

# Wireless networks for spectrum sensing and source localization

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# Radio sources in the 2.4GHz ISM band

Sources transmit **signals** that **may overlap** in time and frequency



# Introduction

- **Source activity** is an on/off signal in time
- A network of sensors measures **average received power** in a **frequency band** with some **time granularity** (e.g.  $T=20\mu\text{s}$ )
- Sensor **measurements** are **collected** and processed using a **centralized scheme**

# Radio sources and sensors



number of sensors  $\geq$  number of sources

# Objectives

Using the collected measurements we want to:

1. Determine the **number of radio sources**
2. Recover the source **signal activities**
3. **Localize** each detected **source**

# Possible applications

- **Monitoring of spectrum** usage in a frequency band
- Detection and localization of interfering radio sources  
(**cooperative spectrum sensing**)

# System model

- Source **activity** from **different networks** is modeled as **statistically independent**
- Sources from the **same network** transmit **non overlapping signals in time**
- Received signals are corrupted by **additive noise** only

# Average received power

Approximate **power at sensor**  $j$  over interval  $[(k-1)T, kT]$

$$p_{Rj}(k) = \sum_{i=1}^M g_{ji} p_i(k) + \sigma_j^2 \quad j = 1, \dots, N \quad k = 1, \dots, K$$

channel gain coefficient

average power of the  $i$ -th source

noise variance

number of sensors

number of measurements



# Blind signal separation model

We define **zero-mean signals**

$$p'_{Rj}(k) = p_{Rj}(k) - \frac{1}{K} \sum_{m=1}^K p_{Rj}(m) \quad p'_i(k) = p_i(k) - \frac{1}{K} \sum_{m=1}^K p_i(m)$$

This leads to the **blind signal separation model**

$$\mathbf{p}'_R(k) = \mathbf{G}\mathbf{p}'(k) \quad k = 1, \dots, K$$

$$\mathbf{p}'_R(k) = [p'_{R1}(k) \quad \dots \quad p'_{RN}(k)]^T \quad \mathbf{p}'(k) = [p'_1(k) \quad \dots \quad p'_M(k)]^T$$

$$[\mathbf{G}]_{ij} = g_{ij}$$

# Blind signal separation problem

**Goal:** recover **gain matrix**  $\mathbf{G}$  and **activity signals**  $\mathbf{p}'(k)$   
from **received power vectors**  $\mathbf{p}'_R(k)$

This can be solved if:

1. The number of sensors is at least equal to the number of sources
2. Gain matrix has **full column rank**
3. Source signals have special properties (different spectra, statistical independence, constant modulus, **finite alphabet**...)

# Finite alphabet property

- If sources operate with **constant power** when they are on, then each source is characterized by an **on/off signal**

$$p_i(k) \in \{0,1\}$$

- Gain matrix and source signals are recovered by using this **finite alphabet property**

# Existing finite alphabet algorithms

- Existing methods assume statistically independent signals
- Groups of non overlapping (**statistically dependent**) signals in time
  - Hence, **existing methods** are **not directly applicable**

# Solution: prefiltering step

Number of sources is found as the rank of

$$P_R = [p'_R(1) \quad \cdots \quad p'_R(K)] = U\Sigma V^T$$

Dimension reduction prefiltering

$$\tilde{p}_R(k) = \Sigma^{-1}U^T p'_R(k) = \Sigma^{-1}U^T Gp'(k) = Tp'(k)$$

$$T = \Sigma^{-1}U^T G$$

# Restoring the finite alphabet property

- Source signals are recovered by finding the **matrix  $W$**

$$\hat{p}'(k) = W^T \tilde{p}_R(k)$$

$$W^T = T^{-1}$$

- **Enforcing the finite alphabet property** (on/off) of the recovered signals
  - Leads to a **generalized eigenvector problem** for a unique  $W$

# Restoring the finite alphabet property: (generalized eigenvector problem)

Computation of the matrix  $W$ :

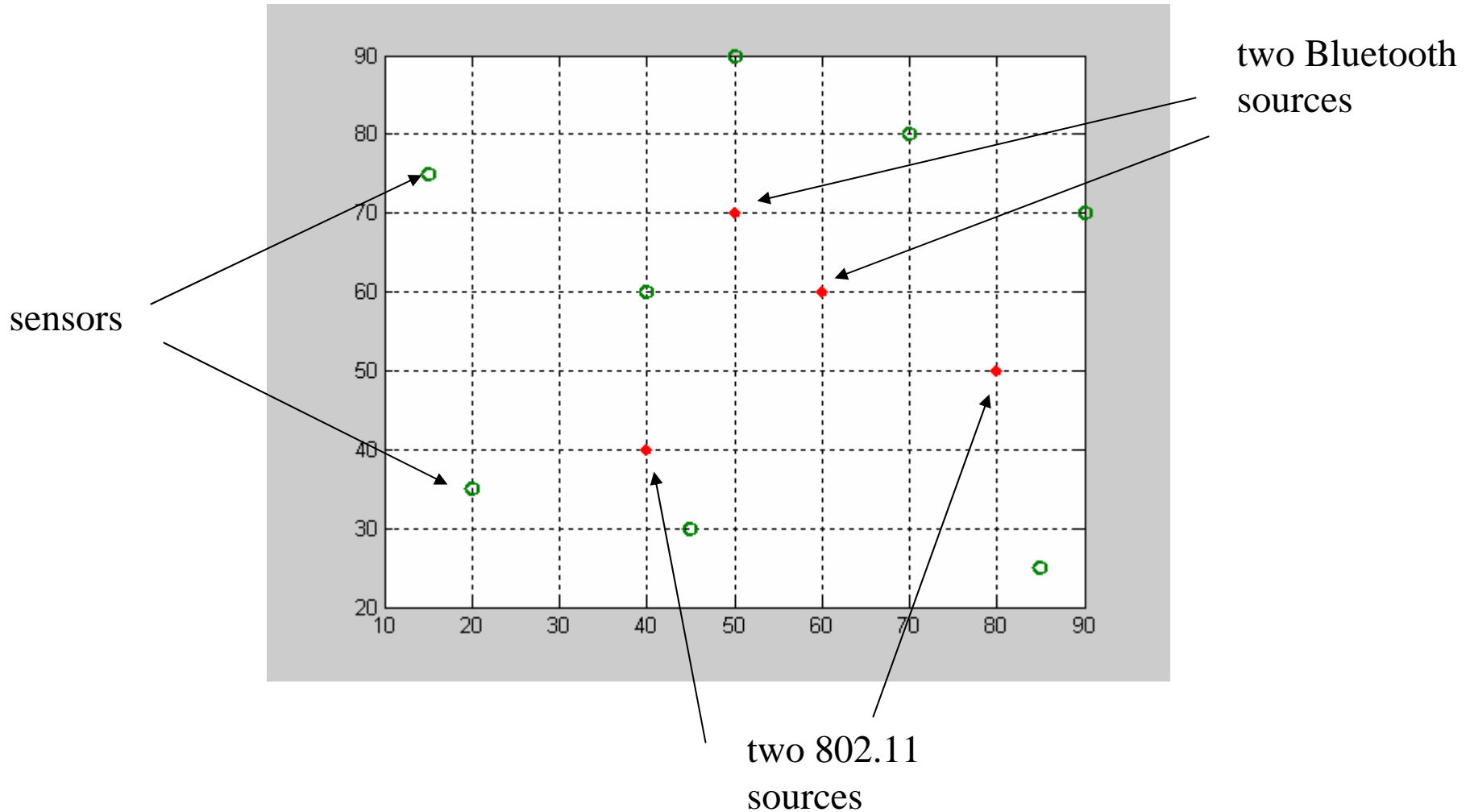
- For **statistically independent** source activity:
  - **joint diagonalization** of a set of matrices obtained from  $\tilde{p}_R(k)$
- For groups of sources with **non overlapping signals** in time:
  - **joint block diagonalization** of a set of matrices obtained from  $\tilde{p}_R(k)$

# Solution

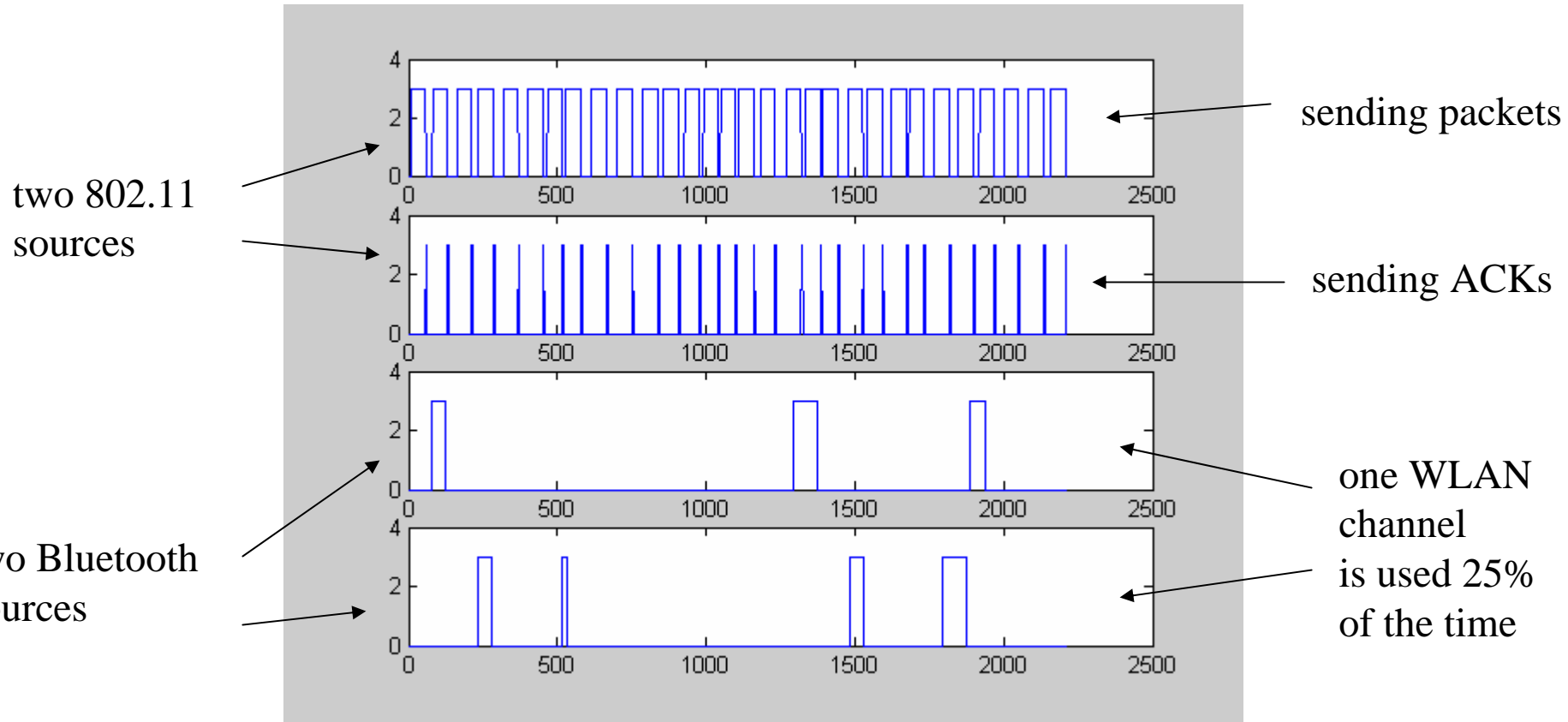
- Recovered signals are partitioned into groups
- Each group consists of source signals belonging to the same network (non overlapping signals in time)
- Recovered signals from different groups are statistically independent



# Simulation example

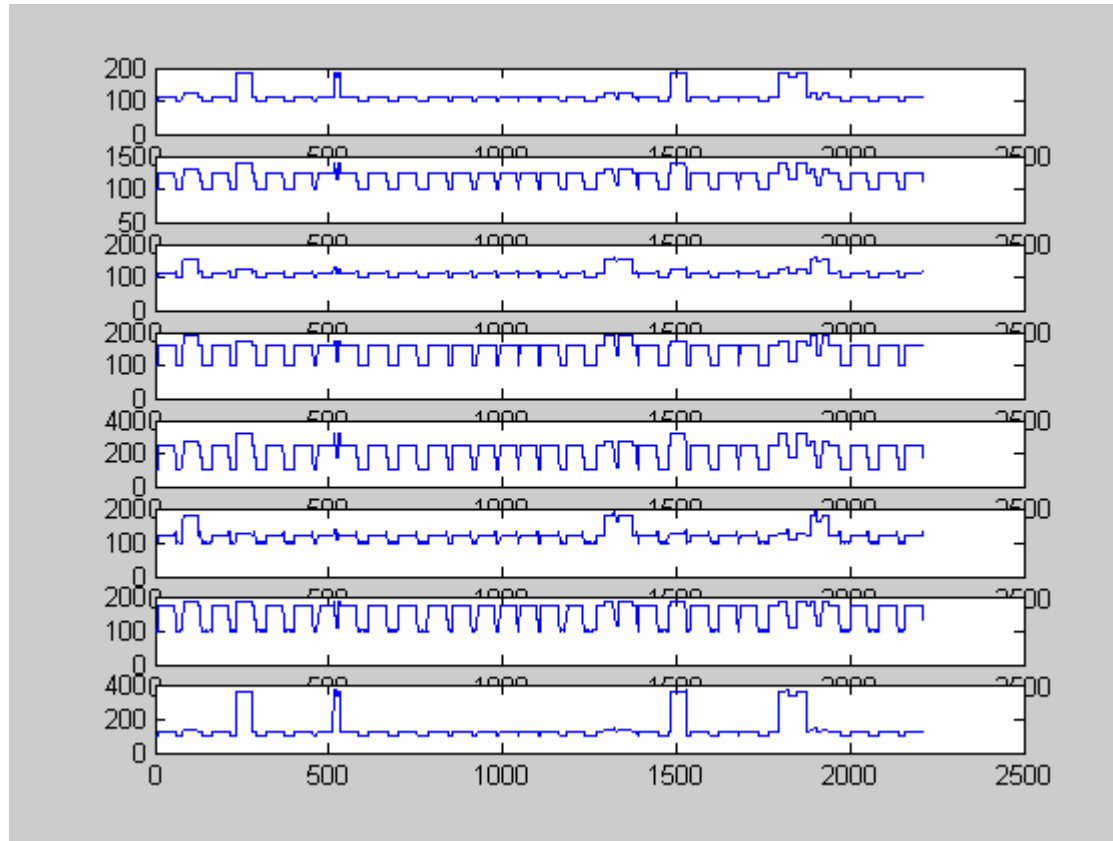


# Original source signals



Source signal activities in one 20MHz wide WLAN channel

# Signals measured by sensors

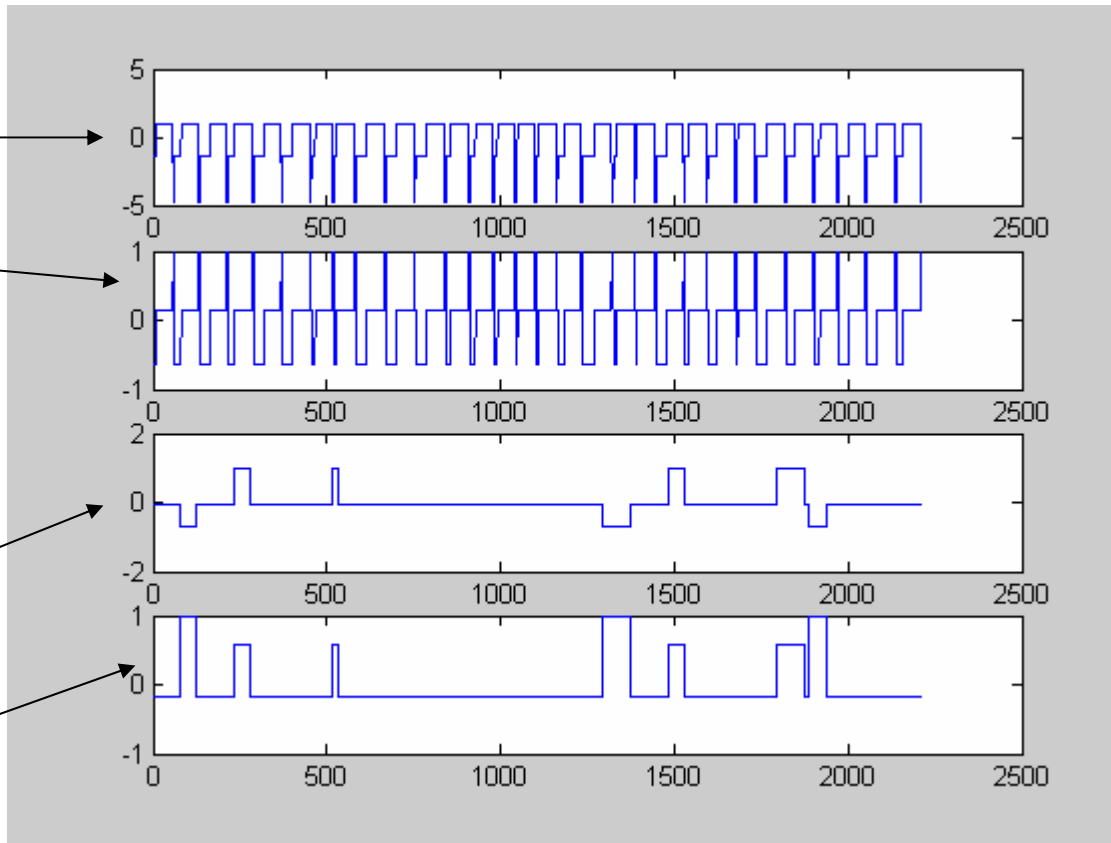


Average power is measured with time granularity  $T=20\mu\text{s}$

# Signals recovered after joint block diagonalization

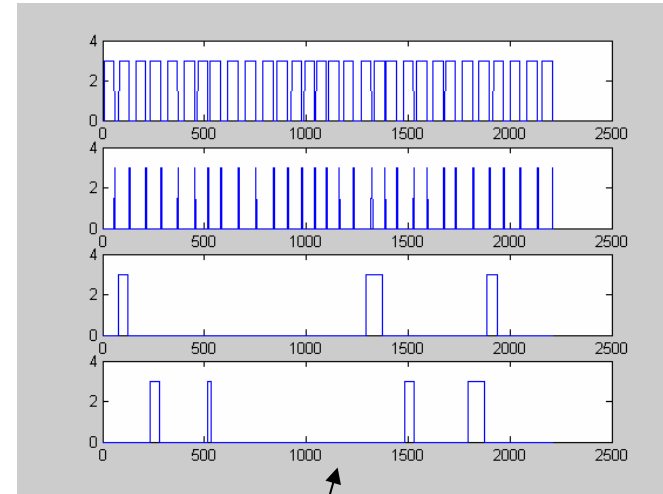
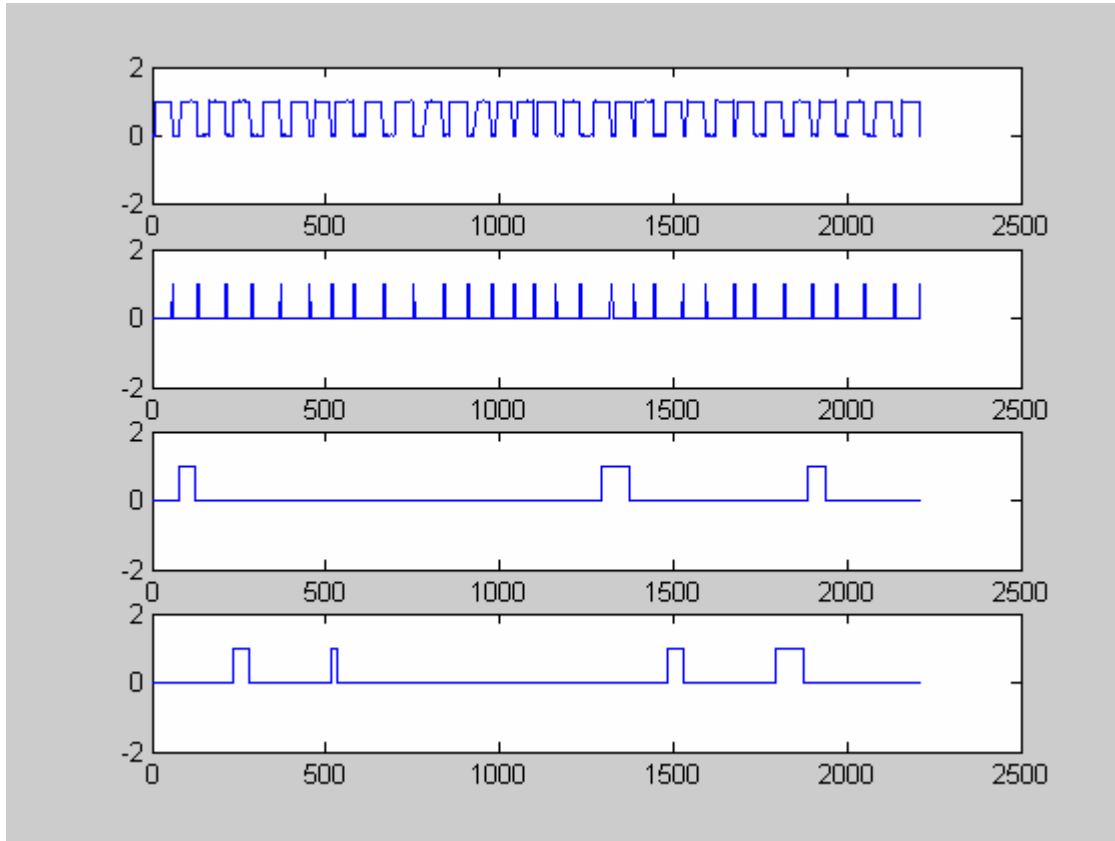
linear combinations of 802.11 signals

linear combinations of Bluetooth signals



Recovered signals are partitioned into two independent groups

# Final recovered signals



Original source signals

# Source localization

Gain matrix entries for path loss coefficient 2

$$[\mathbf{G}]_{ij} = g_{ij} = \frac{c}{(x_{r,i} - x_j)^2 + (y_{r,i} - y_j)^2}$$

Location of the  $i$ -th sensor

Location of the  $j$ -th source

# Source localization

For known sensor locations the  $j$ -th source can be localized by solving

$$\begin{array}{l} \text{Estimated} \\ \text{gain matrix} \\ \text{coefficients} \end{array} \begin{array}{l} \longrightarrow \hat{g}_{ij} \\ \longrightarrow \hat{g}_{i+1,j} \end{array} = \frac{(x_{r,i+1} - x_j)^2 + (y_{r,i+1} - y_j)^2}{(x_{r,i} - x_j)^2 + (y_{r,i} - y_j)^2}$$
$$i = 1, \dots, N - 1$$

# Conclusion

- Source signals can be recovered by
  - exploiting their **finite alphabet property** and
  - **spatial diversity** provided by the network of sensors
- If the path loss coefficient and sensor locations are known detected **sources can be localized**