Optimal Sampling for Uncertainty-of-Information Minimization in a Remote Monitoring System

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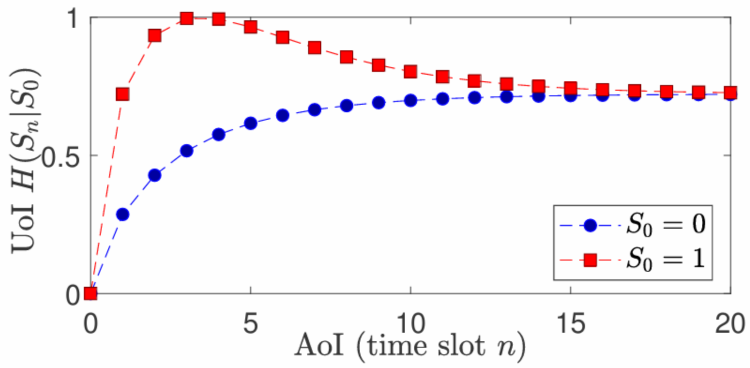
Introduction

- **Why focus on *Uncertainty-of-Information* [1],[2]?**
  - **Non-monotonic relationship with AoI**, unlike some of other information freshness metrics which are non-decrease functions of AoI [3],[4]
  - **UoI's dependence on AoI varies with the latest observed state**. UoI reflects the different rates of information quality evolution caused by different values of the last observation



UoI vs. AoI and the latest observed state S_0 ***(Fig. 1)***

UoI: Uncertainty-of-Information   AoI: Age-of-Information

[1] G. Chen, S. C. Liew, and Y. Shao, "Uncertainty-of-information scheduling: A restless multi-armed bandit framework," IEEE Trans. Inf. Theory, vol. 68, no. 9, pp. 6151–6173, Sep. 2022.
[2] G. Chen and S. C. Liew, "An index policy for minimizing the uncertainty-of-information of Markov sources," IEEE Trans. Inf. Theory, vol. 70, no. 1, pp. 698–721, Jan. 2023.
[3] Y. Sun and B. Cyr, "Sampling for data freshness optimization: Nonlinear age functions," J. Commun. Networks, vol. 21, no. 3, pp. 204–219, 2019.
[4] J. P. Champati, M. Skoglund, M. Jansson, and J. Gross, "Detecting state transitions of a Markov source: Sampling frequency and age trade-off," IEEE Trans. Commun., vol. 70, no. 5, pp. 3081–3095, Jun. 2022.

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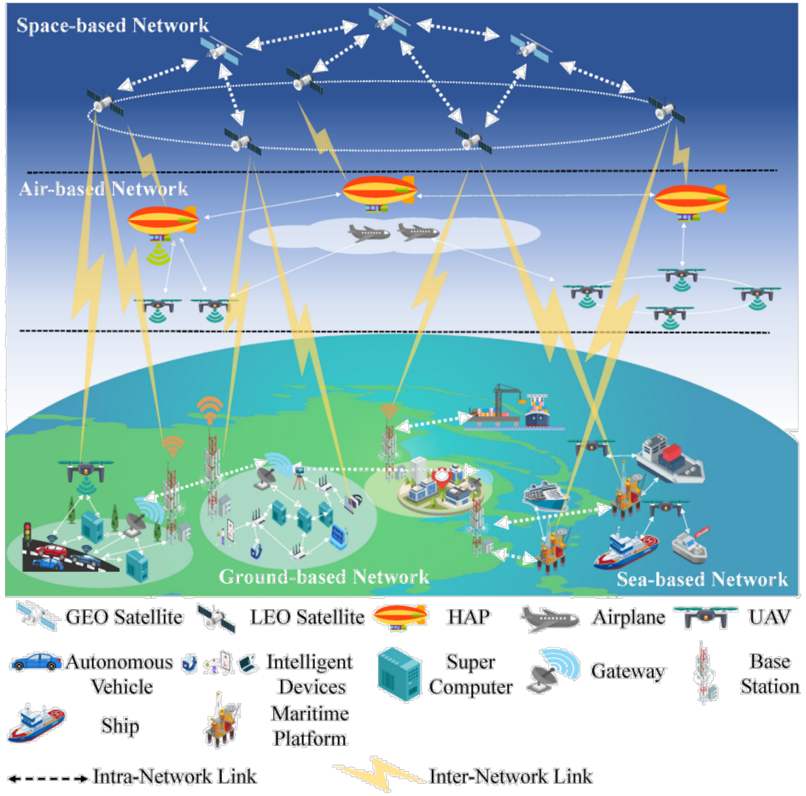
Introduction

- **Motivation of a Remote Monitoring System**
  - *Remote* here means random and large delays
  - *Random and large delays* are common in communication networks, for example, SAGSIN integrated network [3]
  - *Random and large delays* are caused by network loading, routing, retransmission and so on [4]
  - The optimization of UoI under random delay remains *large-ly unexplored*



An illustration of the SAGSIN. ***(Fig. 2 【from [3]】)***

SAGSIN: Space-Air-Ground-Sea Integrated Network

[3] S. Meng, S. Wu, J. Zhang, J. Cheng, H. Zhou, and Q. Zhang, "Semantics-empowered space-air-ground-sea integrated network: New paradigm, frameworks, and challenges," IEEE Commun. Surv. Tutorials (Early Access), 2024.
[4] W. Yao, L. Jiang, Q. H. Wu, J. Y. Wen, and S. J. Cheng, "Delay dependent stability analysis of the power system with a wide-area damping controller embedded," IEEE Trans. Power Syst., vol. 26, no. 1, pp. 233–240, Dec. 2011.

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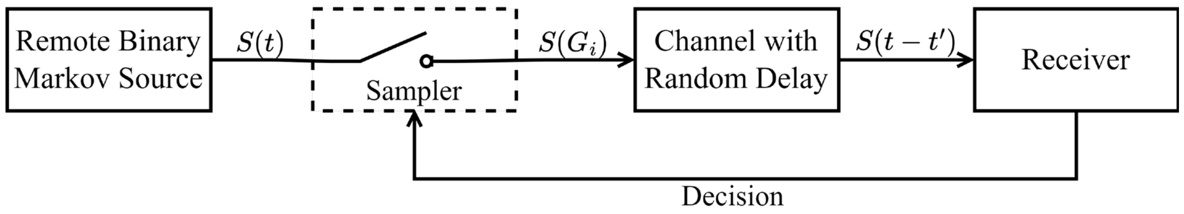
System Model

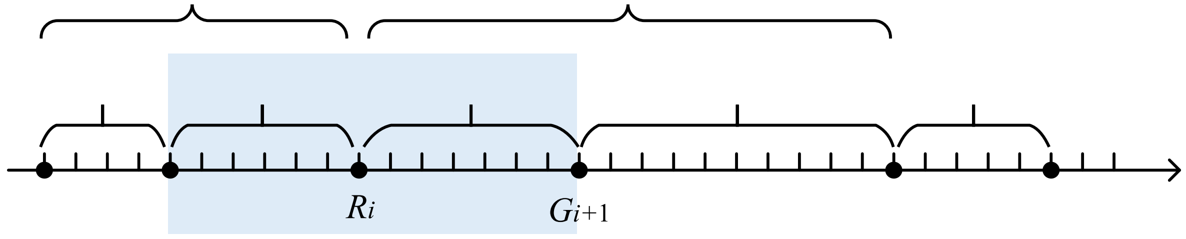
- **A Discrete-time Remote Monitoring System**

Sampling process (begin from the i-th packet)

1. **Sampler:** Sampling and sending at time G_i
2. **Channel:** Transmitting with random delay Y_i
3. **Receiver:** Receiving at time R_i, waiting for time Z_{i+1}, and sending decision of sampling at time G_{i+1}
4. **Sampler:** Receiving decision and sampling (Return to step 1)



System model of the considered remote monitoring system ***(Fig. 3)***



A sample evolution for two transmission periods ***(Fig. 4)***

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System Model

- **Binary Markov Source**

A discrete-time binary Markov process

with a state at time t denoted by $S(t) \in \{0,1\}$

- **One-step transition matrix $\boldsymbol{P}$**

$$\begin{array}{c c} & \begin{array}{cc} \text{State 0} & \text{State 1} \end{array} \\ \begin{array}{c} \text{State 0} \\ \text{State 1} \end{array} & \begin{bmatrix} 1-p & p \\ q & 1-q \end{bmatrix} \end{array} \quad (1)$$

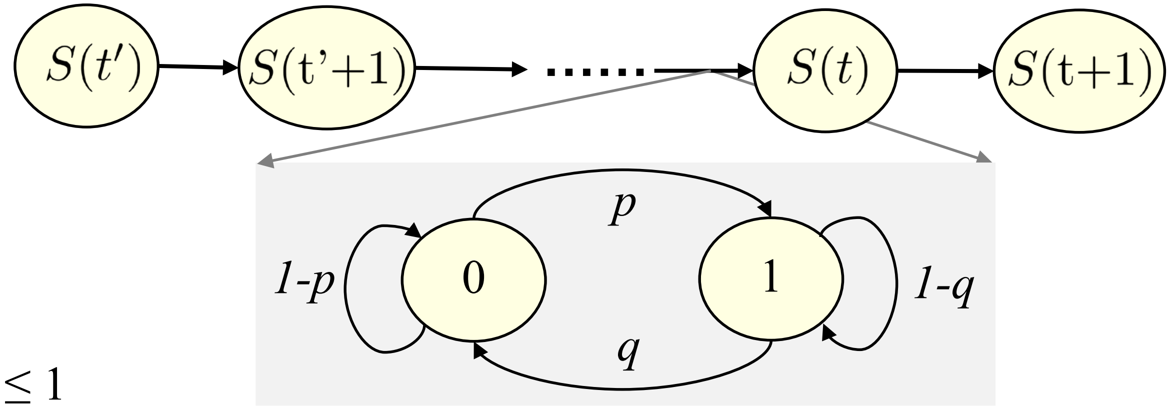
where $0 < p \leq q < 1,\ p+q \leq 1$

- ***n*-step transition matrix** [5, Appendix A]

$$\mathbf{P}^n = \begin{bmatrix} 1-p^{(n)} & p^{(n)} \\ q^{(n)} & 1-q^{(n)} \end{bmatrix} \quad (2)$$

$$\mathbf{P}^n = \begin{bmatrix} 1-p^{(n)} & p^{(n)} \\ q^{(n)} & 1-q^{(n)} \end{bmatrix}$$

where $p^{(n)} \triangleq \frac{p-p(1-p-q)^n}{p+q},\ q^{(n)} \triangleq \frac{q-q(1-p-q)^n}{p+q},\ n \in \mathbb{N}^+$



*Binary Markov process **(Fig. 4)***

[5] M. L. Puterman, Markov Decision Processes: Discrete Stochastic Dynamic Programming. Hoboken, NJ, USA: Wiley, 2005.

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Problem Formulation

- **Definition of UoI**
  - **Original definition** [4]

$$U(t) = -\sum_{i\in\{0,1\}} \mathrm{P}[S(t)=i|S(t')]\log_2 \mathrm{P}[S(t)=i|S(t')] \quad (4)$$

where $t' \triangleq \max_i\{G_i : R_i \le t\}$ is the time stamp of the most recently received update

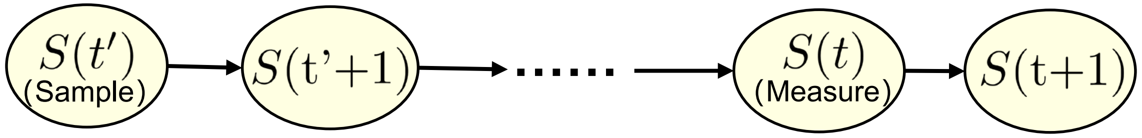
  - **A piecewise function**

$$U(t) = -\sum_{i\in\{0,1\}} P[S(t)=i|S(G_i)]\log_2 P[S(t)=i|S(G_i)], \quad \text{if } R_i \le t < R_{i+1}, \forall i\in\mathbb{N}. \quad (5)$$

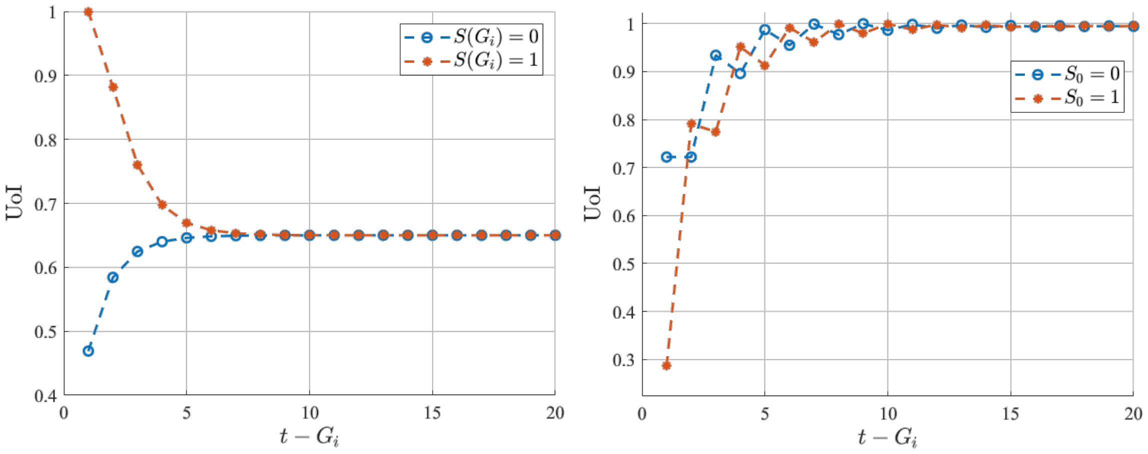
With (2)

$$U(t) = \begin{cases} H(p^{(t-G_i)}), \text{ if } S(G_i)=0, R_i \le t < R_{i+1}, \forall i \in \mathbb{N} \\ H(q^{(t-G_i)}), \text{ if } S(G_i)=1, R_i \le t < R_{i+1}, \forall i \in \mathbb{N}. \end{cases} \quad (6)$$

AoI indicates



Binary Markov process to explain (4) ***(Fig. 5)***



p=0.1, q=0.5 ***(Fig. 6.a)***   *p=0.8, q=0.95* ***(Fig. 6.b)***

UoI v.s. AoI based on (6), for R_i<t<R_{i+1} ***(Fig. 6)***

UoI: Uncertainty-of-Information $H(p) = -p\log_2(p) - -(1-p)\log_2(1-p)$

[4] G. Chen, S. C. Liew, and Y. Shao, “Uncertainty-of-information scheduling: A restless multi-armed bandit framework,” IEEE Trans. Inf. Theory, vol. 68, no. 9, pp. 6151–6173, Sep. 2022.

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Problem Formulation

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Original definition [4]

$$U(t) = -\sum_{i\in\{0,1\}} \mathrm{P}[S(t)=i|S(t')]\log_2 \mathrm{P}[S(t)=i|S(t')] \quad (4)$$

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A piecewise function

$$U(t) = -\sum_{i\in\{0,1\}} P[S(t)=i|S(G_i)]\log_2 P[S(t)=i|S(G_i)], \quad \text{if } R_i \le t < R_{i+1}, \forall i \in \mathbb{N}. \quad (5)$$

With (2)

$$U(t) = \begin{cases} H(p^{(t-G_i)}), \text{ if } S(G_i)=0, R_i \le t < R_{i+1}, \forall i \in \mathbb{N} \\ H(q^{(t-G_i)}), \text{ if } S(G_i)=1, R_i \le t < R_{i+1}, \forall i \in \mathbb{N}. \end{cases} \quad (6)$$

AoI indicates

Problem Formulation

A sampling Policy (equivalence)

Time stamps of *sampling times* for each packet

Time stamps of *waiting times* for each packet

Because , given $(Y_0, Y_1 \ldots)$, $(G_1, G_2, \ldots)$ depends only on $(Z_1, Z_2, \ldots)$

Goal

UoI: Uncertainty-of-Information $H(p) = -p\log_2(p) - -(1-p)\log_2(1-p)$

[4] G. Chen, S. C. Liew, and Y. Shao, “Uncertainty-of-information scheduling: A restless multi-armed bandit framework,” IEEE Trans. Inf. Theory, vol. 68, no. 9, pp. 6151–6173, Sep. 2022.

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Solution

- **Belief State**
  - **Why introduce *Belief State***

    The problem (7) → a *POMDP*→ MDP(SMDP)
  - **Original Definition**

    The probability of $S(t)=1$ given the observation $S(t')$

    $$\Omega(t) = \mathrm{P}\left[S(t)=1 | S(t')\right].$$
  - **A piecewise function**

    $$\Omega(t) = \begin{cases} p^{(t-G_i)}, & \text{if } S(G_i)=0 \\ 1-q^{(t-G_i)}, & \text{if } S(G_i)=1. \end{cases} \tag{9}$$

- **Lemma 1**

  Given $\Omega(t)=\omega \in \{\mathrm{p}^{(n)}, 1-\mathrm{q}^{(n)}\}$, $\Omega(t+k)$ can be calculated by

  $$\Omega(t+k) = \frac{p-p(1-p-q)^k}{p+q} + \omega(1-p-q)^k, \tag{10}$$

  the right-hand side of which is denoted as $\tau^{k}(\omega)$

- **Corollary 1**

  The *equilibrium belief state* of $\Omega(t)$ is

  $$\omega^* \triangleq \lim_{k\to\infty} \tau^k(\omega) = \frac{p}{p+q}. \tag{11}$$

POMDP: Partially Observed Markov Decision Process $H(p) = -p\log_2(p) - -(1-p)\log_2(1-p)$

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Solution

- **Reformulation of Problem (7)**
  - **Recall the goal**

$$\inf_{\pi\in\Pi} \limsup_{T\to\infty} \frac{1}{T}\mathbb{E}\left[\sum_{t=0}^{T-1} U(t)\right] \tag{7}$$

  - **Combing (6) and (9)** we have $\boldsymbol{U(t)} = \boldsymbol{H\big(\Omega(t)\big)}$

$$U(t)=\begin{cases} H(p^{(t-G_i)}), \text{ if } S(G_i)=0, R_i\le t<R_{i+1}, \forall i\in\mathbb{N} \\ H(q^{(t-G_i)}), \text{ if } S(G_i)=1, R_i\le t<R_{i+1}, \forall i\in\mathbb{N}. \end{cases} \tag{6}$$

$$\Omega(t)=\begin{cases} p^{(t-G_i)}, & \text{if } S(G_i)=0 \\ 1-q^{(t-G_i)}, & \text{if } S(G_i)=1. \end{cases} \tag{9}$$

- **Reformulation**

(7)$\longrightarrow$ $$\bar{p}_{\text{opt}} = \inf_{\pi\in\Pi} \limsup_{T\to\infty} \frac{1}{T}\mathbb{E}\left[\sum_{t=0}^{T-1} H(\Omega(t))\right] \tag{13}$$

where $\bar{p}_{\text{opt}}$ is the optimum value of

- **Analysis for problem (13)**

An infinite-horizon average cost *SMDP* [5, Chapter 11]

SMDP: Semi-Markov Decision Process $H(p) = -p\log_2(p) - -(1-p)\log_2(1-p)$

[5] M. L. Puterman, Markov Decision Processes: Discrete Stochastic Dynamic Programming. Hoboken, NJ, USA: Wiley, 2005.

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Solution

- **An Optimal Sampling Policy**

  - **Recall the goal→SMDP**

$$\bar{p}_{\text{opt}} = \inf_{\pi\in\Pi} \limsup_{T\to\infty} \frac{1}{T}\mathbb{E}\left[\sum_{t=0}^{T-1} H(\Omega(t))\right] \quad (13)$$

  - **Bellman optimality equation**

$$\begin{aligned} V^*(\omega) = \inf_{Z_{i+1}\in\mathbb{N}} \Bigg\{ &\mathbb{E}\left[\sum_{k=0}^{Z_{i+1}+Y_{i+1}-1} \left(H(\tau^k(\omega)) - \bar{p}_{\text{opt}}\right)\right] \\ &+ \mathbb{E}\Big[\underline{\tau^{Z_{i+1}+Y_{i+1}}(\omega)V^*(1-q^{(Y_{i+1})})} \\ &\underline{+ (1-\tau^{Z_{i+1}+Y_{i+1}}(\omega))V^*(p^{(Y_{i+1})})}\Big]\Bigg\}, \end{aligned} \quad (18)$$

Depends on Z_{i+1}, hard to solve

where $V^*(\omega)$ is the relative value function

- **Transformation of (13)** [5, Chapter 11]

$$(13) = \inf_{\pi\in\Pi} \lim_{n\to\infty} \frac{\sum_{i=0}^{n-1} \mathbb{E}\left[\sum_{k=0}^{Z_{i+1}+Y_{i+1}-1} H(\tau^k(\omega))\right]}{\sum_{i=0}^{n-1} \mathbb{E}[Z_{i+1}+Y_{i+1}]}$$

$$g(\beta) \triangleq \inf_{\phi\in\Phi} \lim_{n\to\infty} \frac{1}{n} \sum_{i=0}^{n-1} \mathbb{E}\left[\sum_{k=0}^{Z_{i+1}+Y_{i+1}-1} [H(\tau^k(\omega)) - \beta]\right]. \quad (33)$$

SMDP→MDP

- **Two assertions** [6]

(i) $\bar{p}_{\text{opt}} \lesseqqgtr \beta$ if and only if $g(\beta) \lesseqqgtr 0$

(ii) $\bar{p}_{\text{opt}}$ is the unique root of $g(\beta) = 0$

[5] M. L. Puterman, Markov Decision Processes: Discrete Stochastic Dynamic Programming. Hoboken, NJ, USA: Wiley, 2005.
[6] W. Dinkelbach, “On nonlinear fractional programming,” Manag. Sci, vol. 13, no. 7, pp. 492–498, 1967.

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Solution

- **An Optimal Sampling Policy**

  - **Recall the goal SMDP→MDP→ $g(\beta) = 0$**

$$g(\beta) \triangleq \inf_{\phi\in\Phi} \lim_{n\to\infty} \frac{1}{n} \sum_{i=0}^{n-1} \mathbb{E}\left[\sum_{k=0}^{Z_{i+1}+Y_{i+1}-1} [H(\tau^k(\omega)) - \beta]\right] \quad (33)$$

  - **Optimality equation**

$$g(\beta) + \widetilde{V}(\omega,\beta) = \inf_{Z_{i+1}\in\mathbb{N}} \{c(\omega, Z_{i+1}, \beta) + r(\omega, Z_{i+1}, \beta)\}, \quad (38)$$

$$g(\beta) = \inf_{Z_{i+1}\in\mathbb{N}} \{c(p, Z_{i+1}, \beta) + r(p, Z_{i+1}, \beta)\}, \quad (39)$$

where

$$c(\omega, Z_{i+1}, \beta) = \mathbb{E}\left[\sum_{k=0}^{Z_{i+1}+Y_{i+1}-1} (H(\tau^k(\omega)) - \beta)\right]$$

$$r(\omega, Z_{i+1}, \beta) = \mathbb{E}\Big[\tau^{Z_{i+1}+Y_{i+1}}(\omega)\widetilde{V}(1-q^{(Y_{i+1})}, \beta) + (1-\tau^{Z_{i+1}+Y_{i+1}}(\omega))\widetilde{V}(p^{(Y_{i+1})}, \beta)\Big]$$

- **Algorithm 1**

Algorithm 1: Bisec-RVI algorithm

Input: $l = 0$, $u = 1$, tolerance $\epsilon > 0$

```
while u − l ≥ ϵ do
    β := (l + u)/2;
    Run RVI to solve g(β) and Ṽ(ω, β);
    if g(β) > 0 then
        l := β;
    else
        u := β;
```

Output: $\bar{p}_{\mathrm{opt}} = \beta$

Inner layer

Outer layer

Find $g(\beta) = 0$, Get the *optimal sampling policy* at the same time

SMDP: Semi-Markov Decision Process MDP: Markov Decision Process

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Solution

- **A Sub-optimal Index-based Policy**
  - **Motivation for sub-optimal policy**

    1. *High computing complexity* caused by executing the RVI algorithm repeatedly

    2. *Large delays* are common in communication networks, e.g., SAGSIN integrated network [3]

  - **Explanation for Large delays**

    The transmission process spends a long time, i.e., the value of $E[Y_i], \forall i \in N$ is large enough

- **Core assumption**

  Constant state transition probabilities (**Corollary 1**)

$$\mathrm{P}[\Omega(R_{i+1}) = 1 - q^{(Y_{i+1})} | \Omega(R_i)] = \tau^{Z_{i+1}+Y_{i+1}}(\omega) = \omega^* \tag{19}$$

- **Corollary 1 (Recall)**

  The *equilibrium belief state* of $\Omega(t)$ is

$$\omega^* \triangleq \lim_{k\to\infty} \tau^k(\omega) = \frac{p}{p+q}. \tag{11}$$

SAGSIN: Space-Air-Ground-Sea Integrated Network

[3] S. Meng, S. Wu, J. Zhang, J. Cheng, H. Zhou, and Q. Zhang, "Semantics-empowered space-air-ground-sea integrated network: New paradigm, frameworks, and challenges," IEEE Commun. Surv. Tutorials (Early Access), 2024.

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Solution

- **A Sub-optimal Index-based Policy**

  - **Goal**

$$\bar{p}_{\text{nopt}} = \inf_{\psi\in\Pi} \limsup_{T\to\infty} \frac{1}{T}\mathbb{E}\left[\sum_{t=0}^{T-1} H(\Omega(t))\right] \qquad (20)$$

  - **Bellman optimality equation**

$$V_\psi(\omega) = \inf_{Z_{i+1}\in\mathbb{N}} \left\{ \mathbb{E}\left[\sum_{k=0}^{Z_{i+1}+Y_{i+1}-1} (H(\tau^k(\omega)) - \bar{p}_{\text{nopt}})\right]\right\} + \mathbb{E}\left[\omega^* V_\psi(1-q^{(Y_{i+1})}) + (1-\omega^*)V_\psi(p^{(Y_{i+1})})\right], \qquad (24)$$

Not depends on Z_{i+1}, easy to solve

for all $\omega \in \{p^{(n)}, 1-q^{(n)}\}$, $n \in \mathbb{N}$, where $V_\psi^*(\omega)$ is the relative value function

  - **An index function**

$$\eta(\omega) \triangleq \inf_{Z_i\in\mathbb{N}^+} \frac{1}{Z_i}\sum_{k=0}^{Z_i-1} \mathbb{E}\left[H(\tau^{k+Y_i}(\omega))\right], \qquad (21)$$

where $\omega \in \{p^{(n)}, 1-q^{(n)}\}$, $n \in \mathbb{N}$

  - **An index-based policy**

$$Z_{i+1}(\beta_\psi) = \min\{k\in\mathbb{N} : \eta(\Omega(t+k)) \geq \beta_\psi, t \geq R_i(\beta_\psi)\}, \qquad (22)$$

and β_ψ is the unique root of

$$\mathbb{E}\left[\sum_{R_i(\beta_\psi)}^{R_{i+1}(\beta_\psi)-1} H(\Omega(t))\right] - \beta_\psi \mathbb{E}\left[R_{i+1}(\beta_\psi) - R_i(\beta_\psi)\right] = 0 \qquad (23)$$

β_ψ is exactly the optimum value of (20), i.e., $\beta_\psi = \bar{p}_{\text{nopt}}$

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Solution

- **A Sub-optimal Index-based Policy**
  - **An index-based policy**

$$Z_{i+1}(\beta_\psi) = \min\{k \in \mathbb{N} : \eta(\Omega(t+k)) \geq \beta_\psi, t \geq R_i(\beta_\psi)\}, \tag{22}$$

and β_ψ is the unique root of

$$\mathbb{E}\left[\sum_{R_i(\beta_\psi)}^{R_{i+1}(\beta_\psi)-1} H(\Omega(t))\right] - \beta_\psi \mathbb{E}\left[R_{i+1}(\beta_\psi) - R_i(\beta_\psi)\right] = 0 \tag{23}$$

β_ψ is exactly the optimum value of (20), i.e., $\beta_\psi = \overline{p}_{\text{nopt}}$

  - **Notation**

Rewrite (23) as

$$f(\beta_\psi) = f_1(\beta_\psi) - \beta_\psi f_2(\beta_\psi) = 0 \tag{25}$$

- **Algorithm 2**

Algorithm 2: Bisec-index algorithm

Input: $l = 0$, $u = 1$, tolerance $\epsilon > 0$
while $u - l \geq \epsilon$ **do**
  $\beta_\psi := (l+u)/2$;
  $c := f(\beta_\psi) = f_1(\beta_\psi) - \beta_\psi f_2(\beta_\psi)$;
  if $c > 0$ **then**
    $l := \beta_\psi$;
  else
    $u := \beta_\psi$;
Output: $\bar{p}_{\text{nopt}} = \beta_\psi$

Find *the zero point of (25)*

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Numerical Result

- ## Benchmark
  - **Zero wait:** An update is transmitted once the previous update is received, maximizing throughput
  - **AoI-optimal:** The AoI-optimal policy determines waiting time Z_i by [7,Theorem 4] and [7,Algorithm 2]

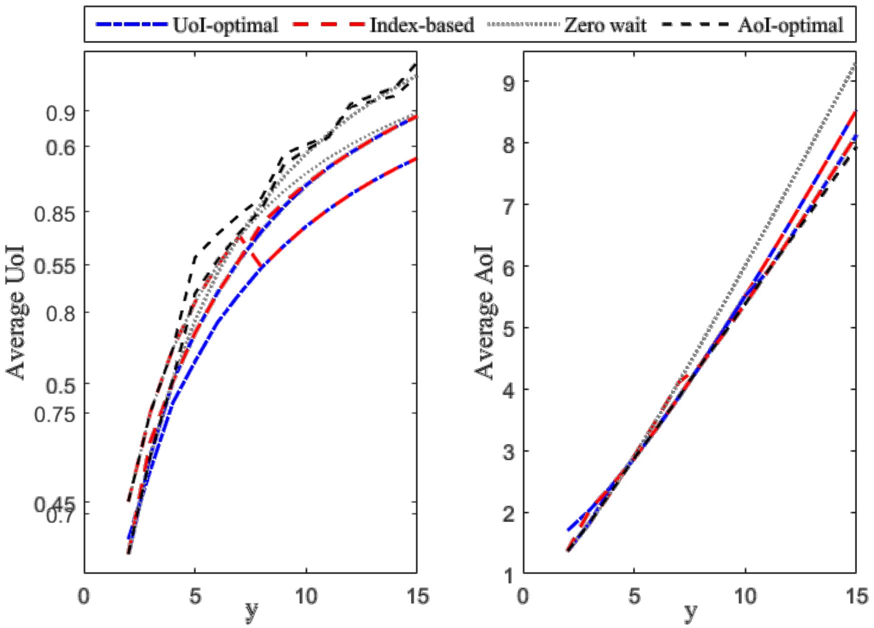
- ## Insight

1. The average UoI obtained by the index-based policy: The sub-optimal policy cannot always take future circumstances into account if the value of $E(Y_i)$ is small, thus ignores the different result

1. *A watershed phenomenon* occurs for the index-based policy: *very close to* the UoI-optimal policy when $p+q<1$
2. The desired goal the receiver tends to achieve leads to oscillation of UoI when $p+q>1$

2. The lowest AoI is obtained by AoI-optimal policy

- ## Results Analysis



The dynamics of the Markov source depicted as $p = 0.05$ and $q = 0.03$ (Fig. 9.a)

Average UoI and Average AoI v.s. y with i.d.d random delay, where P[Yi = 1] = 0.8 and P[Yi = y] = 0.2 ***(Fig. 9)***

[7] Y. Sun, E. Uysal-Biyikoglu, R. D. Yates, C. E. Koksal, and N. B. Shroff, “Update or wait: How to keep your data fresh,” IEEE Trans. Inf. Theory, vol. 63, no. 11, pp. 7492–7508, Mar. 2017.

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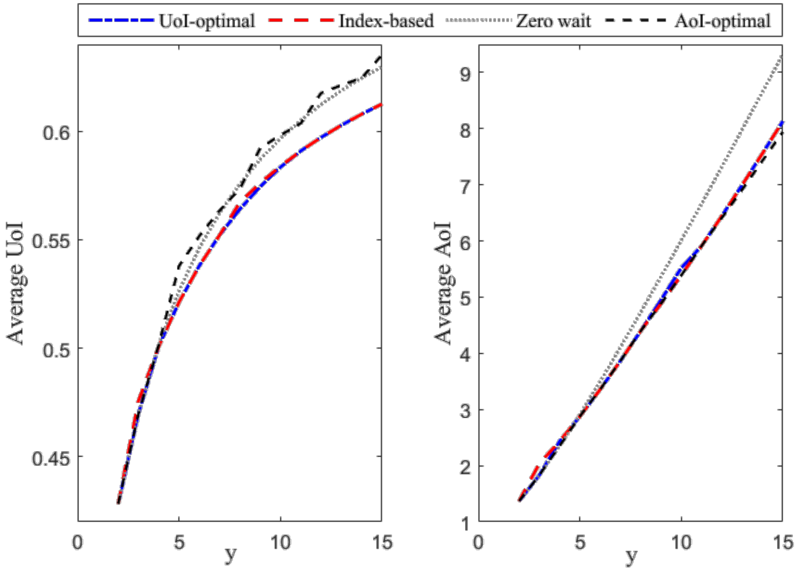
Numerical Result

Insight

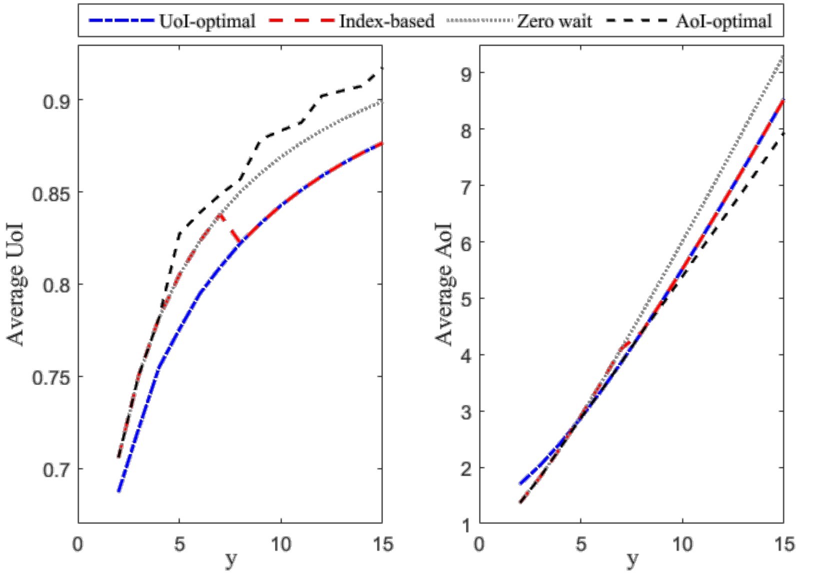
1. When $E(Y_i)$ *is large enough*, the result of *index policy* is the same as that of the *UoI-optimal policy*, consistent with the theoretical induction we proposed before

2. The performance *gains of UoI-optimal* and *index-based policies* are close to *the best average AoI*, making them better choices when the system aims to optimize both AoI and UoI simultaneously.

Result Analysis



The dynamics of the Markov source depicted as $p = 0.05$ and $q = 0.2$ (Fig. 9.a)



The dynamics of the Markov source depicted as $p = 0.7$ and $q = 0.95$ (Fig. 9.b)

Average UoI and Average AoI v.s. y with i.d.d random delay, where P[Yi = 1] = 0.8 and P[Yi = y] = 0.2 ***(Fig. 9)***

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Conclusion

- **Brief summary of results**
  - **Using UoI to estimate the value of information in a remote monitoring system**
  - **An optimal sampling policy,** to minimize the time-average expected sum-UoI by two-layered *bisec-RVI* algorithm
  - **A sub-optimal index-based sampling policy,** owning lower computing complexity than the optimal one
  - **Both of the proposed sampling policies** outperform the zero wait policy and the AoI-optimal policy

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THANKS!