



### **KEY QUESTIONS**

- Q1: Wouldn't achieving an accurate and efficient search be possible by mitigating information loss in the video-level approach?
- Q2: Should irrelevant frames (red boxes) be suppressed in the untrimmed videos?



## **KEY INSIGHTS**

If irrelevant frames are ideally suppressed, the video-level approaches can be more accurate (even comparable to the frame-level SOTA).



**Temporal annotation** (Jo *et al.*, IEEE Access, 2023)



## **CONTACT INFORMATION**



## METHOD

### **Proposed Framework**

Understand irrelevant frames for describing a distinct video-level feature in an untrimmed video





# **Easy Distractor Eilmination Stage**

### **Distractor Discrimination Module**



# CONCLUSION

## VVS: Video-to-Video Retrieval with Irrelevant Frame Suppression <sup>1</sup>Won Jo, <sup>1</sup>Geuntaek Lim, <sup>1</sup>Gwangjin Lee, <sup>1</sup>Hyunwoo Kim, <sup>2</sup>Byungsoo Ko, <sup>1</sup>Yukyung Choi

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An example of the untrimmed video

• Eliminate easy distractors, which are frames with little variation and few low-level characteristics (edges, corners, etc.)

• Train by generating pseudo-labels, leveraging the fact that the easy distractor's feature mainly exhibits a small magnitude due to having fewer elements activated from the backbone network

### **Suppression Weight Generation Stage** for Hard Distractor

### **Temporal Saliency Module**

- Suppress hard distractors by assessing frames based on the saliency signal
- Train by generating pseudo-labels, leveraging the fact that the highly activated part in the tuned frame-level similarity map represents frames with a strong correlation between a positive pair



### **Topical Guidance Module**

- Suppress hard distractors by measuring the relevance of frames to the overall topic of a video
- Train with refining an initial state, leveraging the fact that the topic of a video is determined by the predominant content within it



• In this paper, we demonstrate that suppression of irrelevant frames is essential in describing an untrimmed video with long and varied content as a video-level feature.

• Our method removes clearly identifiable frames and determines the extent to which the remaining frames should be suppressed, utilizing saliency information and topic relevance.





Approach	Reference	SumMe		TVSum		Averag
		F-score	Rank.	F-score	Rank.	Rank.
Random summary	-	40.2	19	54.4	16	17.5
SUM-FCN <sub>unsup</sub>	(Rochan, Ye, and Wang 2018)	41.5	17	52.7	17	17
DR-DSN	(Zhou, Qiao, and Xiang 2018)	41.4	18	57.6	13	15.5
EDSN	(Gonuguntla et al. 2019)	42.6	15	57.3	14	14.5
$RSGN_{unsup}$	(Zhao et al. 2021)	42.3	16	58.0	12	14
UnpairedVSN	(Rochan and Wang 2019)	47.5	12	55.6	15	13.5
PCDL	(Zhao, Li, and Lu 2019)	42.7	14	58.4	10	12
ACGAN	(He et al. 2019)	46.0	13	58.5	9	11
$SUM-Ind_{LU}$	(Yaliniz and Ikizler-Cinbis 2021)	46.0	13	58.7	8	10.5
ERA	(Wu, Lin, and Silva 2021)	48.8	9	58.0	12	10.5
SUM-GAN-sl	(Apostolidis et al. 2019)	47.8	11	58.4	10	10.5
SUM-GAN-AAE	(Apostolidis et al. 2020b)	48.9	8	58.3	11	9.5
$MCSF_{late}$	(Kanafani et al. 2021)	47.9	10	59.1	6	8
$SUM-GDA_{unsup}$	(Li et al. 2021)	50.0	7	59.6	5	6
CSNet+GL+RPE	(Jung et al. 2020)	50.2	6	59.1	6	6
CSNet	(Jung et al. 2019)	51.3	2	58.8	7	4.5
DSR-RL-GRU	(Phaphuangwittayakul et al. 2021)	50.3	5	60.2	4	4.5
AC-SUM-GAN	(Apostolidis et al. 2020a)	50.8	4	60.6	3	3.5
CA-SUM	(Apostolidis et al. 2022)	51.1	3	61.4	2	2.5
<b>VVS</b> 3840 (ours)	-	51.7	1	61.5	1	1