Project: IEEE P802.15 Working Group for Wireless Personal Area Networks (WPANs)

Submission Title: Three Dimensional Angle of Arrival Estimation in Dynamic Indoor THz Channel Using Forward-Backward Algorithm

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Abstract: In many application scenarios, the user equipment is moved by the user during the data transmission and the angle of arrival (AoA) is not constant. The novel algorithm exploits the fact that the AoA movement can be represented as a Markov process and the Bayesian inference can be used to provide a more precise estimate than using the likelihood alone.
Purpose: Information of IG THz

Three Dimensional Angle of Arrival Estimation in Dynamic Indoor THz Channel Using Forward-Backward Algorithm

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TU Braunschweig

The results presented in this contribution are based on [1] and [2]

Outline

- **Motivation**
- User Movement Model
- Estimation Algorithm
- Simulation Results
- Extension with Reinforcement Learning
- Conclusion

Motivation

- 2 main difficulties in the future indoor THz communications:
  - High path loss
  - Intersymbol interference
- The high gain antenna as the solution to both problems:
  - High antenna gain
  - High directivity
- A precise Angle of Arrival (AoA) estimation is a precondition for the application of high gain antenna.
- The AoA estimation in a **dynamic** scenario is more challenging.
  - The AoA changes along time due to the moving user equipment.
- **Objective: AoA estimation in a dynamic scenario with realistic channel and movement models.**

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Measurement of User Movement

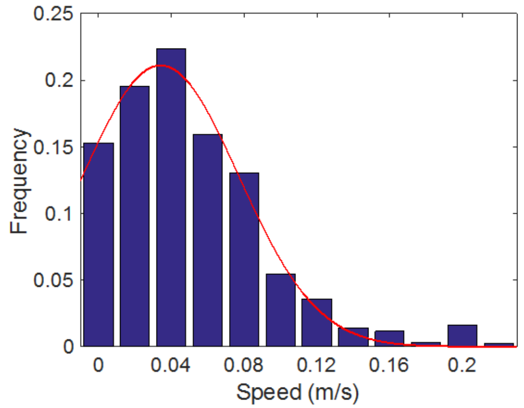
- Three user states:
  - Sitting with smartphone
  - Walking with smartphone
  - Laptop on legs

	Definition	Impact on AoA
Translational	Displacement of gravity center	On both access point and user equipment
Rotational	Change of direction	Only on user equipment

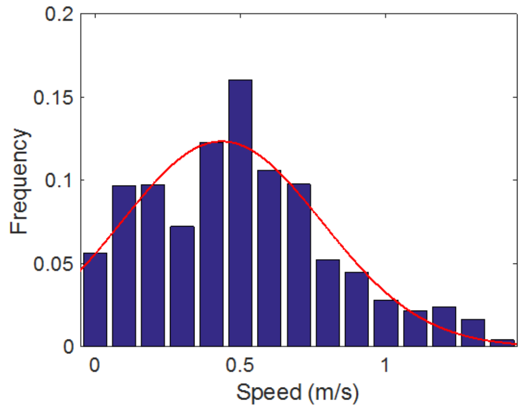
- Measurement is carried out with the sensor kinetics app on iPhone 6 with validated measurement accuracy.

Translational Movement

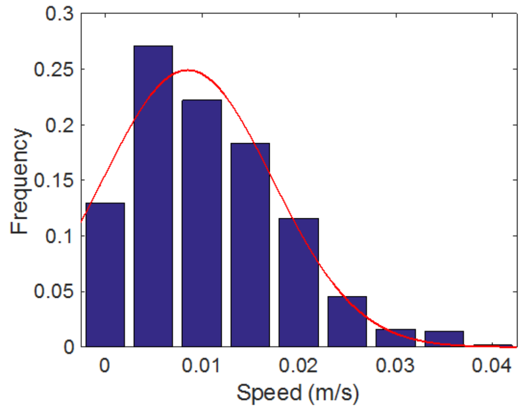
Translational speed in 3 scenarios:



Sitting with smartphone



Walking with smartphone



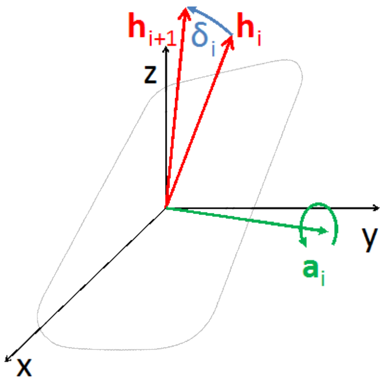
Laptop on legs

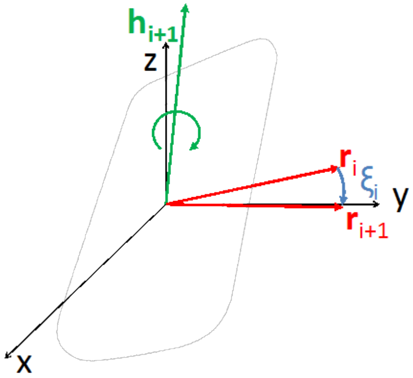
- The speed distribution can be approximated by the normal distribution.
- The movement direction depends on the scenario.

Modeling Rotational Movement

- Step 1: rotation of the heading direction (from bottom to top) about a given axis
- Step 2: rotation of the side direction (from left to right) about the heading direction.

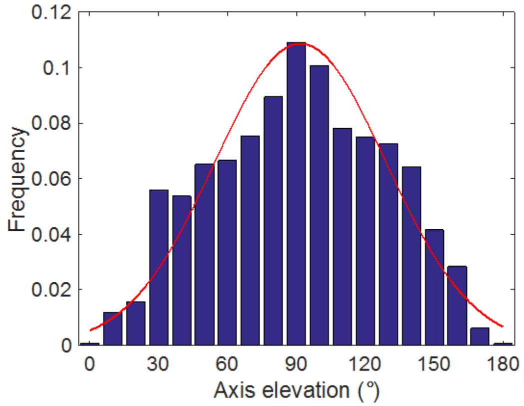
- Parameters:
  - Heading direction axis
  - Angular speed of heading directions
  - Angular speed of side directions



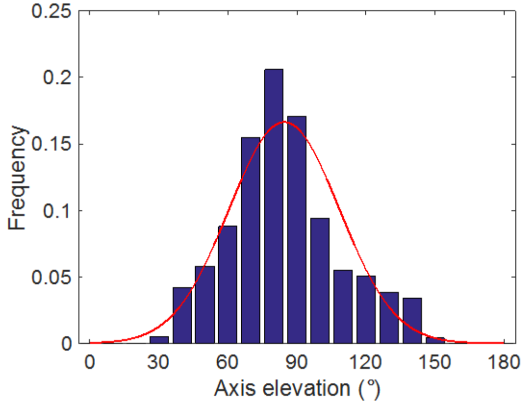


Rotational Movement – Axis Elevation

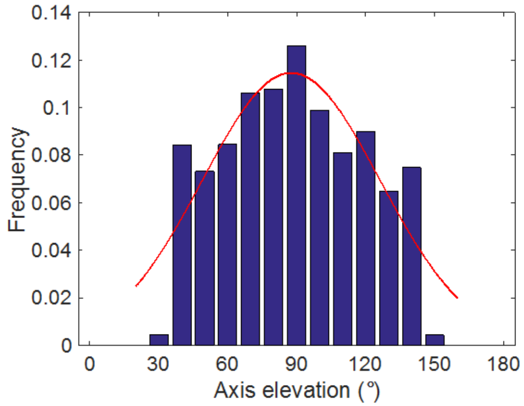
Rotational axis elevation distributions in 3 scenarios:



Sitting with smartphone



Walking with smartphone

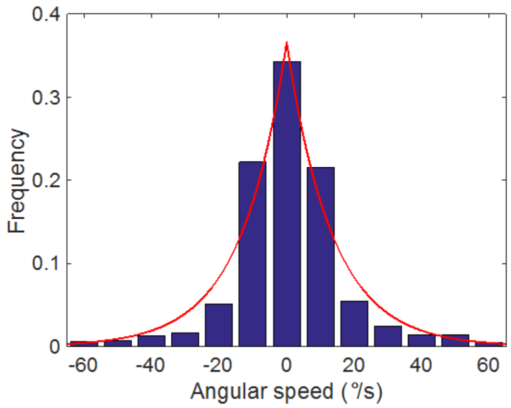


Laptop on legs

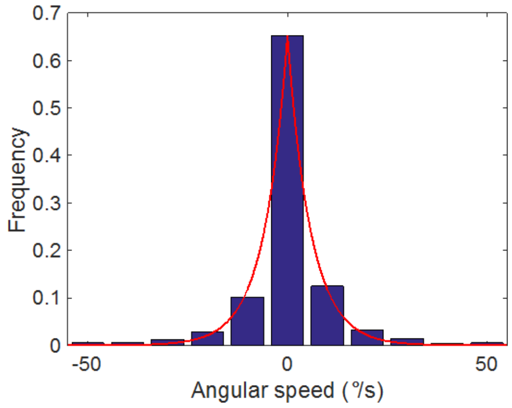
- Approximated by the normal distribution.
- Because the axis must be perpendicular to the current heading direction, the axis azimuth is determined once the elevation is given.

Rotational Movement – Heading Direction Angular Speed

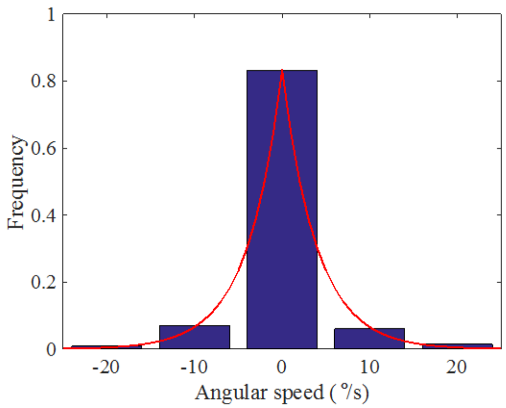
Heading direction rotational speed distributions in 3 scenarios:



Sit with smartphone



Walk with smartphone

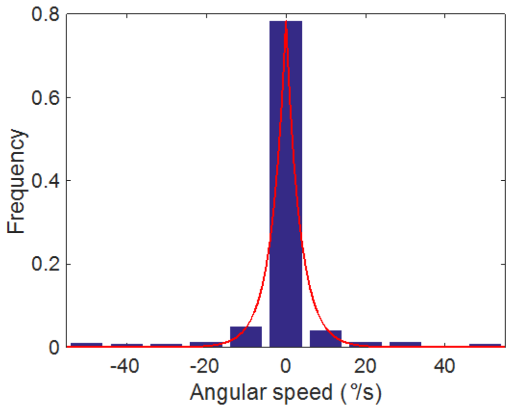


Laptop on legs

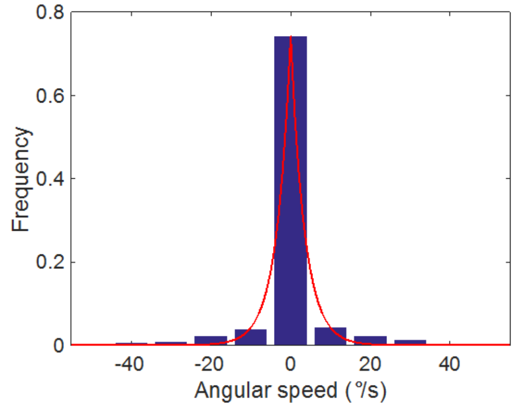
- Approximated by the Laplace distribution.

Rotational Movement – Side Direction Angular Speed

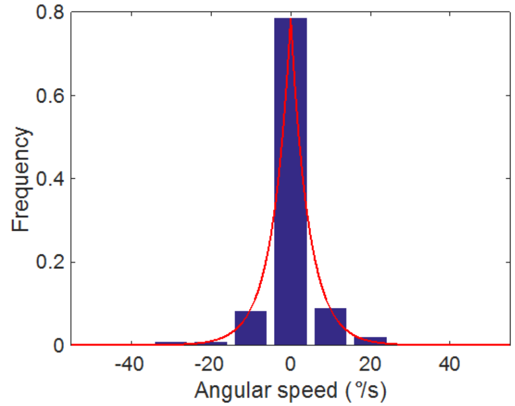
Side direction rotational speed distributions in 3 scenarios:



Sitting with smartphone



Walking with smartphone



Laptop on legs

- Approximated by the Laplace distribution.

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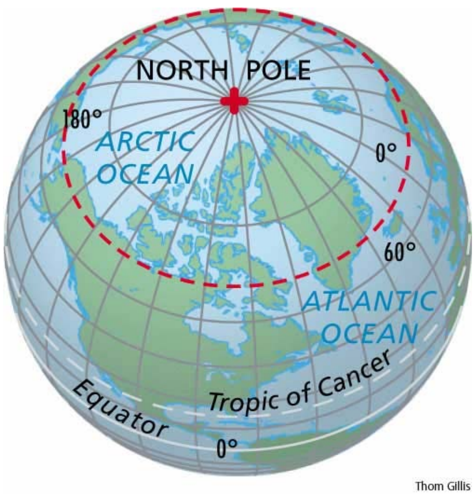
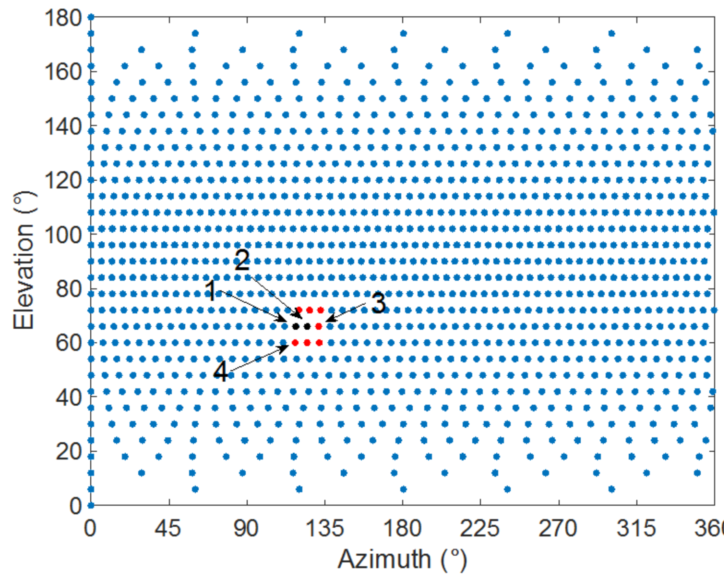
Beam Switching and Spherical Coordinate System

- We define uniformly distributed main lobe directions with resolution of 6° and select the direction which is nearest to the true AoA in the application.
- The "uniform" distribution is not quite *uniform* in the spherical coordinate system.





Continuous AoA Movement

2 Observations of the AoA movement along time

- If we know that AoA is 1 at time instant i and AoA is 2 at time instant i+1 (**black dots**),
- Then we can infer
  - The AoA at time instant i+2 must be an adjacent dot of 2 (**red** or **black** dots)
  - The adjacent dots have different a-priori probabilities (e.g. the a-priori probability of “3” is higher than “4”).
- The a-prioru probability can be derived from the memory, therefore we can use the **Hidden Markov Model** for the inference along time.

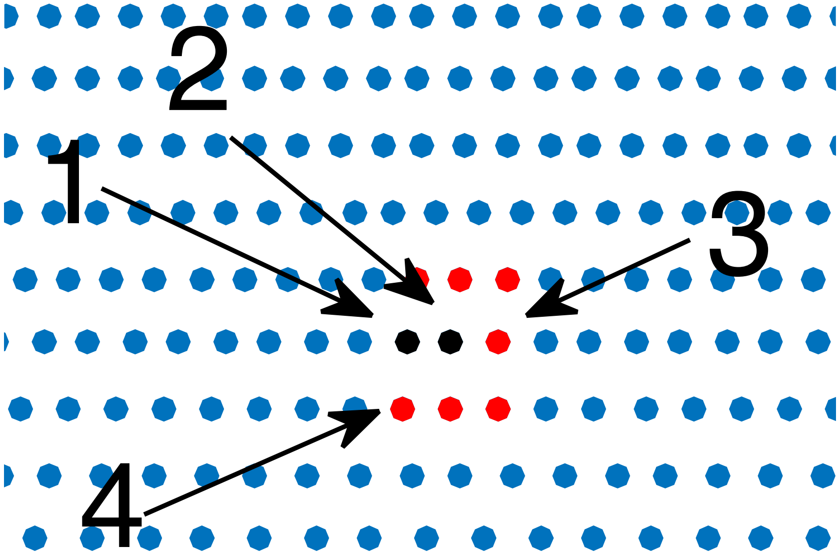
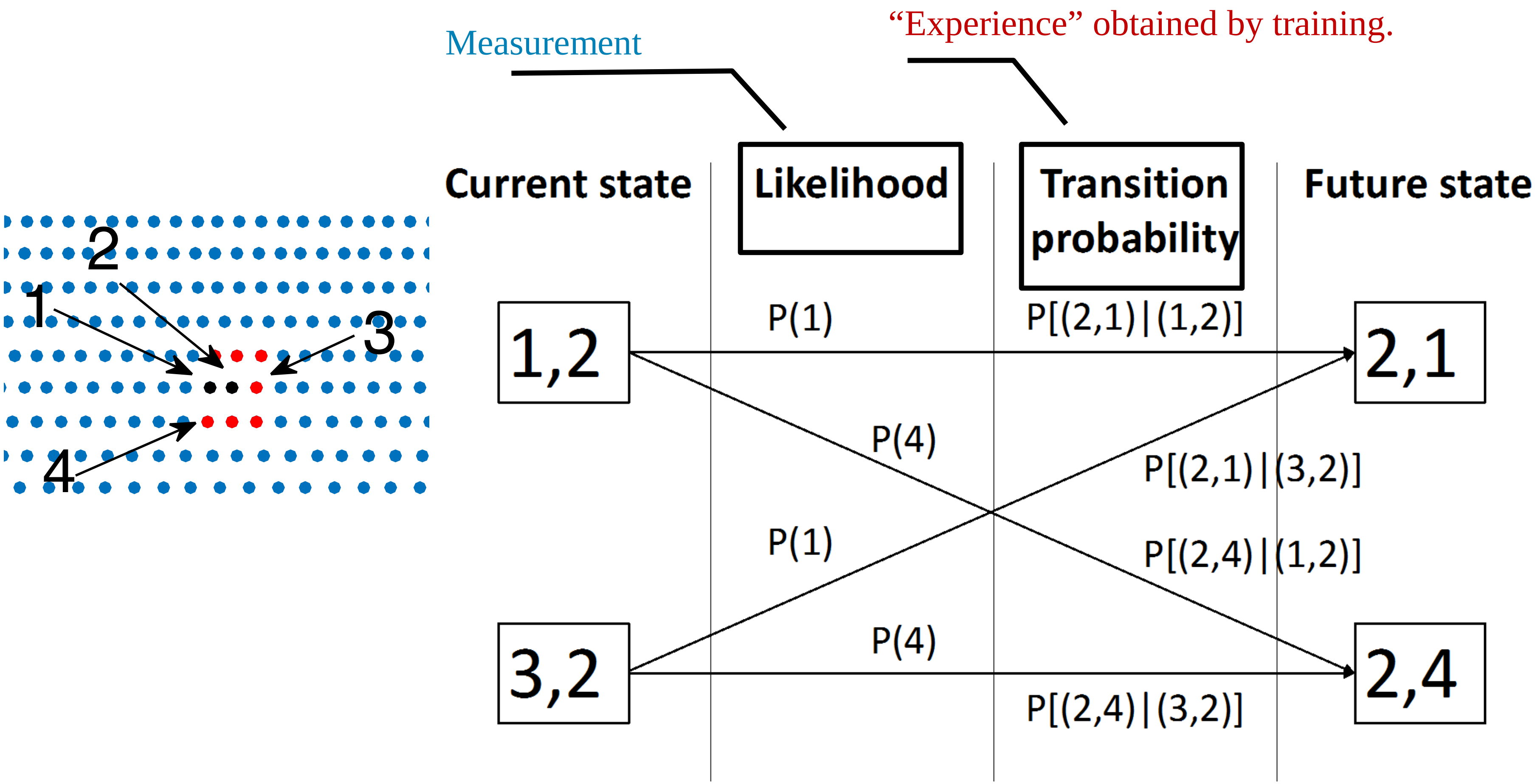
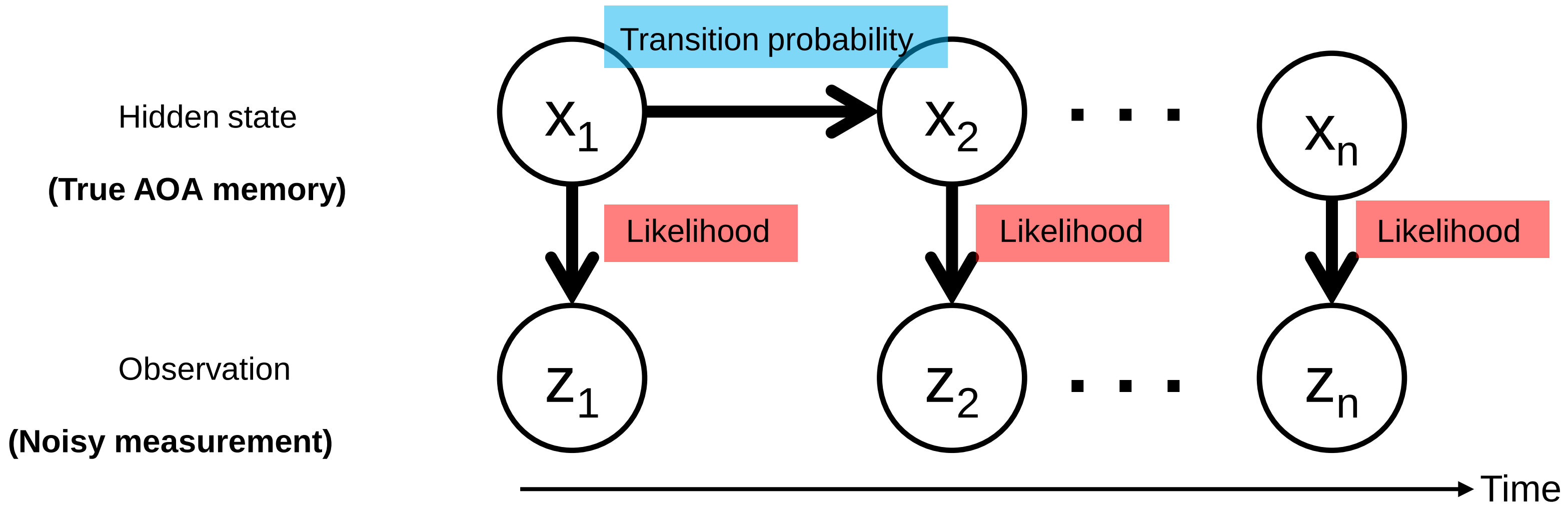


Illustration of State Transition



Forward-Backward Inference



On-line estimation with forward algorithm:

$$p(\mathbf{z}_{1:i}|x_i) = p(\mathbf{z}_{1:i-1}|x_i)p(z_i|x_i) = \alpha(x_i)\beta(x_i)$$

Off-line estimation with forward-backward algorithm:

$$p(\mathbf{z}_{1:n}|x_i) = p(\mathbf{z}_{1:i-1}|x_i)p(z_i|x_i)p(\mathbf{z}_{i+1:n}|x_i) = \alpha(x_i)\beta(x_i)\gamma(x_i)$$

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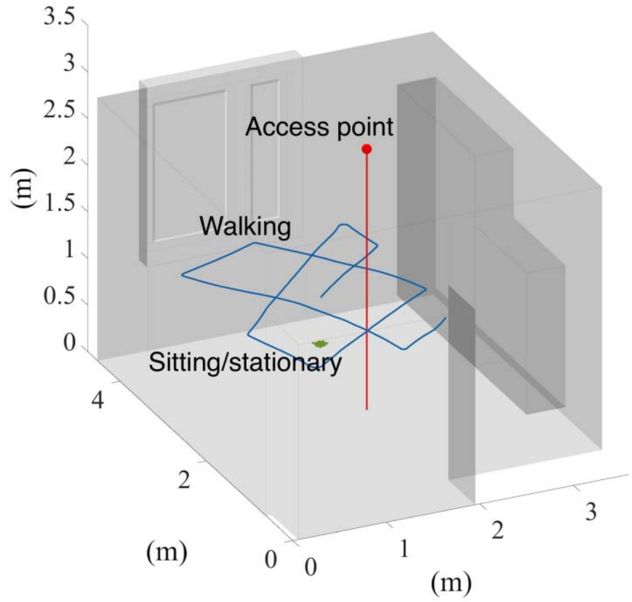
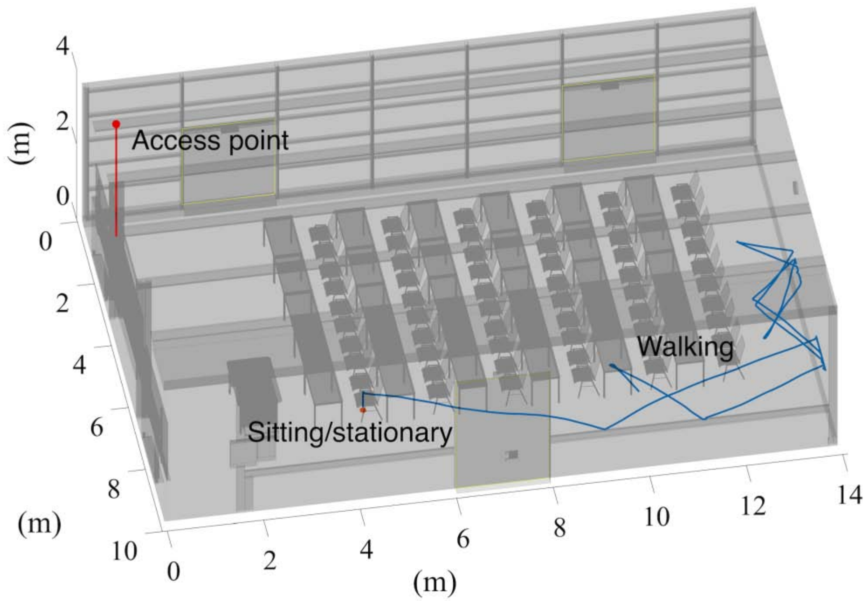
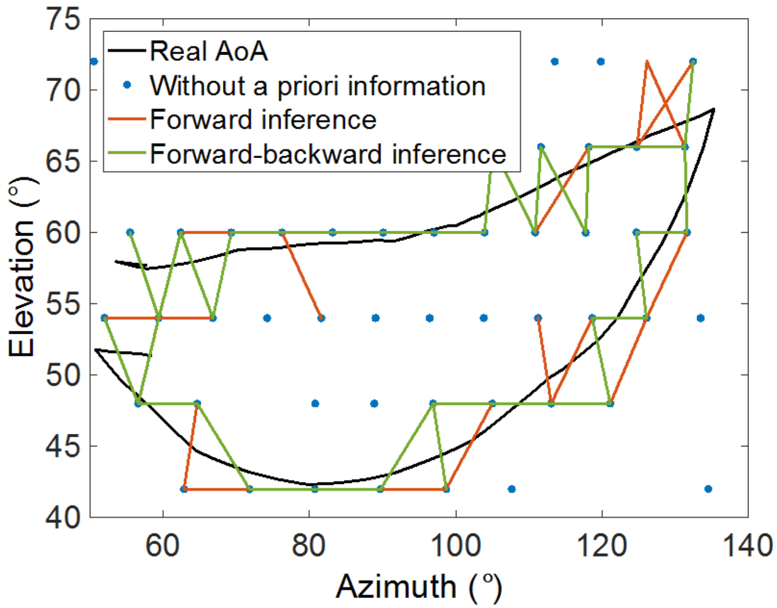
Simulation Environment

- An office scenario and a lecture room scenario are chosen for demonstrating the algorithm performance.
- Three movement states – stationary, sitting and walking are considered.
- Channel models are generated using the ray-launching simulator.

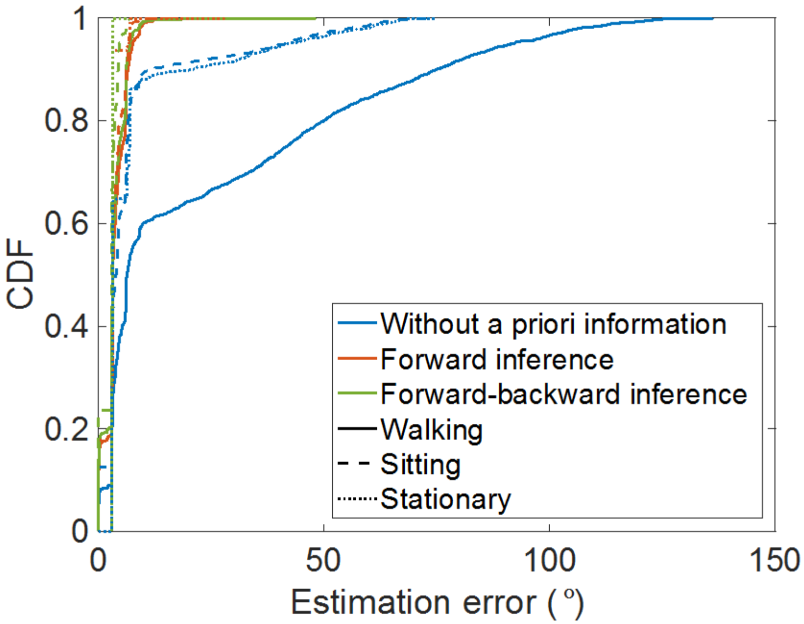




Estimated AoA



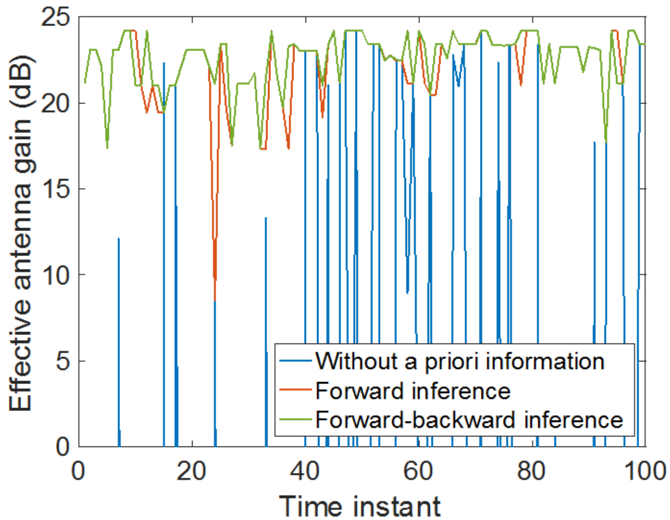
Real & estimated AoA



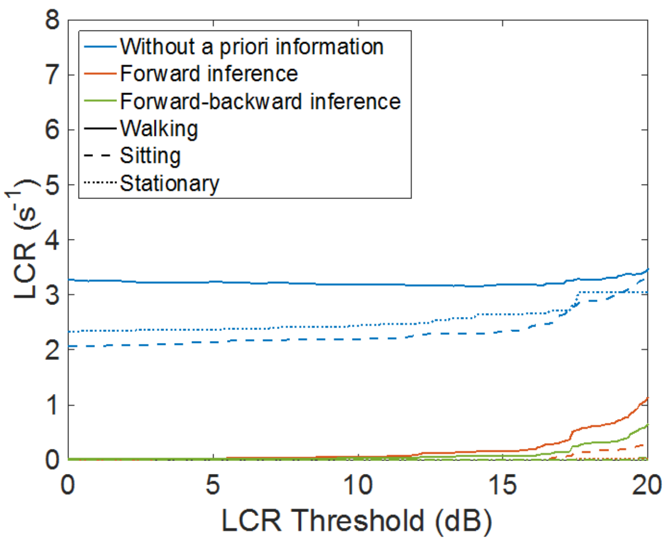
CDF of estimated errors

- Results in the small office scenario is presented as an example.
- The novel algorithm outperforms the traditional method clearly.
- The forward-backward inference outperforms the forward inference slightly.

Effective Antenna Gain and Level Crossing Rate



Effective antenna gain in 100 time instants



Level crossing rate of effective antenna gain

- The novel algorithm provides not only higher but also more stable effective antenna gain.
- The forward-backward inference is better than the forward inference alone.

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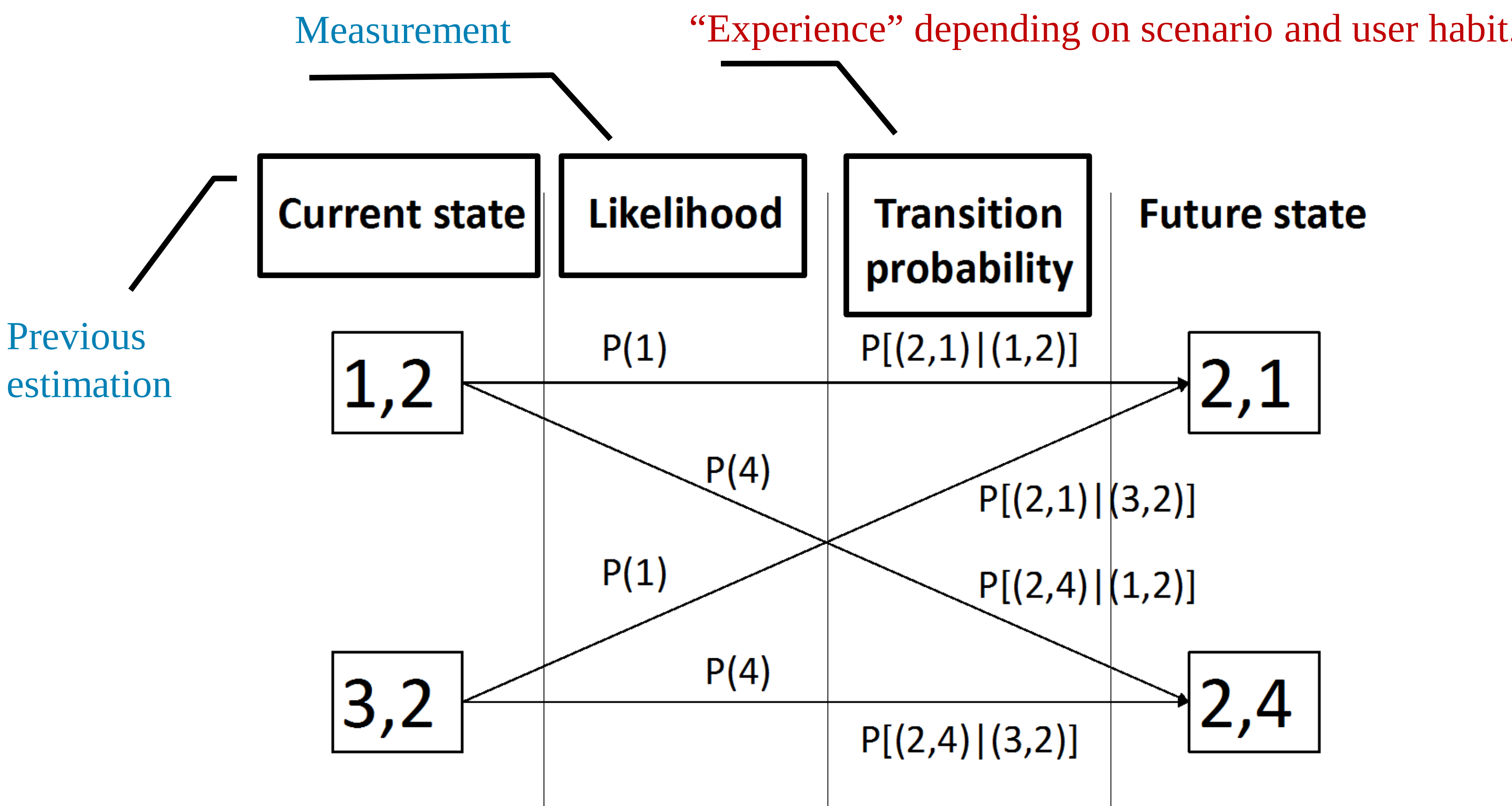
Review of State Transition



For example, in a big scenario where the access point is far from the user equipment, the same user movement results in less AoA change and the prior probability of states (1, 1) is higher.

Application of Reinforcement Learning

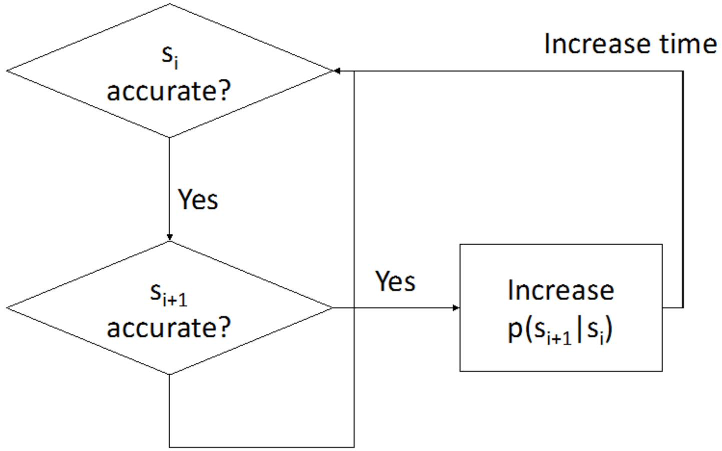
- Application of reinforcement learning to optimize transition probabilities, making them adapting to scenario and user habit.

- We assume the decoding feedback provides information, whether the AoA is correctly estimated or not.

- If a state transition is estimated successfully, the corresponding transition probability is increased as a “reward”.
  - The punishment is not advisable because reasons for failed decoding are various.

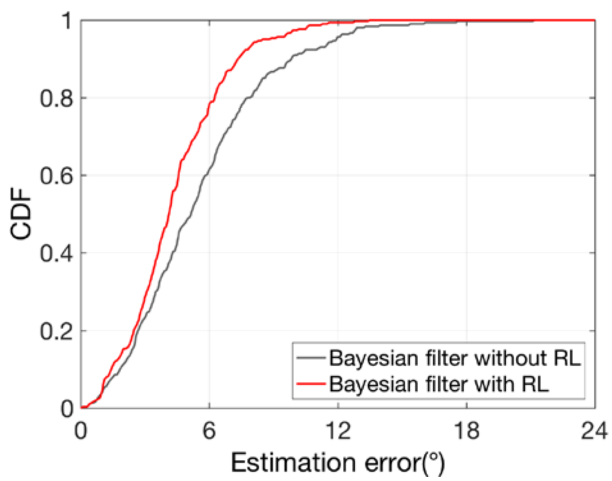
- The transition probability is calculated as

$$p(s_{i+1}|s_i) = \frac{n(s_{i+1}|s_i)}{n(s_i)}$$

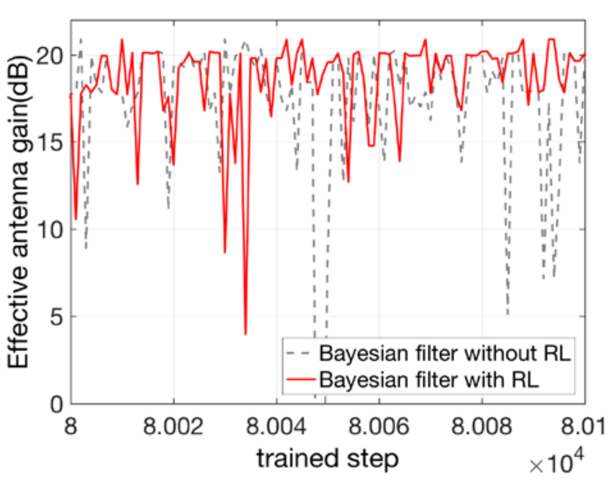


Simulation Results

- The comparison is between Bayesian filter with and without reinforcement learning after 80000 training steps.
- A low estimation error realizes a high antenna gain.
- Simulation results show a significant improvement of estimation precision with reinforcement learning.



CDF of estimate error



Realized antenna gain

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Conclusion

- A novel Bayesian inference algorithm is presented for the 3 dimensional AoA estimation for dynamic indoor THz channels.
- A microscopic human movement model is derived from measurements.
- The simulation shows significant performance improvement against methods without Bayesian inference.
- The reinforcement learning is applied to learn from previous estimations for better future inference.

Reference

1. Peng, Bile, and Thomas Kürner. "Three dimensional angle of arrival estimation in dynamic indoor terahertz channels using forward-backward algorithm." *IEEE Transactions on Vehicular Technology* (2016).
2. Peng, Bile, Qi Jiao, and Thomas Kürner. "Angle of arrival estimation in dynamic indoor THz channels with Bayesian filter and reinforcement learning." *Signal Processing Conference (EUSIPCO), 2016 24th European*. IEEE, 2016.