UNIVERSIDAD DE LAS PALMAS DE GRAN CANARIA
Escuela de Ingeniería de Telecomunicación
y Electrónica

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Instituto para el Desarrollo Tecnológico y la Innovación en Comunicaciones

Compressive Sensing Techniques for Cognitive Radio Systems in HF

Invited lecture at Centre Tecnològic de Telecomunicacions de Catalunya

Adrián García Rodríguez, 29th January 2012

Presented by Laura Melián Gutiérrez, IDeTIC, 22nd February 2012

Contents

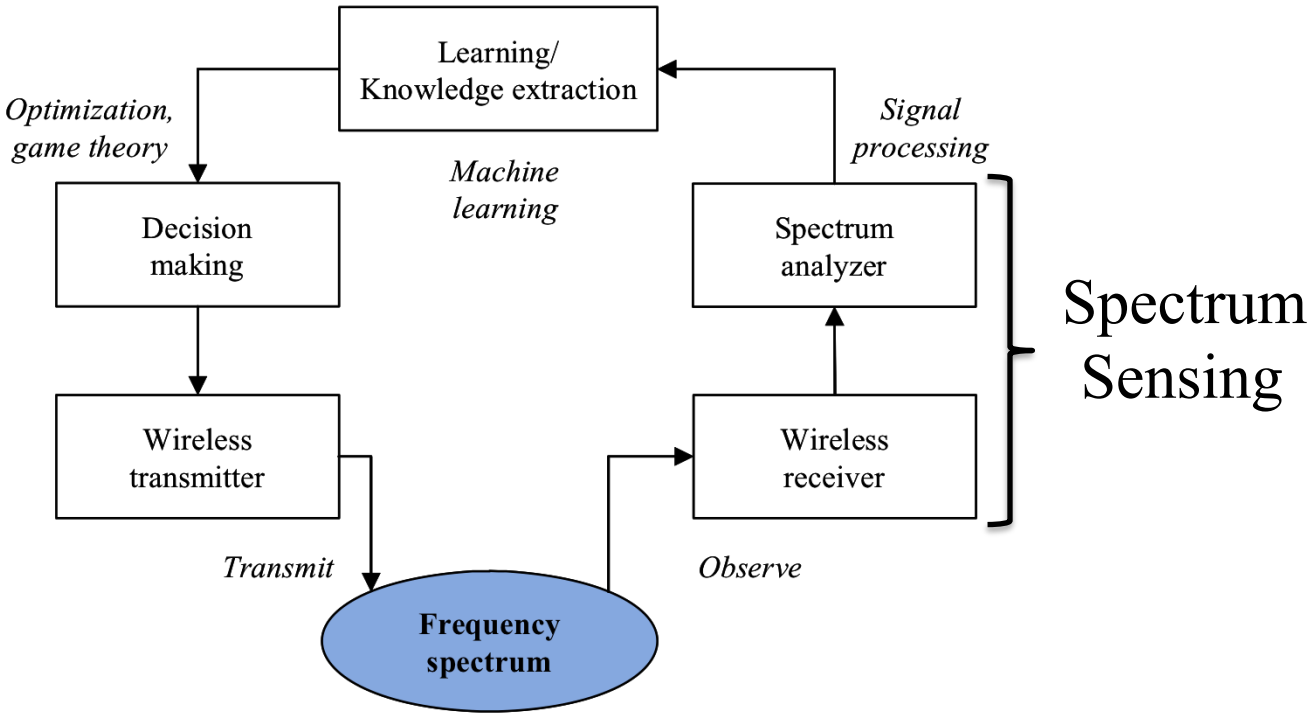
Contents

Cognitive Radio in HF

- Research line in HF communications since 1999
  - 3-30 MHz frequency band
  - Ionospheric propagation
  - Unstable channel with a high amount of interferences
- HFDVL modem: Multicarrier techniques
  - Digital interactive voice
  - High data rates
- M3HF
  - MIMO
  - Construction of the B-HF wideband transceiver
- CR4HFDVL

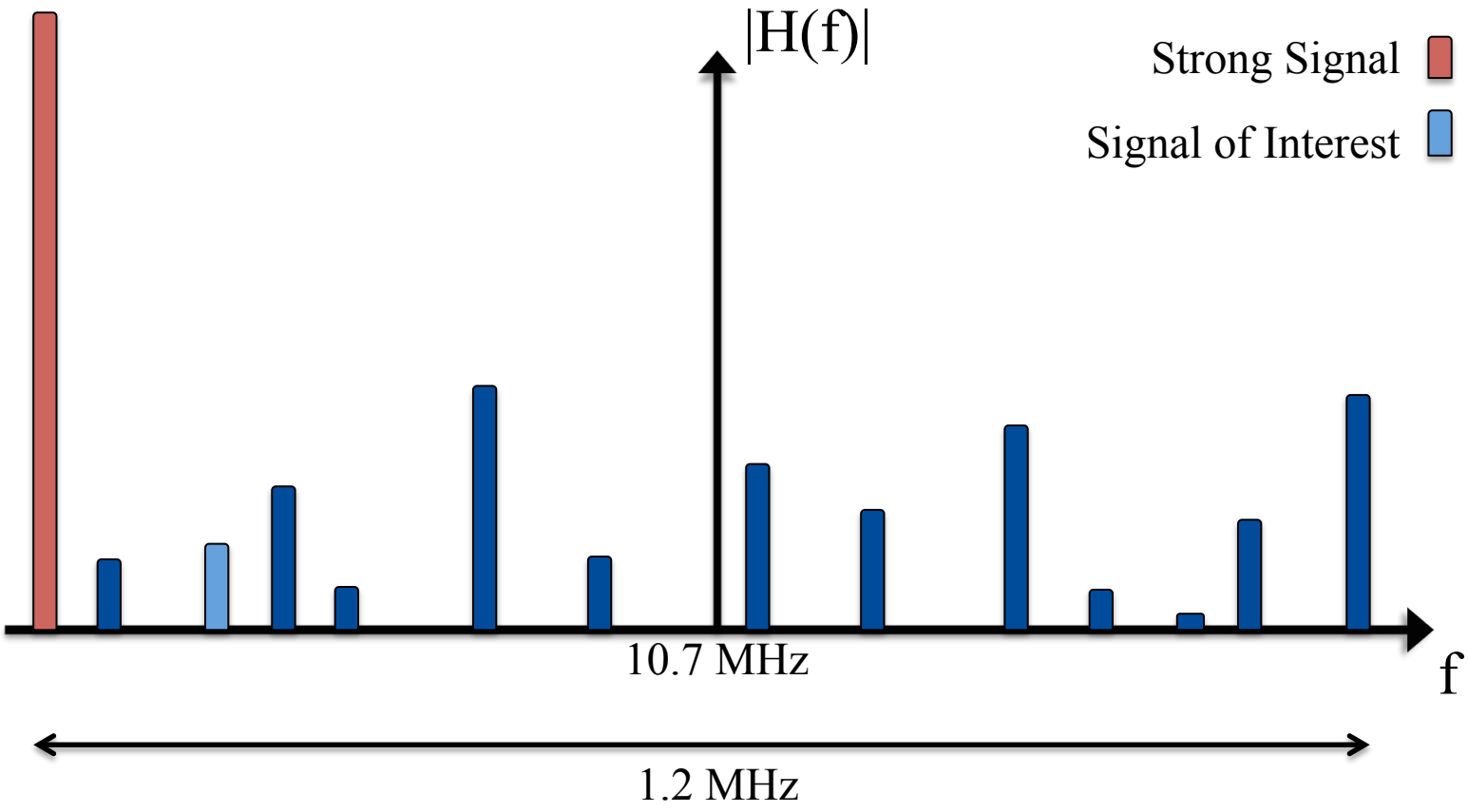
Cognitive Radio in HF

- Cognitive Radio and Spectrum Sensing
  - Wideband transceiver
    - Interferences



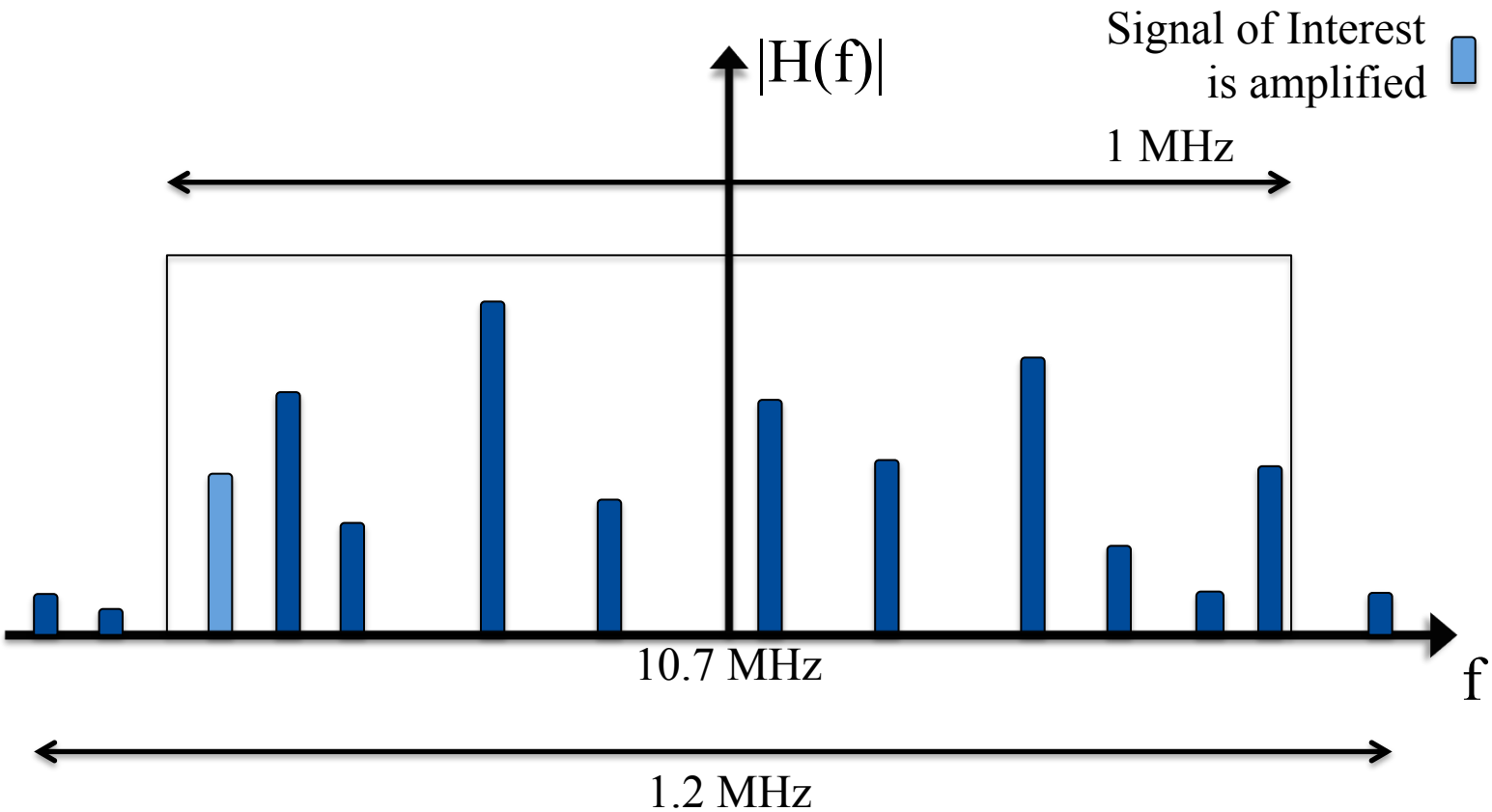
Cognitive Radio in HF

- Effect of interferences in the B-HF.



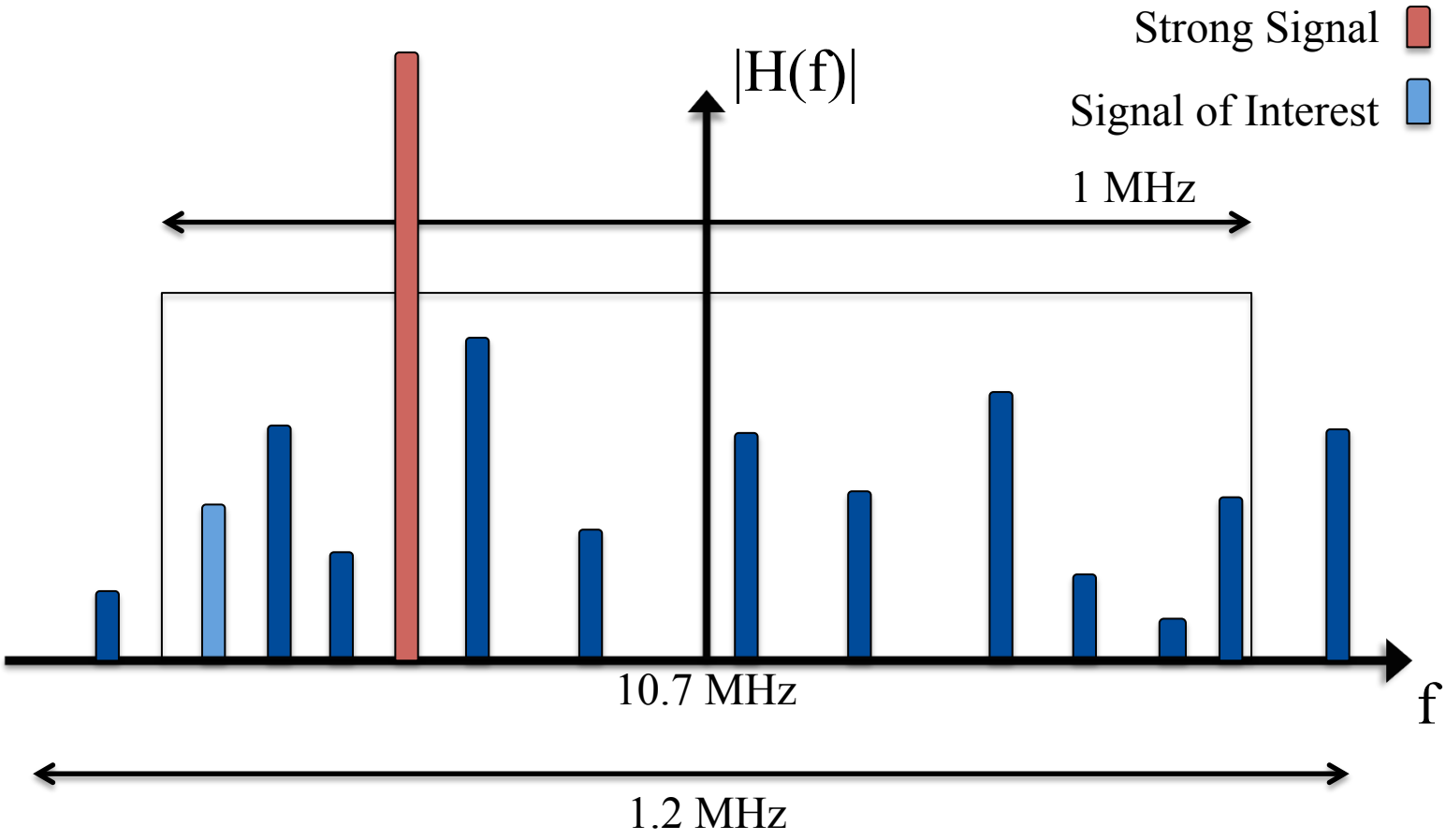
Cognitive Radio in HF

- Effect of interferences in the B-HF
  - Interference outside the acquisition bandwidth



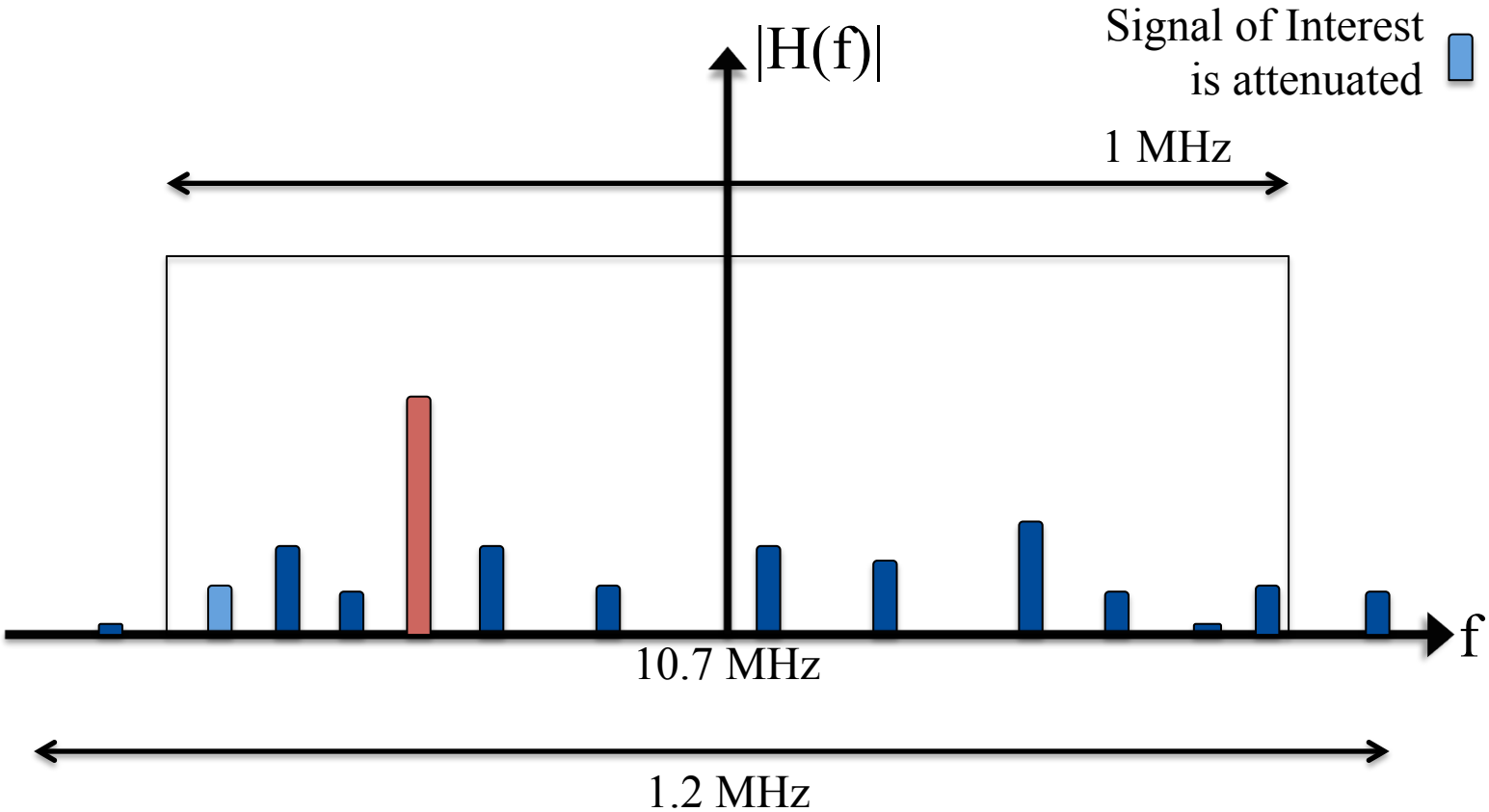
Cognitive Radio in HF

- Effect of interferences in the B-HF



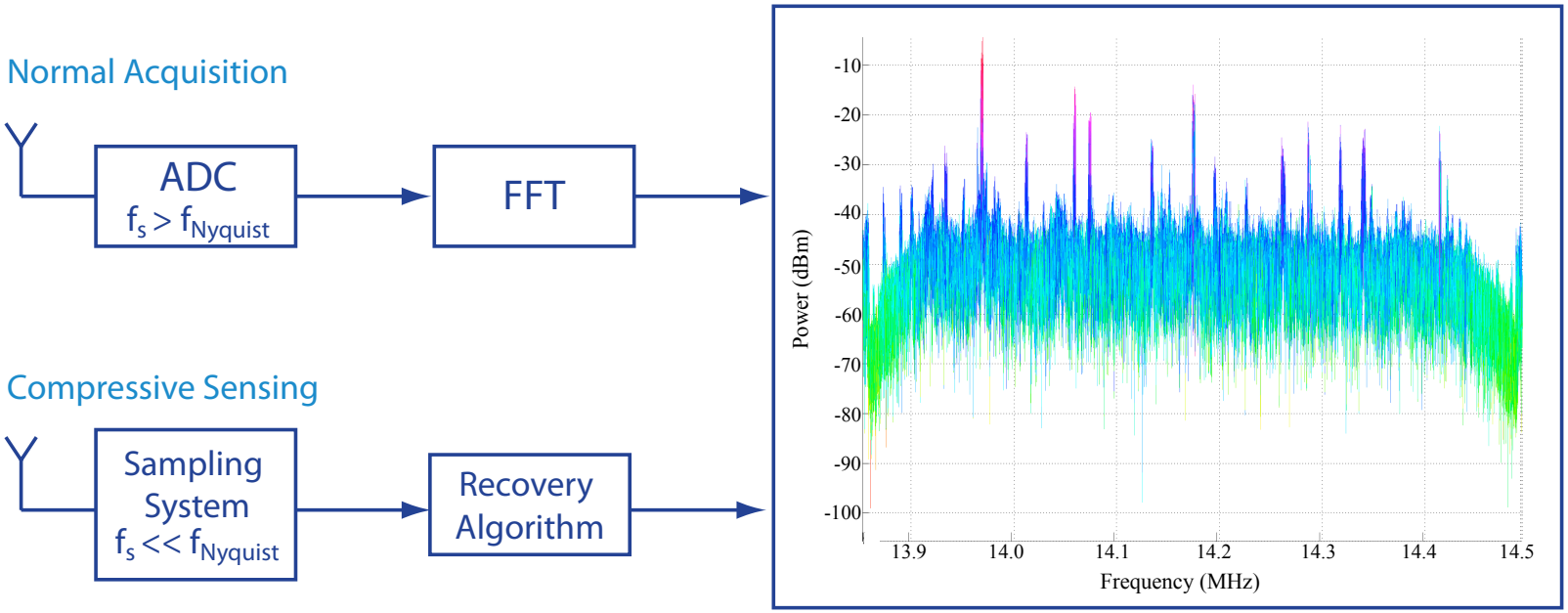
Cognitive Radio in HF

- Effect of interferences in the B-HF
  - Interference inside the acquisition bandwidth



Cognitive Radio in HF

Cognitive Radio in HF



Contents

Introduction to Compressive Sensing

1. Image acquisition

N pixels

JPEG
Wavelet Transform

2. Compression algorithm (JPEG)

K coefficients and their location

Compressive Sensing

Introduction to Compressive Sensing

$$\mathbf{y} = \mathbf{\Phi x}$$

x = Original Signal
N pixels

Linear measurement process

$$\mathbf{\Phi}$$

M *x* N transformation
(M < N)

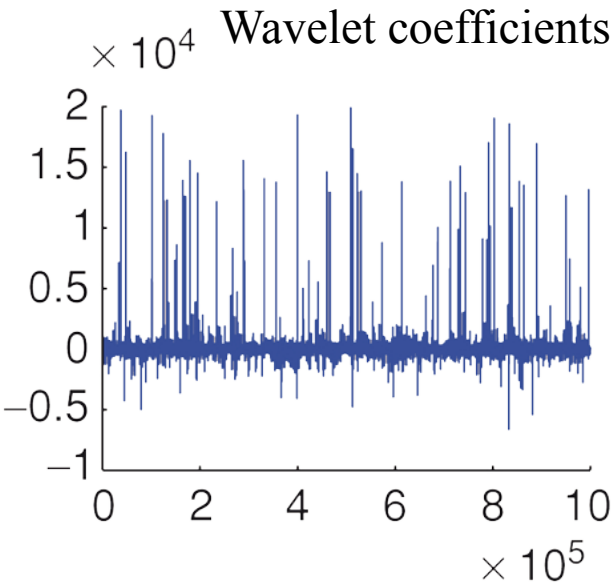
y = Linear measurements
M measurements

Sparse and compressible signals

$\boldsymbol{\Psi}$
Wavelet Basis

$$\mathbf{x} = \boldsymbol{\Psi}\mathbf{s}$$

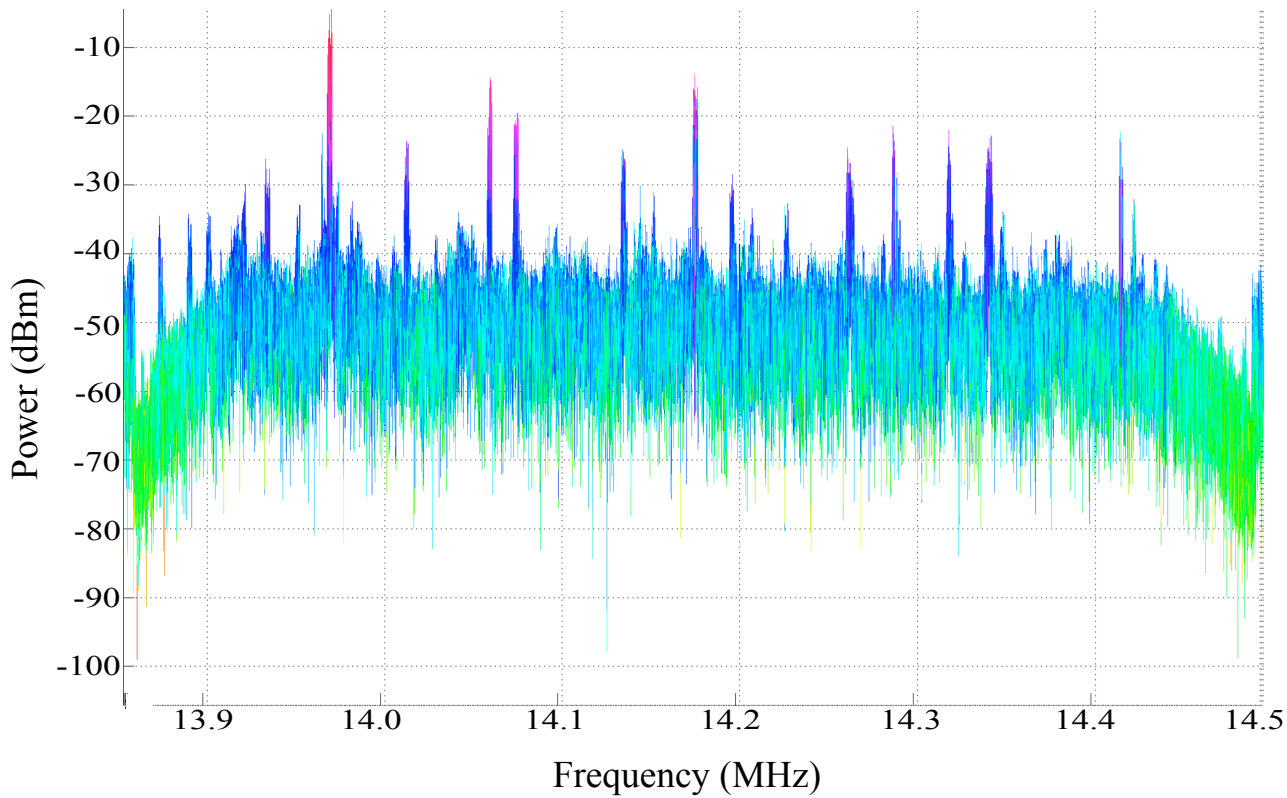
K = Number of significative coefficients



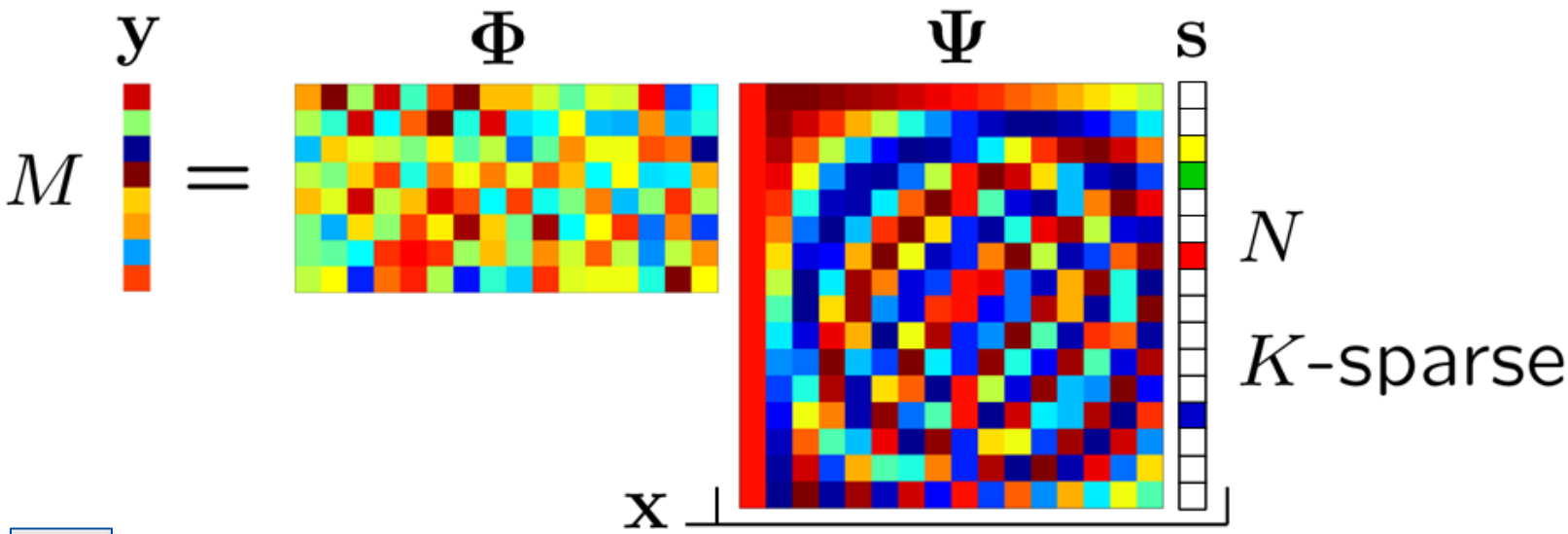
Sparse and compressible signals

$\boldsymbol{\Psi}$
Fourier Basis

$$\mathbf{x} = \boldsymbol{\Psi}\mathbf{s}$$



Introduction to Compressive Sensing



Ψ Sparsity basis

Φ Measurement matrix

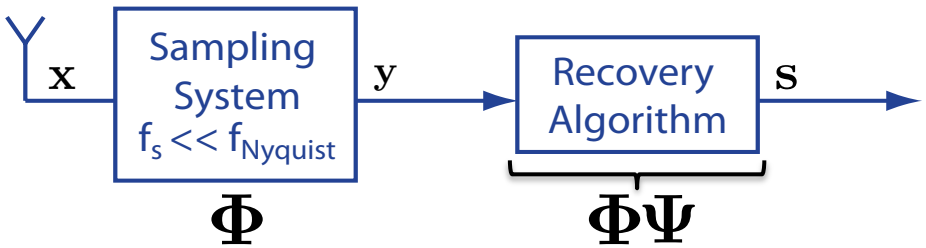
y Compressive measurements

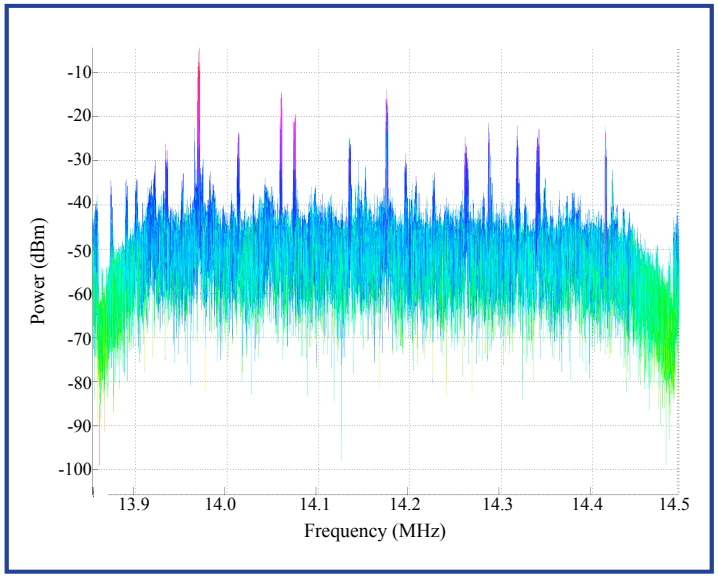
x Original signal

s Original signal in sparse domain

Introduction to Compressive Sensing

Compressive Sensing





Ψ Sparsity basis

Φ Measurement matrix

$\mathbf{y}$ Compressive measurements

$\mathbf{x}$ Original signal

$\mathbf{s}$ Original signal in sparse domain

Contents

Sampling sparse signals

- The measurement process must satisfy certain requirements:
  - Incoherence

$$\mu(\mathbf{\Phi}, \mathbf{\Psi}) = \sqrt{N} \cdot \max_{m \leq M, j \leq N} |\langle \boldsymbol{\phi}_m, \boldsymbol{\psi}_j \rangle|$$

  - Restricted Isometry Property (RIP)

$$(1 - \delta_K)\|\mathbf{s}\|_{l_2}^2 \leq \|\mathbf{\Phi}\mathbf{\Psi}\mathbf{s}\|_{l_2}^2 \leq (1 + \delta_K)\|\mathbf{s}\|_{l_2}^2$$

$\mathbf{\Phi}$ Measurement matrix $\mathbf{\Psi}$ Sparsity basis $\mathbf{S}$ Sparse signal

Sampling sparse signals

- If $\delta_{2K} < \sqrt{2} - 1$, then the solution $\mathbf{s}^\star$ satisfies:

$$\|\mathbf{s}^\star - \mathbf{s}\|_{l_2} \leq C_0 \cdot \frac{\|\mathbf{s} - \mathbf{s_K}\|_{l_1}}{\sqrt{K}}$$
$$\|\mathbf{s}^\star - \mathbf{s}\|_{l_1} \leq C_0 \cdot \|\mathbf{s} - \mathbf{s_K}\|_{l_1}$$

where $\mathbf{s_K}$ is an approximation to the original signal with all but the largest K coefficients set to zero.

Sampling sparse signals

- The measurement process must satisfy certain requirements:
  - Gaussian or Bernouilli measurements

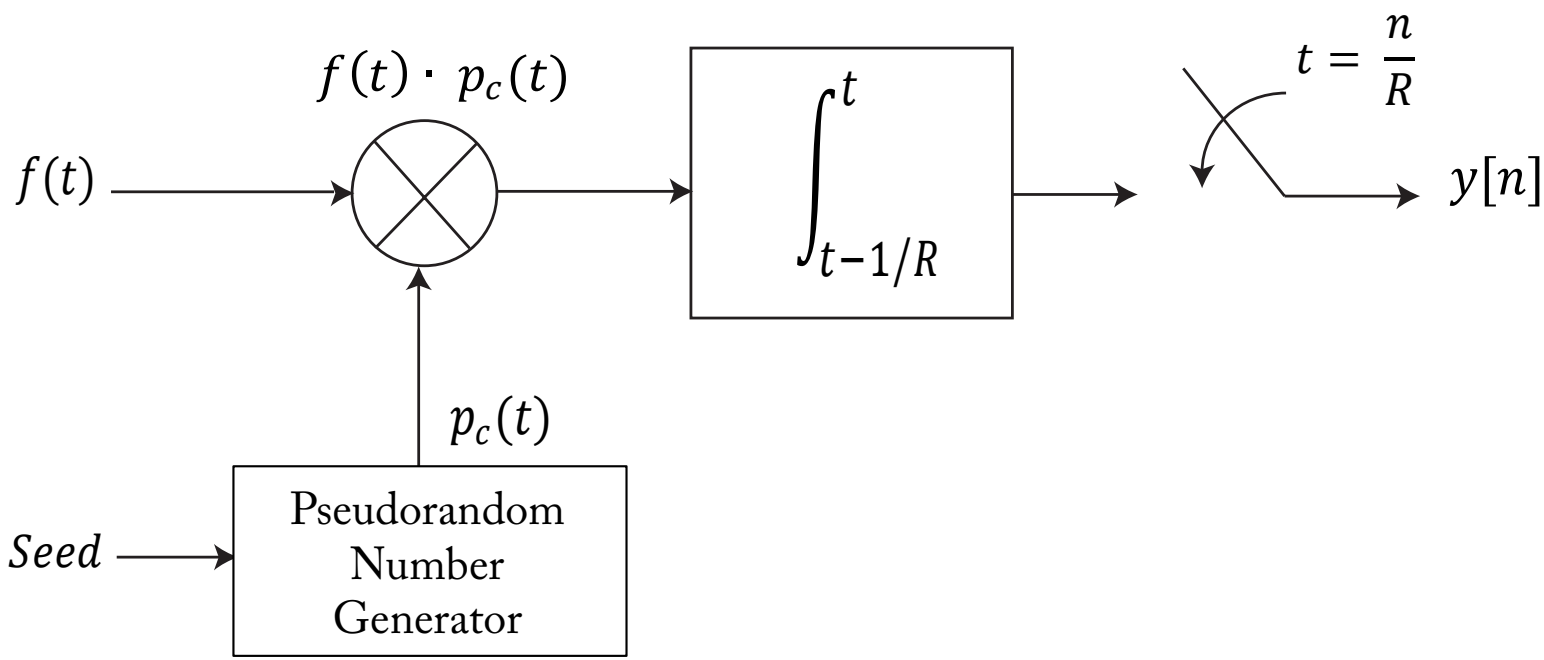
$$M \geq C\, K \log (N/K)$$

  - We have to find another alternatives

M = Number of measurements
K = Sparsity level
N = Original signal length
C = Arbitrary constant

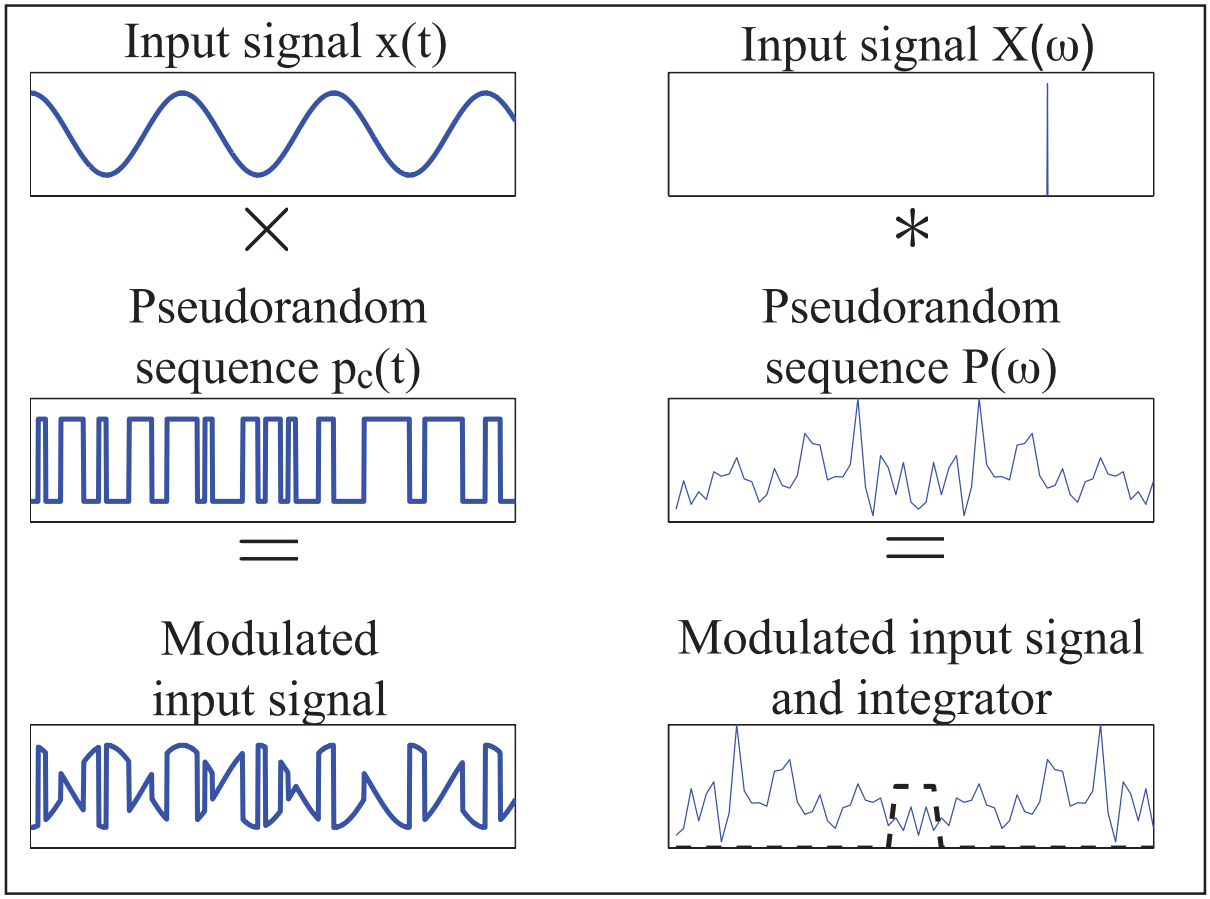
Sampling sparse signals

Random Demodulator



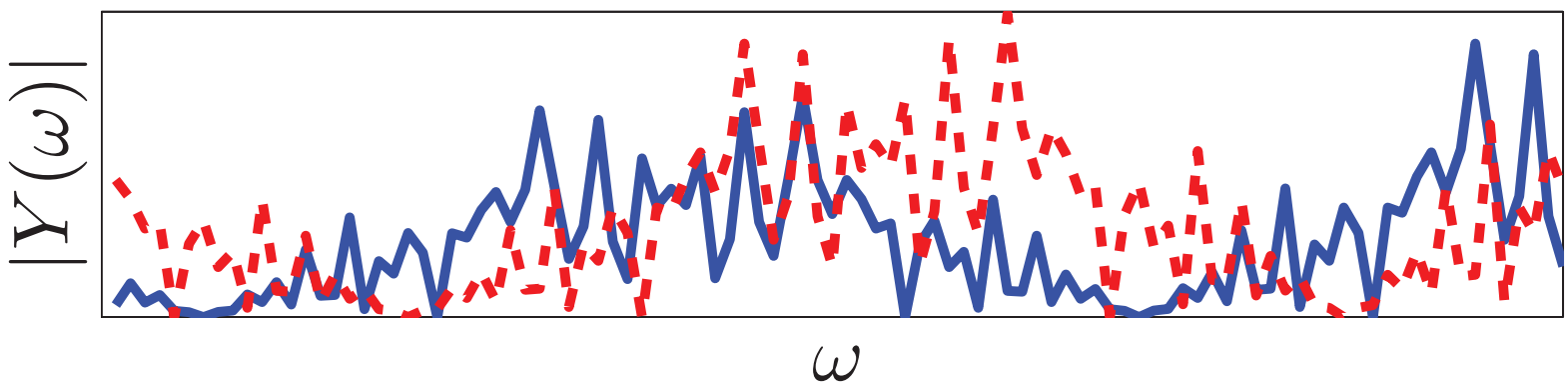
Sampling sparse signals

Random Demodulator



Sampling sparse signals

Random Demodulator

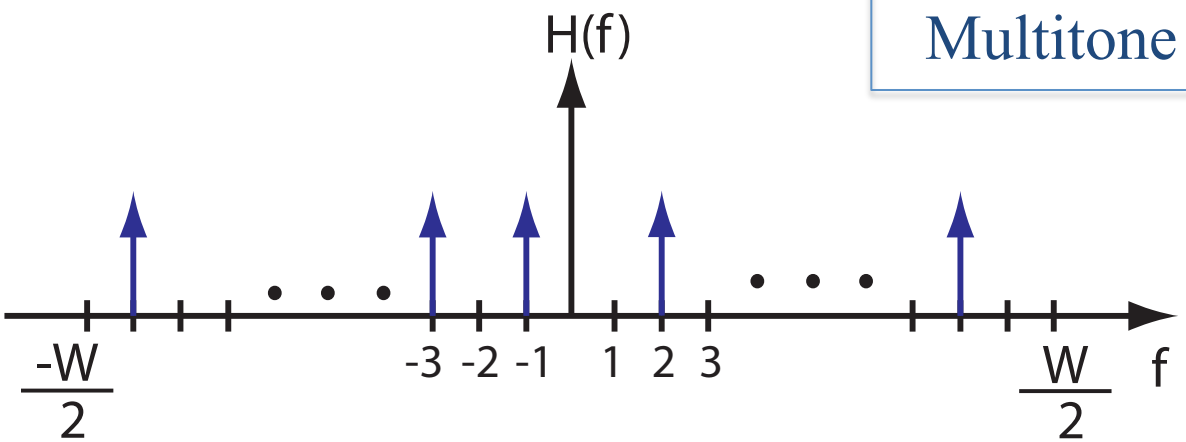


Two different signals can be clearly distinguished after low-pass filtering

Sampling sparse signals

Random Demodulator

Multitone signals



$$\Omega \subset \{0, \pm 1, \pm 2, \ldots, \pm(W/2 - 1), W/2\}$$

$$R \geq 1.7\, K \log (W/K + 1)$$

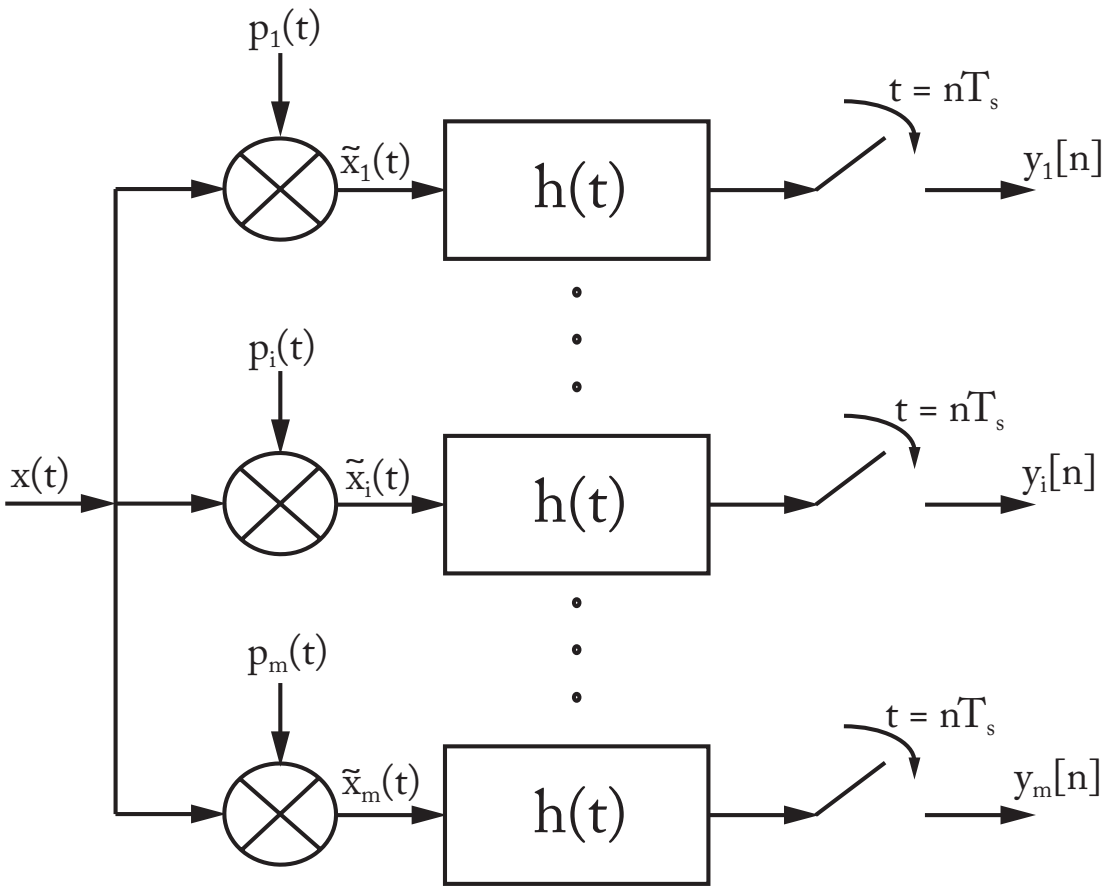
R : Sampling rate

K : Sparsity level

W : Nyquist rate

Sampling sparse signals

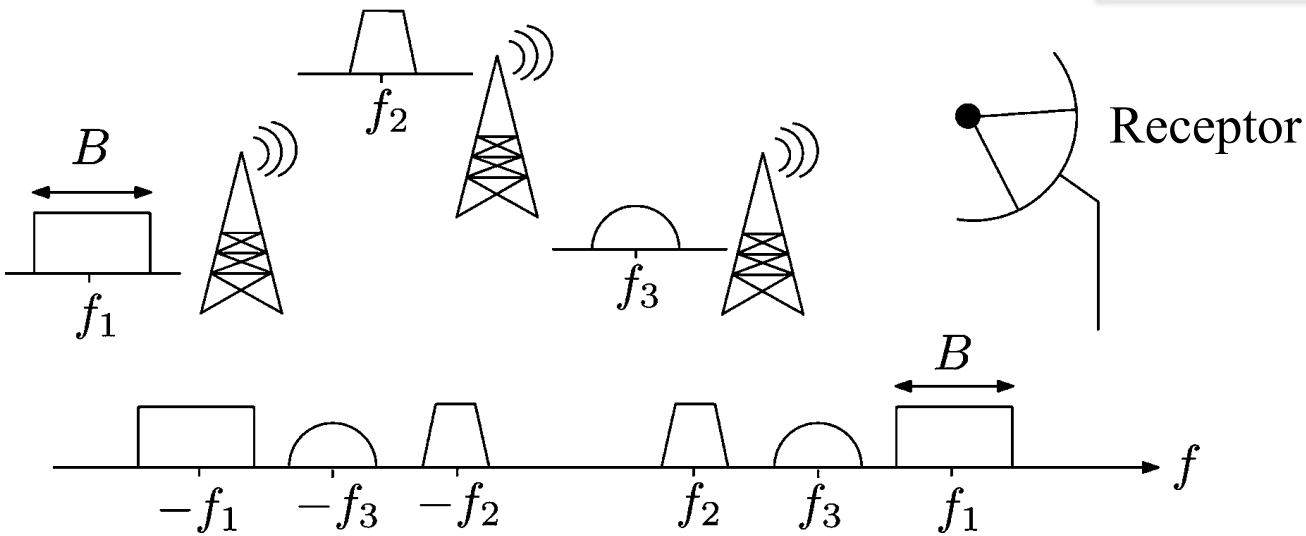
Modulated Wideband Converter



Sampling sparse signals

Modulated Wideband Converter

Multiband Signals



Minimal sampling rate = 2NB

N : Number of bands

B : Maximum bandwidth

Contents

Reconstruction of sparse signals

– L_1-norm minimization

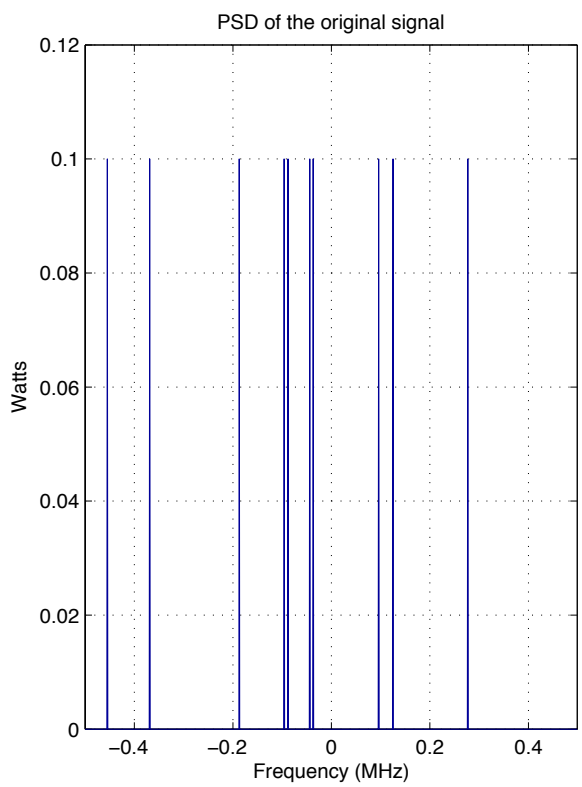
$$\mathbf{s}^{\star} = \underset{\mathbf{s}\in\Re^N}{min} \|\tilde{\mathbf{s}}\|_{l_1} \; subject \; to \; \mathbf{y} = \mathbf{\Theta}\tilde{\mathbf{s}}$$

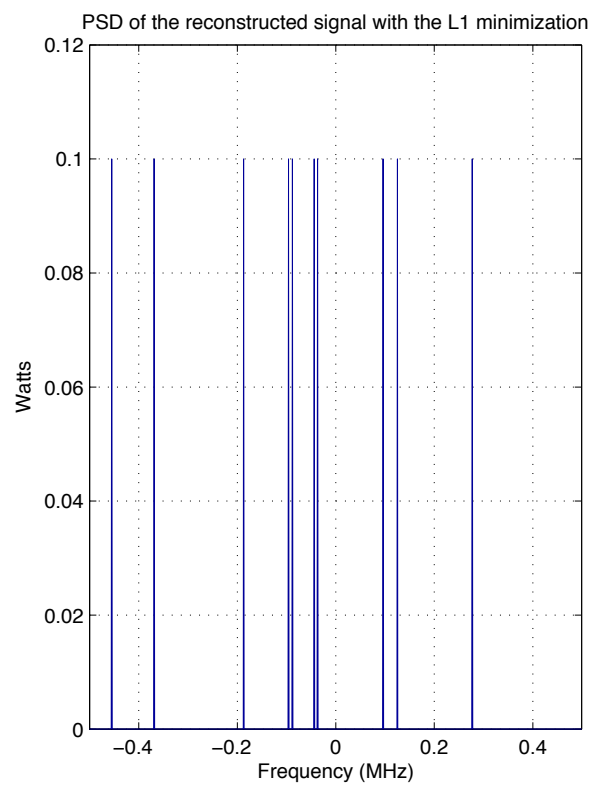
- Computationally feasible
- Guarantees the exact reconstruction of sparse signals
- L_1 norm definition:

$$\|s\|_{l_1} = \sum_{i=1}^{N} |s_i|$$

Reconstruction of sparse signals

– L_1-norm minimization





K = Sparsity level

M = # of measurements

N = # of samples of the original signal

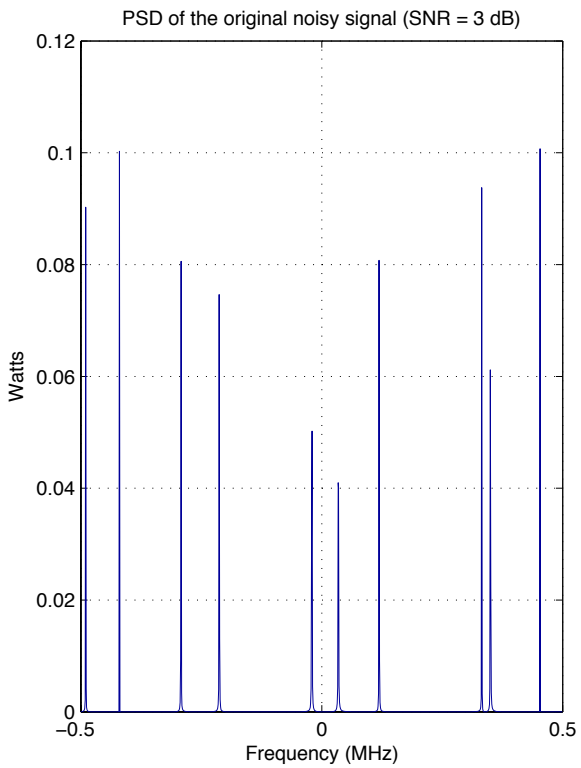
K = 10

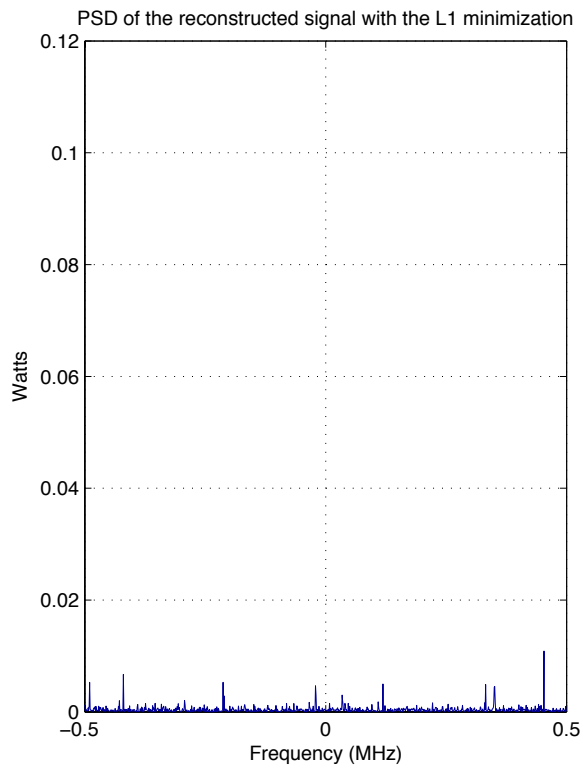
M = 100

N = 1000

Reconstruction of sparse signals

– L_1-norm minimization
  - Problem: Noise effect





K = Sparsity level

M = # of measurements

N = # of samples of the original signal

K = 10

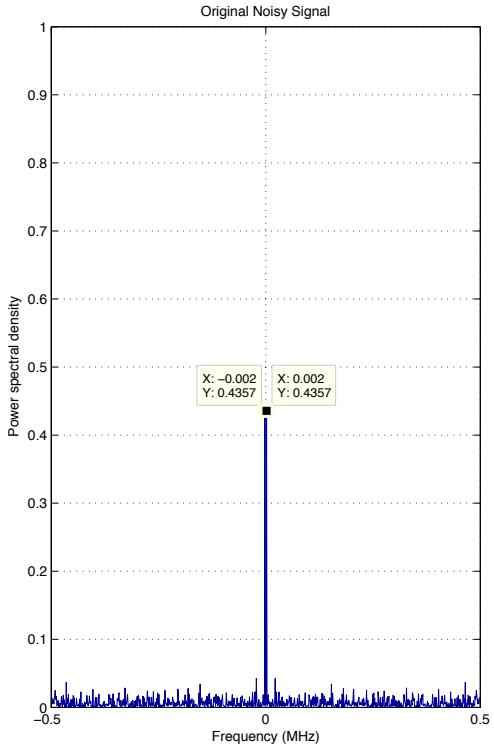
M = 250

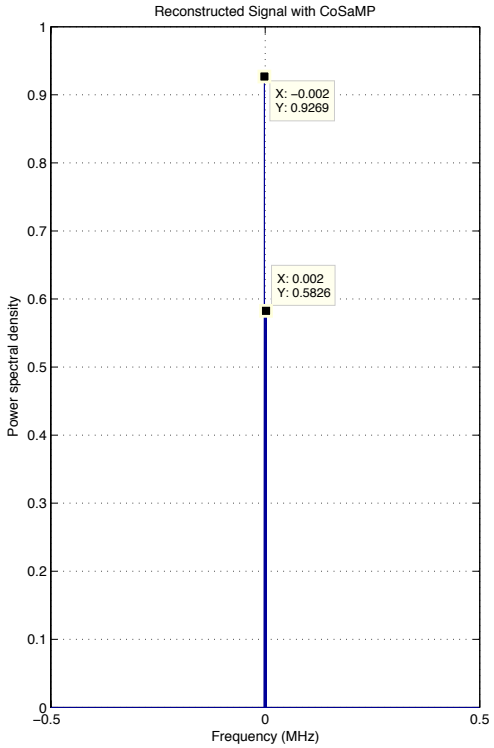
N = 1000

SNR = 3 dB

Reconstruction of sparse signals

- Compressive Sampling Matching Pursuit (CoSaMP)
  - Greedy algorithm
  - It needs an approximation of the sparsity level K





K = Sparsity level

M = # of measurements

N = # of samples of the original signal

K = 2

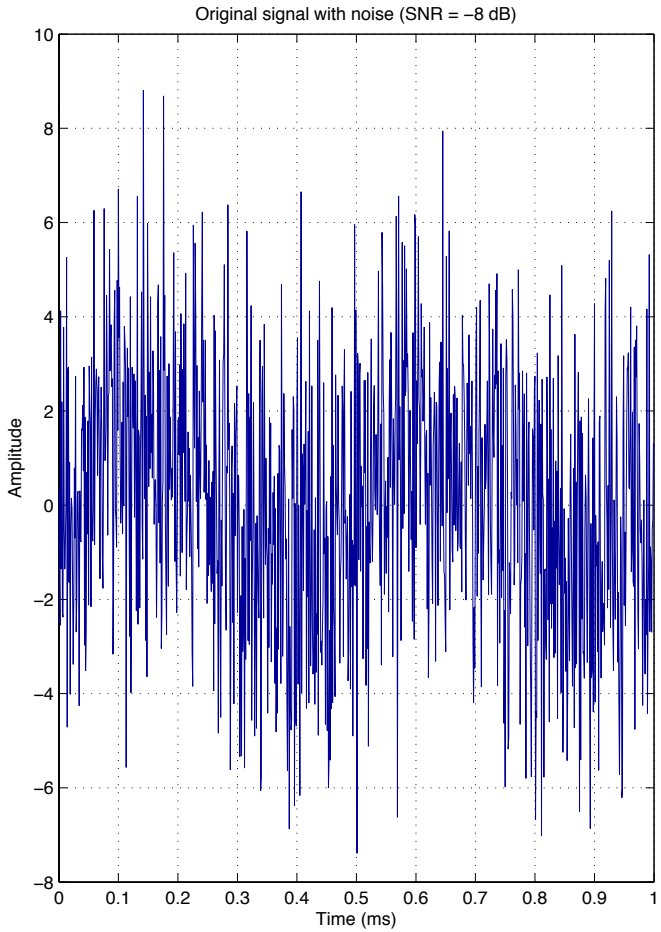
M = 250

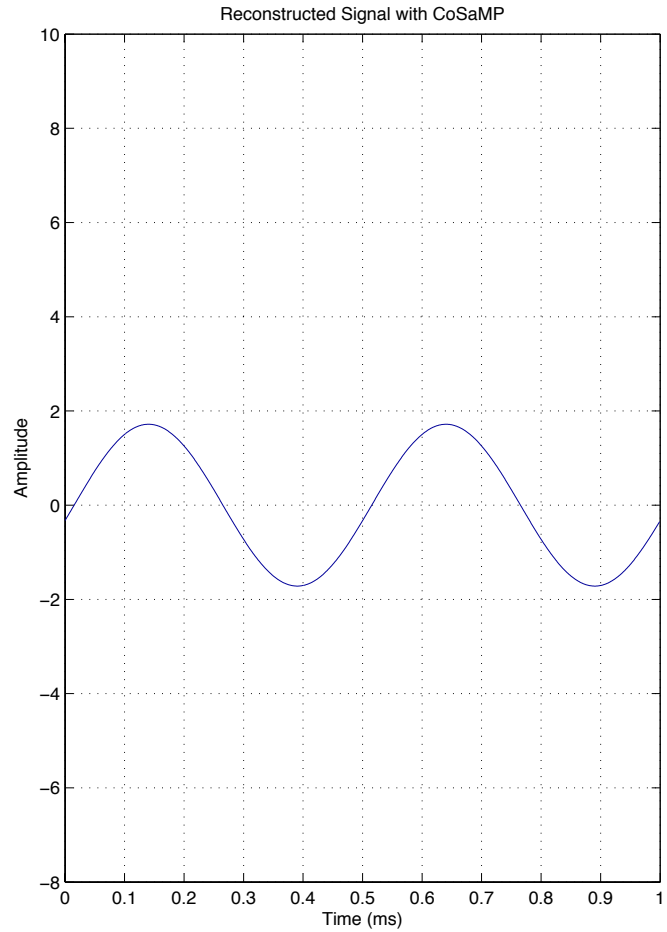
N = 1000

SNR = -8 dB

Reconstruction of sparse signals

- Compressive Sampling Matching Pursuit (CoSaMP)

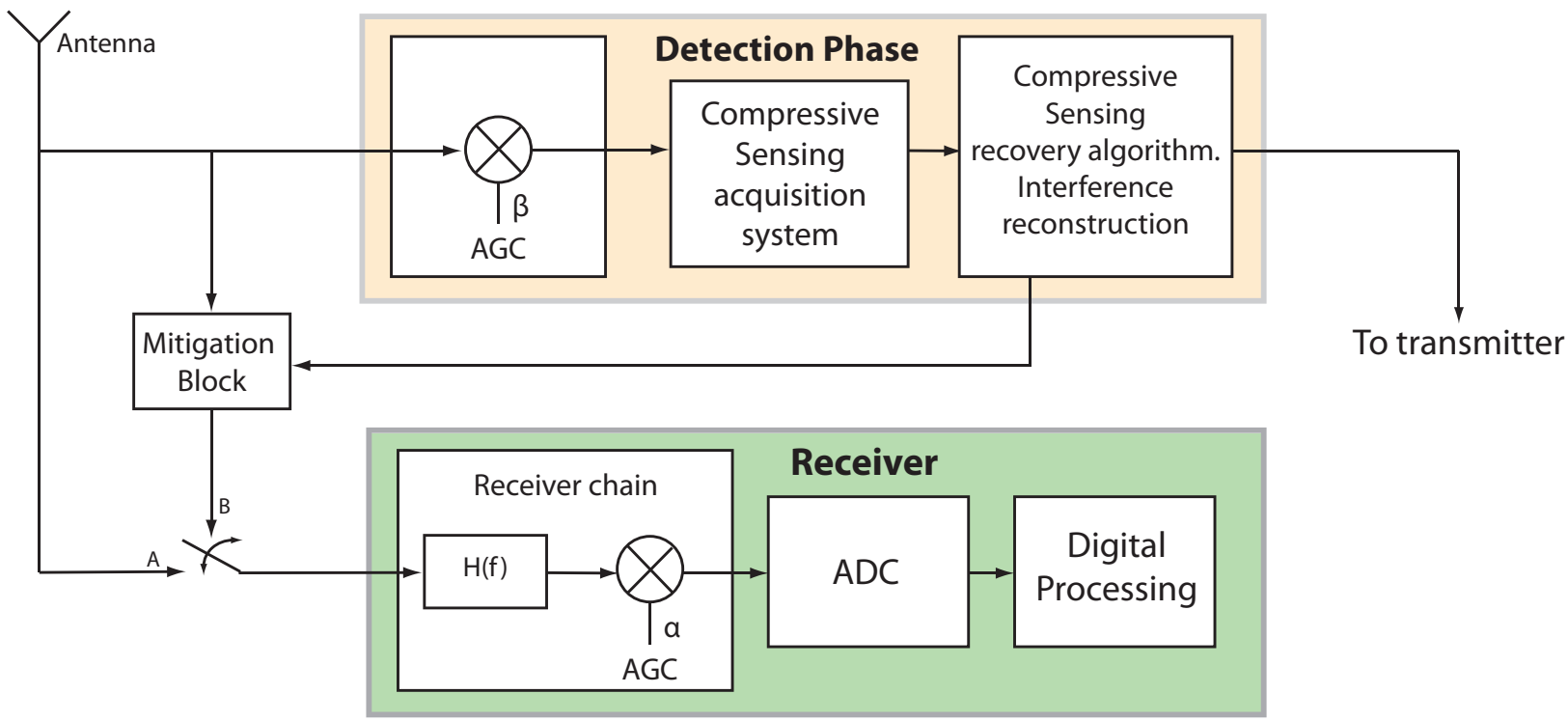




Contents

Compressive Sensing systems in HF

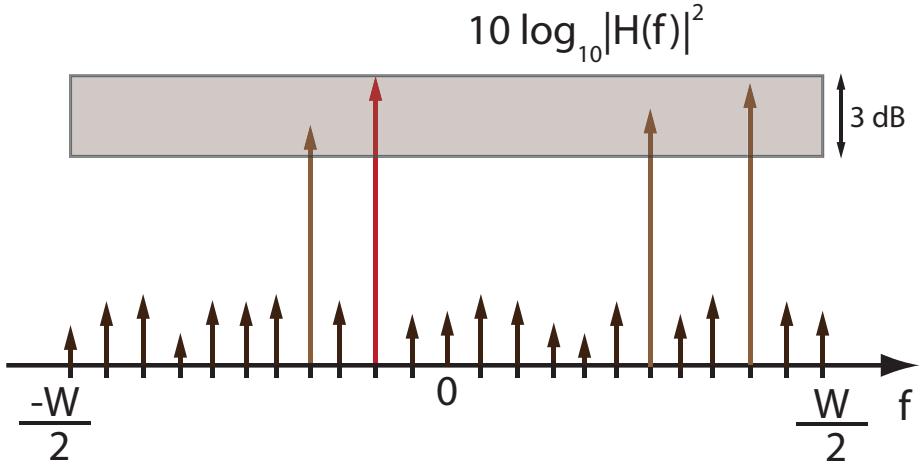
- Interference mitigation system



Compressive Sensing systems in HF

- Strongest interference detection

Scenario	One Strong Interference	High Activity	Normal Activity	Total
Number of acquisitions	3400	8700	8700	20880
Wrong identifications percentage	8.4 %	12.7 %	12.8 %	11.8 %
% of errors ≥ 3 dB	1.3 %	0.56 %	2.12 %	1.07 %



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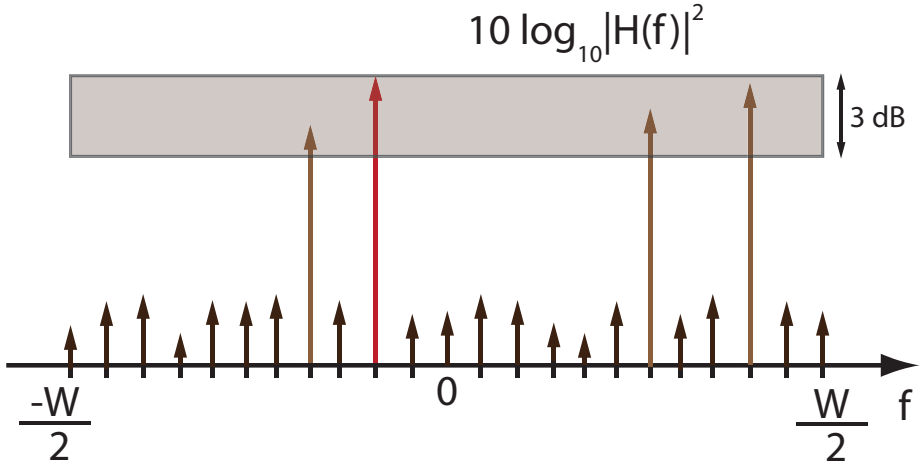

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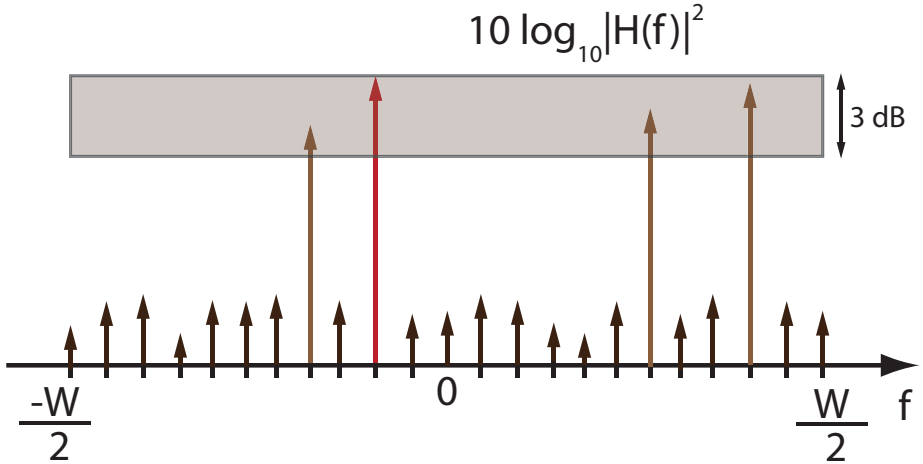

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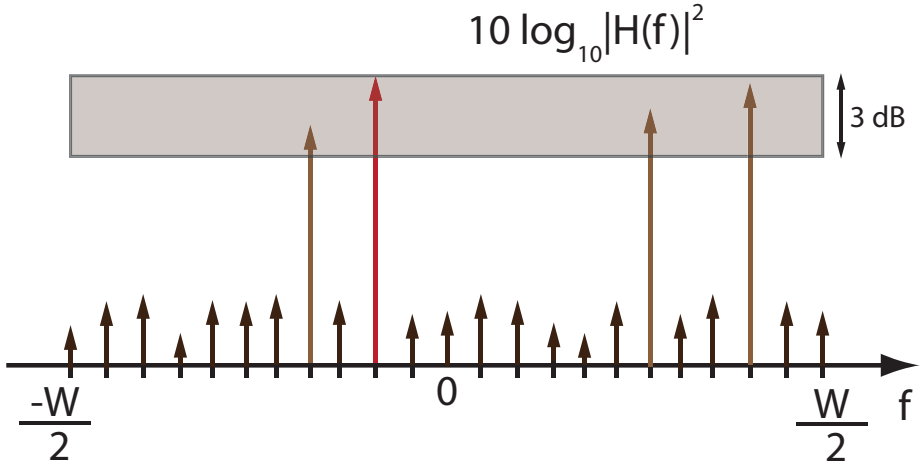

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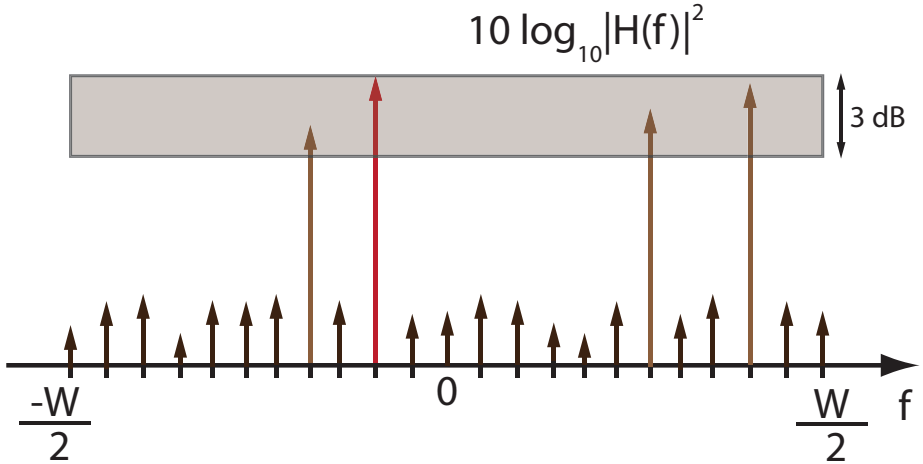
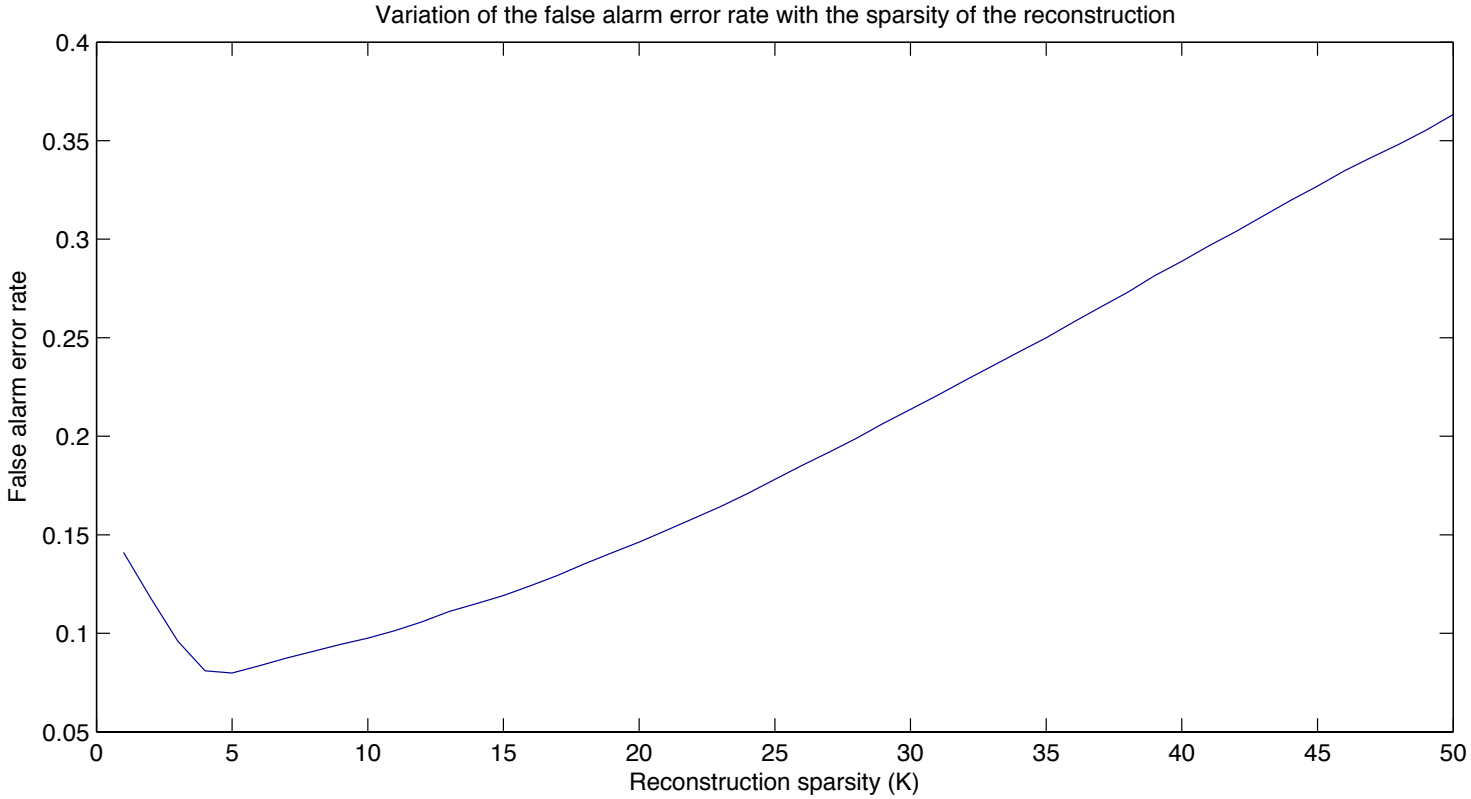


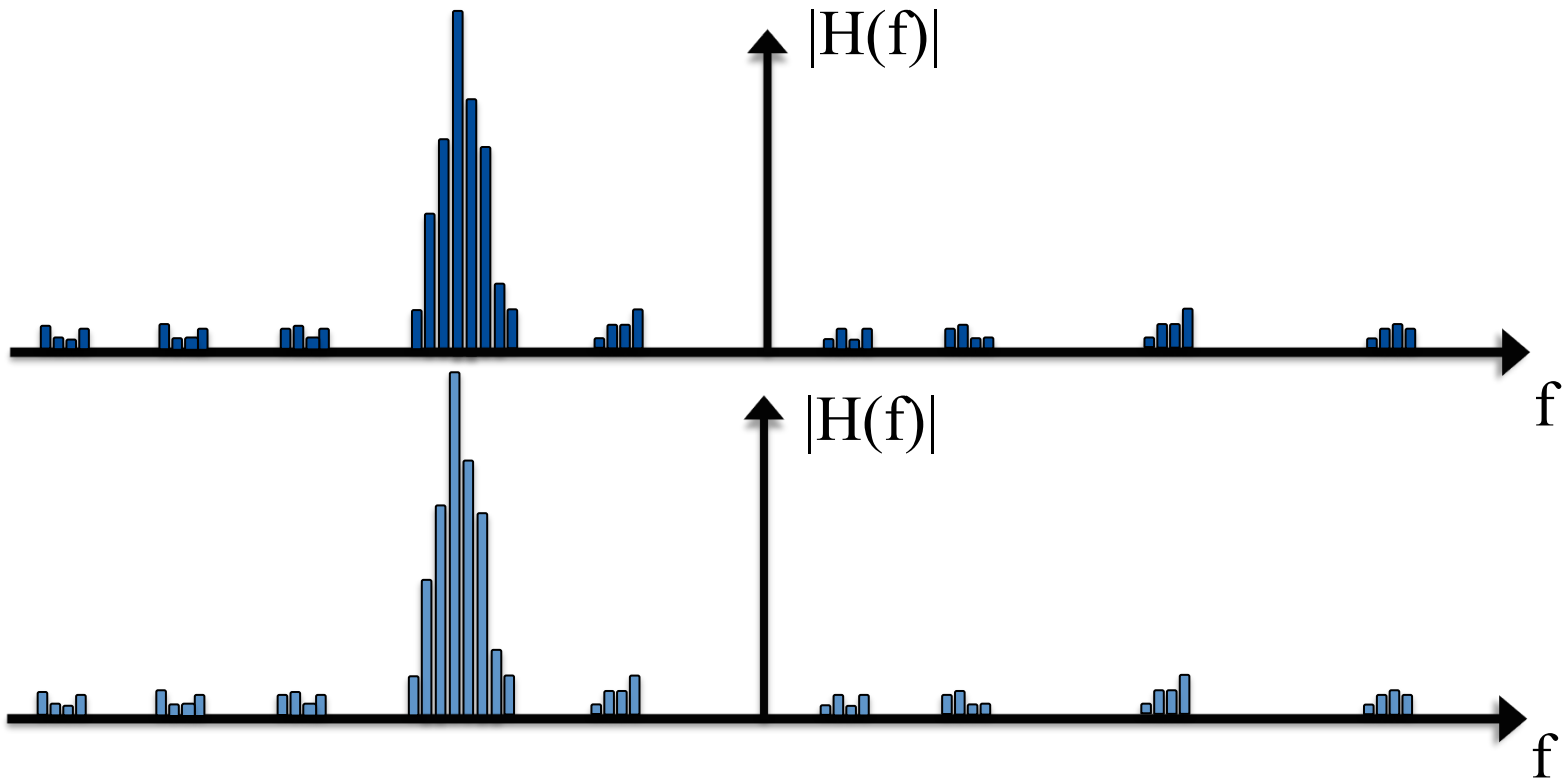
Compressive Sensing systems in HF

- Several interferences detection
  - Strong interference scenario



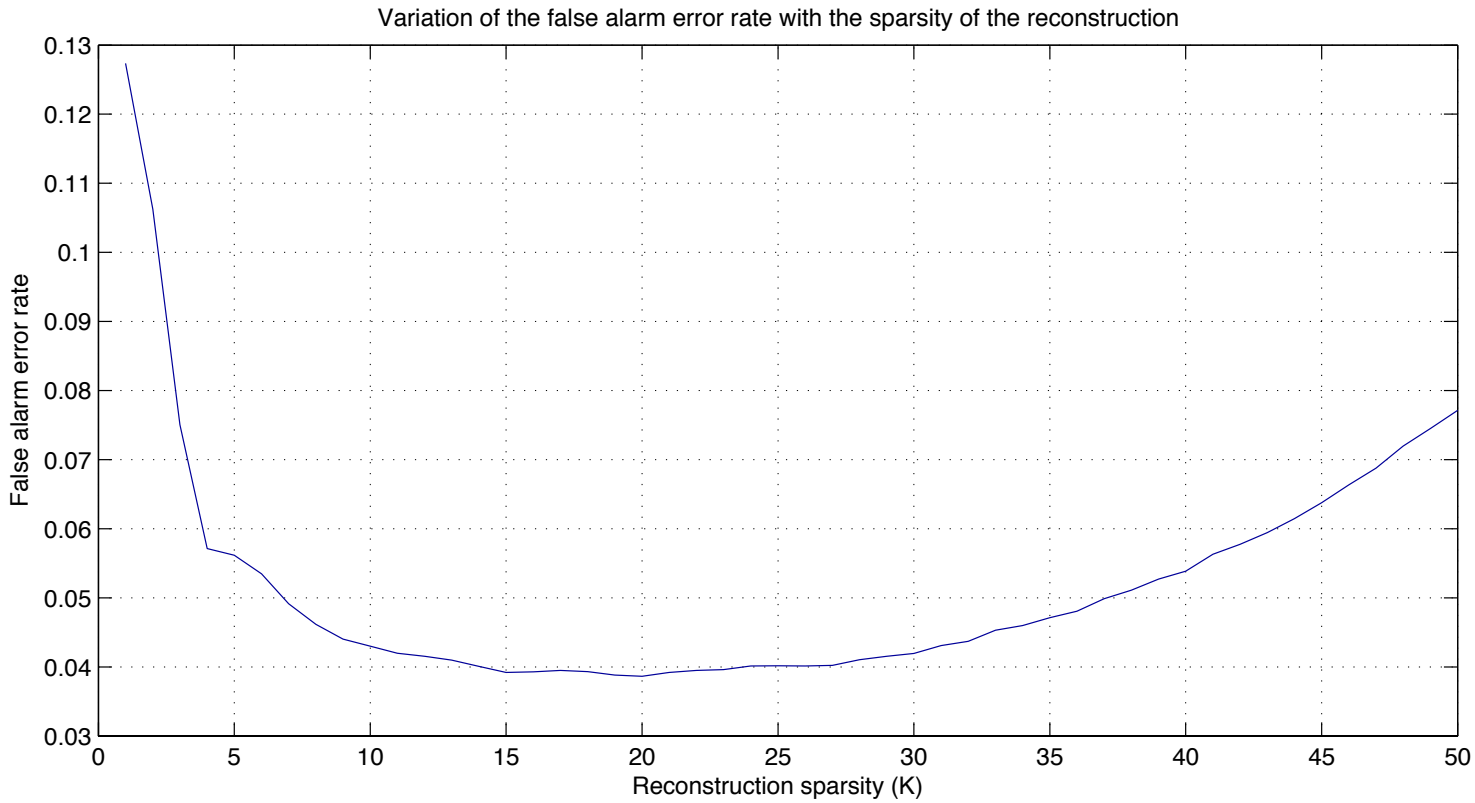
Compressive Sensing systems in HF

- Several interferences detection
  - One strong interference scenario



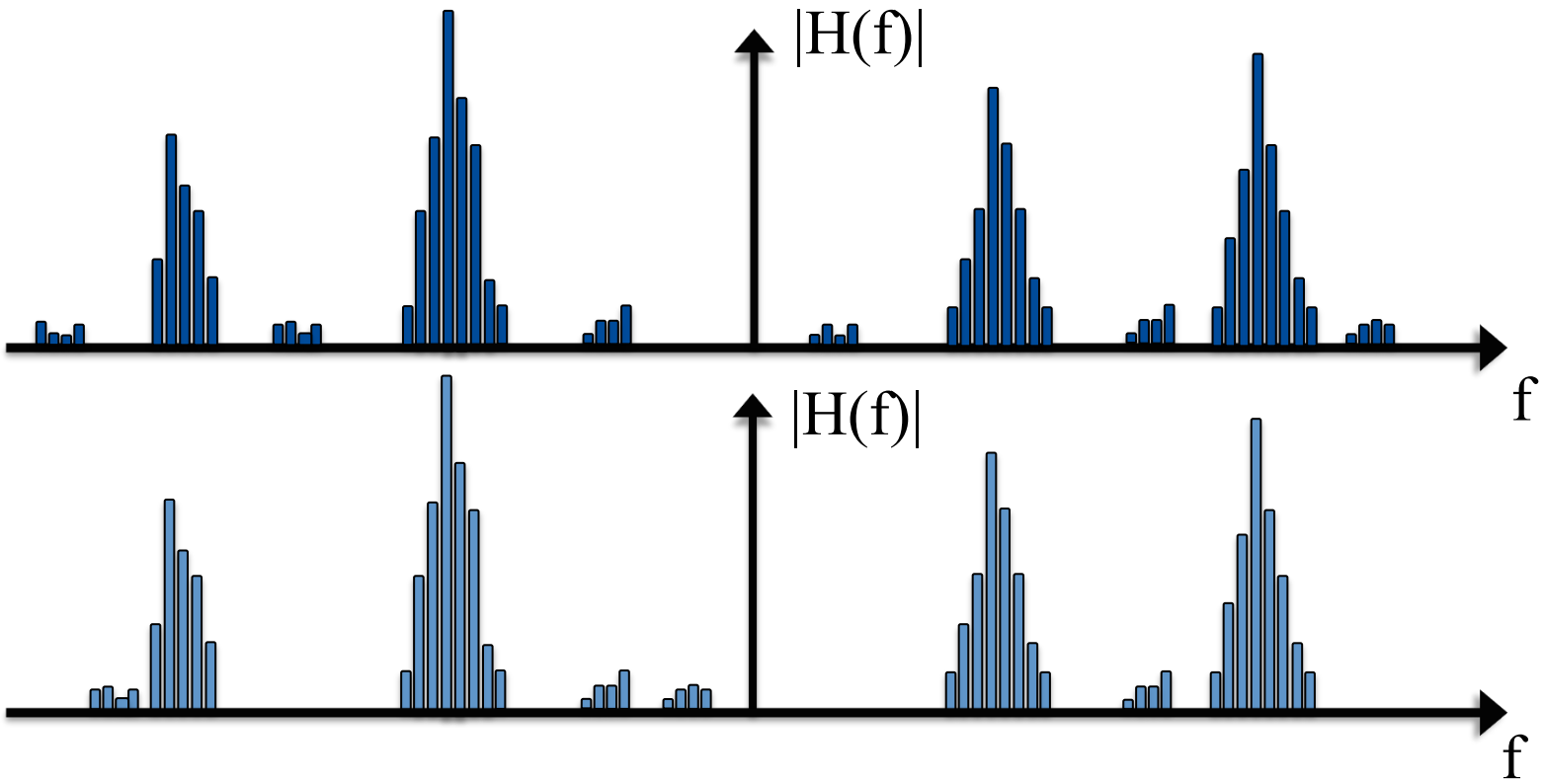
Compressive Sensing systems in HF

- Several interferences detection
  - High activity scenario



Compressive Sensing systems in HF

- Several interferences detection
  - High activity scenario



Contents

Conclusions

- Architecture of an interference detection system based on Compressive Sensing.

- It is possible to use the RD and the CoSaMP to obtain information about HF signals at a sub-Nyquist rate.

- Learning and prediction techniques must be used to improve the interference detection system.

Future research lines

- Test of the limits of the reduction in the sampling rate.
- Perform an accurate characterisation of the MWC.
- Generation of a C code which implements the Compressive Sensing recovery algorithms.

Contents

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Adrián García Rodríguez, 29th January 2012

Presented by Laura Melián Gutiérrez, IDeTIC, 22nd February 2012