for 2 years
- 2005: Renewed for 3 years
- 2008: Renewed for 5 years

• Separate Operational Budgets for UH and UC Berkley
• Additional funds to UH from NSF peer reviewed PI projects
GeMS: Geodetic Mapping Systems

Research-grade LiDAR Data to the Scientific Community
Full Suite of Sensors for Active and Passive Remote Sensing
Collaborate with more than 30 universities and 100 PIs
12 funded NSF programs so far
NCALM Research Grants for 2010 at UH for LiDAR only: > $2.5 million

Cessna 337  GEMINI LIDAR  Aerial Camera  Hyperspectral Imager  Green Laser  CATS  Terrestrial Lasers
Lidar Example

Critical Zone Observatory
Jamez, New Mexico
(June 30 – July 7, 2010)
Full Waveform LiDAR Samples
Multiple Spectrum

Reflectance vs. wavelength for different materials. The dashed vertical lines correspond to laser wavelengths commonly used for airborne LiDAR

Question:
1. Sparsity over time
2. Redundancy in Spectrum
Proposed Optical Part

Schematic of Proposed Multi-Channel 3D LiDAR System
Proposed Electrical Part

Compressive sensing system model
Results on Simulated System with Real Data

Correct detection rate versus downsampling rate

SNR remained in the recovery results under different levels of noise.
Part II
Other Examples

- OFDM Channel Estimation
- Joint Sparsity Recovery Algorithm for MIMO System
- Localization
- Seismic Data Simultaneous Acquisition using CS
- Concrete Flaw Detection using CS
- Offshore Oil Spilling Sensing
Introduction to OFDM

- Orthogonal frequency-division multiplexing (OFDM) has been widely applied in wireless communication systems:
  - High rate transmission capability
  - High bandwidth efficiency
  - Robust with regard to multi-path fading and delay

- Two main challenges in designing channel estimators for wireless OFDM systems:
  - The arrangement of pilot information — the reference signal known by both transmitters and receivers.
  - The design of an estimator with both low complexity and good channel tracking capability.
Simulations

\[ h(n) = \sum_{m=1}^{M} \alpha_m \delta(n - \tau_m T_s) \]

Sampling interval

Multipath components

IEEE 802.11a System MSE vs No. Multi-path
At Different SNR
Joint Sparsity Recovery Algorithm for MIMO System

- MIMO is of great importance
  - MIMO offers additional parallel channels in spatial domain to boost the data rate (High data rate);
  - Enhancing system performance in terms of capacity and diversity

- MIMO leads to joint sparsity
  - Spatial correlated channels
  - Channel impulse response show joint sparsity structure

5 GHz 40-transmitter-40-receiver ray tracing experiment, channel impulse response show joint sparsity.
Localization

Sparsity: PU locations

Two papers with Dr. Wu already

Hardware Implement.
Another Problem ...

Shot ➔ Wait until all waves died out ➔ Setup for another shot
What if We Shot Simultaneously
MMSE Solution

SNR = 8.9 dB
50% subsampled shot from uniformly missing shot positions
CS Leads to the Magic

SNR = 16.1 dB
50% subsampled shot from simultaneous shots
Concrete Flaw Detection using CS

- Smaller Seismic Problem
  - Indirect measurement (usually reflective manner) of under surface discontinuity

- Differences Lies in
  - Size of the target at the magnitude of $\mu m$, high resolution needed
  - Size of the concrete structure (building, bridge) is small, limited measurements

- Goal: A system with a small number of built in sensors for real time monitoring with dynamic CS algorithm
Offshore oil spill sensing

![Drilling platform](image1.jpg)

![Emissivity spectra](image2.png)

- Water
- Oil 10 μm
- Oil 50 μm
- Oil 100 μm
Conclusions

- **Random is good**
  - Sparsity
  - Random Projection (RIP condition)
  - Reconstruct with high fidelity
  - Move the burden from sampling to computation.

- **Challenge**: everything happens before ADC, how to construct the random mixture before sampling is a design challenge
  - Other applications?

- **Book**:
Overview of Wireless Amigo Lab

- **Lab Overview**
  - 6 Ph.D. students, 2 Joint postdocs (with Rice and Princeton)
  - Currently supported by 4 concurrent NSF grants

- **Current Concentration**
  - Compressive sensing and its application
  - Game theoretical approach for wireless networking
  - Security
  - Smartgrid communication

- **Complimentary to Wiser Lab**
  - ECE vs. CS
  - F16 vs. F15, F35 vs. F22
Cooperation with Coalition

• Game theoretical Approach, Coalitional Game
  1. Mutual benefits different from noncooperative game
  2. Several different types
     • Classic Canonical Game
     • Coalition Formation Game
     • Coalition Graph Game

• Applications
  1. Spectrum sensing
  2. UAV
  3. Vehicular network
  4. Physical layer security
  5. MIMO/Relay network
  6. Exploration and exploitation for CR network
  7. Cognitve pilot channel
  8. Femtocell
Other Work

• **Security**
  1. Device identification by Baysian nonparametric method
  2. Trust management
  3. Belief network
  4. Gossip based distributed Kalman filter
  5. Quickest detection
  6. Physical layer security
  7. Primary user emulation attack

• **Smart Grid Comm**
  1. False data injection attack
  2. PHEV optimization
  3. Distributed microgrid control
  4. Renewable energy

• **Eager to find possible collaboration**
Thank you very much
Why $\ell_1$ (2D-Example)

$$\ell_p \text{ ball: } \|x\|_p^p = \sum_i |x_i|^p$$

$$\min_{x_1,x_2} |x_1|^p + |x_2|^p \quad \text{s.t.} \quad y = \phi_1 x_1 + \phi_2 x_2$$

$L_0$: NP hard; $L_2$: multiple solutions; $L_1$: linear programming
Simulation Settings – Evaluation

- Performance was evaluated in terms of POD, FAR and MDR:
  - FAR = \frac{\text{No. False}}{\text{No. False} + \text{No. Hit}}
  - MDR = \frac{\text{No. Miss}}{\text{No. Miss} + \text{No. Correct}}
  - POD = \frac{\text{No. Hit}}{\text{No. Hit} + \text{No. Miss}}

- Sampling Rate is defined as:

\[
\frac{\text{No. received measurements at the fusion center}}{\text{No. channels} \times \text{No. CRs}}
\]
Critical Zone Observatory
Jamez, New Mexico
(June 30 – July 7, 2010)
New Technology: **CATS**

**Properties:**
- Laser wavelength of 532 nm chosen to penetrate water
- 800,000 pps (100 channels, 8kHz each)
- Overlapping footprints eliminate coverage gaps
- Multi-channel detector gives 20cm contiguous spatial sampling vs sub-meter by ALSM
- Multi-event timer electronics will give “deep” returns for robust 3D sampling
- **Topographic and bathymetry data collection by a single sensor at the same time**
- **Shorter Pulse Width**
- **Low Power and small size targetted towards UAV Applications**

Coastal Area Tactical-mapping System
Funded by ONR; prototype already flight tested