

Cognitive Medium Access: Exploration, Exploitation and Competition

by L. Lai, H. El Gamal, H. Jiang, and H.V. Poor
(submitted to IEEE Trans. Networking, October 2007)

proposed by Jan

CTG Reading Group
October 29, 2008

- **Radio spectrum** has traditionally been organized according to fixed frequency plans defined through government licences
⇒ Inefficient spectrum utilization
- **Cognitive Radio**: An intelligent radio that is aware of its environment and adapts accordingly
- Usually, focus on opportunistic **channel access** based on **spectrum sensing** capabilities

Three key issues

- **Exploration** of given channel resources to decide on availability
- **Exploitation** of available channels for own data transmission
- **Competition** with other cognitive users in multi-user scenario

- **Radio spectrum** has traditionally been organized according to fixed frequency plans defined through government licences
⇒ Inefficient spectrum utilization
- **Cognitive Radio:** An intelligent radio that is aware of its environment and adapts accordingly
- Usually, focus on opportunistic **channel access** based on **spectrum sensing** capabilities

Three key issues

- **Exploration** of given channel resources to decide on availability
- **Exploitation** of available channels for own data transmission
- **Competition** with other cognitive users in multi-user scenario

Side constraint: Availability probabilities of each channel **unknown**

- Lay **mathematical foundation** for cognitive medium access (MAC) using tools from
 - ▶ Reinforcement machine learning
 - ▶ Game theory
- Highlight **trade-off** between exploration and exploitation
- Design efficient **protocols** for cognitive MAC
- Derive theoretical **limits** & prove **optimality** of proposed schemes

Scenarios

- Single-user – single-channel setup
- Multi-user – single-channel setup
- Single-user – multiple-channel setup

Side constraint: Availability probabilities of each channel **unknown**

- Lay **mathematical foundation** for cognitive medium access (MAC) using tools from
 - ▶ Reinforcement machine learning
 - ▶ Game theory
- Highlight **trade-off** between exploration and exploitation
- Design efficient **protocols** for cognitive MAC
- Derive theoretical **limits** & prove **optimality** of proposed schemes

Scenarios

- **Single-user – single-channel setup**
- Multi-user – single-channel setup
- Single-user – multiple-channel setup

Problem Setup

- N primary channels given, each with bandwidth B
- Synchronous time-slotted communication (T time slots per block)
- θ_i : Probability of channel i being free; $\theta := [\theta_1, \dots, \theta_N]$
- θ block-wise constant and unknown *a priori* to cognitive user
 - ⇒ Balance between exploiting channel i using current knowledge of θ and exploring other channels to improve knowledge of θ
 - ⇒ Related to classic 'multi-armed bandit problem'
- Reward function:
$$W = \sum_{j=1}^T B Z_{S(j)}(j)$$

$S(j)$ channel chosen for sensing (and access), time slot j
 $Z_i(j) = 1$ if channel i free at time slot j ; $Z_i(j) = 0$ otherwise

 - ⇒ Goal: Maximize expected throughput per block, $E\{W\}$

Problem Setup

- N primary channels given, each with bandwidth B
- Synchronous time-slotted communication (T time slots per block)
- θ_i : Probability of channel i being free; $\theta := [\theta_1, \dots, \theta_N]$
- θ block-wise constant and unknown *a priori* to cognitive user

⇒ Balance between exploiting channel i using current knowledge of θ and exploring other channels to improve knowledge of θ

⇒ Related to classic 'multi-armed bandit problem'

- Reward function:
$$W = \sum_{j=1}^T B Z_{S(j)}(j)$$

$S(j)$ channel chosen for sensing (and access), time slot j

$Z_i(j) = 1$ if channel i free at time slot j ; $Z_i(j) = 0$ otherwise

⇒ Goal: Maximize expected throughput per block, $E\{W\}$

Problem Setup

- N primary channels given, each with bandwidth B
- Synchronous time-slotted communication (T time slots per block)
- θ_i : Probability of channel i being free; $\theta := [\theta_1, \dots, \theta_N]$
- θ block-wise constant and unknown *a priori* to cognitive user

⇒ Balance between exploiting channel i using current knowledge of θ and exploring other channels to improve knowledge of θ

⇒ Related to classic 'multi-armed bandit problem'

- Reward function:

$$W = \sum_{j=1}^T B Z_{S(j)}(j)$$

$S(j)$ channel chosen for sensing (and access), time slot j

$Z_i(j) = 1$ if channel i free at time slot j ; $Z_i(j) = 0$ otherwise

⇒ Goal: Maximize expected throughput per block, $E\{W\}$

Optimal Bayesian Approach

- Assumption: PDF of θ known *a priori* $\rightarrow f(\theta)$
- Update PDF $f(\theta)$ with each new sensing result $z_i(j)$
- Optimal MAC strategy Γ^* depends on $f(\theta)$ and complete set $\Psi(j) = \{z_{s(1)}(1), \dots, z_{s(j-1)}(j-1)\}$ of past sensing results
- Optimal trade-off between short-term gain (exploitation) and long-term gain (better knowledge of θ)
- Iterative solution stated in paper (plus some nice examples)
- Still, optimal strategy has prohibitive computational complexity
- Optimal Bayesian approach serves as ultimate theoretical limit

Optimal Bayesian Approach

- Assumption: PDF of θ known *a priori* $\rightarrow f(\theta)$
- Update PDF $f(\theta)$ with each new sensing result $z_i(j)$
- Optimal MAC strategy Γ^* depends on $f(\theta)$ and complete set $\Psi(j) = \{z_{s(1)}(1), \dots, z_{s(j-1)}(j-1)\}$ of past sensing results
- Optimal trade-off between short-term gain (exploitation) and long-term gain (better knowledge of θ)
- Iterative solution stated in paper (plus some nice examples)
- Still, optimal strategy has prohibitive computational complexity
- Optimal Bayesian approach serves as ultimate theoretical limit

Suboptimum MAC Strategies

- Loss entailed by suboptimum MAC strategy Γ with respect to genie-aided strategy

$$L(\theta, \Gamma) = \sum_{j=1}^T B \theta_{i^*} - \sum_{j=1}^T B \sum_{i=1}^N \theta_i \Pr\{\Gamma(\Psi(j)) = i\}$$

where $\theta_{i^*} = \max\{\theta\}$

- Example: Consider MAC strategy which randomly selects channel i and sticks with it
 - ▶ $i = i^* \Rightarrow L(\theta, \Gamma) = 0$
 - ▶ $i \neq i^* \Rightarrow L(\theta, \Gamma)$ grows linearly with T (i.e., $L(\theta, \Gamma) \sim \mathcal{O}(T)$)
- Other examples show that there are several heuristic suboptimal MAC strategies that incur $L(\theta, \Gamma) \sim \mathcal{O}(T)$
- Goal: Design suboptimum MAC strategy which entails a smaller loss (if possible without requiring prior knowledge of $f(\theta)$)

Suboptimum MAC Strategies

- Loss entailed by suboptimum MAC strategy Γ with respect to genie-aided strategy

$$L(\boldsymbol{\theta}, \Gamma) = \sum_{j=1}^T B \theta_{i^*} - \sum_{j=1}^T B \sum_{i=1}^N \theta_i \Pr\{\Gamma(\Psi(j)) = i\}$$

where $\theta_{i^*} = \max\{\boldsymbol{\theta}\}$

- Example: Consider MAC strategy which randomly selects channel i and sticks with it
 - ▶ $i = i^* \Rightarrow L(\boldsymbol{\theta}, \Gamma) = 0$
 - ▶ $i \neq i^* \Rightarrow L(\boldsymbol{\theta}, \Gamma)$ grows linearly with T (i.e., $L(\boldsymbol{\theta}, \Gamma) \sim \mathcal{O}(T)$)
- Other examples show that there are several heuristic suboptimal MAC strategies that incur $L(\boldsymbol{\theta}, \Gamma) \sim \mathcal{O}(T)$
- Goal: Design suboptimum MAC strategy which entails a smaller loss (if possible without requiring prior knowledge of $f(\boldsymbol{\theta})$)

Suboptimum MAC Strategies

- Loss entailed by suboptimum MAC strategy Γ with respect to genie-aided strategy

$$L(\boldsymbol{\theta}, \Gamma) = \sum_{j=1}^T B \theta_{i_*} - \sum_{j=1}^T B \sum_{i=1}^N \theta_i \Pr\{\Gamma(\Psi(j)) = i\}$$

where $\theta_{i_*} = \max\{\boldsymbol{\theta}\}$

- Example: Consider MAC strategy which randomly selects channel i and sticks with it
 - ▶ $i = i_* \Rightarrow L(\boldsymbol{\theta}, \Gamma) = 0$
 - ▶ $i \neq i_* \Rightarrow L(\boldsymbol{\theta}, \Gamma)$ grows linearly with T (i.e., $L(\boldsymbol{\theta}, \Gamma) \sim \mathcal{O}(T)$)
- Other examples show that there are several heuristic suboptimal MAC strategies that incur $L(\boldsymbol{\theta}, \Gamma) \sim \mathcal{O}(T)$
- Goal: Design suboptimum MAC strategy which entails a smaller loss (if possible without requiring prior knowledge of $f(\boldsymbol{\theta})$)

Order Optimal MAC Strategy

- It is shown that $L(\theta, \Gamma)$ scales at least with $L(\theta, \Gamma) \sim \mathcal{O}(\ln T)$ if $f(\theta)$ is not known, as we need at least $\mathcal{O}(\ln T)$ time slots to sample each channel and get a reliable estimate of θ
- Proposed order optimal MAC strategy:
 - ▶ At the beginning of each block sense each channel once
 - ▶ At the beginning of time slot j calculate estimate

$$\hat{\theta}_i(j) = X_i(j) / Y_i(j)$$

$Y_i(j)$: Number of time slots in which channel i was already sensed

$X_i(j)$: Number of time slots in which channel i was found free

- Assign index to channel i

$$\Lambda_i(j) := \hat{\theta}_i(j) + \sqrt{2 \ln j / Y_i(j)}$$

- In time slot $(j+1)$ choose channel with largest index $\Lambda_i(j)$ to sense
- Correction term in $\Lambda_i(j)$ makes sure that channel i^* is sensed many times before it is declared best

Order Optimal MAC Strategy

- It is shown that $L(\theta, \Gamma)$ scales at least with $L(\theta, \Gamma) \sim \mathcal{O}(\ln T)$ if $f(\theta)$ is not known, as we need at least $\mathcal{O}(\ln T)$ time slots to sample each channel and get a reliable estimate of θ
- Proposed order optimal MAC strategy:
 - ▶ At the beginning of each block sense each channel once
 - ▶ At the beginning of time slot j calculate estimate

$$\hat{\theta}_i(j) = X_i(j) / Y_i(j)$$

$Y_i(j)$: Number of time slots in which channel i was already sensed

$X_i(j)$: Number of time slots in which channel i was found free

- Assign index to channel i

$$\Lambda_i(j) := \hat{\theta}_i(j) + \sqrt{2 \ln j / Y_i(j)}$$

- In time slot $(j+1)$ choose channel with largest index $\Lambda_i(j)$ to sense
- Correction term in $\Lambda_i(j)$ makes sure that channel i^* is sensed many times before it is declared best

- With respect to exploitation/exploration trade-off same goals for each individual cognitive user
- Additionally, minimize collision probability, i.e., different cognitive users should sense different channels
 - ▶ Optimal distributed MAC protocol proposed which is based on symmetric rule (θ known)
 - ▶ Game-theoretic approach investigated to operate at Nash equilibrium