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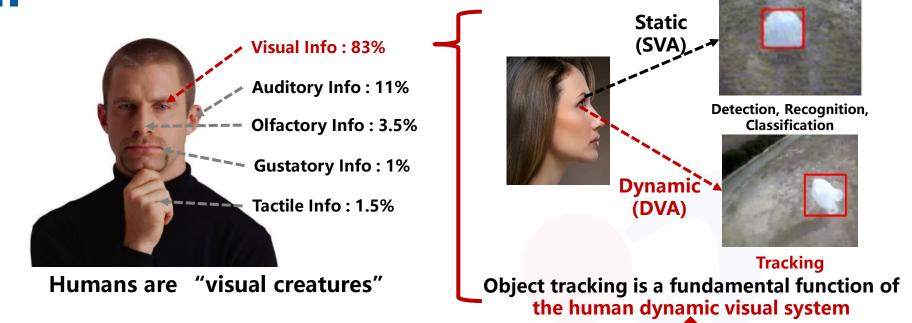
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Task Definition



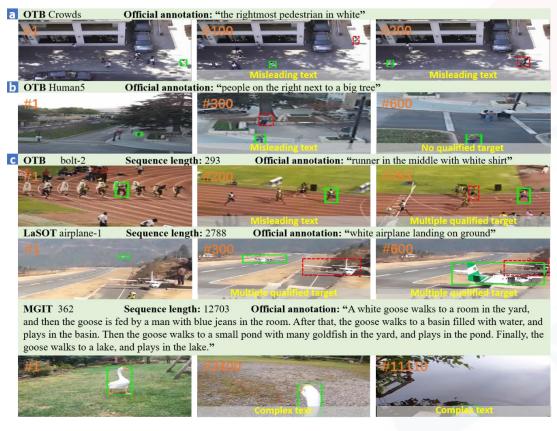
VLT (Visual Language Tracking)

• **Definition**: Only providing the initial position and natural language descriptions of a moving object and continuously locating it in a video sequence.



Motivation

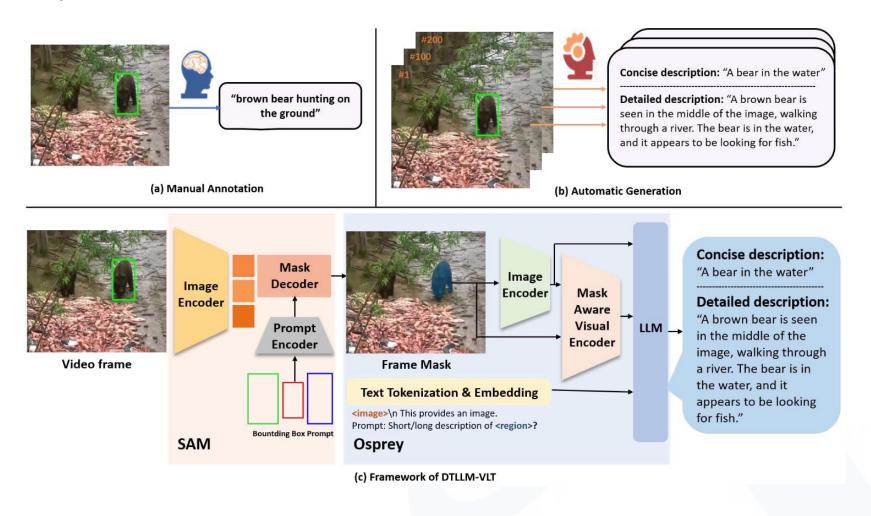
- Most VLT benchmarks are annotated in a single granularity and lack a coherent semantic framework to provide scientific guidance.
- Current VLT benchmarks considers studying from different perspective :
 - Limitations1. Semantic annotations in OTB99_Lang mainly describe the first frame, which may misguide the algorithm.
 - Limitations2. Sequence in MGIT has such complex text that they are not conducive to algorithmic learning.



Research objective:
Using LLM to provide
multi-granularity
semantic information for
VLT from efficient and
diverse perspectives,
enabling fine-grained
evaluation. This work can
be extended to more
datasets to support vision
datasets understanding.

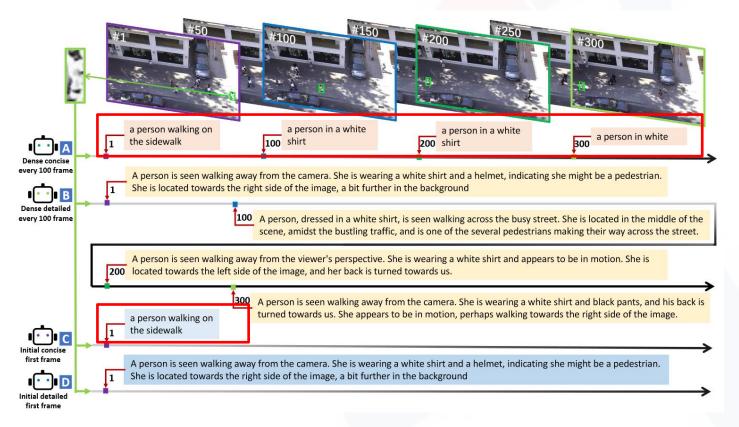
Contribution 1: Diverse text generation method based on LLM (DTLLM-VLT)

• **Diverse texts** matter → Integrating the **LLM** into the text generation process, offer a **diverse environment** conducive to VLT research.



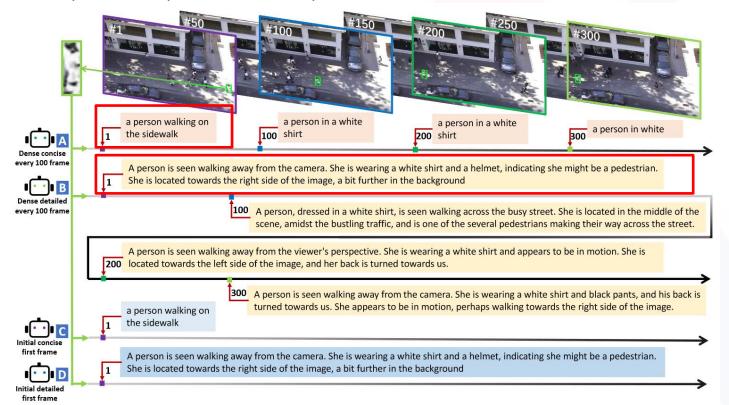
Contribution 2: Multi-Granularity Diverse Semantic Generation Strategy

- Applying multi-granularity generation
 - Initial texts: Following the text annotations method in OTB99_Lang and TNL2K, we generate text for the initial frame of each video.
 - Dense texts: Considering the worst situation and infer that the algorithm lacks an efficient memory system. Consequently, at 25 FPS, equating to every 100 frames in 4 seconds, we supply the algorithm with relevant generated text.



Contribution 2: Multi-Granularity Diverse Semantic Generation Strategy

- Applying multi-granularity generation
 - Concise texts: if the BBox already sufficiently describes the temporal and spatial changes
 of the object, the text descriptions should focus on providing essential semantic details
 like the category and positions of the object.
 - Detailed texts: In cases where the BBox lacks sufficient information for effective learning by the tracker, more elaborate texts are necessary to compensate for the missing temporal and spatial relationships.



Contribution 2: Multi-Granularity Diverse Semantic Generation Strategy

Diverse Generation

- **1.9M** words
- **14.8K** non-repetitive words.
- 7,238 initial descriptions
- 128.4K dense descriptions

Dataset	Number of Language Description							
	Official	Dense Concise	Dense Detailed	Initial Concise	Initial Detailed			
OTB99_Lang	99	596	596	99	99			
LaSOT	1,400	35.2K	35.2K	1,400	1,400			
TNL2K	2,000	12.4K	12.4K	2,000	2,000			
MGIT	1,753	16.1K	16.1K	120	120			



(a) The word cloud of initial concise texts



(c) The word cloud of dense concise texts



(b) The word cloud of initial detailed texts



(d) The word cloud of dense detailed texts

Contribution 3: Evaluation mechanism and analysis for VLT task

Mechanism A: Utilizing the official weight files provided, we keep all
parameters unchanged and directly test the tracking performance.

Method	OTB99_Lang [19]			MGIT [9]			LaSOT [3]		
	AUC	P _{Norm}	P	AUC	P _{Norm}	P	AUC	P _{Norm}	P
Official	69.0	82.0	89.5	73.5	77.2	54.3	69.9	82.2	75.7
Initial Concise	70.6	84.2	91.1	73.9	77.8	54.9	69.0	81.1	74.7
Initial Detailed	68.0	81.5	88.4	72.7	76.2	53.4	68.7	80.7	74.4
Dense Concise	70.2	84.0	90.8	74.2	77.9	55.0	69.1	81.3	74.8
Dense Detailed	68.6	82.4	89.4	72.9	76.6	53.5	69.0	81.1	74.7

 Mechanism B: We continue training for an additional 50 epochs based on the official weights, using datasets such as OTB99_Lang, LaSOT, TNL2K, and RefCOCOg. During the training process, we replace the official texts with different texts.

Method	OTB99_Lang [19]			MGIT [9]			LaSOT [3]		
	AUC	P _{Norm}	P	AUC	P _{Norm}	P	AUC	P _{Norm}	P
Official	69.0	82.0	89.5	73.5	77.2	54.3	69.9	82.2	75.7
Initial Concise	70.0	84.3	90.5	73.6	77.4	54.2	69.6	81.8	75.4
Initial Detailed	70.3	85.6	91.4	74.1	78.3	54.5	69.4	81.5	75.1
Dense Concise	71.3	86.0	92.5	74.0	77.6	54.2	69.5	81.6	75.3
Dense Detailed	69.8	84.8	90.6	74.4	78.5	54.6	69.8	82.1	75.6

Experimental analysis: Diverse texts are suitable for different tasks

- The existing algorithm tends to learn and understand short text.
- For short-term tracking task, dense concise text will bring greater gains.
 While dense detailed text is more suitable for the other two tasks.
- The text processing method and multi-modal alignment ability need to be adjusted and improved.

Series Work on SOT and VLT



VideoCube Platform (TPAMI'23 & NIPS'23): http://videocube.aitestunion.com/
SOTVerse Platform (IJCV'23): http://metaverse.aitestunion.com/
GOT-10k Platform (TPAMI'21): http://got-10k.aitestunion.com/







Thanks!

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