Dynamic Uploading Scheduling in mmWave-Based Sensor Networks via Mobile Blocker Detection

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Introduction

Motivation

1. The vulnerability of mmWave communication to link blockage postpones real-time communications, and thus results in outdated Age of Information (AoI) in Wireless Sensor Networks (WSNs).
2. Fortunately, with wireless sensing technologies, the locations of signal reflectors (e.g., walls), the real-time position and motion pattern of an environmental blocker (e.g., a human body) can be detected to predict future wireless channels [1][2].
3. As a result, future AoI degradation arising from link blockage can be forecast. Although we can not prevent the coming link blockage, future AoI outdatedness can be mitigated by taking action in advance. For example, the server prefer to sample and collect the status information from the sensor more frequently just before its link blockage.

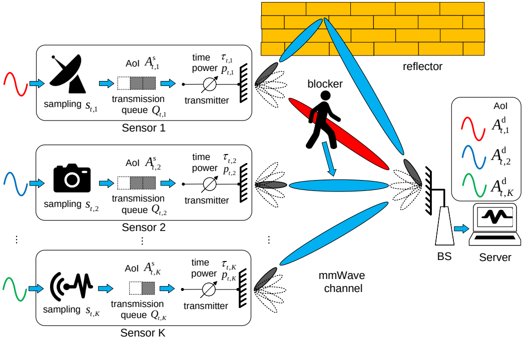
[1] Y. Sun, et al., "An Indoor Environment Sensing and Localization System via mmwave Phased Array," JCIN, 2022.
[2] C. Yu, Y. Sun, et al., "mmAlert: mmWave Link Blockage Prediction via Passive Sensing," IEEE WCL, 2023.

System Model

Network Description

We consider a mmWave-based wireless monitoring system consisting of one server connected with the base station (BS) and K sensors in an indoor space with a mobile blocker.

- **Sampling and uploading.** The sensors measure the status of physical process (e.g., photos) and upload the sample by transmitter via mmWave uplink channel. The server collects the received samples and maintains the latest sample.

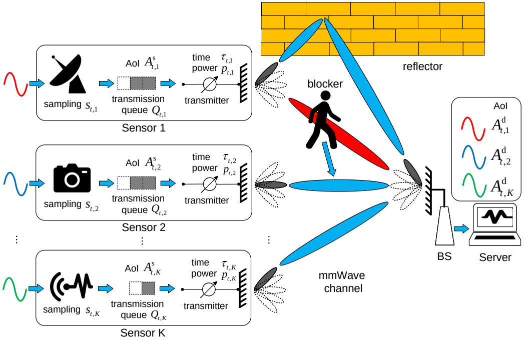


System Model

Network Description

We consider a mmWave-based wireless monitoring system consisting of one server connected with the base station (BS) and K sensors in an indoor space with a mobile blocker.

- **Sampling and uploading.**
- **AoI-aware.** The AoI of a sample is defined as the time elapsed since it is generated at the sensor.

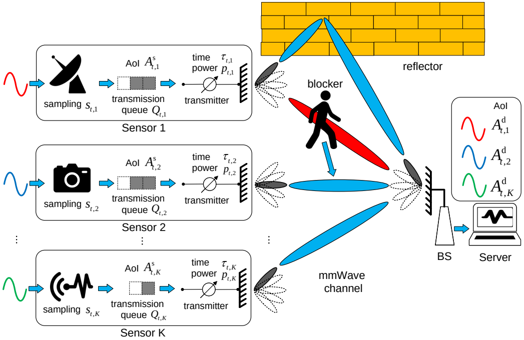


System Model

Network Description

We consider a mmWave-based wireless monitoring system consisting of one server connected with the base station (BS) and K sensors in an indoor space with a mobile blocker.

- **Sampling and uploading.**
- **AoI-aware.**
- **Blocker-aware.** It is assumed that the real-time position and motion pattern (position transitions) of the blocker can be detected via wireless sensing technologies.



System Model

Network Description

- **Discretized time.** The uplink transmission time is organized by physical-layer frames with constant duration, where the channel state information (CSI) is assumed to be quasi-static in one frame.
- **Discretized space.** The locations of the indoor space are quantized into grids with indexes.
- It is assumed that the mobility of the blocker follows a time-invariant Markov chain, with the following transition probabilities,

$$\Pr\left[l_{t+1}^{\mathrm{B}}=\ell' \middle| l_t^{\mathrm{B}}=\ell\right] = \left[\mathbf{P}^{\mathrm{B}}\right]_{\ell,\ell'}, \ \forall t, \ \forall \ell, \ell' \in \mathbb{L},$$

where $\mathbf{P}^{\mathrm{B}} \in \mathbb{R}^{|\mathbb{L}|\times|\mathbb{L}|}$ denotes the transition matrix of the blocker's mobility.

System Model
Channel Model

We consider the geometric channel model with at most M NLoS paths and one LoS path from each sensor to the BS. Hence, the channel matrix $\mathbf{H}_{t,k} \in \mathbb{C}^{N_\mathrm{R} \times N_\mathrm{T}}$ from the k-th sensor to the BS in the t-th frame can be written as

$$\mathbf{H}_{t,k} = \sum_{i \in \mathcal{M}} \underbrace{B_{t,k,i}(l_t^\mathrm{B})}_{\substack{\text{blockage}\\ \text{indicator}}} \underbrace{\alpha_{t,k,i}}_{\substack{\text{complex}\\ \text{gain}}} \underbrace{\mathbf{a}_\mathrm{R}(\phi_{k,i})\mathbf{a}_\mathrm{T}^\mathsf{H}(\theta_{k,i})}_{\substack{\text{array response}\\ \text{w.r.t. AoA/AoD}}}.$$

The human blocker is modeled as a disk with radius r_B, and hence, given l_t^B, the blockage indicator $B_{t,k,i}$ can be determined in a geometric way.

The path loss of the LoS path is usually much smaller than that of the NLoS paths. Therefore, the uplink transmission suffers from significant degradation when the LoS path is blocked.

System Model
Channel Model

Given the transmission power at the sensor, the uplink capacity of the k-th sensor in the t-th frame after precoding and combining can be expressed by

$$R_{t,k} \triangleq W \log_2 \left(1 + p_{t,k} \underbrace{\frac{\left| \mathbf{w}_{t,k}^{\mathsf{H}} \mathbf{H}_{t,k} \mathbf{f}_{t,k} \right|^2}{\|\mathbf{w}_{t,k}\|^2 N_0 W}}_{\text{Baseband gain } Y_{t,k}} \right).$$

Time-Division Multiple Access (TDMA) is adopted in each frame. The transmission time allocated to the k-th sensor, $\tau_{t,k}$ is constrained by

$$\begin{aligned} &\textstyle\sum_{k \in \mathcal{K}} \tau_{t,k} = T_{\mathrm{F}}, \ \forall t, \\ &0 \le \tau_{t,k} \le T_{\mathrm{F}}, \ \forall t, k \in \mathcal{K}. \end{aligned}$$

With the packet size N_{b}, the number of packets transimitted in a frame can be expressed by

$$D_{t,k} = \left\lfloor \frac{R_{t,k} \tau_{t,k}}{N_{\mathrm{b}}} \right\rfloor.$$

System Model

Queuing and AoI Model

The data volume of each sample generated by the k-th sensor consists of L_k packets, which may not be completely uploaded in one frame. Let $s_{t,k} \in \{0,1\}$ be the sampling action. Since each sensor only transmits data packets of the latest sample, the queue dynamics of the k-th sensor (in terms of packets) is given by

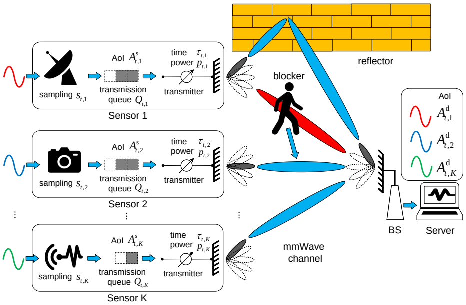
$$Q_{t+1,k} = \begin{cases} (Q_{t,k} - D_{t,k})^+, & s_{t,k} = 0 \\ L_k - D_{t,k}, & s_{t,k} = 1 \end{cases}$$

The AoI dynamics at the k-th sensor is given by

$$A^{\mathrm{s}}_{t+1,k} = \begin{cases} \min\{A^{\mathrm{s}}_{t,k} + 1, A_{\max}\}, & s_{t,k} = 0 \\ 1, & s_{t,k} = 1 \end{cases}$$

The AoI dynamics for the k-th sensor at the server is given by

$$A^{\mathrm{d}}_{t+1,k} = \begin{cases} \min\{A^{\mathrm{s}}_{t,k} + 1, A_{\max}\}, & (Q_{t,k} - D_{t,k})^+ = 0 \\ \min\{A^{\mathrm{d}}_{t,k} + 1, A_{\max}\}, & \text{otherwise} \end{cases}$$



Problem Formulation

Infinite-horizon MDP

To formulate the problem as an infinite-horizon MDP, we shall define:

System State

At the beginning of the t-th frame, the **global system state** is defined by $\mathcal{S}_t \triangleq (l_t^{\mathrm{B}}, \mathcal{Y}_t, \mathcal{Q}_t, \mathcal{A}_t^{\mathrm{s}}, \mathcal{A}_t^{\mathrm{d}})$ consisting of blocker location, and baseband channel power gains, queue lengths, AoIs at the sensors, AoIs for the sensors at the server.

Action and Policy

The **global scheduling action** is defined by $\mathbf{a}_t \triangleq (s_{t,k}, \tau_{t,k}, p_{t,k})_{k\in\mathcal{K}}$, including the sampling decision, and uplink transmission time and power. Hence, the **scheduling policy** is a mapping from the system state to the scheduling actions, $\Omega(\mathcal{S}_t) = \mathbf{a}_t$.

Problem Formulation

Infinite-horizon MDP

Per-frame Cost

In the t-th frame, the **per-frame cost** is defined by

$$g(\mathcal{S}_t, \Omega(\mathcal{S}_t)) = \sum\nolimits_{k\in\mathcal{K}} \Big[\underbrace{A^{\mathrm{d}}_{t,k}}_{\text{AoI at the server}} + w_{\mathrm{P}} \big(\underbrace{s_{t,k} C^{\mathrm{s}}}_{\text{sampling energy}} + \underbrace{\tau_{t,k} p_{t,k}}_{\text{transmission energy}} \big) + w_{\mathrm{Q}} \underbrace{\mathbb{I}[A^{\mathrm{d}}_{t,k} = A_{\max}]}_{\text{AoI outdatedness penalty}} \Big],$$

where w_{P} and w_{Q} denote the weights for energy consumption and AoI outdatedness penalty, respectively.

Problem Formulation

Infinite-horizon MDP

Infinite-horizon MDP

As a result, the joint sampling and uploading optimization can be formulated as the infinite-horizon MDP with discounted cost,

$$\text{P1}: \ \Omega^{\star} = \arg\min_{\Omega} \lim_{T\to\infty} \left[\mathbb{E}_{\mathcal{Y},\mathcal{L}^{\mathrm{B}}} \sum\nolimits_{t=1}^{T} \gamma^{t-1} g_t(\mathcal{S}_t, \Omega(\mathcal{S}_t)) \middle| \mathcal{S}_1 \right]$$

$$\text{s.t. } p_{t,k} \le P_{\max}, \ \forall t, k \in \mathcal{K},$$

$$\sum\nolimits_{k\in\mathcal{K}} \tau_{t,k} = T_{\mathrm{F}}, \ \forall t,$$

$$0 \le \tau_{t,k} \le T_{\mathrm{F}}, \ \forall t, k \in \mathcal{K}.$$

Problem Formulation

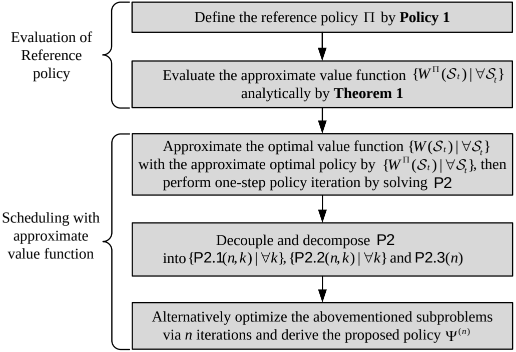
Infinite-horizon MDP

The Bellman's equations of the above MDP are

$$W(\mathcal{S}) = \min_{\Omega(\mathcal{S})} \Big[g\big(\mathcal{S}, \Omega(\mathcal{S})\big) + \gamma \sum_{\mathcal{S}'} W(\mathcal{S}') \Pr[\mathcal{S}' | \mathcal{S}, \Omega(\mathcal{S})] \Big], \forall \mathcal{S},$$

Although conventional approaches such as policy iteration (PI) and value iteration (VI) can be used to find the optimal scheduling policy by recursion of the Bellman equation, they suffer from the *curse of dimensionality*: due to the huge system state space, the evaluation of value function is prohibitive.

Proposed Solution



The proposed suboptimal solution achieves a good balance between complexity and performance.

- **Low Complexity.**
  1. Analytically expressed and decoupled value function of reference policy.
  2. One-step policy improvement instead of iteration.
  3. Alternative optimization for the decoupled actions during policy improvement.
- **Performance Guarantee.** The performance of the proposed policy is lower-bounded by a roughly-good reference policy.

Simulation Results

Benchmarks

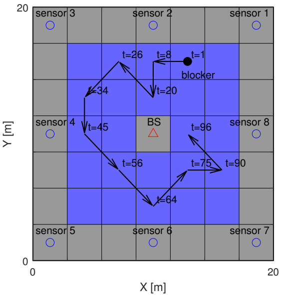
We compare the proposed policies with three benchmarks. For fair comparison, all the benchmarks adopt the same sampling policy and transmission power as the reference policy of our proposed framework, while the time allocation is:

- **BM 1** (Reference Policy) The transmission time allocation of each sensor is proportional to the corresponding data volume of sample at each sensor, i.e., $\tau_{t,k} = T_{\mathrm{F}} L_k / \sum_{k' \in \mathcal{K}} L_{k'}$.
- **BM 2** (Largest-AoI First) The sensor with the largest AoI at the server, i.e., $\arg\max_k A^{\mathrm{d}}_{t,k}$, is scheduled for transmission sequentially, until transmission time of the frame is used up.
- **BM 3** (Dynamic Backpressure) The sensor with the largest product of buffer length and uplink capacity, i.e., $\arg\max_k Q_{t,k} R_{t,k}$, is scheduled for transmission sequentially, until transmission time of the frame is used up.

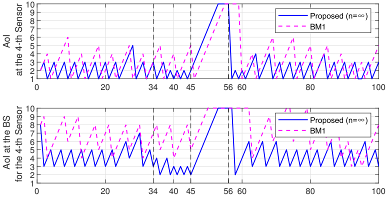
Simulation Results

A Deeper Look at How it Works

We consider a 20m$\times$20m square room with 8 sensors and the mobility of the human blocker follows a modified random walk.



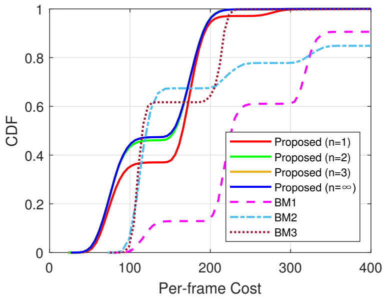
The insights on blockage-predictive scheduling of the proposed policy can be obtained, which shows the dynamics of the AoI at the 4-th sensor and the corresponding AoI at the server.

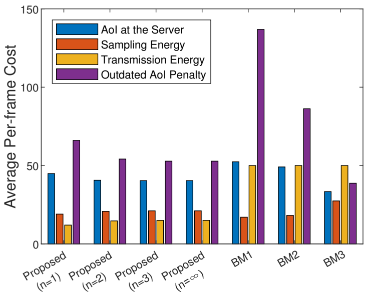


Simulation Results

Comparison with Benchmarks

Our proposed scheme can converge after only a few iterations and reduce the average per-frame cost by 13.5%–49.6% compared with the benchmarks.

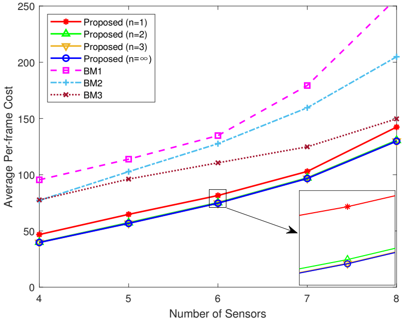




Simulation Results

Impact of the Number of Sensors

Our proposed scheme shows the better performance compared to the benchmarks with robustness against the number of sensors.



Conclusion

- A predictive scheduling framework is provided for environment-aware transmission scheduling. In the proposed MDP formulation, the future AoI degradation due to potential link blockage is naturally considered in the current scheduling according to the Bellman's equations.
- We propose a low-complexity AMDP framework with a guarantee of the worst-case performance. Specifically, we first introduce a decoupling principle to design heuristic scheduling polices as the reference policy, whose average cost can be derived analytically. With the expression of the value function, the above policy iteration can be formulated analytically, whose optimization efficiency is significantly better than the conventional numerical search.
- Simulations show that compared with several heuristic benchmarks, our proposed policy, benefiting from the awareness of the link blockage, can reduce the average cost with a high performance gain.