Zero-Shot Video-Text Retrieval with Hallucination-Based Captioning and Structural Information Extraction

Anonymous ACL submission

Abstract

While recent progress in video-text retrieval has been advanced by the exploration of better representation learning, in this paper, we present a novel zero-shot framework, HALISIE, to retrieve video/text with off-the-shelf captioning methods, large language models (LLMs), and text retrieval methods. Specifically, we first map videos into captions with video captioning methods and then retrieve video captions and text using text retrieval methods, without any training or fine-tuning on models. However, due to the limited power of captioning methods, the captions often miss important content in the video, resulting in unsatisfactory retrieval performance. To translate more information into video captions, we designed a novel **hallucination-based caption generation** method, that injects LLMs' hallucinated information into video captions. Moreover, to emphasize key information in the video, we extract key visual tokens from captions and design different templates for structuring these tokens with the proposed **structural information extraction**, further boosting the retrieval performance. Benefiting from the hallucinated captions and structuralized information, extensive experiments on several video-text retrieval benchmarks demonstrate the superiority of our proposed zero-shot method, HALISIE, over existing fine-tuned and pretraining methods without any data. Codes and data will be released.

1 Introduction

Video-text retrieval (VTR) (Luo et al., 2022; Gao et al., 2021; Ma et al., 2022; Liu et al., 2022a; Zhao et al., 2022; Gorti et al., 2022; Fang et al., 2022) aims to retrieve the corresponding video or text given the query in another modality. Recent years have witnessed the rapid development of VTR with the support from powerful pretraining models (Luo et al., 2022; Gao et al., 2021; Ma et al., 2022; Liu et al., 2022a), improved retrieval methods (Bertasius et al., 2021; Dong et al., 2019; Jin et al., 2021), and video-language datasets construction (Xu et al., 2016). However, it remains challenging to precisely match video and language due to the raw data being in heterogeneous spaces with significant differences.

The most popular paradigm in VTR (Luo et al., 2022; Ma et al., 2022; Liu et al., 2022b) firstly learns a joint feature space across modalities and then compares representations in this space. However, with the discrepancy between different modalities and the design of modality-independent encoders, it is challenging to directly compare and calculate the similarities between representations of different modalities generated from different encoders (Liang et al., 2022). A pioneering work (Wang et al., 2022e) converts videos into captions to eliminate this discrepancy for better presentation learning on video-language tasks. It demonstrates that vision-language models with image captioners are able to do multiple few-show tasks.

In this work, to take one step forward, we present a zero-shot video-text retrieval paradigm, HALISIE, along with our proposed hallucination-based captioning and structural information extraction. HALISIE first captions videos into video captions. However, we notice that the captions always miss important information in the video, thus leading to bad retrieval performance (see table 1 without paraphrase and visual tokens). To this end, we propose **hallucination-based captioning**, which augments video captions by leveraging the hallucination of large language models (LLMs). Later, to emphasize the important information in the captions, *e.g.*, objects, events, and attributes, we design a **structural information extraction** procedure for extracting "visual tokens". Finally, HALISIE utilizes off-the-shelf text retrieval methods for zero-shot text retrieval using captions and corresponding visual tokens.

Finally, to evaluate the effectiveness of our pro-

posed HALISIE, we conducted experiments on three representative video-text benchmarks (Chen and Dolan, 2011; Fabian Caba Heilbron and Niebles, 2015; Xu et al., 2016). Results show that our proposed zero-shot method outperforms previous methods, including fine-tuning methods and few-shot methods, on multiple metrics, benefiting from hallucination-based captioning and structural information extraction.

In summary, our contributions are as follows:

- We propose a real zero-shot video-text retrieval method without requiring any training procedure or human-annotated data, only using the off-the-shelf captioning method, large language models, and text retrieval methods.
- Our proposed HALISIE achieves SOTA performance on several metrics across three VTR benchmarks.
- Detailed analysis reveals the importance of hallucination-based captioning and structural information extraction.
- We will open-source the code and data to facilitate future research.

2 Related Work

In this section, we briefly review the literature on video-text retrieval and zero-shot cross-modal retrieval.

Video-text retrieval, which involves cross-modal alignment and abstract understanding of temporal images (videos), has been a popular and fundamental task of language-grounding problems (Wang et al., 2020a,b, 2021; Yu et al., 2023). Most of the existing video-text retrieval frameworks (Yu et al., 2017; Dong et al., 2019; Zhu and Yang, 2020; Miech et al., 2020; Gabeur et al., 2020; Dzabraev et al., 2021; Croitoru et al., 2021) focus on learning powerful representations for video and text and extracting separated representations. For example, in Dong et al. (2019), videos and texts are encoded using convolutional neural networks and a bi-GRU (Schuster and Paliwal, 1997) while mean pooling is employed to obtain multi-level representations. MMT (Gabeur et al., 2020) uses a cross-modal encoder to aggregate features extracted by temporal images, audio, and speech for encoding videos. Following that, MDMMT (Dzabraev et al., 2021) further utilizes knowledge learned from multi-domain datasets to improve performance empirically. Further, MIL-NCE (Miech et al., 2020) adopts Multiple Instance Learning and Noise Contrastive Estimation for end-to-end video representation learning, addressing the problem of visually misaligned narrations from uncurated videos.

Recently, with the success of self-supervised pretraining methods (Devlin et al., 2019; Radford et al., 2019; Brown et al., 2020), vision-language pretraining (Li et al., 2020b; Gan et al., 2020; Singh et al., 2022) on large-scale unlabeled cross-modal data has shown promising performance in various tasks, *e.g.*, image retrieval (Radford et al., 2021), image captioning (Chan et al., 2023), and video retrieval (Luo et al., 2022; Wang and Shi, 2023a). Recent works (Lei et al., 2021; Cheng et al., 2021; Gao et al., 2021; Ma et al., 2022; Park et al., 2022a; Wang et al., 2022b,d; Zhao et al., 2022; Gorti et al., 2022) have attempted to pretrain or fine-tune video-text retrieval models in an end-to-end manner. CLIPBERT (Lei et al., 2021; Bain et al., 2021), as a pioneer, proposes to sparsely sample video clips for end-to-end training to obtain clip-level predictions and then summarize them. Frozen in time (Bain et al., 2021) uses end-to-end training on both image-text and video-text pairs data by uniformly sampling video frames. CLIP4Clip (Luo et al., 2022) finetunes models and investigates three similarity calculation approaches for video-sentence contrastive learning on CLIP (Radford et al., 2021). Further, TS2-Net (Liu et al., 2022b) proposes a novel token shift and selection transformer architecture that adjusts the token sequence and selects informative tokens in both temporal and spatial dimensions from input video samples. While the mainstream of VTR models (Xue et al., 2023; Wu et al., 2023) focuses on fine-tuning powerful image-text pre-trained models, on the other side, as a pioneer, (Tiong et al., 2022; Wang et al., 2022e) propose to use large language models (LLMs) for zero-shot video question answering.

Zero-shot cross-modal retrieval. With the huge success of pretrained visual-language model (Radford et al., 2021; Luo et al., 2022), zero-shot cross-modal retrieval has attracted more and more research interest recently. Due to the powerful representation learning ability in image and text domains, CLIP (Radford et al., 2021) achieves satisfying zero-shot retrieval performance on several representative image-text retrieval bench-

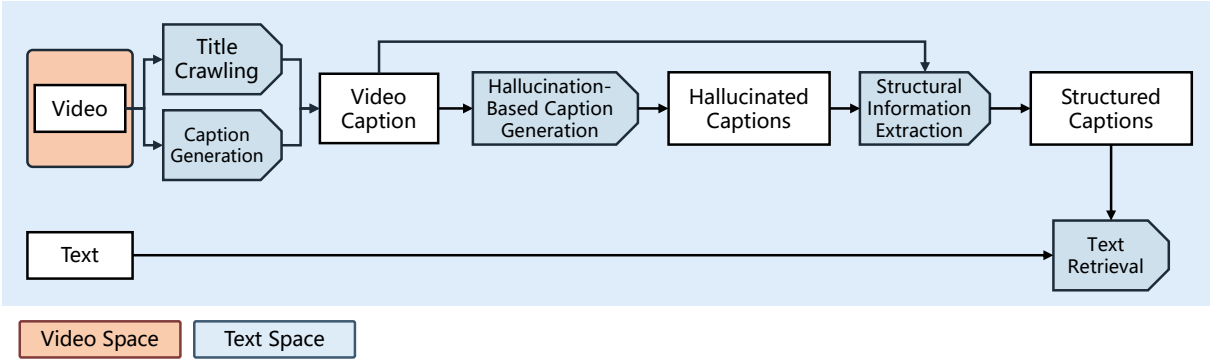

Figure 1: The illustration of our proposed HALISIE. HALISIE includes four steps. First, we generate video captions for video using off-the-shelf video captioning methods. Second, to enrich the captions, we propose the hallucination-based caption-generation method using large language models. Third, to emphasize the important information in the captions, we propose a novel structural information extract module. Finally, after obtaining structured video captions, we employ off-the-shelf text retrieval methods to perform zero-shot video-text retrieval.

marks (Huiskes and Lew, 2008; Lin et al., 2014). Inspired by this achievement, Liu et al. (2023a,b); Chen et al. (2023c); Liu et al. (2024); Guo et al. (2024) boost the performance of zero-shot image-text retrieval by better representation learning methods. On the other side, benefiting from large-scale video-text benchmarks (Xu et al., 2016; Chen and Dolan, 2011; Fabian Caba Heilbron and Niebles, 2015), video-language pre-trained models (Wang et al., 2022c; Chen et al., 2023a; Xu et al., 2023; Chen et al., 2023c; Li et al., 2023; Liu et al., 2023c; Zhu et al., 2024) also achieve satisfying zero-shot video-text retrieval results.

In this paper, inspired by these pioneering works, to explore zero-shot video-text retrieval, we step forward and propose a simple but effective zero-shot video-text retrieval method, HALISIE, by utilizing off-the-shelf captioning, large language models, and text retrieval methods.

3 HALISIE - Zero-Shot Video Text Retrieval

In this section, we present the details of our proposed method, HALISIE. Specifically, we first generate captions for videos using video caption generation methods. Then, to cover most of the details in videos, with our proposed hallucination-based caption generation, we obtain a detailed caption containing almost all the details of the video. Finally, to ease the job of the text retrieval method, we use the proposed structural information extraction to emphasize important information in the captions for better video-text retrieval performance. The whole procedure is summarized in fig. 1.

3.1 Video Caption Generation

To generate captions for videos, we employ two methods and combine the generated text to serve as the final caption.

Crawling of Video Titles. We extract video titles using the meta information in the dataset, where we retrieve the title of the video from its original source (*e.g.*, YouTube) using the video's unique identifier. This title is then used as the video's caption.

Video Captioning with Off-the-shelf Models. In contrast to the previous approach that relies on the meta information, we use off-the-shelf large-scale captioning models to generate varied and detailed captions. To achieve this, we employ Tewel et al. (2021, 2022) to generate video captions and then use GPT-2 (Radford et al., 2019) to enrich sentences using the prompts, *i.e.*, "Video presents".

3.2 Hallucination-Based Caption Generation

As shown in fig. 3, we notice that the generated captions always miss some important information that is vital in the video, leading to unsatisfying retrieval performance. A simple solution to this problem is to fine-tune the captioning models, which will improve their caption-generation abilities. However, this approach needs a huge amount of annotated video-caption data and expensive computation resources, and the fine-tuned models are always not able to be transferred to other benchmarks. To this end, we propose the **hallucination-based caption generation**, which is training-free and able to generate detailed captions that contain almost every detail of the video.

Specifically, we use large language models

(LLMs) (Touvron et al., 2023; Brown et al., 2020) to conduct the hallucination-based generation using the following prompt template.

```
The following is a caption from a video: [" + <Video Caption> + "]. Based on this caption, generate two paraphrased captions capturing the key information and main themes, each of which should be in one sentence with up to twenty words. Meanwhile, please be creative, you can have some imagination and add the necessary details. Generated sentences should be in the number list. Also please generate text without any comment.
```

Our proposed method generates multiple captions (*e.g.*, 1, 2, and 3). However, some of these captions might introduce noise or lack strong relevance to the video's content. To mitigate potential negative impacts, we apply a filtering method to assess the semantic similarity between hallucinated captions and the original video caption by leveraging a pre-trained text encoder (Reimers and Gurevych, 2019). Then we concatenate the filtered captions along with the original video caption to obtain the final captions.

3.3 Structural Information Extraction

To understand which kind of information is essential to video-text retrieval, we analyze the contextual text of video captions by breaking down the video captions into four different visual tokens using NLTK (Bird et al., 2009), *i.e.*, phrase, object, event, and attribute. Then we structure the information into the following structure.

```
<Caption> <Phrases> <Attributes> <Events> <Objects>
```

3.4 Video (Video Caption)-Text Retrieval

Finally, after obtaining structured video caption data, we are ready to perform the retrieval step. Specifically, we compute the similarity score at the video level between text and video caption using off-the-shelf retrieval methods (Robertson and Walker, 1994; Reimers and Gurevych, 2019).

Due to the computational resource limit, we use BM25 (Robertson and Walker, 1994) and Sentence transformers (Reimers and Gurevych, 2019) to perform HALISIE.

4 Experiments

4.1 Benchmarks, Baselines, and Evaluation Metrics

Benchmarks. Following previous work (Luo et al., 2022; Ma et al., 2022), we use three representative benchmarks for evaluating HALISIE, *i.e.*, MSR-VTT, MSVD, and ActivityNet.

Baselines. To show the empirical efficiency of our HALISIE, we compare it with fine-tuned models (LiteVL (Chen et al., 2022), NCL (Park et al., 2022b), TABLE (Chen et al., 2023b), VOP (Huang et al., 2023), X-CLIP (Ma et al., 2022), Discrete-Codebook (Liu et al., 2022a), TS2-Net (Liu et al., 2022b), VCM (Cao et al., 2022), HiSE (Wang et al., 2022b), CenterCLIP (Zhao et al., 2022), X-Pool (Gorti et al., 2022), and S3MA (Wang and Shi, 2023b)), pre-trained methods (VLM (Xu et al., 2021a), HERO (Li et al., 2020a), VideoCLIP (Xu et al., 2021b), EvO (Shvetsova et al., 2022), OA-Trans (Wang et al., 2022a), RaP (Wu et al., 2022), OmniVL (Wang et al., 2022c), mPLUG-2 (Xu et al., 2023), InternVL (Chen et al., 2023c), and LangaugeBind (Zhu et al., 2024)), and a few-shot method, *i.e.*, VidIL (Wang et al., 2022e).

Evaluation metric. To evaluate the retrieval performance of our proposed model, we use recall at Rank K (R@K, higher is better), median rank (MdR, lower is better), and mean rank (MnR, lower is better) as retrieval metrics, which are widely used in previous retrieval works (Radford et al., 2021; Luo et al., 2022; Ma et al., 2022).

4.2 Implementation Details

For video caption generation, we use Tewel et al. (2021, 2022) to generate video captions and GPT-2 (Radford et al., 2019) to enrich sentences. For hallucination-based caption generation, we employ LLaMA2-7b-chat-hf (Touvron et al., 2023) and get two hallucinated captions. For structural information extraction, we use NLTK (Bird et al., 2009). For text retrieval, we use BM25 (Robertson and Walker, 1994).

4.3 Quantitative Results

In this part, we present the qualitative results of our proposed HALISIE on three representative benchmarks in video-text retrieval.

MSR-VTT. We found that the contextual video text obtained directly through video captioning methods generally have mediocre performance (R@1:

Methods	Venue	Text-to-Video Retrieval					Video-to-Text Retrieval				
		R@1↑	R@5↑	R@10↑	MdR↓	MnR↓	R@1↑	R@5↑	R@10↑	MdR↓	MnR↓
Training-based											
LiteVL-S	EMNLP'22	46.7	71.8	81.7	2.0	-	-	-	-	-	-
X-Pool	CVPR'22	46.9	72.8	82.2	2.0	14.3	-	-	-	-	-
CenterCLIP	SIGIR'22	44.2	71.6	82.1	2.0	15.1	42.8	71.7	82.2	2.0	10.9
TS2-Net	ECCV'22	47.0	74.5	83.8	2.0	13.0	45.3	74.1	83.7	2.0	9.2
X-CLIP	ACM MM'22	46.1	74.3	83.1	2.0	13.2	46.8	73.3	84.0	2.0	9.1
NCL	EMNLP'22	43.9	71.2	81.5	2.0	15.5	44.9	71.8	80.7	2.0	12.8
TABLE	AAAI'23	47.1	74.3	82.9	2.0	13.4	47.2	74.2	84.2	2.0	11.0
VOP	CVPR'23	44.6	69.9	80.3	2.0	16.3	44.5	70.7	80.6	2.0	11.5
DiscreteCodebook	ACL'22	43.4	72.3	81.2	-	14.8	42.5	71.2	81.1	-	12.0
VCM	AAAI'22	43.8	71.0	-	2.0	14.3	45.1	72.3	82.3	2.0	10.7
CenterCLIP	SIGIR'22	48.4	73.8	82.0	2.0	13.8	47.7	75.0	83.3	2.0	10.2
HiSE	ACM MM'22	45.0	72.7	81.3	2.0	-	46.6	73.3	82.3	2.0	-
TS2-Net	ECCV'22	49.4	75.6	85.3	2.0	13.5	46.6	75.9	84.9	2.0	8.9
S3MA	EMNLP'23	53.1	78.2	86.2	1.0	10.5	52.7	79.2	86.3	1.0	8.2
Zero-Shot (Pretrained Models)											
VLM	ACL'21	28.1	55.5	67.4	4.0	-	-	-	-	-	-
HERO	EMNLP'21	16.8	43.3	57.7	-	-	-	-	-	-	-
VideoCLIP	EMNLP'21	30.9	55.4	66.8	-	-	-	-	-	-	-
EvO	CVPR'22	23.7	52.1	63.7	4.0	-	-	-	-	-	-
OA-Trans	CVPR'22	35.8	63.4	76.5	3.0	-	-	-	-	-	-
RaP	EMNLP'22	40.9	67.2	76.9	2.0	-	-	-	-	-	
OmniVL	NeurIPS'22	34.6	58.4	66.6	-	-	-	-	-	-	-
mPLUG-2	ICML'23	48.3	75.0	83.2	-	-	-	-	-	-	-
InternVL	Arxiv'23	42.4	65.9	75.4	-	-	**46.3**	**70.5**	**79.6**	-	-
LanguageBind	ICLR'24	42.6	65.4	75.5	-	-	-	-	-	-	-
Few-Shot											
VidIL	NeurIPS'22	40.8	65.2	-	-	-	39.6	64.5	-	-	-
Zero-Shot											
HALISIE w/o paraphrase and visual tokens		20.3	40.9	51.7	9.0	60.3	17.5	36.7	47.3	12.0	82.3
HALISIE w/o visual tokens		54.0	73.9	80.2	1.0	24.5	27.9	41.3	47.3	15.0	136.2
HALISIE		**58.2**	**75.8**	**83.9**	1.0	**18.9**	36.4	56.5	63.8	3.0	**75.7**

Table 1: Video-Text retrieval results on MSR-VTT. The best results are marked in **bold**. The second best results are underlined. "NC" refers to Neurocomputing.

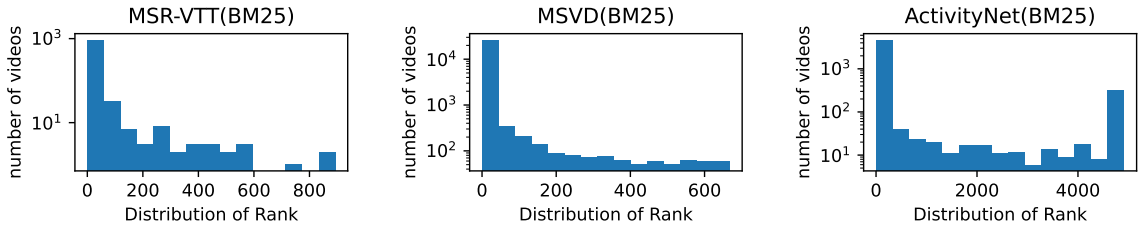

Figure 2: These figures illustrate the distribution of the rank of each (test) gallery video (captions) retrieved by (test) text queries.

20.3) compared to other baseline Text-Video Retrieval method. However, after using LLM to do hallucination-based generation from the video caption, the R@1 of our method nearly doubled (R@1 = 40.9) shown in Table 5 . Therefore, we further hallucinated each sentence and expanded it into two sentences. From the results presented in Table 1, it can be seen that this approach outperforms the second-best method by 9.9. This indicates the significant impact of hallucinating and expanding captions on enhancing the performance of Text-Video Retrieval systems. Compared to DiscreteCodebook (Liu et al., 2022a), which aligns modalities in an unsupervised manner, HALISIE outperforms DiscreteCodebook on every metric. Meanwhile, HALISIE also outperforms VidIL (Wang et al., 2022e), which uses few-shot prompting, demonstrating the usability of integrating zero-shot LLM on text-to-video retrieval. This suggests that leveraging zero-shot on large language models (LLMs) is a promising approach to enhance text-to-video retrieval performance.

Also, we notice that HALISIE has bad results on mean rank. To understand why this happens,

Caption	Phrase	Object	Event	Attribute	Text-to-Video Retrieval					Video-to-Text Retrieval				
					R@1↑	R@5↑	R@10↑	MdR↓	MnR↓	R@1↑	R@5↑	R@10↑	MdR↓	MnR ↓
✓					54.0	73.9	80.2	1.0	24.5	27.9	41.3	47.3	15.0	136.2
✓	✓				57.4	76.2	83.0	1.0	19.3	29.9	45.6	52.3	8.0	115.4
✓		✓			56.9	**77.5**	83.8	1.0	18.6	35.8	56.9	64.8	3.0	73.9
✓			✓		54.2	73.2	79.6	1.0	24.9	28.4	42.7	49.1	12.0	130.3
✓				✓	55.0	74.2	80.2	1.0	24.1	28.6	43.3	48.9	11.0	132.2
✓	✓	✓			57.4	76.2	83.9	1.0	18.7	34.5	54.0	62.5	4.0	79.9
✓	✓		✓		57.3	76.3	82.6	1.0	19.8	31.5	47.3	54.2	7.0	109.0
✓	✓			✓	57.6	76.3	83.5	1.0	19.1	31.0	47.4	54.7	7.0	110.5
✓		✓	✓		56.9	76.6	83.2	1.0	19.3	35.9	57.9	65.6	3.0	71.2
✓		✓		✓	57.6	77.4	83.8	1.0	**18.2**	37.4	58.5	66.3	3.0	71.8
✓			✓	✓	54.0	73.3	79.6	1.0	24.9	30.0	44.3	51.1	10.0	126.1
✓	✓	✓	✓		58.0	75.9	83.7	1.0	19.3	35.1	55.1	63.0	4.0	77.3
✓	✓	✓		✓	57.8	76.3	**84.1**	1.0	18.3	35.7	55.5	63.1	3.0	78.3
✓	✓		✓	✓	57.8	76.0	82.5	1.0	19.5	31.8	48.5	55.2	6.0	106.6
✓		✓	✓	✓	57.3	76.7	83.2	1.0	18.9	**37.5**	**59.4**	**67.0**	3.0	**69.2**
✓	✓	✓	✓	✓	**58.2**	75.8	83.9	1.0	18.9	36.4	56.5	63.8	3.0	75.7

Table 2: Retrieval performance with different combinations of four visual tokens (Phrase, Object, Event, Attribute) on MSR-VTT using HALISIE.Best in **Bold**.

Methods	Venue	Text-to-Video Retrieval			
		R@1↑	R@5↑	R@10↑	MnR↓
MSVD					
RaP	EMNLP'22	35.9	64.3	73.7	-
LanguageBind	ICLR'24	52.2	79.4	87.3	-
HALISIE		**57.2**	**80.0**	**88.2**	15.6
ActivityNet					
LanguageBind	ICLR'24	35.1	63.4	76.6	-
HALISIE		**59.0**	**71.4**	**77.0**	387.4

Table 3: Text-Video retrieval results on MSVD and ActivityNet. The best results are marked in **bold**.

we visualize the distribution of rank in fig. 2. It is obvious that though most of the videos have very good rank, *e.g.*, lower than 10, there are still some captions ranked in the last. This might be due to the failure of caption generation for some videos, where the generated captions do not contain any information from the video.

MSVD and ActivityNet. The results on MSVD and ACticityNet are shown in Table 3. HALISIE achieves the best R@1 on text-to-video retrieval on two datasets compared to the previous methods.

4.4 Ablation Studies

In this part, we present a series of ablation experiments on MSR-VTT to better understand the effectiveness of different components of HALISIE, using LLaMA2-7b-chat-hf and BM25. Due to space limitations, the ablation study on different retrieval methods is presented in appendix A.2.

Impact of combination of structural information (visual tokens). To choose the best combination method for the extracted visual tokens (phrases, attributes, objects, and events), we conduct experiments using different arrangements of these visual tokens, as shown in Table 2. By reducing the inclusion of visual tokens, the retrieval performance of HALISIE decreases, thereby proving the superiority of integrating these four visual tokens together.

The order of different structural information. Another important factor to consider is the order of these visual tokens. To this end, we systematically evaluate which specific order of <phrase>, <object>, <attribute>, and <event> maximizes the efficiency and accuracy of the retrieval process. The results are shown in Table 4. We discover that among various arrangements, the model performs best when either phrases or objects are placed at the end of the sequence. This superior performance might be due to the detailed and specific information that phrases and objects offer, enhancing the model's ability to accurately match and retrieve relevant video content.

Number of hallucinated captions (visual tokens). In this part, we aim to explore how many hallucinated captions work the best. More captions have the potential to offer more detailed descriptions, which may enhance the viewer's comprehension of the visual content. Previous studies (Biten et al., 2019; Tang et al., 2023) have demonstrated that longer captions tend to be more descriptive and semantically rich, achieving improved comprehension and retrieval performance. However, more hallucinated captions also mean more noises are injected. So balancing the number of hallucinated captions would be highly important. From the re-

Order List	Text-to-Video Retrieval					Video-to-Text Retrieval				
	R@1↑	R@5↑	R@10↑	MdR↓	MnR↓	R@1↑	R@5↑	R@10↑	MdR↓	MnR ↓
Order List 1	**58.2**	75.8	**83.9**	1.0	18.9	36.4	56.5	63.8	3.0	**75.7**
Order List 2	57.9	**75.9**	83.6	1.0	**18.7**	**36.7**	56.4	**64.4**	3.0	75.3
Order List 3	58.0	75.7	83.5	1.0	19.1	36.3	**56.6**	64.2	3.0	75.0

Table 4: Retrieval performance with different order of four visual tokens (Phrase, Object, Event, Attribute) on MSR-VTT using HALISIE. Best in **Bold**. We discovered three unique sequencing methods for visual tokens, each producing distinct outcomes based on their specific arrangements. Order List 1 places objects or phrases to the end, *i.e.*, {Caption}, . . ., {Phrase/Object}, Order List 2 represents {Caption}, . . ., {Event}, and Order List 3 represents {Caption}, . . ., {Attribute}.

# of Hullucinated Captions	Text-to-Video Retrieval					Video-to-Text Retrieval				
	R@1↑	R@5↑	R@10↑	MdR↓	MnR↓	R@1↑	R@5↑	R@10↑	MdR↓	MnR ↓
1	40.9	55.5	60.9	3.0	227.3	34.3	54.2	62.6	4.0	114.0
2	**58.2**	**75.8**	**83.9**	1.0	**18.9**	**36.4**	**56.5**	**63.8**	3.0	**75.7**
3	55.7	73.9	82.2	1.0	21.2	35.1	52.8	62.4	4.0	87.1

Table 5: Retrieval performance with different numbers of hallucinated captions on MSR-VTT using HALISIE. Best in **Bold**.

Template	Text-to-Video Retrieval					Video-to-Text Retrieval				
	R@1↑	R@5↑	R@10↑	MdR↓	MnR↓	R@1↑	R@5↑	R@10↑	MdR↓	MnR ↓
Basic Template	**58.2**	**75.8**	**83.9**	1.0	**18.9**	**36.4**	**56.5**	**63.8**	3.0	**75.7**
Structured Template	55.7	74.6	81.2	1.0	21.1	31.0	45.4	51.5	9.0	77.2
Template with Detailed Description	55.9	74.6	81.7	1.0	21.2	34.3	53.9	61.7	4.0	84.7
Narrative Format Template	56.5	74.7	81.7	1.0	20.9	26.9	43.4	49.0	11.0	129.7

Table 6: Retrieval performance with different template formats on MSR-VTT using HALISIE. Best in **Bold**.

sults shown in Table 5, we notice that paraphrasing into two or three sentences significantly improved R@1, R@5, and R@10. Considering computational constraints and the similar effectiveness of paraphrasing into two and three sentences, we decide to hallucinate into two sentences.

Complexity of prompt templates for structural information extraction. The complexity of the prompt plays a pivotal role in shaping the output generated by the model, influencing the depth of analysis and the richness of information conveyed. An intricate prompt may provide the model with additional context and guidance, enabling it to produce more detailed responses. Specifically, we compare four templates (Basic, Structured, Detailed Description, and Narrative Format) offering different levels of complexity for organizing video content as follows,

1. Basic Template: the simplest, providing a straightforward list of video elements, the one shown in section 3.3.

2. Structured Template: It adds categorized elements, making the information easier to navigate for the retrieval method.

```
Video Caption : <Caption>. Key
Phrases: <{Phrases}>. Main
Objects: <Objects>. Notable
Features: <{Attributes}>. Key
Events: <Events>
```

3. Template with Detailed Description: This further elaborates on each element, offering in-depth insights.

```
Detailed Video Description:
Caption: <{Caption}> Objects and
 Attributes Overview: Each
object, <{Objects}>, is detailed
 with attributes such as <{
Attributes}> to provide a
clearer image. Event Analysis:
The video's narrative is driven
by events like <{Events}>, which
 are elaborated for better
understanding. Phrases Insight:
Phrases like <{Phrases}> are
explained for their significance
 to the content.
```

LLM	Text-to-Video Retrieval					Video-to-Text Retrieval				
	R@1↑	R@5↑	R@10↑	MdR↓	MnR↓	R@1↑	R@5↑	R@10↑	MdR↓	MnR ↓
LLaMA	58.2	75.8	83.9	1.0	18.9	**36.4**	56.5	63.8	3.0	**75.7**
GPT 3.5	**61.2**	**80.4**	**86.8**	1.0	**15.0**	35.5	**58.3**	**65.5**	3.0	77.6

Table 7: Retrieval performance with different LLM models on MSR-VTT using HALISIE. Best in **Bold**.

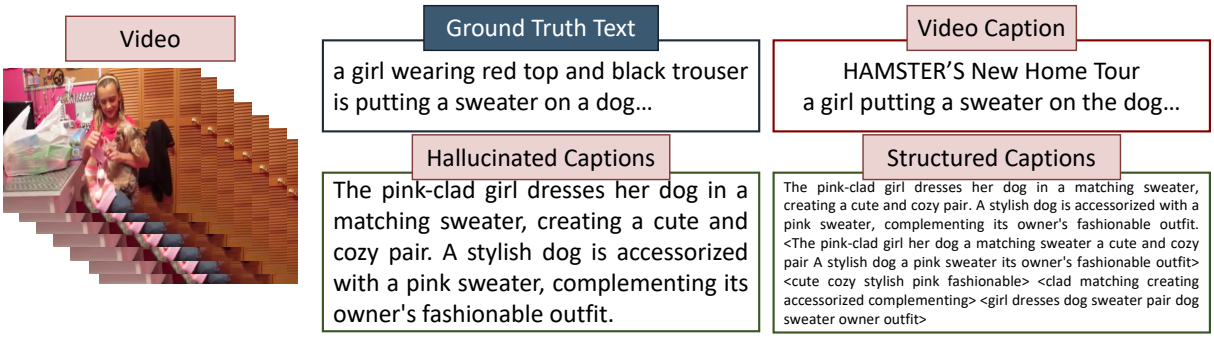

Figure 3: An example. Hallucinated captions contain more information compared to vanilla video captions in the video though some noises are also injected.

4. Narrative Format Template: it weaves the elements into a cohesive story, enhancing engagement and providing a thematic understanding.

```
Caption: <Caption> In this video
, we observe <{Objects}> with <{
Attributes}>, a vivid
representation of <{Events}>.
Phrases such as <{Phrases}>
punctuate the narrative,
offering insights into the
unfolding story.
```

Each template caters to different needs, from quick reference to comprehensive analysis, reflecting a progression from functional simplicity to narrative depth. The results are shown in Table 6. We notice that intricate prompts provide the model with additional context and guidance, enabling it to produce more detailed responses. However, it may also lead to a loss of information, which is important for the retrieval performance. The results show that with the narrative format template, R@1, R@5, and R@10 on text-to-video retrieval are improved. This might be because the simplest format template provides insights into storytelling elements such as objects, events, and phrases, which leads to more precise keyword assignments.

4.5 Qualitative Results

To qualitatively validate the effectiveness of HALISIE, we present an example in fig. 3, respectively. The retrieval results show that hallucinated captions have more information in the video than vanilla video captions. Moreover, our proposed structural information extraction methods clearly emphasize the important visual tokens, *i.e.*, phrase, object, event, and attribute, which further boosts the performance.

5 Conclusion

In this paper, we present an innovative zero-shot framework, HALISIE, which revolutionizes video-text retrieval by capitalizing on existing captioning methods, large language models (LLMs), and text retrieval techniques. By sidestepping the need for model training or fine-tuning, our framework offers a streamlined approach to retrieval. To overcome the shortcomings of traditional captioning methods, we propose a groundbreaking hallucination-based caption generation technique that incorporates LLMs' hallucinated information into video captions. Moreover, our introduction of structural information extraction further enhances retrieval performance by highlighting key visual tokens. Through extensive experimentation across diverse benchmarks, we demonstrate the superior efficacy of HALISIE compared to conventional fine-tuned and pretraining methods, even in the absence of training data.

Limitations

In the future, it would be interesting to explore more detailed methods for zero-shot video-text retrieval, such as incorporating the audio modality and corresponding off-the-shelf foundation models. Moreover, as a pioneering work, our work mainly focuses on establishing the paradigm. It would be great if we could explore more text retrieval methods, video captioning methods, and LLMs for hallucinated caption generation.

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A Experiments

A.1 Details of Benchmarks

- **MSR-VTT** (Xu et al., 2016) contains 10,000 videos with length varying from 10 to 32 seconds, each paired with about 20 human-labeled captions. Following the evaluation protocol from previous works (Yu et al., 2018; Miech et al., 2019), we use the training-9k / test 1k-A splits for training and testing respectively.

- **MSVD** (Chen and Dolan, 2011) contains 1,970 videos with a split of 1200, 100, and 670 as the train, validation, and test set, respectively. The duration of videos varies from 1 to 62 seconds. Each video is paired with 40 English captions.

- **ActivityNet** (Fabian Caba Heilbron and Niebles, 2015) is consisted of 20,000 Youtube videos with 100,000 densely annotated descriptions. For a fair comparison, following the previous setting (Luo et al., 2022; Gabeur et al., 2020), we concatenate all captions together as a paragraph to perform a video-paragraph retrieval task by concatenating all the descriptions of a video. Performances are reported on the "val1" split of the ActivityNet.

A.2 Choice of Retrieval Methods

In this part, we investigate the impact of different retrieval methods, *i.e.*, BM25 (Robertson and Walker, 1994) and sentence transformers (Reimers and Gurevych, 2019). The results are shown in section 5. It shows that BM25 outperforms the sentence transformer.

Retrieval Methods	Text-to-Video Retrieval					Video-to-Text Retrieval				
	R@1↑	R@5↑	R@10↑	MdR↓	MnR↓	R@1↑	R@5↑	R@10↑	MdR↓	MnR ↓
BM25	**58.2**	**75.8**	**83.9**	1.0	**18.9**	**36.4**	56.5	63.8	3.0	75.7
Sentence Transformer	41.2	62.1	70.5	2.0	33.5	34.7	**57.8**	**67.5**	3.0	**36.0**

Table 8: Retrieval performance with different retrieval models on MSR-VTT using HALISIE. Best in **Bold**.