

(1)

ACCUSTOM

Adaptive Control & Coordination of UAV Swarms for Traffic Offloading in MIMO ecosystem.

 $g \in \{1, 2, 3, \dots, G\}$

① \times UAV Rx ANT (n) $n \in \{1, 2, 3, \dots, N\}$

 $p_n = [x_n, y_n, z_n]$ $n \in \{1, 2, 3, \dots, N\}$

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GN Tx ANT (m)
position

 $p_m = [x_m, y_m, z_m]$
 $m \in \{1, 2, 3, \dots, M\}$

$$h_{mn} = \beta_{mn} - 10 \alpha \log_{10} d_{mn} + \xi_{mn} + \lambda_{mn} \quad (\text{dB})$$

channel gain β_{mn} avg. channel gain at distance of 1m pathloss exponent 3D distance shadow fading component small-scale fading component

$$\xi_{mn} \sim \mathcal{N}(0, \sigma_{ssf, mn}^2) \text{ and } \lambda_{mn} \sim \mathcal{CN}\left(\frac{K_{mn}}{\sqrt{K_{mn}+1}}, \frac{1}{K_{mn}+1}\right).$$

② Let $\mathcal{D} \subset \mathbb{R}^6$ be the set of all possible GN-UAV position pairs.

Let R be the number of site partitions for our radio map generation, i.e.,

$$\mathcal{D} = D_1 \cup D_2 \cup D_3 \cup \dots \cup D_R ; D_i \cap D_j = \emptyset, \forall i, j \in \{1, 2, 3, \dots, R\}, i \neq j.$$

$$\therefore h_{mn} = h(p_m, p_n) = \sum_{r=1}^R \left(\beta_r - 10 \alpha_r \log_{10} d(p_m, p_n) + \xi_r + \lambda_r \right)$$

Tx ANT position Rx ANT position $\sum \{(p_m, p_n) \in D_r\}$

③ Measurements on Wireless In Site:

$$\mathcal{M} \triangleq \left\{ \underbrace{(p_m^{(l)}, p_n^{(l)}, h_{mn}^{(l)})}_{\substack{\text{Tx ANT} \\ \text{Rx ANT}}} : l = 1, 2, 3, \dots, L \right\}$$

individual measurement + channel gain at position $(p_m^{(l)}, p_n^{(l)})$

Tx ANT Rx ANT

Assuming a measurement sample $(p_m, p_n, h_{mn}) \in \mathcal{M}$ is classified into

⑥ belongs to partition $r \in \{1, 2, 3, \dots, R\}$:

$$h_{mn} = \beta_r - 10 \alpha_r \log_{10} d_{mn} + \xi_r + \lambda_r$$

channel gain

$\sim \mathcal{N}(0, \sigma_{SF,Y}^2)$

for this measurement @ this partition pair

$$\text{CN}\left(\frac{\beta_r}{\lambda_r}, \frac{1}{K_r+1}, \frac{1}{K_r+1} \right)$$

$\sim \mathcal{N}(\mu_{SSF,Y}, \sigma_{SSF,Y}^2)$

Joint PDF

$$\text{Conditioned on belonging to } r : f_r(p_m, p_n, h_{mn}) = \frac{1}{\sqrt{2\pi(\sigma_{SF,Y}^2 + \sigma_{SSF,Y}^2)}} \exp \left\{ -\frac{(h_{mn} - \beta_r + 10 \alpha_r \log_{10} d_{mn} - \mu_{SSF,Y})^2}{2(\sigma_{SF,Y}^2 + \sigma_{SSF,Y}^2)} \right\}$$

General Joint PDF :

(Total Prob. Law)

$$P(P = (p_m, p_n), H = h_{mn}, Z) = \sum_{r=1}^R P(P = (p_m, p_n), H = h_{mn} \mid Z_r = z_r = 1) \frac{P(Z_r = z_r = 1)}{P(Z_r = z_r = 1)}$$

a.r.v. for channel gain a.r.v. for the partition classification vector

e.g., $Z = \underline{z}^{(l)} = [z_1^{(l)}, z_2^{(l)}, z_3^{(l)}, \dots, z_R^{(l)}]$,
 with $z_r^{(l)} \in \{0, 1\}$, $l \in \{1, 2, 3, \dots, L\}$,
 for any measurement sample $l \in \{1, 2, 3, \dots, L\}$

$$f(p = (p_m, p_n), H = h_{mn}, Z) = \sum_{r=1}^R f_r(p_m, p_n, h_{mn}) \cdot \Pi_r$$

r.v. for e.g. (p_m, p_n) r.v. for h_{mn} e.g. $\underline{z}^{(l)}$

Equation ①

$$= \prod_{r=1}^R \left(f_r(p_m, p_n, h_{mn}) \right)^{z_r} \cdot \prod_{r=1}^R \Pi_r^{z_r},$$

with $\sum_{r=1}^R \Pi_r = \sum_{r=1}^R P(Z_r = z_r = 1) = 1$.

(3)

- estimated
 (4) Set of channel parameters to be associated with site partitions:

$$\mathcal{B} = \left\{ (\alpha_r, \beta_r, \sigma_{SF,r}, K_{SF,r}, \pi_r) : r = 1, 2, 3, \dots, R \right\}$$

For site partition r :
 pathloss exponent ↓
 avg. channel gain at 0 dist. of 1m ↓
 shadowing std. deviation ↓
 Rician fading K-factor ↓
 $\Rightarrow P(z_r = 1)$
 $r \in \{1, 2, 3, \dots, R\}$

marginal probability that (P_m, P_n, h_{mn}) belongs to the r^{th} deployment partition

$$(5) \quad \mathcal{M} = \left\{ \left(P_m^{(l)}, P_n^{(l)}, h_{mn}^{(l)}, [z_1^{(l)}, z_2^{(l)}, z_3^{(l)}, \dots, z_R^{(l)}] \right) : l = 1, 2, 3, \dots, L \right\}$$

$z^{(l)}$

MAXIMUM LIKELIHOOD ESTIMATION (MLE):

Likelihood function:

$$g(\mathcal{B}) = \prod_{l=1}^L P(P = (P_m^{(l)}, P_n^{(l)}), H = h_{mn}^{(l)}, Z_l = z_l^{(l)} | \mathcal{B});$$

maximize $\mathcal{B}, \{z^{(l)} : l = 1, 2, 3, \dots, L\}$ subject to $\sum_{r=1}^R \pi_r = 1;$

\Downarrow

(From Equation ①)

$\prod_{r=1}^R \left(f_r \left(P_m^{(l)}, P_n^{(l)}, h_{mn}^{(l)} \right) \right) \prod_{r=1}^R \pi_r^{z_r^{(l)}}$

This is equivalent to maximizing $\log g(\mathcal{B})$, s.t. $\sum_{r=1}^R \pi_r = 1;$

marginal prob. that any (P_m, P_n, h_{mn}) belongs to the r^{th} site partition

maximize $\mathcal{B}, \{z^{(l)} : l = 1, 2, 3, \dots, L\}$ s.t. $\sum_{r=1}^R \pi_r = 1;$

\Rightarrow

$$\sum_{l=1}^L \sum_{r=1}^R \left[\log \left(f_r \left(P_m^{(l)}, P_n^{(l)}, h_{mn}^{(l)} \right) \right)^{z_r^{(l)}} + \log (\pi_r)^{z_r^{(l)}} \right]$$

$$\text{maximize}_{\mathcal{B}, \{z_l^{(l)} : l=1, 2, 3, \dots, L\}} \sum_{l=1}^L \sum_{r=1}^R \left[z_r^{(l)} \left(\log f_r(p_m^{(l)}, p_n^{(l)}, h_m^{(l)}) + \log \pi_r \right) \right]$$

(6) Let $\bar{z}_r^{(l)}(\mathcal{B}) \triangleq \mathbb{E} [z_r^{(l)}] \mid P = (p_m^{(l)}, p_n^{(l)}), H^{(l)} = h_m^{(l)}, \mathcal{B}$

Bernoulli r.v.
 $z_r^{(l)} = z_r^{(l)} \in \{0, 1\}$

$$= \mathbb{P}(Z_r^{(l)} = z_r^{(l)} = 1 \mid P^{(l)} = (p_m^{(l)}, p_n^{(l)}), H^{(l)} = h_m^{(l)}, \mathcal{B})$$

let this
 be temporarily referred
 to as **D** **A** **B** **C**
 temporary references

Aside: $\mathbb{P}(D \mid A, B, C) = \frac{\mathbb{P}(A, B, C \mid D) \mathbb{P}(D)}{\mathbb{P}(A, B, C)} \quad (\because \text{BAYES' RULE})$

$$= \frac{\mathbb{P}(A, B \mid C, D) \mathbb{P}(C) \mathbb{P}(D)}{\mathbb{P}(A, B \mid C) \mathbb{P}(C)} \quad (\because \text{Definition of conditional probability})$$

$$= \frac{\mathbb{P}(A, B \mid C, D) \mathbb{P}(D)}{\sum_F \mathbb{P}(F) \mathbb{P}(A, B \mid C, F)} \quad (\because \text{Total Probability})$$

$\therefore \bar{z}_r^{(l)}(\mathcal{B}) = \frac{\mathbb{P}(P = (p_m^{(l)}, p_n^{(l)}), H^{(l)} = h_m^{(l)} \mid \mathcal{B}, Z_r^{(l)} = z_r^{(l)} = 1)}{\mathbb{P}(Z_r^{(l)} = z_r^{(l)} = 1)}$

equation (2)

$$= \frac{\sum_{r'=1}^R \mathbb{P}(Z_r^{(l)} = z_r^{(l)} = 1) \mathbb{P}(P = (p_m^{(l)}, p_n^{(l)}, h_m^{(l)}) \mid \mathcal{B}, Z_{r'}^{(l)} = z_{r'}^{(l)} = 1) \mathbb{P}(Z_{r'}^{(l)} = z_{r'}^{(l)} = 1)}{\sum_{r'=1}^R \mathbb{P}(f_{r'}(p_m^{(l)}, p_n^{(l)}, h_m^{(l)} \mid \mathcal{B}) \pi_{r'})}$$

(5)

$$\begin{aligned}
 ① \quad \mathbb{E}[g(\beta)] &= \mathbb{E}\left[\sum_{l=1}^L \sum_{r=1}^R \left[\bar{z}_r^{(l)} \left(\log f_r(p_m^{(l)}, p_n^{(l)}, h_{mn}^{(l)}) + \log \pi_r \right) \right] \right] \\
 &= \sum_{l=1}^L \sum_{r=1}^R \left\{ \mathbb{E}\left[\bar{z}_r^{(l)} \mid P^{(l)} = (p_m^{(l)}, p_n^{(l)}), H^{(l)} = h_{mn}^{(l)}, \beta\right] \right\} \\
 &\quad \left(\log f_r(p_m^{(l)}, p_n^{(l)}, h_{mn}^{(l)}) + \log \pi_r \right) \\
 &= \sum_{l=1}^L \sum_{r=1}^R \left[\bar{z}_r^{(l)}(\beta) \left(\log f_r(p_m^{(l)}, p_n^{(l)}, h_{mn}^{(l)}) + \log \pi_r \right) \right].
 \end{aligned}$$

⑥ Reformulated MLE: maximize $\mathbb{E}[g(\beta)]$ subject to

$$\sum_{r=1}^R \pi_r = 1.$$

Non-convex: Iterative search to find sub-optimal solution

$\bar{z}_r^{(l)}(\beta)$ can be found easily using equation ②
Fix $\bar{z}_r^{(l)}(\beta)$ and the objective is convex in $\pi_r, \alpha_r, \beta_r, \sigma_{SSF,r}^2$ and $K_{SSF,r}$.

At the i^{th} iteration:

$$\begin{aligned}
 ⑦ \quad \text{Compute } \bar{z}_r^{(l)}(\beta^{(i)}) &= \frac{f_r(p_m^{(l)}, p_n^{(l)}, h_{mn}^{(l)} \mid \beta^{(i)}) \pi_r}{\sum_{r'=1}^R f_r(p_m^{(l)}, p_n^{(l)}, h_{mn}^{(l)} \mid \beta^{(i)}) \pi_{r'}} \pi_r
 \end{aligned}$$

$$\begin{aligned}
 ⑧ \quad \text{Next, } \mathbb{E}[g(\beta^{(i)})] &= \sum_{l=1}^L \sum_{r=1}^R \left[\bar{z}_r^{(l)}(\beta^{(i)}) \left(\log \frac{1}{\sqrt{2\pi(\sigma_{SSF,r}^2 + \sigma_{SSF,r}^{(i)})}} \exp(-Ch_{mn} - \beta_r + 10\alpha_r \log d_{mn}) \right) \right. \\
 &\quad \left. + \log \pi_r \right]
 \end{aligned}$$

with $\mu_{SSF,r} = \frac{f_r}{K_{SSF,r} + 1}$, $\sigma_{SSF,r}^2 = \frac{1}{K_{SSF,r} + 1}$,

Fix all parameters in $\beta^{(i)}$ except for (α_x, β_x) ; $x = 1, 2, 3, \dots, R$:

(C)

OPT VARS: $\{(\alpha_x, \beta_x) : x = 1, 2, 3, \dots, R\}$

FIXED VARS: $\sigma_{SF,x}^{(i)}$

$$\underbrace{\pi_x}_{K_{SSF,x}} = \sigma_{SF,x}^{(i)}; \quad \Pi_x = \Pi_x^{(i)}$$

$$K_{SSF,x} = K_{SSF,x}^{(i)}, \quad x \in \{1, 2, 3, \dots, R\}$$

Get $\sigma_{SSF,x}$ and $\sigma_{SF,x}^{(i)}$ from the K-factor

$$\mathbb{E} \left[g \left(\underline{\alpha}, \beta, \sigma_{SF}^{(i)}, K_{SSF}^{(i)}, \Pi^{(i)} \right) \right],$$

OPT VARS: $[\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_R]$

FIXED VARS: $[K_{SF,1}^{(i)}, K_{SF,2}^{(i)}, K_{SF,3}^{(i)}, \dots, K_{SF,R}^{(i)}]$

OPT VARS: $[\pi_1^{(i)}, \pi_2^{(i)}, \pi_3^{(i)}, \dots, \pi_R^{(i)}]$

OPT VARS: $[\beta_1, \beta_2, \beta_3, \dots, \beta_R]$

(I)

Similarly,

OPT VARS: $\{\sigma_{SF,x}^{(i)} : x = 1, 2, 3, \dots, R\}$

FIXED

$$\text{VARS: } \alpha_x = \alpha_x^{(i)}; \beta_x = \beta_x^{(i)}; K_{SSF,x} = K_{SSF,x}^{(i)};$$

$$\Pi_x = \Pi_x^{(i)}, \quad x \in \{1, 2, 3, \dots, R\}$$

$$\mathbb{E} \left[g \left(\underline{\alpha}^{(i)}, \beta^{(i)}, \sigma_{SF}^{(i)}, K_{SSF}^{(i)}, \Pi^{(i)} \right) \right],$$

(II)

Similarly,

OPT VARS: $K_{SSF,x}^{(i)}$

$$\text{maximize } \mathbb{E} \left[g \left(\underline{\alpha}^{(i)}, \beta^{(i)}, \sigma_{SF}^{(i)}, K_{SSF}^{(i)}, \Pi^{(i)} \right) \right], \text{ and}$$

$$\text{FIXED VARS: } \alpha_x = \alpha_x^{(i)}; \beta_x = \beta_x^{(i)}; \Pi_x = \Pi_x^{(i)};$$

$$\sigma_{SF,x}^{(i)}, \quad x \in \{1, 2, 3, \dots, R\}$$

(III)

Finally,

OPT VARS: $\{\Pi_x : x = 1, 2, 3, \dots, R\}$

FIXED VARS:

$$\alpha_x = \alpha_x^{(i)}; \beta_x = \beta_x^{(i)}; \sigma_{SF,x}^{(i)} = \sigma_{SF,x}^{(i)}$$

$$K_{SF,x} = K_{SF,x}^{(i)}, \quad x \in \{1, 2, 3, \dots, R\}$$

$$\text{p.t. } \sum_{x=1}^R \Pi_x = 1.$$

(IV)

(7)

$$\forall r \in \{1, 2, 3, \dots, R\}$$

Solve I: $\frac{\partial}{\partial \alpha_r} \mathbb{E} \left[g(\underline{\alpha}, \beta, \underline{\sigma}_{SF}^{(i)}, \underline{k}_{SSF}^{(i)}, \underline{l}_{SF}^{(i)}) \right] = 0 \text{ and}$

$$\frac{\partial}{\partial \beta_r} \mathbb{E} \left[g(\underline{\alpha}, \beta, \underline{\sigma}_{SF}^{(i)}, \underline{k}_{SSF}^{(i)}, \underline{l}_{SF}^{(i)}) \right] = 0;$$

$$\sum_{l=1}^L \bar{z}_r^{(l)} (\beta^{(i)}) \left[\frac{1}{D(l)} \cdot \frac{(-1 \cdot (10 \log_{10} d)^2)}{2(l_m - \beta_r + 10 \alpha_r \log_{10} d_m)} \right] = 0,$$

$$\left\{ (\alpha_r, \beta_r, \sigma_{SF}^{(i)}, k_{SSF}^{(i)}, l_{SF}^{(i)}), r=1, 2, 3, \dots, R \right\}$$

$$\sum_{l=1}^L \bar{z}_r^{(l)} (\beta^{(i)}) \cdot \frac{-2 \left(h_{mn}^{(l)} - \beta_r + 10 \alpha_r \log_{10} d_{mn}^{(l)} - h_{SSF,r}^{(i)} \right) \cdot (10 \log_{10} d_{mn}^{(l)})}{2(d_m^{(l)} + \sigma_{SF}^{(i)})} = 0,$$

$$\sum_{l=1}^L \bar{z}_r^{(l)} (\beta^{(i)}) \left((10 \log_{10} d_{mn}^{(l)}) \left(h_{mn}^{(l)} - \beta_r + 10 \alpha_r \log_{10} d_{mn}^{(l)} - h_{SSF,r}^{(i)} \right) \right) = 0;$$

$$- \sum_{l=1}^L \bar{z}_r^{(l)} (\beta^{(i)}) \left((10 \log_{10} d_{mn}^{(l)}) h_{mn}^{(l)} \right) + \sum_{l=1}^L \bar{z}_r^{(l)} (\beta^{(i)}) \left((10 \log_{10} d_{mn}^{(l)}) \beta_r^{(i)} \right)$$

$$+ \sum_{l=1}^L \bar{z}_r^{(l)} (\beta^{(i)}) \left((10 \log_{10} d_{mn}^{(l)}) / h_{SSF,r}^{(i)} \right)$$

$$= \sum_{l=1}^L \bar{z}_r^{(l)} (\beta^{(i)}) \left((10 \log_{10} d_{mn}^{(l)}) \left(10 \alpha_r^{(i+1)} \log_{10} d_{mn}^{(l)} \right) \right);$$

$$\alpha_r^{(i+1)} \left(\sum_{l=1}^L \bar{z}_r^{(l)} (\beta^{(i)}) \left((10 \log_{10} d_{mn}^{(l)})^2 \right) \right)$$

$$\therefore \alpha_r^{(i+1)} = \frac{1}{\sum_{l=1}^L \bar{z}_r^{(l)} (\beta^{(i)}) \left((10 \log_{10} d_{mn}^{(l)})^2 \right)} \left\{ \sum_{l=1}^L \bar{z}_r^{(l)} (\beta^{(i)}) \left((10 \log_{10} d_{mn}^{(l)}) \beta_r^{(i)} \right) + \right. \\ \left. \sum_{l=1}^L \bar{z}_r^{(l)} (\beta^{(i)}) \left((10 \log_{10} d_{mn}^{(l)}) h_{mn}^{(l)} \right) - \right. \\ \left. \sum_{l=1}^L \bar{z}_r^{(l)} (\beta^{(i)}) \left((10 \log_{10} d_{mn}^{(l)}) / h_{mn}^{(l)} \right) \right\} \text{ and}$$

$$\text{Similarly, } \beta_r^{(i+1)} = \frac{1}{\sum_{l=1}^L \bar{z}_r^{(l)} (\beta^{(i)}) \left((10 \log_{10} d_{mn}^{(l)}) \right)} \left\{ \sum_{l=1}^L \bar{z}_r^{(l)} (\beta^{(i)}) \left((10 \log_{10} d_{mn}^{(l)})^2 \alpha_r^{(i+1)} - \sum_{l=1}^L \bar{z}_r^{(l)} (\beta^{(i)}) \left((10 \log_{10} d_{mn}^{(l)}) \right) h_{mn}^{(l)} \right) + \right. \\ \left. \sum_{l=1}^L \bar{z}_r^{(l)} (\beta^{(i)}) \left((10 \log_{10} d_{mn}^{(l)}) h_{mn}^{(l)} \right) \right\}.$$

$$\frac{1}{x} \cdot \frac{x(a) - x(b)}{2\pi}$$

Solve (II) $\frac{\partial}{\partial \sigma_{SF,Y}} \mathbb{E} \left[g(\underline{\alpha}^{(i)}, \beta^{(i)}, \underline{\sigma}_{SF}^{(i)}, \underline{K}_{SSF}^{(i)}, \underline{\pi}_Y^{(i)}) \right] = 0,$

$$\sum_{l=1}^L \bar{z}_Y^{(l)}(\beta^{(i)}) \left(\frac{1}{m^{(i)}} \cdot \frac{1}{\sqrt{2\pi(\sigma_{SF,Y}^{(i)})^2 + \sigma_{SSF,Y}^{(i)})^2}} \exp(-\frac{(y_l - \beta^{(i)})^2}{2(\sigma_{SF,Y}^{(i)})^2 + (\sigma_{SSF,Y}^{(i)})^2}) \right) = 0$$

$$\left\{ (\underline{\alpha}_l^{(i)}, \beta_l^{(i)}, \underline{\sigma}_{SF,Y}^{(i)}, \underline{K}_{SSF,Y}^{(i)}, \underline{\pi}_Y^{(i)}), l = 1, 2, 3, \dots, L \right\}$$

$$\sum_{l=1}^L \bar{z}_Y^{(l)}(\beta^{(i)}) \left(\frac{1}{m^{(i)}} \left(\frac{m^{(i)} \cdot ((h_m^{(i)} - \beta^{(i)}) + 10 \alpha_0^{(i)} \log d_m^{(i)} - h_{SF,Y}^{(i)})^2 \sigma_{SF,Y}^{(i)}}{\sqrt{2\pi((\sigma_{SF,Y}^{(i)})^2 + (\sigma_{SSF,Y}^{(i)})^2)}} \right) \right) = 0$$

$$\sum_{l=1}^L \bar{z}_Y^{(l)}(\beta^{(i)}) \left(\sigma_{SF,Y}^{(i+1)} \left(h_m^{(i)} - \beta^{(i)} + 10 \alpha_0^{(i)} \log d_m^{(i)} - h_{SF,Y}^{(i)} \right)^2 \right) = 0$$

$$\sigma_{SF,Y}^{(i+1)}$$

$$\sigma_{SF,Y}^{(i+1)} + \sigma_{SSF,Y}^{(i)} \sigma_{SF,Y}^{(i+1)}$$

$$\sigma_{SF,Y}^{(i+1)} \sum_{l=1}^L \bar{z}_Y^{(l)}(\beta^{(i)}) \left(h_m^{(i)} - \beta^{(i)} + 10 \alpha_0^{(i)} \log d_m^{(i)} - h_{SF,Y}^{(i)} \right)^2 = \frac{\sigma_{SF,Y}^{(i+1)}}{\sigma_{SF,Y}^{(i+1)} + \sigma_{SSF,Y}^{(i)}} \sum_{l=1}^L \bar{z}_Y^{(l)}(\beta^{(i)})$$

$$\sigma_{SF,Y}^{(i+1)} = \sum_{l=1}^L \bar{z}_Y^{(l)}(\beta^{(i)}) - \sigma_{SSF,Y}^{(i)}$$

$$\sum_{l=1}^L \bar{z}_Y^{(l)}(\beta^{(i)}) \left(f_{\text{enc}}(\beta^{(i)}) \right)^2$$

(Solve III) $\sigma_{SSF,Y}^{(i+1)}$ and $\sigma_{SF,Y}^{(i+1)}$, $\forall x \in \{1, 2, 3, \dots, L\}$

$$\sigma_{SSF,Y}^{(i+1)} = \sum_{l=1}^L \bar{z}_Y^{(l)}(\beta^{(i)}) - \sigma_{SF,Y}^{(i+1)} \quad \text{and}$$

$$\frac{\partial \mathbb{E}[g(\underline{\alpha}^{(i)}, \beta^{(i)}, \underline{\sigma}_{SF,Y}^{(i)}, \underline{K}_{SSF,Y}^{(i)}, \underline{\pi}_Y^{(i)})]}{\partial \sigma_{SF,Y}^{(i+1)}} = 0$$

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$$\frac{\partial}{\partial \mu_{SSF,Y}} \mathbb{E} \left[g \left(\alpha^{(i)}, \beta^{(i)}, \sigma_{SF}^{(i)}, \mu_{SSF}, \sigma_{SSF}^{(i)}, \pi^{(i)} \right) \right] = 0;$$

$$\sum_{l=1}^L \bar{z}_y^{(0)}(\beta^{(i)}) \left(\frac{1}{m^{(i)}} \cdot m(\dots) \cdot \frac{1}{2 \left(\frac{\sigma_{SF,l}^{(i)}}{m^{(i)}} + \frac{\sigma_{SSF,l}^{(i)}}{m^{(i)}} \right)^2} \right) \cdot \left(h_{mn}^{(i)} - \beta_y^{(i)} + 10 \alpha_y^{(i)} \log d_{mn}^{(i)} - \mu_{SSF,Y}^{(i+1)} \right) \cdot \pi^{(i)}$$

$$\left\{ (\alpha_y^{(i)}, \beta_y^{(i)}, \sigma_{SF,y}^{(i)}, \mu_{SSF,Y}^{(i)}, \sigma_{SSF,Y}^{(i)}, \pi_y^{(i)}) : y = 1, 2, 3, \dots, R \right\} = 0;$$

$$\sum_{l=1}^L \bar{z}_y^{(0)}(\beta^{(i)}) \left(h_{mn}^{(i)} - \beta_y^{(i)} + 10 \alpha_y^{(i)} \log d_{mn}^{(i)} - \mu_{SSF,Y}^{(i+1)} \right) = 0,$$

$$\therefore \mu_{SSF,Y}^{(i+1)} = \frac{1}{\sum_{l=1}^L \bar{z}_y^{(0)}(\beta^{(i)})} \left(\sum_{l=1}^L \bar{z}_y^{(0)}(\beta^{(i)}) \left(h_{mn}^{(i)} + 10 \alpha_y^{(i)} \log d_{mn}^{(i)} \right) - \beta_y^{(i)} \right)$$

value IV

$$\mathcal{L}(\pi, \lambda | \beta^{(i)}) = \mathbb{E} \left[g(\beta^{(i)}) \right] + \lambda \left(\sum_{y=1}^R \pi_y - 1 \right);$$

$$\left\{ (\alpha_y^{(i)}, \beta_y^{(i)}, \sigma_{SF,y}^{(i)}, \mu_{SSF,Y}^{(i)}, \pi_y^{(i)}) : y = 1, 2, 3, \dots, R \right\}$$

KKT

$$\frac{\partial}{\partial \pi_y} \mathcal{L}(\pi, \lambda | \beta^{(i)}) = 0; \quad \lambda \left(\sum_{y=1}^R \pi_y - 1 \right) = 0; \quad \lambda > 0$$

primal feasibility

CS

dual feasibility

$$\sum_{l=1}^L \bar{z}_y^{(0)}(\beta^{(i)}) \frac{1}{\pi_y} + \lambda = 0;$$

With $\sum_{y=1}^R \pi_y = 1, \lambda = 0 \rightarrow \therefore \pi_y^{(i+1)} = \frac{1}{L} \sum_{l=1}^L \bar{z}_y^{(0)}(\beta^{(i)})$.

At iteration i :

$$\therefore \bar{\pi}_r^{(i+1)} = \frac{1}{L} \left[\sum_{l=1}^L \bar{z}_r^{(l)}(\bar{B}^{(i)}) \right], \forall r \in \{1, 2, 3, \dots, R\},$$

This first term
took
involved in
the ref paper

**DOUBLE
CHECK**

$$\therefore \sigma_{SF, r}^{2(i+1)} = \frac{\sum_{l=1}^L \bar{z}_r^{(l)}(\bar{B}^{(i)})}{\sum_{l=1}^L \bar{z}_r^{(l)} \left(h_{mn}^{(l)} - \beta_r^{(i)} + 10 \alpha_r^{(i)} \log_{10} d_{mn}^{(l)} - \mu_{SF, r}^{(i)} \right)^2} - \sigma_{SF, r}^{(i)2},$$

$$\forall r \in \{1, 2, 3, \dots, R\};$$

Again,

**DOUBLE
CHECK
(inverted!)**

$$\therefore \sigma_{SF, r}^{2(i+1)} = \frac{\sum_{l=1}^L \bar{z}_r^{(l)}(\bar{B}^{(i)})}{\sum_{l=1}^L \bar{z}_r^{(l)} \left(h_{mn}^{(l)} - \beta_r^{(i)} + 10 \alpha_r^{(i)} \log_{10} d_{mn}^{(l)} - \mu_{SF, r}^{(i)} \right)^2} - \sigma_{SF, r}^{(i)2},$$

$$\forall r \in \{1, 2, 3, \dots, R\};$$

$$\therefore \mu_{SF, r}^{(i+1)} = \frac{1}{\sum_{l=1}^L \bar{z}_r^{(l)}(\bar{B}^{(i)})} \left[\sum_{l=1}^L \bar{z}_r^{(l)}(\bar{B}^{(i)}) \left(h_{mn}^{(l)} - \beta_r^{(i)} + 10 \alpha_r^{(i)} \log_{10} d_{mn}^{(l)} \right) \right],$$

$$\forall r \in \{1, 2, 3, \dots, R\};$$

**Double
Check**

$$\therefore \alpha_r^{(i+1)} = \frac{1}{\sum_{l=1}^L \bar{z}_r^{(l)}(\bar{B}^{(i)})} \left[\sum_{l=1}^L \bar{z}_r^{(l)}(\bar{B}^{(i)}) (10 \log_{10} d_{mn}^{(l)}) \left(\beta_r^{(i)} + \frac{\mu_{SF, r}^{(i)}}{h_{mn}^{(l)}} \right) \right],$$

$$\forall r \in \{1, 2, 3, \dots, R\}, \text{ and}$$

$$\therefore \beta_r^{(i+1)} = \frac{1}{\sum_{l=1}^L \bar{z}_r^{(l)}(\bar{B}^{(i)}) (10 \log_{10} d_{mn}^{(l)})} \left[\sum_{l=1}^L \bar{z}_r^{(l)}(\bar{B}^{(i)}) (10 \log_{10} d_{mn}^{(l)}) \left(h_{mn}^{(l)} + 10 \alpha_r^{(i)} \log_{10} d_{mn}^{(l)} - \frac{\mu_{SF, r}^{(i)}}{h_{mn}^{(l)}} \right) \right].$$

Summary

- R partitions of the deployment site.
 - Each partition represented by : $(\alpha_r, \beta_r, \sigma_{SF,Y}^2, K_{SSF,Y}, \pi_r), \forall r \in \{1, 2, 3, \dots, R\}$
- \downarrow
 $\mu_{SSF,Y}, \sigma_{SSF,Y}$ position index

Additionally, each partition is represented by a subset of measurements from \mathcal{M} whose $z_r^{(l)} = 1$, for any $l \in \{1, 2, 3, \dots, L\}$.

$$\text{So, } \mathcal{R} = \left\{ (\alpha_r, \beta_r, \sigma_{SF,Y}^2, K_{SSF,Y}, \pi_r, \left\{ \begin{array}{c} (l) \\ p_m, p_n, h_{mn}, [z_1^{(1)}, z_2^{(1)}, z_3^{(1)}, \dots, z_R^{(1)}] \\ z_r^{(1)} = 1, z_s^{(1)} = 0, \forall s \neq r \end{array} \right\}) \right\}_{r=1}^R.$$

- What the NMLE procedure does is to obtain this set \mathcal{R} , i.e., the channel parameters, for each partition and the representative set of measurements that belong to each partition, from the labeled measurements.
- (in terms of
channel
gain)

ALGORITHM

Initialization: Partition $\mathcal{M} = \{(p_m, p_n, h_{mn}, z^{(l)}) : l = 1, 2, 3, \dots, L\}$ into R partitions using the K -means clustering algorithm, with the channel gains used as the clustering variable.

$$\underset{\{\mathcal{R}_1, \mathcal{R}_2, \mathcal{R}_3, \dots, \mathcal{R}_R\}}{\operatorname{argmin}} \sum_{r=1}^R \sum_{h_{mn} \in \mathcal{R}_r} \|h_{mn} - \bar{h}_{r,mn}\|_2^2 \quad \text{s.t.}$$

$$R \ll L \text{ and } |\mathcal{R}_1| + |\mathcal{R}_2| + |\mathcal{R}_3| + \dots + |\mathcal{R}_R| = L,$$

$$\text{where } \bar{h}_{r,mn} = \frac{1}{|\mathcal{R}_r|} \sum_{h_{mn} \in \mathcal{R}_r} h_{mn}, \forall r \in \{1, 2, 3, \dots, R\}.$$

K-means clustering

Fancy

Initialization: Randomly choose R measurements from \mathcal{M} and treat them as the centroids of the R partitions.

Iteration

$$\text{Assignment: } \mathcal{R}_r^{(i)} = \left\{ h_{mn}^{(l)}, l = \{1, 2, 3, \dots, L\} : \left\| h_{mn}^{(l)} - \bar{h}_{mn}^{(i)} \right\|_2^2 \leq \left\| h_{mn}^{(l)} - \bar{h}_{mn}^{(r')} \right\|_2^2 \right\},$$

$$\forall r \in \{1, 2, 3, \dots, R\}, \forall r' \in \{1, 2, 3, \dots, R\}, r \neq r'$$

Update:

$$\bar{h}_{mn}^{(i)} = \frac{1}{|\mathcal{R}_r^{(i)}|} \sum_{h \in \mathcal{R}_r^{(i)}} h.$$

Iteration index (i)
for K-means clustering

Termination: Assignments no longer change.

(12) Then, $\bar{z}_r^{(i)}(\mathcal{B}^{(0)}) = 1$, if $h_{mn}^{(l)} \in \mathcal{R}_r^{(i)}$, i.e.,

$(p_m^{(0)}, p_n^{(0)}, b_{mn}^{(0)}) \in \mathcal{M}$ belongs to $\mathcal{R}_r^{(i)}$,

$\forall r \in \{1, 2, 3, \dots, R\}$,

Else $\bar{z}_r^{(i)}(\mathcal{B}^{(0)}) = 0$.

Iteration A: Using these estimates of $\bar{z}_r^{(i)}(\mathcal{B}^{(0)})$, $\forall l \in \{1, 2, 3, \dots, L\}$, $\forall r \in \{1, 2, 3, \dots, R\}$,

$\left\{ \begin{array}{l} \text{find } \alpha_r^{(i)}, \beta_r^{(i)}, \sigma_{SF,r}^{(i)}, h_{SSF,r}^{(i)}, \sigma_{SSF,r}^{(i)}, \pi_r^{(i)} \text{ using (1)-(5),} \\ \forall r \in \{1, 2, 3, \dots, R\} \end{array} \right.$

$\left. \begin{array}{l} \alpha_r^{(i)}, \beta_r^{(i)}, \sigma_{SF,r}^{(i)}, h_{SSF,r}^{(i)}, \sigma_{SSF,r}^{(i)}, \pi_r^{(i)} \\ \vdots \end{array} \right.$

Termination: until these values do not change above a preset threshold.

(13)

Thus, we now have

$$\mathcal{R} = \{R_1, R_2, R_3, \dots, R_R : r = 1, 2, 3, \dots, R\}, \text{ where}$$

$$R_r = \left\{ (\alpha_r, \beta_r, \sigma_{SF,r}^{(0)}, K_{SF,r}^{(0)}, \Pi_r, \left\{ \begin{array}{c} \{z_r^{(1)}, z_r^{(2)}, \dots, z_r^{(L)}\} \\ \{p_{mr}^{(1)}, p_{nr}^{(1)}, \dots, p_{mr}^{(L)}, p_{nr}^{(L)}\} \\ z_r^{(1)} = 1, z_r^{(2)} = 0, \dots, z_r^{(L)} = 0 \\ L = 1, 2, 3, \dots, L \end{array} \right\}) : r = 1, 2, 3, \dots, R \right\}.$$

Next, we need to dynamically classify each positional pair $(p_m, p_n) \notin \mathcal{R}$ but in the wider deployment site as a whole using KNN classification.

Classification (1) Define the index set of S -nearest neighbors of $(p_m, p_n) \in \mathcal{D}$ as

$$S(p_m, p_n) = \underset{\substack{S \subseteq \{1, 2, 3, \dots, L\} \\ |S|=S}}{\operatorname{argmin}} \sum_{l \in S} \left[\|p_m - p_m^{(l)}\|_2 + \|p_n - p_n^{(l)}\|_2 \right] \quad \text{s.t. } R \ll L \text{ and } S \ll L.$$

Then, the partition to which $(p_m, p_n) \in \mathcal{D}$ belongs to is given by

$$\hat{z}(p_m, p_n) = \mu \sum_{l \in S(p_m, p_n)} K(p_m, p_n, p_m^{(l)}, p_n^{(l)}) \hat{z}^{(l)}, \text{ where } \hat{z}^{(l)} \text{ is the probability of being in partition } l, \text{ from Eq. (1)}$$

$$K(p_m, p_n, p_m^{(l)}, p_n^{(l)}) \triangleq \exp \left\{ - \frac{\left(\|p_m - p_m^{(l)}\|_2 + \|p_n - p_n^{(l)}\|_2 \right)^2}{s} \right\}, \text{ kernel function}$$

s is the kernel parameter and $\mu > 0$ is chosen such that

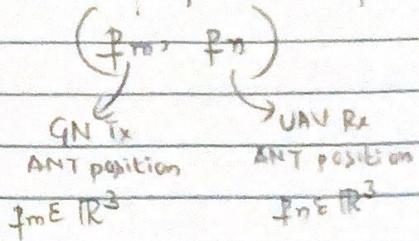
$$(s > 0)$$

$$\sum_{l=1}^R \hat{z}_l(p_m, p_n) = 1.$$

(probabilistically speaking...)

Classifying the unknown positional pair into 1 of R partitions, then, we have the channel parameters for this positional pair.

Finally, to get the channel gain at this positional pair :



$$\hat{h}_{mn}(f_m, f_n) = \sum_{r=1}^R \left(\beta_r - 10\alpha_r \log_{10} d_{mn} + \xi_r + \lambda_r \frac{1}{\|f_m - f_n\|_2} \right)$$

where $\xi_r \sim \mathcal{N}(0, \sigma_{SF,r}^2)$ and $\lambda_r \sim \mathcal{CN}\left(\frac{K_{SF,r}}{\sqrt{K_{SF,r}} + 1}, \frac{1}{K_{SF,r} + 1}\right)$