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Video Semantic Segmentation via Sparse Temporal Transformer

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SenseTime Research,
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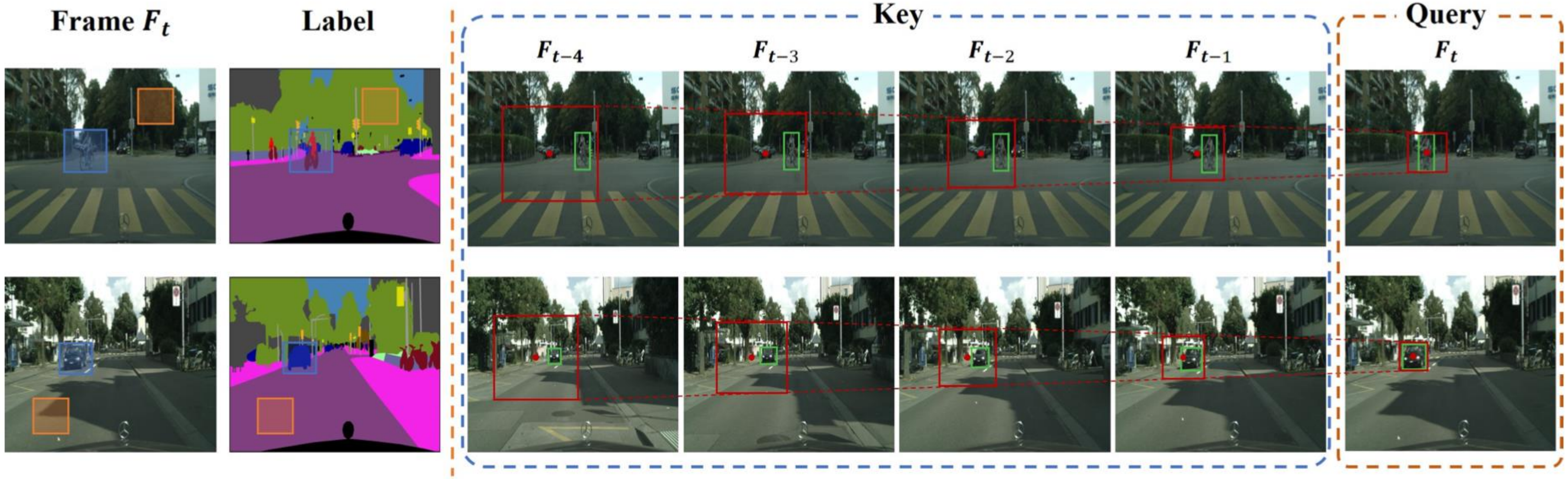
Challenges & Previous Solution

- **Challenge 1.** The demand of temporal consistency in a semi-supervised manner
    - NetWarp [1] and GRFP [2] estimated frame-to-frame motion warping (e.g., optical flow) to segment consecutive frames
    - ETC [3] adopted warped prediction loss to constrain the prediction of current frame during training and performed single-frame prediction during inference.
- **Challenge 2.** The balance between segmentation accuracy and inference efficiency for real-time applications
    - DVSNet [4] employed large models towards the key frames, and propagate to non-key frames using optical flows.
    - Accel [5] employed large models towards the key frames, and utilized small model to process the non-key frames.
    - TDNet [6] adopted knowledge distillation from large model towards small model to improve the segmentation efficiency without increasing the computational cost.

[1] Raghudeep Gadde, Varun Jampani, and Peter V Gehler. 2017. Semantic video cnns through representation warping. In ICCV 2017.
[2] David Nilsson and Cristian Sminchisescu. 2018. Semantic video segmentation by gated recurrent flow propagation. In CVPR 2018.
[3] Yifan Liu, Chunhua Shen, Changqian Yu, and Jingdong Wang. 2020. Efficient Semantic Video Segmentation with Per-frame Inference. In ECCV 2020.
[4] Yu-Syuan Xu, Tsu-Jui Fu, Hsuan-Kung Yang, and Chun-Yi Lee. 2018. Dynamic video segmentation network. In CVPR 2018.
[5] Samvit Jain, Xin Wang, and Joseph E Gonzalez. 2019. Accel: A corrective fusion network for efficient semantic segmentation on video. In CVPR 2019.
[6] Ping Hu, Fabian Caba, Oliver Wang, Zhe Lin, Stan Sclaroff, and Federico Perazzi. 2020. Temporally distributed networks for fast video semantic segmentation. In CVPR 2020.

Our Solution

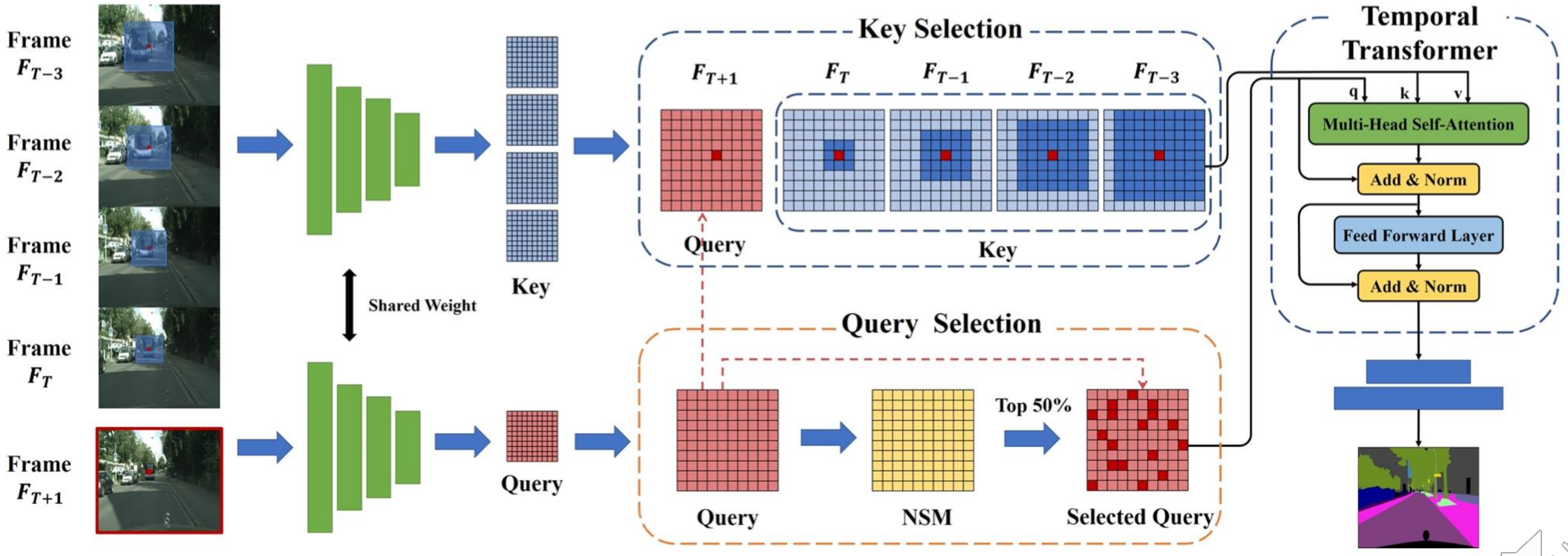
- For **Challenge 1.** The demand of temporal consistency in a semi-supervised manner
  - We propose to incorporate a temporal transformer into existing segmentation models as an adaptive module to capture the temporal relation among consecutive frames.
- For **Challenge 2.** The balance between segmentation accuracy and inference efficiency for real-time applications
  - We propose two selection strategies towards the temporal transformer framework (i.e., query selection and key selection).



(a) Query Selection (b) Key Selection

Proposed Method

- Sparse Temporal Transformer



Proposed Method

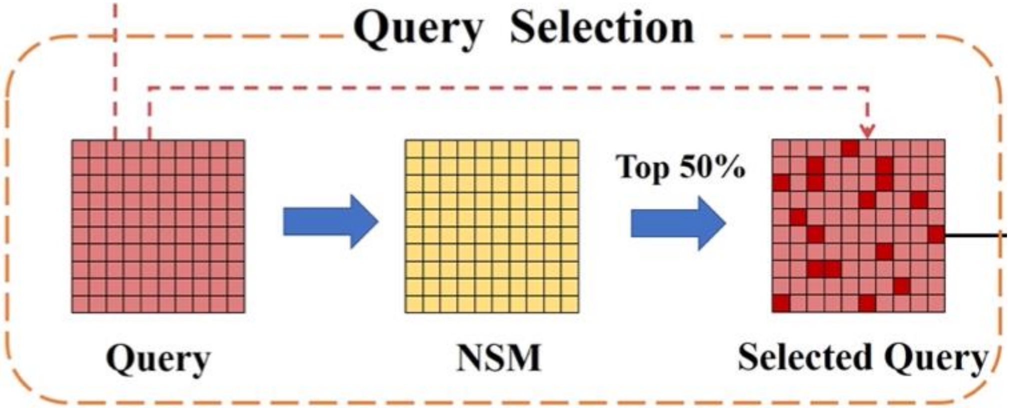
- Query Selection
  - Motivation: semantic boundary regions (complex regions) need more representation [1].
  - Identification of complex regions: the similarity between the feature region and its neighboring --- Neighboring Similarity Matrix (NSM)

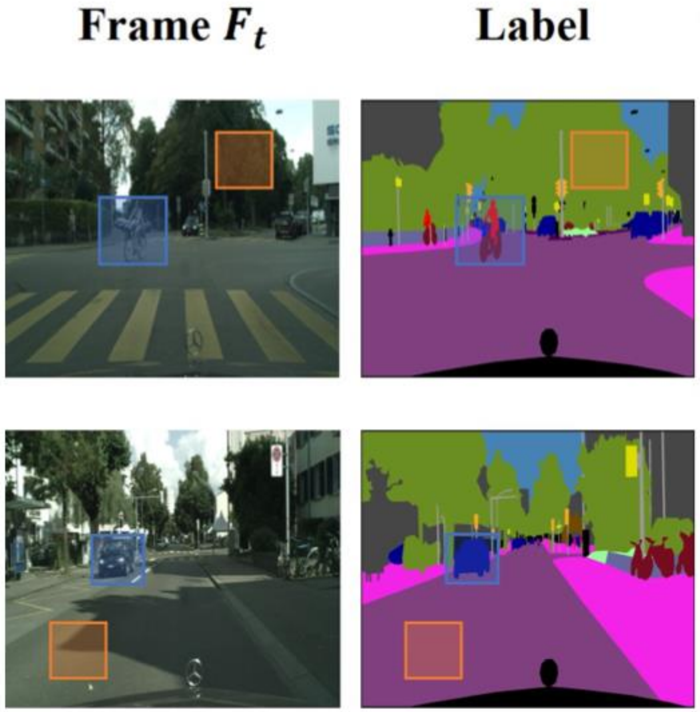
$$\mathbf{p}_{sim} = \mathrm{SoftMax}(\mathbf{Q^n} \cdot \mathbf{q}^T),$$

$$\mathcal{D}_{KL} = KL(\mathbf{p}_u || \mathbf{p}_{sim}) = \sum_{i=1}^{n_b} p_{u[i]} \log \frac{p_{sim[i]}}{p_{u[i]}},$$

$$\mathcal{D}_{cos} = \frac{1}{n_b} \sum_{i=1}^{n_b} (1 - \frac{\mathbf{Q^n_{[i]}} \cdot \mathbf{q}^T}{||\mathbf{Q^n_{[i]}}||_2 ||\mathbf{q}||_2}),$$

$$\mathcal{D}_{NSM} = \mathcal{D}_{KL} + \mathcal{D}_{cos},$$

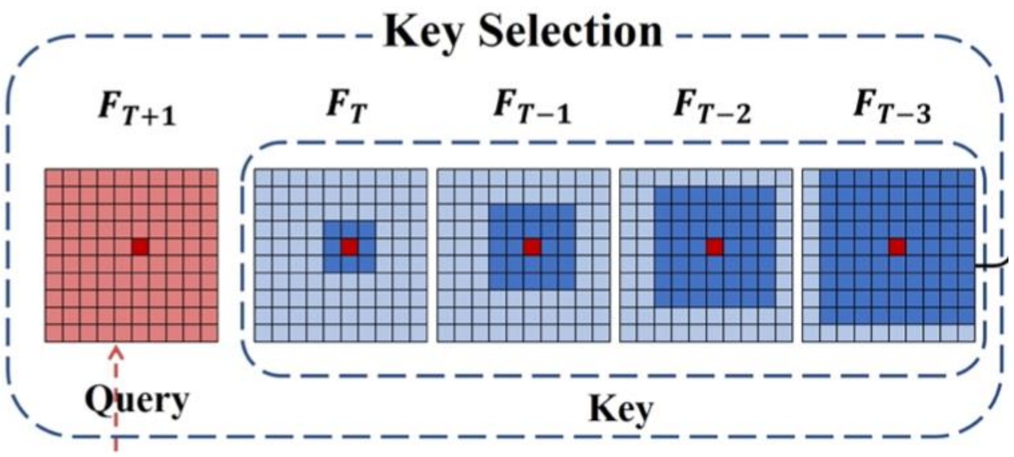




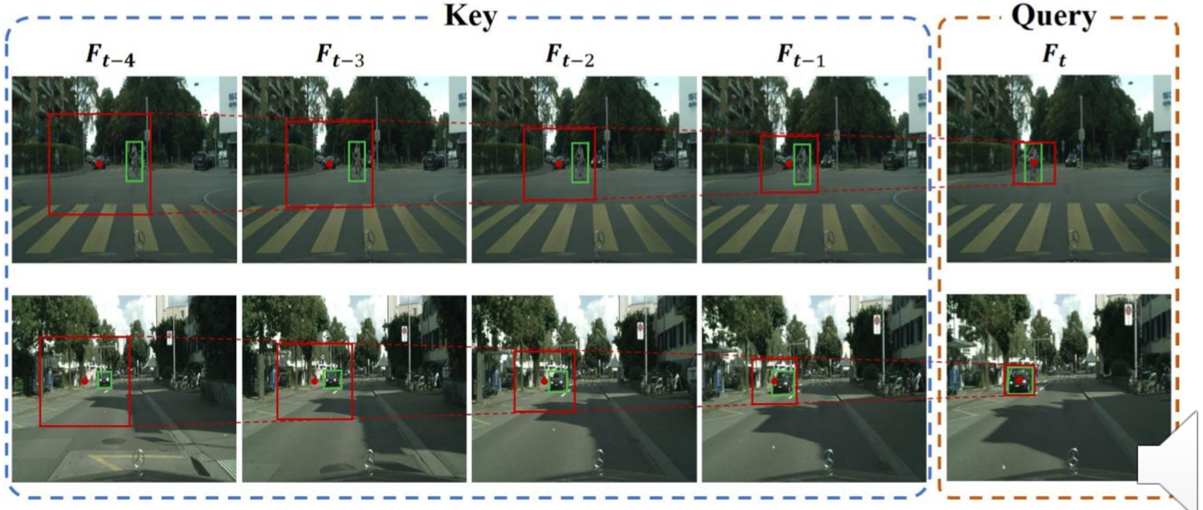
[1] Dmitrii Marin, Zijian He, Peter Vajda, Priyam Chatterjee, Sam Tsai, Fei Yang, and Yuri Boykov. 2019. Efficient segmentation: Learning downsampling near semantic boundaries. In ICCV 2019.

Proposed Method

- Key Selection
  - Motivation: in consecutive frames, tracking the corresponding small regions in previous frames can bring much useful temporal information.
  - Rules for enlarging the searching regions:
    - The key frame farther from the current frame should have larger key region;
    - The size of key regions should vary within a proper range.



$$l_t = \begin{cases} s + (T - t) * \epsilon & , \text{ if } \quad s + (T - t) * \epsilon < e; \\ e & , \text{ otherwise.} \end{cases}$$



Experimental Results

- Experiment Setup
  - Dataset
    - Cityscapes
      - Training: 2,975 video clips
      - Validation: 500 video clips
      - Test: 1,525 video clips
    - Camvid
      - Training: 367 video clips
      - Validation: 100 video clips
      - Test: 233 video clips
  - Evaluation Metrics
    - For segmentation accuracy: mean Intersection-over-Union (mIoU)
    - For temporal consistency: TC following ETC [1], which measures the consistency based on the mean flow warping error between all consecutive frames.

- Comparison with Existing Methods
  - High-Speed Methods

Method	Backbone	mIoU (%) ↑	TC (%)↑	fps (frame/s) ↑
DVSNet [50]	ResNet18	63.2	-	30.3
ICNet [55]	ResNet50	67.7	-	50.0
LadderNet [31]	DenseNet121	72.8	-	30.3
SwiftNet [41]	ResNet18	75.4	-	43.5
BiSeNet18 [53]	ResNet18	73.8	-	50.0
BiSeNet34 [53]	ResNet34	76.0	-	37.0
TDNet-BiSe18 [25]	ResNet18	75.0	70.2	47.6
TDNet-BiSe34 [25]	ResNet34	76.4	71.1	38.5
ETC-Mobi [37]	MobileNetV2	73.9	69.9	20.8
STT-BiSe18	ResNet18	**75.8**	**71.4**	44.2
STT-BiSe34	ResNet34	**77.3**	**72.0**	33.8

[1] Yifan Liu, Chunhua Shen, Changqian Yu, and Jingdong Wang. 2020. Efficient Semantic Video Segmentation with Per-frame Inference. In ECCV 2020.

Experimental Results

- Comparison with Existing Methods
    - High-Quality Methods

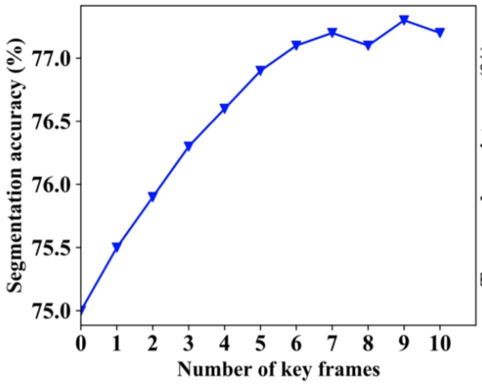
Method	Backbone	Cityscapes			Camvid		
		mIoU (%) ↑	TC (%) ↑	fps (frame/s) ↑	mIoU (%) ↑	TC (%) ↑	fps (frame/s) ↑
NetWarp [20]	ResNet101	80.6	-	0.3	67.1	-	2.8
DFF [61]	ResNet101	68.7	71.4	9.7	-	-	-
GRFP [40]	ResNet101	69.4	-	3.2	66.1	-	4.4
LVS [33]	ResNet101	76.8	-	5.9	-	-	-
Accel [28]	ResNet101/18	72.1	70.3	3.6	66.7	-	7.6
PSPNet18 [56]	ResNet18	75.5	68.5	10.8	71.0	-	24.4
PSPNet50 [56]	ResNet50	78.1	-	4.2	74.7	-	8.5
PSPNet101 [56]	ResNet101	79.4	69.7	2.1	77.6	77.1	4.1
TDNet-PSP18 [25]	ResNet18	76.8	70.4	11.8	72.6	73.2	25.2
TDNet-PSP50 [25]	ResNet50	79.9	71.1	5.6	76.0	77.4	11.1
ETC-PSP18 [37]	ResNet18	73.1	70.6	10.8	75.2	77.3	24.4
ETC-PSP101 [37]	ResNet101	79.5	71.7	2.1	79.4	78.6	4.1
STT-PSP18	ResNet18	**77.3**	**73.0**	11.5	**76.1**	**81.4**	24.7
STT-PSP101	ResNet101	**82.5**	**73.9**	2.2	**80.2**	**82.3**	4.2

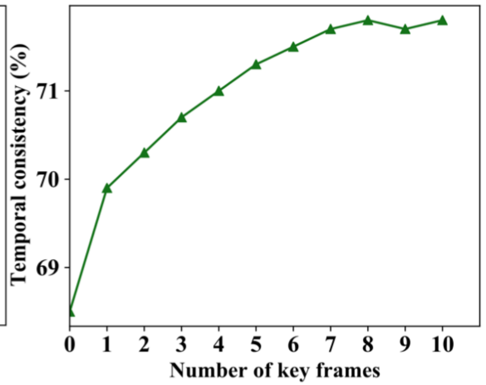
Experimental Results

- Ablation Study
  - Key selection

	SS (s)	ES (e)	EC (ϵ)	key size	mIoU (%)	TC (%)	fps (frame/s)
1	1	5	1	527	77.2	73.0	11.5
2	2	5	1	639	77.3	72.9	11.1
3	3	5	1	735	77.1	73.0	10.7
4	1	3	1	279	76.5	72.1	11.9
5	1	7	1	679	77.3	72.8	11.0
6	1	5	2	663	77.1	72.8	11.0
7	1	5	3	695	77.2	72.9	11.0
8	-	-	-	57344	75.1	69.9	0.2

  - Numbers of key frames



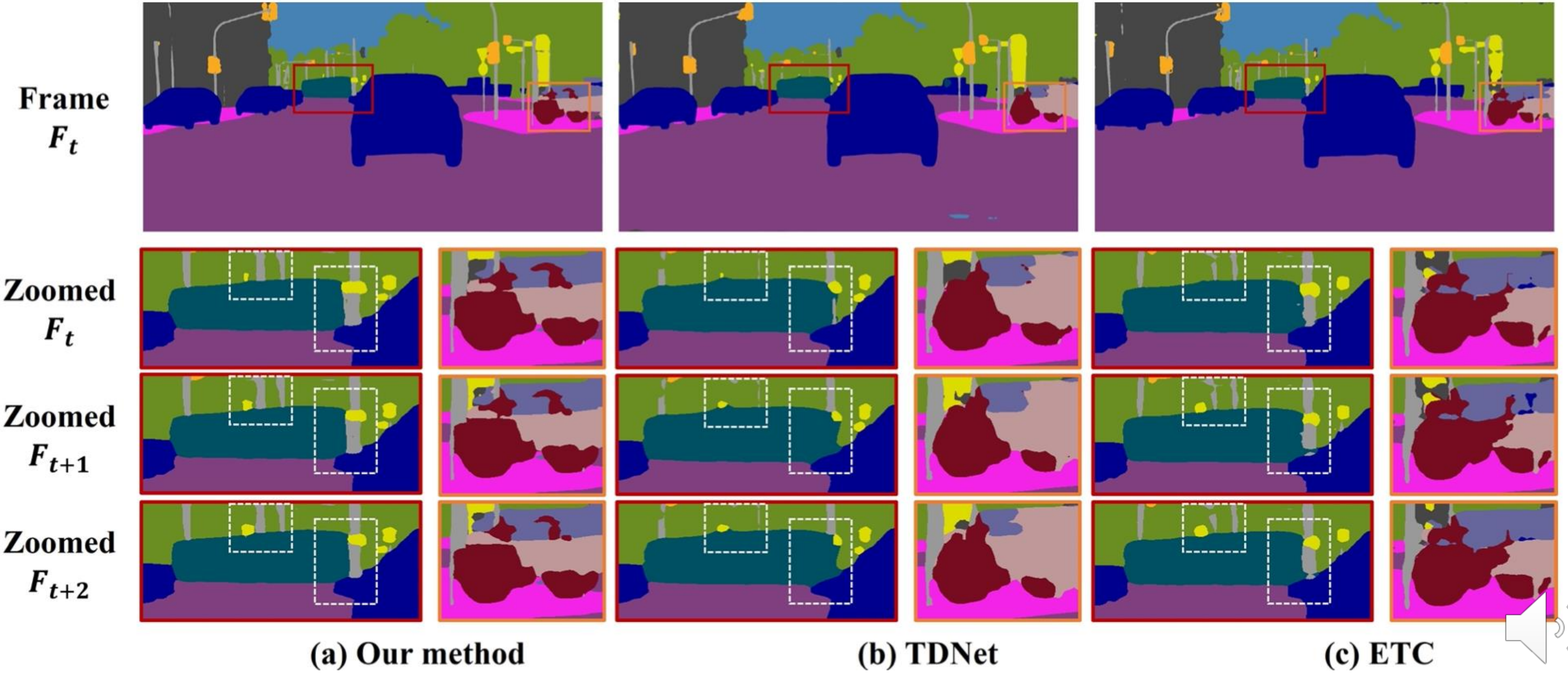


  - Query selection

	NR (r)	TR	mIoU (%)	TC (%)	fps (frame/s)
1	1	50 %	76.1	71.2	11.5
2	3	50 %	77.1	72.8	11.5
3	5	50 %	77.3	73.0	11.5
4	7	50 %	77.2	72.9	11.5
5	9	50 %	76.8	72.1	11.5
6	5	0 %	75.3	68.7	13.6
7	5	25 %	76.7	72.4	12.6
8	5	75 %	77.3	72.7	10.5
9	5	100 %	77.2	72.9	9.4

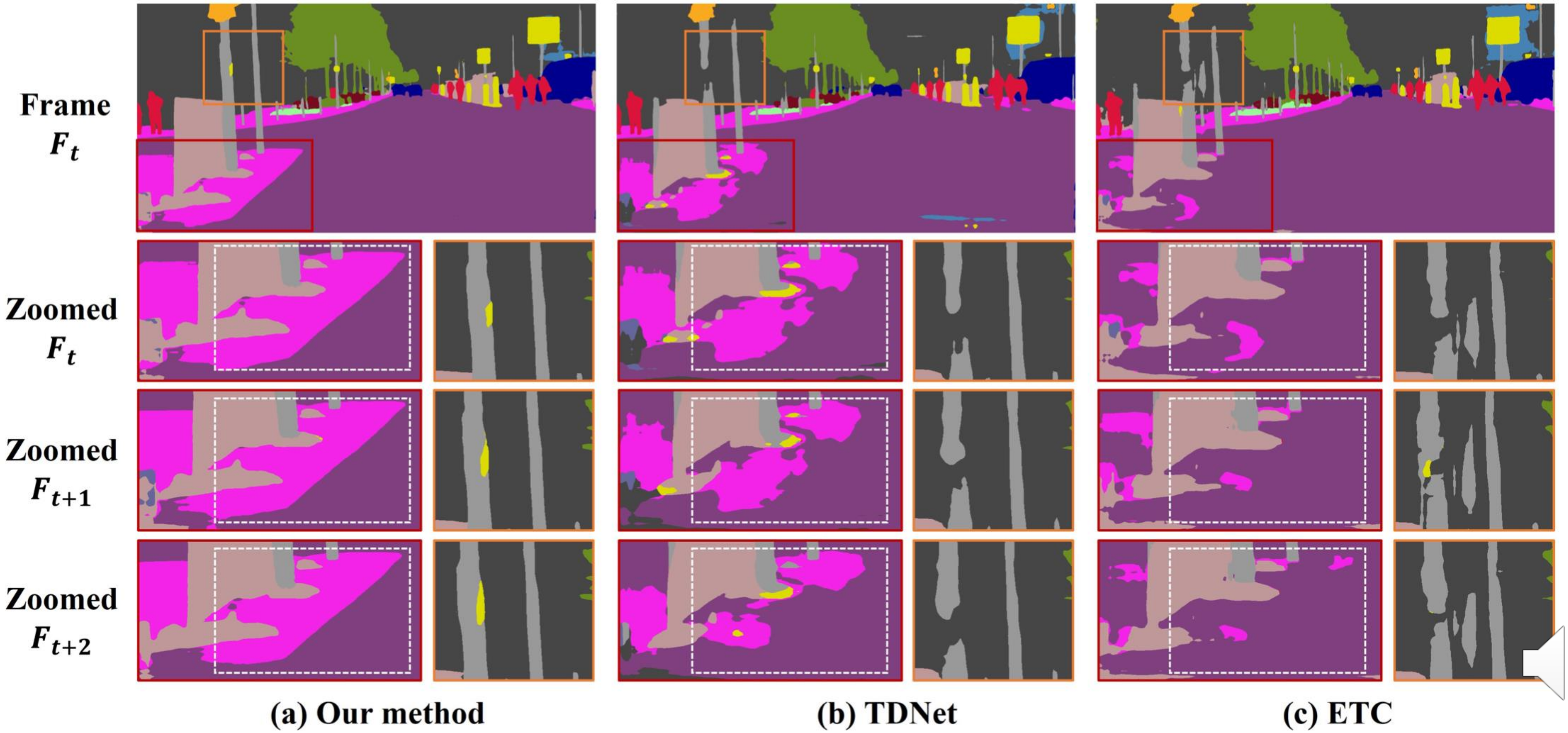
Experimental Results

- Case study



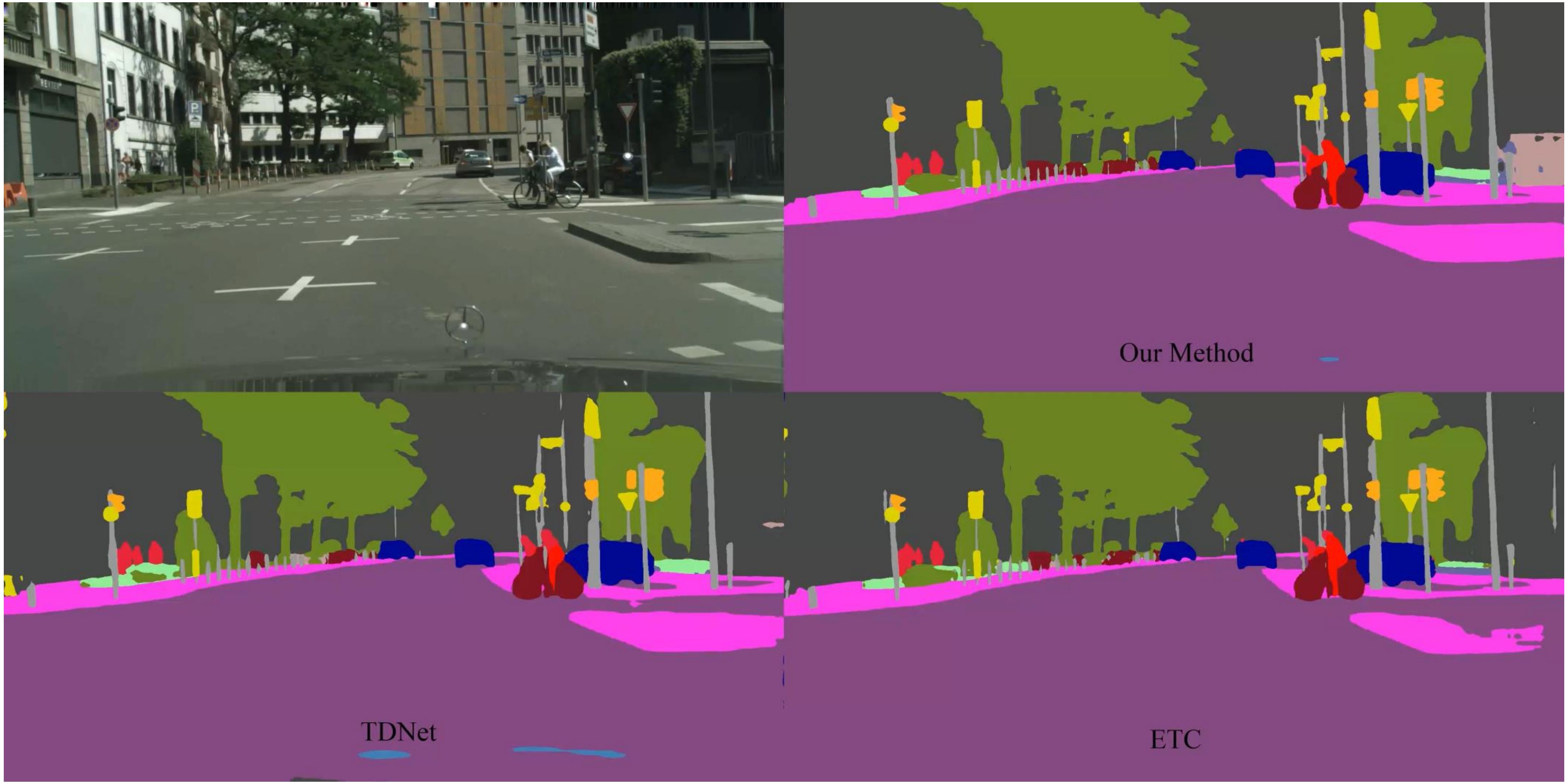
Experimental Results

- Case study



Experimental Results

- Case study



Thanks for watching!

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