W11: Wireless Communications 2

Predictive Beamforming With Active Inference in Hierarchical Codebooks

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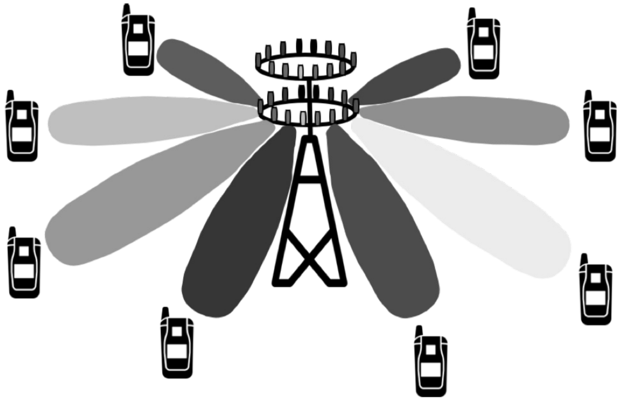
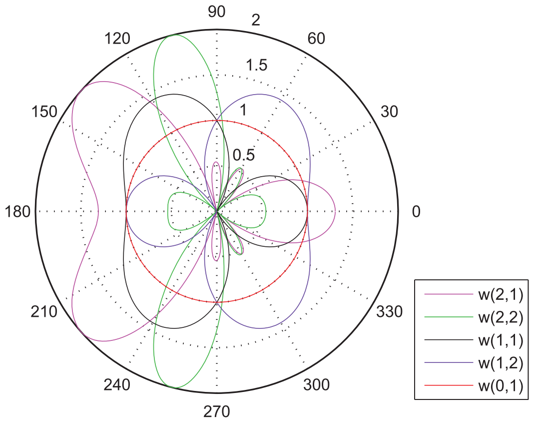
Introduction (1/2)

Beamforming for massive MIMO

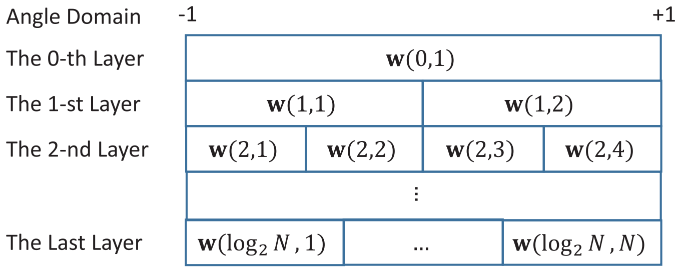


Massive Multiple Output–Multiple Output (MIMO) beamforming [1].

Hierarchical Codebook



Beam patterns in a Hierarchical Codebook [2].

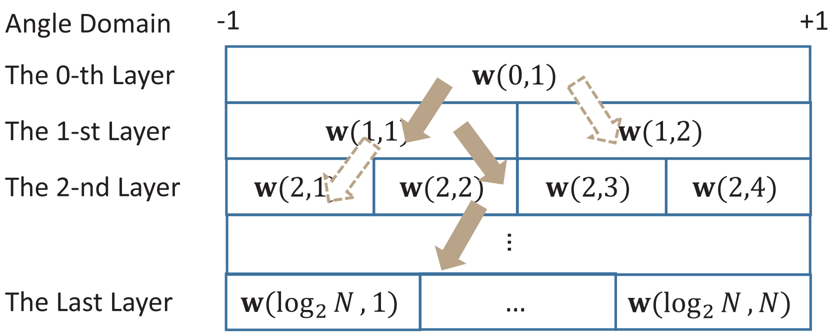


Binary tree-structured beam vectors [2].

[1] R. Chataut and R. Akl, “Massive mimo systems for 5g and beyond networks—overview, recent trends, challenges, and future research direction,” Sensors, vol. 20, no. 10, p. 2753, 2020.
[2] Z. Xiao, T. He, P. Xia and X. -G. Xia, "Hierarchical Codebook Design for Beamforming Training in Millimeter-Wave Communication," in *IEEE Transactions on Wireless Communications*, vol. 15, no. 5, pp. 3380-3392, May 2016, doi: 10.1109/TWC.2016.2520930.

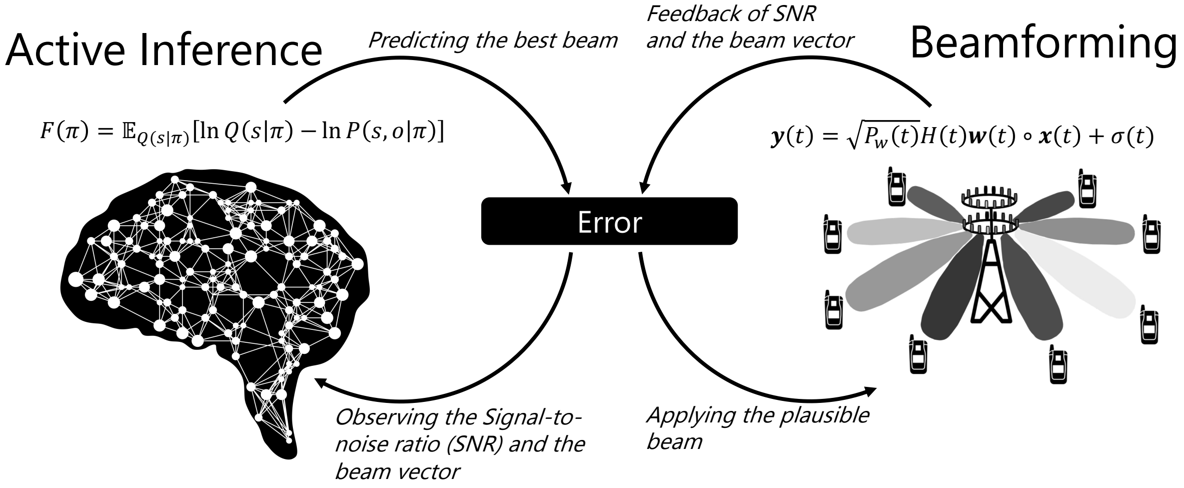
Introduction (2/2)

Beam Training (classical search algorithm)



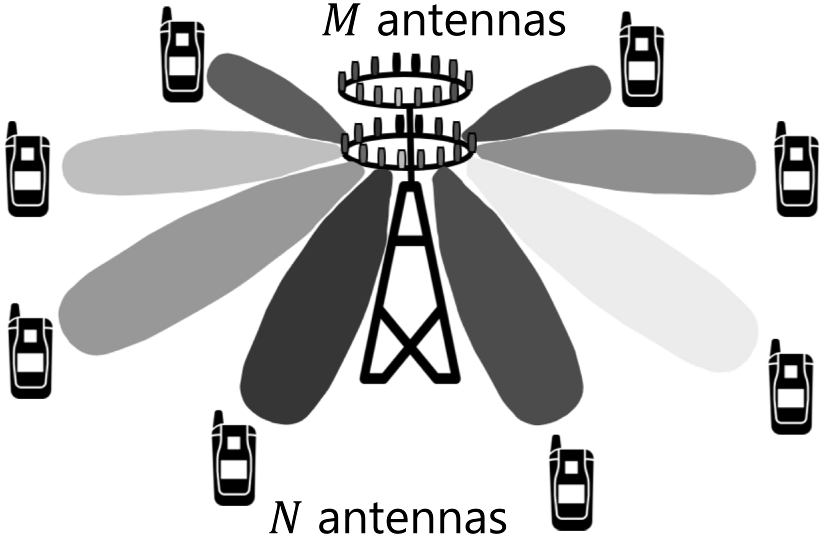
Binary tree-structured beam vectors [2].

Beam Prediction (proposal)



System Model and Problem Formulation (1/2)

A. Beamforming



Massive Multiple Output–Multiple Output (MIMO) beamforming [1].

Received Signal

$$\boldsymbol{y}(t) = \sqrt{P_{\mathrm{w}}(t)}H(t)\boldsymbol{w}(t) \circ \boldsymbol{x}(t) + \sigma(t)\boldsymbol{e}$$

SNR

$$\gamma(t) = P_w(t)|H(t)w(t)|^2/\sigma^2(t)$$

Transmission rate [3]

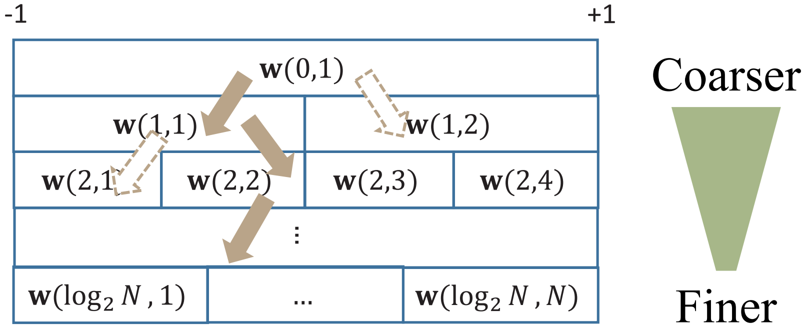
$$\Gamma(t) = \log\big(1 + \gamma(t)\big)$$

amplitude $P_{\mathrm{w}}(t)$, channel matrix $H(t)$, beam vector $\boldsymbol{w}(t)$, transmitted signal $\boldsymbol{x}(t)$, noise $\sigma(t)$, unit vector $\boldsymbol{e}$

[3] K. Yu, G. Wu, S. Li and G. Y. Li, "Local Observations-Based Energy-Efficient Multi-Cell Beamforming via Multi-Agent Reinforcement Learning," in Journal of Communications and Information Networks, vol. 7, no. 2, pp. 170-180, June 2022, doi: 10.23919/JCIN.2022.9815200.

System Model and Problem Formulation (2/2)

B. Hierarchical Codebook



Binary tree-structured beam vectors [2].

Beam vector $\boldsymbol{w}_k^l$

$$\boldsymbol{w}_k^l = \left[\boldsymbol{a}\left(2^l, -1 + \frac{2k-1}{2^l}\right)^{\mathrm{T}}, \mathbf{0}^{\mathrm{T}}_{(K_L - 2^l)\times 1}\right]^{\mathrm{T}}$$

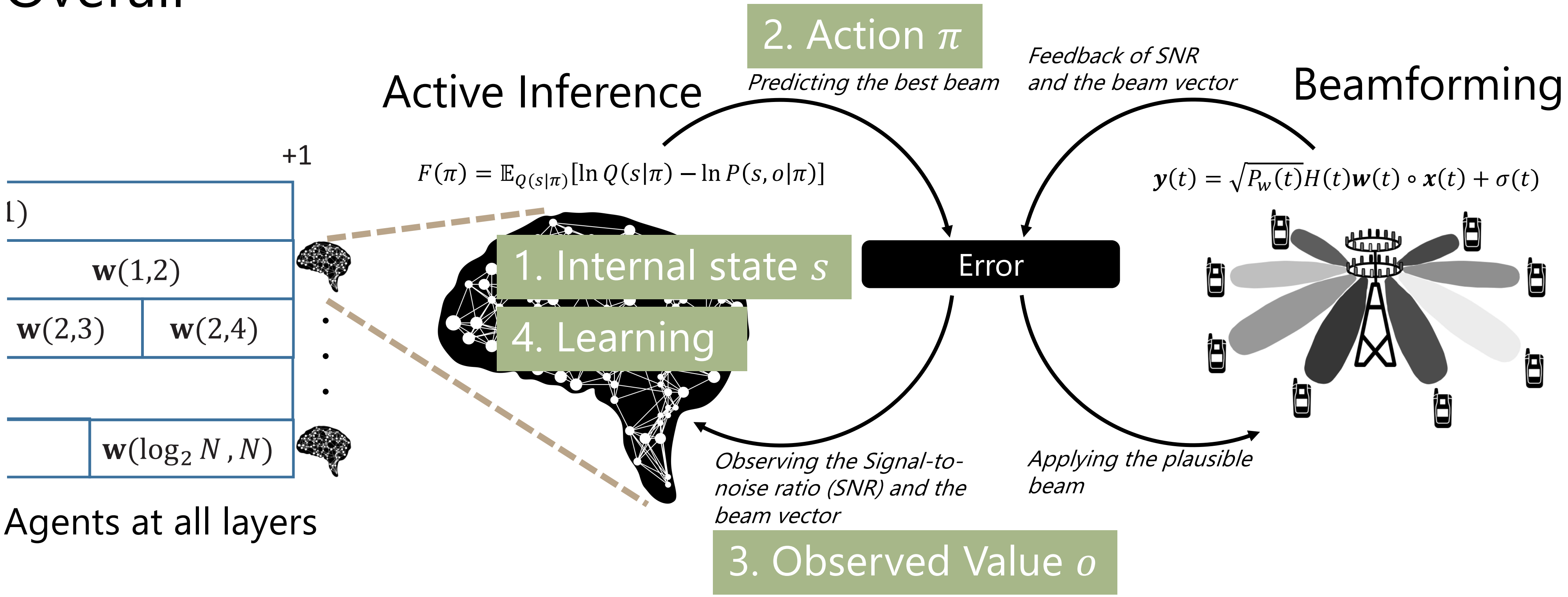
$$a(n, \Omega) = \frac{1}{\sqrt{n}}\left[e^{i\pi 0 \Omega}, \cdots, e^{i\pi(\mathrm{n}-1)\Omega}\right]^{\mathrm{T}}$$

$$K_l = 2^l \quad (l = 0, 1, \cdots, L)$$

in bipartite hierarchical codebook [2]

Proposal Model (1/3)

Overall

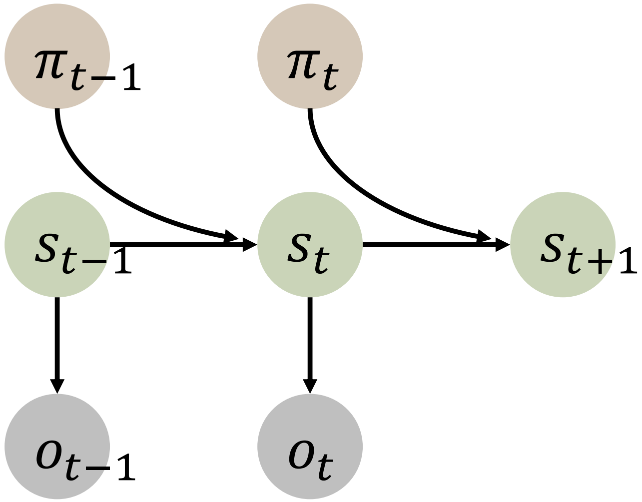


Proposal Model (2/3)

1. Internal State (→channel state)

$F(\pi) = \mathbb{E}_{Q(\tilde{s}|\pi)}[\ln Q(\tilde{s}|\pi) - \ln P(\tilde{s}, \tilde{o}|\pi)]$
$Q^*(\tilde{s}|\pi) = \arg\min_Q F(\pi)$

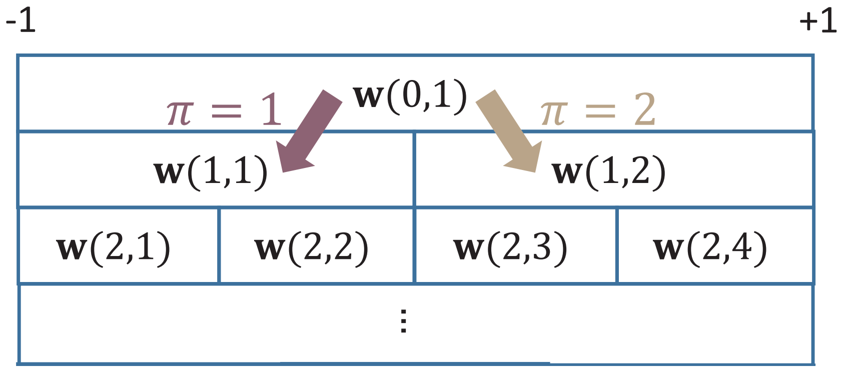
Time series of internal state, action $\tilde{s}, \tilde{o}$ and action π



POMDP in Active Inference Model [4].

2. Action (= codebook code)

$G(\pi)$
$= \mathbb{E}_{Q(\tilde{s},\tilde{o}|\pi)}[\ln Q(\tilde{s}|\pi) - \ln Q(\tilde{s}|\tilde{o}, \pi)P(\tilde{o}|C)]$
$Q^*(\pi)$
$= \arg\min_Q(-G(\pi) - F(\pi) + \ln P(\pi_0))$
$\pi \in \{0, 1, 2, 3\}$



Binary tree-structured beam vectors [2].

[4] Thomas Parr, Giovanni Pezzulo, Karl J.Friston, "Active Inference: The Free Energy Principle in Mind, Brain, and Behavior", The MIT Press, 2022

Proposal Model (3/3)

3. Observed Value (= SNR, code)

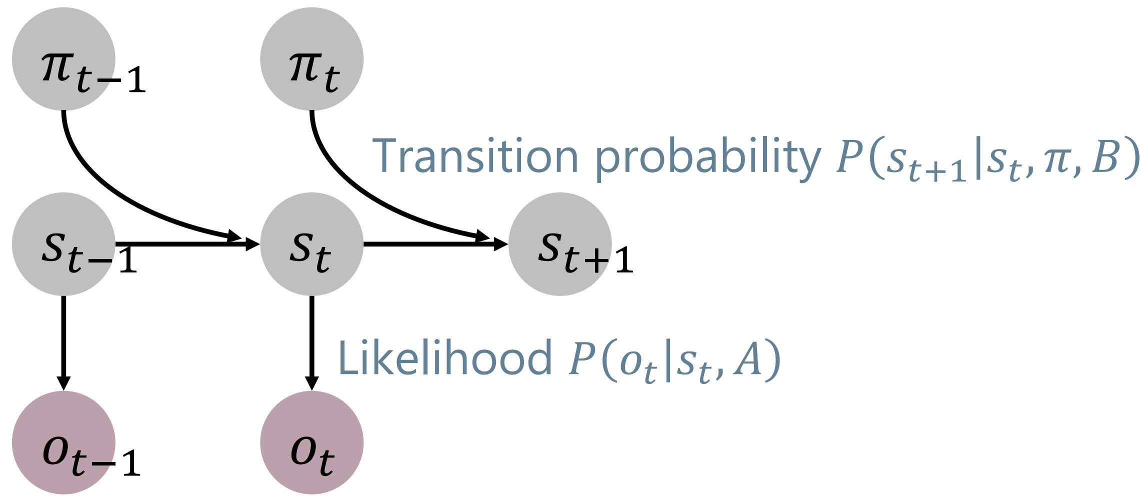
1. $\pi = 0$ or not at the other layer.
2. Quantized SNR

4. Learning

$$\mathcal{F} = \mathbb{E}_Q[\ln Q(\tilde{s}, A, B, \pi) - \ln P(\tilde{s}, \tilde{o}, A, B, \pi)]$$

$$A^* = \arg\min_A \mathcal{F}, B^* = \arg\min_B \mathcal{F}$$

Learnable parameters A, B



POMDP in Active Inference Model [4].

Improvements

1. Inference Period T_{infer}

   Coarser beam layer's T_{infer} > Finer beam layer's T_{infer}

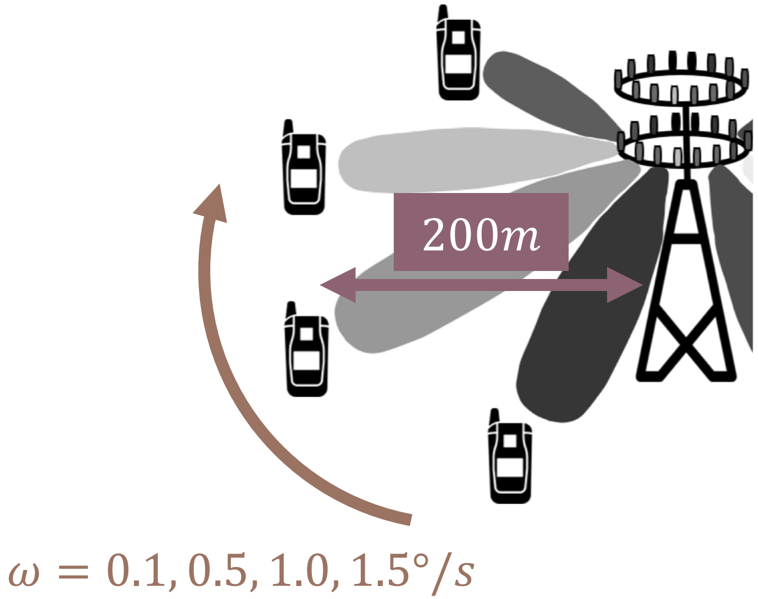
2. Introducing $\pi = 3$

   $\pi = 3$ means that the codebook code does not change.

3. High Recursive Transition Probability when $\pi = 3$

   A stable internal state leads to stable learning of the likelihood $P(o_t|s_t, A)$.

Setting and Method



- Beamforming Settings
  - 3-layer hierarchical codebook (0^{th}, 1^{st}, 2^{nd})
  - 30 rounds, min 1sec SNR feedback period,
- Active Inference
  - Observing -> Inferring the internal state -> Inferring the action -> Learning
  - Inference periods $T_{\text{train}} = 2, 1\ sec$ of the upper or lower layer
- Beam Training (BT)
  - Divide and Conquer Algorithm
  - Training periods $T_{\text{train}} = 10, 60, 100\ sec$ of BT10, BT60, BT100
- Nondirectional (baseline)
  - Nondirectional Beam

Result (1/3)

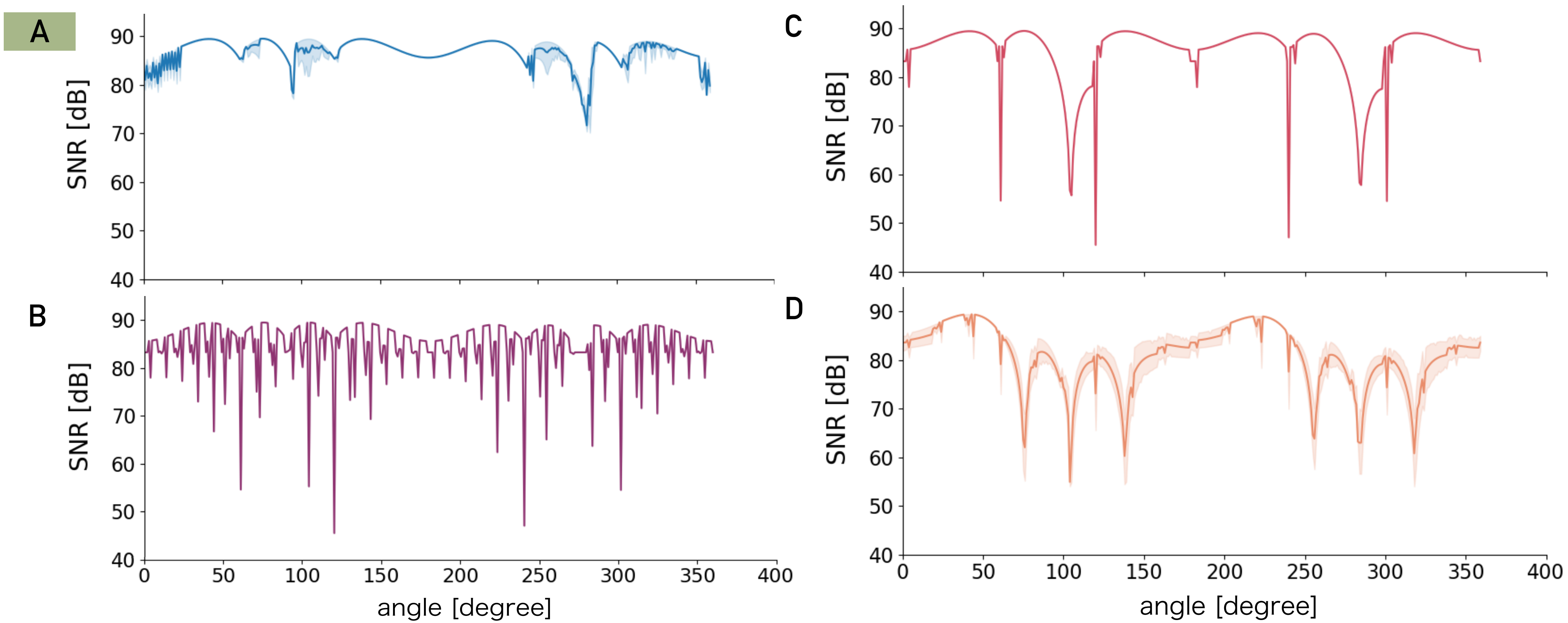


Fig. 1. SNR averages at each angle from the base station at $\omega = 1.0°/s$ with (A) Active Inference, (B) BT10, (C) BT60, (D) BT100.

Result (2/3)

TABLE I
SNR AVERAGES IN dB.

Method	Angular velocity			
	$0.1\,°/\mathrm{s}$	$0.5\,°/\mathrm{s}$	$1.0\,°/\mathrm{s}$	$1.5\,°/\mathrm{s}$
Active Inference	87.0	**86.6**	**86.7**	**85.3**
BT10	84.5	84.4	84.3	84.3
BT60	87.1	86.5	85.1	82.5
BT100	**87.2**	83.4	80.8	80.2
Nondirectional	83.3	83.3	83.3	83.3

Result (3/3)

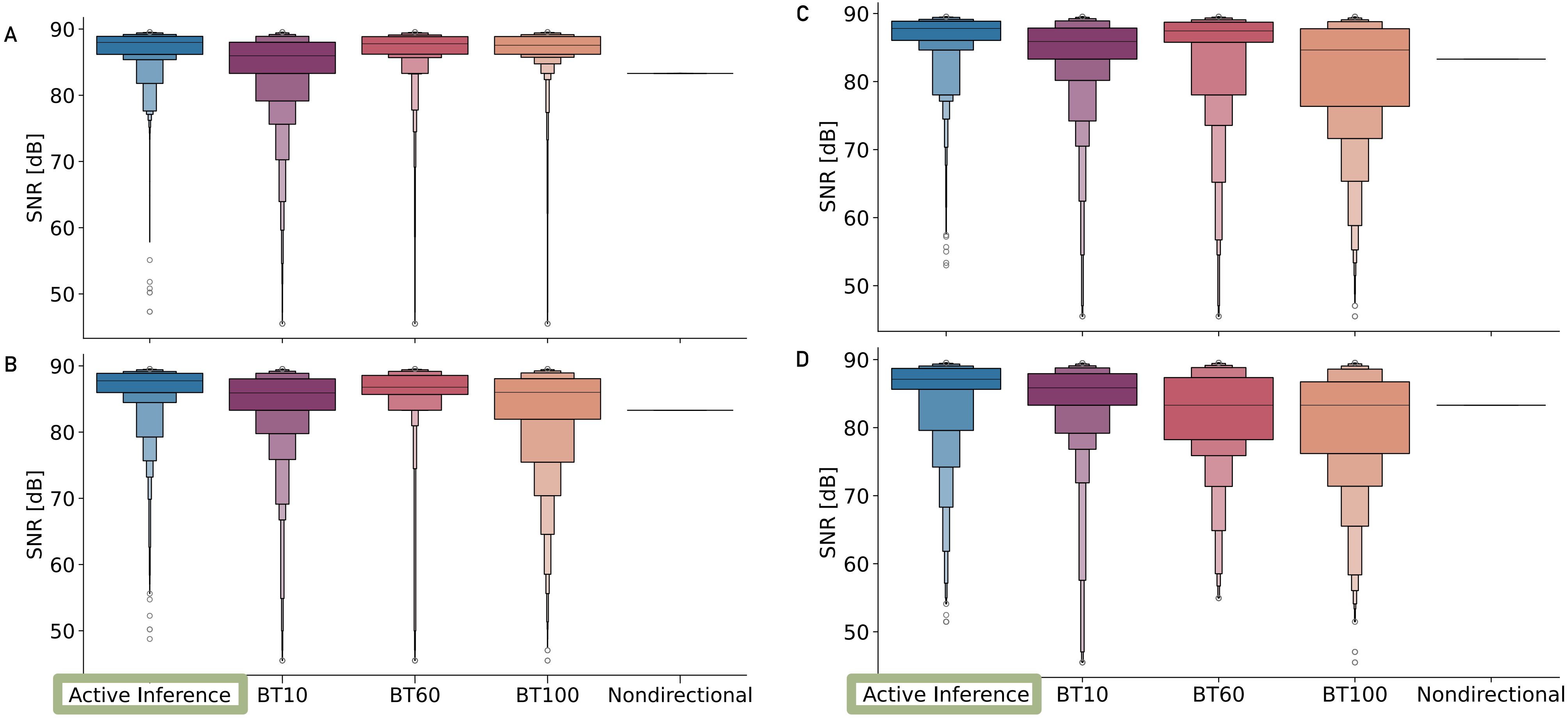


Fig. 2. Letter Value Plots of SNR at (A) $\omega = 0.1°/s$, (B) $\omega = 0.5°/s$, (C) $\omega = 1.0°/s$, (D) $\omega = 1.5°/s$

Conclusion

- In this paper, we propose a beam prediction beamforming method using Active Inference under conditions with channel condition changes such as moving UEs.
- Classical beam training methods for hierarchical codebooks temporarily degrade the SNR significantly with each beam training.
- Compared to the conventional beam training method, the active inference method not only increases the average SNR, but also prevents transient SNR degradation over a wide range of channel state changes.
- This indicates that the proposed method using Active Inference for hierarchical codebooks is useful for beamforming tasks with channel condition changes.

Thank you for your attention.

Please ask me one question at a time.