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Sparse Directed Graph Learning for Head Movement Prediction in 360 Video Streaming

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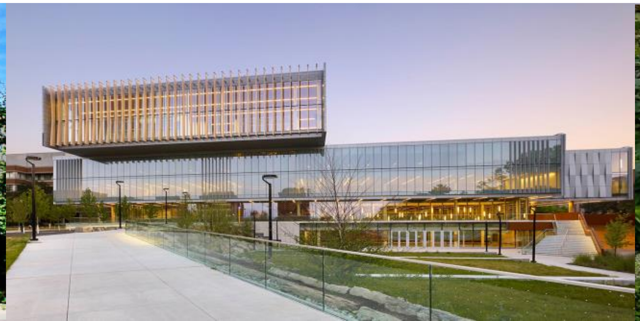
ICASSP2020
Barcelona

Session: TH3.PI: Image/Video Processing II

--7th May, 2020

Outline

- Motivation
- Related Works
- Contributions
- Sparse Directed Graph Learning
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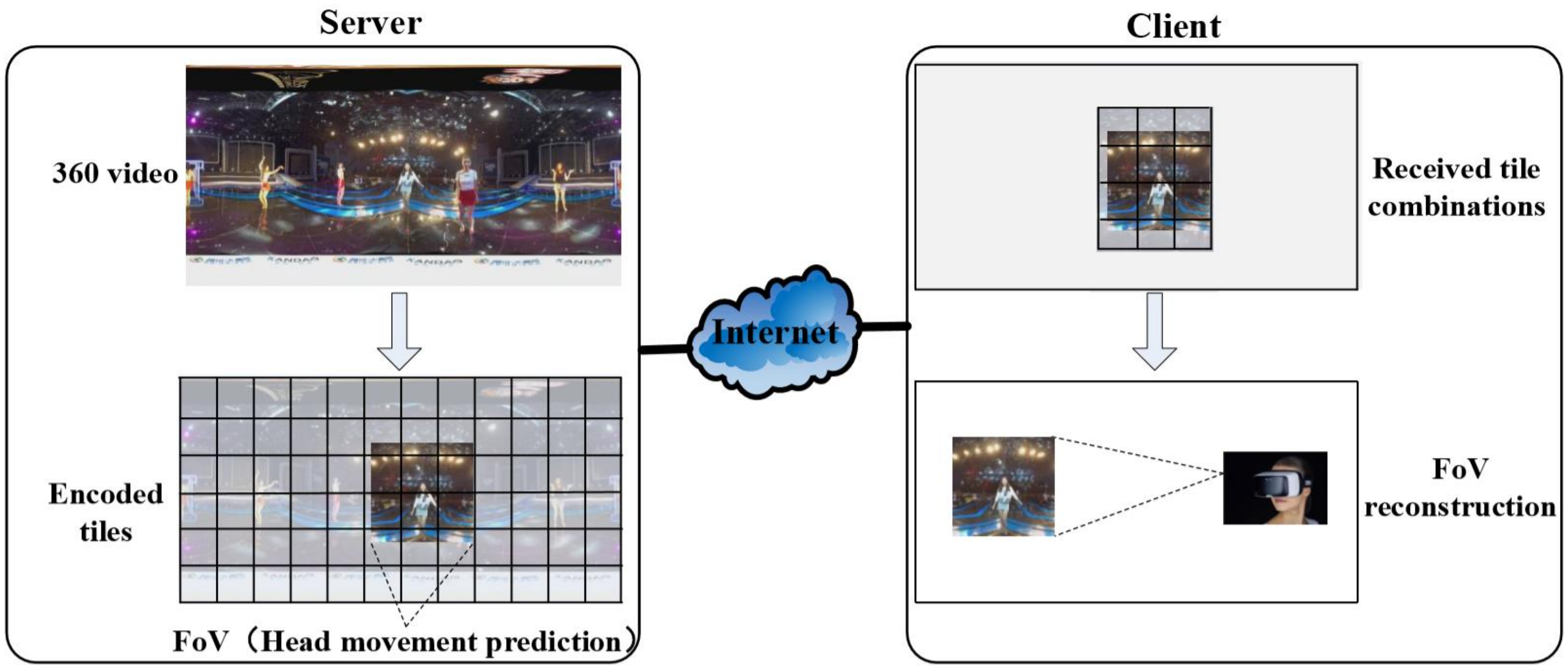
Motivation

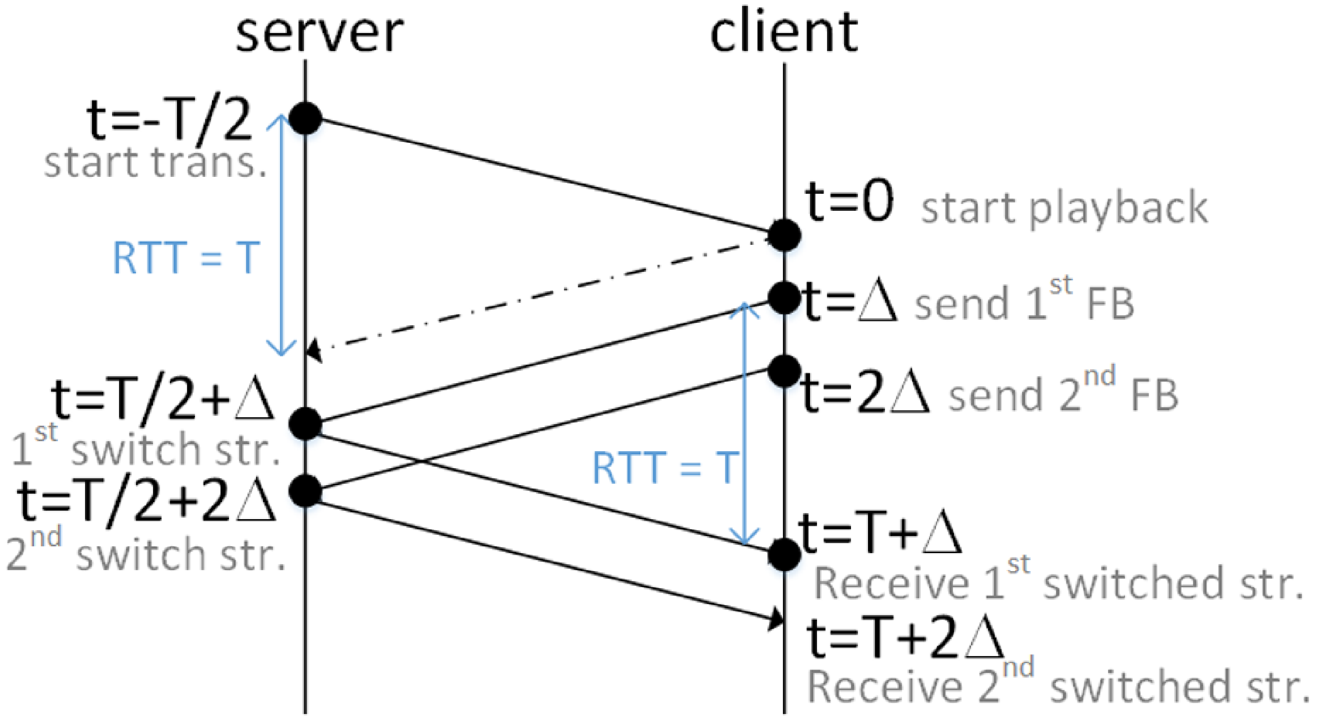
➢ Challenges in interactive 360 video streaming scenario



- 360 videos: high spatial resolution (*e.g.*,10K 10240×4320)
- Bandwidth-limited networks
- Extract and transport only a sub-region corresponding to a viewer's current field-of-view (FoV)
- Round-trip-time (RTT) delay: head movement prediction foretelling a viewer's future FoVs

Motivation (cont'd)

- **What is RTT?**



Interaction between server and client where RTT is T and frame interval is Δ.
A switched stream arrives T seconds after a feedback is sent.

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Related works

- **Linear regression models** [1][2]
  - pro: historical samples and dead-reckoning algorithms to extrapolate the trends
  - con: prediction accuracy drops precipitously for larger RTTs

- **Pure data-driven model learning**
  - pro: using neural networks [3] or reinforcement learning scheme [4]
  - con: 1) a huge dataset of traces for training a large number of network parameters;
    2) training is typically specific to particular setups (*e.g.*, RTT mean and variance).

[1] L. Xie, Z. Xu, Y. Ban, X. Zhang, and Z. Guo, “360probdash: Improving QOE of 360 video streaming using tile-based http adaptive streaming,” *ACM MM’17*, pp. 315–323.
[2] S. Petrangeli, V. Swaminathan, M. Hosseini, and F. De Turck, “An HTTP/2-based adaptive streaming framework for 360 virtual reality videos,” *ACM MM’17*, pp. 306–314.
[3] C.-L. Fan, S.-C. Yen, C.-Y. Huang, and C.-H. Hsu, “Optimizing fixation prediction using recurrent neural networks for 360 video streaming in head-mounted virtual reality, *TMM*, vol.22, no.3, pp. 744 – 759, March 2020.
[4] M. Xu, Y. Song, J. Wang, M. Qiao, L. Huo, and Z. Wang, “Predicting head movement in panoramic video: A deep reinforcement learning approach,” *TPAMI*, vol. 41, no. 11, pp. 2693–2708, July 2018.

Related works (cont'd)

- **Visual attention (VA) detection** (*e.g.*, ICME Grand Challenge "salient360!")

  - **pro**: 1) datasets [5];
    2) toolbox to facilitate the development of VA models [6];
    3) framework to evaluate VA models [7];
    4) ad-hoc VA models for 360 contents [8].

  - **con**: 1) more an "aggregate" behavior rather than an individual behavior;
    2) target prediction is in time horizon of typically 10s to 15s viewing time not the typical RTT.

[5] Y. Rai, J. Gutierrez, and P. Le Callet, "A dataset of head and eye movements for 360 degree images," *ACM MMSys'17*, pp. 205–210.
[6] J. Gutierrez, E. David, Y. Rai, and P. Le Callet, "Toolbox and dataset for the development of saliency and scanpath models for omnidirectional / 360◦ still images," *Signal Processing: Image Communication*, vol. 69, pp. 35–42, November 2018
[7] M. Silva, J. Gutierrez, A. Coutrot and P. Le Callet, "Introducing un salient360! benchmark: A platform for evaluating visual attention models for 360◦ contents," *IEEE QoMEX'18*, Italy.
[8] Y. Zhu, G. Zhai, and X. Min, "The prediction of head and eye movement for 360 degree images," *Signal Processing: Image Communication*, vol. 69, pp. 15–25, 2018.

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Contributions

Sparse directed graph learning

discrete angles in the 360 view are nodes in a graph

a 360 image saliency map + collected viewers' head movement traces + a biological head rotation model

an estimate of stationary probability distribution

instantiation of the state transitions

physical constraints on the state transitions

a unified Markov model → **a probability transition matrix $\boldsymbol{P}$**

One can evaluate the view probability distribution $\boldsymbol{v}_{t+T}$ one RTT T later as $\boldsymbol{v}_{t+T} = \boldsymbol{v}_t \boldsymbol{P}^T$ given original distribution $\boldsymbol{v}_t$ at time t.

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Outline

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Define two variables:

- $\boldsymbol{P}$: $K \times K$ *view transition probability matrix* ($360°$ sphere is discretized uniformly into K angles)
- $\boldsymbol{q}$: stationary *view probability vector*
- $\boldsymbol{qP} = \boldsymbol{q}$

A *maximum a posteriori* (MAP) optimization problem to find a Markov model for head movement prediction

➢ **Likelihood Term** (depends on data traces)

$$P(\mathcal{X}|\boldsymbol{\theta}) = \prod_{k=1}^{K} q_k^{N_k} \prod_{l=1}^{K} p_{kl}^{N_{kl}}$$

number of occurrences of angle k in set $\mathcal{X}$

number of occurrences of switching from angle k to angle l in set $\mathcal{X}$

where $\mathcal{X}$ is the training set of observed angle switches in traces

$$\boldsymbol{\theta} = \{\{q_k\}, \{p_{kl}\}\}$$

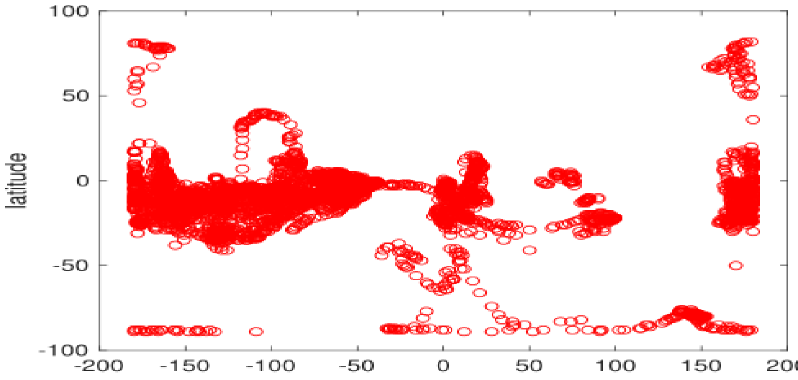
Sparse Directed Graph Learning (cont'd)

➢ Prior Term

- The prior for $\boldsymbol{q}$ depends on a computed *360 saliency* map [6]

$$P(\mathbf{q}) = \prod_{k=1}^{K} \exp\left(\frac{-(q_k - \hat{q}_k)^2}{\sigma_q^2}\right)$$

the normalized saliency of angle k



user scanpath

- The prior for $\boldsymbol{P}$ depends on a *sparse graph assumption*

$$P(\mathbf{P}) = \exp\left(\frac{- \| \mathbf{P} \|_0}{\sigma_p^2}\right)$$

[6] J. Gutierrez, E. David, Y. Rai, and P. Le Callet, "Toolbox and dataset for the development of saliency and scanpath models for omnidirectional / 360◦ still images," *Signal Processing: Image Communication*, vol. 69, pp. 35–42, November 2018.

Sparse Directed Graph Learning (cont'd)

- **MAP Estimation**

$$\arg\min_{\{\{q_k\},\{p_{kl}\}\}} -\sum_{k=1}^{K}\left(N_k \ln q_k + \sum_{l=1}^{K} N_{kl} \ln p_{kl}\right) + \sum_{k=1}^{K}\frac{(q_k-\hat{q}_k)^2}{\sigma_q^2} + \frac{1}{\sigma_p^2}\sum_{k,l}\omega_{kl}\,(p_{kl})^2 \quad (10)$$

$$\text{s.t.} \quad \sum_{k=1}^{K} q_k p_{kl} = q_l, \quad \forall l \quad (8c)$$

$$\sum_{k=1}^{K} q_k = 1, \quad \sum_{l=1}^{K} p_{kl} = 1, \quad \forall k \quad (8d)$$

$$q_k \geq \epsilon_q, \quad \forall k, \quad p_{kl} \geq \begin{cases} \epsilon_p, & \text{if } \forall k, \forall l \in \mathcal{N}(k) \\ 0, & \text{otherwise} \end{cases} \quad (8e)$$

Iterative reweighted least square (IRLS) [9]

$$\omega_{kl} = \frac{1}{\left(\tilde{p}_{kl}^2 + \varepsilon_s\right)}$$

using previous estimate $\tilde{p}_{kl}$ to promote sparsity in $\boldsymbol{P}$

the neighborhood of K, to ensure that transition probabilities between adjacent angles are non-zero based on a biological head movement model.

[9] I. Daubechies, R. DeVore, M. Fornasier, and C S. Gunturk, "Iteratively reweighted least squares minimization for sparse recovery," *Communications on Pure and Applied Mathematics: A Journal Issued by the Courant Institute of Mathematical Sciences*, vol. 63, no. 1, pp. 1–38, 2010.

Sparse Directed Graph Learning (cont'd)

- **Optimizing P when q is fixed:**

$$\min_{\mathbf{P}} -\sum_{k=1}^{K}\sum_{l=1}^{K} N_{kl}\ln p_{kl} + \frac{1}{\sigma_p^2}\sum_{k=1}^{K}\sum_{l=1}^{K}\omega_{kl}\left(p_{kl}\right)^2$$

$$\text{s.t.} \sum_{k=1}^{K} q_k p_{kl} = q_l,\ \ \forall l, \quad \sum_{l=1}^{K} p_{kl} = 1,\ \ \forall k,$$

$$p_{kl} \geq \begin{cases} \epsilon_p, & \text{if } \forall k, \forall l \in \mathcal{N}(k) \\ 0, & \text{otherwise} \end{cases}$$

- **Optimizing q when P is fixed:**

$$\min_{\mathbf{q}} -\sum_{k=1}^{K} N_k \ln q_k + \sum_{k=1}^{K}\frac{(q_k-\hat{q}_k)^2}{\sigma_q^2}$$

$$\text{s.t.} \quad \max\{\epsilon_q, \tilde{q}_k - \delta\} \leq q_k \leq \max\{\epsilon_q, \tilde{q}_k + \delta\}, \quad \forall k$$

$$\sum_{k=1}^{K} q_k = 1$$

$\tilde{q}P = \tilde{q}$

the eigenvector of P corresponding to eigenvalue 1.

❖ Frank-Wolfe optimization strategy (projection-free):

linear approximation in each iteration → Find the optimal direction $\mathbf{s}$ by solving:

$$\min_{\mathbf{s}} \ \mathbf{s}^\top \nabla f(\mathbf{P}(t)) \quad \text{such that } \mathbf{s} \in \mathcal{R}$$

← *Linear Program* benefits from warm start.

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Experiments

- **Six 360 VR sequences** at 30fps with length around 60 seconds [10]
  - two 8K resolution (7680 × 3840) with around 110 traces
  - four 4K resolution (3840 × 1920) with around 50 traces

- **Comparison algorithms**
  - regression models:
    linear regression "LR" [1], weighted linear regression "WLR" [11] and "Heuristic" [2].
  - a naive approach: "Saliency".

- **Prediction error of each trace**: $Er = -\frac{\sum_{t=1}^{L} \ln g_t(T)}{L}$

Where $g_t(T)$ is the view probability of correct prediction for each instant t.

L is the length of each collected trace.

[1] L. Xie, Z. Xu, Y. Ban, X. Zhang, and Z. Guo, "360probdash: Improving QOE of 360 video streaming using tile-based http adaptive streaming," *ACM MM'17*, pp. 315–323.
[2] S. Petrangeli, V. Swaminathan, M. Hosseini, and F. De Turck, "An HTTP/2-based adaptive streaming framework for 360 virtual reality videos," *ACM MM'17*, pp. 306–314.
[10] https://www.kandaovr.com/
[11] F. Qian, L. Ji, B. Han, and V. Gopalakrishnan, "Optimizing 360 video delivery over cellular networks," *All Things Cellular: Operations, Applications and Challenges*, 2016, pp. 1–6.

Experiments (cont'd)

Results

Table 1. The average Er of different models when $T = 0.5$s.

Seq.	LR	WLR	Heuristic	Saliency	Proposed
On the hill	5.61	5.58	6.29	4.49	**0.16**
Beijing	3.73	3.69	6.27	4.71	**0.15**
Guangzhou	1.35	1.34	3.62	4.87	**0.07**
Huizhou	3.07	2.97	5.67	4.19	**0.20**
Concert	9.83	9.51	6.46	4.31	**0.19**
Lamborghini	5.76	5.71	5.22	4.61	**0.13**

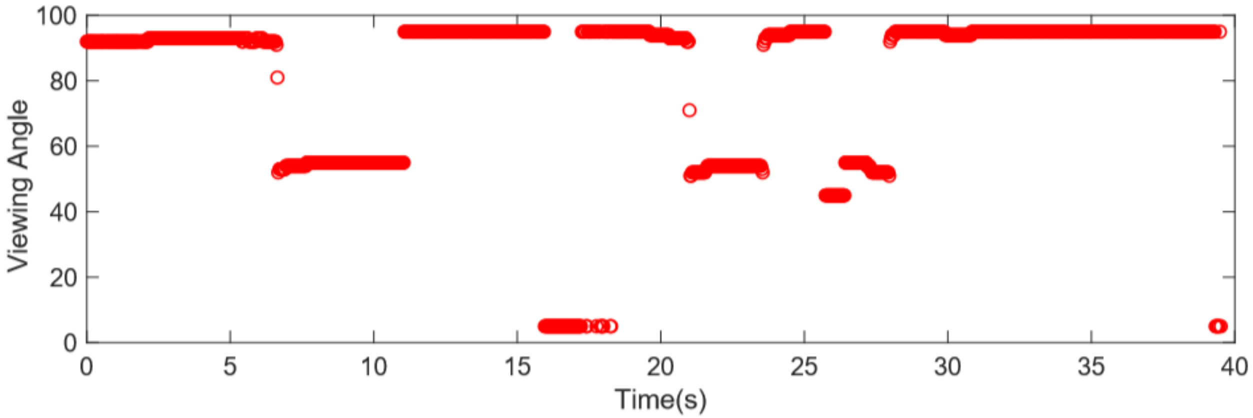

Fig. 2. The variation of user's angles over time in one trace of *On the hill*.

Note that when users have large and frequent head motions, it is difficult for competitors to predict accurately but not for our proposed model.

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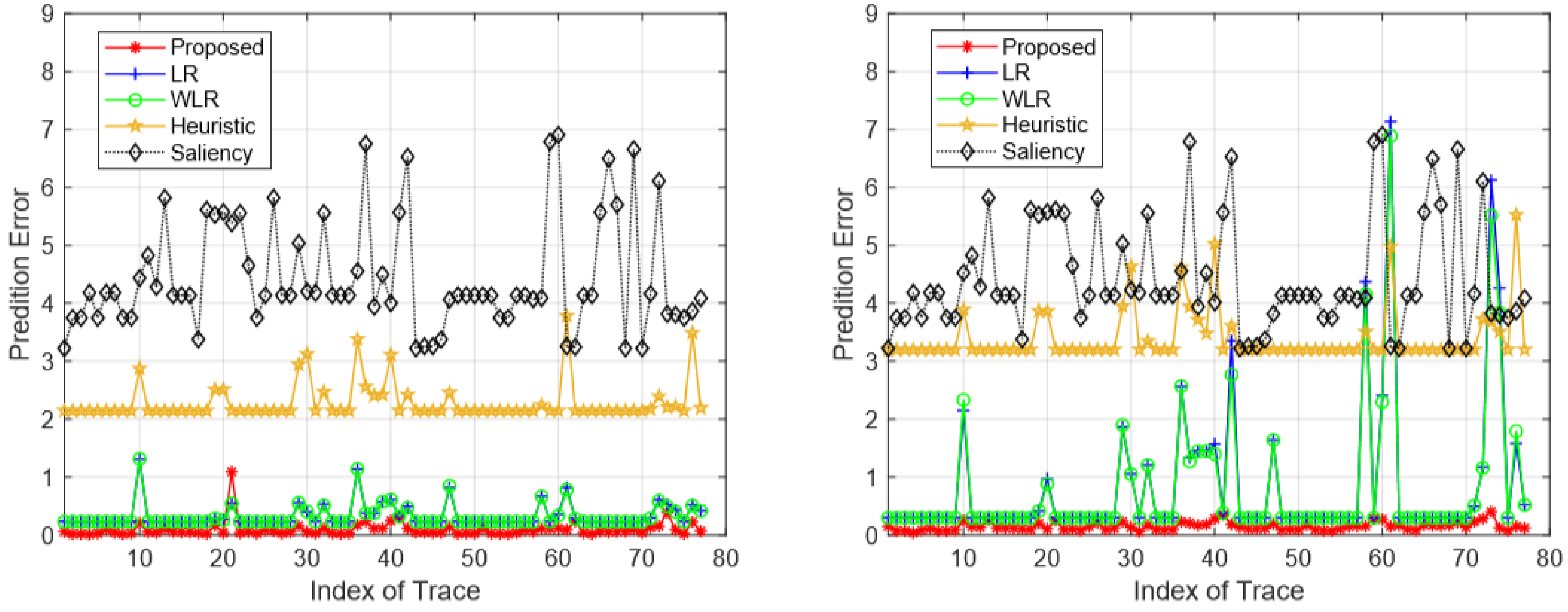
Experiments (cont'd)



(a) $T = 0.5s$ (b) $T = 2s$

Fig. 3. Prediction error smaller than 10 for *On the hill*.

Benefiting from projection-free FW and warm start in LP, our strategy has reduced complexity.

Q&A

Thank You !

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