EARS: Providing Predictable Service and Spectrum Access With Realtime Decision in Cognitive Multihop Wireless Networks

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Outline

- Coexistence of ZigBee and WiFi
- Decentralized Channel Access in Multihop Networks

ZIMO: Cross-Technology MIMO to Harmonize Coexistence of ZigBee with WiFi without Intervention

Results published at ACM MobiCom 2013

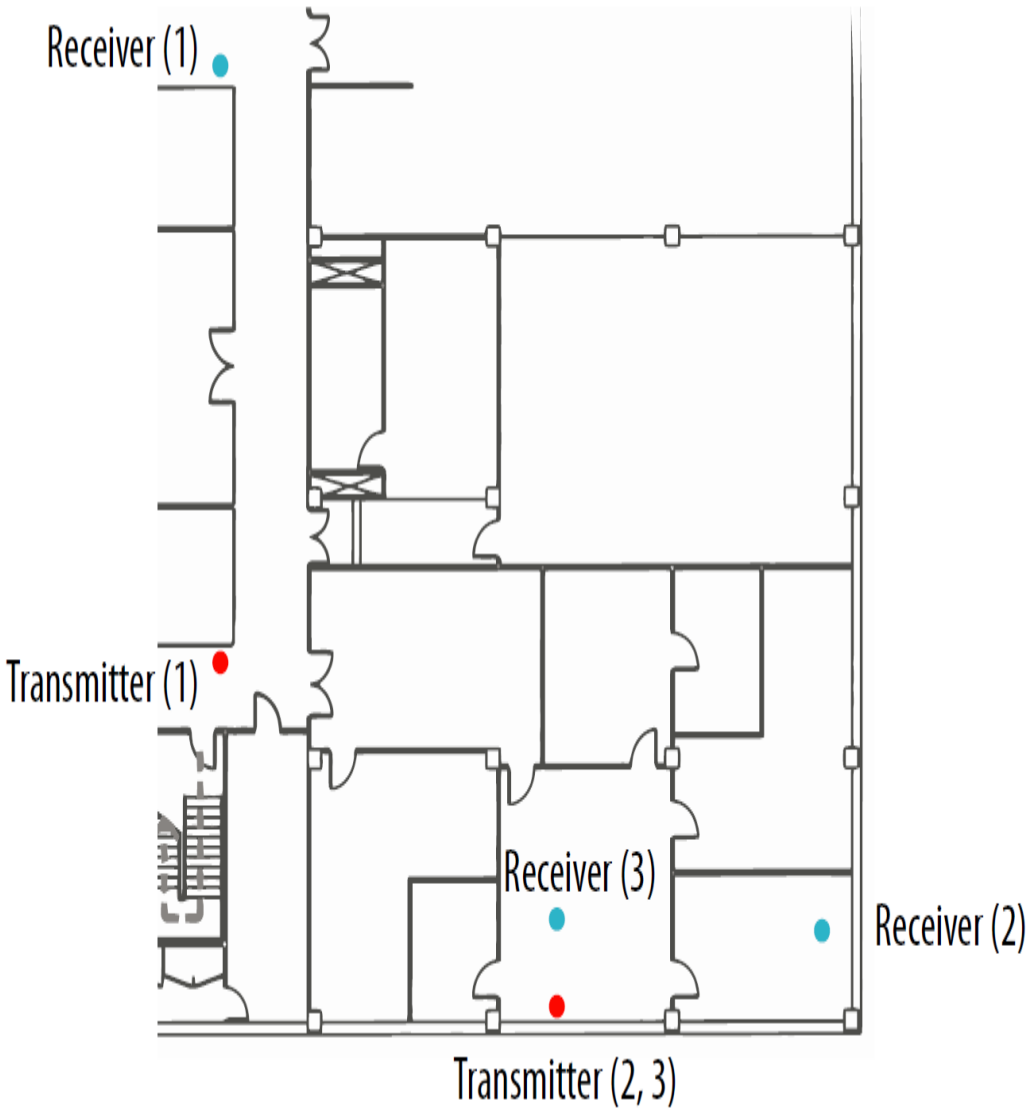
Coexistence in ISM Band

ISM band interferences are pervasive and crowded
WiFi signal is the primary and first class passenger

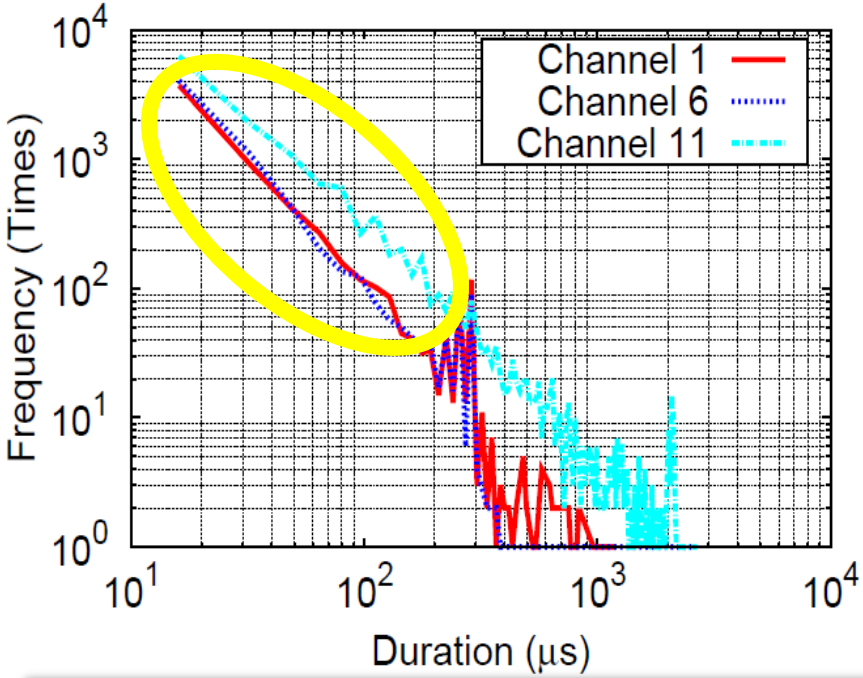
- Existing Works mainly protect WiFi signal and mitigate cross technology interference [TIMO]
- Some ZigBee signal protection works need modifications or degrade WiFi [Sensys10, Liang]

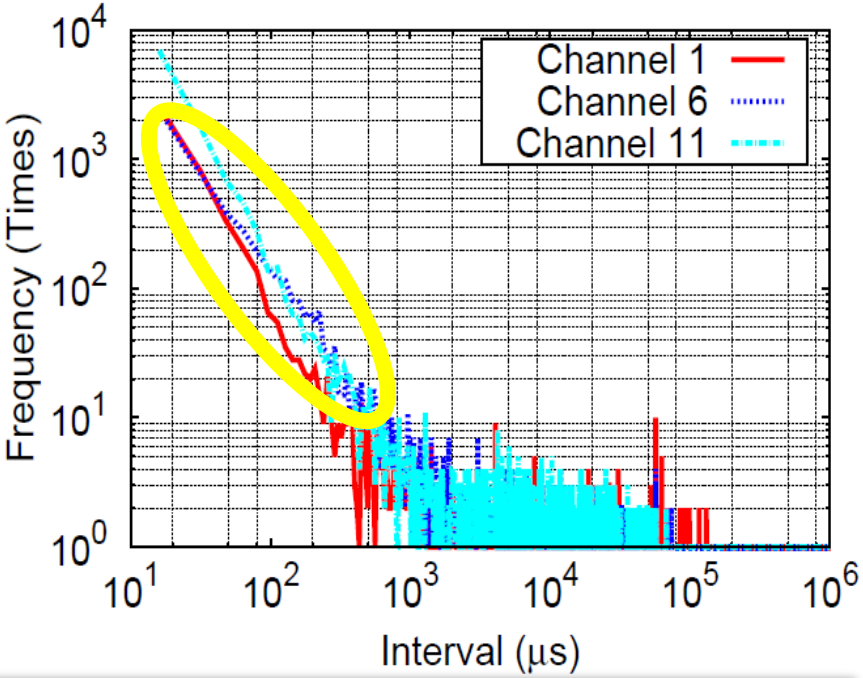
Experiment Setup

- Two ZigBee Nodes (TX&RX)
- WiFi APs are in IIT campus
- ZigBee nodes are configured to receive full spectrum interference in full time scale
- Adding controllable AP for tunable interference



Effect of WiFi interference on ZigBee

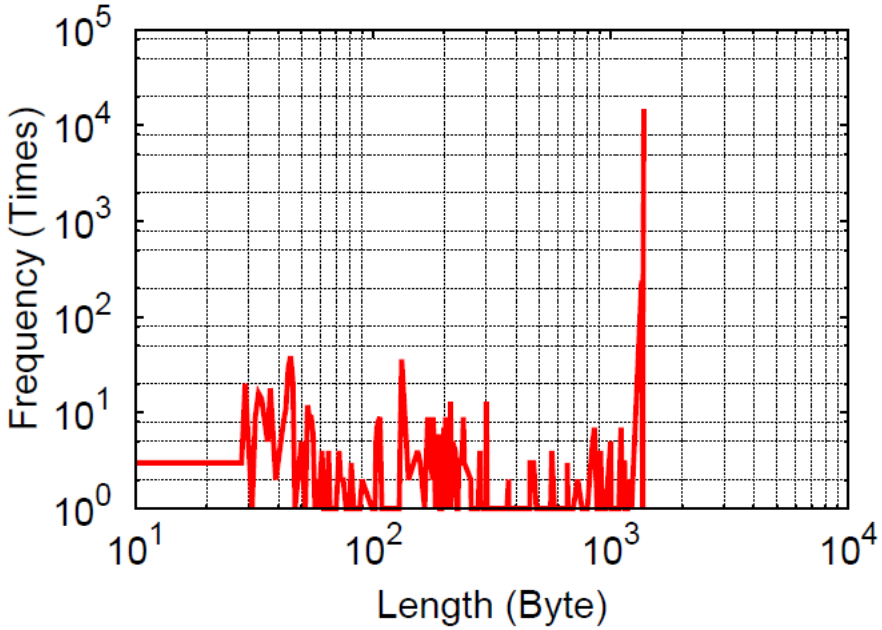




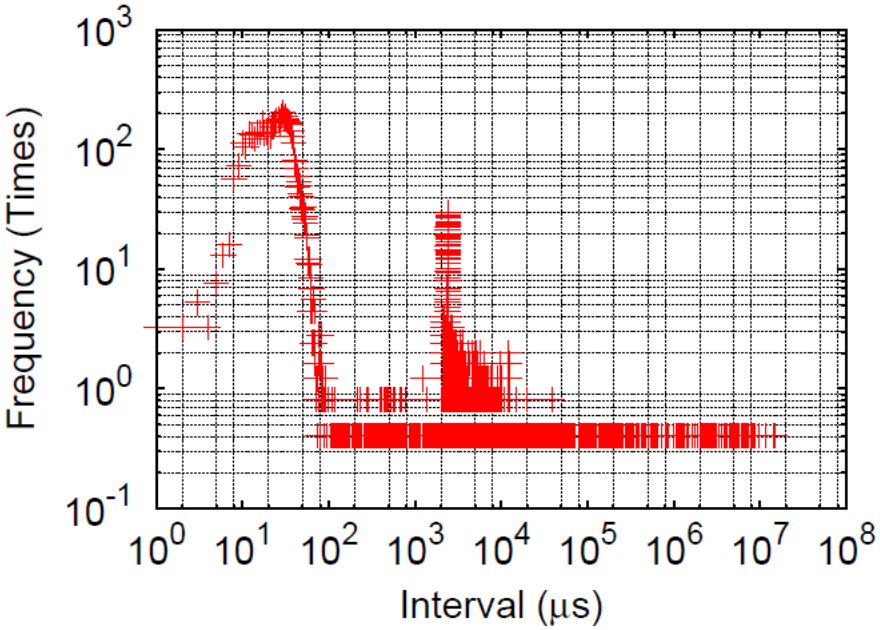
✓Short and frequent WiFi data transmission (i.e., flash) play the main role of WiFi interference on ZigBee.

✓Power-law like distribution indicates the shorter flashes interfere ZigBee signal with exponentially increasing probability, which is a drastic threat for ZigBee signal.

Effect of WiFi interference on ZigBee



(a) Length statistics



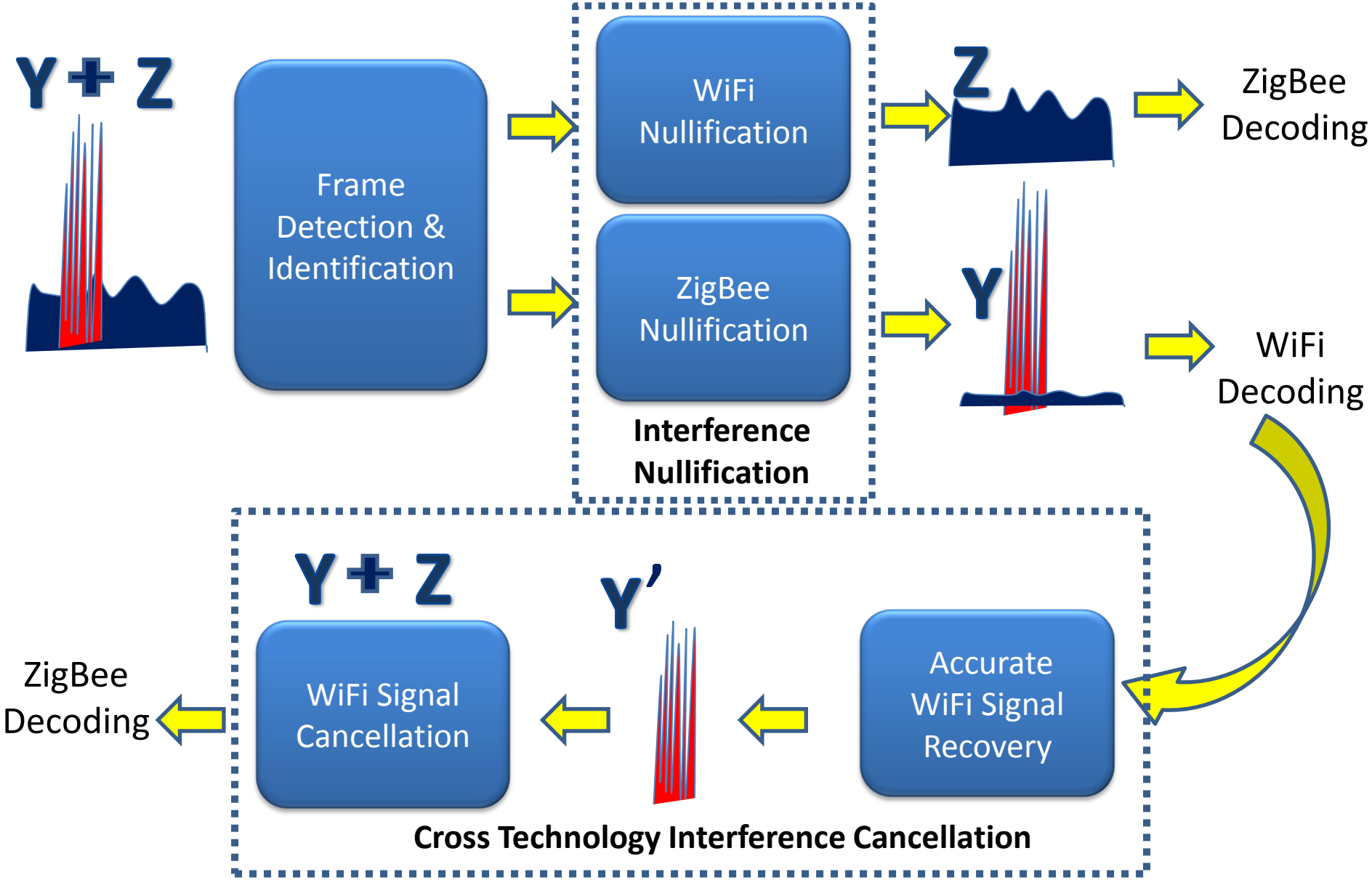
(b) Interval statistics

- ✓ The WiFi interference is distributed across ZigBee symbols, rather than concentrated on particular positions.
- ✓ We need to resort to the signal processing techniques for fundamental solutions.

ZIMO: Sink Based Design

Cons No.1: ZIMO has more antennas than WiFi AP (N+1)
Cons No.2: ZIMO needs at least one preamble is clear
Cons No.3: Can work with one ZigBee and multiple WiFi

How ZIMO works?



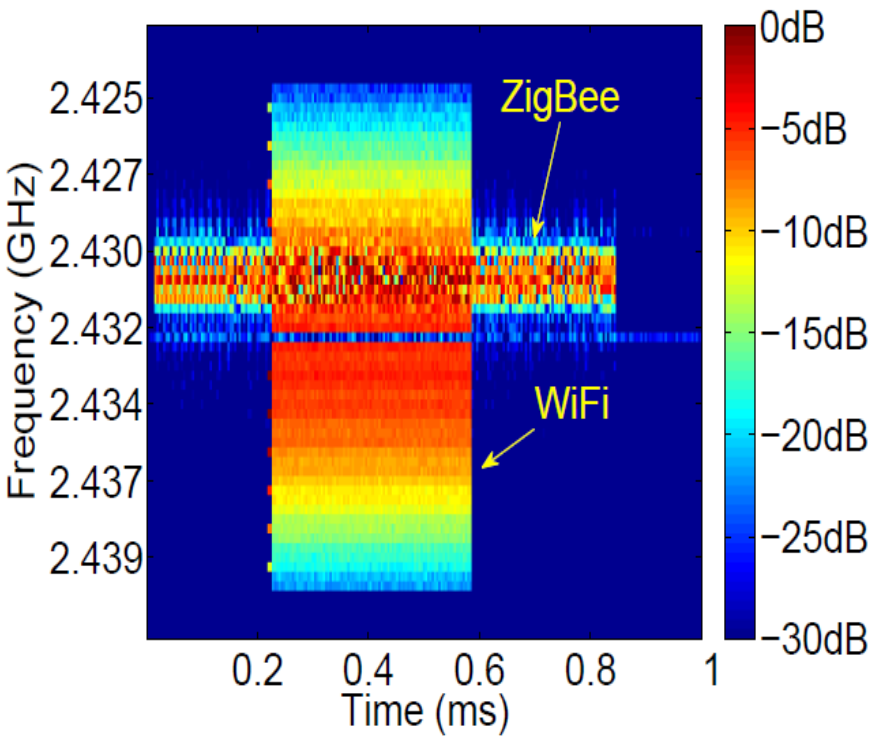
Main challenge: accurate WiFi signal recovery

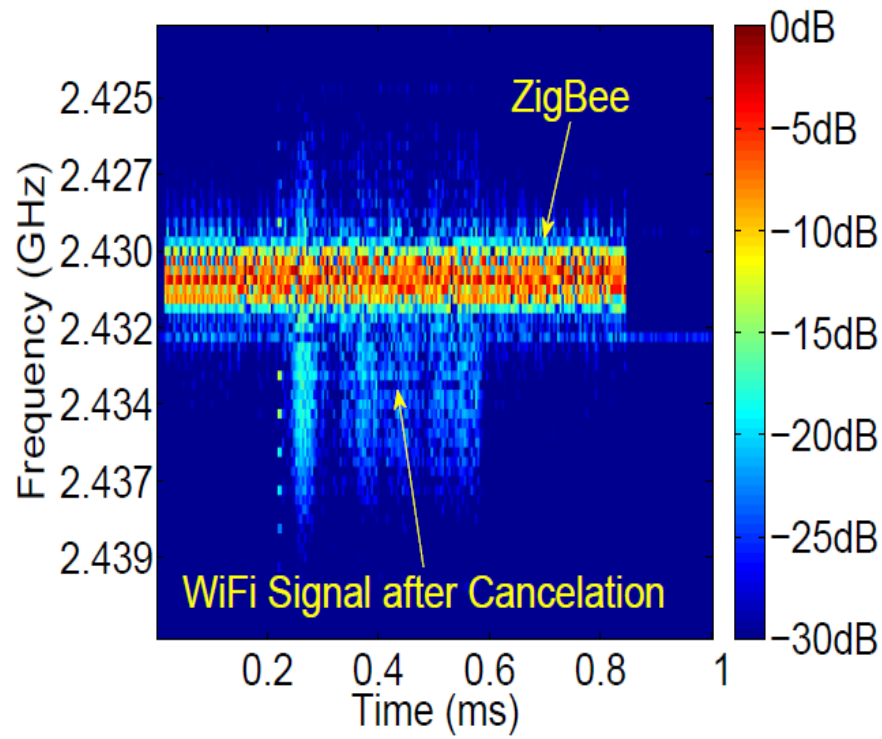
- Channel Coefficient Recovery
  - Interference in frequency domain
  - Sufficient for decoding, insufficient for accurate signal recovery

- CFO Compensation
  - Well done for preamble, insufficient for whole data scale
  - Extremely large with the increasing packet length

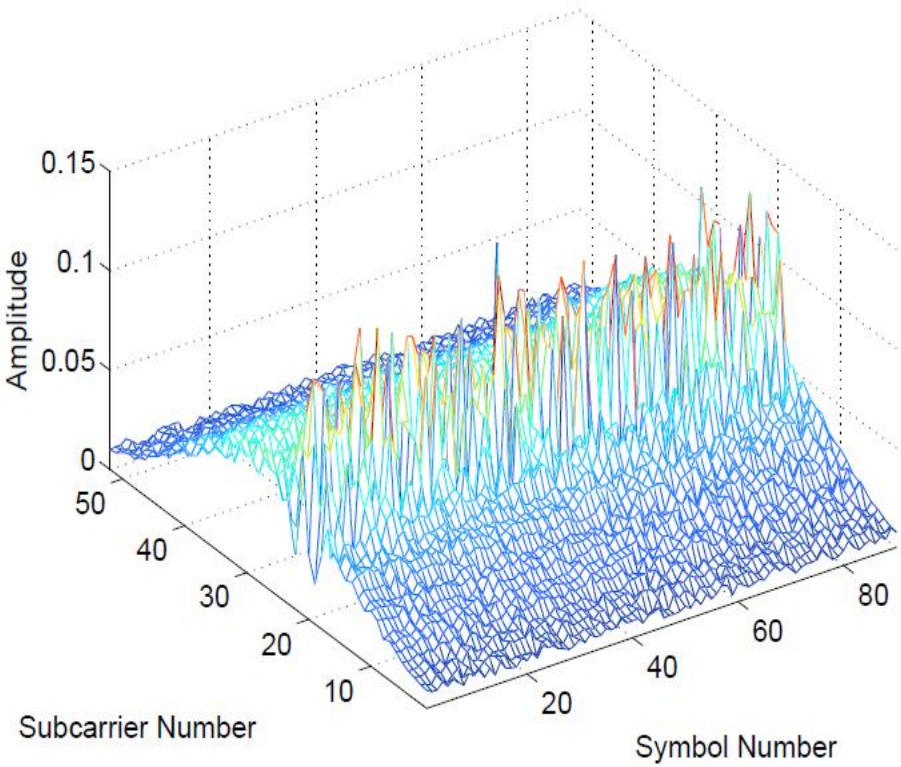
Where is the opportunity?

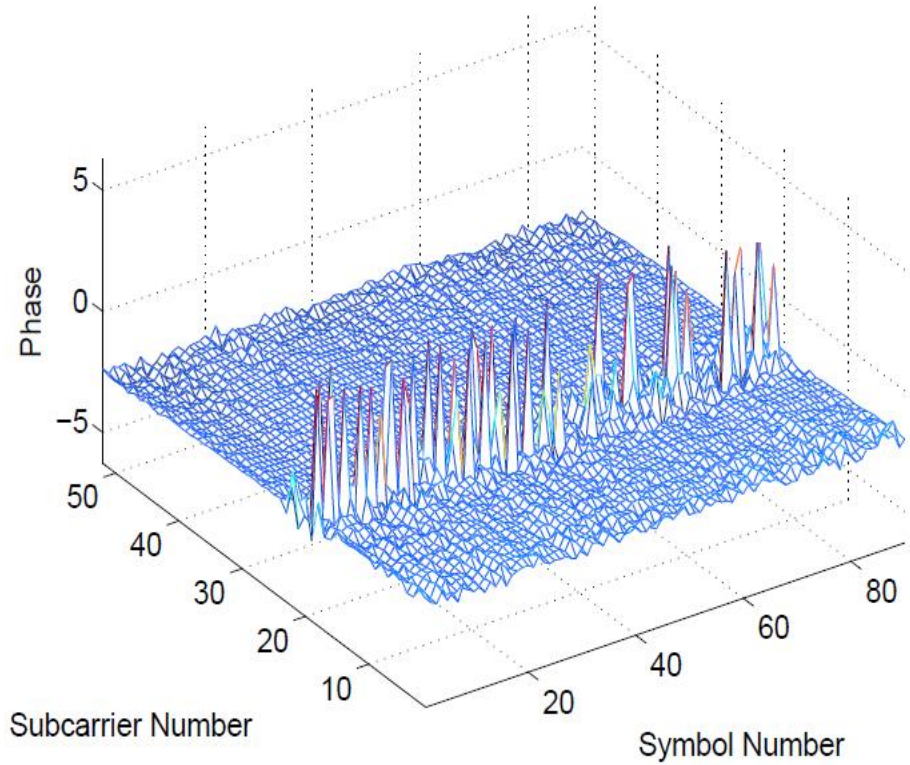
- Frequency domain is partially overlapped
- Time domain also partially overlapped
- Power domain shows significant difference





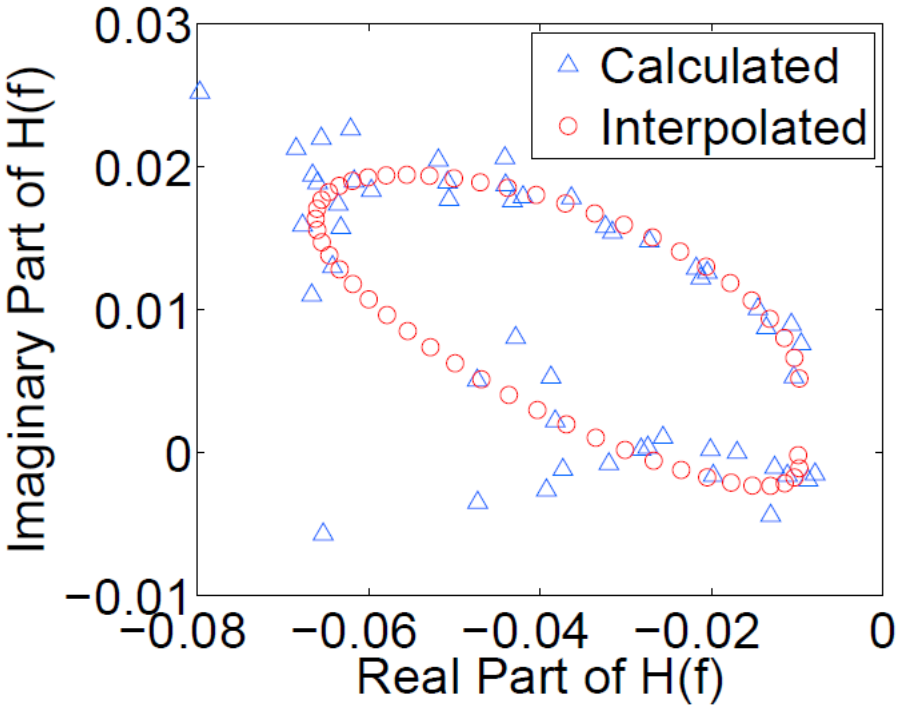
Where is the opportunity?

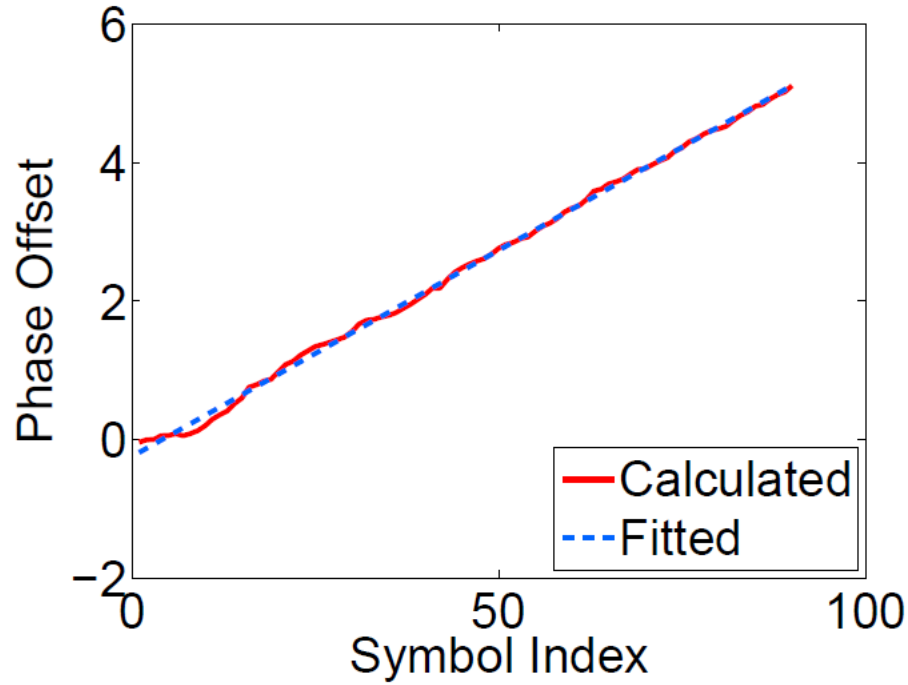




For channel coefficient: Interpolation is simple, effective

Where is the opportunity?

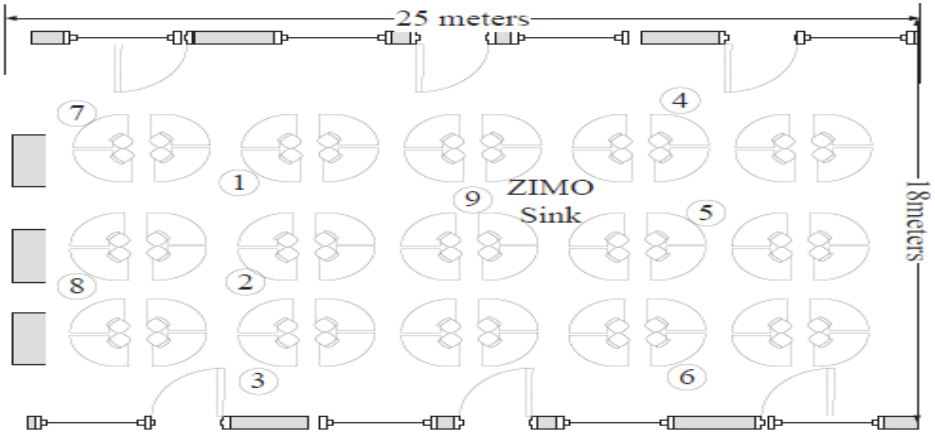




CFO

Linear regression is accurate enough for CFO

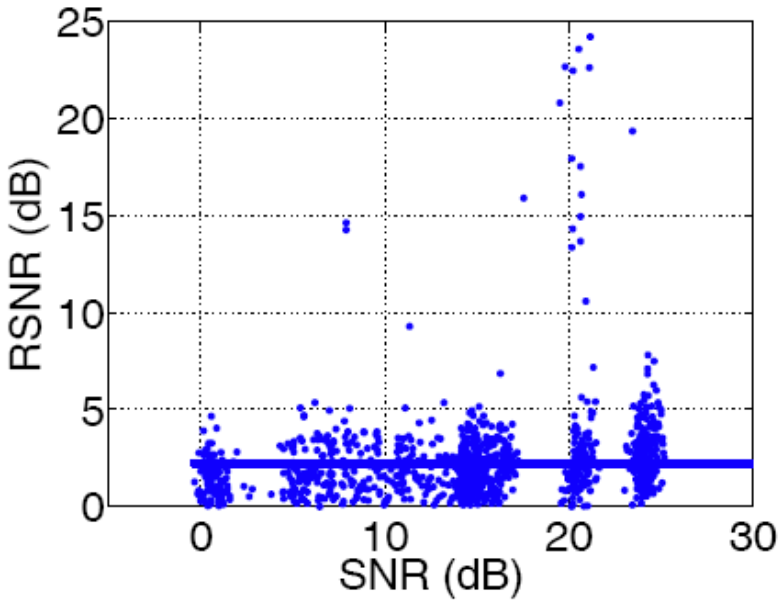
Implementation



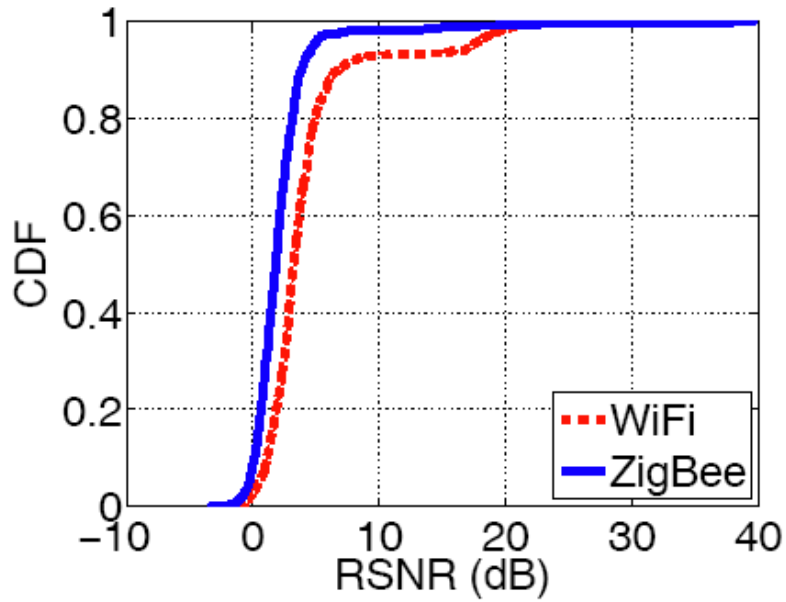
- Implement using USRP2 N200
- IEEE STD 802.15.4, 2 MHz Bandwidth
- OFDM is 20 MHz Bandwidth
- Real trace driven ZIMO decoding
- No carrier sense and MAC timing control

Experimental Results: Micro Benchmark

- Zigbee IN and IC



(a) RSNR across different SNR values

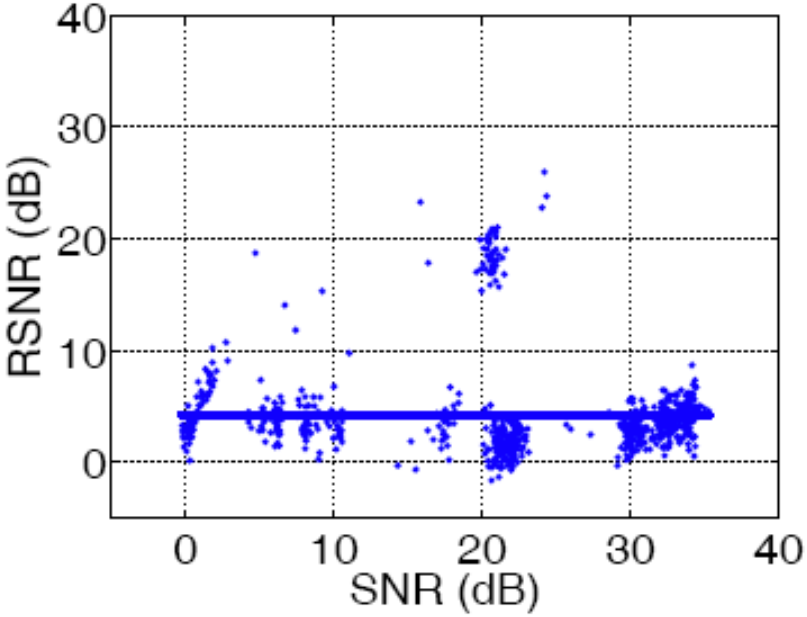


(b) CDF of RSNR, with ZigBee & WiFi signals

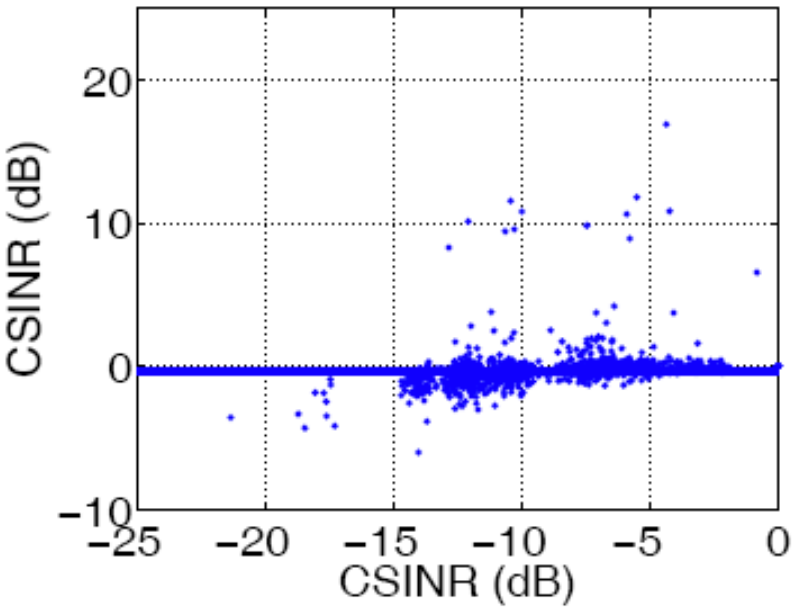
RSNR=(I+N)/N

Experimental Results: Micro Benchmark

- WiFi IN and IC



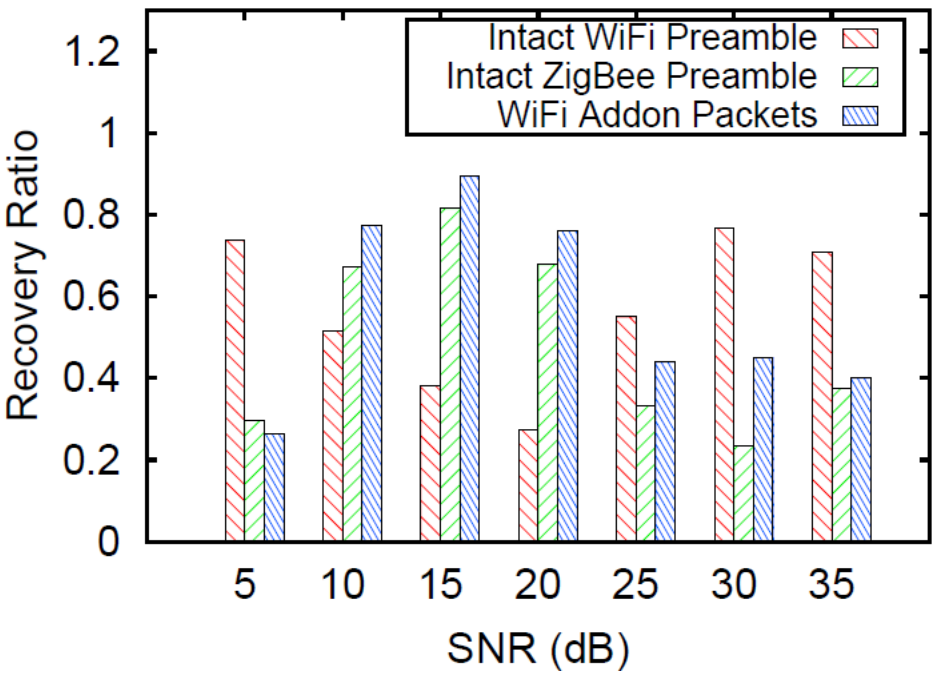
(a) RSNR of WiFi Nullification

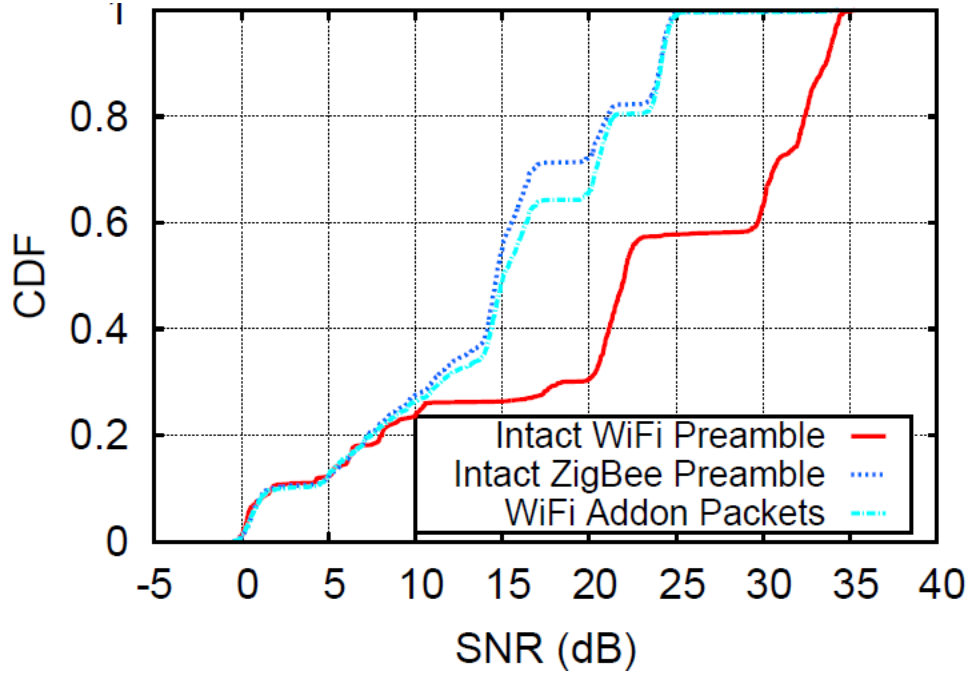


(b) CSINR of WiFi Cancelation

Experimental Results: Macro Benchmark

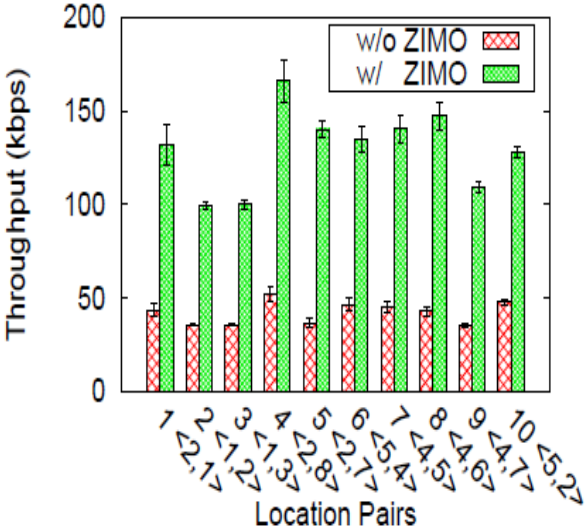
- Recovery ratio



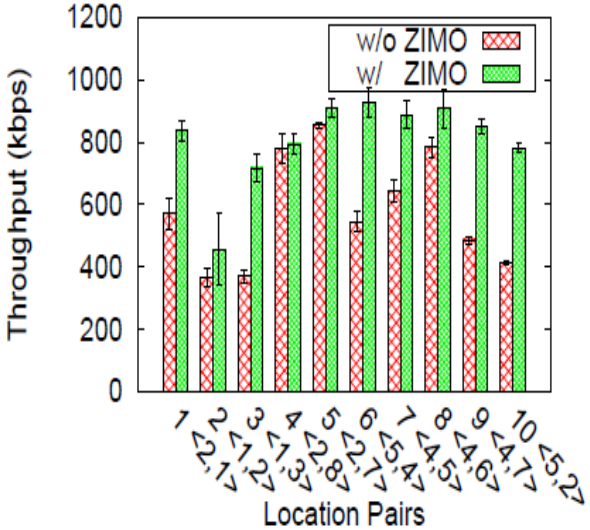


Experimental Results: Macro Benchmark

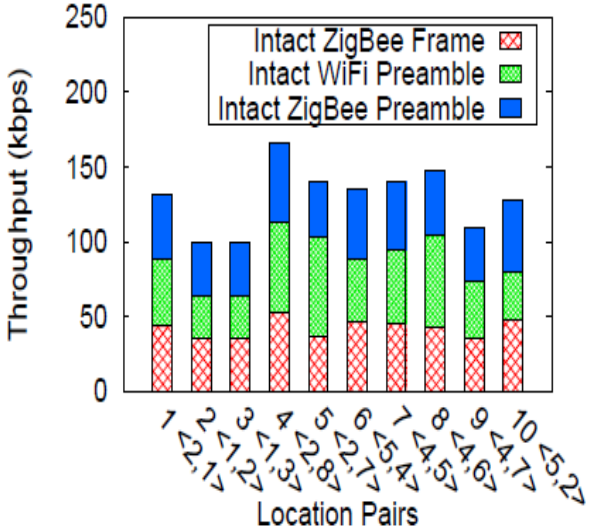
- Throughput



Zigbee Baseline



WiFi Baseline

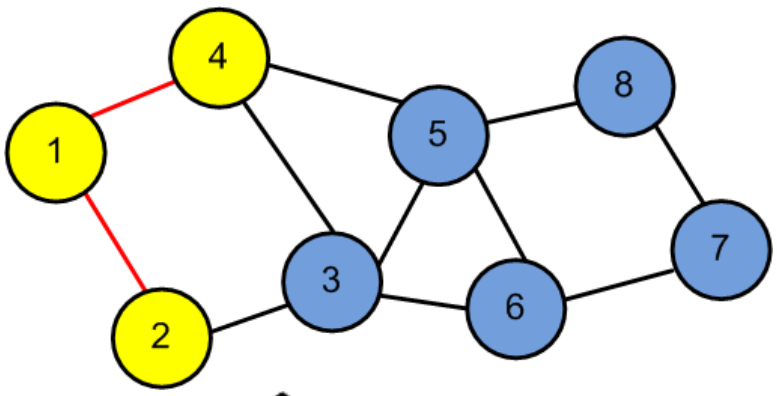


Interference patterns

Decentralized Learning for Multihop Wireless Networks

Results submitted for publication

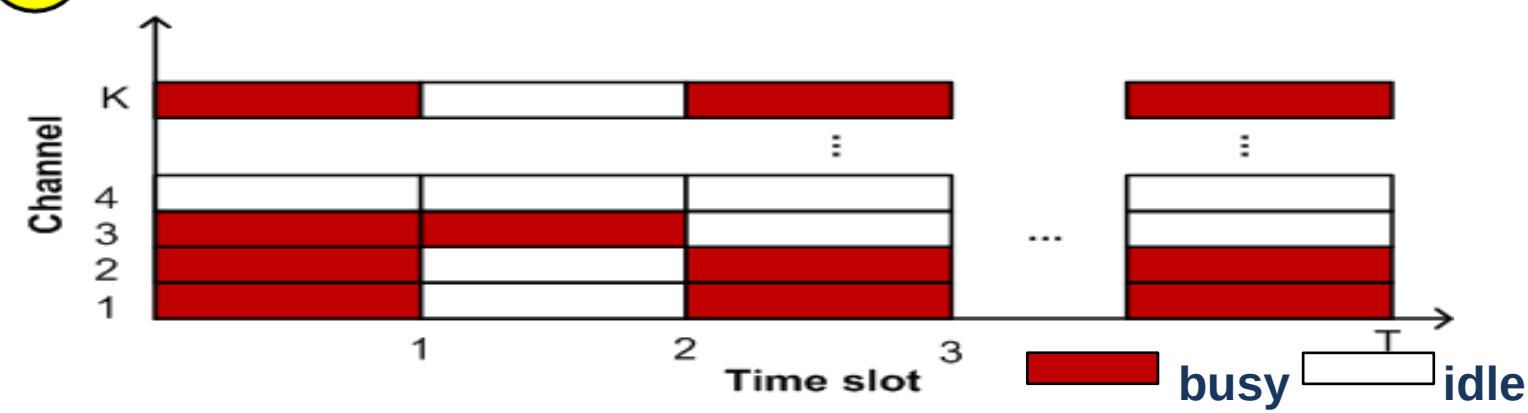
Distributed Dynamic Channel Access



General Conflict

in multihop CRN with

***M* SU and *N* channels**

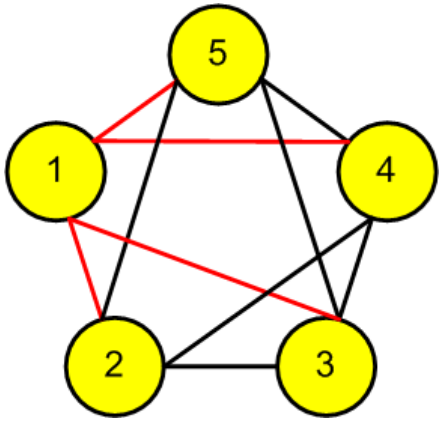


- Time is slotted
- Unknown dynamic channel availability and quality
- Each node decides which channel to use at each time slot

Approach: Online Learning

- **MAB formulation: multi-armed bandit problem**
- **Learning is based on tradeoff between**
  - Exploration of choices that might have higher gain
  - Exploitation of choices that did well in the past
- **The optimal static policy**
  - This is a choice with the best average reward
- **Regret**
  - Reward difference between the learning policy and the optimal static policy
  - zero regret if it is sublinear with time
    - UCB, epsilon-greedy for stochastic rewards
    - Exp3 for adversarial rewards

Classic MAB Formulation Fails



Complete Conflict

in MAB with multi-users

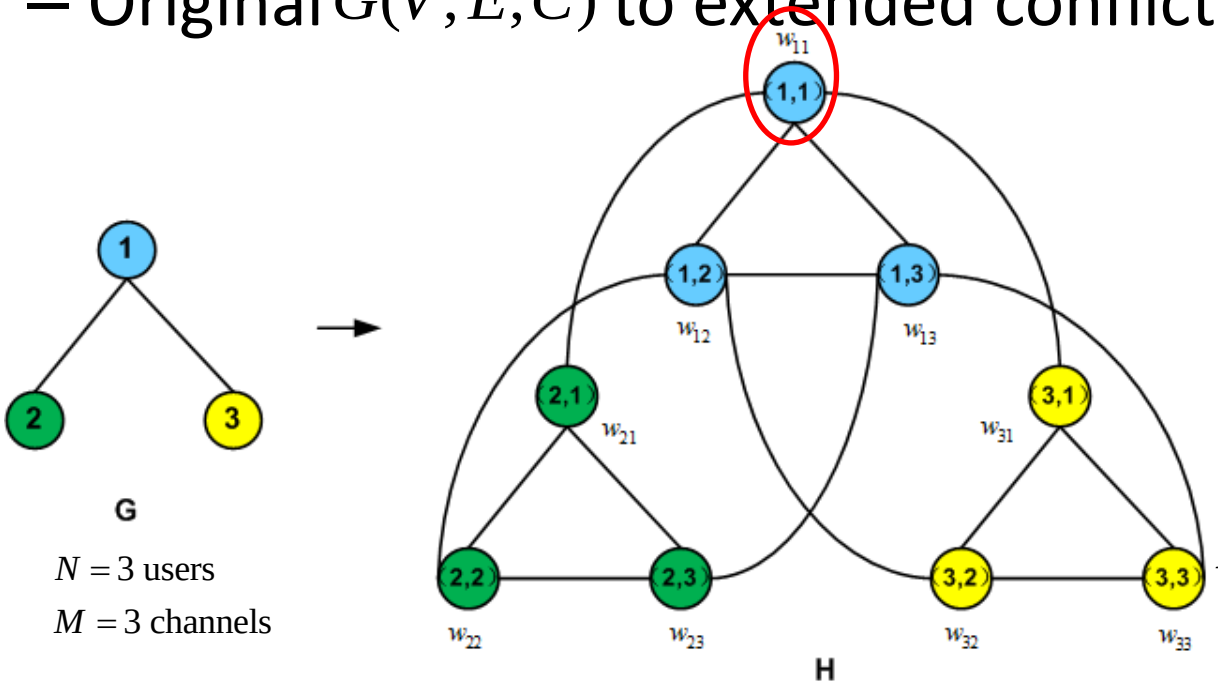
Only single-hop CRN fits

(distributed MAB, Liu, Zhao, 2010)

- **If adopt simple MAB formulation,**
  - Exponential regret $O(M^N)$
  - Exponential computation/storage complexity
- **More practical challenges**
  - Efficient distributed implementation with low cost

Our Formulation

- **Remodel network conflict graph**
  - Original $G(V,E,C)$ to extended conflict graph $H(\tilde{V},\tilde{E})$



v_{ij}, associated with weight w_{ij} that is quality of channel c_j observed by user v_i

$K = N \times M = 9$ vertexes

The optimal static solution is to find an MWIS in H where weight is mean of channel quality.

Linearly Combinatorial MAB Formulation

- **As channel quality is unknown, we have to**
  - Find MWIS by learning weight of each vertex
- **Challenge**
  - Existing results on regret heavily depends on the distribution of strategies, i.e., $\Delta_{\min}$

$$\mathbb{R}(n) \to \infty, \text{ if } \Delta_{\min} \to 0$$

  - Here $\Delta_{\min}$ is the reward difference between the best and second best strategy set.

Gai, Krishnamachari, Jain, IEEE/ACM Transaction on Networking, 2012

Distribution-free Learning Policy

- **For each round *t*, select a strategy s_x that**

$$\mathbf{s}_x = \arg\max_{\mathbf{s}_x \in F} \sum_{s_{x,i} \in \mathbf{s}_x} \left(\tilde{\mu}_{s_{x,i}}(t) + \sqrt{\frac{\max(\ln \frac{t^{2/3}}{K m_{s_{x,i}}}, 0)}{m_{s_{x,i}}}} \right) \quad (1)$$

estimated weight $w_{s_{x,i}}$

- **For NP-hard problem in (1),**
  - **Design β-approximation method**
  - **distribution-free,**
  - **β-zero-regret: OPT/β – learningPolicy =o(t)**

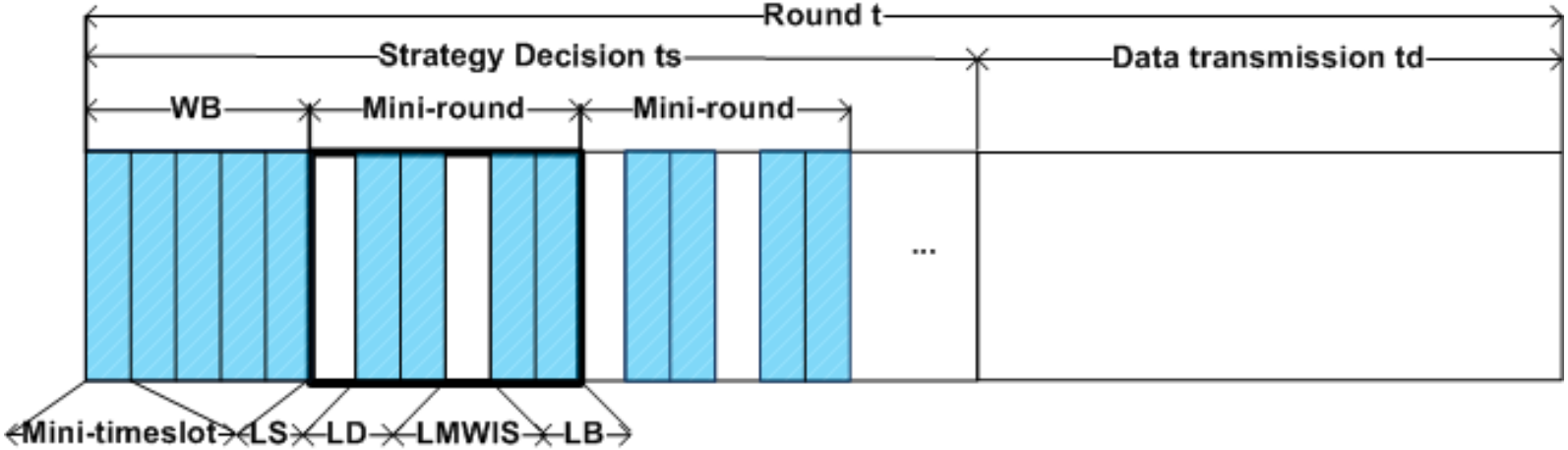
Distribution-free Learning Policy

- **For NP-hard problem in (1), we prove that**
  - **Our learning policy results distribution-free, β-zero-regret for any β-approximation method for MWIS, if β>ω(1/n$^{1/12}$)**

$$\sup \mathrm{R}_{\beta}(n) \le \frac{1}{\beta} NK + \left(\sqrt{eK} + \frac{16}{e\beta}(1+N)N^3 \right) n^{\frac{2}{3}} + \frac{1}{\beta}\left(1 + \frac{4\sqrt{K}N^2}{e\beta^2} \right) N^2 K n^{\frac{5}{6}}$$

Distributed Implementation

- **Overview**
  - **Decision phase**
    - **Weight update,**
    - **Local leader selection, local leader declaration, local MWIS, local broadcast of MWIS ←repeat these constant rounds**
  - **data phase**

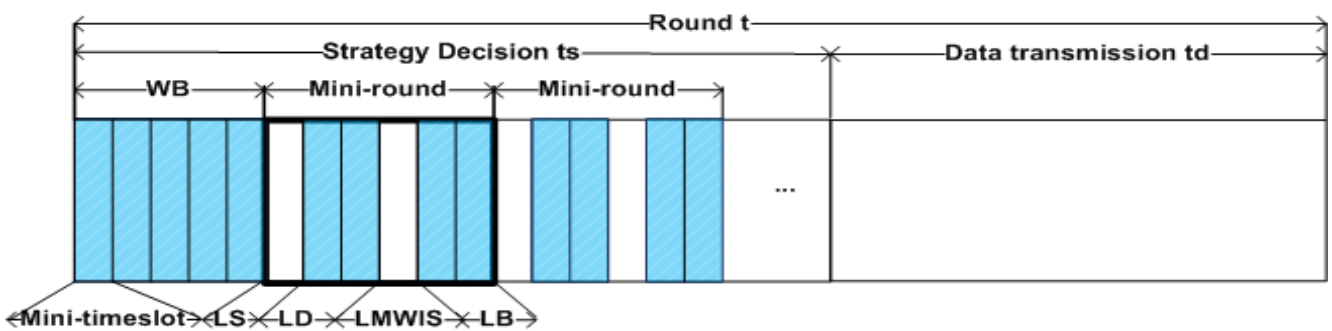


Theoretical results

- **Practical regret**
  - Consider missed throughput due to time spent on learning

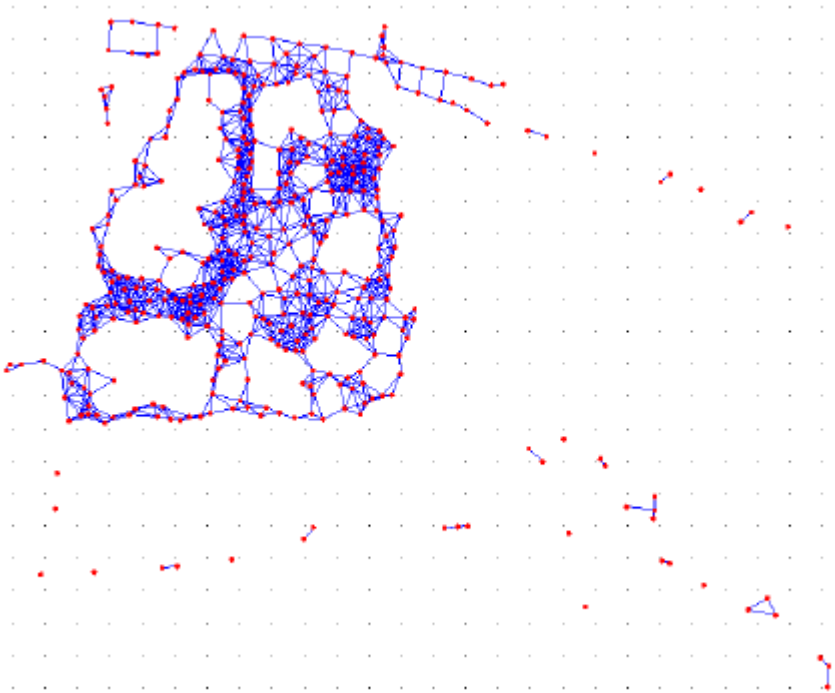
$$\sup \mathrm{R}_p(n) \le \frac{1}{\alpha} NK + \left(\sqrt{eK} + \frac{16}{e\alpha}(1+N)N^3 \right) n^{\frac{2}{3}} + \frac{1}{\alpha}\left(1 + \frac{4\sqrt{K}N^2}{e(\theta\alpha)^2} \right) N^2 K n^{\frac{5}{6}}$$

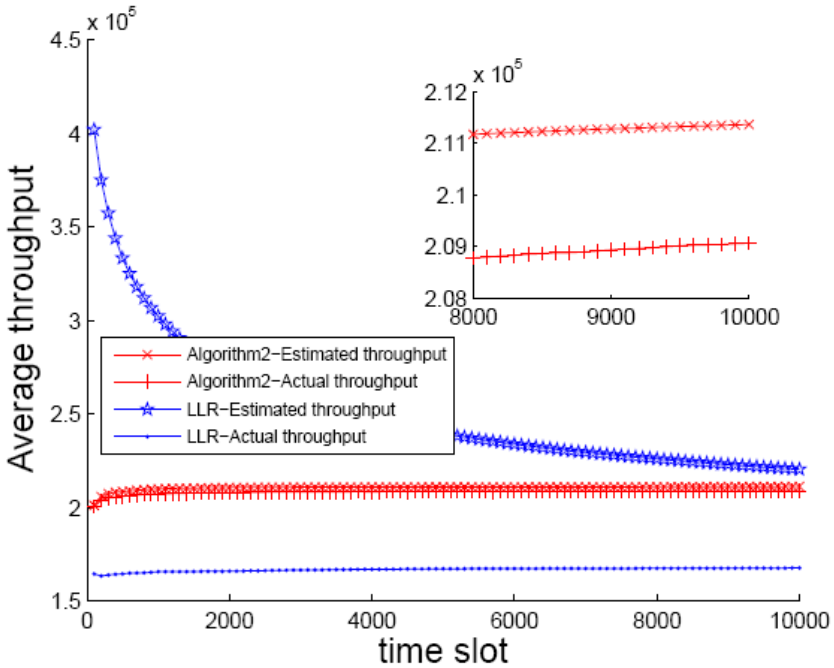
where $\theta = \frac{t_d}{t_s + t_d}$, and α is approximation ratio



Trace Driven Simulations

- CitySee network trace (1100 nodes deployed)





(c) 10 time slots every period

Thank you !

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