JOINT SENSING AND RESOURCE ALLOCATION FOR UNDERLAY COGNITIVE RADIOS

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ABSTRACT

Spectrum-sharing (CSK), spectrum-sensing, and dynamic resource allocation are coupled tasks. However, most existing design-optimizes each of them separately. This work optimizes them jointly for an underlay CSK paradigm. The formulation considers that secondary users adopt their power and rate based on the available important channel state information, while taking into account the cost associated with acquiring such information. The objective of the optimization is twofold: maximize the (instantaneous) performance of the CSK and protect the primary users through an average interference constraint. Designing the sensing is our underlay paradigm amounts to decide what channels are sensed at every time instant. Partial observability of the channel state due to noisy and outdated information calls for (Bayesian) sequential estimates to keep track of the interference channel gains, as well as for dynamic programming tools to design the optimal schemes. Together with the optimal schemes, a simple approximate solution is also developed.

SYSTEM MODEL

- M Secondary Users (SU), orthogonal access
- K channels, 1 Primary User (PU) per channel
- Long-term constraints: QoS, average interference power over the PUs
- Perfect CSK (last fading)

Primary Users (PU)

Secondary Users (SU)

Interference channels

Primary CSI

Secondary CSI

Interference channel

Stochastic filter for the CSK

- The SU-to-PU channels are kept track of by a stochastic filter (prediction, update). Analog measurements are used to update the belief on PU-to-SU channel gain. EXAMPLE - Circular Symmetric Gaussian:

\[ \hat{x}_n^m = \begin{cases} 0, & n = 0 \text{ or channel } k \text{ is sensed before } n \text{ times} \\ \hat{x}_n^m + \gamma_n \left( y_n - C_n^m \hat{x}_n^m \right), & \text{otherwise} \end{cases} \]

where \( \gamma_n \) is a discount factor that is typically included in the formulation but is not considered in this case.

Problem formulation

Objective: minimize \( \max_{y_n} \sum_{n=1}^{\infty} \left( \max_{u_n} \left( E \left[ x_n^m \right] \right) \right) \)

Subject to:

1. \( \sum_{n=1}^{\infty} \left( \max_{u_n} \left( E \left[ x_n^m \right] \right) \right) \leq \sum_{n=1}^{\infty} y_n \) (power constraints)
2. \( \sum_{n=1}^{\infty} \left( \max_{u_n} \left( E \left[ x_n^m \right] \right) \right) \leq \sum_{n=1}^{\infty} \gamma_n \) (long-term power constraints)

Optimal Access

- orthogonally access: \( w_n^m \neq 0 \) and \( \sum_{m=1}^{M} w_n^m = 1 \)

This is an infinite-horizon POMDP because \( x_n^m \) has (throughout \( F_n^m \) and \( F_n^{m+1} \)) an impact on \( F_n^{m+1} \) (i.e. on the information about \( h_n^m \)).

2-STEP STRATEGY

We split the solution into 2 steps (sub-problems) without loss of optimality:

- Step 1: assume the sensing scheme is given and optimize power and access for any sensing scheme
- Step 2: use the solution from Step 1 to reverse the joint optimization as an unconstrained POMDP

Optimal Power and Access

If \( x_n^m \) is given, the problem can be recast as a convex one. After dualizing (2) and (3), define the Lagrangian indicator (LQI) for user \( m \) at channel \( k \):

\[ \mathcal{L}(\theta^m) = \mathcal{L}(\theta^m, \phi^m) = E \left[ \sum_{n=1}^{\infty} \left( \max_{u_n^m} \left( E \left[ x_n^m \right] \right) \right) \right] \]

(6)

1. Optimize power for each user-channel pair separately

\[ p_n^m = \arg \max \mathcal{L}(\theta^m) \]

(7)

2. Schedule user with best indicator for each channel

\[ \hat{w}_n^m = \arg \max \mathcal{L}(\theta^m) \]

(9)

Optimal Sensing

Instantaneous utility (as a function of \( p_n^m \) and therefore valid for any sensing scheme [6]:

\[ R_n^m \left[ \sum_{n=1}^{\infty} \left( \max_{u_n^m} \left( E \left[ x_n^m \right] \right) \right) \right] \]

Substituting the optimal RA and (9) into the Lagrangian of (1):

\[ \max_{y_n} \sum_{n=1}^{\infty} \left( \max_{u_n} \left( E \left[ x_n^m \right] \right) \right) \]

which is an unconstrained DP. The objective is split into present and future time instants:

\[ \sum_{n=1}^{\infty} \left( \max_{u_n} \left( E \left[ x_n^m \right] \right) \right) \]

The value function \( V^m(b_n, F_n^m) \) is as described for the current actions in future instants. Since \( C_n^m \) is i.i.d. across time and independent of \( x_n^m \), the Bellman equations that drive the optimal solution can be expressed in terms of \( V^m(b_n, F_n^m) \):

\[ V^m(b_n, F_n^m) = \max_{F_n^{m+1}} \left( E \left[ R_n^m \left[ \sum_{n=1}^{\infty} \left( \max_{u_n^m} \left( E \left[ x_n^m \right] \right) \right) \right] \right] \]

(10)

Standard methods to estimate the function \( V^m(b_n, F_n^m) \) (and have guaranteed convergence. However, they are computationally expensive.

Greedyity Approach

Regardless of the method used to approximate \( V^m(b_n, F_n^m) \), at every time instant, an exhaustive search over \( 2^M \) needs to be done. To reduce the complexity of the sensing decision, we use a greedy approach - users are sequentially selected to measure channel:

Algorithm 1 Greedyity approach to the optimal sensing policy:

1. \( k = 0 \) and \( M = \{1, \ldots, M\} \)
2. Repeat:
   3. Choose \( m \) s.t. \( \max_{m \in M} \left( E \left[ R_n^m \left[ \sum_{n=1}^{\infty} \left( \max_{u_n^m} \left( E \left[ x_n^m \right] \right) \right) \right] \right] \) \)
   4. Define \( M \leftarrow M \setminus \{m\} \)
   5. Until \( k < 0 \) or \( k = 1 \)
   6. Return \( \hat{w}_n^m \)

REFERENCES


Preliminary Results

To evaluate the greedy approximation, the performance of the myopic policy \( V^m(\cdot, F_n^m) \) is compared using: i) exhaustive search (combinatorial complexity); ii) Algorithm 1 (proposed, polynomial complexity); iii) Round-robin (sequentially select a single user to sense), deterministic schemes that \( w_n^m \) (always sense, \( v \) never sense, and \( w \) an upper bound).