Learning from the Sky: Autonomous Flying access Networks for Beyond 5G

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Why flying access networks?

- Drone-as-a-relay, Drone-as-a-base station (≠ Drone-as-a-terminal)
- Flexibly adapts to time-varying channel conditions and traffic patterns
- Maintains good connectivity to both infrastructure and ground users

DaaR

- Hot-spots, sport events, flashcrowds

DaaR

- Range extension
- Disaster recovery

DaaB

- IoT data harvesting, smart city, agriculture, caching
Yet.. no lack of issues 😊

- **Regulatory**
  - Safety (for autonomous flight), privacy
- **Operational**
  - Max payload weight, battery autonomy, density of UAVs
- **Robotics**
  - Navigation control
  - Packaging (esp. micro-drone)
- **RF design**
  - Antenna design, RF coupling issues
- **Networking**
  - Handover
  - Intermittent connectivity
  - *interference issues*
- **UAV (self-)Placement**
Outline

- Introduction to placement problems
- Channel prediction
- Learning maps
- Using maps for UAV placement
- Perspectives
Placement-related problems

- Optimal position vs. path planning
- Off line vs. on line learning
- Single UAV vs. multiple UAVs
- Max throughput vs. fair QoS
- Finite user population vs. fluid models
- Mixed robotic-communication models (power usage, trajectory dynamics, etc.)
Path planning (IoT scenario)

\[
\max_{x(t), y(t)} \min \left\{ \int_{t=0}^{T} R_1(t)dt, \int_{t=0}^{T} R_2(t)dt, \ldots, \int_{t=0}^{T} R_K(t)dt \right\} \quad \text{(Max-min rate)}
\]

Subject to \( \sqrt{\dot{x}(t)^2 + \dot{y}(t)^2} \leq V \), \( t \in [0, T] \) \quad \text{(Velocity Constraint)}

\[
x(0) = x_0, y(0) = y_0, x(T) = x_F, y(T) = y_F \quad \text{(Start and end location)}
\]

IoT Path planning with “Landing Spots”

- Goal: mitigate the UAV autonomy problem
- Introducing concept of Landing Spot akin to bird’s restspot
- Use DP (or machine learning) to design optimal trajectory

Example with single Landing Spot (easily generalizes to many)

[Gangula et al, ICC18 Workshop on UAVs]
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Channel prediction

- **Probabilistic (LoS) prediction**
  - Ex: LoS probability model
    \[
    P(\text{LoS}, \theta) = \frac{1}{1 + a \exp\left(-b|\theta - \alpha|\right)}
    \]

- **Map-based prediction**

## Map-based vs Probabilistic models

<table>
<thead>
<tr>
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<th>Pros</th>
<th>Cons</th>
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<tbody>
<tr>
<td>Probabilistic</td>
<td>• Easily tractable</td>
<td>• No strict performance guarantee</td>
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<tr>
<td>[Hourani et al]</td>
<td>• Lends itself to mean performance analysis</td>
<td>• In-field implementation difficult</td>
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<tr>
<td>[Mozaffari et al]</td>
<td>• Altitude optimization</td>
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<td>[Zhang et al]</td>
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<td>[Verdone et al]</td>
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<tr>
<td>Map-based</td>
<td>• Powerful data sets (has local terrain features)</td>
<td>• Non directly differentiable (?)</td>
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<tr>
<td>[Gesbert-Chen-Esrafilian]</td>
<td>• Yields higher throughputs</td>
<td>• Map non directly available (needs learning)</td>
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<td>• Enables in-field performance guarantee</td>
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Learning-based placement

Training Data Collection (RSSI, traffic)

Radio Map Reconstruction

Automatic Drone Position Computation

Autonomous Drone Navigation

On-line

Off-line
Segmented Channel model

Received power map
UAV 100 meter above
center of Bristol

Proposed Model: Ray-tracing with Segmented Approximation

- Classical log-distance model
  \[ 10 \log_{10} \left( g_U(x) \right) = 10 \log_{10} (\beta) - 10 \alpha \log_{10} (\|x - x_U\|) + \xi \]

- Segmented propagation model: \( K \) segments
  \[ g_U(x) = \sum_k g_k(x) \mathbb{I}\{(x, x_U) \in D_k\} \]
  \[ 10 \log_{10} \left( g_k(x) \right) = 10 \log_{10} (\beta_k) - 10 \alpha_k \log_{10} (\|x - x_U\|) \]

- Shadowing (e.g., LOS/NLOS), reflection, and diffraction, etc.
  \[ \xi_k + \tilde{\xi}_k \]
  Ignore small residual
  Captured by classification to
  propagation segments, e.g.,
  LOS/NLOS
Segmented Regression Learning

- Noisy power \( y \) measurement on UAV position \( x \)
  \[
  y = \alpha_k g(x) + \beta_k + \xi_k
  \]

- PDF at \( x \):
  \[
  p_k(x, y) = \frac{1}{\sqrt{2\pi\sigma_k}} \exp \left\{ -\frac{(y - \alpha_k g(x) - \beta_k)^2}{2\sigma_k^2} \right\}
  \]

- \( z^{(l)} = (z_1, z_2, \ldots, z_K) \) segment-fitting vector for training UAV point \( x^{(l)} \)

- Objective: Max likelihood Estimate of \( \theta \)
  \[
  \theta = \{\alpha_k, \beta_k, \sigma_k, \pi_k\}_{k=1}^K
  \]

\[
\text{maximize} \quad \prod_{l=1}^{N} p(x^{(l)}, y^{(l)}, z^{(l)} | \theta) \\
\text{subject to} \quad \sum_{k=1}^{K} \pi_k = 1
\]

Expectation-Maximization Algorithm
Kernel-based Radio Map Reconstruction

Given a position \( x \), find a set of points from training data set \( \{ x^{(m)} \} \)

\[
\mathcal{N}(x) \triangleq \arg \min_{S \subseteq \{1, 2, \ldots, N\}, |S| = M} \sum_{m \in S} \| x - x^{(m)} \|
\]

Estimate segment labels through:

\[
\hat{z}(x) = \mu \sum_{m \in \mathcal{N}(x)} K(x, x^{(m)}) \bar{z}^{(m)}
\]

using the kernel function

\[
K(x, x^{(m)}) = \exp \left\{ - \frac{\| x - x^{(m)} \|^2}{s} \right\}
\]

Soft SNR reconstruction

\[
\hat{\gamma}_S(x) = \sum_{k=1}^{K} \left( \beta_k - 10\alpha_k \log_{10} d(x) \right) \hat{z}_k(x)
\]
Reconstruction performance

Comparison reference:
K nearest neighbors (KNN) applied on signal power vectors (no channel model)

\[ \hat{\gamma}_{\text{KNN}}(x) = \sum_{m \in \mathcal{N}(x)} k(x, x^{(m)})y^{(m)} \]

[J. Chen & D. Gesbert, ICC17]
Radio map reconstruction

Dense Training

Sparse Training

Role of 3D maps?
Role of 3D maps in UAV-aided networks

- 3D maps reveal the topology which correlates radio maps across users
- 3D maps can be obtained “for free” as side-product of UAV flight mission
- 3D maps play a role to enhance radio map reconstruction

Joint 3D and radio map reconstruction!
Learning the 3D map from radio measurements

Traditional 3D city map reconstruction:

1. Camera image processing
2. Laser image processing
3. Radar processing

Proposed concept:

1- Learn propagation parameters using previous EM algorithm
2- Soft-classify users into LoS/NLoS
3- Reconstruct 3D map from “radio shadow” data

Connections with
- 3D Imaging with WiFi [Y. Mostofi et al. @ UCSB]
- GPS based 3D imaging [Madhow et al @ UCSB]

[Esrafilian, Gesbert, Globecom 2017]
3D Building map reconstruction algorithms

City discretized over 2D grid coordinates $\hat{G} = \{\hat{g}_1, \hat{g}_2, ... , \hat{g}_n \mid \hat{g}_i = (x_i, y_i, \hat{z}_i)\}$

1. Deterministic Reconstruction using hard LoS decision
   - For each LoS user $X_U$ and UAV located at $X_D$, we solve for inequalities:
     \[
     \hat{z}_i \leq \frac{(x_i-x_D)(-z_D)}{x_U-x_D} + H_D \; ; \; \forall \; \hat{g}_i \in \hat{G}
     \]

2. Probabilistic reconstruction using soft LoS decision
   Use soft output from EM-based LoS classification algorithm $\text{Prob}(\text{LoS})$
3D Reconstruction Performance

UAV trajectory

Reconstructed map with 1500 users*

800 m

1 km

*K=32 UAV locations, spatial smoothing applied
Optimized flying altitude in closed form (Globecom 17)
Optimizing the UAV path for 3D reconstruction

Arbitrary Paths

Dynamic Programming Optimized Path

NMSE = 0.2488

Refinement Graph

NMSE = 0.343 (averagr across arbitray paths)

[Esrafilian, Gesbert, 2017]
Joint 3D and radio map reconstruction

An orthoimagery of an area at center Washington DC, USA

Radio map estimate

3D map estimate

Radio map reconstruction

Joint approach

(a) True radio map
(b) KNN
(c) Direct reconstruction [8]

[Chen, Esrafilian, Gesbert, Mitra, Robotics, Science and Systems, MIT, 2017]
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Nested Propagation Segment Property
Nested Propagation Segment Property (K=2)

- Two regions only: LoS and NLoS
- LoS “irreversibility”
Big building hole breaks LoS irreversibility

CCTV Building
Beijing, China
Proposition [J Chen & D. Gesbert 2017]:
“The optimal single-UAV relay position is found either (i) on the BS-UE axis, or (ii) on the boundary of segment $D_k$ for one of the $D_k$ segments $k=1,..K-1$.”

Best drone position under Probabilistic model

Optimal drone position
UAV-induced capacity gains

10,000 random user locations, buildings 5 - 45 meters, UAV 50 meter height

Decode-and-Forward Relaying

Simple UAV positioning: Only search over the BS-user line segment

Probabilistic UAV positioning:
\[ P(\text{LOS}, \theta) = \left[ 1 + a \exp(-b[\theta - a]) \right]^{-1} \]

Direct BS-user link: Directly BS \( \rightarrow \) user transmission without UAV relaying
Map-based placement for multi-user case

- Overcoming non-differentiability:
  - Map Compression [Esrafilian-Gangula-Gesbert 2018]

Global Probability model
\[ P(\text{LoS}, \theta) = \frac{1}{1 + a \exp(-b[\theta - a])} \]

Local Probability model
\[ P(\text{LoS}, \theta, \text{user m}) \]
DroneFor5GLab @ EURECOM

- LTE license
- Outdoor (EURECOM SophiaTech Campus)
- Integrated autonomous UAV-base station with full LTE functionality -> World’s first?
  - OpenAirInterface for communication layer
  - On-line learning for placement
DroneFor5GLab @ EURECOM

Video of demo available: www.youtube.com/watch?v=GI_IOsg_qmQ
Perspectives

UAV-aided networks: Promising technology

- Brings data contents closer to the user
- Ultra-flexible
- Low cost (?)

Plenty of hard problems (theoretical/experimental)

- Optimally combining 3D map and radio map reconstruction
- Map compression for many user case
- Coordinated multi-UAV setting
- Onboard RF/antenna design
- Networking issues (UAV and terrestrial co-existence)
- Onboard vs. offboard computing