Missing Spectrum-Data Recovery in Cognitive Radio Networks Using Piecewise Constant Nonnegative Matrix Factorization

Alireza Zaeemzadeh, Mohsen Joneidi, Behzad Shahrasbi, and Nazanin Rahnavad
School of Electrical Engineering and Computer Science
University of Central Florida
Outline

• Spectrum Sensing in Cognitive Radio Networks: (which is prone to missing data)

• Piecewise Constant Nonnegative Matrix Factorization

• Majorization-Minimization to Solve the PC-NMF Problem

• Results and Conclusion
Spectrum Sensing in Cognitive Radio Networks

• The radio frequency (RF) spectrum is a precious resource that must be utilized efficiently.
• The main feature of CRs is the opportunistic usage of spectrum efficiency.
• CR systems try to improve the spectrum efficiency by using the spectrum holes in frequency, time, and space domains.

Picture source: Yu, Chung-Kai, and Kwang-Cheng Chen. "Spectrum map retrieval using cognitive radio network tomography." GLOBECOM Workshops (GC Wkshps), 2011 IEEE. IEEE, 2011.
Spectrum Sensing in Cognitive Radio Networks

- **PUs:** Primary Users or licensed users that have higher priorities to use the spectrum.

- **SUs:** Secondary Users or unlicensed users that try to utilize the spectrum in an opportunistic manner.

There are some missing entries among our data set.

- Hardware Limitations
- Energy Limitations
- Network Traffic
- Connection Failure

\[ s_i(t) = \sum_{j=1}^{N_{PU}} p_j(t) \gamma_{ij}(t) + z_i(t) \]
The received power at $i^{th}$ SU at time $t$ can be formulated as:

$$s_i(t) = \sum_{j=1}^{N_{PU}} p_j(t) \gamma_{ij}(t) + z_i(t)$$

Vector Form:

$$s(t) = \sum_{j=1}^{N_{PU}} p_j(t) \gamma_j(t) + z(t)$$

Matrix Form:

$$S = \Gamma P + Z$$

- $N_{PU} \times T$
- $N_{SU} \times N_{PU}$
Piecewise Constant Nonnegative Matrix Factorization

\[ P_{\text{transition}} \ll 1 \]

The power levels of PUs tend to be piecewise constant

- \( D_W \) is a weighted measure of fit
- \( F(P) \) is a penalty which favors piecewise constant solutions

\[ F(P) = \sum_{t=2}^{T} \| P_t - P_{(t-1)} \|_0 \]

\[
\begin{align*}
\text{minimize} & \quad D_W(S|\Gamma P) + \beta F(P), \\
\text{subject to} & \quad \Gamma > 0, P > 0.
\end{align*}
\]
Majorization-Minimization to Solve the PC-NMF Problem

**Definition 1** \( G(h, h') \) is an auxiliary function for \( F(h) \) if the conditions
\[
G(h, h') \geq F(h), \quad G(h, h) = F(h)
\]
are satisfied.

\[
h^{t+1} = \arg \min_h G(h, h^t)
\]

\[
F(h^{t+1}) \leq G(h^{t+1}, h^t) \leq G(h^t, h^t) = F(h^t)
\]

Picture source: Lee, Daniel D., and H. Sebastian Seung. "Algorithms for non-negative matrix factorization." *Advances in neural information processing systems*. 2001.
Results

• The proposed method decreases the effect of noise and fading.
• The sharp transitions are preserved.
Results

Performance of the PC-NMF vs Weighted and NMF and a method based on Dictionary Learning.

- About 10% less RMSE

MM methods converge much faster than methods based on gradient descent.

| Method  | Average Running Time (s) |
|---------|--------------------------|
| SS-DL   | 10.3039                  |
| WNMF    | 0.0944                   |
| PC-NMF  | 0.0952                   |
Any Questions?

Thank You

Zaeemzadeh@knights.ucf.edu