

Privacy-Aware Video Anomaly Detection through Orthogonal Subspace Projection

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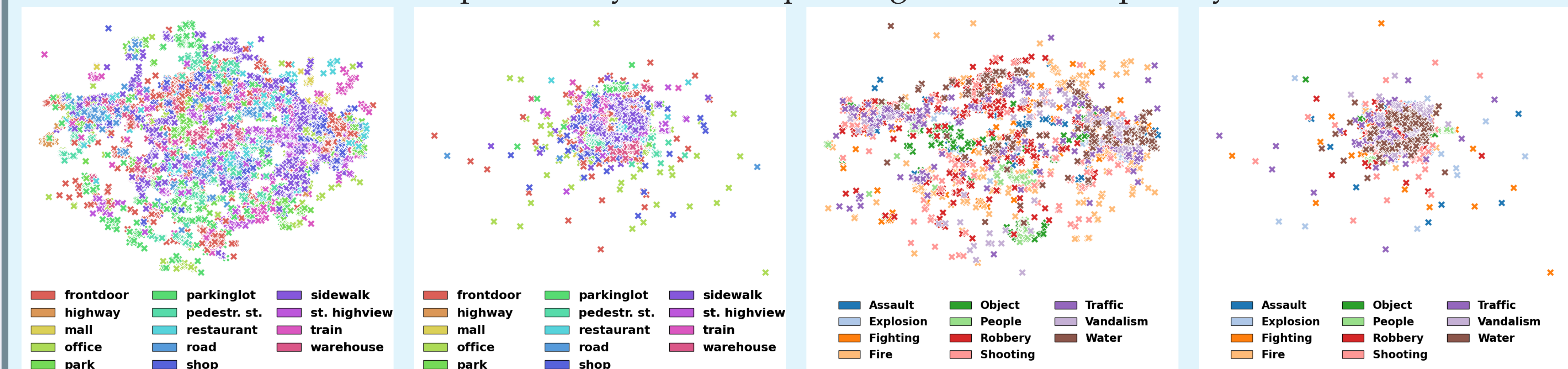


Motivation and key ideas

UMAP of removed features on MSAD.

OPL removes nuisance factors, yielding dispersed clusters, while G-OPL suppresses facial cues, producing a compact, overlapping distribution not aligned with anomaly types.

This contrast shows their complementary roles in separating nuisance and privacy-sensitive information.



OPL: By scenario. G-OPL: By scenario. OPL: By anomaly type. G-OPL: By anomaly type.

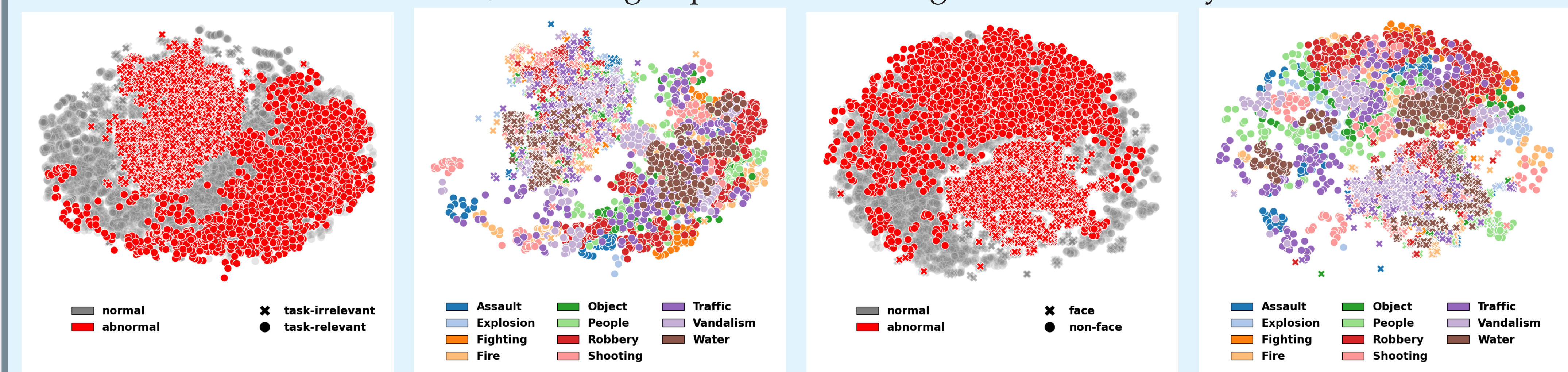
Qualitative results

UMAP plots visualize task-relevant (dots) and removed nuisance/sensitive (crosses) features after the first OPL/G-OPL (using RTFM-I3D on MSAD).

Colors indicate *frame-level* labels (normal, abnormal, anomaly types). Removal operates at the feature level, anomalies are detected from the remaining task-relevant features, not from removed components.

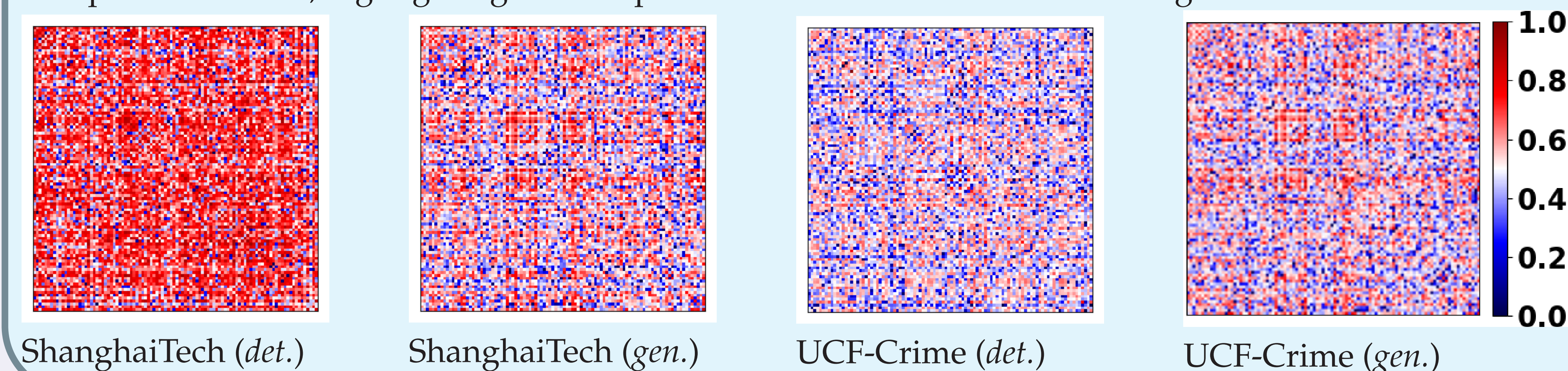
(a) vs. (c): Both OPL and G-OPL successfully disentangle nuisance/sensitive features (crosses) from task-relevant ones (dots), but G-OPL yields more compact clusters of removed features due to its guidance from facial cues, offering clearer separation of irrelevant information.

(b) vs. (d): For task-relevant features, G-OPL preserves more compact and semantically meaningful clusters for *human-centric* anomalies, revealing improved disentanglement of anomaly-relevant factors.



Visualization of QQ^T (G-OPL of RTFM model) from detected (*det.*) and generated (*gen.*) faces.

All matrices are log-scaled, globally min-max normalized. Differences reflect dataset- and signal-specific subspace structures, highlighting distinct patterns of sensitive feature disentanglement.



Quantitative results

Performance by anomaly type on MSAD. Bold marks the best, underlined the second-best.

We compare against recent methods: RTFM, MGFN, UR-DMU, EGO, and IEF-VAD.

Our **G-OPL/OPL** achieves competitive or superior results across anomaly types, highlighting its robustness, especially when paired with strong base models (e.g., RTFM with I3D).

Method	Assault		Explosion		Fighting		Fire		Obj. Fall		People Fall		Robbery		Shooting		Traffic Acc.		Vandalism		Water Inc.		Overall	
	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP
RTFM (I3D)	53.9	66.4	66.0	76.6	79.8	88.6	44.9	71.1	84.6	89.3	45.7	52.6	70.2	88.0	87.5	89.2	64.1	57.7	74.9	73.0	98.1	99.6	86.6	68.4
MGFN (SwinT)	50.2	49.6	50.9	58.1	57.2	67.1	51.4	74.2	41.3	51.6	44.4	40.3	40.1	68.5	51.4	63.9	50.4	42.3	42.6	40.9	58.6	87.2	69.3	33.6
MGFN (I3D)	53.9	60.2	59.1	66.5	80.6	89.5	66.1	82.9	89.9	94.6	53.6	44.9	72.2	85.4	68.3	80.6	66.9	54.7	84.4	78.5	81.9	96.1	81.2	59.3
UR-DMU	56.9	64.5	67.9	74.5	83.9	90.4	61.2	82.9	92.1	95.8	42.5	43.7	63.5	79.3	81.4	87.8	62.0	55.6	84.7	77.0	98.5	99.5	85.0	68.3
EGO	52.2	57.5	57.6	74.4	66.5	72.8	62.9	86.7	92.3	94.8	35.4	43.8	64.8	87.5	68.6	78.4	69.9	64.3	88.1	<u>81.4</u>	81.9	95.4	87.3	64.4
IEF-VAD	66.0	-	66.3	-	79.8	-	49.4	-	75.9	-	42.5	-	66.9	-	86.9	-	70.1	-	75.8	-	88.9	-	82.1	-
RTFM-OPL (I3D)	57.0	62.4	77.7	85.7	74.1	84.8	49.6	75.5	87.7	92.1	53.3	50.4	72.4	89.0	84.1	89.5	69.5	58.7	84.8	80.9	99.2	99.8	86.5	68.2
MGFN-OPL (SwinT)	59.1	56.5	52.7	57.0	44.3	55.2	63.0	76.4	58.3	59.3	40.6	36.0	49.5	70.7	55.3	62.1	49.1	39.6	60.8	53.7	44.4	78.9	78.2	47.5
MGFN-OPL (I3D)	71.3	69.4	61.8	73.0	87.8	92.8	81.0	93.0	94.3	96.5	45.9	45.0	65.1	81.1	82.7	89.1	64.2	55.2	90.8	86.4	68.7	92.0	86.2	68.3
RTFM-G-OPL/OPL (I3D)	50.2	62.4	69.4	80.6	69.5	84.4	71.8	87.0	88.7	92.4	52.3	53.3	71.4	88.2	87.8	91.0	62.5	54.7	82.0	79.6	97.5	99.4	88.0	70.9
MGFN-G-OPL/OPL (I3D)	52.4	59.8	66.5	76.8	88.8	<u>92.2</u>	<u>77.2</u>	<u>89.0</u>	90.5	95.1	45.9	42.8	65.4	80.1	71.9	81.8	53.9	46.4	83.1	75.1	81.5	96.0	84.0	65.8

Performance by scenario on MSAD.

Results on 12 test scenarios (excluding Highway and Park without anomalies) show our method's strong adaptability and robustness, consistently outperforming or matching top baselines and recent state-of-the-art methods while achieving better balance across scenarios (this table) and anomaly types.

Method	Frontdoor		Mall		Office		Parkinglot		Pedestr. st.		Restaurant		Road		Shop		Sidewalk		St. highview		Train		Warehouse		Overall	
	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP
RTFM (I3D)	81.8	79.3	88.1	76.6	76.6	72.8	80.7	45.8	94.0	48.5	88.3	79.1	84.3	57.9	85.3	75.6	88.3	68.8	72.0	28.5	51.4	3.3	82.7	57.0	86.6	68.4
MGFN (SwinT)	59.5	51.7	18.5	20.1	64.1	52.3	67.9	19.0	75.9	9.7	67.9	44.0	70.6	26.3	62.7	43.0	69.0	25.9	75.3	23.3	65.4	5.2	70.1	30.1	69.3	33.6
MGFN (I3D)	82.5	80.8	73.8	71.3	71.5	58.2	68.9	14.8	94.8	36.2	95.1	91.3	76.5	35.8	85.6	78.4	78.5	57.2	77.9	29.3	40.3	2.1	58.3	24.2	81.2	59.3
UR-DMU	84.8	82.8	91.0	83.8	77.8	67.3	91.4	53.9	81.9	11.5	93.1	87.4	83.0	64.4	81.3	64.5	86.5	64.1	85.0	37.7	59.0	3.1	81.2	59.1	85.0	68.3
EGO	85.2	81.6	82.3	73.4	80.0	71.7	96.8	75.2	97.5	52.0	94.3	73.9	89.8	64.6	83.4	72.2	87.1	45.0	28.2	10.1	80.8	7.8	84.7	46.6	87.3	64.4
IEF-VAD	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	82.1
RTFM-OPL (I3D)	85.6	82.3	85.6	80.2	77.2	72.0	76.9	26.4	96.6	50.5	90.2	81.3	76.9	53.3	88.6	82.8	84.9	56.5	66.8	26.7	42.4	2.3	86.1	66.8	86.5	68.2
MGFN-OPL (SwinT)	68.5	57.8	89.0	61.8	68.4	55.4	79.4	39.0	74.5	5.0	51.6	36.1	67.3	28.1	77.1	60.3	81.1	41.9	87.1	45.8	83.5	11.9	83.8	52.4	78.2	47.5
MGFN-OPL (I3D)	84.4	84.1	80.2	74.7	74.7	65.0	87.0	30.9	93.5	53.1	91.2	87.6	80.0	55.7	82.1	69.4	86.8	63.8	98.1	95.1	70.8	9.1	89.9	76.1	86.2	68.3
RTFM-G-OPL/OPL (I3D)	82.0	79.3	91.0	81.4	74.3	72.0	79.4	27.2	86.9	36.1	90.3	81.4	72.4	46.7	89.0	82.5	87.0	65.1	84.9	37.8	70.4	12.0	86.3	79.6	88.0	70.9
MGFN-G-OPL/OPL (I3D)	84.4	83.3	90.0	84.8	75.9	62.3	70.4	16.9	90.5	25.8	95.7	<u>90.2</u>	71.4	43.1	79.7	64.5	83.8	63.3	87.7	41.3	44.7	2.3	64.8	41.1	84.0	65.8

Results on ShanghaiTech, UCF-Crime, CUHK Avenue, and UCSD Ped2.

† uses RetinaFace embeddings; NA denotes undetectable faces on UCSD Ped2 due to low resolution. **Bold** highlights performance surpassing the baseline or the best privacy variant.

G-OPL/OPL are further evaluated using privacy metrics (SSC \uparrow , ARD \downarrow , FPD \downarrow). Privacy metrics may underperform on datasets with low resolution or small/occluded faces.

We also include ArcFace-based identity retrieval as a classifier-based privacy probe (Arc \downarrow), providing an external reference point for comparison. MGNAD and SPAct are adapted to VAD; TeD-SPAD follows its own setup using MGFN+I3D.

This is the first comprehensive privacy analysis for VAD across datasets.

Method	ShanghaiTech					UCF-Crime					CUHK Avenue					UCSD Ped2									
	AUC	AP	SSC \uparrow	ARD \downarrow	FPD \downarrow	Arc \downarrow	AUC	AP	SSC \uparrow	ARD \downarrow	FPD \downarrow	Arc \downarrow	AUC	AP	SSC \uparrow	ARD \downarrow	FPD \downarrow	Arc \downarrow	AUC	AP	SSC \uparrow	ARD \downarrow	FPD \downarrow	Arc \downarrow	
USTN-DSC	73.8	-	-	-	-	-	-	-	-	-	-	-	89.9	-	-	-	-	-	-	98.1	-	-	-	-	-
FPDM	78.6	-	-	-	-	-	74.7	-	-	-	-	-	90.1	-	-	-	-	-	-	-	-	-	-	-	
HSC	83.4	-	-	-	-	-	-	-	-	-	-	-	93.7	-	-	-	-	-	-	98.1	-	-	-	-	-
PELAVAD	98.1	72.6	-	-	-	-	86.8	34.0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
VadCLIP	-	-	-	-	-	-	88.0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
TeD-SPAD	90.6	-	-	-	-	-	74.8	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
SPAct	87.7	-	-	-	-	-	73.9	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
MGNAD	70.5	-	-	-	-	-	-	-	-	-	-	-	88.5	-	-	-	-	-	-	97.0	-	-	-	-	
MGFN	75.3	22.7	-	-	0.98	0.14	77.0	13.0	-	0.79	0.05	67.3	37.7	-	-	0.94	0.44	86.8	76.7	-	-	-	0.91	-	
MGFN-G-OPL/OPL	83.7	42.0	0.10	0.23	0.96	0.01	83.3	15.2	0.99	0.07	0.49	0.02	70.8	40.5	0.39	18.0	0.58	1.13	93.9	93.6	0.39	0.94	0.31	-	
MGFN-G-OPL/OPL†	89.5	41.9	0.52	0.16	0.68	0.01	80.9	14.8	0.72	6.46	0.01	0.03	69.1	43.5	0.81	23.6	1.0	0.31	NA	NA	NA	NA	NA	-	
RTFM	96.8	71.6	-	-	0.72	0.99	74.3	20.1	-	0.68	1.0	83.3	66.3	-	-	1.0	1.0	85.6	82.0	-	-	-	0.31	-	
RTFM-G-OPL/OPL	97.3	74.7	0.97	0.29	0.19	0.01	78.3	30.9	0.98	0.03	0.23	0.03	84.9	66.2	0.89	0.26	0.0	0.31	89.6	75.0	0.98	0.06	0.29	-	
RTFM-G-OPL/OPL†	97.2	74.6	0.20	0.17	0.01	0.02	74.1	30.1	0.33	0.30	0.64	0.02	83.9	65.7	0.11	3.									