Fast Online Learning of Antijamming and Jamming Strategies

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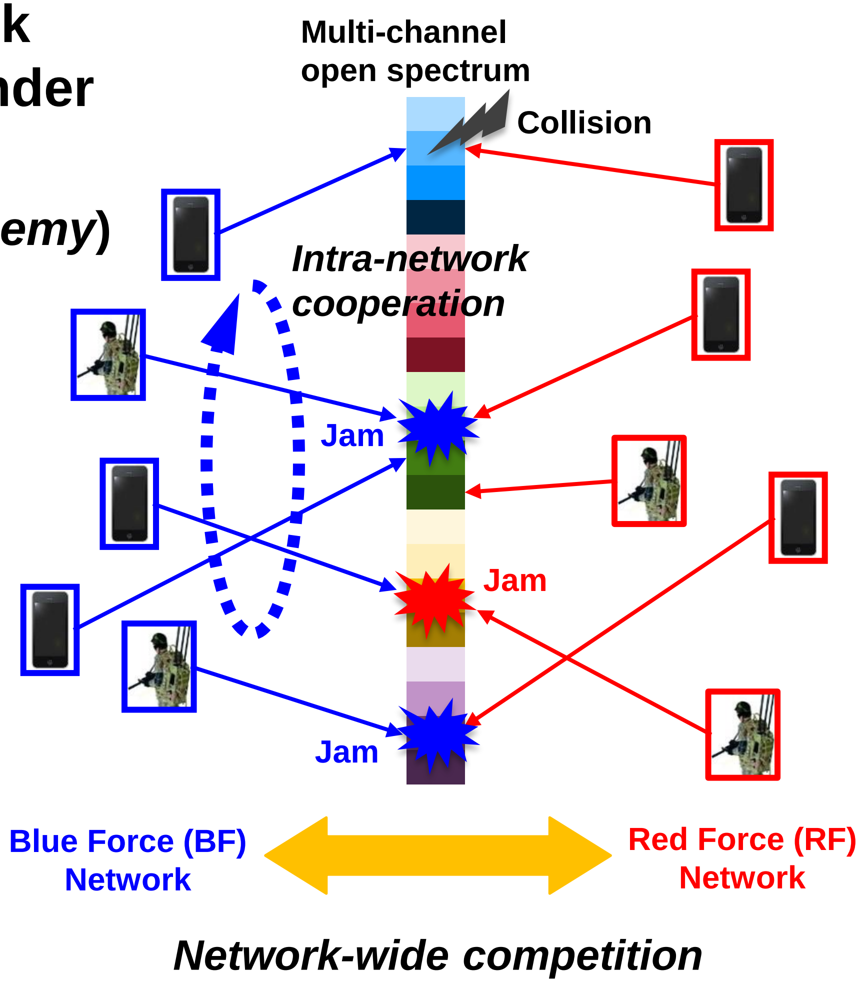
Outline

- **Introduction**
- **Background: Competing Cognitive Radio Network**
- **Problem**
- **Model**
- **Solution approaches**
- **Evaluation**
- **Conclusion**

Introduction

- **Competing Cognitive Radio Network (CCRN) models mobile networks under competition**
  - **Blue Force (*ally*) vs. Red Force (*enemy*)**
  - **Dynamic, open spectrum resource**
  - **Nodes are cognitive radios**
    - ➢ **Comm nodes and jammers**
  - **Opportunistic data access**
  - **Strategic jamming attacks**



Background: Competing Cognitive Radio Network

- **Formulation 1: Stochastic MAB**
  - **$<A_B, A_R, R>$**
    - **Blue-force (B) & Red-force (R) action sets:** **$a_B = \{a_{BC}, a_{BJ}\} \in A_B$, $a_R = \{a_{RC}, a_{RJ}\} \in A_R$**
    - **Reward: $R \sim \mathrm{PD}(r|a_B,a_R)$**
  - **Regret $\Gamma = \max_{a \in AB} \sum_T r(a) - \sum_T r(a_B{}^t)$**
    - **Optimal regret bound in $O(\log T)$ [Lai&Robbins'85]**

- **Formulation 2: Markov Game**
  - **$<A_B, A_R, \mathrm{S}, R, \mathrm{T}>$**
    - **Stateful model with states S and probabilistic transition function T**
  - **Strategy π: $S \longrightarrow \mathrm{PD}(A)$ is probability distribution over action space**
    - **Optimal strategy $\pi^* = \arg\max_\pi \mathrm{E}[\sum \gamma R(s,a_B,a_R)]$ can be computed by Q-learning via linear programming**

New Problem Formulation

- **Assume intelligent adversary**
  - **Hostile Red-force can learn as efficiently as Blue-force**
  - **Also, applies cognitive sensing to compute strategies**

- **Consequences**
  - **Well-behaved stochastic channel reward invalid ⇒ *time-varying* channel rewards**
    - **More difficult to predict or model**
  - **Nonstationarity in Red-force actions**
    - **Random, arbitrary changepoint ⇒ introduces dynamic changes**

Revised Regret Model

- **Stochastic MAB problems model regret Γ using reward function r(a)**
  - $\Gamma = \max_{a \in AB} \sum_T r(a) - \sum_T r(a_B^t)$

- **Using loss function l(a), we revise Γ**
  - **Revised regret Λ with loss function *l*(.)**

    $\Lambda = \sum l\,(a_B^t) - \min_{a \in AB} \sum l\,(a)$

- **Loss version is equivalent to reward version Γ**
  - **But provides *adversarial view* as if:**

    "Red-force alters potential loss for Blue-force over time, revealing only $l^t(a_B^t)$ at time t"

New Optimization Goals

- **Find best Blue-force action that minimizes Λ over time**

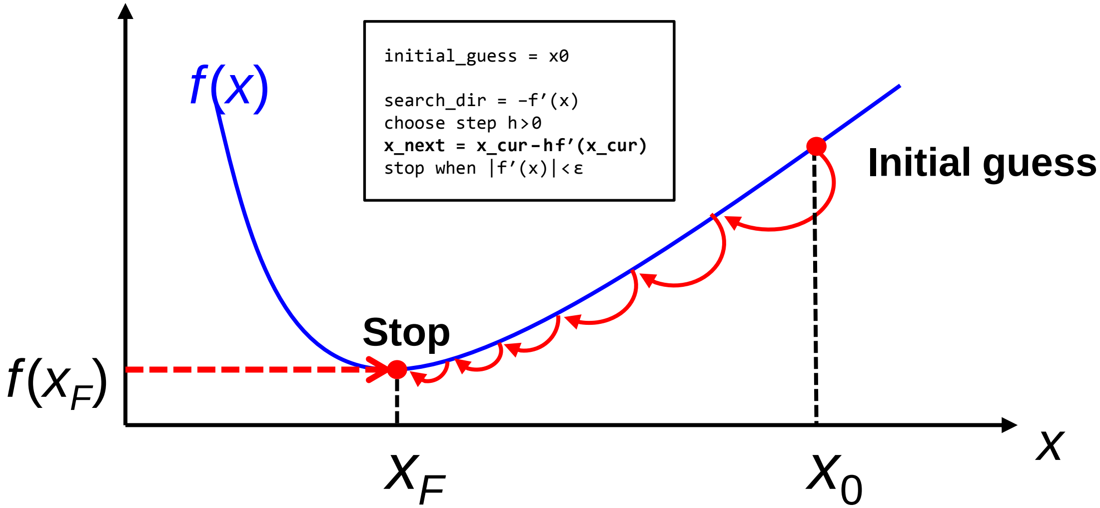
  $a^* = \arg\min_a \sum l^t(a_B{}^t) - \min_{a \in AB} \sum l^t(a)$

- **It's critical to estimate $l^t(.)$ accurately for new optimization**
  - **$l(.)$ evolves over t, and intelligent adversary makes it difficult to estimate**

Our Approach: Online Convex Optimization

- If $l^t(.) \in$ convex set, optimal regret bound can be achieved by online convex programming [Zinkevich'03]
  - Underlying idea is gradient descent/ascent

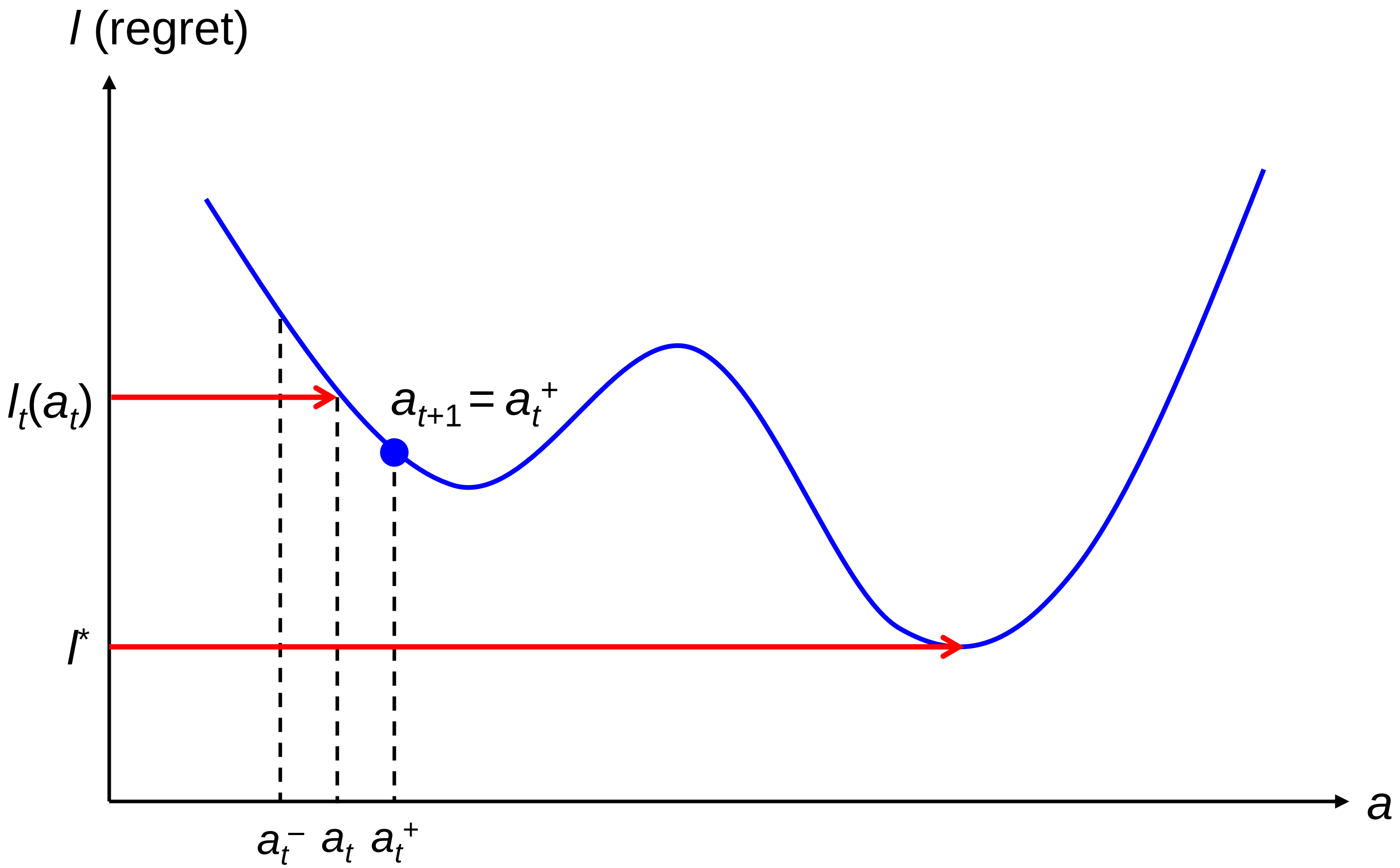
- What is gradient descent?
  - Find minima of loss by tracing estimated gradient (slope) of loss



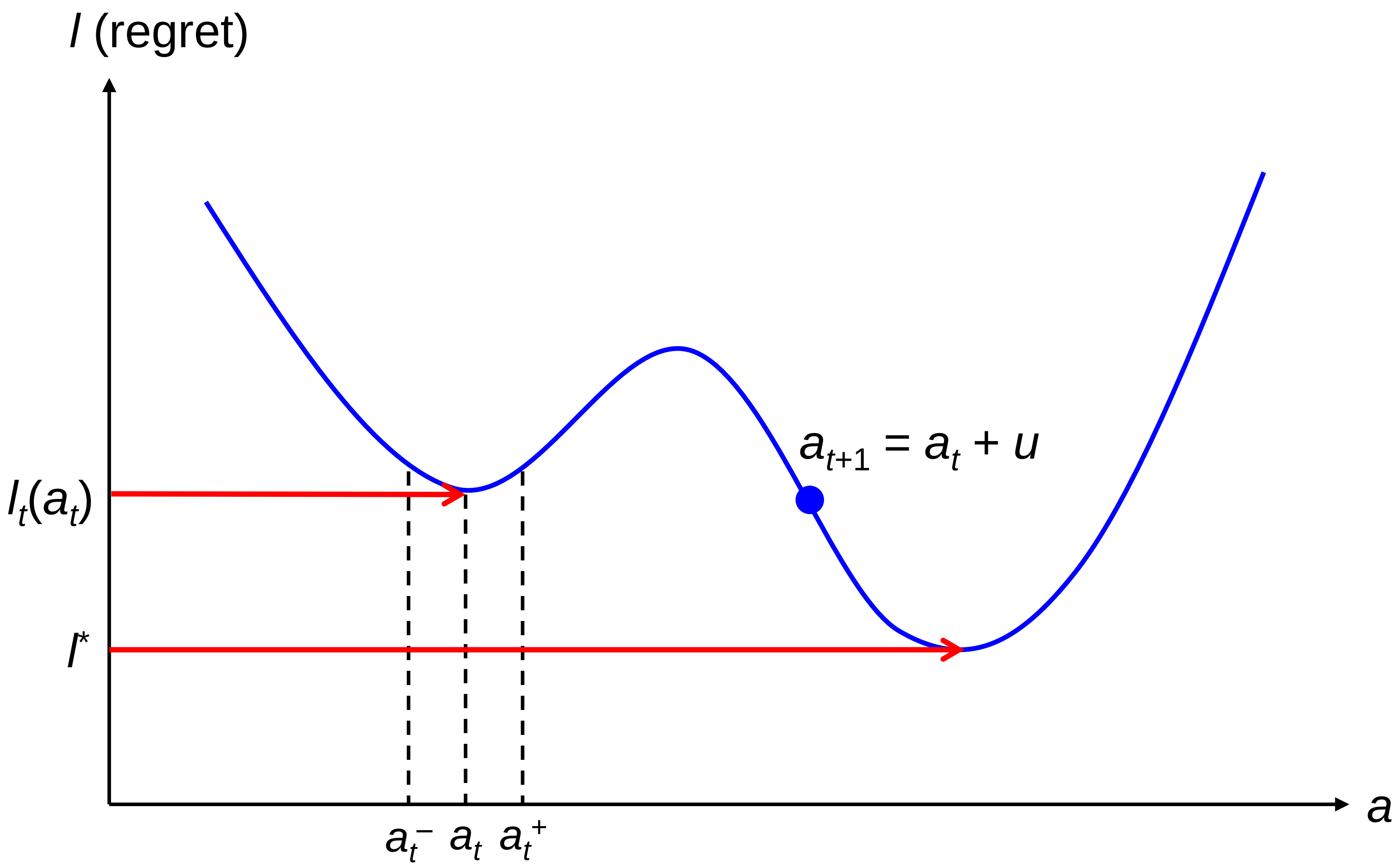
Our New Algorithm: Fast Online Learning

- **Sketch of key ideas**
  - **Estimate expected loss function for next time**
  - **Take gradient that leads to minimum loss iteratively**
  - **Test if reached minimum is global or local**
  - **When stuck at inefficiency (undesirable local min), use escape mechanism to get out**
  - **Go back and repeat until convergence**

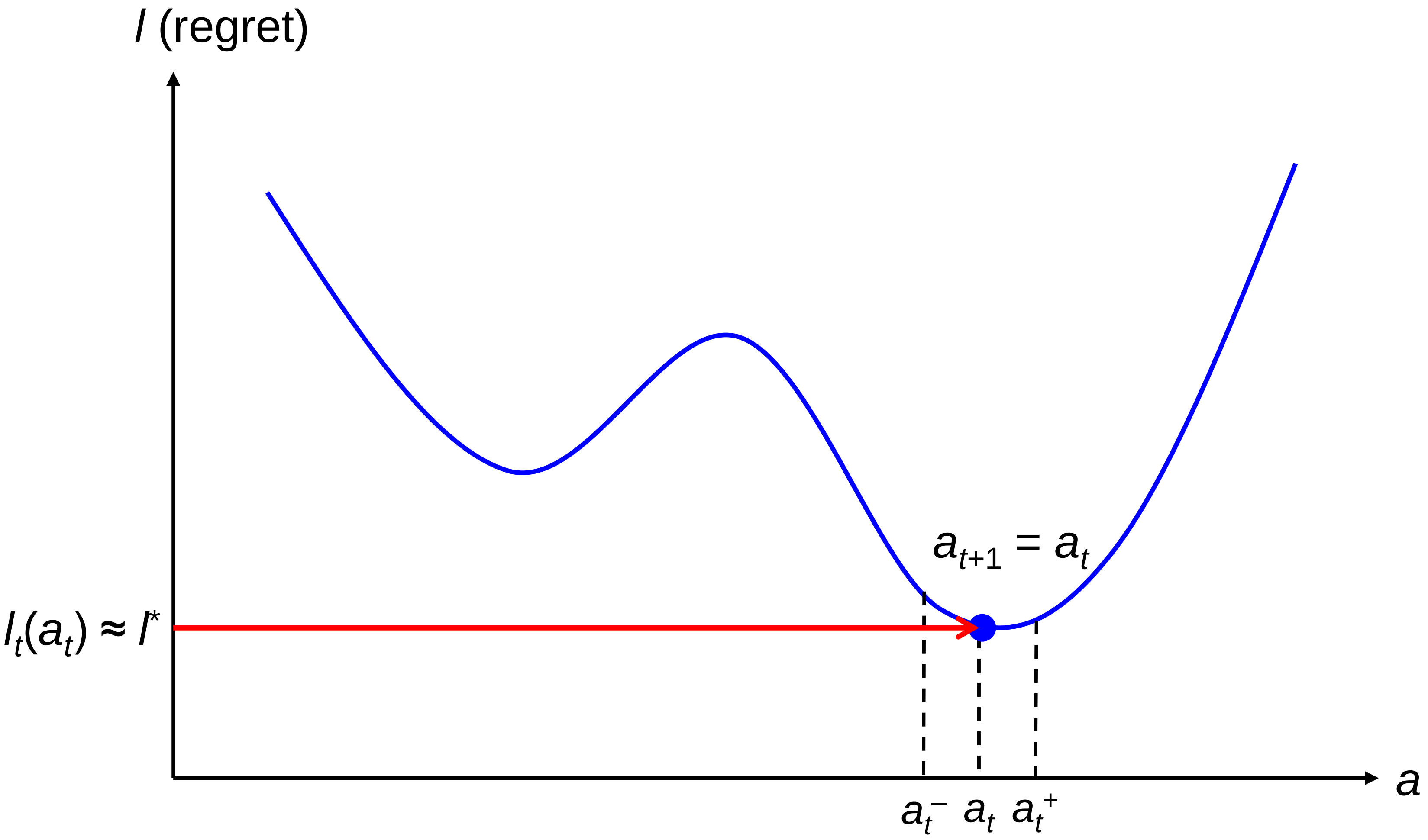
New Algorithm Explained (1)



New Algorithm Explained (2)



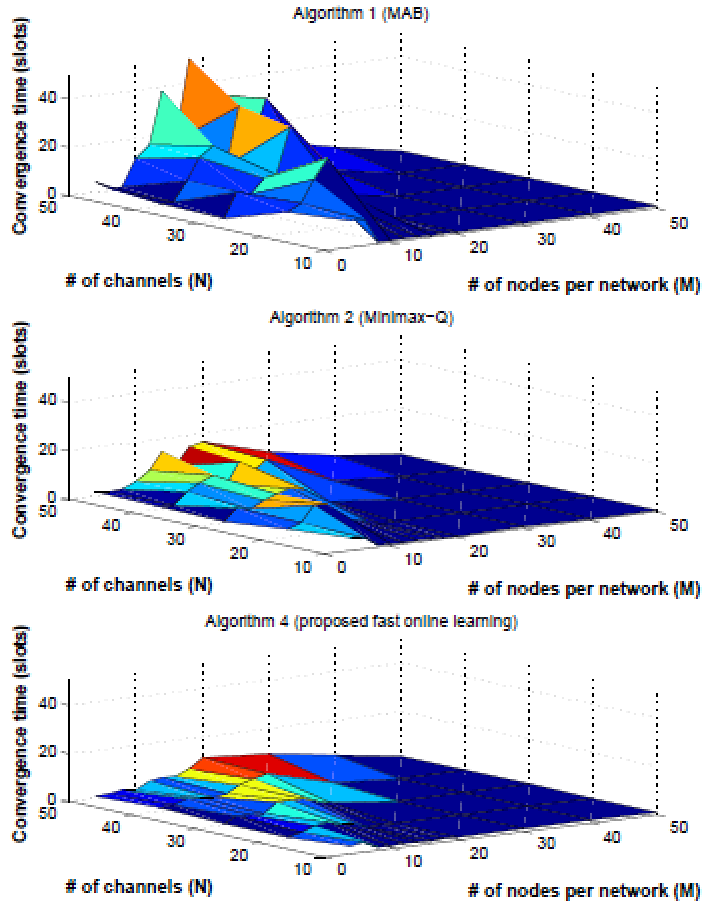
New Algorithm Explained (3)



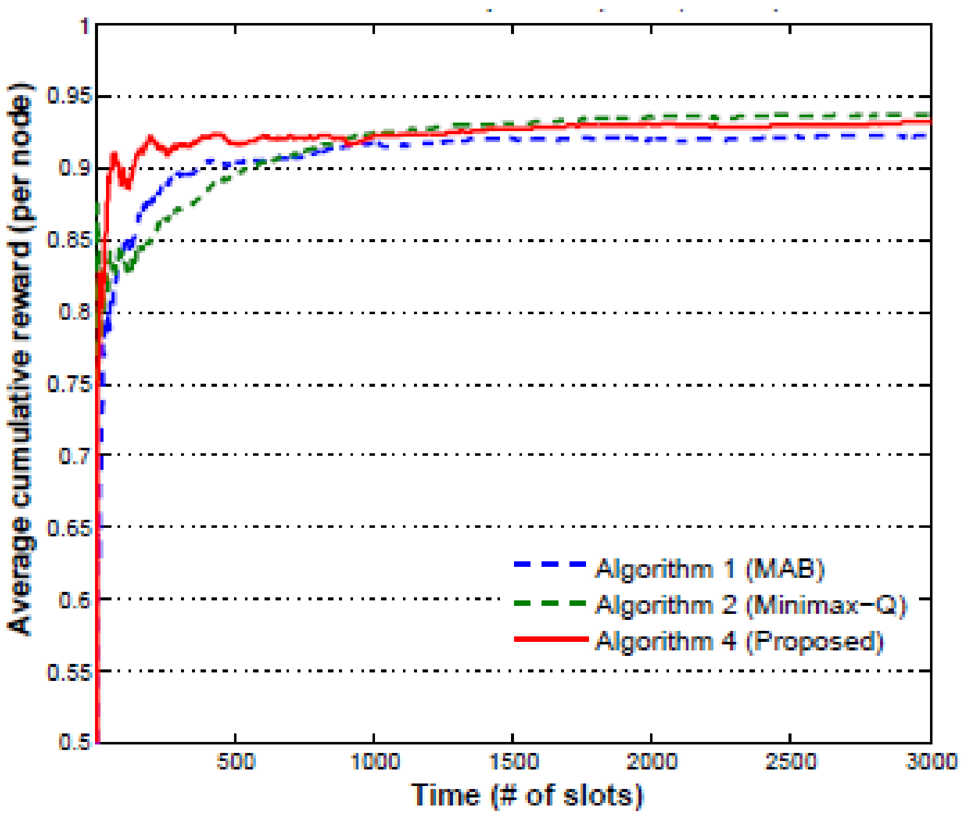
Evaluation

- Wrote custom simulator in MATLAB
  - Simulated spectrum with N = 10, 20, 30, 40, 50 channels
  - Varied number of nodes M = 10 to 50
    - Number of jammers in M total nodes varied 2 to 10
  - Simulation duration = 5,000 time slots
- Algorithms evaluated
  1. MAB (Blue-force) vs. random changepoint (Red-force)
  2. Minimax-Q (Blue-force) vs. random changepoint (Red-force)
  3. Proposed online (Blue-force) vs. random changepoint (Red-force)
- All algorithmic matchups in centralized control

Results: Convergence Time



Results: Average Reward Performance (N = 40, M = 20)



New algorithm finds optimal strategy much more rapidly than MAB and Q-learning based algorithms

Summary

- **Extended Competing Cognitive Radio Network (CCRN) to harder class of problems under nonstochastic assumptions**
  - **Random changepoints for enemy channel access & jamming strategies, time-varying channel reward**
- **Proposed new algorithm based on online convex programming**
  - **Simpler than MAB and Q-learning**
  - **Achieved much better convergence property**
  - **Finds optimal strategy faster**
- **Future work**
  - **Better channel activity prediction can help estimate more accurate loss function**

Support Materials

Proposed Algorithm

Algorithm 4 (CCRN online gradient descent learning)

choose a^1 randomly
while $t \geq 1$
  execute a^t and observe r^t
  compute $\hat{l}^t(a^t)$
  if $|l^* - \hat{l}^t(a^t)| < \epsilon$
    $a^{t+1} := a^t$
    continue
  end
  $a_-^t := a^t - \delta_-$ such that $\|a^t\|_0 = \left\|a_-^t\right\|_0$
  $a_+^t := a^t + \delta_+$ such that $\|a^t\|_0 = \left\|a_+^t\right\|_0$
  $\nabla \hat{l}^t := \min\{\hat{l}^t(a_-^t), \hat{l}^t(a_+^t)\}$
  if $\nabla \hat{l}^t < \hat{l}^t(a^t)$
    $a^{t+1} := \arg\min_{x \in \{a_-^t, a_+^t\}} \hat{l}^t(x)$
  else
    $a^{t+1} := a^t - w + u$
  end
end

Channel Activity Matrix, Outcome, Reward, State (1/2)

- **Example: there are two comm nodes and two jammers for each BF and RF network**
  - **BF uses channel 10 for control, RF channel 1**

- **At time *t*, actions are the following**
  - $A_B^t = \{a_{B,comm} = [7\ 3],\ a_{B,jam} = [1\ 5]\}$
    - $a_{B,comm} = [7\ 3]$ **means BF comm node 1 transmit at channel 7, and comm node at 2 channel 3**
  - $A_R^t = \{a_{R,comm} = [3\ 5],\ a_{B,jam} = [10\ 9]\}$

- **How to figure out channel outcomes, compute rewards, and determine state?**
  - **Channel Activity Matrix**

Channel Activity Matrix, Outcome, Reward, State (2/2)

CH	Blue Force		Red Force		Outcome	Reward	
	Comm	Jammer	Comm	Jammer		BF	RF
1	–	Jam	–	–	BF jamming success	+1	0
3	Tx	–	Tx	–	BF & RF comms collide	0	0
5	–	Jam	Tx	–	BF jamming success	+1	0
7	Tx	–	–	–	BF comm Tx success	+1	0
9	–	–	–	Jam	RF jamming fail	0	0
10	–	–	–	Jam	RF jamming success	0	+1