PolySmart and VIREO @ TRECVid 2024 Ad-hoc Video Search

Jiaxin Wu[†], Chong-Wah Ngo[⋆], Xiao-Yong Wei[§†], Qing Li[†]

[†]*Department of Computing, The Hong Kong Polytechnic University*
[⋆]*School of Computing and Information Systems, Singapore Management University*
[§]*Department of Computer Science, Sichuan University*
{jiaxwu, cs007.wei, prof.li}@polyu.edu.hk, cwngo@smu.edu.sg

Abstract

In this paper, we summarize our run and results submitted for the Ad-hoc Video Search (AVS) task at TRECVid 2024 [1].

Ad-hoc Video Search (AVS): This year, we explore generation-augmented retrieval for the TRECVid AVS task. Specifically, the understanding of textual query is enhanced by three generations, including Text2Text, Text2Image, and Image2Text, to address the out-of-vocabulary problem. Using different combinations of them and the rank list retrieved by the original query, we submitted four automatic runs. For manual runs, we use a large language model (LLM) (i.e., GPT4) to rephrase test queries based on the concept bank of the search engine, and we manually check again to ensure all the concepts used in the rephrased queries are in the bank. The result shows that the fusion of the original and generated queries outperforms the original query on TV24 query sets. The generated queries retrieve different rank lists from the original query. We briefly summarize our runs as follows:

- *F_M_C_D_PolySmartAndVIREO.24_1*: This automatic run reaches the mean xinfAP= 0.294 on the main task using caption-to-video retrieval.

- *F_M_C_D_PolySmartAndVIREO.24_2*: This automatic run attains the mean xinfAP= 0.283 on the main task by image-to-video search.

- *F_M_C_D_PolySmartAndVIREO.24_3*: This automatic run obtains the mean xinfAP= 0.277 on the main task. It combines the rank lists of image-to-video and caption-to-video searches with equal weights.

- *F_M_C_D_PolySmartAndVIREO.24_4*: This automatic run attains the mean xinfAP= 0.277 on the main task. It ensembles the results of run *F_D_C_D_PolySmartAndVIREO.24_3*, BLIP2 [2], CLIP [3] and Imagebind [4].

- *F_M_N_D_PolySmartAndVIREO.24_1*: This novelty run is based on the embedding-based search of our interpretable embedding model (ITV) [5] with generated captions. As a result, this run attains mean xinfAP= 0.0.216 for the main task.

- *M_M_C_D_PolySmartAndVIREO.24_2*: This manual run is based on the same system with the same settings presented in the run *F_M_C_D_VIREO.24_2* with manual selected visual queries. This run obtains 0.274 in the main task.
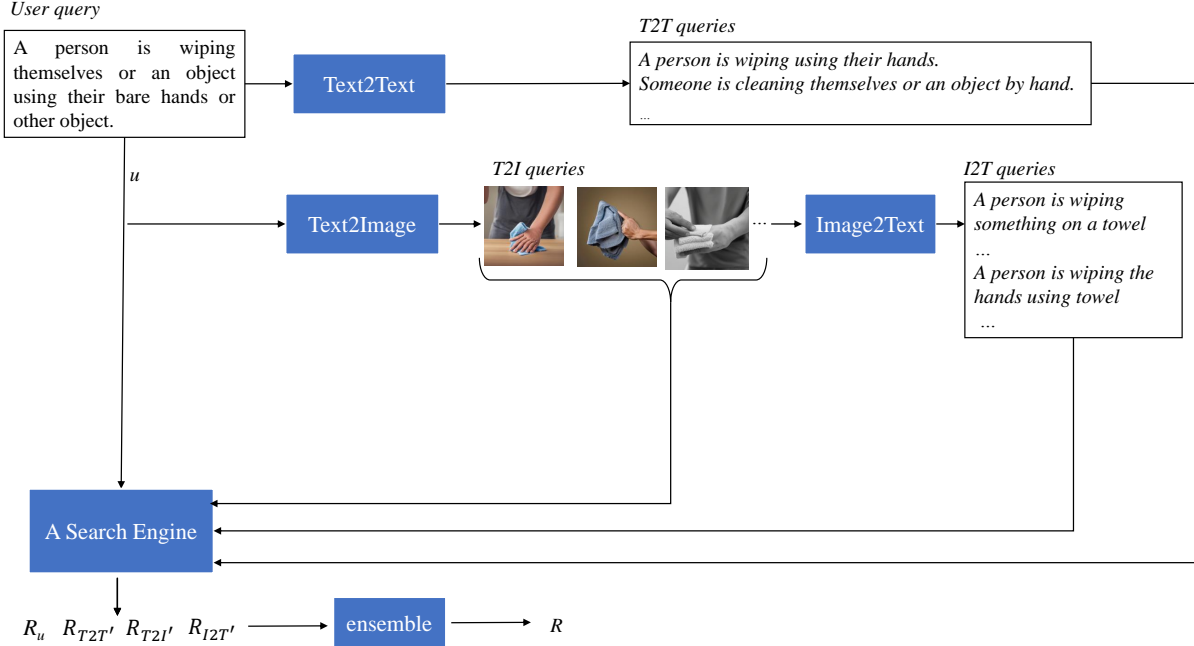
User query

A person is wiping themselves or an object using their bare hands or other object.

Text2Text

T2T queries

A person is wiping using their hands.
Someone is cleaning themselves or an object by hand.
...

Text2Image

T2I queries

Image2Text

I2T queries

A person is wiping something on a towel
...
A person is wiping the hands using towel
...

A Search Engine

R_u $R_{T2T'}$ $R_{T2I'}$ $R_{I2T'}$ → ensemble → R

Figure 1: The overview of the generation-augmented retrieval plug-in module.

- *M_M_C_D_PolySmartAndVIREO.24_3*: This manual run is based on the same setting presented in the run *F_M_C_D_VIREO.24_3* but with manual queries. It decreases the automatic result from 0.277 to 0.280.

1 Ad-hoc Video Search (AVS)

Ad-hoc video search [1] allows users to input ad-hoc queries to the search system to retrieve related videos. Due to the open-vocabulary setting, the existing AVS methods [6, 7, 8, 9, 10, 11] usually fail badly on out-of-vocabulary (OOV) queries, logical queries and queries with spatial constraints. In light of the recent advance of the generative models on understanding natural language and transform it to images, we propose a retrieval-augmented query understanding plug-in module on top of our existing AVS model for TRECVid AVS task this year. The overview of the module is shown in Figure 1. We perform three kinds of transformations to address the OOV problem, including Text2Text (T2T), Text2Image (T2I), and Image2Text (I2T) transformations. Through these three generations, we replace the OOV words with existing concepts. Furthermore, we explicitly translate textual OOV words to visual concepts to narrow the cross-modality challenge for the retrieval system.

2 Understanding the Query by generations

Given an AVS query, it is input to three cross-model generative models (i.e., T2T, T2I, and I2T) as a prompt to generate texts/images/captions to rephrase the query to different modalities and with different context. For the T2T transformation, an LLM (e.g., LlaMA 3 [12]) accepts the existing knowledge of the search system (e.g., concept bank of a concept-based model) as context, and rephrases the OOV words with synonyms in the concept bank. For example, for the query *Find shots of people standing in line*
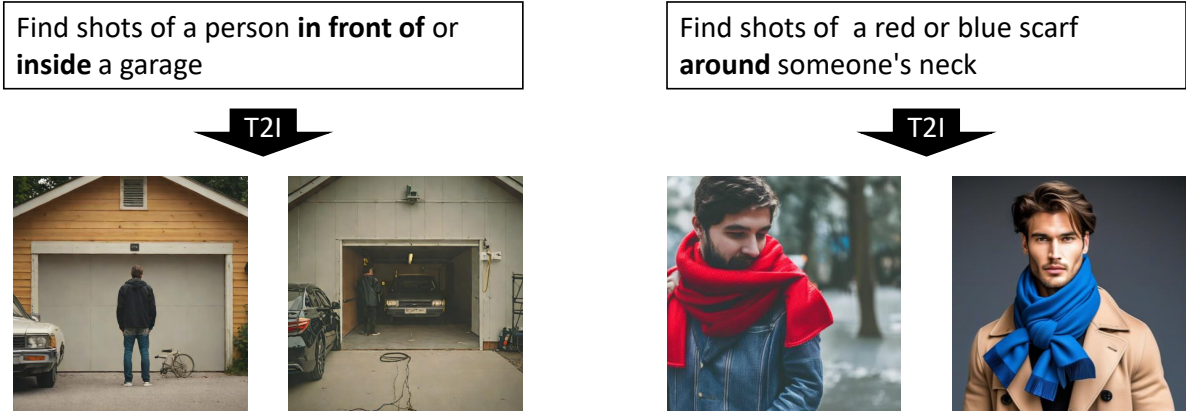
Figure 2: Example of an improved query by the generation.

outdoors, "standing in line" is a OOV phrase, Through T2T generation, the query is changed to *Find shots of people lineup outdoors*. For the T2I transformation, the textual query is input to a text-to-image generation model (e.g., stable diffusion [13]) to map the textual words to visual concepts. By performing text-to-image generation, the OOV words are eliminated, and the logical and spatial constrains in the query are encoded in the images, For the I2T transformation, we use an image captioning model (e.g., BLIP-2 [2]) to further transform the generated images back to text with rich context. After three generations, the textual query along with three types of generated queries are input our existing AVS model [14] to obtain four rank lists. We fuse these four rank lists with linear combination using equal weights.

3 Results analysis

Figure 2 shows two examples of T2I generations of queries with spatial and logical constraints. For the query having restricted spatial constraints of a person and a garage, the T2I queries could represent the search intension accurately. For the query looking for blue or red scarf, a scenario of a man wearing blue scarf and a image of a man with red scarf around the neck are generated.

Table 1: Retrieval performance comparison on TRECVid AVS main query set (tv24).

Run ID	Query	xinfAP
Run 1	original + T2T + T2I + I2T queries	**0.294**
Run 2	T2T query	0.283
Run 3	I2T query	0.277
Run 4	original query	0.277
Run Novelty	T2I query	0.216

In this year's AVS benchmarking, the evaluation is conducted on the V3C2 dataset [15] with 30 queries. The overall results are shown in Table 1. The fusion of the original query and three types of generated queries obtains the best result. The I2T query obtains a similar performance to the original query, and the T2T outperforms them by 0.05. The T2I queries get the lowest performance.

Figures 3 and 4 visualizes a performance-improved query and a performance-dropped query, respec-

Find shots of two women together wearing hats, excluding caps, outdoors

Original Query   T2T:Two women wearing stylish hats outside

Figure 3: Example of an improved query by the generation.
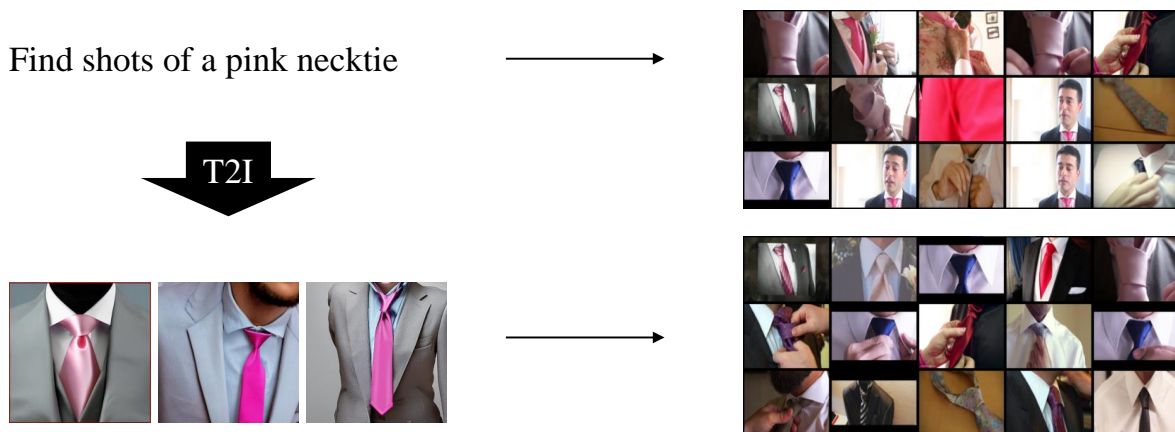
Find shots of a pink necktie

T2I

Figure 4: Example of an improved query by the generation.

tively. Figures 3 compares the top-15 videos found by the original query (i.e., *Find shots of two women together wearing hats, excluding caps, outdoors*) and the T2T query (i.e., *Find shots of two women wearing stylish hats outside*). As can be seen, the videos retrieved from the original query are mixed with people wearing hats or caps. With the T2T transformation, the main proportion of top-15 videos become stylish hats. On the other hand, Figure 4 shows a performance-dropped query due to bad image-to-video retrieval on colour. As can be seen, the generated images are good and trustworthy compared to the original query. However, the retrieved videos have the semantic meaning with the generated images (i.e., *a person wearing a suit and a tie*) but not pink necktie. Thus, the performance is dropped seriously.

We also found that the results retrieved by the T2I queries have the biggest difference from the original query. An example is shown in Figure 5 for the query *Find shots of a rainy day outdoors*. The original and the T2T queries tend to retrieve videos without a person and an umbrella. In contrast, the T2I and the I2T queries mainly find videos of a person holding an umbrella and walking in the rain, which resembles the content represented by the T2I queries.

The manual queries are shown in Table 2. We manually pick one from the generated query as the manual query. Manually picking visual queries do not improve performance, while manual I2T queries boost automatic queries by 0.03.
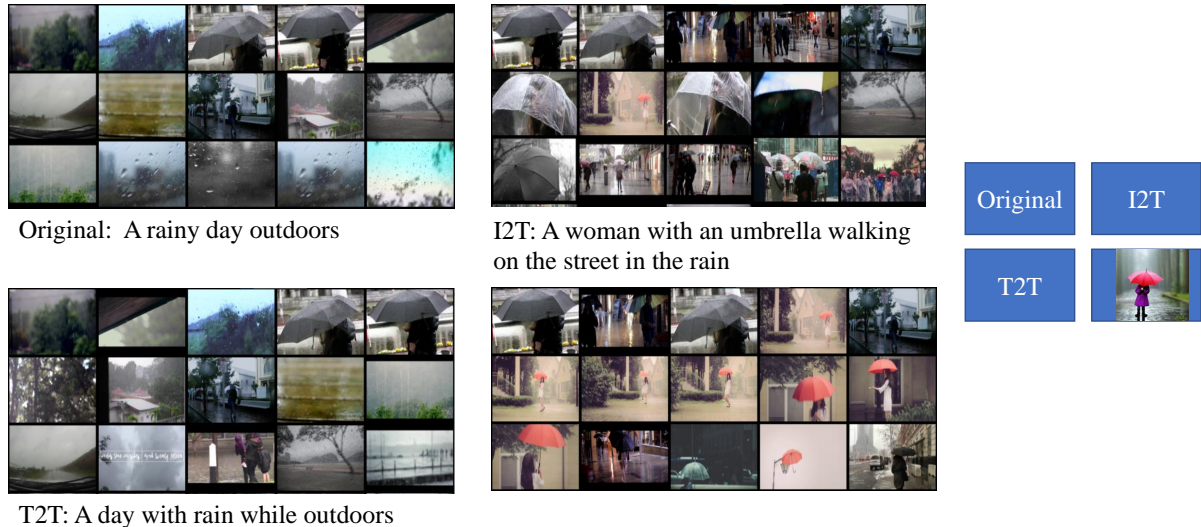
Original: A rainy day outdoors

I2T: A woman with an umbrella walking on the street in the rain

T2T: A day with rain while outdoors

Figure 5: Example of an improved query by the generation.

Table 2: manually generated queries for tv24

	Original query	Manually formulated query	Manually selected T2T queries	Manually selected I2T queries
751	A bald man with glasses	A bald man wearing glasses	751 A bald man wearing glasses	751 a man with glasses and a bald head
752	A rainy day outdoors	A rainy day outdoors in street	752 A day with rain while outdoors	752 a woman with an umbrella walking on the street in the rain
753	A pink necktie	A pink colored necktie	753 A pink-colored necktie	753 a man in a suit and a pink tie'
754	A white sweater	A white long sleeves sweater made of wool, cotton, synthetic fibers	754 A white knitted sweater	754 a woman standing on a street wearing a white sweater
755	A person is wiping themselves or an object using their bare hands or other object.	A person is wiping something with a towel	755 A person is wiping using their hands	755 a person is wiping something on a towel
756	A man is putting on a jacket or a t-shirt	A man is putting on a jacket	756 A man is putting on a jacket or a t-shirt	756 a man putting his jacket on while standing
757	A man wearing a checked shirt	A man wearing a checked-pattern shirt	757 A man with a checked pattern shirt	757 a man in a checked shirt is looking at the camera
758	A woman wearing a floral top or dress	A woman wearing a floral dress	758 A woman wearing a dress or shirt with floral patterns	758 a pretty woman wearing a floral dress
759	People inside an airport terminal	People inside an airport terminal with Flight arriving or departure boards	759 people walking down an airport terminal with luggage	759 people walking down an airport terminal with luggage
760	A man inside a workshop	A man inside a workshop holding tools	760 A man crafting something inside a workshop	760 a man standing in a workshop with tools
761	A traffic light seen at an intersection of a road or street	A traffic light seen at an intersection	761 A traffic light seen at a road crossing	761 traffic lights at a street intersection with cars going both ways
762	A map seen on a wall indoors	A map hanging on a wall indoors	762 A map hanging on a wall inside	762 the world map is on a wall
763	At least two persons in a hallway are seen walking	two persons in a hallway are seen walking indoors	763 A group of people walking in a corridor	763 two people walking down the hallway in a building
764	An adult is sitting in a glass walled building	An adult is sitting in a building with glass walls	764 An adult sitting in a glass-walled building	764 a man is sitting on a chair inside of a glass building
765	An adult is wrapped in a blanket	An woman or man is wrapped in a blanket	765 An adult wrapped in a blanket	765 a person that is wrapped in a blanket
766	A person holding a pen	A person writing	766 An individual holding a writing pen	766 a person is writing on something with a pen
767	A seated person reading from a paper or book outdoors during daytime	A person sitting and reading a book outdoors during daytime	767 A person sitting and reading a book outside	767 a man sits outside while reading a book
768	A woman wearing a silver necklace around her neck	A woman wearing a silver necklace around her neck	768 A woman wearing a silver necklace around her neck	768 a woman wearing multiple silver chains around her neck'
769	Two or more persons indoors with coffee cups or mugs seen with them.	Two persons inside a coffee shop with cups or mugs.	769 Two or more individuals holding coffee cups inside	769 three persons sitting at a table with cups of coffee'
770	Two women together wearing hats, excluding caps, outdoors	Two women wearing hats outdoors	770 Two women wearing stylish hats outside	770 two beautiful ladies are wearing hats outdoors'

4 Conclusion

Our study this year aims to explore generation-augmented queries to enhance the model's understanding of AVS queries. We find that the fusion of the original and generated queries could obtain better performance than the original query, and the generated queries could address the OOV words and logical/spatial queries. However, the current image-to-video retrieval should be improved with query attention. The manual query does not bring significant improvement to the original query.

5 Acknowledgments

References

[1] G. Awad, K. Curtis, A. A. Butt, J. Fiscus, A. Godil, Y. Lee, A. Delgado, E. Godard, L. Diduch, Y. Graham, , and G. Quénot, "Trecvid 2023 - a series of evaluation tracks in video understanding," in *Proceedings of TRECVID 2023.* NIST, USA, 2023.

[2] J. Li, D. Li, S. Savarese, and S. C. H. Hoi, "BLIP-2: Bootstrapping language-image pre-training with frozen image encoders and large language models," *ArXiv*, vol. abs/2301.12597, 2023. [Online]. Available: https://api.semanticscholar.org/CorpusID:256390509

[3] A. Radford, J. W. Kim, C. Hallacy, A. Ramesh, G. Goh, S. Agarwal, G. Sastry, A. Askell, P. Mishkin, J. Clark, G. Krueger, and I. Sutskever, "Learning transferable visual models from natural language supervision," in *ICML*, 2021.

[4] R. Girdhar, A. El-Nouby, Z. Liu, M. Singh, K. V. Alwala, A. Joulin, and I. Misra, "Imagebind: One embedding space to bind them all," in *CVPR*, 2023.

[5] J. Wu, C.-W. Ngo, W.-K. Chan, and Z. Hou, "(Un)likelihood training for interpretable embedding," in *ACM Transactions on Information Systems*, 2023.

[6] J. Wu, Z. Ma, C.-W. Ngo, and S.-H. Zhong, "VIREO@TRECVid 2023: Ad-hoc video search," in *In NIST TRECVID Workshop*, 2023.

[7] J. Wu, Z. Ma, and C.-W. Ngo, "VIREO@TRECVid 2022: Ad-hoc video search," in *In NIST TRECVID Workshop*, 2022.

[8] J. Wu, Z. Hou, Z. Ma, and C.-W. Ngo, "VIREO@TRECVid 2021: Ad-hoc video search," in *In NIST TRECVID Workshop*, 2021.

[9] C.-W. Ngo, S.-A. Zhu, H.-K. Tan, W.-L. Zhao, and X.-Y. Wei, "VIREO at TRECvID 2010: Semantic indexing, known-item search, and content-based copy detection," in *TRECVID*, 2010.

[10] C.-W. Ngo, Y.-G. Jiang, X.-Y. Wei, W. Zhao, F. Wang, X. Wu, and H.-K. Tan, "Beyond semantic search: What you observe may not be what you think," in *IEEE Computer Society*, 2008.

[11] C.-W. Ngo, Z. Pan, X. Wei, X. Wu, H.-K. Tan, and W. Zhao, "Motion driven approaches to shot boundary detection, low-level feature extraction and bbc rushes characterization at TRECVid 2005," in *TRECVID*, 2005.

[12] Y. Li, C. Wang, and J. Jia, "Llama-vid: An image is worth 2 tokens in large language models," in *European Conference on Computer Vision.* Springer, 2025, pp. 323–340.

[13] R. Rombach, A. Blattmann, D. Lorenz, P. Esser, and B. Ommer, "High-resolution image synthesis with latent diffusion models," in *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, jun 2022, pp. 10 674–10 685.

[14] J. Wu, C. wah Ngo, and W.-K. Chan, "Improving interpretable embeddings for ad-hoc video search with generative captions and multi-word concept bank," in *Proceedings of the ACM on International Conference on Multimedia Retrieval*, 2024, pp. 1–10.

[15] L. Rossetto, H. Schuldt, G. Awad, and A. A. Butt, "V3C–a research video collection," in *International Conference on Multimedia Modeling.* Springer, 2019, pp. 349–360.