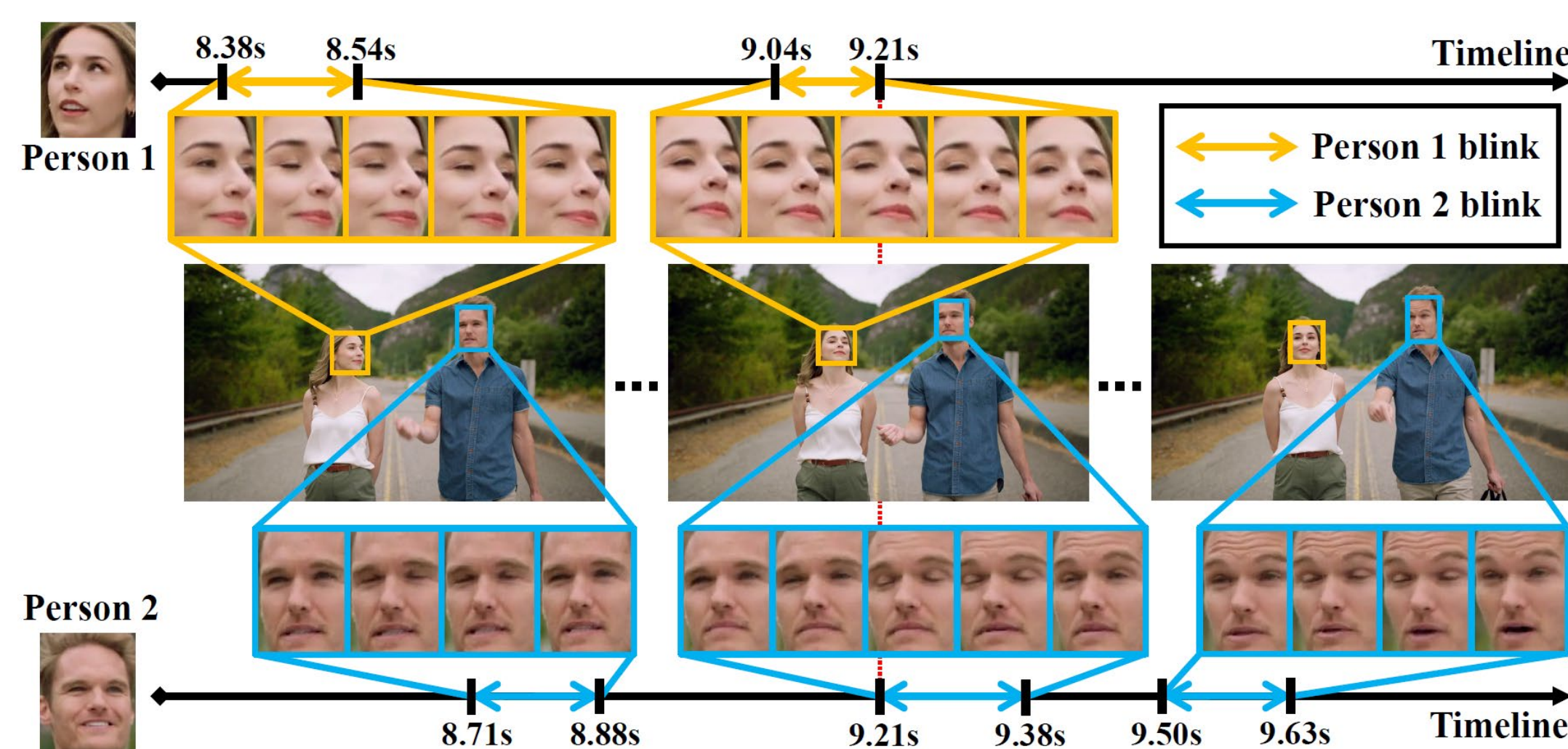


Understanding Eyeblink Behaviors at Multi-instance Level



Our Contributions

- A new task called multi-person eyeblink detection in the wild in untrimmed videos is formally defined and explored.
- An unconstrained multi-person eyeblink detection dataset MPEblink that featured with more realistic and challenging.
- A one-stage multi-person eyeblink detection method InstBlink that can jointly perform face detection, tracking, and instance-level eyeblink detection.

Applications



Definition of Multi-instance Eyeblink Detection

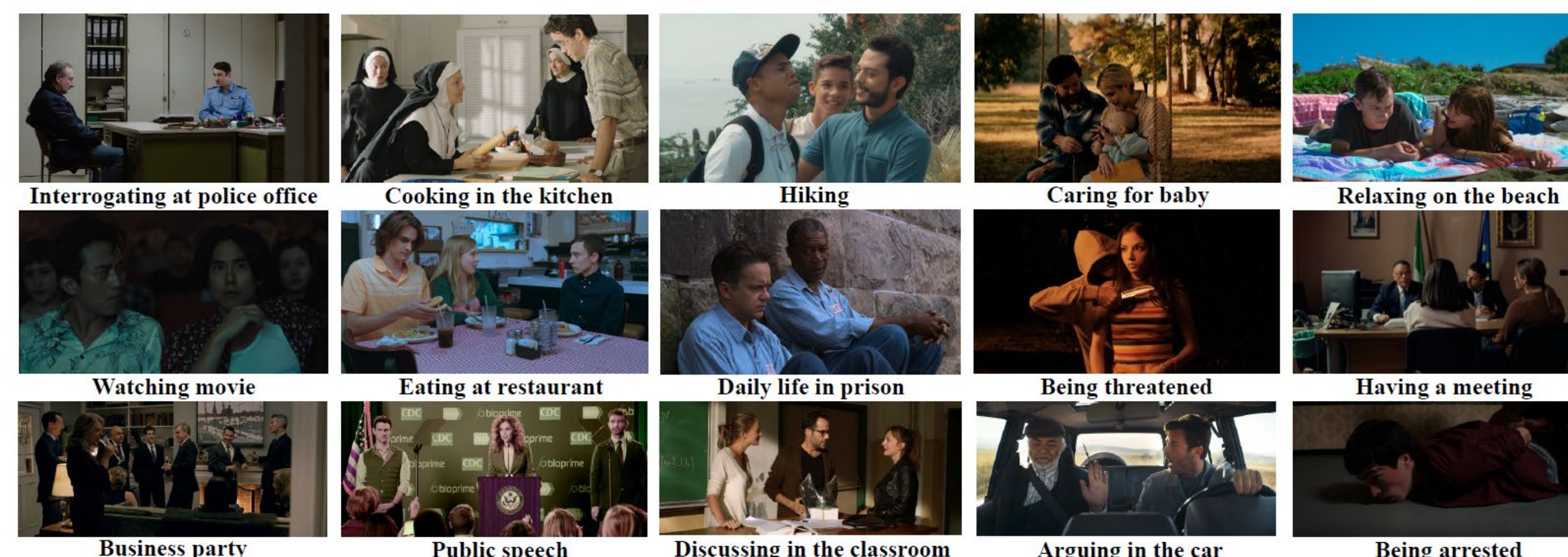
A good multi-person eyeblink detection algorithm should be able to:

- Detect and track human instances' faces reliably to ensure the instance-level analysis ability along the whole video.
- Detect eyeblink boundaries accurately within each human instance to ensure the precise awareness of their eyeblink behaviors.

New Evaluation Metrics

- Inst-AP: Evaluating instance detection and tracking ability.
- Blink-AP: Reflecting eyeblink detection accuracy within each instance.

The MPEblink Dataset



Distinguishing characteristics

Multi-person Unconstrained Untrimmed

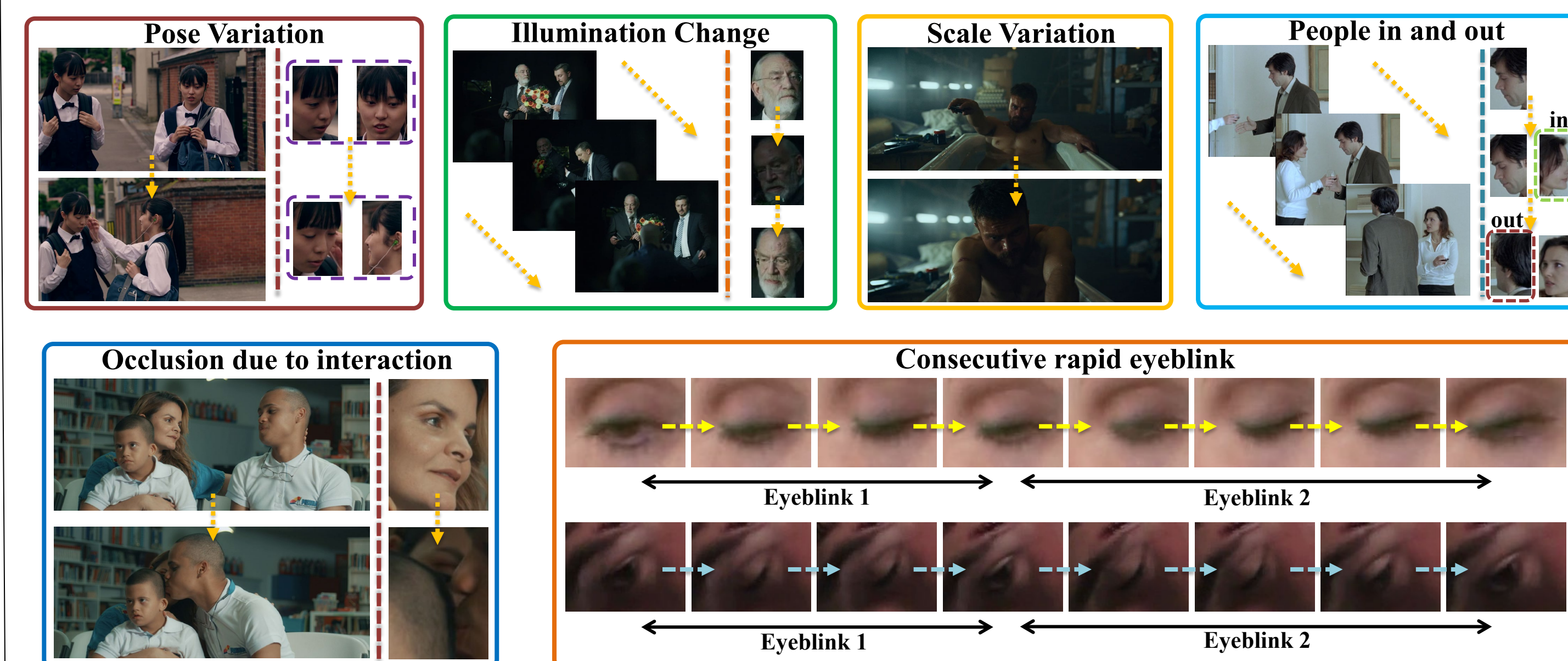
Diverse movie data sources

- 86 movies with 16 different genre.
- Filmed in 28 countries from 6 continents.
- Scenarios with potential down-stream applications (e.g., fatigue detection, affective analysis).

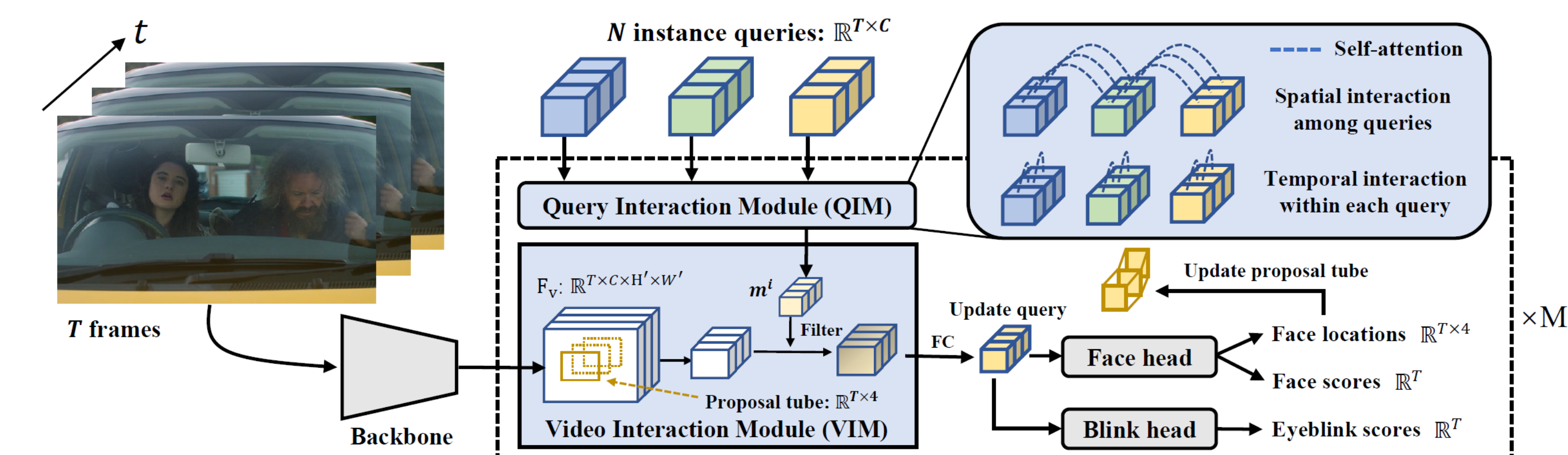
Annotation

- Instance-level face bounding boxes & landmarks across video
- Instance-level eyeblink event intervals (start & end time point)

Challenges



InstBlink: Towards One Stage Multi-person Eyeblink Detection



- Shared face and blink features.
- Apply multi-task learning to simultaneously address face detection, tracking, and blink detection.

Benefits

- Eyeblink features can be facilitated via the face's global context with joint optimization and interaction.
- Features can be effectively shared to meet real-time running requirement.

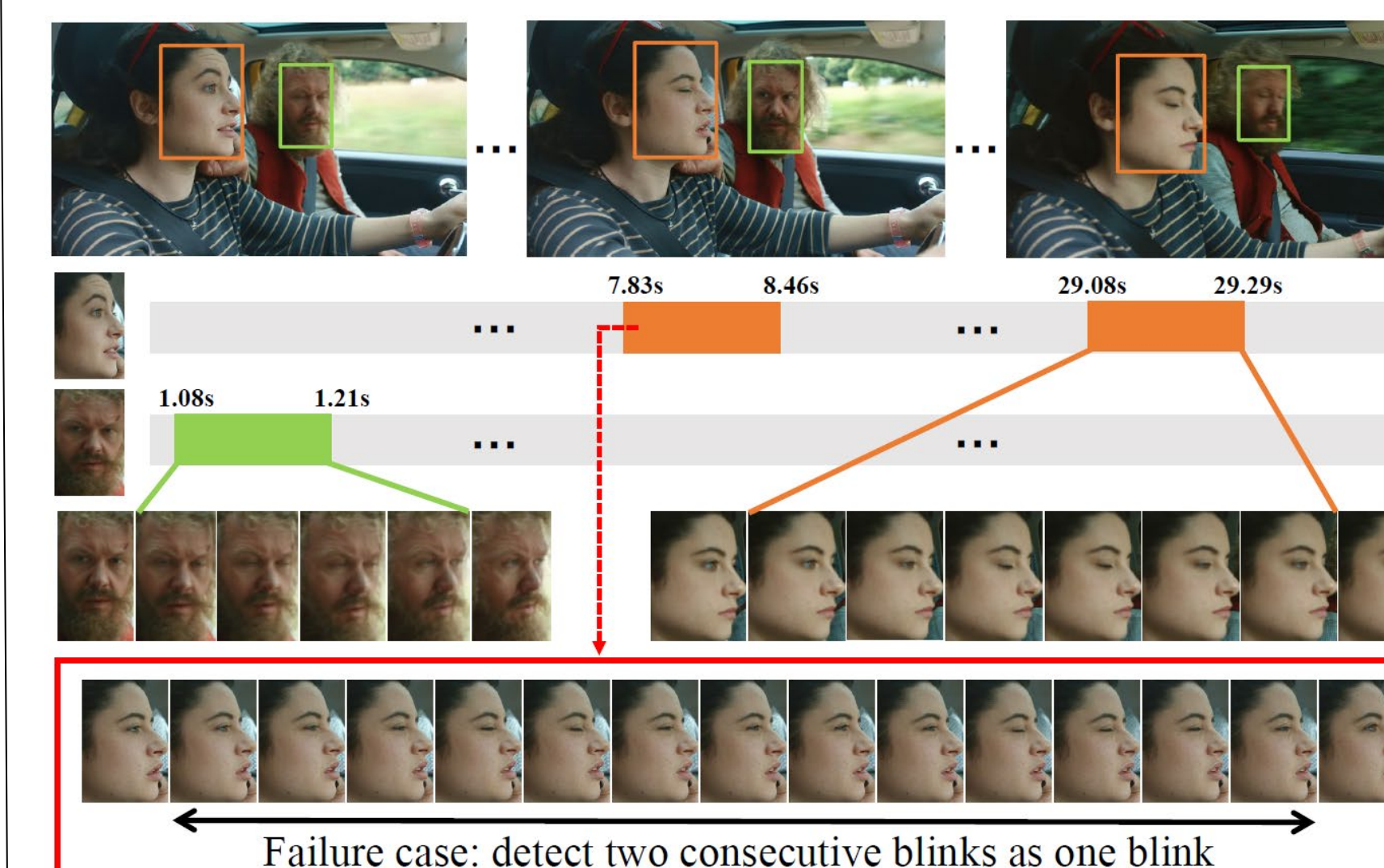
Evaluation on MPEblink

Type	Method	Blink-AP ₅₀	Blink-AP ₇₅	Inst-AP
Landmark	Soukupová and Cech [40]	0.50	0.05	56.70
	Blink detection+ [35]	0.62	0.08	
Region	Hu et al. [19]	2.68	0.04	67.89
	Daza et al. [9]	5.85	0.88	
	InstBlink (Ours)	27.19	7.16	

Effect of QIM & VIM

Method	Blink-AP ₅₀	Blink-AP ₇₅	Inst-AP
w/o QIM	3.20	0.39	58.93
w/o temporal interaction in QIM	4.58	0.55	63.61
w/o spatial interaction in QIM	26.65	6.18	62.45
w/o filter operation in VIM	22.27	4.59	65.01
Full model	27.19	7.16	67.89

Qualitative result



Effect of multi-task learning

Blink head	Inst-AP	Inst-AP ₅₀	Inst-AP ₇₅
×	65.86	81.73	71.23
✓	67.89	84.51	73.76

Evaluation on HUST-LEBW

Training set	Method	Eye	Recall	Precision	F1
HUST-LEBW [19]	Soukupová and Cech [40]	Left	36.07	64.71	46.32
		Right	30.16	57.58	39.58
	Hu et al. [19]	Left	54.10	89.19	67.35
		Right	44.44	76.71	56.28
		Both	58.99	80.05	67.90
		Both	97.64	56.62	71.68
mEBAL [10]	Daza et al. [10]	Left	96.03	60.80	74.46
		Right	79.50	73.48	76.37
	Daza et al. [9]	Both	93.39	75.33	83.39
MPEblink	InstBlink_cross (Ours)	Both	91.34	76.82	83.45

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