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北京科技大学
University of Science and Technology Beijing

NANYANG TECHNOLOGICAL UNIVERSITY SINGAPORE

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From Machine-Machine Comparison to Human-Machine Comparison: Adapting Visual Turing Test in Visual Object Tracking

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Prof. Xin Zhao received his PhD degree from the University of Science and Technology of China (USTC) in 2013. His research interests include video analysis and performance evaluation, especially for object tracking tasks. He has published the international journal and conference papers, such as the IJCV, IEEE TPAMI, IEEE TIP, IEEE TCSVT, CVPR, ICCV, NeurIPS, AAAI, IJCAI. Recently, he has mainly conducted research on human-computer vision evaluation. He has built several widely-used computer vision benchmarks (i.e., GOT-10k, VideoCube, SOTVerse, Biodrone, etc.) with online evaluation platforms. He has regularly served as program committee member or peer reviewer for the following conferences and journals: CVPR, ICCV, ECCV, ICML, NeurIPS, ICLR, IJCV, IEEE TPAMI, IEEE TIP, IEEE TMM, etc.

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Dr. Shiyu Hu received her PhD degree from the University of Chinese Academy of Sciences in Jan. 2024. She has authored or coauthored more than 20 research papers in the areas of computer vision and pattern recognition at international journals and conferences, including TPAMI, IJCV, NeurIPS, etc. Her research interests include computer vision, visual object tracking, and visual intelligence evaluation.

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- Part 2. Experimental Environments
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- Part 4. Human Visual Abilities and Visual Turing Test
- Trends and Future Directions

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Introduction

- **What is Visual Object Tracking?**

Visual information: 83%

Auditory information: 11%

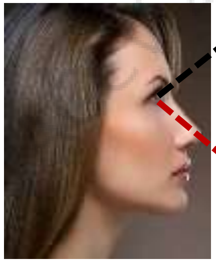
Olfactory information: 3.5%

Taste information: 1%

Tactile information: 1.5%

Humans are "visual animals"

Static Visual Ability (SVA)



Detection, recognition, classification …

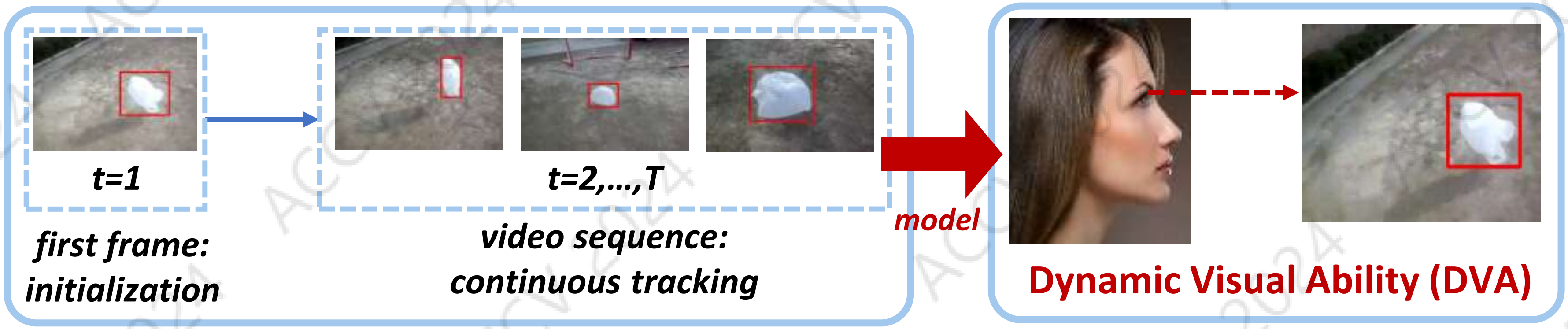
Dynamic Visual Ability (DVA)

Tracking

Visual object tracking (single object tracking) is a basic function of the human dynamic visual system.

Introduction

- **What is Visual Object Tracking?**

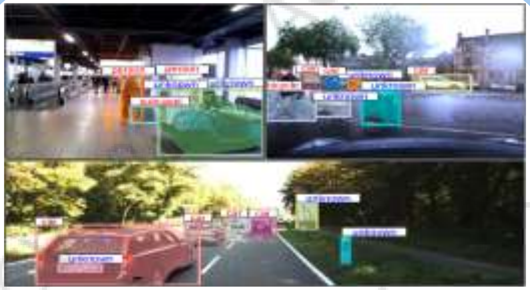


- **Definition:** Provides only the initial position of a moving object, and continuously locates it in a video sequence.
- **Characteristics:**
  - **Sequential decision:** locating the target with the help of previous frames
  - **Category agnostic:** without any assumption about the target category (open-set setting)
  - **Instance-level prediction:** need to distinguish the target from others (including objects in the same category)

Introduction

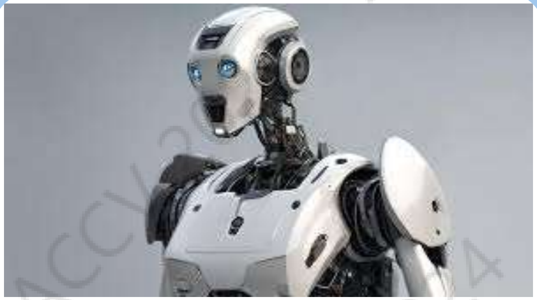
- ## Why is VOT Important?

➢ **Real-world demands**: More **intelligent and robust** visual tracking systems are needed to adapt to complex real-world environments.



Autonomous driving: Tracking vehicles or pedestrians to ensure road safety.

Video surveillance: Real-time tracking of suspicious targets in security systems.



Robot vision: Robots track objects through vision systems to interact with the environment.

Introduction

- ## Why is VOT Important?

➢ **Academic hotspots:**

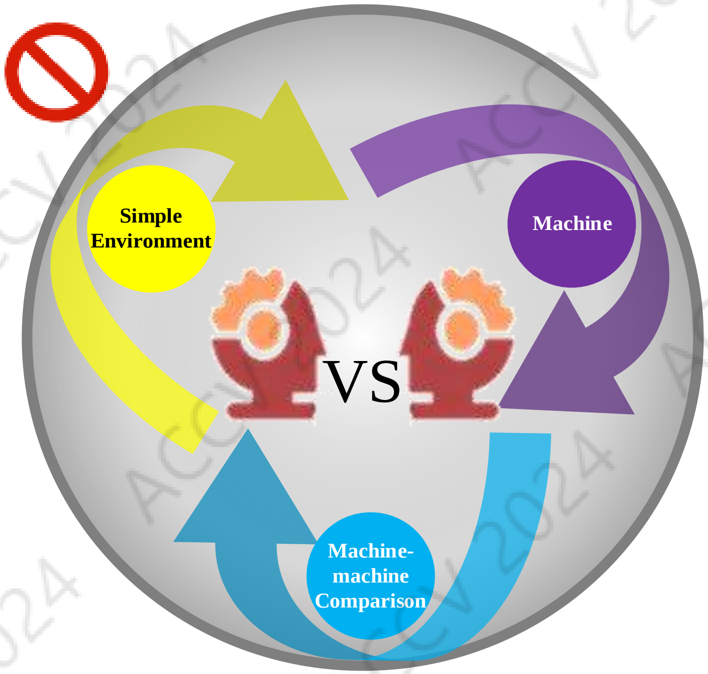
- The graph shows a consistent growth in publications related to "object tracking" over the past decade. Despite minor fluctuations, the overall trend is upward, indicating **sustained interest and ongoing research** in the field.
- This growth reflects the **increasing attention** to visual object tracking, driven by advancements in deep learning and AI technologies.

Increasing number of publications in object tracking from 2014 to 2023. (Data from Web of Science, allintitle: object tracking.)

Importance of Evaluation Techniques

- ## Lagging Evaluation Techniques

➢ **Inadequate Current Evaluation Standards:** Most evaluations **focus on performance but ignore intelligence**. The evaluation is restricted to **machine-to-machine comparisons within simple environments.**

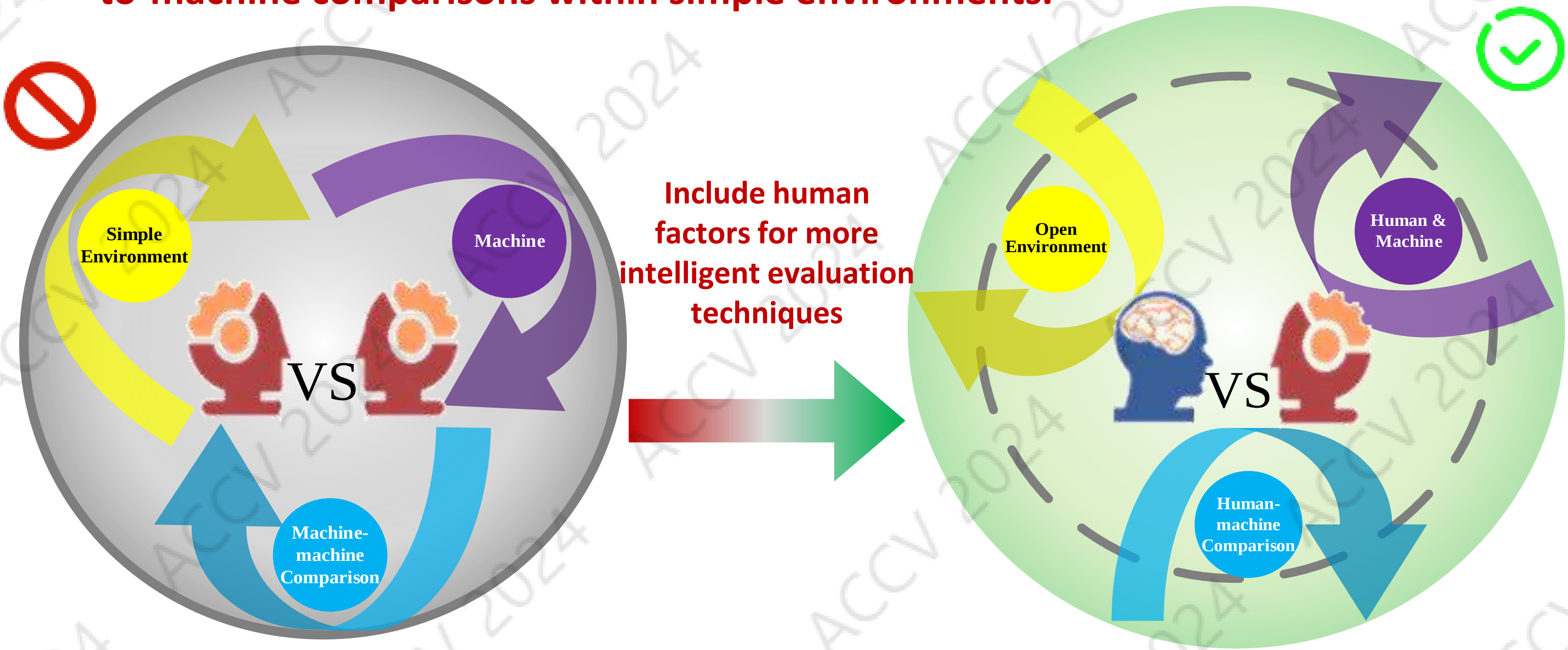


- **Environment:** Current evaluations often use **simple and controlled** environments, which fail to represent the complexities of real-world scenarios.
- **Executor:** The focus is mainly on the **machine's performance**, with little consideration for human capabilities.
- **Evaluation:** Most systems rely on **machine-to-machine comparisons**, which do not fully reflect human-level intelligence or decision-making processes.

Importance of Evaluation Techniques

- **Lagging Evaluation Techniques**

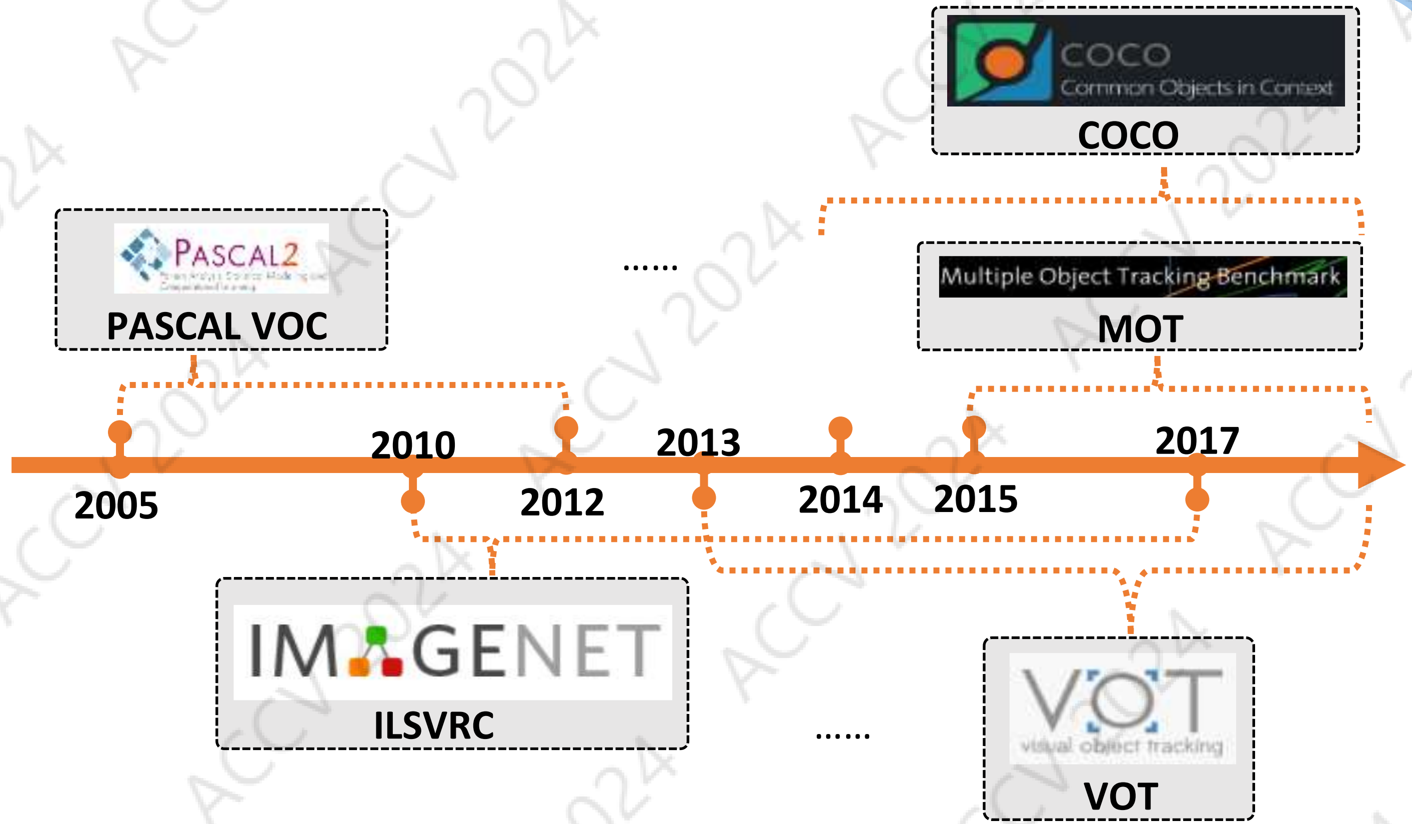
➢ **Inadequate Current Evaluation Standards:** Most evaluations **focus on performance but ignore intelligence**. The evaluation is restricted to **machine-to-machine comparisons within simple environments.**



- The environment is more **open** and reflects real-world complexities.
- There is **comparison between humans and machines**, making the evaluation process more holistic.

Importance of Evaluation Techniques

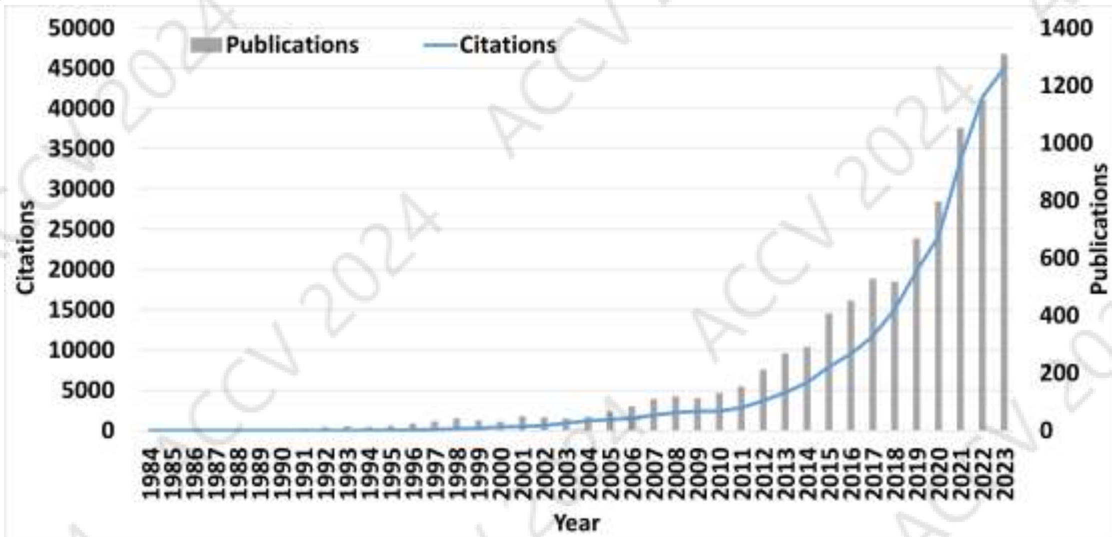
- **Importance of Visual Intelligence Evaluation**
  - **Performance Bottlenecks of Algorithms:** Evaluation techniques can **reveal weaknesses** in algorithms across different scenarios and **provide feedback for design optimization**.



Famous competitions that have advanced computer vision

Importance of Evaluation Techniques

- **Importance of Visual Intelligence Evaluation**
  - **Future Outlook**:The advancement of AI and visual intelligence depends on advanced evaluation techniques. Only through **scientific evaluation** can we **ensure that advancements** in AI and visual intelligence continue at the current pace. Evaluation not only drives innovation but also helps ensure that algorithms meet the complex demands of real-world applications.



Increasing number of publications and citations in computer vision evaluation from 1984 to 2023. (Data from Web of Science, allintitle: computer vision evaluation.)

NEURAL INFORMATION PROCESSING SYSTEMS

NeurIPS datasets & benchmarks track from 2021

Special Issue on IJCV

Structure and Goals of the Tutorial

- **Structure**
  - **Introduction (this section)**
  - **Part 1. Task Definitions and Challenges**: A deep dive into the foundations and challenges of object tracking.
  - **Part 2. Categorization of Evaluation Environments**: Examination of the environments used for evaluating tracking algorithms.
  - **Part 3. Algorithms and Traditional Machine-Machine Comparisons**: Analysis of existing algorithms and their performance comparisons.
  - **Part 4. Human Visual Abilities and Visual Turing Test**: Discussion on human-machine comparison frameworks and the introduction of the Visual Turing Test concept.
  - **Trends and Future Directions**

Structure and Goals of the Tutorial

- **Goals**
  - Help participants understand visual intelligence **evaluation techniques** in visual object tracking.
  - Discuss the **strengths and weaknesses** of existing evaluation mechanisms and offer directions for improvement.
  - **Inspire future research** in visual tracking.

Expected Takeaways:
Through this tutorial, participants will gain a **comprehensive understanding** of visual intelligence evaluation techniques.

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- Introduction
- **Part 1. Visual Object Tracking Task**
  - **Task Definition**
  - **Task Challenge**
- Part 2. Experimental Environments
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Task Definition

Explore the fundamental definitions that shape how we approach human visual tracking ability.

Task: Short-term Tracking (STT)

Visual/Single Object Tracking (VOT/SOT)

- **Characteristics: Sequential decision, category agnostic, instance-level prediction.**

model

Human Visual Tracking

hidden constraints

Characteristics of STT (based on VOT challenge):

- **Single-target**
- **Model-free**
- **~~Causal relationship~~**
- **Short-term**
- **Single-camera**

extra task constraints

A STT demo (≈30s, in single camera)

Definition: Short-term tracking refers to **continuously tracking** a single object within a short sequence, where the **target remains visible** in every frame of the video. It assumes no significant interruptions, occlusions, or camera changes.

Early research simplified the task, which is far away from human visual tracking ability.

Wu Y, Lim J, Yang M H. Online object tracking: A benchmark[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2013: 2411-2418.

Task: Long-term Tracking (LTT)

Visual/Single Object Tracking (VOT/SOT)

- **Characteristics: Sequential decision, category agnostic, instance-level prediction.**

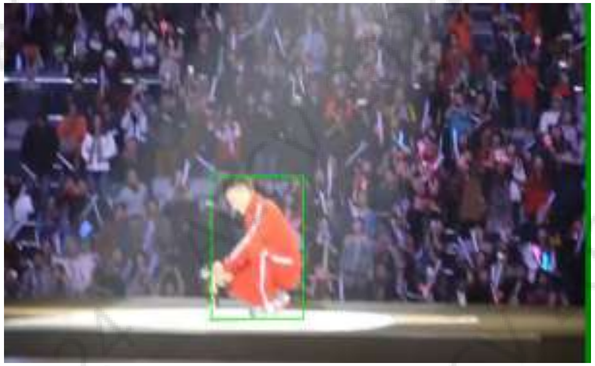
model

still hidden constraint (single-camera)

Characteristics of LTT (cancel short-term constraint):

- **Single-target**
- **Model-free**
- **Causal relationship**
- **Single-camera**

extra task constraint



A LTT demo (≈2mins, in single camera)

Definition: Long-term tracking expands single object tracking to longer time sequences, allowing for **temporary disappearance** of the target (due to occlusion or leaving the frame) and **requiring re-detection** when the target reappears. This is in contrast to short-term tracking, which assumes the target is always present in the frame.

Task: Global Instance Tracking (GIT)

Visual/Single Object Tracking (VOT/SOT)

- **Characteristics: Sequential decision, category agnostic, instance-level prediction.**

model

Alignment

Characteristics of GIT (cancel all extra constraints):

- **Single-target**
- **Model-free**
- **Causal relationship**

A GIT demo (unconstrainted time and space)

Definition: Global instance tracking extends the task of single object tracking by **removing the assumption of continuous motion**, allowing the target to **move freely** between different scenes and camera views. This task aims to **model human dynamic visual capabilities** in more complex and realistic environments.

Global instance tracking is a more human-like task, which allows trackers to align with human visual tracking ability.

Task Challenge

Discuss the various challenges that arise when performing visual object tracking.

Challenges in VOT

- **Challenges are widespread in real world**

➢ **Challenge Overview:** VOT algorithms rely heavily on **appearance and motion information** of the target. When these are disrupted, it leads to errors in predicting the target’s location.

dim light

background clutter

scale / ratio variation

similar object interference

partial occlusion

absent

motion blur

fast motion

Challenges in VOT

- **Challenges in real world → Robustness issues**

➢ SOT is a sequential decision process. The challenging factors in the environment will **cause errors that continue to accumulate** over time, making it **impossible to achieve robust tracking**.

Challenges in VOT

- **Shot-Cut**

➢ **Appearance Information Disruption:**

- **Scene Transition:**
  - ☐ When there is a shot-cut, **the scene may change entirely**, with the target reappearing in a different context, angle, or lighting.
  - ☐ This sudden transition makes it **difficult for the tracker to maintain the target's visual identity**, as the previously known appearance may no longer be applicable.
- **Change in Target Appearance:** The target may also **look different** after the shot-cut due to changes in camera angle or distance, which **disrupts the consistency of visual features** (like size, texture, or shape).

Challenges in VOT

- **Shot-Cut**

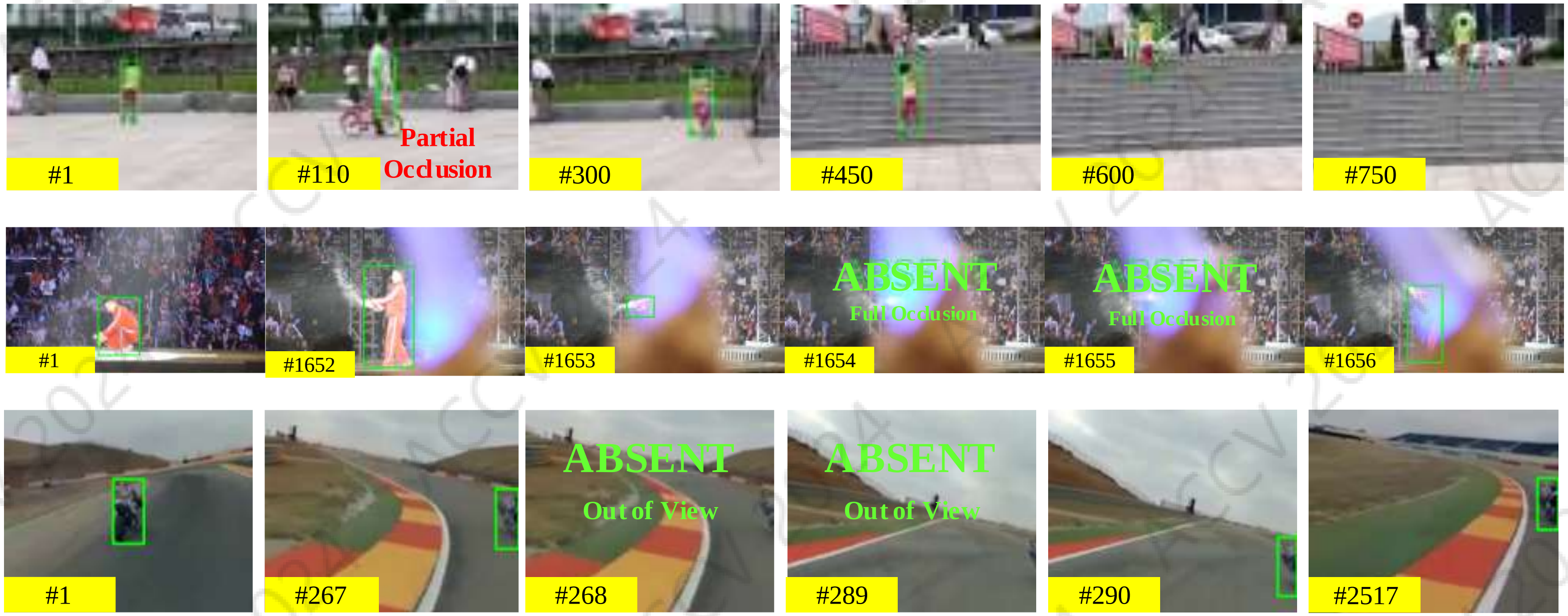
➢ **Motion Information Disruption:**

- The natural motion path of the target is interrupted during a shot-cut, leading to **a loss of temporal continuity**.
- The tracker cannot rely on motion data from the previous shot, forcing it to **re-detect the target** in the new frame.

Effect on Tracking:
The tracker must employ **robust re-detection mechanisms** to quickly locate the target in the new shot. Additionally, **context adaptation is necessary** to handle changes in scene and lighting conditions.

Challenges in VOT

- **Occlusion and Target Disappearance**



➢ **Appearance Information Disruption:**

- **Partial Occlusion:** When the target is partially blocked by another object, the algorithm **loses crucial visual information** like texture or color, making it **harder to maintain a precise appearance model**.
- **Full Occlusion:** If the target is completely occluded, the tracker **loses all appearance data**, forcing the algorithm to **rely on motion models or prediction** until the target reappears.

Challenges in VOT

- **Occlusion and Target Disappearance**

➢ **Motion Information Disruption**:

- **Occlusion Causes Loss of Motion Data:** When the target is occluded, the **motion data becomes unavailable or unreliable**, making it **difficult to predict the target's future location.**
- **Target Disappearance:** When the target leaves the field of view or remains fully occluded for an extended period, the algorithm **must handle re-detection**. If it fails, the tracker **may lose the target permanently**.

Effect on Tracking:
The tracker **must adapt to occlusions by predicting the target's likely path using motion models**. Once the target reappears, the tracker should **quickly re-detect it to avoid losing track**.

Challenges in VOT

- **Lighting Changes**

➢ **Appearance Information Disruption:**

- Changes in lighting (e.g., moving from a brightly lit area to a shaded region) can **drastically alter the target's appearance**. These changes may cause the target's color, texture, or overall brightness to differ significantly from its original appearance.

➢ **Motion Information Disruption:**

- Poor lighting can **obscure motion information**, making it more challenging for the algorithm to correctly interpret the speed and direction of the target's movement.

Effect on Tracking:
Algorithms must **incorporate adaptive lighting models to handle drastic changes**. Inconsistent lighting can confuse the tracker, leading to incorrect target predictions.

Challenges in VOT

- **Background Clutter**

- **Appearance Information Disruption:**
  - **Visual Similarity to Background:**
    - When the target's appearance (e.g., color, texture) is similar to background elements, the tracker may **struggle to differentiate the target from its surroundings**.
    - This makes it difficult to maintain a clear distinction between the target and background.
  - **Distraction by Non-Target Objects:**
    - In a cluttered background, there **may be many objects that distract the tracker**, especially if these objects have similar visual features.
    - This confusion can **lead to the tracker locking onto the wrong object or losing the target**.

Challenges in VOT

- **Background Clutter**

➢ **Motion Information Disruption**:

- **Interference from Moving Background Elements:**
  - ☐ In dynamic environments (e.g., busy streets or crowded places), **background objects in motion can confuse the tracker**.
  - ☐ The movement of background elements can be misinterpreted as the movement of the target, **leading to errors in motion prediction.**
- **Occlusions by Background Objects:** In some cases, cluttered backgrounds **may temporarily occlude the target**, making it harder for the tracker to estimate the correct motion path.

Effect on Tracking:
Robust appearance models and **motion prediction techniques** are required to distinguish the target from the background in cluttered environments.

Challenges in VOT

- **Fast Motion**

➢ **Appearance Information Disruption:**

- **Motion Blur:** When the target moves quickly, **motion blur may occur**, causing the visual details (e.g., texture, edges) of the target to become indistinct. This makes it **difficult to maintain a consistent appearance model** of the target.
- **Loss of Visual Features:** In cases of extreme speed, the target may move across frames too quickly, resulting in **a loss of critical visual features** such as shape or color, which the tracker relies on for identification.

Challenges in VOT

- **Fast Motion**

➢ **Motion Information Disruption**:

- **High-Speed Movement:** Fast motion makes it **difficult to predict the target's movement accurately**. Traditional motion models may fail to keep up with the rapid changes in the target's position, leading to poor tracking performance.
- **Limited Search Window:** Tracking algorithms often use **a defined search window** around the predicted position. If the target moves too fast, **it may exit the search window**, and the tracker may fail to locate it in the next frame.

Effect on Tracking:
Algorithms **should have more advanced motion models** that can handle sudden and rapid changes in speed and direction.

Challenges in VOT

- **Special Scale & Special Ratio**

➢ **Special Scale (Small or Large Targets):**

- **Small Targets:** When tracking small objects, the algorithm may **struggle to capture enough visual detail**, resulting in poor localization accuracy. Small-scale objects have **fewer distinguishable features**, making them harder for the tracker to differentiate from the background.
- **Large Targets:** Conversely, large targets may **exceed the camera's field of view**, resulting in partial occlusion. The tracker must **handle incomplete information**, often leading to inaccuracies in bounding box adjustments.

Challenges in VOT

- **Special Scale & Special Ratio**

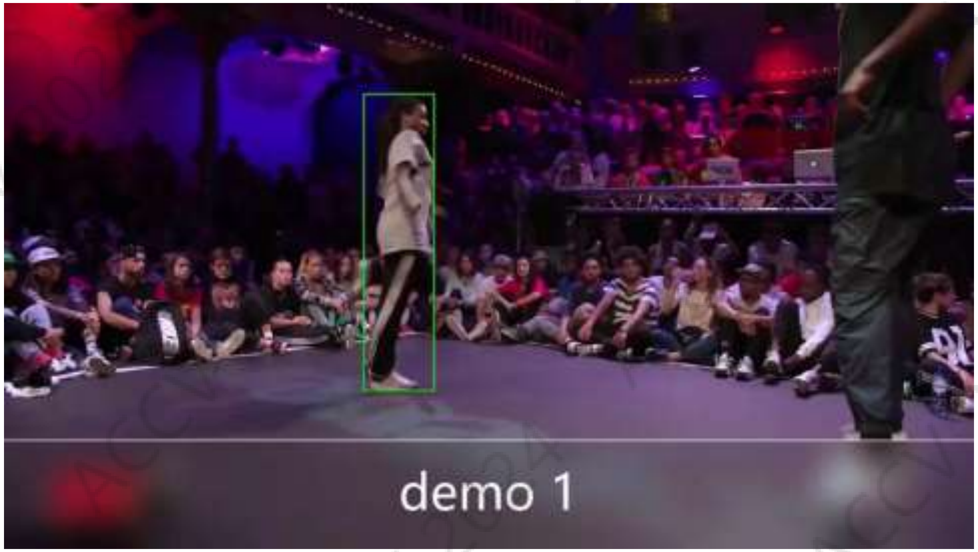
➢ **Special Ratio (Unusual Aspect Ratios):**

- **Tall or Wide Targets:** Objects with extreme aspect ratios (e.g., very tall or wide) challenge the tracker's ability to accurately fit bounding boxes. Standard tracking models often **struggle with highly elongated objects**, leading to **misalignment of the predicted bounding box with the actual target**.
- **Inconsistent Bounding Box Fitting:** The algorithm's reliance on intersection-over-union (IoU) measures means that special ratio targets often result in poor performance when **the bounding box cannot closely match the target's shape**.

Effect on Tracking:
More flexible and adaptive bounding box models are required to improve tracking accuracy for objects with special scale and ratio characteristics.

Challenges in VOT

- **Scale Variation & Ratio Variation**



➢ **Scale Variation:**

- **Dynamic Size Changes**: The target's size in the video frame changes as the relative distance between the target and the camera changes. This **leads to fluctuating scale**, making it difficult for the tracker to maintain accurate predictions.
- **Foreground Feature Alterations:** As the target becomes larger or smaller, key visual features (such as edges, textures) may either become more detailed or be reduced in clarity, **complicating feature extraction for the tracking algorithm.**

Challenges in VOT

- **Scale Variation & Ratio Variation**

➢ **Ratio Variation:**

- **Shape Alterations:** The target's aspect ratio may shift due to rotations or perspective changes, altering the shape of the object in the frame. This **requires the tracker to adjust its bounding box to fit the new shape**, which can be challenging if the ratio changes are extreme.
- **Bounding Box Fitting Issues:** When the aspect ratio changes dramatically, the tracker **may struggle to fit a precise bounding box**, especially in cases where the target becomes highly elongated or compressed.

Effect on Tracking:
More adaptive models capable of **real-time adjustments to both scale and ratio changes** are essential to improve tracking robustness in dynamic scenes.

Conclusion

- **Comprehensive Understanding of the Evaluation Task:**
  - This section introduces visual object tracking (VOT) from two key perspectives—**task definitions** and **task challenges.**
  - The goal is to help researchers fully grasp the evaluation task and lay the foundation for intelligent assessment.
- **Constraints in Task Definitions:**
  - The **inherent constraints** in task definitions **reflect the characteristics** of the tracking task.
  - **Changes in these constraints will shift the focus of the evaluation**. For example, a change in the duration of tracking (e.g., short-term vs. long-term) could change the way algorithms are evaluated.

Conclusion

- **Task Challenges Represent Difficulties:**
  - The challenging factors in SOT represent the **primary difficulties**.
  - A deep understanding of these factors is crucial for researchers to **accurately identify the performance bottlenecks** of tracking algorithms.
- **Importance of Designing Evaluation Environments:**
  - Only by understanding the specific task challenges, such as occlusion, fast motion, and scale variation, can researchers **design the right evaluation environments** that test an algorithm's real capabilities.
  - Proper evaluation ensures that the algorithm's weaknesses are uncovered, **enabling improvement and refinement**.

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General Datasets

General datasets are designed to test the performance of algorithms under a variety of conditions.

General Datasets: Small-scale

- **OTB50 (2013) & OTB100 (2015)**

- OTB50 is **one of the earliest benchmarks** designed specifically for evaluating SOT algorithms. OTB100 extended OTB50 by including more tracking sequences and covering a broader set of tracking scenarios. OTB provides high-precision annotations using horizontal bounding boxes and includes a variety of tracking challenges such as occlusion, fast motion, and scale variation.
  - **Standardization:** OTB helped **standardize SOT evaluations** by offering a set of predefined benchmarks, enabling researchers to compare their algorithms on a unified platform.
  - **Challenge Annotations:** OTB is annotated with **multiple challenge factors**, making it a comprehensive evaluation platform for early tracking algorithms.

Wu Y, Lim J, Yang M H. Online object tracking: A benchmark[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2013: 2411-2418.

General Datasets: Small-scale

- **TColor-128 (2015)**

➢ TColor-128 aims to **evaluate the role of color features** in SOT, particularly in distinguishing targets from complex backgrounds.

- **Focus on Color Features:** Unlike datasets that include grayscale sequences, TColor-128 exclusively **includes color video sequences**, enabling the evaluation of algorithms that rely on color information to differentiate targets.

General Datasets: Small-scale

- **Limitations**

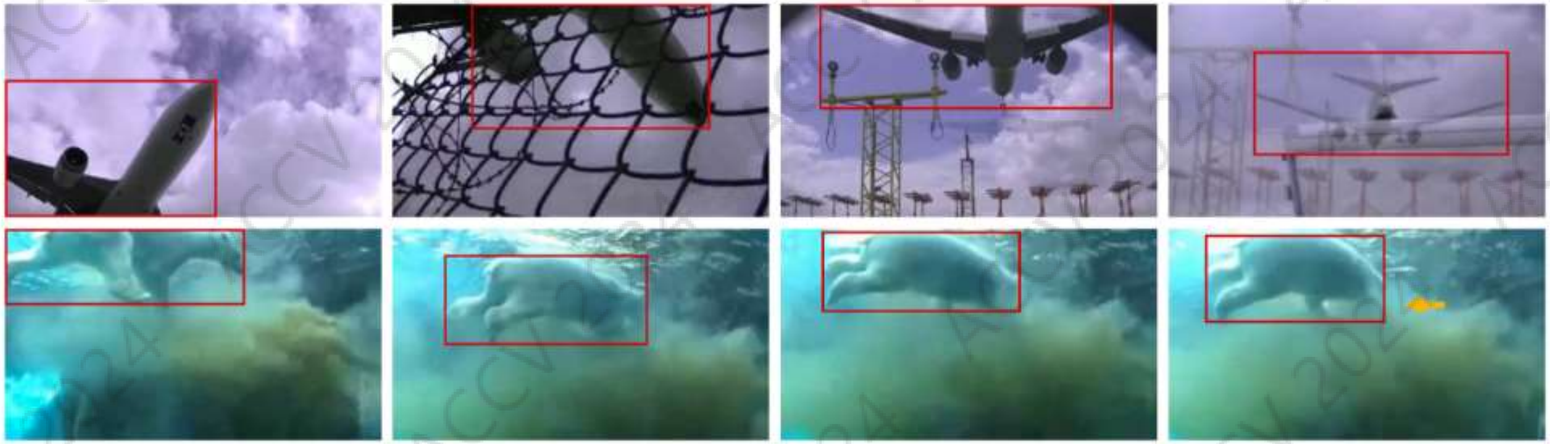
➢ While small-scale datasets, like the ones we've discussed, provide valuable benchmarks, they also come with certain limitations that affect the performance of deep learning models.

- **Data Volume Constraints**: Deep learning models require a **large amount of labeled data** to achieve optimal performance. Many traditional SOT datasets are limited in size, which **constrains the ability of deep learning models to generalize** across diverse scenarios and environments.
- **Poor Generalization**: Models trained on smaller datasets may suffer from **poor generalization** when tested in more complex real-world environments, especially when faced with **unseen target types** or **challenging conditions** like fast motion or occlusion.
- **Lack of Diversity**: Small-scale datasets often **lack diversity in both target types and tracking conditions**, which limits the **robustness** of tracking algorithms. This makes it harder for these models to handle new or unexpected scenarios.

More large-scale tracking datasets with dynamic objects and varied tracking challenges are necessary to enhance the performance of deep learning-based tracking models.

General Datasets: Large-scale

- **ImageNet-VID (2015) & YouTube-BB (2017)**



- ➢ Two datasets from video object detection task:
  - ImageNet-VID contains 5,400 video sequences with annotations for one or more moving objects.
  - YouTube-BB includes 380,000 YouTube video sequences with 5.4 million frames annotated at a rate of 1 Hz.
- ➢ Despite its large size, these datasets focus on **a small number of object categories** and **includes static objects**, which limits their utility for training dynamic object tracking models.
- ➢ To overcome the limitations of small datasets and the static nature of larger datasets like ImageNet-VID and YouTube-BB, there is a need for **more diverse and dynamic large-scale datasets** designed for SOT task.

Russakovsky O, Deng J, Su H, et al. Imagenet large scale visual recognition challenge[J]. International journal of computer vision, 2015, 115: 211-252.
Real E, Shlens J, Mazzocchi S, et al. Youtube-boundingboxes: A large high-precision human-annotated data set for object detection in video[C]//proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2017: 5296-5305.

General Datasets: Large-scale STT

- **TrackingNet (2018)**

➢ TrackingNet is **one of the largest datasets for short-term tracking**, designed to support deep learning-based tracking models.

- **Filtered for Quality:** The dataset **filters out static objects and noisy segments** from YouTube-BB, focusing on moving objects that are relevant for tracking tasks.
- **Combines Manual and Automated Annotations:** Uses discriminative correlation filter (DCF) to **automate annotation**, **combined with manual annotations** for greater precision.

Muller M, Bibi A, Giancola S, et al. Trackingnet: A large-scale dataset and benchmark for object tracking in the wild[C]//Proceedings of the European conference on computer vision (ECCV). 2018: 300-317.

General Datasets: Large-scale STT

- **GOT-10k (2019)**

➢ **SOT Definition:** Provides only the initial position of a moving object, and continuously locates it in a video sequence.

➢ **SOT Characteristics:**

- **Sequential decision:** locating the target with the help of previous frames
- **Category agnostic:** without any assumption about the target category (open-set setting)
- **Instance-level prediction:** need to distinguish the target from others (including objects in the same category)

There are a large number of unknown target categories in the real environment. → **Generalization Challenges**

L. Huang*, X. Zhao*, K. Huang. Got-10k: A large high-diversity benchmark for generic object tracking in the wild[J]. IEEE transactions on pattern analysis and machine intelligence, 2021, 43(5): 1562-1577.

General Datasets: Large-scale STT

- **GOT-10k (2019)**

➢ **Motivation:** Limitations of the existing experimental environment in terms of generalization:

- Weak diversity, non-universal scenarios, **poor generalization ability** (training and test categories completely overlap and have the same distribution)

LaSOT (CVPR'19)
- 70 object categories
- **Training and testing categories completely overlap and have consistent distribution**

TrackingNet (ECCV'19)
- 22 object categories
- **Training and testing categories completely overlap and have consistent distribution**

L. Huang, X. Zhao*, K. Huang. Got-10k: A large high-diversity benchmark for generic object tracking in the wild[J]. IEEE transactions on pattern analysis and machine intelligence, 2021, 43(5): 1562-1577.*

General Datasets: Large-scale STT

- **GOT-10k (2019)**

➢ A large-scale benchmark that covers a wide range of **natural and artificial object categories** and **motion forms** and follows the **open set evaluation protocol.**

L. Huang*, X. Zhao*, K. Huang. Got-10k: A large high-diversity benchmark for generic object tracking in the wild[J]. IEEE transactions on pattern analysis and machine intelligence, 2021, 43(5): 1562-1577.

General Datasets: Large-scale STT

- **GOT-10k (2019)**
  - Large-scale, **unified** training, validation, and test sets.

Dataset	Total Classes	Total Videos	Total Boxes	Train Classes	Train Videos	Train Boxes	Test Classes	Test Videos	Test Boxes	Properties Exp. Setting	Properties Min/Max/Avg. Duration (seconds)	Properties Frame Rate
OTB2015 [12]	22	100	59 k	-	-	-	22	100	59 k	casual	2.4/129/20	30 fps
VOT2019 [2]	30	60	19.9 k	-	-	-	30	60	19.9 k	casual	1.4/50/11	30 fps
ALOV++ [21]	59	314	16 k	-	-	-	59	314	16 k	casual	0.63/199/16	30 fps
NUS_PRO [17]	12	365	135 k	-	-	-	12	365	135 k	casual	4.9/168/12	30 fps
TColor128 [16]	27	129	55 k	-	-	-	27	129	55 k	casual	2.4/129/14	30 fps
NfS [14]	33	100	38 k	-	-	-	33	100	38 k	casual	0.7/86/16	240 fps
UAV123 [15]	9	123	113 k	-	-	-	9	123	113 k	casual	3.6/103/31	30 fps
UAV20L [15]	5	20	59 k	-	-	-	5	20	59 k	casual	57/184/75	30 fps
OxUvA [13]	22	366	155 k	-	-	-	22	366	155 k	open + constrained	30/1248/142	30 fps
LaSOT [20]	70	1.4 k	3.3 M	70	1.1 k	2.8 M	70	280	685 k	fully overlapped	33/380/84	30 fps
TrackingNet [19]	21	31 k	14 M*	21	30 k	14 M*	21	511	226 k	fully overlapped	-/-/16	30 fps
MOT15 [29]	1	22	101 k	1	11	43 k	1	11	58 k	-	3/225/45	2.5~30 fps
MOT16/17 [28]	5	14	293 k	5	7	200 k	5	7	93 k	-	15/85/33	14~30 fps
KITTI [30]	4	50	59 k	4	21	-	4	29	-	-	-	10 fps
ILSVRC-VID [23]	30	5.4 k	2.7 M	30	5.4 k	2.7 M	-	-	-	-	0.2/183/11	30 fps
YT-BB [26]	23	380 k	5.6 M	23	380 k	5.6 M	-	-	-	-	-	1 fps
GOT-10k	**563**	10 k	1.5 M	**480**	9.34 k	1.4 M	**84**	420	56 k	**one-shot**	0.4/148/15	10 fps

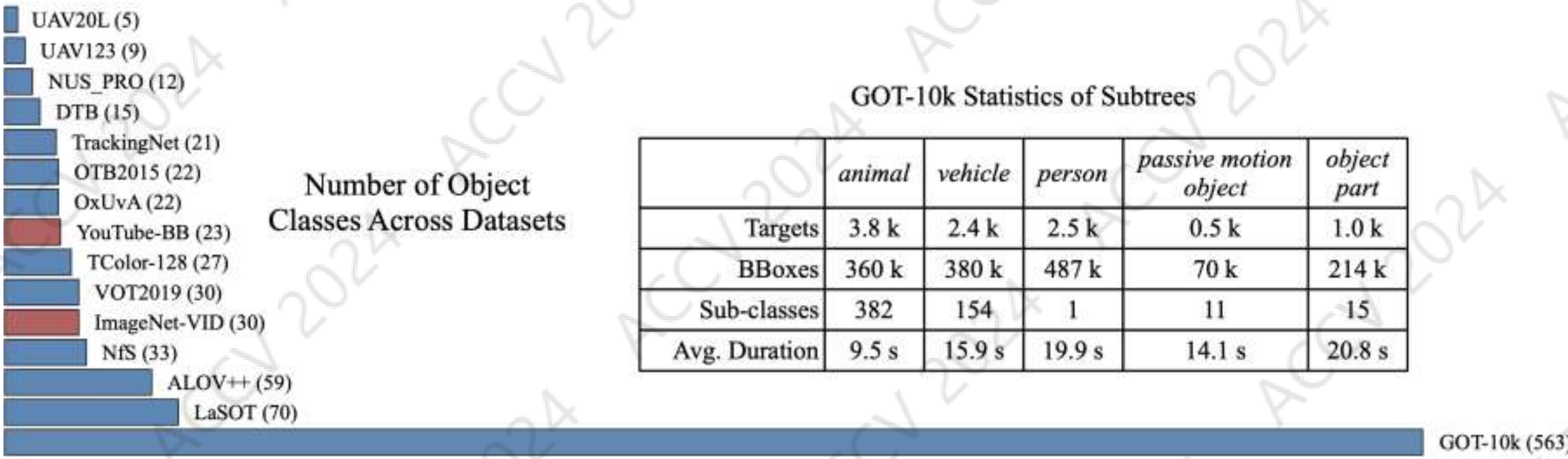
10k videos， 1.5M manual annotations

L. Huang, X. Zhao*, K. Huang. Got-10k: A large high-diversity benchmark for generic object tracking in the wild[J]. IEEE transactions on pattern analysis and machine intelligence, 2021, 43(5): 1562-1577.*

General Datasets: Large-scale STT

- **GOT-10k (2019)**

➢ 563 types of objects, fully covering common natural and man-made moving objects in **WordNet.**



GOT-10k Statistics of Subtrees

	animal	*vehicle*	*person*	*passive motion object*	*object part*
Targets	3.8 k	2.4 k	2.5 k	0.5 k	1.0 k
BBoxes	360 k	380 k	487 k	70 k	214 k
Sub-classes	382	154	1	11	15
Avg. Duration	9.5 s	15.9 s	19.9 s	14.1 s	20.8 s

The number of object categories (563) is nearly 10 times that of other tracking datasets (in 2019)

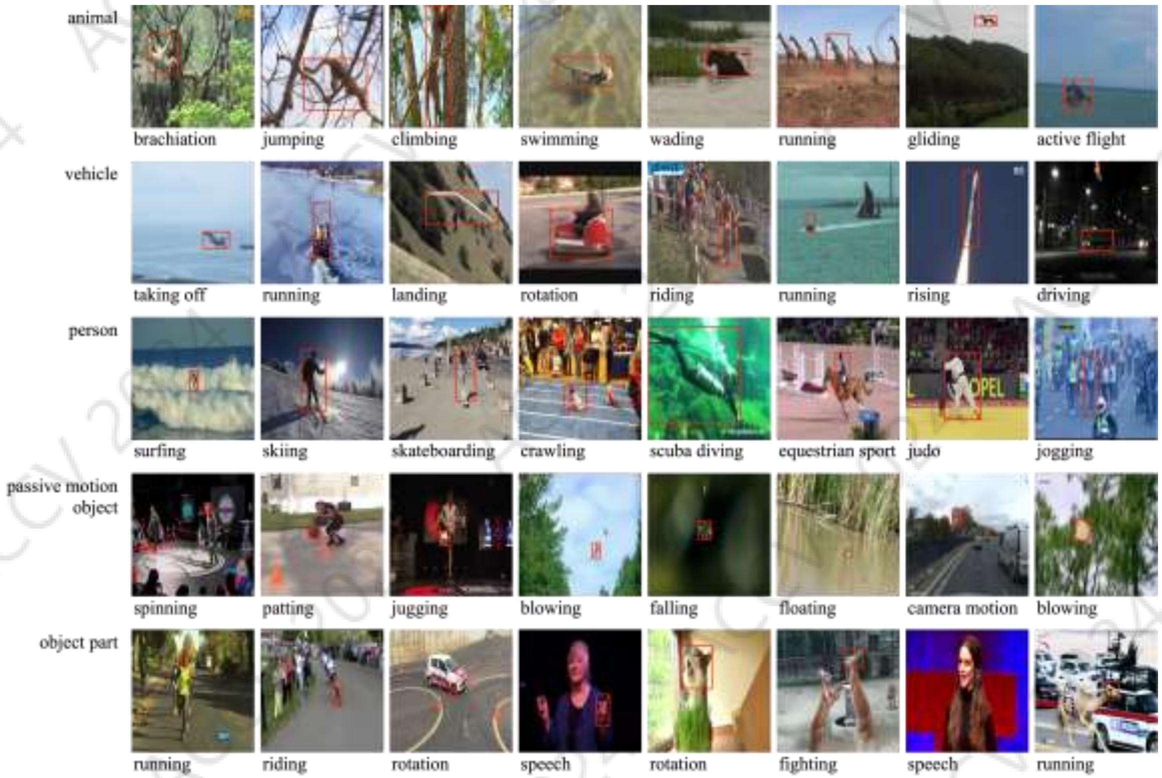
L. Huang, X. Zhao*, K. Huang. Got-10k: A large high-diversity benchmark for generic object tracking in the wild[J]. IEEE transactions on pattern analysis and machine intelligence, 2021, 43(5): 1562-1577.*

General Datasets: Large-scale STT

- **GOT-10k (2019)**

➢ 87 types of motion modes, covering a **wide range** of different forms of sports trajectories.

Object category labels



Motion category labels

Each video sequence includes two labels: object category and motion category.

L. Huang, X. Zhao*, K. Huang. Got-10k: A large high-diversity benchmark for generic object tracking in the wild[J]. IEEE transactions on pattern analysis and machine intelligence, 2021, 43(5): 1562-1577.*

General Datasets: Large-scale STT

- **GOT-10k (2019)**

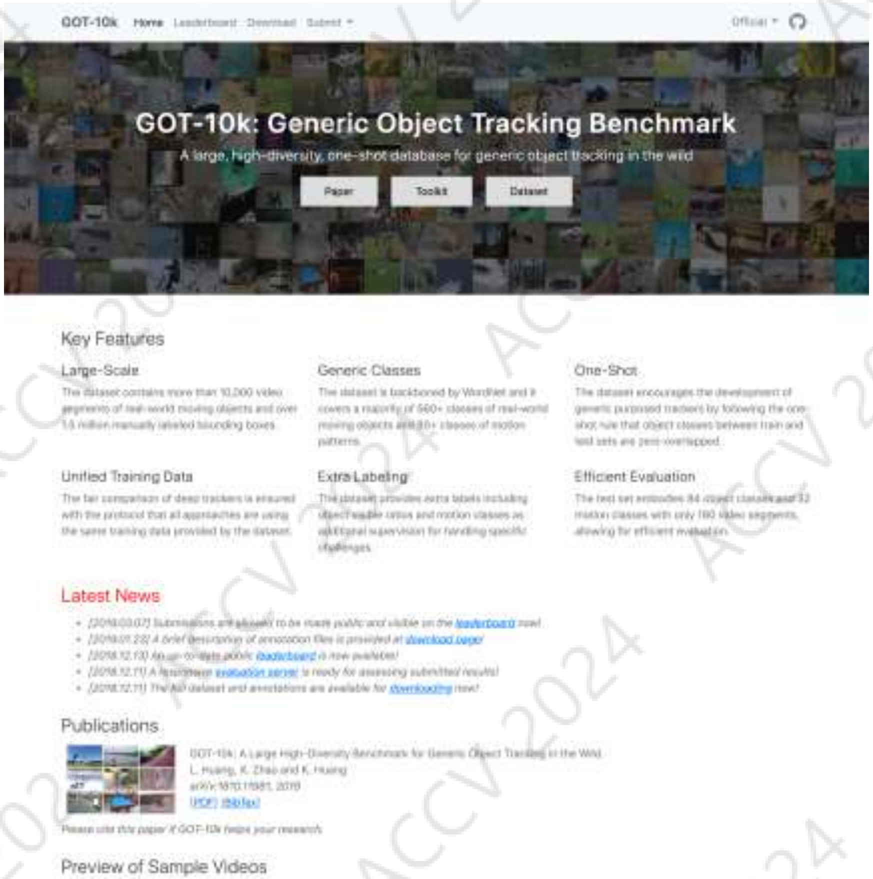
➢ **Open set evaluation specification** (training and test categories do not overlap at all) for **generalization ability evaluation**

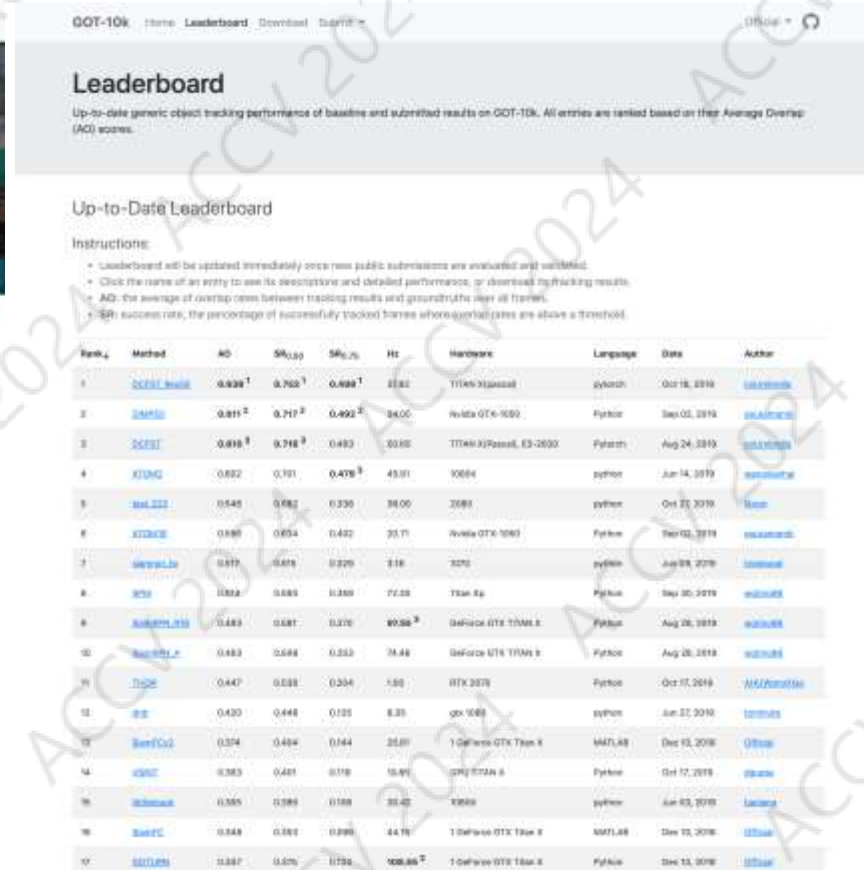
There is no overlap between training and testing categories, and the algorithm is required to accurately track moving objects of unknown categories.

General Datasets: Large-scale STT

- **GOT-10k (2019)**

➢ Complete evaluation platform, **real-time rankings**, open-source toolkits



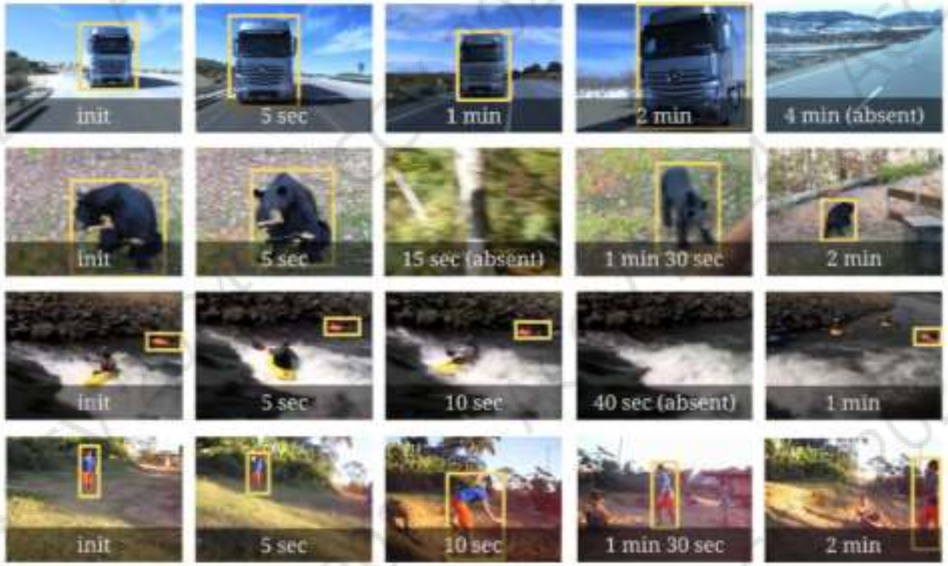


http://got-10k.aitestunion.com/

L. Huang, X. Zhao*, K. Huang. Got-10k: A large high-diversity benchmark for generic object tracking in the wild[J]. IEEE transactions on pattern analysis and machine intelligence, 2021, 43(5): 1562-1577.*

General Datasets: Large-scale LTT

- **OxUvA (2018)**



➢ OxUvA is designed specifically for **long-term object tracking**, testing the ability of algorithms to handle **target disappearance and reappearance** across extended video sequences.

- **Challenging Long-term Evaluations:** This dataset shifts the focus from tracking in consistent, short-term scenarios to more **dynamic and unpredictable** long-term tracking conditions.
- **Benchmark for Robustness:** OxUvA tests the robustness of tracking algorithms by introducing the challenge of **target disappearance**, making it a critical dataset for evaluating next-generation tracking models.

Valmadre J, Bertinetto L, Henriques J F, et al. Long-term tracking in the wild: A benchmark[C]//Proceedings of the European conference on computer vision (ECCV). 2018: 670-685.

General Datasets: Large-scale LTT

- **LaSOT (2019) & LaSOT-ext (2021)**

bear-12: "white bear walking on grass around the river bank"

bicycle-7: "bicycle by a man on the road with other bicycles"

bus-2: "blue bus running on the street"

➢ LaSOT is designed to evaluate long-term single object tracking algorithms, with extended sequences to test tracking robustness over long durations.

- **Standard for Long-term Tracking:** LaSOT is one of the largest and most comprehensive datasets for long-term tracking, offering **diverse sequences and challenges** that test algorithms beyond short-term scenarios.
- **Semantic Annotations:** The dataset also provides **semantic annotations** for each sequence, making it useful for **multimodal research** and advanced tracking techniques that require semantic understanding.

Fan H, Lin L, Yang F, et al. Lasot: A high-quality benchmark for large-scale single object tracking[C]//Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2019: 5374-5383.

General Datasets: Large-scale GIT

- **VideoCube (2023)**

➢ **Motivation:** Limitations of the existing experimental environment in terms of robustness:

  - The continuous motion assumption limits the experimental environment to **simple scenes with slow motion and a single shot.**

LaSOT: Continuous motion assumption, no shot cuts and scene transitions → Simple environment

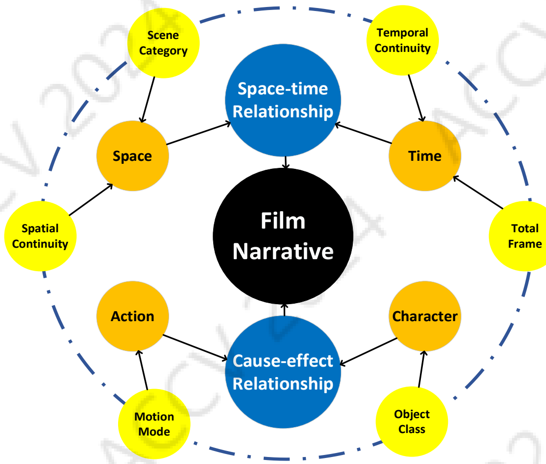
S. Hu, X. Zhao#, L. Huang, et al., "Global instance tracking: Locating target more like humans," IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), vol. 45, no. 1, pp. 576–592, 2023.

General Datasets: Large-scale GIT

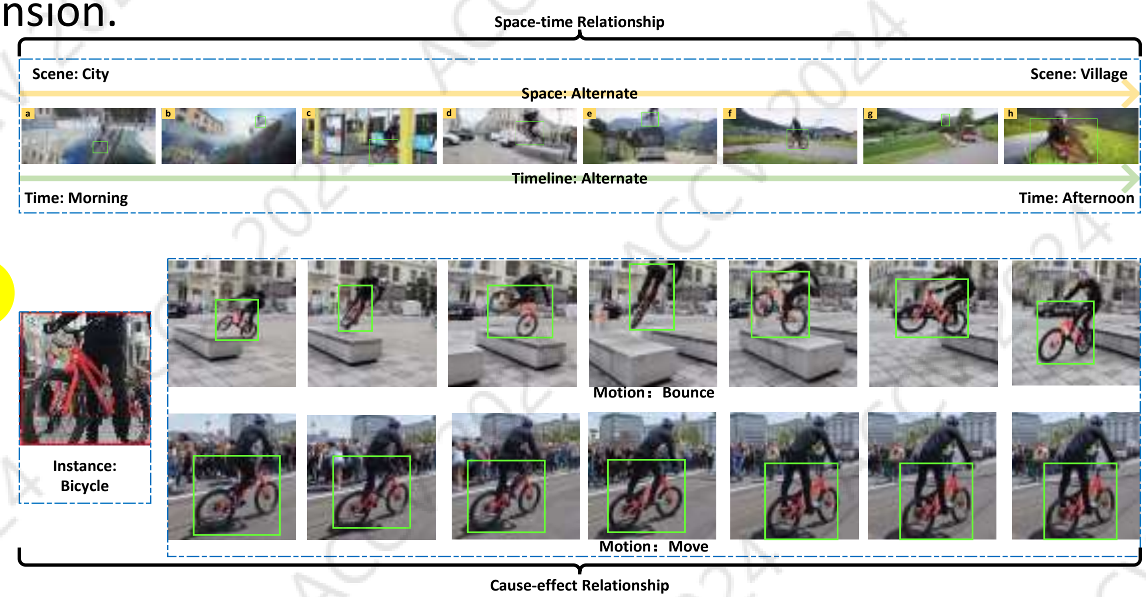
- **VideoCube (2023)**

➢ **Scientific collection principles:**

- Based on the **narrative theory of film**, the 6D principle is proposed to simulate real scenes.
- For the first time, **scene categories and spatio-temporal factors** are included in the collection dimension.



6D Principle



Collection Dimension

Film narrative is a chain of events in **cause-effect relationship** occurring in **space and time**.
(Bordwell & Thompson 2004, Film art : an introduction)

S. Hu, X. Zhao#, L. Huang, et al., "Global instance tracking: Locating target more like humans," IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), vol. 45, no. 1, pp. 576–592, 2023.

General Datasets: Large-scale GIT

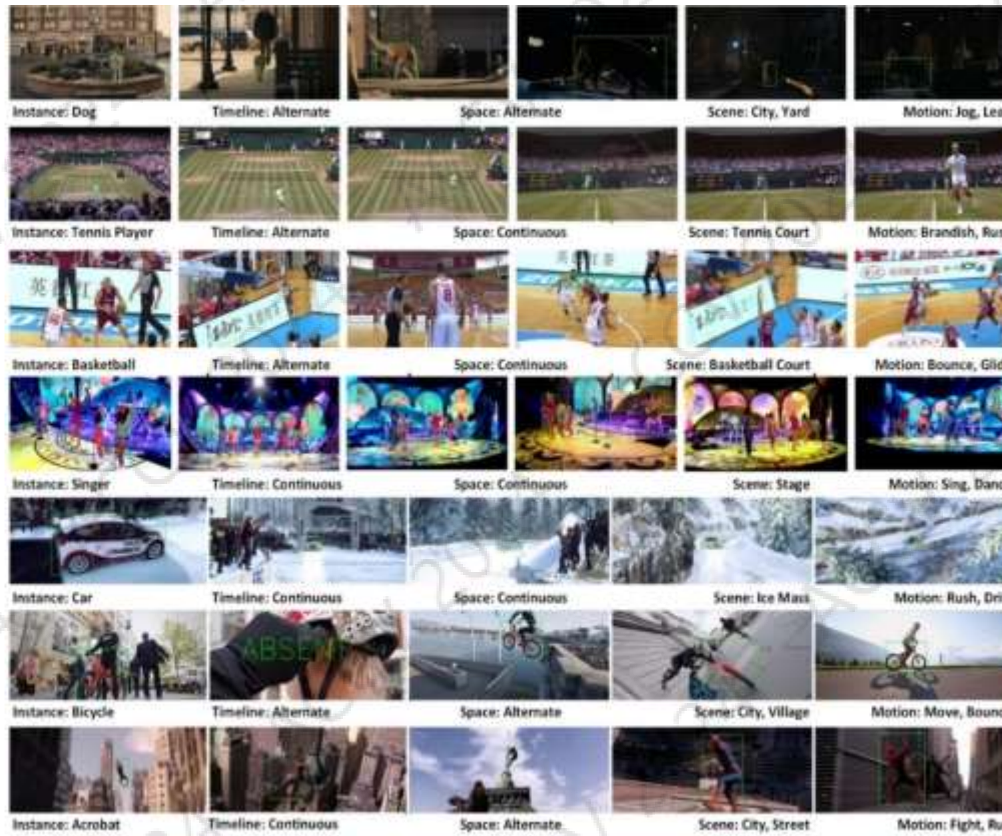
- **VideoCube (2023)**

➢ **Scientific collection principles:**

  - Compared with existing datasets, VideoCube has **richer content.**

LaSOT: Object Classes

GOT-10k: Object categories + motion modes



VideoCube: Target category + motion mode + scene category + spatiotemporal continuity

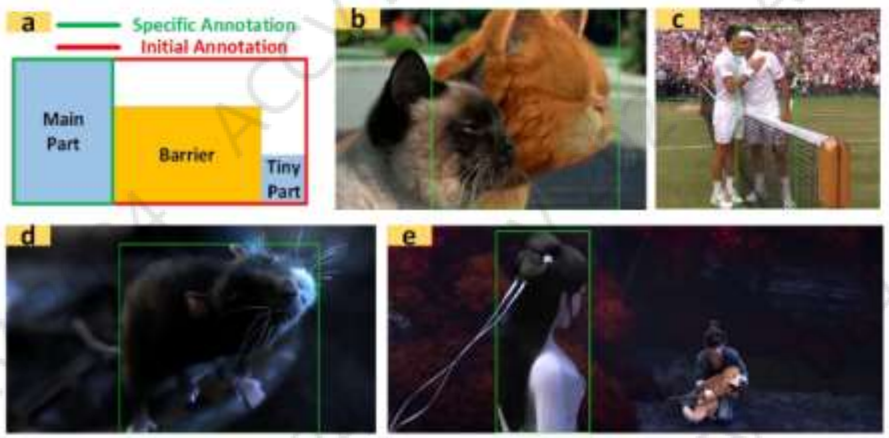
*S. Hu, X. Zhao#, L. Huang, et al., "Global instance tracking: Locating target more like humans," IEEE Transactions on Pattern Analysis and Machine Intelligence (**TPAMI**), vol. 45, no. 1, pp. 576–592, 2023.*

General Datasets: Large-scale GIT

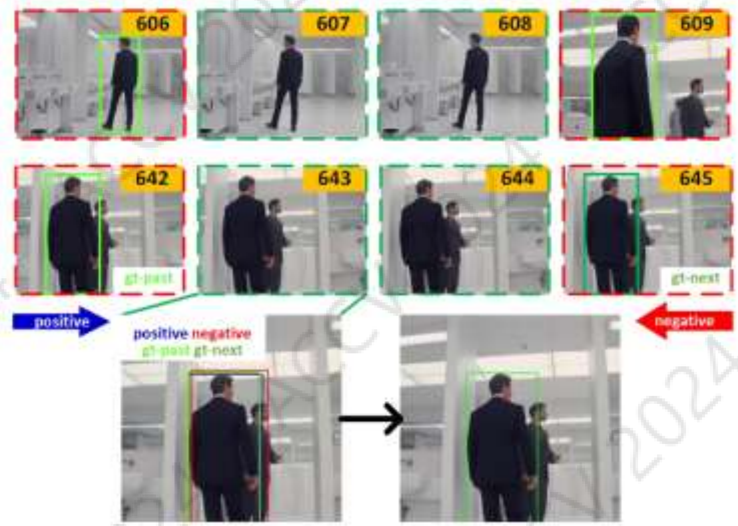
- **VideoCube (2023)**

➢ **High-precision labeling:**

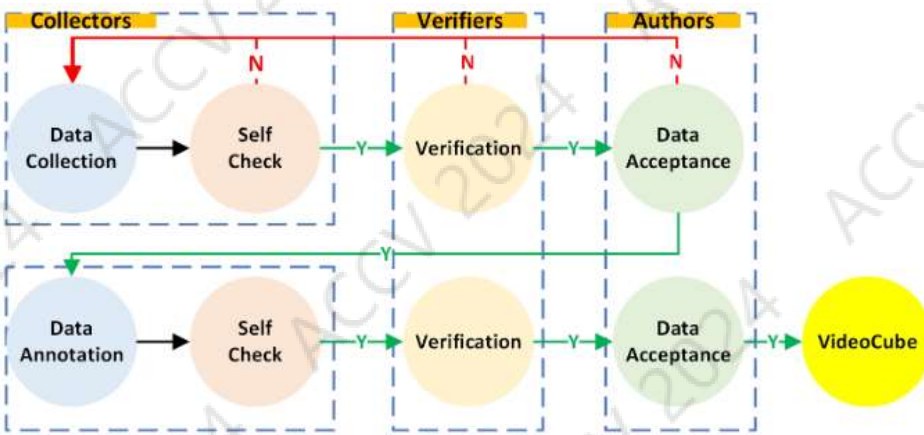
- Standardized labeling criteria + strict review process → **Improve data quality**



Specific rules in annotations



Manual & automatic annotations



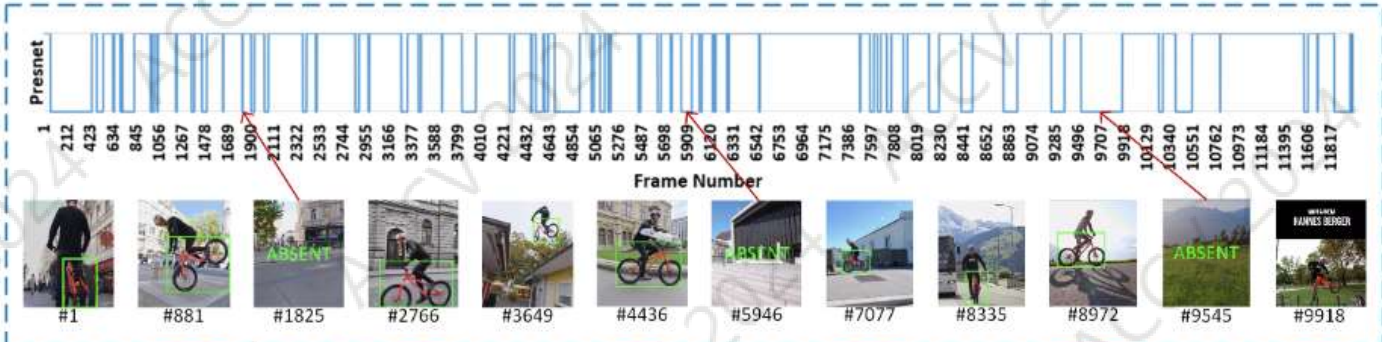
Data checkout process

General Datasets: Large-scale GIT

- **VideoCube (2023)**

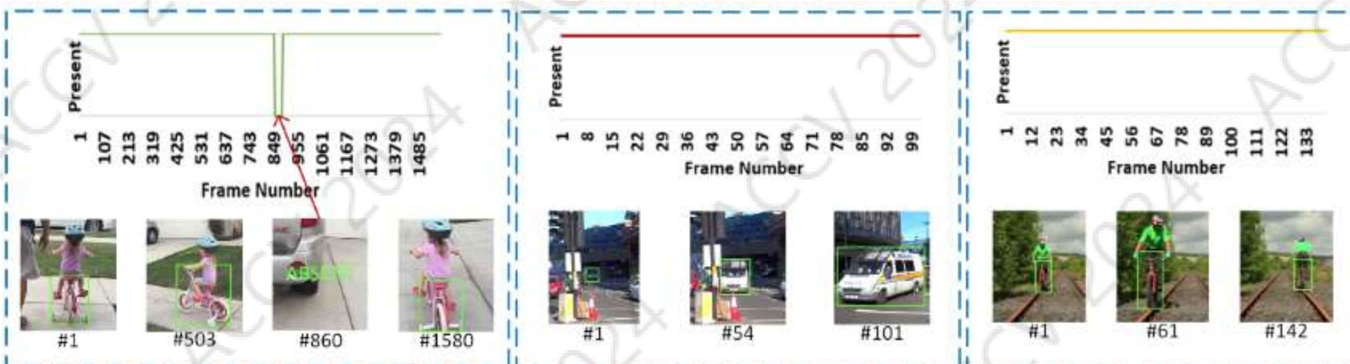
➢ **Large-scale dataset:**

- The duration of a single video segment is much longer than existing tracking datasets and **includes camera switching and scene transitions**.



(a) VideoCube

Long video sequences + rich shot switching and scene transitions



(b) LaSOT **(c) GOT-10k** **(d) OTB100**

Short video sequence + single shot + fixed scene

S. Hu, X. Zhao#, L. Huang, et al., "Global instance tracking: Locating target more like humans," IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), vol. 45, no. 1, pp. 576–592, 2023.

General Datasets: Large-scale GIT

- **VideoCube (2023)**

➢ **Large-scale dataset:**

- One of the largest SOT dataset currently, with an overall size **2~200 times** that of existing datasets

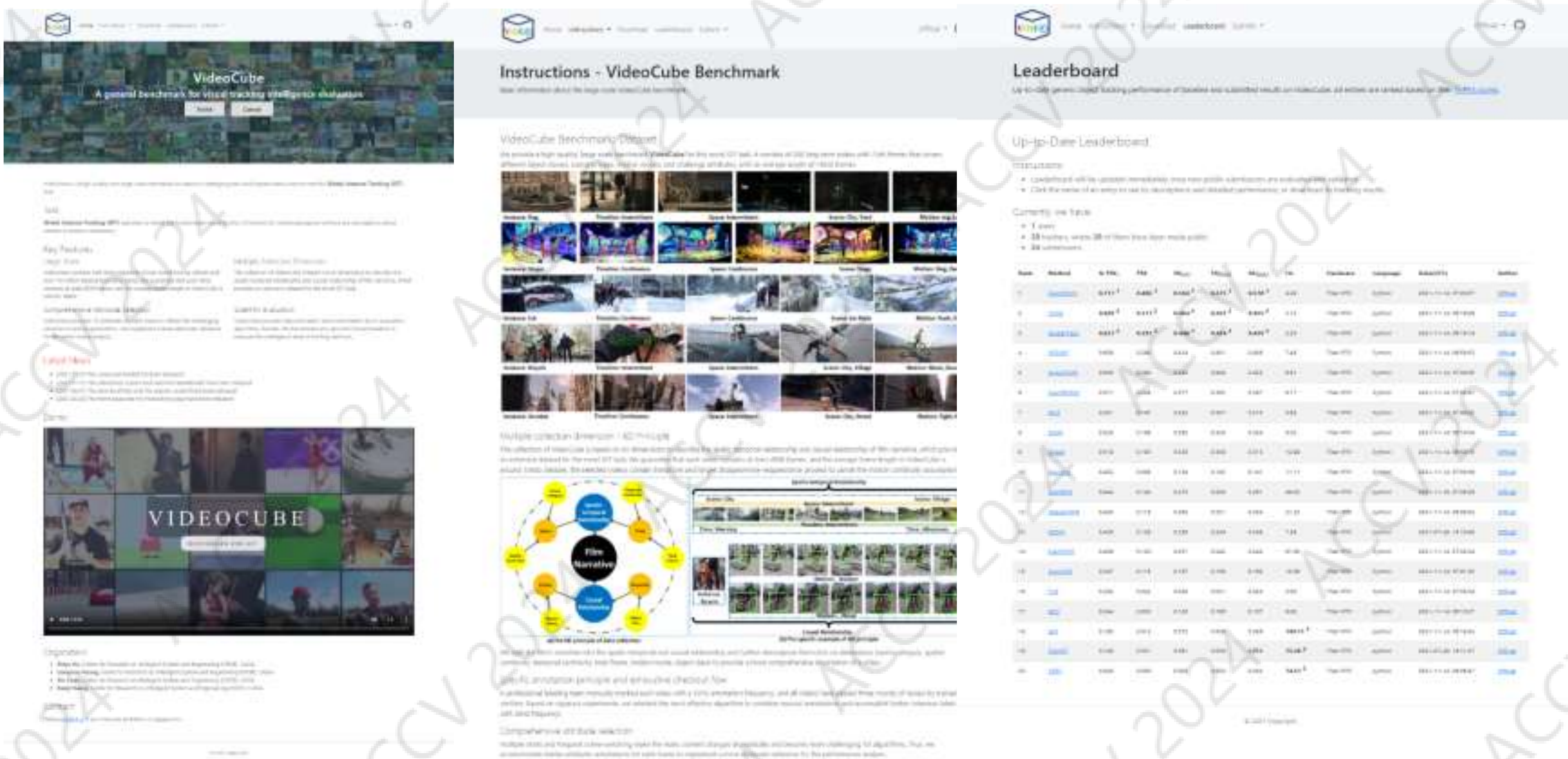
Benchmark	Year	Videos	Min Frame	Mean Frame	Median Frame	Max Frame	Total Frame	Total Duration	Label Density	Attribute Classes (Absent)	Object Classes	Motion Modes	Scene Categories
OTB2013 [34]	2013	51	71	578	392	3872	29K	16.4m	30Hz	11(✗)	10	n/a	n/a
OTB2015 [1]	2015	100	71	590	393	3872	59K	32.8m	30Hz	11(✗)	16	n/a	n/a
TC-128 [41]	2015	129	71	429	365	3872	55K	30.7m	30Hz	11(✗)	27	n/a	n/a
NUS-PRO [42]	2015	365	146	371	300	5040	135K	75.2m	30Hz	n/a	8	n/a	n/a
UAV123 [43]	2016	123	109	915	882	3085	113K	75.2m	30Hz	12(✗)	9	n/a	n/a
VOT-2017 [4]	2017	60	41	356	293	1500	21K	11.9m	30Hz	n/a	24	n/a	n/a
Nfs [44]	2017	100	169	3830	2448	20665	383K	26.6m	240Hz	9(✗)	17	n/a	n/a
TrackingNet [2]	2018	30643	-	498	-	-	14M	141h	1Hz(30Hz)[a]	15(✗)	27	n/a	n/a
GOT-10k [5]	2019	10000	29	149	101	1418	1.45M	40h	10Hz[b]	6(✓)	563[c]	87	n/a
UAV20L [43]	2016	20	1717	2934	2626	5527	59K	32.6m	30Hz	12(✗)	5	n/a	n/a
OxUvA [46]	2018	366	900	4320	2628	37740	1.55M	14.4h	1Hz[d]	(✓)[e]	22	n/a	n/a
LaSOT [3]	2020	1550	1000	2502	2145	11397	3.87M	35.8h	30Hz	14(✓)	85	n/a	n/a
VideoCube	2020	500	4008	14920	14162	29834	7.46M	69.1h	10Hz(30Hz)[f]	12(✓)	9(89)[g]	61	8(55)[h]

Comparison of VideoCube and other representative SOT benchmarks in various statistical dimensions

General Datasets: Large-scale GIT

- **VideoCube (2023)**

➢ Complete evaluation platform, real-time rankings, open-source toolkit.



http://videocube.aitestunion.com/

S. Hu, X. Zhao#, L. Huang, et al., "Global instance tracking: Locating target more like humans," IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), vol. 45, no. 1, pp. 576–592, 2023.

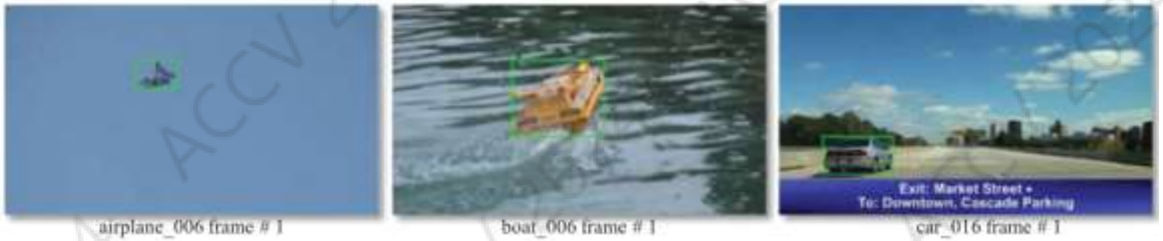
Specialized Datasets

Specialized datasets are designed with specific tracking challenges in mind, focusing on unique scenarios or target types.

Specialized Datasets: Specific Object

Specialized Evaluation Environments:
Specialized environments are designed for specific tasks or special target types and are characterized by their focus on "**small but precise**" datasets. These environments aim to measure tracking performance under specific evaluation requirements and unique scenarios.

- **NUS-PRO (2016)**



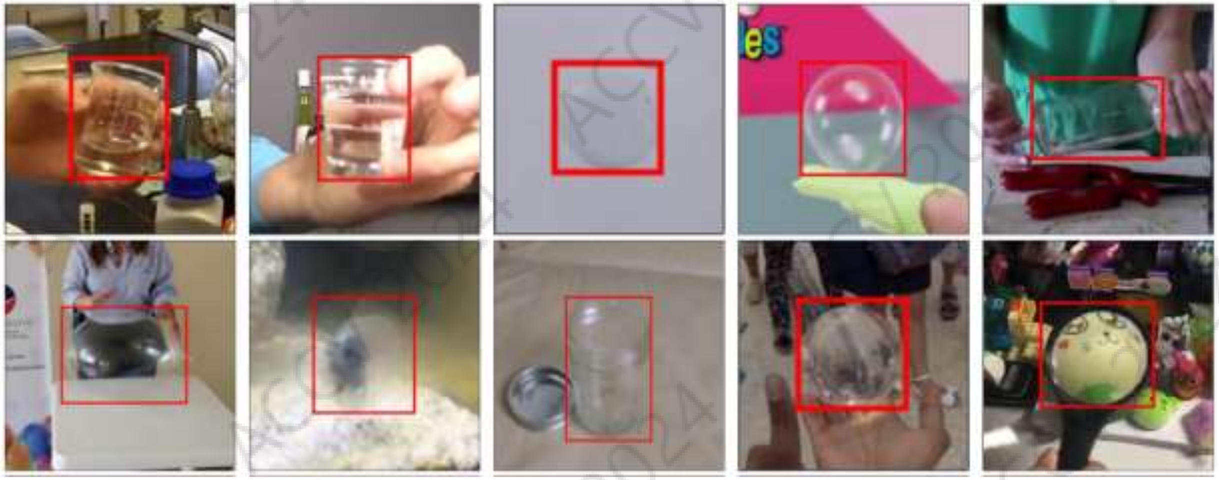
➢ NUS-PRO was developed to test tracking algorithms with a focus on two major target types: **people and rigid objects**, providing challenging sequences for tracking under occlusion conditions.

- **Improved Understanding of Occlusion:** NUS-PRO is particularly useful for evaluating the performance of algorithms in handling occlusion, a common challenge in real-world tracking scenarios.
- **Benchmark for Rigid and Non-rigid Tracking:** By including both people (non-rigid) and rigid objects, the dataset provides a versatile platform for testing the adaptability of tracking algorithms across different target types.

Li A, Lin M, Wu Y, et al. Nus-pro: A new visual tracking challenge[J]. IEEE transactions on pattern analysis and machine intelligence, 2015, 38(2): 335-349.

Specialized Datasets: Specific Object

- **TOTB (2021)**



➢ TOTB is designed specifically for tracking transparent objects, which pose significant challenges due to their weak appearance information and **sensitivity to background interference**.

- **Challenging Scenarios: 67.5% of the video sequences in TOTB contain background clutter**, further complicating the tracking task and emphasizing the robustness required by algorithms to handle these scenarios.
- **Evaluation of Algorithms in Complex Scenarios:** TOTB challenges current tracking algorithms to handle transparency and complex backgrounds, providing a benchmark to **test robustness in more difficult conditions**.

Fan H, Miththanthaya H A, Rajan S R, et al. Transparent object tracking benchmark[C]//Proceedings of the IEEE/CVF International Conference on Computer Vision. 2021: 10734-10743.

Specialized Datasets: Specific Scenario

- **UAV123 & UAV20L (2016)**

➢ UAV123 was created to evaluate the performance of object tracking algorithms in **challenging aerial scenarios captured from UAVs**. UAV20L is a subset of the UAV123 dataset, but focuses on long-duration video sequences to evaluate how well tracking algorithms can handle extended tracking sessions without losing the target.

- **Aerial Perspective:** The dataset emphasizes tracking from an aerial perspective, which introduces challenges like **object size reduction** and **frequent occlusions** due to camera movement.
- **Emphasis on Real-time Processing:** The challenging sequences require fast and efficient algorithms, pushing the boundaries of **real-time object tracking**.

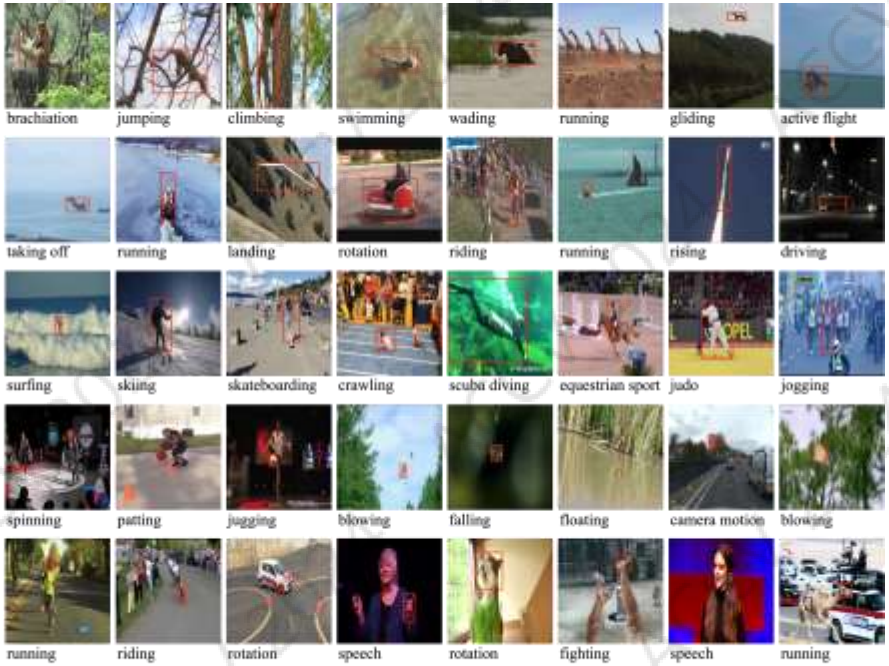
Mueller M, Smith N, Ghanem B. A benchmark and simulator for UAV tracking[C]//Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part I 14. Springer International Publishing, 2016: 445-461.

Specialized Datasets: Specific Scenario

- **BioDrone (2024)**

➢ **Motivation:** Limitations of the existing experimental environment in terms of robustness:

- Mainly focus on general scenarios, **ignoring the attention of highly challenging special scenarios**
- Mainly based on fixed lenses or handheld lenses to record moving targets, resulting in a short distance between the lens and the target, **lack of small targets and fast motion challenges**

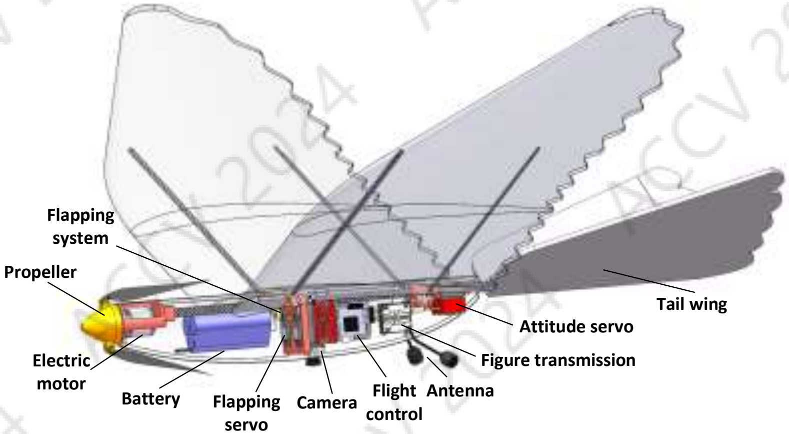


X. Zhao, S. Hu#, Y. Wang, et al., "Biodrone: A bionic drone-based single object tracking benchmark for robust vision," International Journal of Computer Vision (IJCV), 2024.

Specialized Datasets: Specific Scenario

- **BioDrone (2024)**

➢ **Robust Vision Research Dataset:**
- The first SOT dataset from the perspective of a **bionic flapping-wing drone.**
- The aerodynamic structure of a bionic flapping-wing drone is different from that of a traditional fixed-wing or rotary-wing drone, and there is **severe jitter between the shots.**

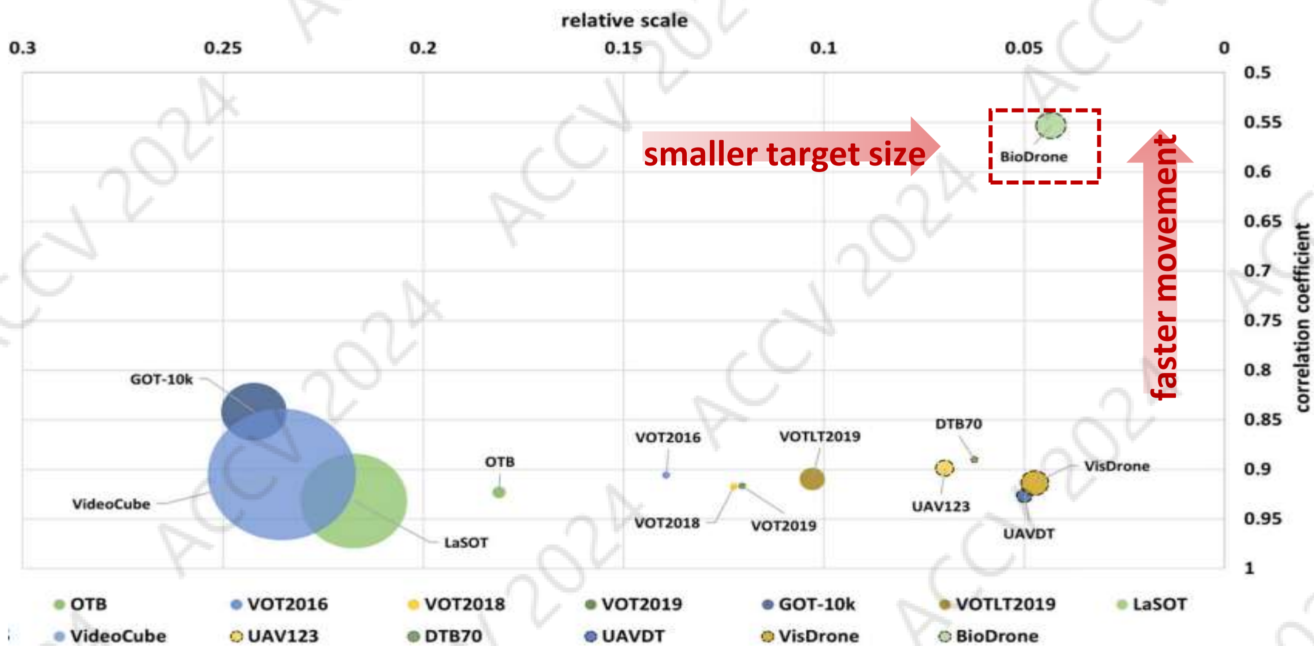


X. Zhao, S. Hu#, Y. Wang, et al., "Biodrone: A bionic drone-based single object tracking benchmark for robust vision," International Journal of Computer Vision (IJCV), 2024.

Specialized Datasets: Specific Scenario

- **BioDrone (2024)**

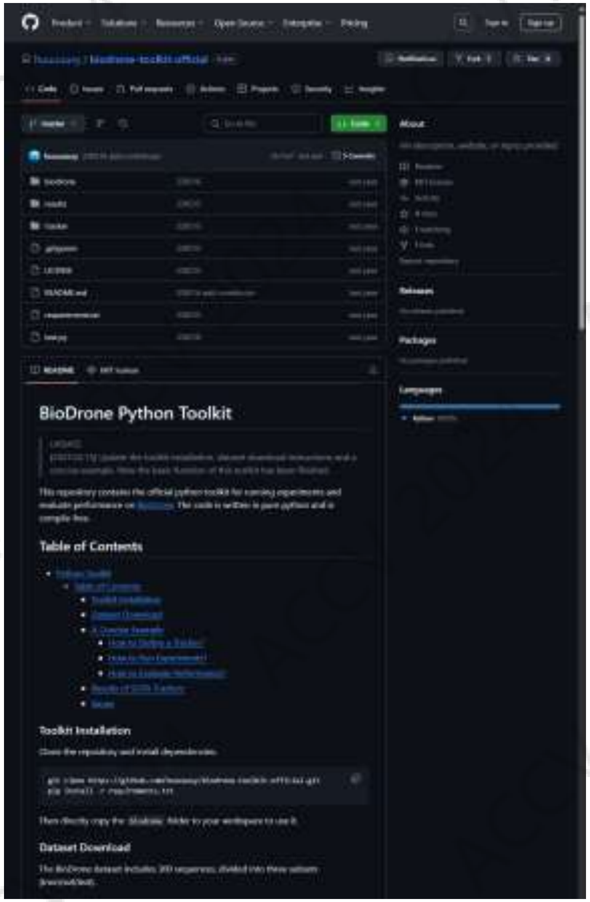
➢ **Robust Vision Research Dataset:**
  - Includes different flight altitudes, flight angles and flight environments, highlighting the challenges of **fast movement and small targets.**



Specialized Datasets: Specific Scenario

- **BioDrone (2024)**

➢ Complete evaluation platform, real-time rankings, open-source toolkit



http://biodrone.aitestunion.com/

X. Zhao, S. Hu#, Y. Wang, et al., "Biodrone: A bionic drone-based single object tracking benchmark for robust vision," International Journal of Computer Vision (IJCV), 2024.

Competition Datasets

Competition datasets provide standardized benchmarks for comparing the performance of tracking algorithms under controlled and real-world conditions.

Competition Datasets

- **VOT-ST -> VOT-LT -> VOT-RGBT / VOT-RGBD**

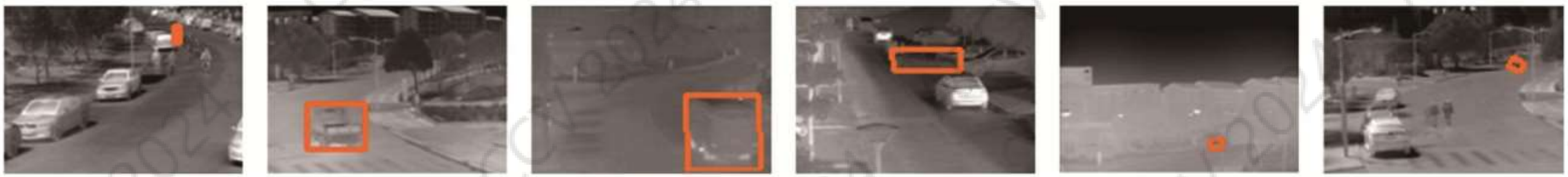
VOT (Visual Object Tracking) Challenge:
The VOT Challenge is an annual event established in 2013. It is **one of the most influential competitions** in the field of visual object tracking, providing standardized evaluation datasets and protocols.

- **VOT-ST competition:** employs **rotated bounding boxes** or **segmentation**, supporting research in joint target segmentation and tracking tasks.

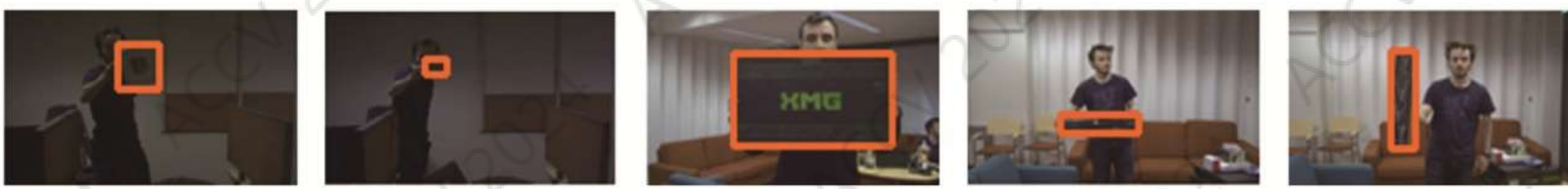
Competition Datasets

- **VOT-ST -> VOT-LT -> VOT-RGBT / VOT-RGBD**

➢ **VOT-LT competition:** allowing target disappearance as the distinguishing criterion between short-term and long-term tracking, and collected **50 long video sequences** as competition data.



➢ **VOT-TIR and VOT-RGBT competitions:** based on **thermal imaging** to conduct target tracking. Thermal imaging information is **less affected by lighting**, so it can still provide environmental information under **special lighting conditions.**



➢ **VOT-D and VOT-RGBD competitions:** focus on **depth information**, which can effectively separate foreground and background while providing additional support for **target occlusion issues.**

Conclusion

ACCV

- **General Evaluation Environments:**
  - General evaluation environments feature an early start in research, numerous representative works, and wide data coverage.
  - These environments aim to **provide a comprehensive experimental platform** for evaluating the **overall capabilities** of tracking algorithms in **general scenarios**.

- **Specialized Evaluation Environments:**
  - Specialized environments are designed for **specific tasks or special target types** and are characterized by their focus on “**small but precise**” datasets.
  - These environments aim to measure tracking performance under **specific evaluation requirements and unique scenarios**.

Conclusion

➢ **Competition-Based Evaluation Environments:**

- Competition environments are released as part of tracking competitions.
- These environments usually feature **highly challenging** video sequences designed to **rapidly expose algorithm weaknesses**.
- The goal is to rank participating algorithms based on **multiple performance dimensions.**

The goal is to help researchers understand the characteristics and focus of each environment, enabling them to build evaluation settings that are better suited for the specific evaluation objectives.

CONTENTS

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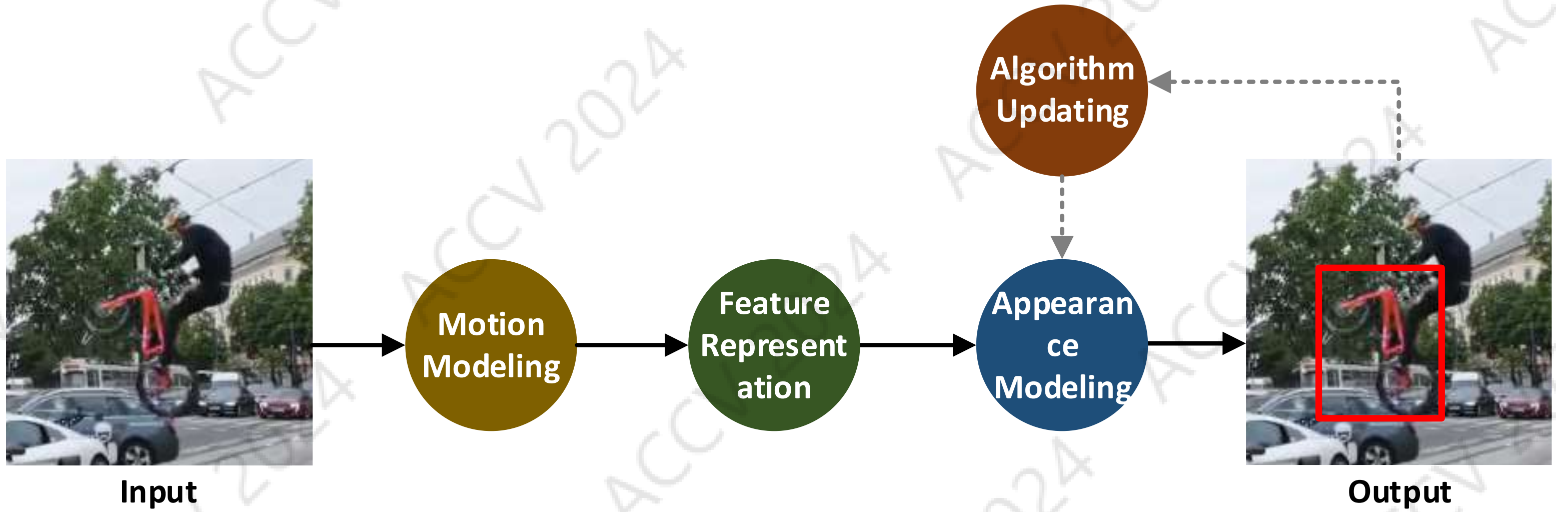
Machines

We will explore different types of machine-based tracking systems, including traditional algorithms and more advanced deep learning models.

Machines: Traditional Trackers

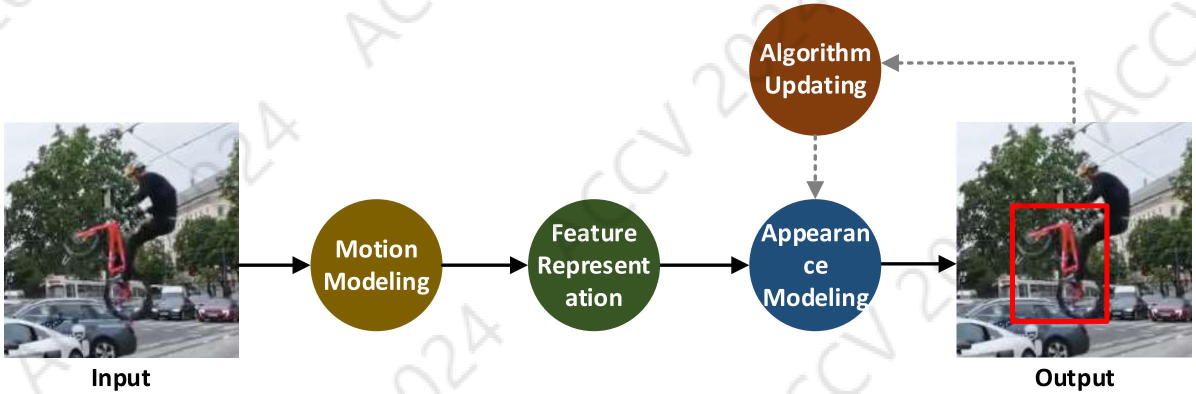
Traditional trackers :
Traditional trackers usually includes the following steps: **motion modeling, feature representation, appearance modeling, and algorithm updating**.



➢ **Motion modeling**

- **Purpose:** Predict the target trajectory in subsequent frames by estimating the position state of the target.
- **Representative Methods:** Particle filtering, Sliding window

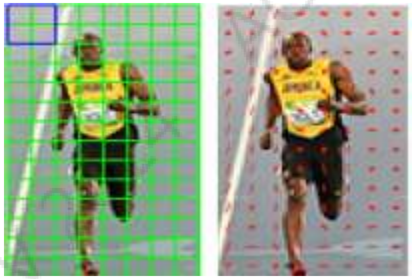
Machines: Traditional Trackers



➢ **Feature Representation**

- **Global Features:** Early methods extracted features from the **entire target**.
  - ☐ Grayscale features, gradient histogram features, and color histogram features

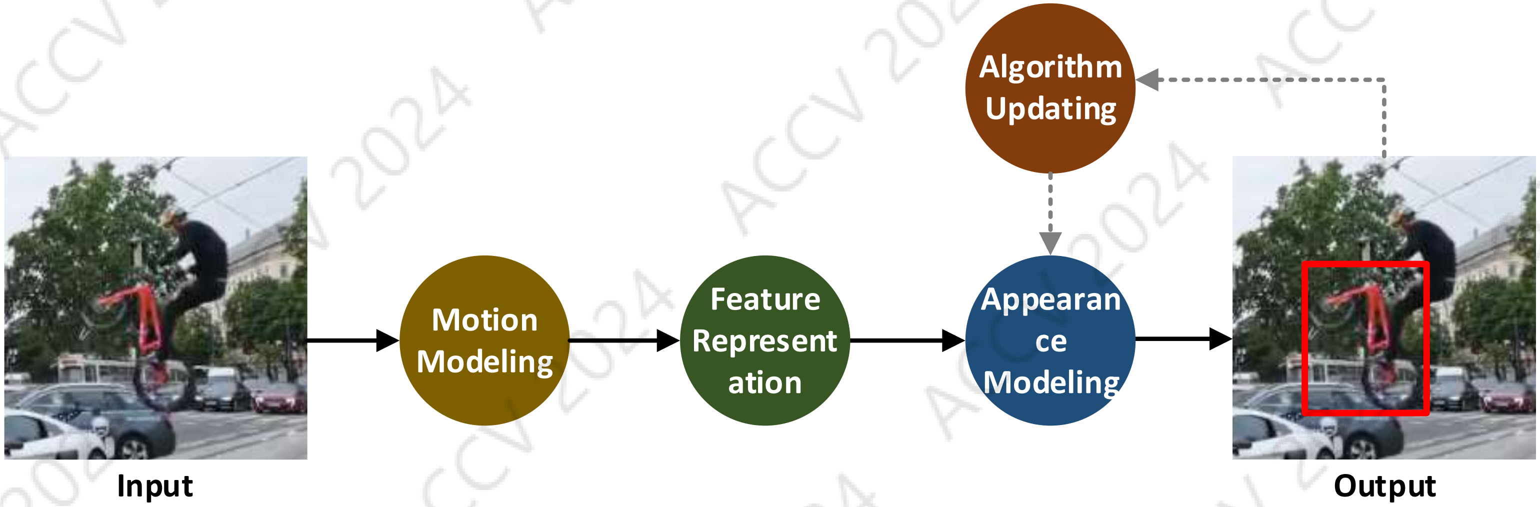
grayscale features



gradient histogram features

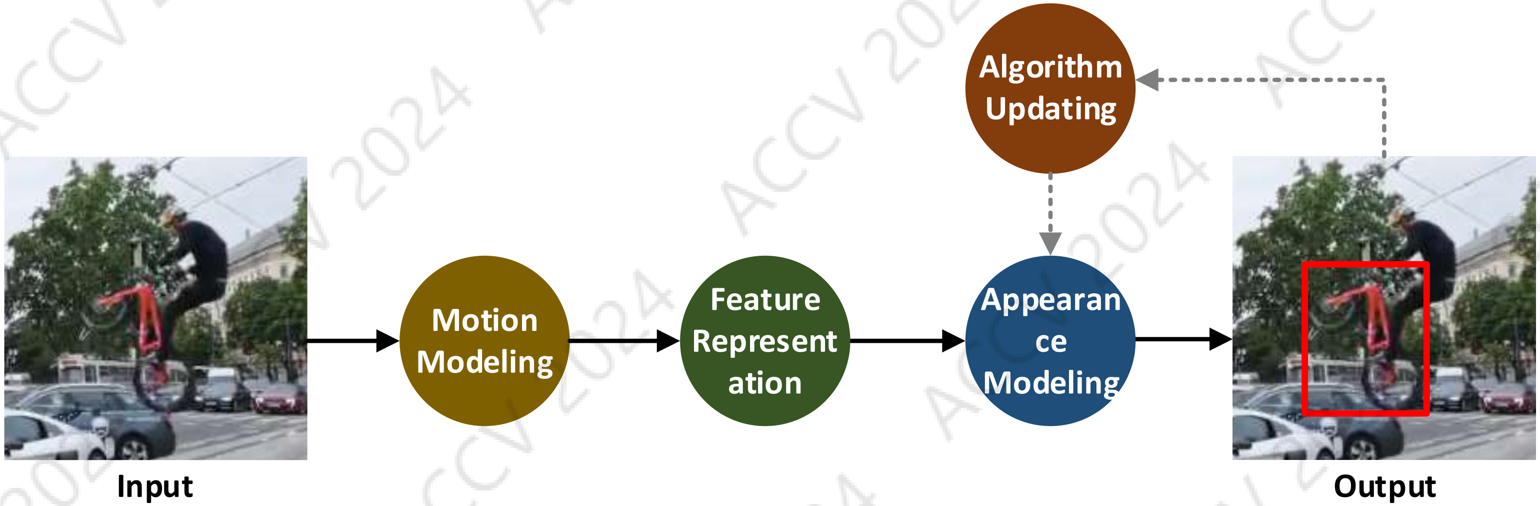
- **Local Features:** To **handle challenges** like occlusion and deformation, local feature extraction methods were applied.
  - ☐ Segment the target into independent regions and fuse information from each part

Machines: Traditional Trackers



- **Appearance Modeling**
  - **Generative Methods:**
    - ☐ First, maintain a target template set using methods like incremental subspace or block sparse representation.
    - ☐ Then, measure **similarity** based on the **distance** between the candidate sample and the target template set.
  - **Discriminative Methods：**
    - ☐ Treat tracking as a **classification problem**, classifying between the target and the background.

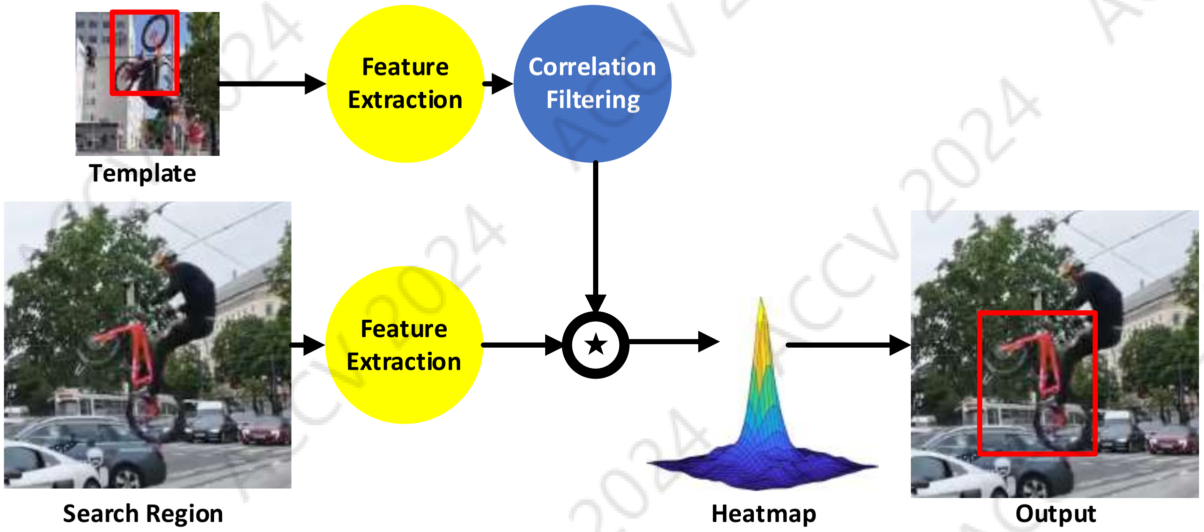
Machines: Traditional Trackers



➢ **Algorithm Updating**

- **Purpose:**
  - ☐ The initial static template struggles to **continuously guide tracking for dynamically changing targets**.
  - ☐ The update strategy ensures that the algorithm **adapts to changes** in the target's appearance.
- **Representative Methods：**
  - ☐ Incremental learning-based updates
  - ☐ Online refactoring of the appearance model

Machines: Correlation Filter Based Trackers



- **Overall Process:** Feature extraction, correlation filtering, output prediction
- **Advantages:**
  - **Correlation filter theory** expands training samples through cyclic shifts, effectively solving the problem of insufficient data in early methods.
  - **Fast Fourier Transform** reduces computational load and improves tracking efficiency.
- **Representative Methods：** KCF, ECO, UPDT

Machines: Correlation Filter Based Trackers

➢ **Kernel Correlation Filter (KCF) Algorithm**

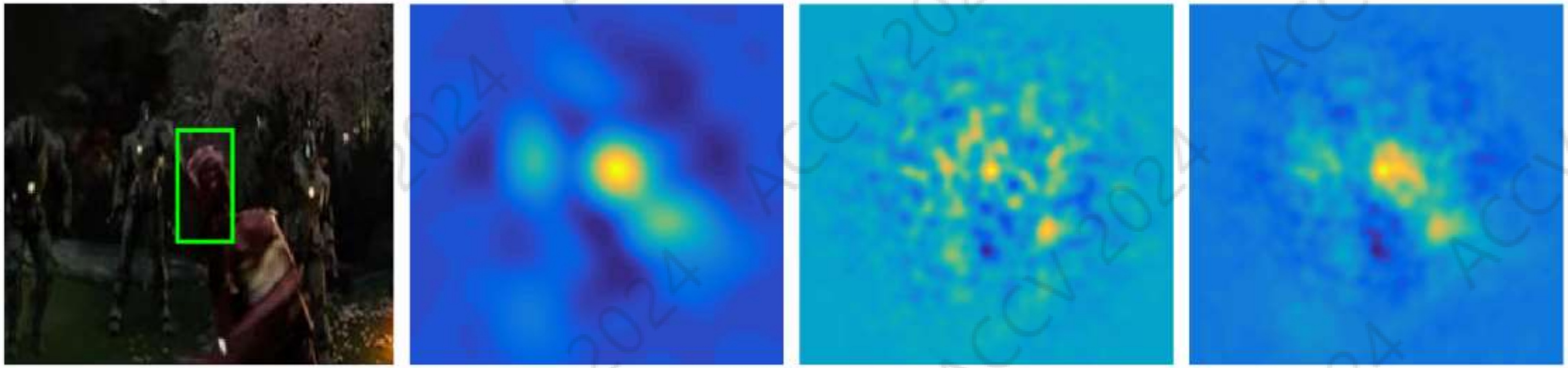
- A typical discriminative object tracking method.
- **Determines the target position by training a filter**, with high computational efficiency and strong tracking performance.
- **Core Design:**
  - ☐ **Target Initialization (t frame)**: Select the target and sample around it to train the classifier (filter).
  - ☐ **Target Position Update (t+1 frame)**: Sample near the target in the t+1 frame, use the classifier to perform correlation operations, and calculate the response at the sampling points.
  - ☐ **Determine Target Position**: Identify the sampling point with the **strongest response** that meets the threshold, and treat it as the target position in the t+1 frame.

Henriques J F, Caseiro R, Martins P, et al. High-speed tracking with kernelized correlation filters[J]. IEEE transactions on pattern analysis and machine intelligence, 2014, 37(3): 583-596..

Machines: Correlation Filter Based Trackers

- **Efficient Convolutional Operators (ECO) Algorithm**
  - Aims to address the **computational complexity and overfitting issues** in Discriminative Correlation Filter (DCF) methods.
  - **Core Design:**
    - ☐ **Factorized Convolution Operators:** Reduced model parameters, lowering complexity and avoiding overfitting.
    - ☐ **Generative Sample Space Model:** A compact sample generation model that enhances the diversity of training samples.
    - ☐ **Conservative Model Update Strategy:** By reducing the frequency of model updates, it improves tracking speed and prevents model drift.

Machines: Correlation Filter Based Trackers

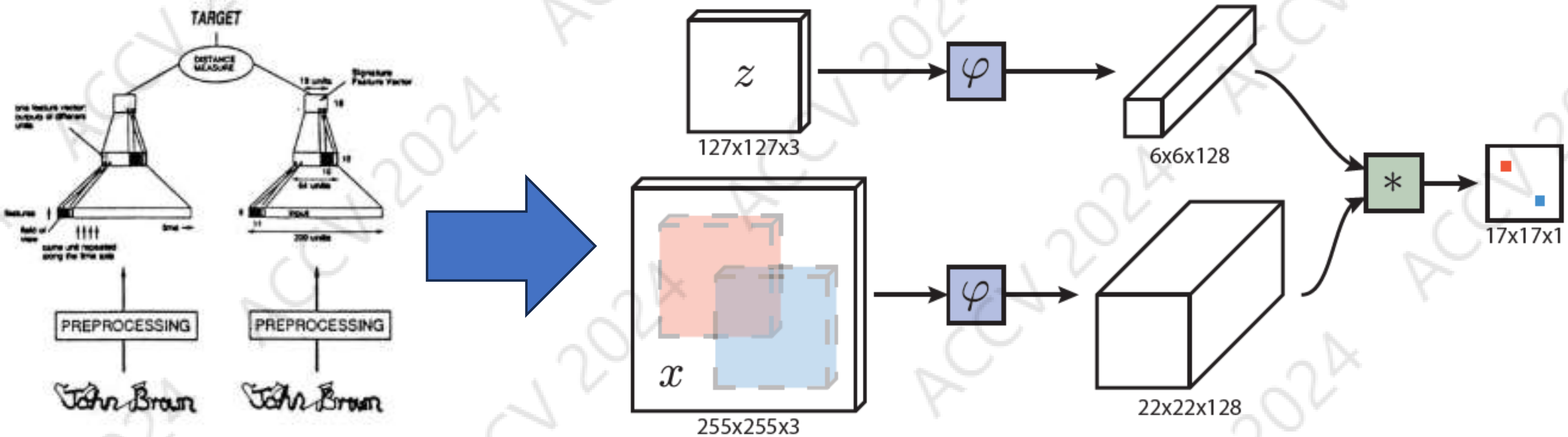


(a) Image sample (b) Deep score (c) Shallow score (d) Fused score

- **Unveiling the Power of Deep Tracking (UPDT) Algorithm**
  - Solves the issue in ECO where **deep features were not fully utilized**.
  - **Core Design:**
    - **Separation of Deep and Shallow Features:** Deep features model high-level semantic information, while shallow features model texture and color information.
    - **Adaptive Response Map Fusion:** Based on detection quality assessment, adaptively fuses the response maps of deep and shallow features with weighted fusion.

Bhat G, Johnander J, Danelljan M, et al. Unveiling the Power of Deep Tracking [J]. arXiv preprint arXiv:1804.06833, 2018.

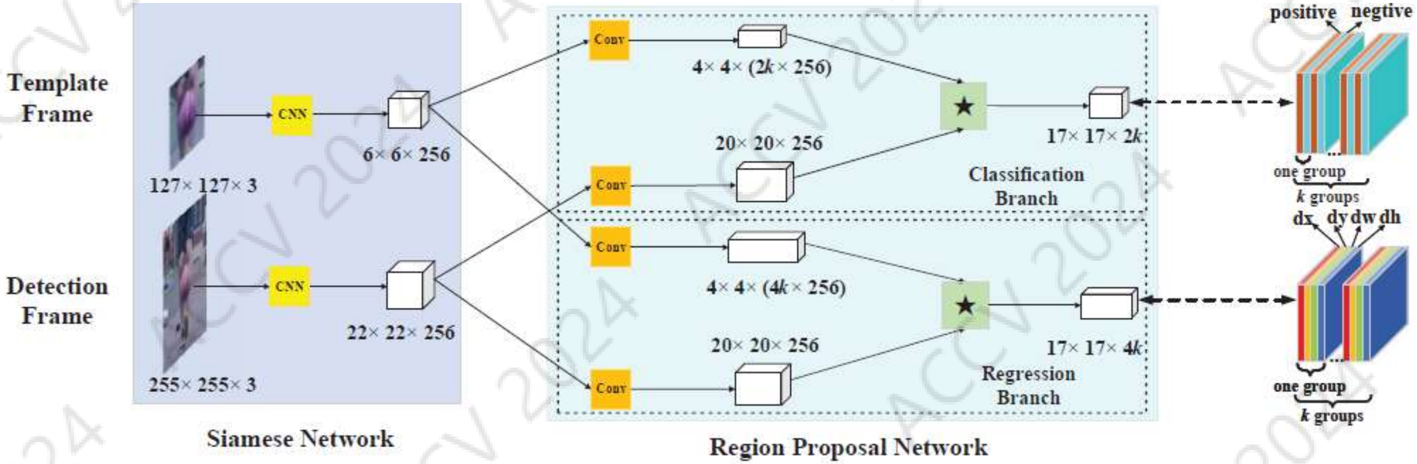
Machines: Siamese Network



- **SiamFC Algorithm**
  - **Network Architecture:** SiamFC uses two identical fully convolutional networks (FCNs) to extract features from the target template in the first frame and the search region in the subsequent frames. The network computes the cross-correlation between the two feature maps to predict the location of the object in the search region.
  - **Core Design:** SiamFC assumes that the object remains within a specific search region and relies on the correlation between frames to track the object **without needing to update the model online.**
  - **Impact**: SiamFC laid the groundwork for further development in deep learning-based object tracking.

Bertinetto, Luca, et al. "Fully-convolutional siamese networks for object tracking." Computer Vision–ECCV 2016 Workshops

Machines: Siamese Network

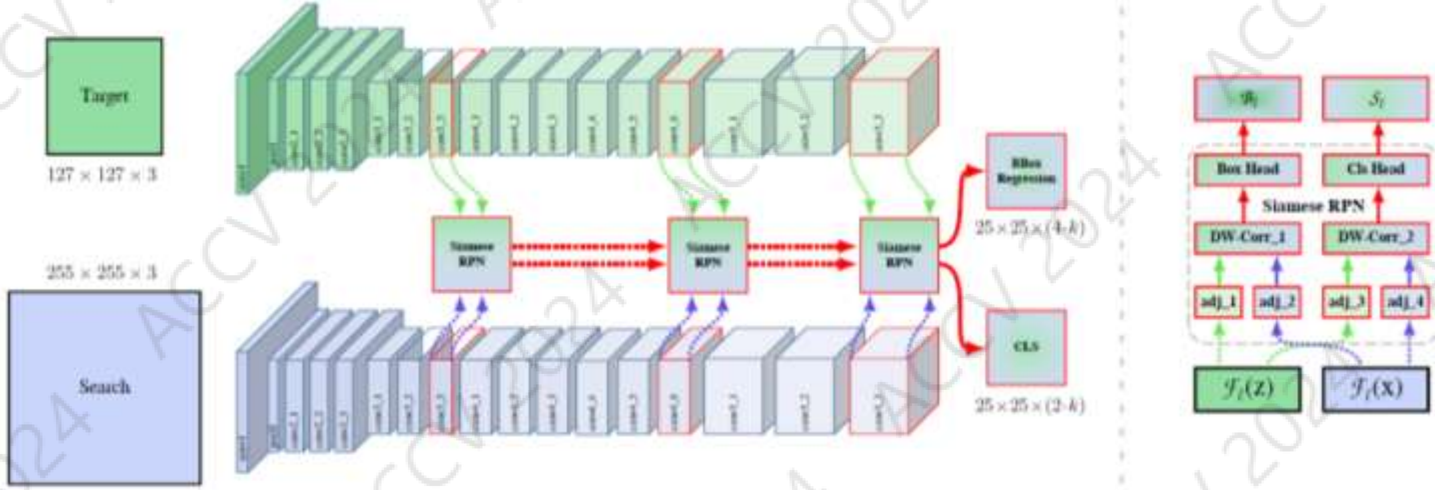


SiamRPN adopts the Region Proposal Network (RPN), enabling the tracker to predict position and shape.

- **SiamRPN Algorithm**
  - **Network Architecture:** SiamRPN consists of two fully convolutional Siamese networks to extract features from the target template and the search region. These features are then passed through the RPN, which generates **region proposals** and refines the bounding box for the tracked object.
  - **Core Design:** SiamRPN treats object tracking as a **detection problem** by using RPN to predict the object's location and bounding box in each frame. This allows for more accurate localization and **bounding box regression**, improving the tracking performance, especially for objects undergoing **scale and shape changes**.

Li, Bo, et al. "High performance visual tracking with siamese region proposal network." CVPR. 2018.

Machines: Siamese Network



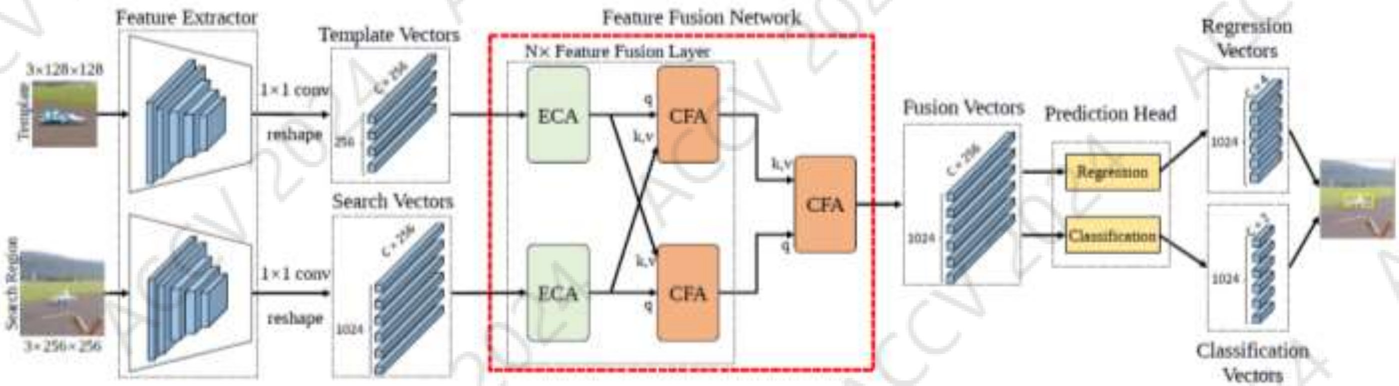
SiamRPN++ adjusted the sampling strategy, making it possible to use deep networks like ResNet-50.

➢ **SiamRPN++ Algorithm**

- **Network Architecture:** SiamRPN++ uses a ResNet backbone to extract more robust and discriminative features. This improves the network's ability to handle complex scenarios, including large appearance variations, occlusion, and background clutter, while maintaining real-time performance.
- **Core Design:** By upgrading the backbone from shallow convolutional networks to **deeper** ones (such as ResNet-50), SiamRPN++ can capture more detailed and **hierarchical feature representations**, which improves tracking performance in challenging conditions.

Li, Bo, et al. "Siamrpn++: Evolution of siamese visual tracking with very deep networks." CVPR. 2019.

Machines: Siamese Network

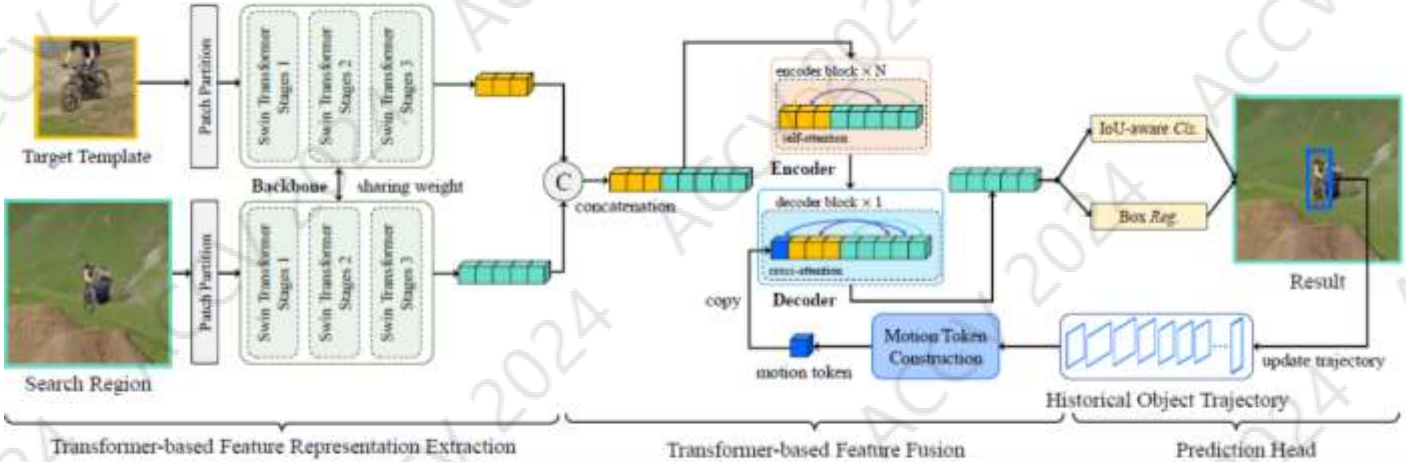


TransT incorporates attention to replace the conventional correlation operation, efficiently merging the features of the template and search region.

- **TransT Algorithm**
  - **Network Architecture:** Unlike simple linear correlation in traditional trackers, TransT applies an attention mechanism in the feature fusion module to extract more comprehensive and context-aware feature representations. The **self-attention mechanism** in Transformers allows the model to capture dependencies between the target and the background more effectively.
  - **Core Design:** The central idea of TransT is to leverage Transformer networks to model **long-range dependencies** and capture **global contextual information** in the feature space, leading to more robust tracking performance, particularly in challenging scenarios like occlusions, scale variation, and background clutter.

Chen, Xin, et al. "Transformer tracking." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2021.

Machines: Siamese Network

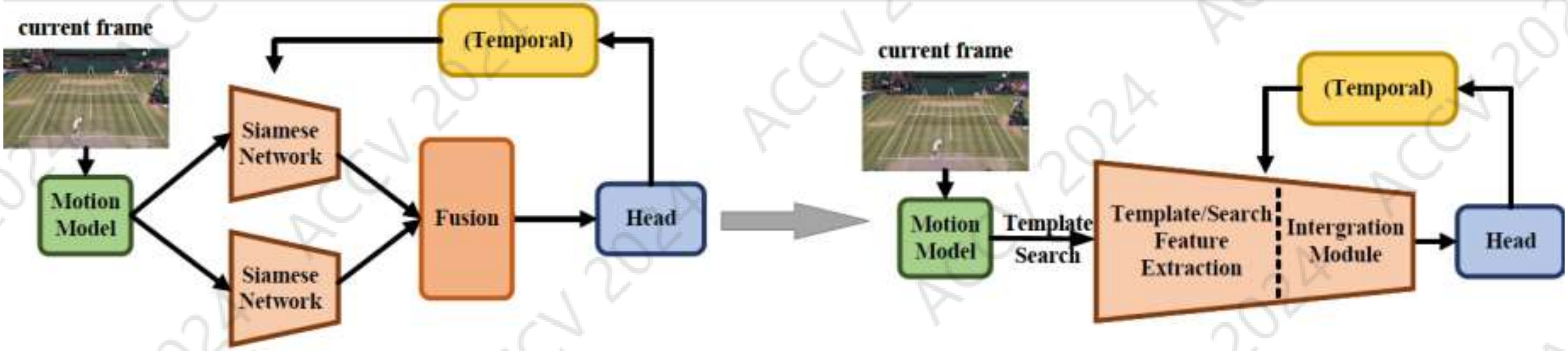


SwinTrack adopts the Swin Transformer as its backbone, while also utilizing an attention-based feature fusion module. This represents a major leap for Transformer-based trackers.

- **SwinTrack Algorithm**
  - **Network Architecture:** SwinTrack is a state-of-the-art object tracking algorithm that leverages the **Swin Transformer** architecture for feature extraction and modeling long-range dependencies. The Swin Transformer, originally proposed for visual recognition tasks, is adapted in SwinTrack to handle the unique challenges of object tracking.
  - **Core Design:** SwinTrack utilizes shifted **window-based attention** to efficiently capture both **local and global contextual information**, making it particularly effective in complex tracking scenarios involving occlusions, background clutter, and varying object scales.

Lin, Liting, et al. "Swintrack: A simple and strong baseline for transformer tracking." NeurIPS 2022.

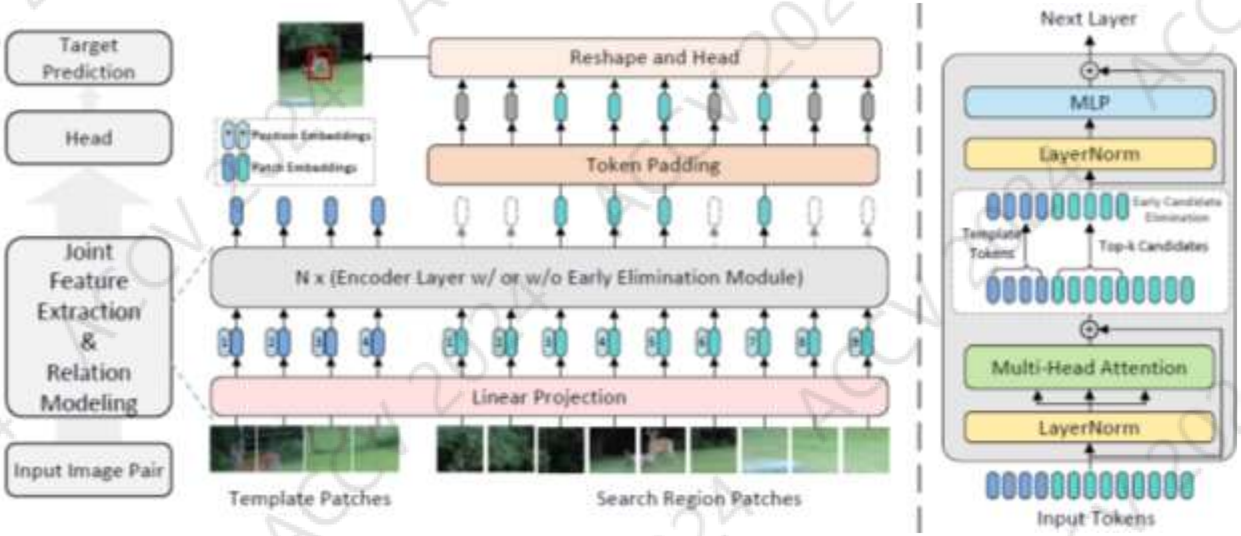
Machines: One-Stream Trackers



(a) pipeline of Siamese Network (b) pipeline of One-Stream Network

- The original Siamese neural network (SiamFC) used a **CNN backbone** and a **cross-correlation layer** for feature fusion. This **two-stream approach** processes the template and search region separately, then merges the results for tracking.
- As the field of computer vision and hardware have progressed, **self-attention mechanisms** have been introduced into Siamese networks. This has led to the development of **Transformer-based one-stream architectures**, which process both the template and search region in a unified manner, ultimately replacing the Siamese structure.

Machines: One-Stream Trackers

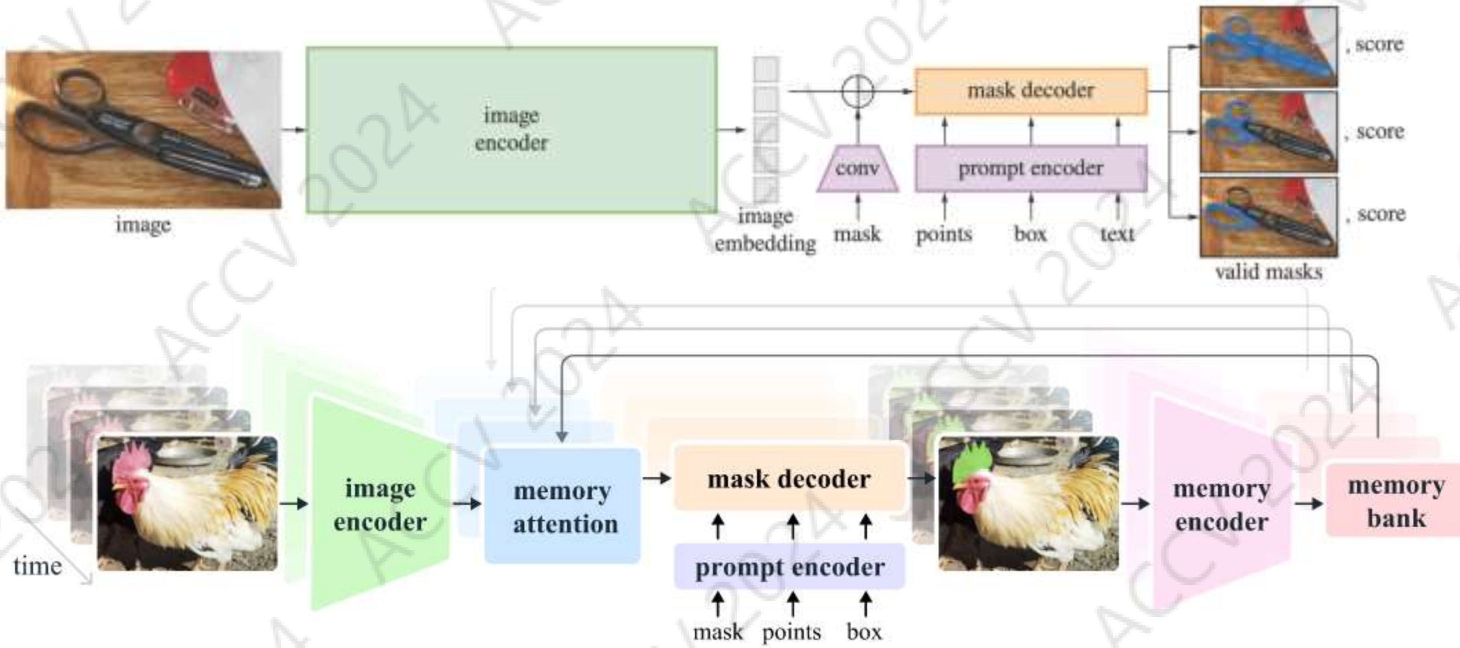


➢ **OSTrack Algorithm**

- OSTrack proposes a unified one-stream architecture where both **feature learning and relation modeling** are performed within a single network. This contrasts with traditional tracking models that may separate feature extraction from the relation modeling process, thus **reducing computational overhead and improving efficiency.**
- **Core Design:** The framework integrates feature learning and the relationship between the target and the search region in **one stream**, ensuring that the network can simultaneously learn object representations and how they relate to the background or other objects in the scene.

Ye, Botao, et al. *"Joint feature learning and relation modeling for tracking: A one-stream framework." ECCV, 2022.*

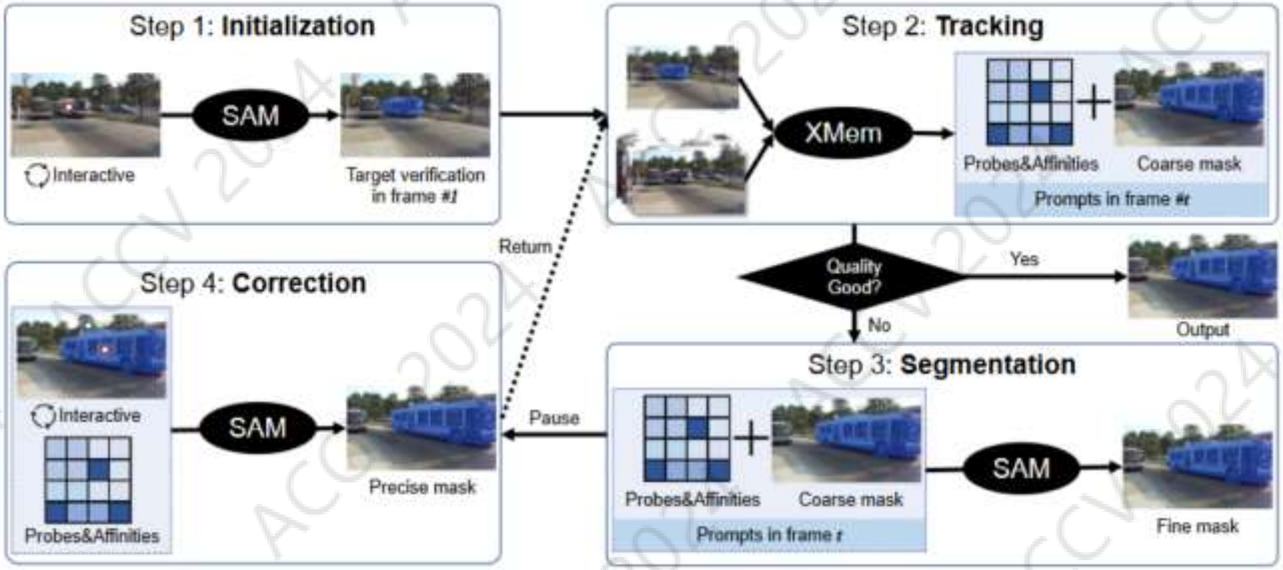
Machines: LVM-based Trackers



SAM & SAM2

- **Background:** Recently, foundational vision/multimodal models have demonstrated exceptional capabilities in perceiving and understanding image/modality content.
  - **How can these models be applied to SOT tasks? → Design a pipeline**
- **Exploratory Works**
  - TAM (Track Anything Model)
  - SAM-Track (Segment and Track Anything)
  - TrackGPT (Tracking with Human-Intent Reasoning)

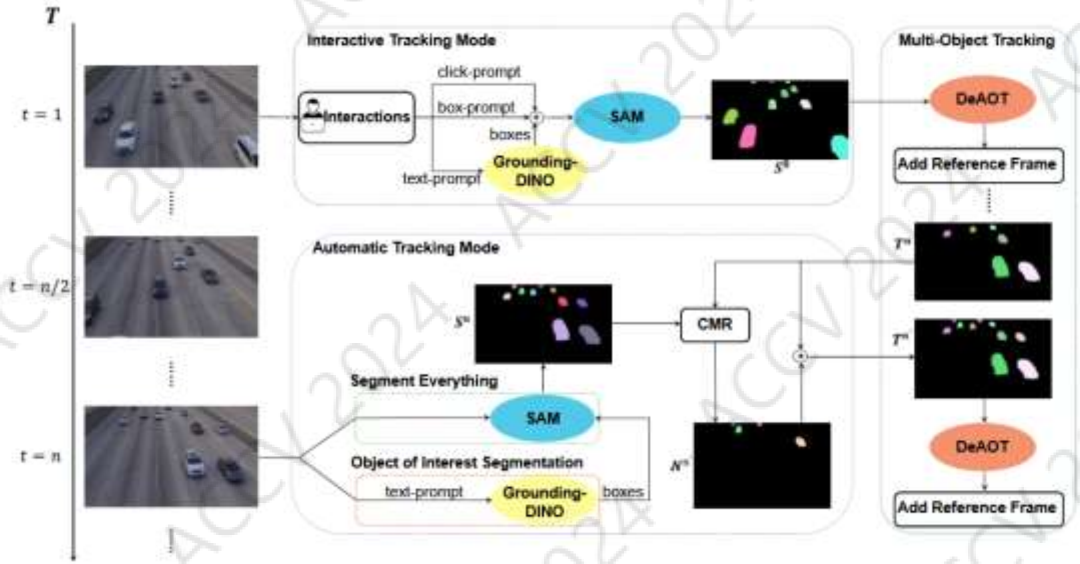
Machines: LVM-based Trackers



- **TAM (Track Anything Model):** Combines SAM, DeAOT, and Grounding-DINO to create an efficient multi-object video segmentation model.
- **Pipeline**
  - Users **interactively initialize** by clicking on the object to define the target.
  - XMem is used to give mask predictions for the object in the next frame based on **temporal and spatial correspondence**.
  - SAM is utilized to provide a more **precise mask description**.
  - Users can **pause** and correct the tracking immediately upon noticing a failure.

Yang J, Gao M, Li Z, et al. Track anything: Segment anything meets videos[J]. arXiv preprint arXiv:2304.11968, 2023.

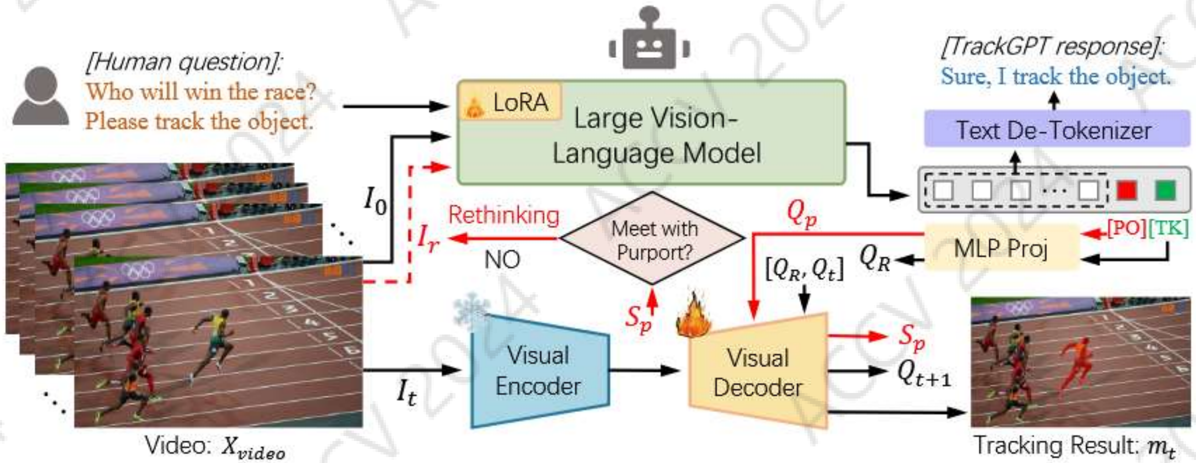
Machines: LVM-based Trackers



- **SAM-Track (Segment and Track Anything):** Applies SAM to the XMem video segmentation model, achieving an interactive video object segmentation model.
- **Pipeline**
  - **Multimodal Interaction:** Users can select the target through clicking, drawing, or text input.
  - **Automatic Tracking:** SAM-Track, combined with DeAOT, automatically tracks multiple objects in the video.
  - **Enhanced Semantic Understanding:** With Grounding-DINO, SAM-Track supports object selection based on natural language.

Cheng Y, Li L, Xu Y, et al. Segment and track anything[J]. arXiv preprint arXiv:2305.06558, 2023.

Machines: LVM-based Trackers



- **TrackGPT:** Proposes a new object tracking task—**Instruction Tracking**. Tracker autonomously reasons and tracks objects in video based on implicit instructions, rather than relying on explicit bounding boxes or language descriptions.
- **Core Design：**
  - **Self-Reasoning:** Utilizes LVLM to understand implicit instructions and reason about the target object.
  - **Cross-Frame Propagation Mechanism:** Adapt to appearance changes.
  - **Rethinking Mechanism:** When the tracking results do not align with the instructions, TrackGPT automatically adjusts and updates the tracking process.

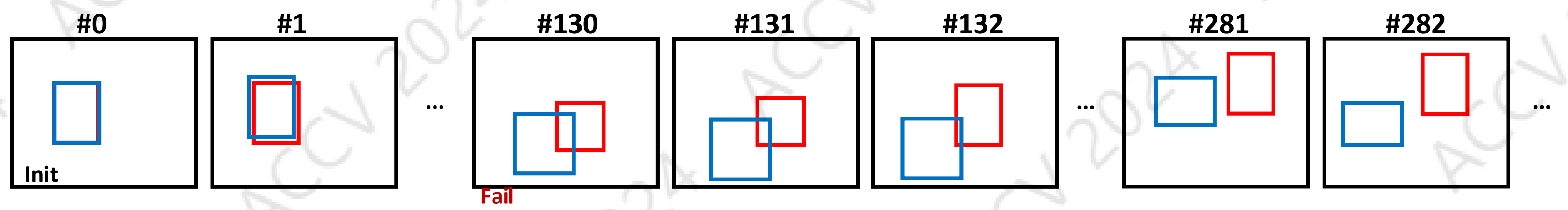
Zhu J, Cheng Z Q, He J Y, et al. Tracking with human-intent reasoning[J]. arXiv preprint arXiv:2312.17448, 2023.

Machine-to-Machine Evaluation

Algorithms are evaluated against benchmarks by comparing their outputs with other algorithms.

Machine-to-Machine Evaluation

- **Evaluation Mechanism: OPE**



Traditional OPE Mechanism

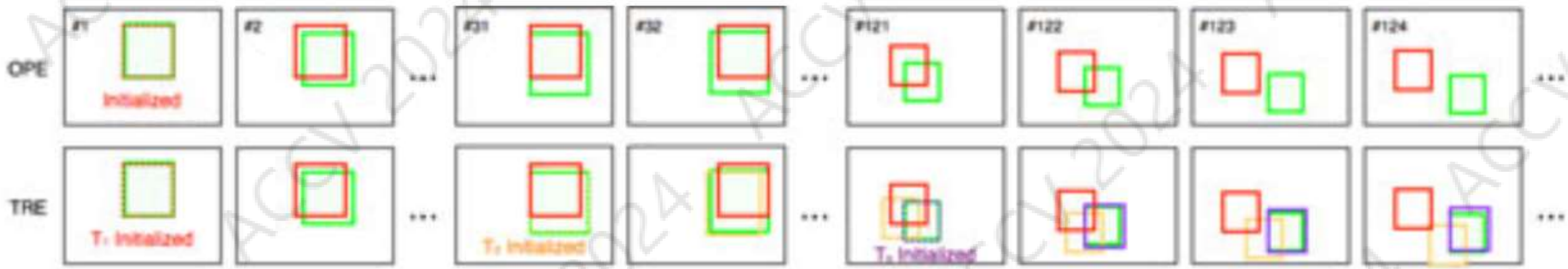
- **OPE (One-Pass Evaluation):** One-Pass Evaluation (OPE) is a fundamental evaluation method in SOT. It evaluates a tracker by **initializing it in the first frame and letting it run through the entire sequence without reinitialization**.
  - **Objective:** Measure the accuracy and robustness of tracking algorithms by allowing the tracker to operate without any manual reinitialization.
  - **Limitations:**
    - **Influence of initialization**: A poor initialization may cause significant variations in results, as **different starting points could lead to major differences** in tracking performance. → **TRE, SRE**
    - **Tracking failure**: When tracking fails, the tracker **continues to lose the target** for the remainder of the sequence, providing no meaningful insights after failure. → **Restart Mechanism**

Wu Y, Lim J, Yang M H. Online object tracking: A benchmark[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2013: 2411-2418.

Machine-to-Machine Evaluation

ACCV

- **Evaluation Mechanism: TRE**



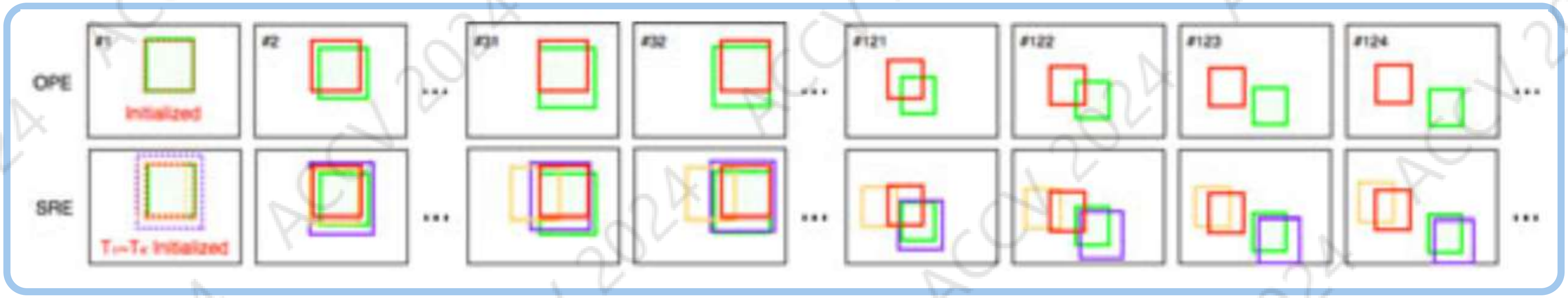
➢ **Temporal Robustness Evaluation (TRE)** tests the robustness of tracking algorithms by **reinitializing the tracker at different starting points** throughout the sequence. This is done to simulate varying temporal conditions.

- **Objective:** Evaluate how well a tracker can **handle different temporal conditions** by restarting tracking from multiple frames.
- **TRE Key Metrics:**
  - ☐ **Average Performance:** The tracker is evaluated on the entire sequence by measuring precision and success from different starting points.
  - ☐ **Consistency:** Measures how consistently the tracker performs when initialized at different times within the same sequence.
- **Applications:** TRE is valuable for testing how well tracking algorithms can recover from failures or adapt to changes in target appearance over time.

Wu Y, Lim J, Yang M H. Online object tracking: A benchmark[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2013: 2411-2418.

Machine-to-Machine Evaluation

- **Evaluation Mechanism: SRE**



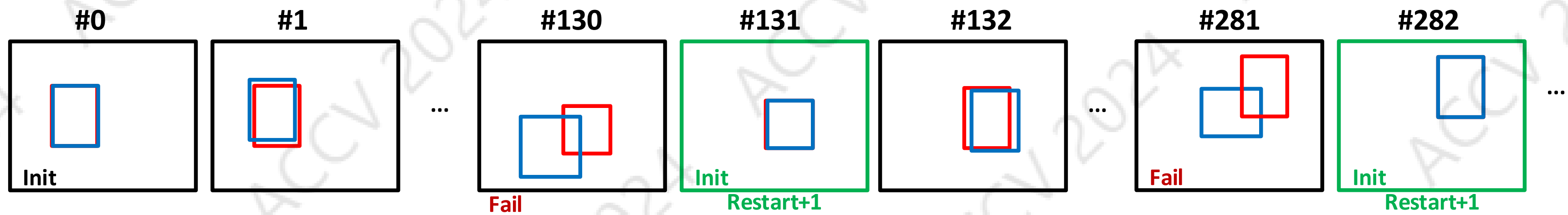
➢ **Spatial Robustness Evaluation (SRE)** involves **perturbing the initial position or scale of the target** in the first frame. This tests how well the tracker can **handle variations in the initial spatial position or size**.

- **Objective:** Evaluate a tracker's robustness to **spatial changes** by starting tracking with slight errors in the initial bounding box.
- **SRE Key Metrics:**
  - ☐ **Tracking Accuracy:** Measures how well the tracker adapts to slight errors in the starting bounding box.
  - ☐ **Resilience to Perturbations:** Evaluates the tracker's ability to handle errors in position or scale during initialization.
- **Applications:** SRE is particularly useful for testing robustness to inaccuracies in manual annotations or initial target detection errors.

Wu Y, Lim J, Yang M H. Online object tracking: A benchmark[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2013: 2411-2418.

Machine-to-Machine Evaluation

- **Evaluation Mechanism: Restart for OTB Benchmark**



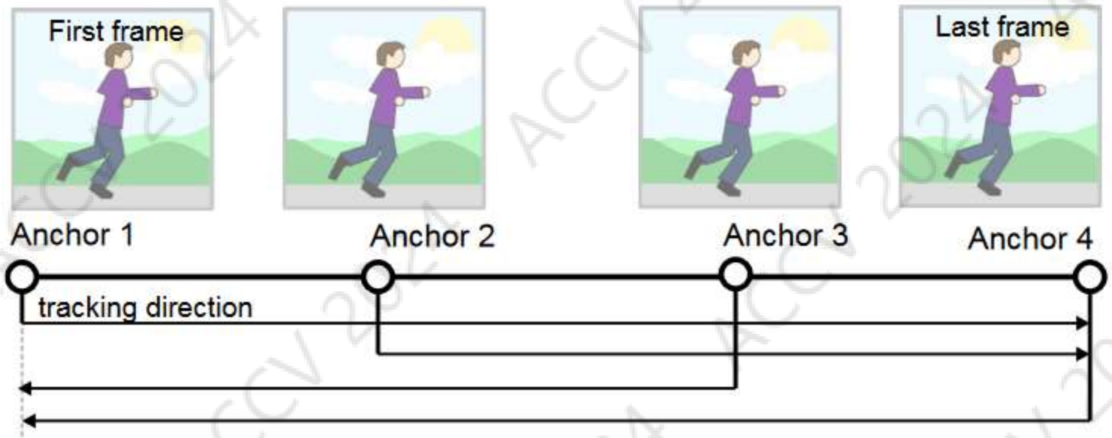
OPER Mechanism in OTB

- **Restart Mechanism** is designed to **reinitialize a tracker when tracking failure is detected**, offering a solution to **prolonged tracking failures**. Originally implemented in OTB, this mechanism has been further developed and adapted to improve evaluation consistency across different tracking scenarios.
  - **OPER (OPE with Restart):** OPER reinitializes the tracking algorithm upon failure and resets the target in the next frame. This ensures that **tracking performance is not unfairly penalized by cumulative errors**, as the evaluation will continue with re-initialized target information.
  - **SRER (SRE with Restart):** SRER similarly handles spatial challenges by reinitializing the tracker in spatially robust environments. It is particularly useful in long-term tracking scenarios where objects reappear after disappearing from the frame.

Wu Y, Lim J, Yang M H. Online object tracking: A benchmark[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2013: 2411-2418.

Machine-to-Machine Evaluation

- **Evaluation Mechanism: Restart for VOT Challenge**

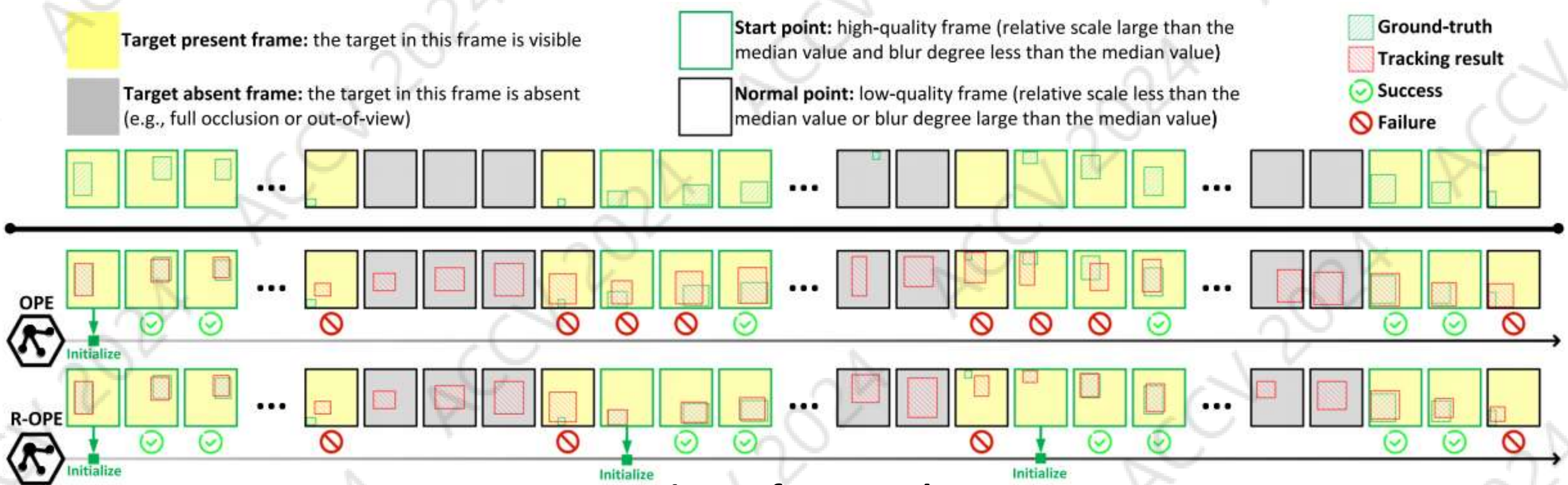


Anchor-based Evaluation Mechanism for VOT2020

- Traditional reset mechanism for VOT is similar to OPER, but this mechanism can **introduce causal correlations** between the first reset and subsequent ones, affecting the evaluation fairness.
- The reset mechanism is replaced by **initialization points** called **anchors**. These are equally spaced along the sequence, removing tracker dependence and ensuring consistency in evaluation.
  - **Anchor Placement:** Anchors are placed **every *Δ*anc frames** throughout the sequence. The first and last anchors are at the start and end of the sequence.
  - **Tracking Direction:** A tracker is run from each anchor either forward or backward to ensure the longest possible sub-sequence is used for evaluation.

Machine-to-Machine Evaluation

- **Evaluation Mechanism: Restart for VideoCube**



Comparison of OPE and R-OPE

- **R-OPE (Restart-Based OPE)** is a new reset mechanism introduced in 2023 for the VideoCube benchmark, particularly designed to address real-world tracking tasks that involve complex scenarios.
- **Key Concept:**
  - In this mechanism, the tracker is reset not immediately after failure, but at the nearest anchor point (**frame with clear appearance information**).
  - By choosing optimal restart points, R-OPE **avoids repeatedly initializing in problematic regions of the video**.

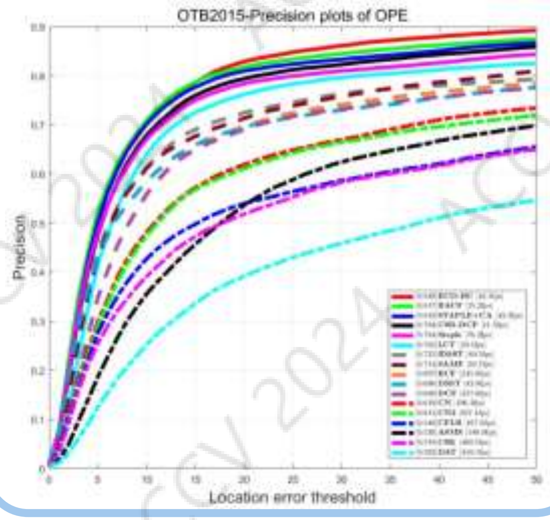
S. Hu, X. Zhao#, L. Huang, et al., "Global instance tracking: Locating target more like humans," IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), vol. 45, no. 1, pp. 576–592, 2023.

Machine-to-Machine Evaluation

- **Evaluation Metris: Precision**

$$P(G) = \frac{1}{|G|}\sum_{s_i \in G}\frac{1}{|s_i|}\left|\{F_i : d_c \le \theta_d\}\right|$$

$$d_c = \left\| c_p - c_g \right\|_2$$



➢ **Precision (PRE):** Precision is one of the most commonly used evaluation metrics in single object tracking tasks, primarily used to measure the accuracy of the predicted result. It reflects **how closely the predicted target position matches the actual target position in each frame.**

➢ **Calculation Method:** Precision is typically calculated by measuring the **Euclidean distance between the predicted target center and the ground truth center**. If this distance is smaller than a predefined threshold, the frame is considered as correctly tracked. The proportion of such frames over the total number of frames gives the precision.

- **Common Threshold:** A typical threshold for tracking tasks is **20 pixels**, meaning if the distance between the predicted center and the true center is less than 20 pixels, the tracking is deemed successful for that frame.

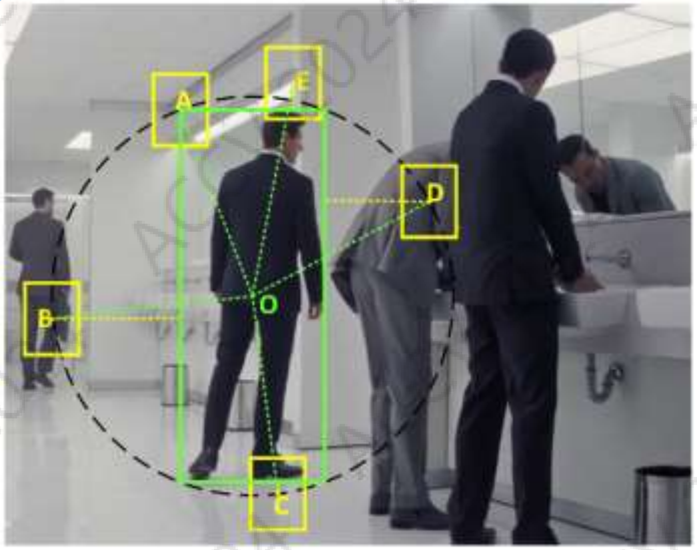
Limitations:
In cases where the target's size changes significantly or has irregular shapes, evaluating solely by center point distance can introduce biases.

Wu Y, Lim J, Yang M H. Online object tracking: A benchmark[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2013: 2411-2418.

Machine-to-Machine Evaluation

ACCV

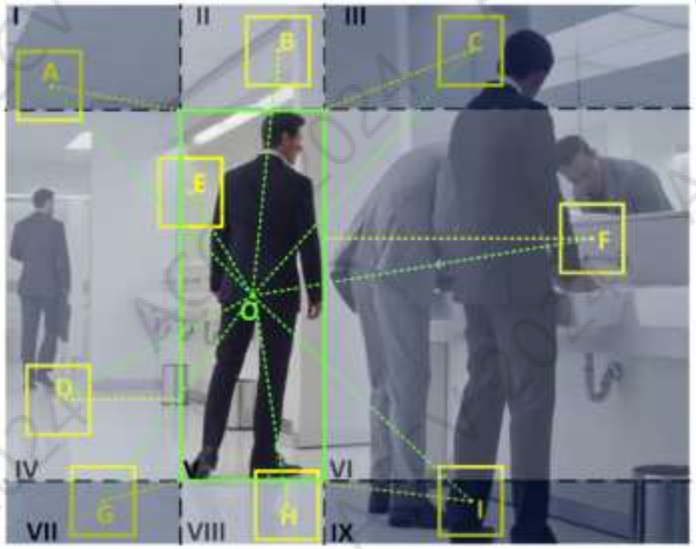
- **Evaluation Metris: Precision**



PRE: A=B=C=D=E

$$P(G)=\frac{1}{|G|}\sum_{s_i\in G}\frac{1}{|s_i|}\left|\{F_i: d_c\leqslant\theta_d\}\right|$$

$$d_c=\left\|c_p-c_g\right\|_2$$



N-PRE:E is the best

$$P'(G)=\frac{1}{|G|}\sum_{s_i\in G}\frac{1}{|s_i|}\left|\{F_i: N'(d_c)\leqslant\theta'_d\}\right|$$

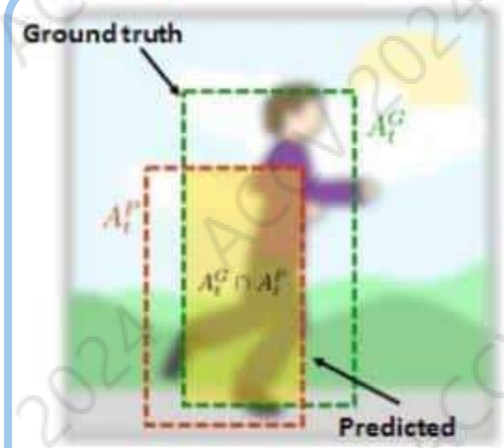
$$N'(d_c)=\frac{d'_c}{\max(\{d'_i|i\in F_i\})}$$

➢ **Normalized Precision (N-PRE):** Normalized precision is calculated by **normalizing the center error** as a ratio of the target's scale. Specifically, **the target width and frame resolution** are combined as the normalization factor, and the Euclidean distance between the predicted center and the groundtruth center is normalized. A normalized threshold is then used to determine if the tracking is accurate.

*S. Hu, X. Zhao#, L. Huang, et al., "Global instance tracking: Locating target more like humans," IEEE Transactions on Pattern Analysis and Machine Intelligence (**TPAMI**), vol. 45, no. 1, pp. 576–592, 2023.*

Machine-to-Machine Evaluation

- **Evaluation Metris: Success Rate**



$$S(G) = \frac{1}{|G|}\sum_{s_i \in G}\frac{1}{|s_i|}|\{F_i : s_i \geq \theta_i\}|$$

$$s_i = \Omega(p_i, g_i) = \frac{p_i \cap g_i}{p_i \cup g_i}$$

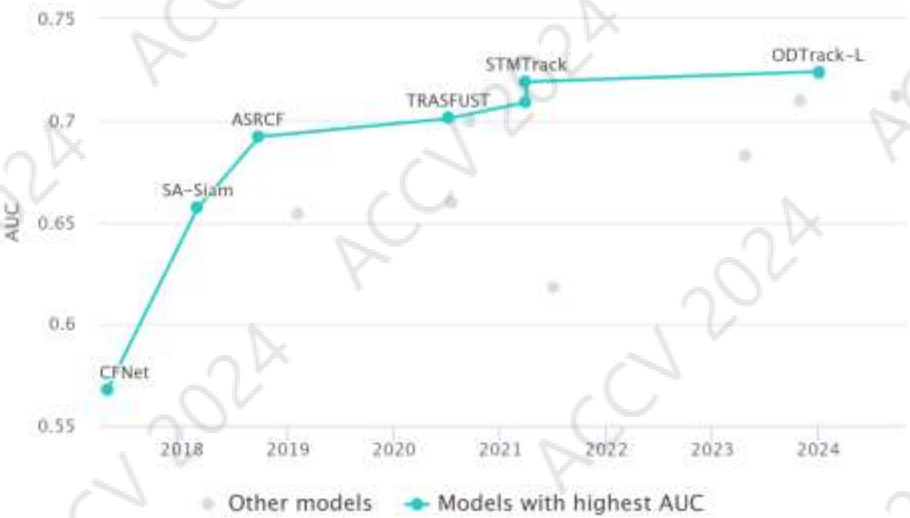
Limitations:
In cases where the predicted and ground truth bounding boxes have little to no overlap, IoU cannot capture the spatial relationship between them, leading to a zero score.

- **Success Rate (SR):** SR is one of the key evaluation metrics used in single object tracking tasks to assess the overall performance of tracking algorithms. Unlike PRE, which focuses on the accuracy of the center point, success rate evaluates **how well the predicted bounding box overlaps with the ground truth bounding box**, providing a more comprehensive measure of the tracking performance in terms of object detection and position tracking.
- **Calculation Method:** Success rate is determined by calculating the **Intersection over Union (IoU)** between the predicted bounding box and the ground truth bounding box. IoU measures the overlap between the two bounding boxes as a ratio of their intersection area to their union area. If the IoU is greater than a predefined threshold (**typically 0.5**), the frame is considered to be successfully tracked.

Wu Y, Lim J, Yang M H. Online object tracking: A benchmark[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2013: 2411-2418.

Machine-to-Machine Evaluation

- **State-of-the-art Results: OTB100**



Rank	Model	AUC	Precision	Paper	Code	Result	Year
1	**PiVOT-L**	0.712	0.946	Improving Visual Object Tracking through Visual Prompting			2024
2	**TRASFUST**	0.701	0.931	Tracking-by-Trackers with a Distilled and Reinforced Model			2020
3	**AAA**	0.70	0.91	AAA: Adaptive Aggregation of Arbitrary Online Trackers with Theoretical Performance Guarantee			2020
4	**GradNet**		0.861	GradNet: Gradient-Guided Network for Visual Object Tracking			2019

https://paperswithcode.com/sota/visual-object-tracking-on-otb-2015

Machine-to-Machine Evaluation

ACCV

- **State-of-the-art Results: TrackingNet**

Rank	Model	Accuracy	Normalized Precision	Precision	Success Rate	AUC	Paper	Code	Result	Year
1	ARTrackV2-L	86.1	90.4	86.2			ARTrackV2: Prompting Autoregressive Tracker Where to Look and How to Describe			2023
2	MixViT-L (ConvMAE)	86.1	90.3	86.0			MixFormer: End-to-End Tracking with Iterative Mixed Attention			2023
3	ODTrack-L	86.1					ODTrack: Online Dense Temporal Token Learning for Visual Tracking			2024
4	LoRAT-g-378	86.0	90.2	86.1			Tracking Meets LoRA: Faster Training, Larger Model, Stronger Performance			2024
5	LoRAT-L-378	85.6	89.7	85.4			Tracking Meets LoRA: Faster Training, Larger Model, Stronger Performance			2024

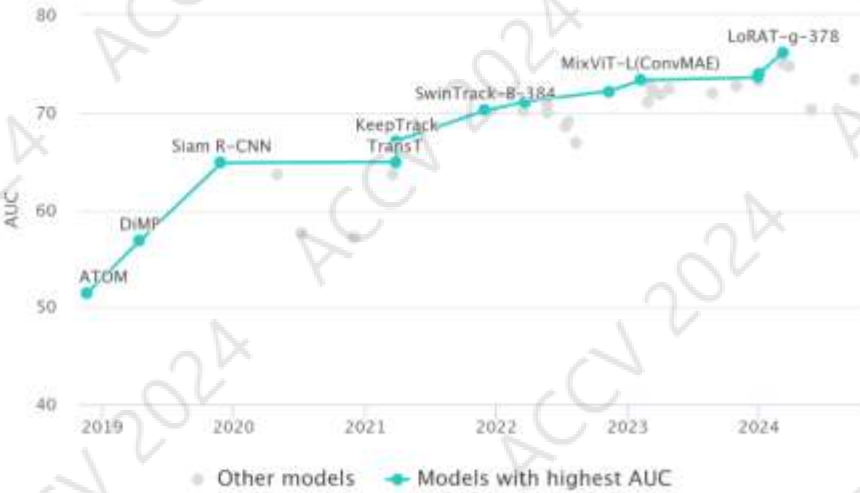
Machine-to-Machine Evaluation

- **State-of-the-art Results: GOT-10k**

Rank	Model	Average Overlap	Success Rate 0.5	Success Rate 0.75	Paper	Code	Result	Year
1	**LoRAT-g-378**	78.9	87.8	80.7	Tracking Meets LoRA: Faster Training, Larger Model, Stronger Performance			2024
2	**ARTrackV2-L**	79.5	87.8	79.6	ARTrackV2: Prompting Autoregressive Tracker Where to Look and How to Describe			2023
3	**LoRAT-L-378**	77.5	86.2	78.1	Tracking Meets LoRA: Faster Training, Larger Model, Stronger Performance			2024
4	**ARTrack-L**	78.5	87.4	77.8	Autoregressive Visual Tracking			2023
5	**RTracker-L**	77.9	87	76.9	RTracker: Recoverable Tracking via PN Tree Structured Memory			2024

Machine-to-Machine Evaluation

- **State-of-the-art Results: LaSOT**



Rank	Model	AUC	Normalized Precision	Precision	Paper	Code	Result	Year
1	**LoRAT-g-378**	76.2	85.3	83.5	Tracking Meets LoRA: Faster Training, Larger Model, Stronger Performance			2024
2	**PiVOT-L**	73.4	84.7	82.1	Improving Visual Object Tracking through Visual Prompting			2024
3	**LoRAT-L-378**	75.1	84.1	82.0	Tracking Meets LoRA: Faster Training, Larger Model, Stronger Performance			2024
4	**ARTrackV2-L**	73.6	82.8	81.1	ARTrackV2: Prompting Autoregressive Tracker Where to Look and How to Describe			2023
5	**MixViT-L** (ConvMAE)	73.3	82.8	80.3	MixFormer: End-to-End Tracking with Iterative Mixed Attention			2023

Conclusion

➢ **Machines:**

- Traditional Trackers
- Correlation Filter Based Trackers
- Siamese Neural Network Based Trackers
- One-stream Trackers
- LVM-based Trackers
- **Impact:** These advancements highlight the shift from basic motion modeling to sophisticated, context-aware algorithms **that bring machine performance closer to human-like tracking abilities**.

Conclusion

➢ **Machine-to-Machine Evaluation:**

- Machine-to-machine evaluation has **long served as the primary method** for assessing tracking performance, relying on benchmarks that compare algorithmic outputs with ground-truth data in controlled environments.
- This approach focuses on metrics like accuracy, robustness, and computational efficiency, which are **valuable for assessing fundamental tracking capabilities**.

Time Break

About 20 Minutes

ACCV

CONTENTS

- Introduction
- Part 1. Visual Object Tracking Task
- Part 2. Experimental Environments
- Part 3. Algorithms and Traditional Machine-Machine Comparisons
- **Part 4. Human Visual Abilities and Visual Turing Test**
  - Humans
  - Visual Turing Test
- Trends and Future Directions

Scan to download this tutorial PPT

Humans

We will learn some basic information about human visual theories and abilities.

Humans: Visual Theories

- **Introduction to Visual Theories**

Visual information: 83%

Auditory information: 11%

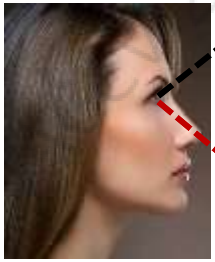
Olfactory information: 3.5%

Taste information: 1%

Tactile information: 1.5%

Humans are "visual animals"

Static Visual Ability (SVA)



Detection, recognition, classification …

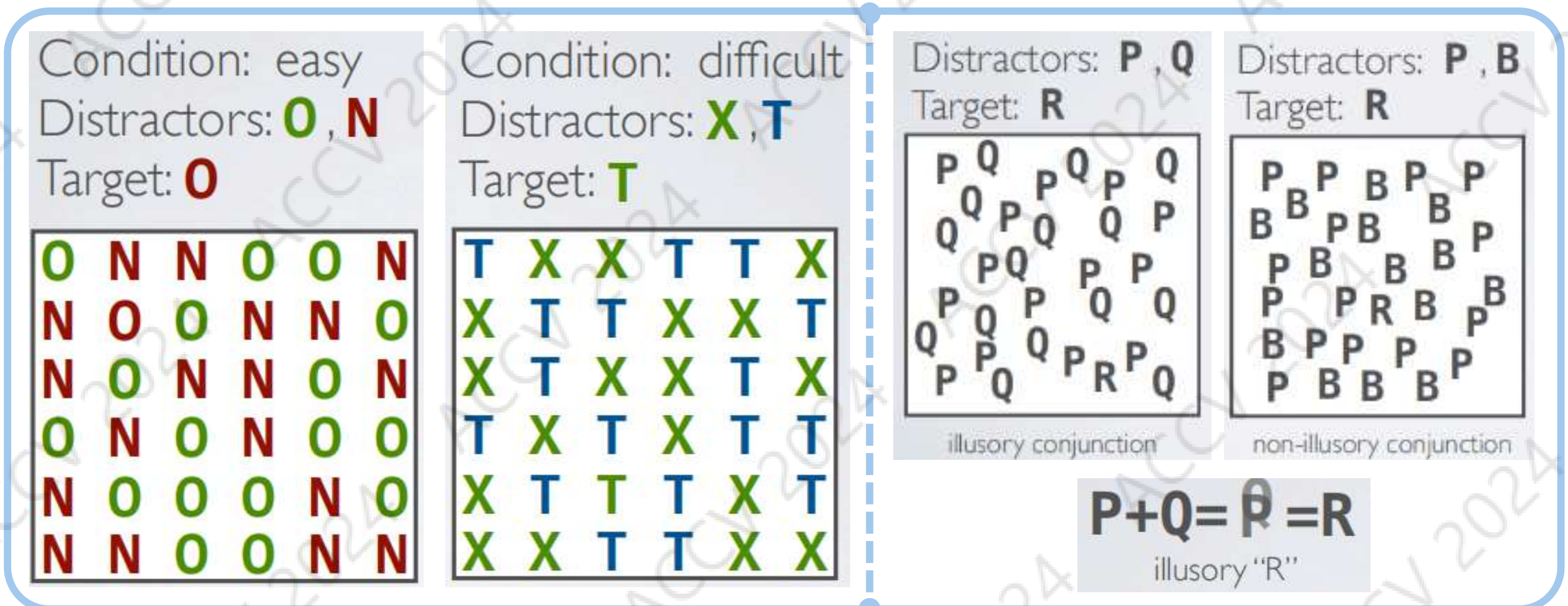
Dynamic Visual Ability (DVA)

Tracking

- Visual theories offer insights into **how humans process and interpret visual information**, providing a foundation for improving algorithms.
- Theories such as **Feature Integration Theory, Recognition-by-Components**, and **Visual Computation** have inspired the development of advanced computer vision systems.

Humans: Visual Theories

- **Feature Integration Theory (1980)**

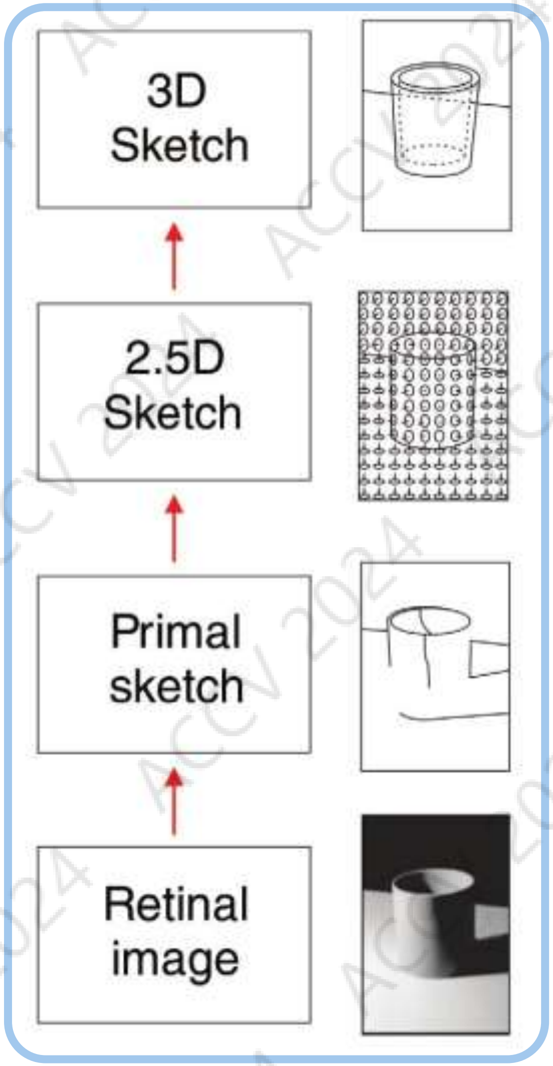


- ➢ This theory explains how humans **combine separate visual features** (such as color, shape, size) **to form a coherent object perception**. It suggests that the brain **processes simple features in parallel** and integrates them into a unified perception during focused attention.
- ➢ **Applications:** Feature-based tracking algorithms mimic this theory by **extracting multiple object characteristics** (such as color, texture, shape) to maintain robust tracking performance, especially in complex environments.

TREISMAN A M, GELADE G. A feature-integration theory of attention[J]. Cognitive psychology, 1980, 12(1): 97-136.

Humans: Visual Theories

- **Visual Computation Theory (1982)**



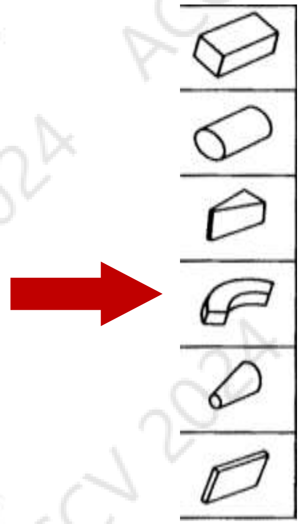
- Describes how the brain processes visual information through a series of **hierarchical stages**, starting from a basic edge detection to the construction of complex, 3D object representations. The theory breaks down vision into three main levels:
  - **Raw primal sketch**: Initial edge and texture information.
  - **2.5D sketch**: Intermediate-level representation of objects' positions and orientation.
  - **3D representation**: Full object understanding for recognition and interaction.
- **Applications:** This theory underlies many modern tracking algorithms, where visual data is processed hierarchically, starting from **low-level features** (e.g., edges, textures) to **high-level representations** (e.g., object shapes, motions).

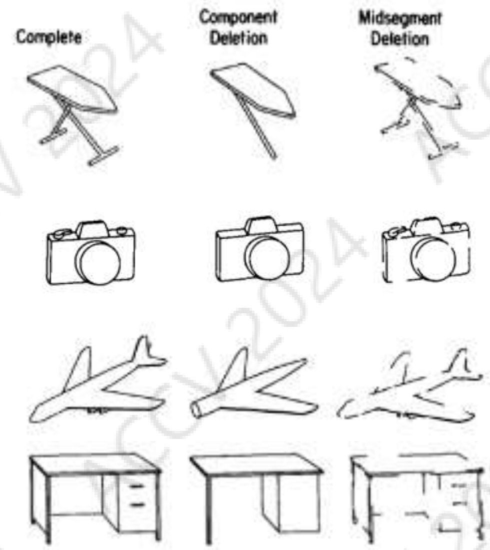
Marr D. Vision: A computational investigation into the human representation and processing of visual information[M]. MIT press, 2010.

Humans: Visual Theories

- **Recognition-by-Components Theory (1987)**

Figure 1. A do-it-yourself object. (There is strong consensus in the segmentation loci of this configuration and in the description of its parts.)



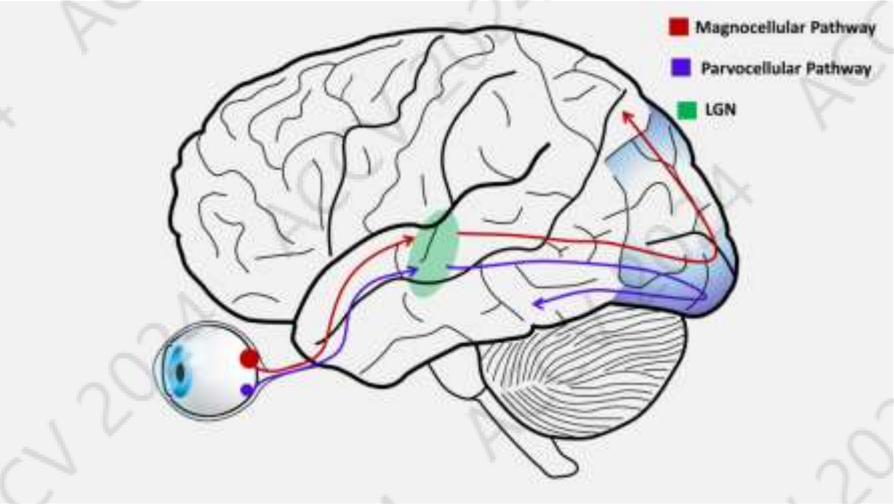


- ➢ Suggests that humans recognize objects by breaking them down into basic geometric shapes, called "**geons**." These geons form the building blocks of object recognition. The theory argues that recognizing the components is sufficient for object identification, even if some parts of the object are obscured.
- ➢ **Applications:** Inspired object segmentation techniques in tracking, where objects are broken down into parts for **more accurate identification and tracking**.

Biederman I. Recognition-by-components: a theory of human image understanding[J]. Psychological review, 1987, 94(2): 115.

Humans: Visual Ability

- **Overview of Human Visual Capabilities**



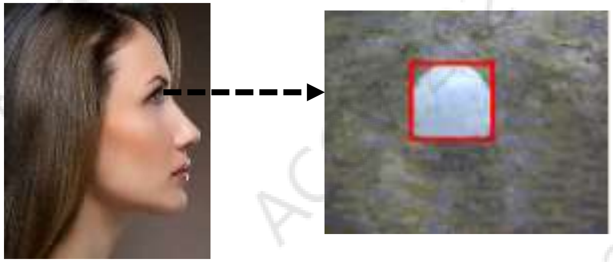
- The **magnocellular** (M cell) pathway carries information about **large, fast things** (low spatial frequency; high temporal frequency) and is **colorblind**.
- The **parvocellular** (P Cell) pathway carries information about **small, slow, colorful things** (high spatial frequency information; low temporal frequency information).

- Pioneering research from a neurophysiological has allowed distinction between the two main types of visual acuity:
  - **Static Visual Ability:** The ability to perceive and interpret **stationary or slow-moving objects**, whose basic neural support is the **parvocellular system.**
  - **Dynamic Visual Ability:** The ability to perceive and track **fast-moving objects** or predict their trajectories, whose basic neural support is the **magnocellular system.**

JW M, Ludvigh E. The effect of relative motion on visual acuity[J]. Survey of Ophthalmology, 1962, 7: 83-116.

Humans: Visual Ability

- ## Static Visual Capability



Detection, recognition, classification …

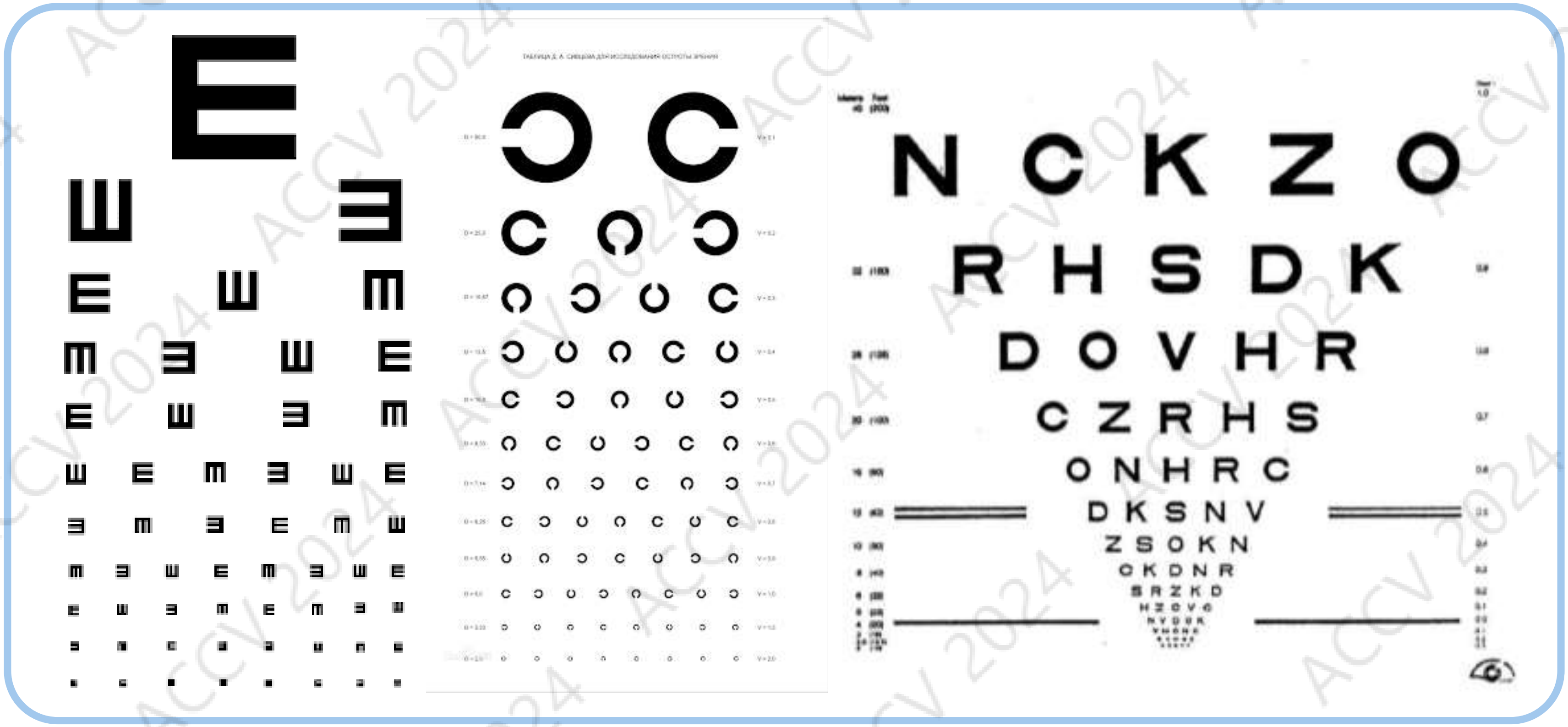
➢ **Definition:** SVA is defined as the ability to distinguish the details of **static objects** whose image is formed on the retina when the evaluated subject is also **stationary.**

➢ **Key points for measuring SVA:** In assessing this visual ability, some basic thresholds can be considered:

- **Minimum detectable threshold:** ability to perceive the smallest object in the visual field.
- **Minimum resolution threshold**: ability to perceive as separate two objects that are very close together.
- **Minimum perceptible alignment threshold**: refers to the ability to detect the alignment between two discontinuous segments whose ends are very close together.
- **Minimum recognition threshold**: ability to properly identify the shape or orientation of an object (e.g. a letter). This threshold is commonly referred to as visual acuity.

Humans: Visual Ability

- **Static Visual Capability**



➢ **Measurement Technology:** The limit of **spatial resolution (the smallest size)** that the subject can visually resolve is reached when he is unable to identify the letters of a row (or perceive the distance between two points or lines or the opening of a ring).

Humans: Visual Ability

- **Static Visual Capability**

➢ **Influencing Factors:** Among the subject factors that may **influence** SVA:

- The most determinants is the **refractive error**, which, in most cases, would require the appropriate optical prescription to achieve normal visual acuity.
- Another very important element is the **age of the subject**, which is known to lead to anatomical and physiological changes that adversely affect visual perception.

➢ **Limitations:** There are two limitations that show the inadequacy of measuring only SVA to assess the functioning of the visual system:

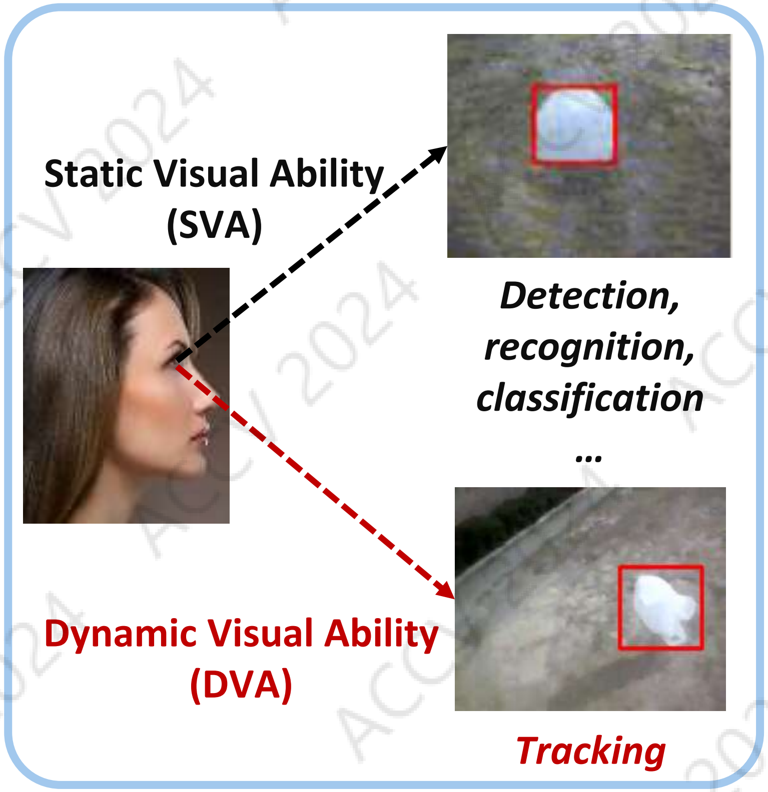
- Many visual stimuli to which we must respond to in real life **are often in motion.**
- The SVA tests refer to letters or symbols often displayed under conditions of **maximum contrast (black on white),** even though such high level of contrast is seldom observed in the different situations of daily life.

Long, G. M., & Zavod, M. J. (2002). Contrast sensitivity in a dynamic environment: Effects of target conditions and visual impairment.

Humans: Visual Ability

- ## Dynamic Visual Capability

➢ **Definition:** Dynamic visual acuity (DVA) describes the ability to visually **resolve subtle spatial details** of an object when the object, the observer, or both, are **moving**.



➢ **Correlation between DVA and SVA**

- **Static vs. Dynamic:** While dynamic visual capability often builds on static capability, research shows that **having excellent static visual capability does not always mean strong dynamic capability**. Individuals with high static visual acuity might struggle with tracking moving objects.
- **Complementary Abilities: Both capabilities are essential in designing tracking systems** that can handle a wide range of visual tasks, from identifying stationary objects to tracking fast-moving targets in real time.

Aznar-Casanova, J. A., Quevedo, L. 1., & Sinnet, S. (2005). The effects of drift and displacement motion on dynamic visual acuity

Humans: Visual Ability

- **Dynamic Visual Capability**

➢ **Measurement Technology:** Unfortunately, despite the importance of DVA, specific instruments with proven reliability and validity that enable further research of such ability are **inadequate and chaotic.**

➢ **Bernell's Rotator (1990s):** The dynamic visual acuity values are recorded as a combination of **visual acuity** and **speed** in rpm.

Humans: Visual Ability

- **Dynamic Visual Capability**

➢ **Measurement Technology:** Unfortunately, despite the importance of DVA, specific instruments with proven reliability and validity that enable further research of such ability are **inadequate and chaotic.**

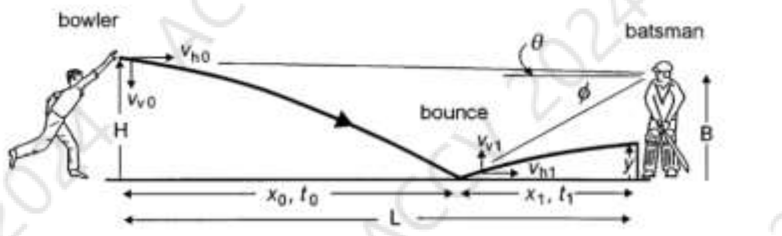
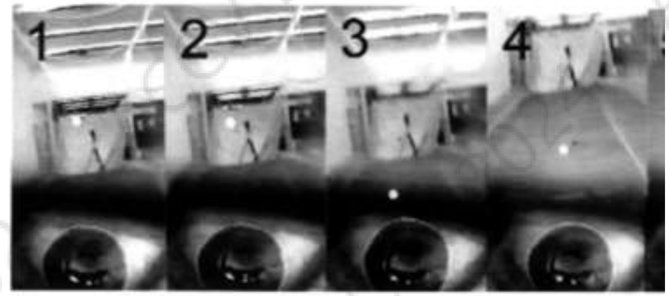
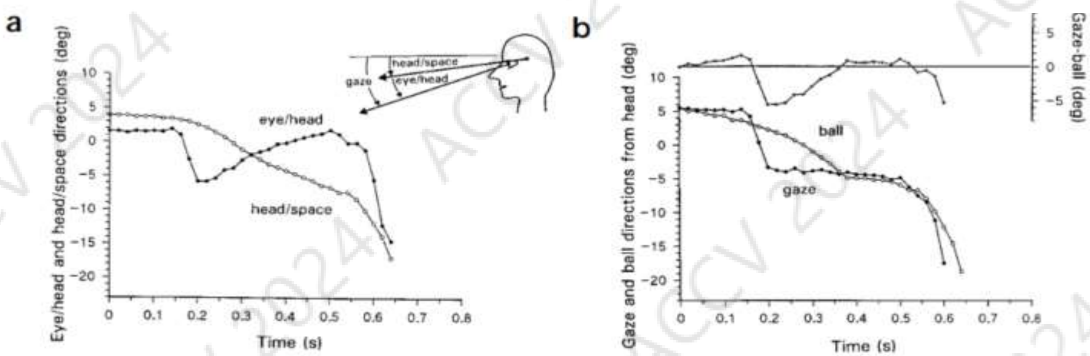


Fig. 1. The physical parameters that determine where and when the ball will reach the batsman, and the measurements he can make to determine the time and point of contact. The batsman's task is to estimate when it will reach him (t_1), and at what height (y). Other definitions are in text.





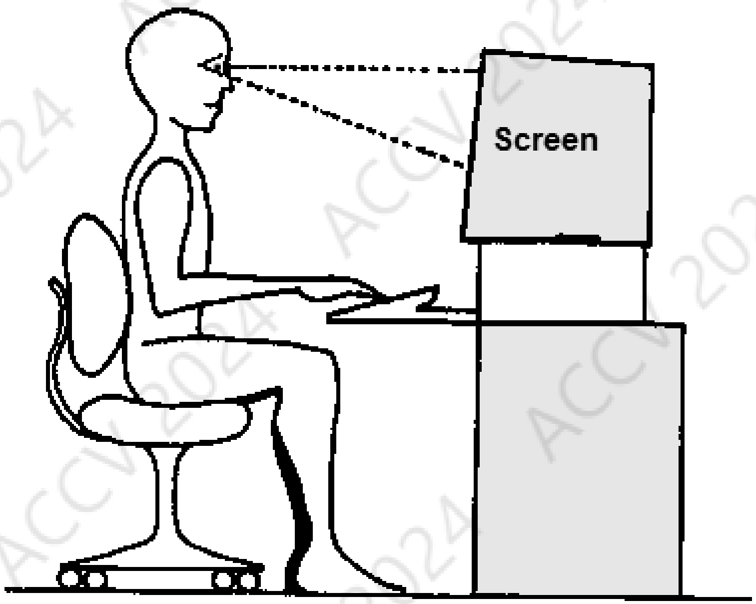
➢ **Ball game (2000s):** Research in the 2000s focused on **testing athletes' dynamic visual abilities**, primarily in **baseball**, where the athletes' eye movements were recorded and analyzed by cameras.

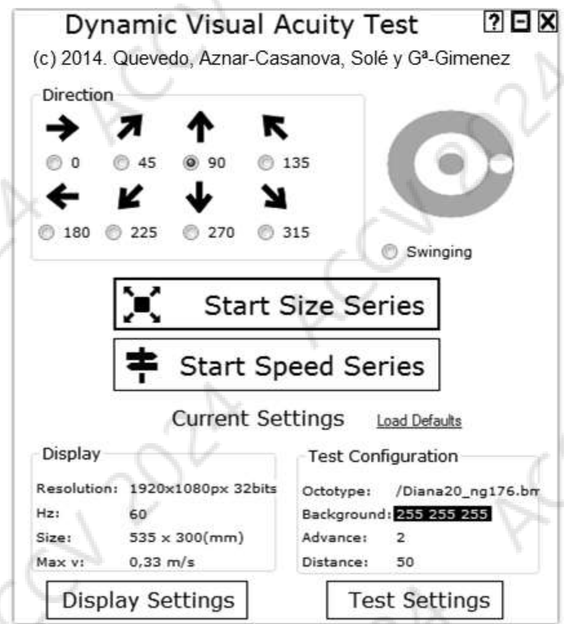
Land M F, McLeod P. From eye movements to actions: how batsmen hit the ball[J]. Nature neuroscience, 2000, 3(12): 1340-1345.
McLeod P, Reed N, Dienes Z. How fielders arrive in time to catch the ball[J]. Nature, 2003, 426(6964): 244-245.

Humans: Visual Ability

- ## Dynamic Visual Capability

➢ **Measurement Technology:** Unfortunately, despite the importance of DVA, specific instruments with proven reliability and validity that enable further research of such ability are **inadequate and chaotic.**





➢ **DynVA (2010s):** The DynVA is a computer software designed to assess DVA. The researcher can select the optotype to be presented in the two forms of the test: **(a)Size Series; (b) Speed Series.**

Humans: Visual Ability

- **Dynamic Visual Capability**

➢ **Influencing Factors:** Among the subject factors that may **influence** DVA:

- **Age:**
  - ☐ From an evolutionary point of view, it has been found that DVA is one of the abilities that **more greatly deteriorates with age**. DVA deterioration is more marked than SVA, and also begins earlier.
  - ☐ A research noted that DVA develops rapidly between 5 and 15 years of age, and that it begins to **decline after the age of 20**.
- **Sports:**
  - ☐ The anticipatory ability based on DVA is crucial to **intercept a moving object** (e.g. a ball) and to **predict the spatial location of items of interest.**
  - ☐ This is the main reason why numerous scientific studies report a **greater DVA for elite athletes compared to sedentary population.**
  - ☐ Moreover, differences have also been found when comparing athletes' DVA in **a dynamic context** (e.g. basketball or tennis) with other modalities with less "visual" requirements such as swimming, **with a marked superiority** in favor of the first.

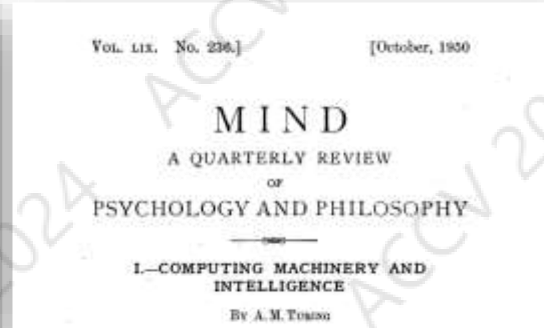
Beals, R. P., Mayyasi, A. M., Templeton, A. E., &Johnson, W. G. (1971). The relationship between basketball shooting performance and certain visual attributes.
National Research Council's Committee on Vision.(1985). Emergent Techniques for Assessment of Visual Performance.

Visual Turing Test

Human tracking abilities are used as a baseline for evaluating machine intelligence.

Human-to-Machine Evaluation

- **How to evaluate intelligence? Turing Test**


Vol. lix. No. 236.] [October, 1950

MIND

A QUARTERLY REVIEW

OF

PSYCHOLOGY AND PHILOSOPHY

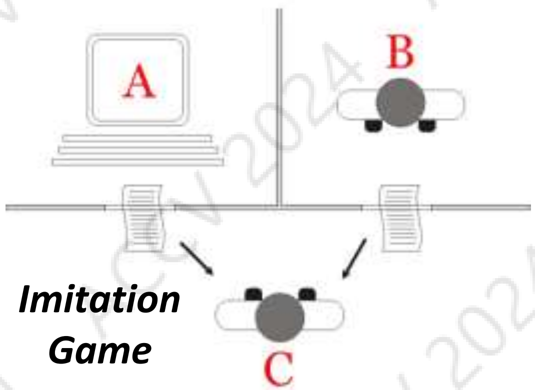
I.—COMPUTING MACHINERY AND INTELLIGENCE

By A. M. Turing

Can machine think?

Computing Machinery and Intelligence. Mind, 1950 (236): 433–460

1950: Alan Turing, the father of artificial intelligence, proposed the **Turing Test**.



The explain of the Turing test:

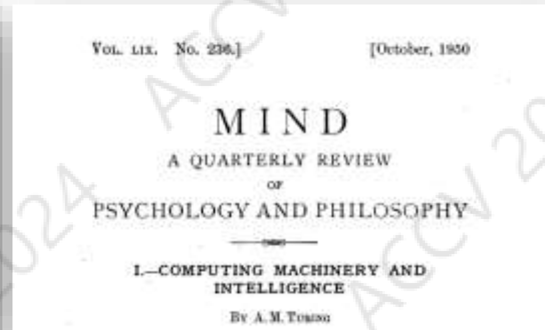
- Player C is given the task of trying to determine **which player – A or B – is a computer and which is a human**.
- The player C is limited to using the responses to **written questions** to make the judgment.

- The Turing test gives a **concrete and operational way** to measure intelligence and provides **an objective standard** for judging intelligence.
- It **avoids unnecessary debates about the nature of intelligence**.

Human-to-Machine Evaluation

Introduce human factor is important!

- **How to evaluate intelligence? Turing Test**



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Keypoint: **Human-Machine Comparison**

Milestone works in decision-making tasks:

1997: DeepBlue defeated Garry Kasparov in international chess competitions.

2016: AlphaGo defeated Lee Sedol in a Go competition.

2017: DeepStack defeated human professional players in Texas Hold'em poker.

Human-to-Machine Evaluation

- **How to evaluate visual intelligence? Visual Turing Test.**
  - **Visual Turing Test** is an evaluation paradigm inspired by the traditional Turing Test, designed to assess whether computer vision systems **possess human-level visual understanding.**
    - The core objective is to compare machine and human performance on visual tasks, determining if the algorithm exhibits sufficient intelligence to **match or exceed human capabilities in complex scenarios.**
  - **Principles of Visual Turing Test:** The Visual Turing Test requires a machine to produce results in **specific visual tasks**, which are then compared to **human results**. Typical tasks include object recognition, tracking, and image classification.
    - In the test, if the machine's performance is highly similar to human results or indistinguishable, it is considered that the machine has achieved human-like visual understanding.

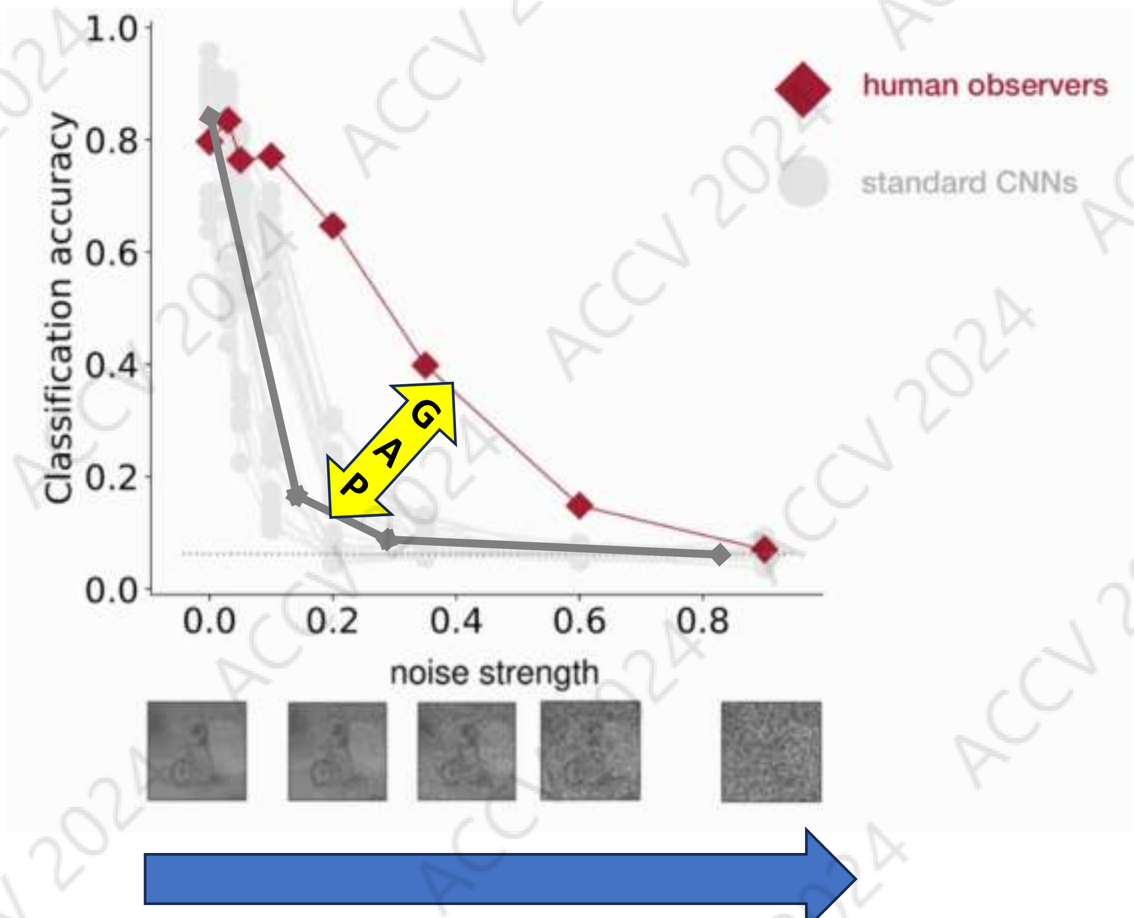
Human-to-Machine Evaluation

- **Example 1. Visual Turing Test in Classification**

NeurIPS 2021 Oral

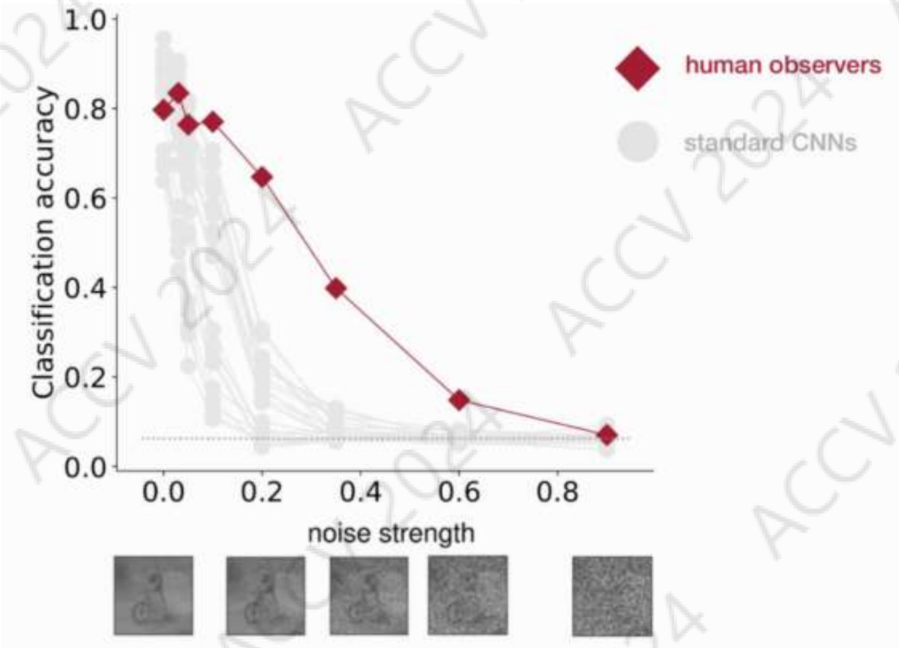
Partial success in closing the gap between human and machine vision

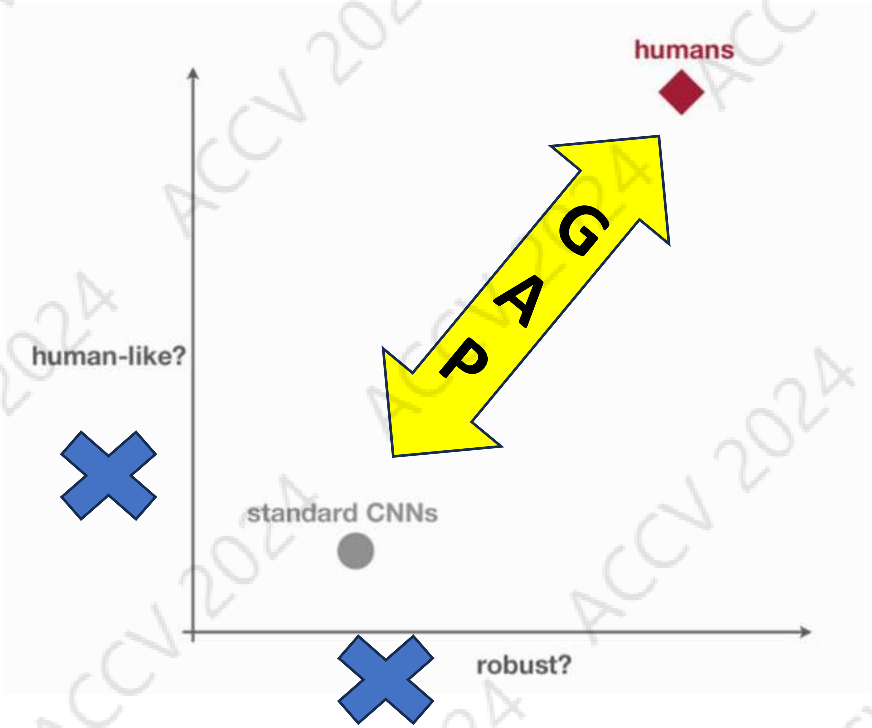
Robert Geirhos[1,2§] Kantharaju Narayanappa[1] Benjamin Mitzkus[1]
Tizian Thieringer[1] Matthias Bethge[1*] Felix A. Wichmann[1*] Wieland Brendel[1*]
[1]University of Tübingen
[2]International Max Planck Research School for Intelligent Systems



Human-to-Machine Evaluation

- **Example 1. Visual Turing Test in Classification**



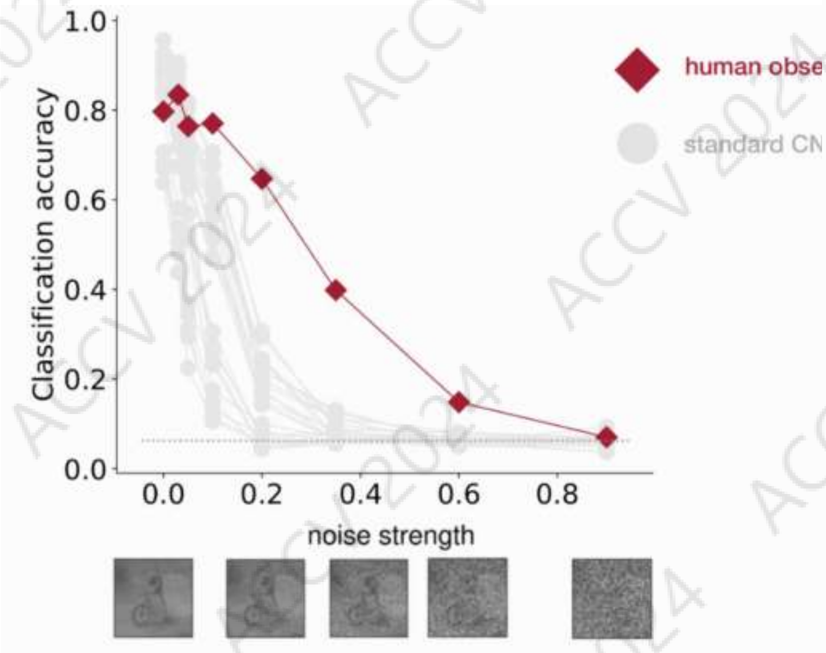


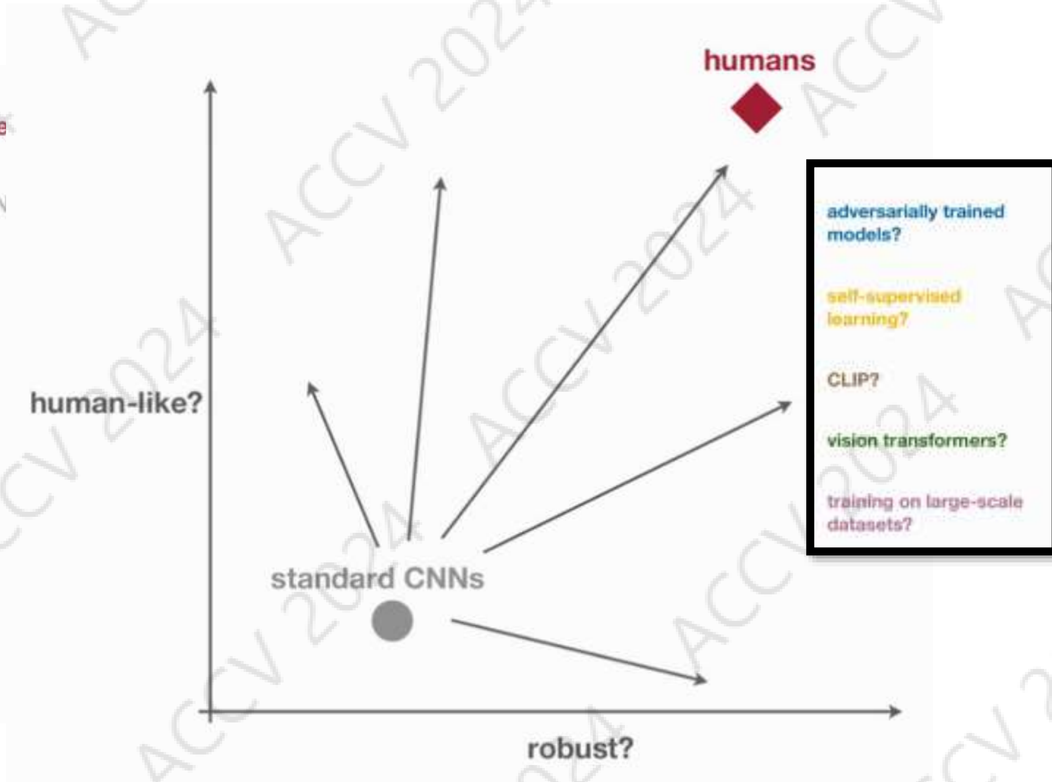
Big robustness gap between CNNs & humans

Geirhos R, Narayanappa K, Mitzkus B, et al. Partial success in closing the gap between human and machine vision[J]. Advances in Neural Information Processing Systems, 2021, 34: 23885-23899.

Human-to-Machine Evaluation

- **Example 1. Visual Turing Test in Classification**



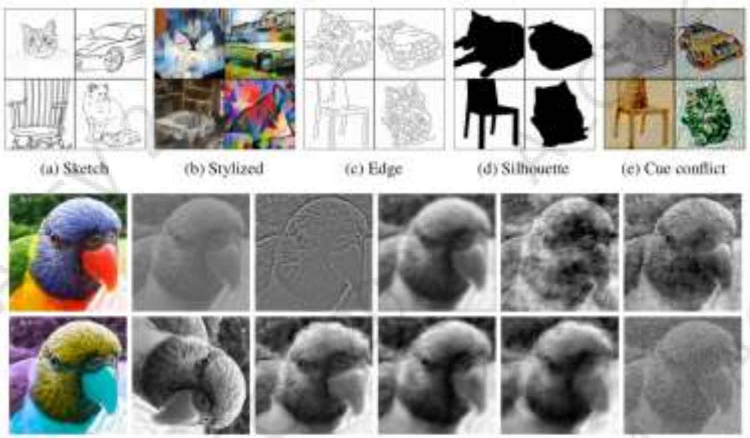


Are we making progress in closing the gap between human and machine vision?

Human-to-Machine Evaluation

- **Example 1. Visual Turing Test in Classification**

Are we making progress in closing the gap between human and machine vision?



17 image processing styles

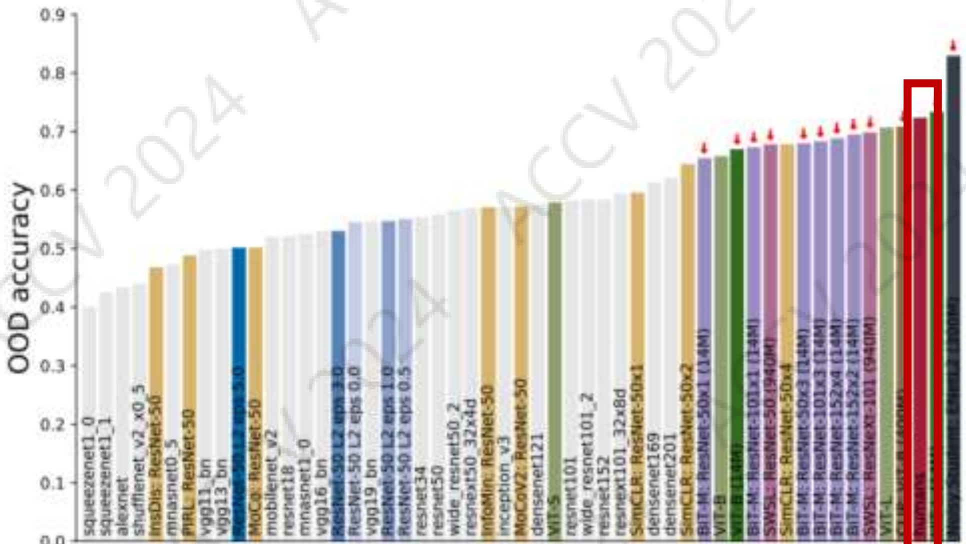
Participants were explained how to respond (via **mouse click**), instructed to respond **as accurately as possible**, and to go with their **best guess if unsure**.

Geirhos R, Narayanappa K, Mitzkus B, et al. Partial success in closing the gap between human and machine vision[J]. Advances in Neural Information Processing Systems, 2021, 34: 23885-23899.

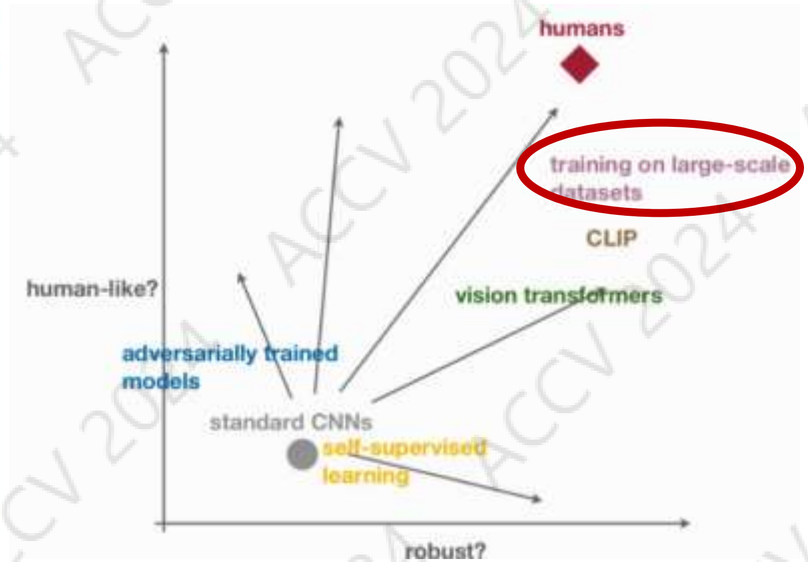
Human-to-Machine Evaluation

- **Example 1. Visual Turing Test in Classification**

Are we making progress in closing the gap between human and machine vision?



(a) OOD accuracy (higher = better).



The longstanding OOD robustness gap between human and machine vision is closing.

Geirhos R, Narayanappa K, Mitzkus B, et al. Partial success in closing the gap between human and machine vision[J]. Advances in Neural Information Processing Systems, 2021, 34: 23885-23899.

Human-to-Machine Evaluation

- **Example 2. Visual Turing Test in Image Distortion**

Patterns

CellPress OPEN ACCESS

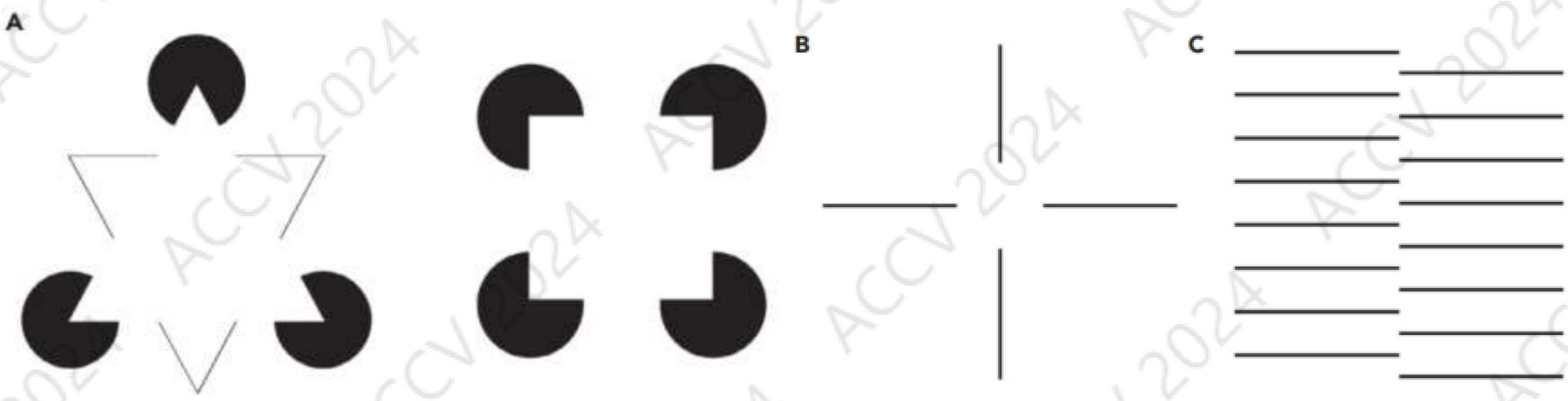
Cell Patterns 2023

Article

Challenging deep learning models with image distortion based on the abutting grating illusion

Jinyu Fan[1,6] and Yi Zeng[1,2,3,4,5,6,7,*]
[1]Brain-inspired Cognitive Intelligence Lab, Institute of Automation, Chinese Academy of Sciences, Beijing 100190, China
[2]National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences, Beijing 100190, China
[3]School of Future Technology, University of Chinese Academy of Sciences, Beijing 100049, China
[4]School of Artificial Intelligence, University of Chinese Academy of Sciences, Beijing 100049, China
[5]Center for Excellence in Brain Science and Intelligence Technology, Chinese Academy of Sciences, Shanghai 200031, China
[6]These authors contributed equally
[7]Lead contact
*Correspondence: yi.zeng@ia.ac.cn
https://doi.org/10.1016/j.patter.2023.100695

Illusory contours **evoke the perception of a distinct boundary without color contrast or luminance gradients across that boundary.**



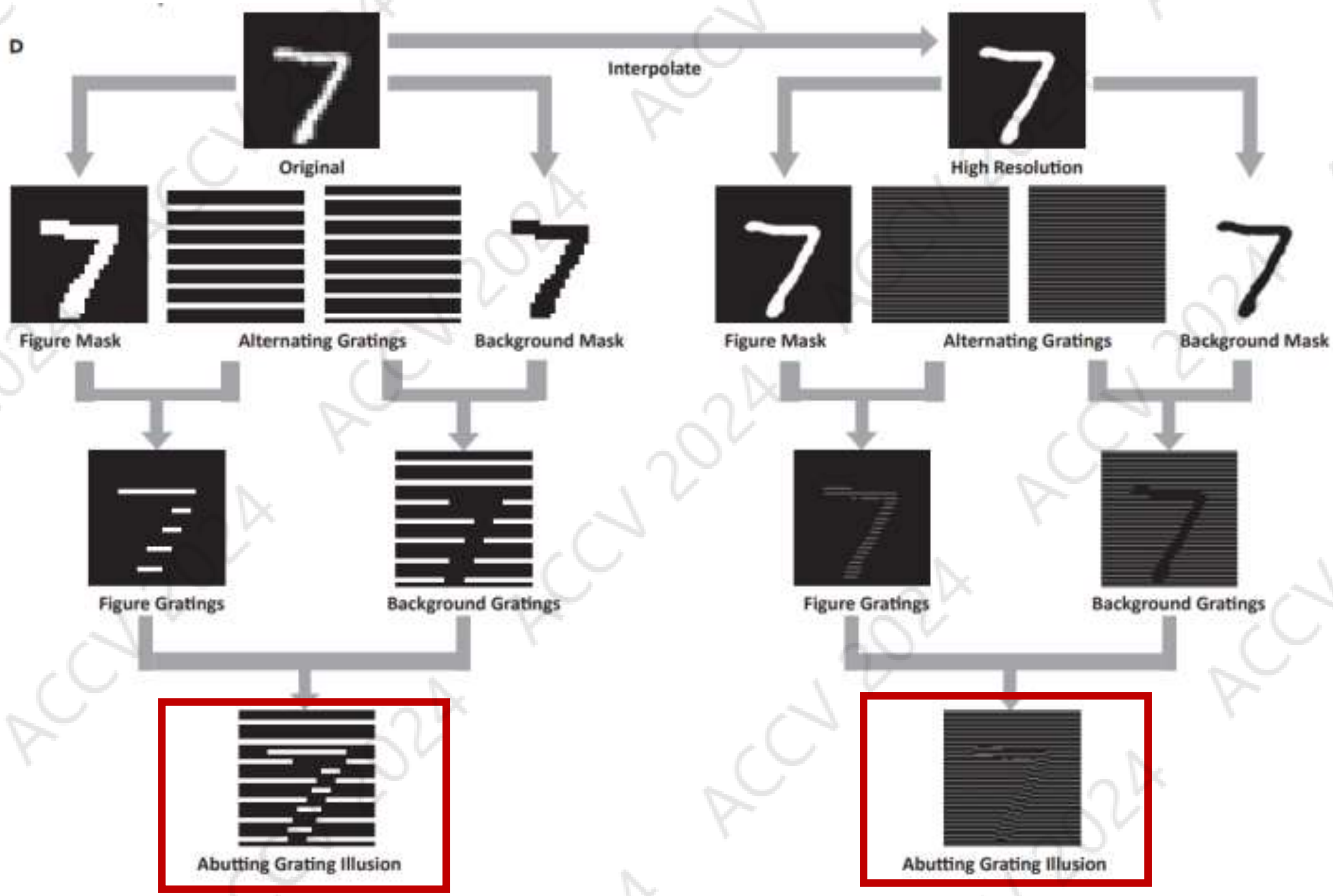
Kanizsa triangle and Kanizsa square **Ehrenstein illusion** **Abutting grating illusion**

Fan J, Zeng Y. Challenging deep learning models with image distortion based on the abutting grating illusion[J]. Patterns, 2023, 4(3).

Human-to-Machine Evaluation

ACCV

- **Example 2. Visual Turing Test in Image Distortion**



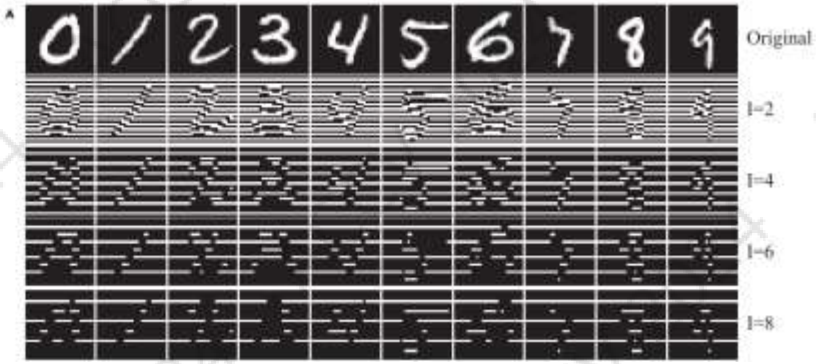
AG-MNIST (1*28*28)

High-resolution AG-MNIST (3*224*224)

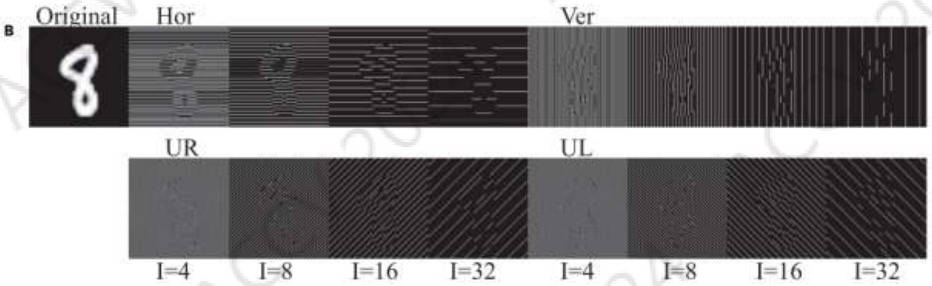
Fan J, Zeng Y. Challenging deep learning models with image distortion based on the abutting grating illusion[J]. Patterns, 2023, 4(3).

Human-to-Machine Evaluation

- **Example 2. Visual Turing Test in Image Distortion**

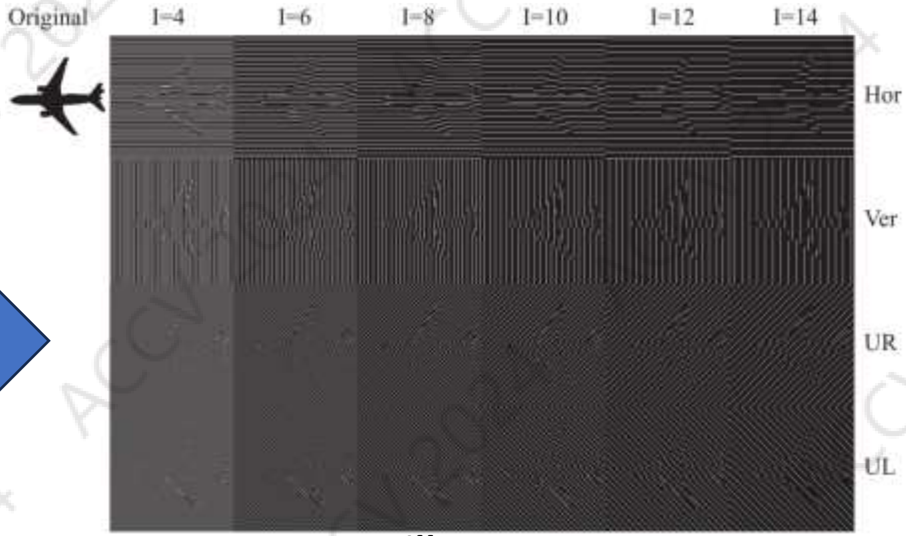


AG-MNIST:
Different spacing



High-resolution AG-MNIST:
Different spacing & Different orientations

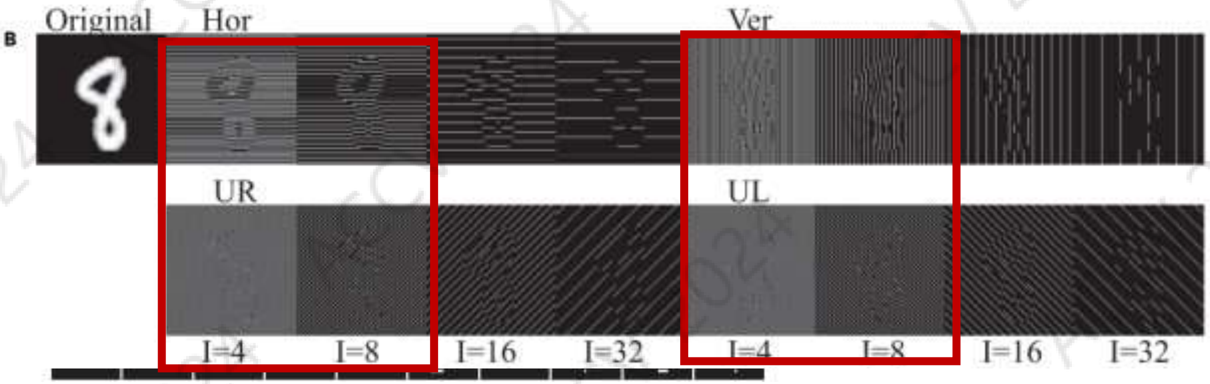
Silhouettes



AG-silhouettes:
Different spacing & Different orientations

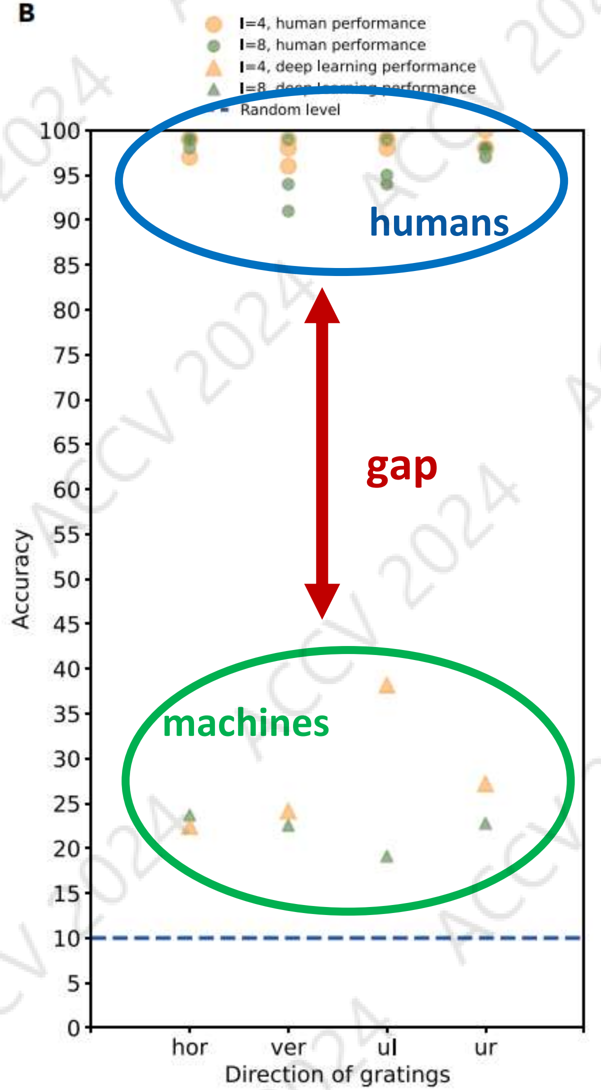
Human-to-Machine Evaluation

- **Example 2. Visual Turing Test in Image Distortion**



High-resolution AG-MNIST

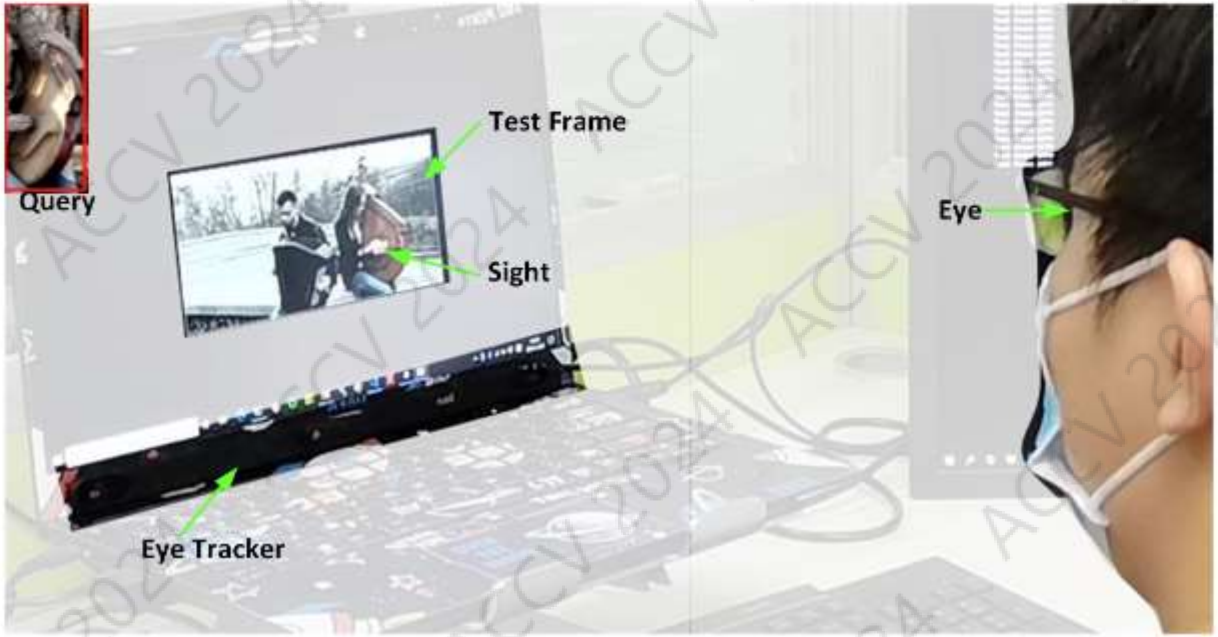
The gap between humans and deep learning models is still immense.



Fan J, Zeng Y. Challenging deep learning models with image distortion based on the abutting grating illusion[J]. Patterns, 2023, 4(3).

Human-to-Machine Evaluation

- **Example 3. Visual Turing Test in Global Instance Tracking**



Schematic diagram of the human visual tracking experiment.

➢ **Eye-Tracking Experiments:** By using **eye-tracking devices**, human visual tracking data, such as gaze focus points and eye movements during a tracking task, are collected. This data reflects how humans track objects in visual tasks and serves as a reference for evaluating the performance of machine vision.

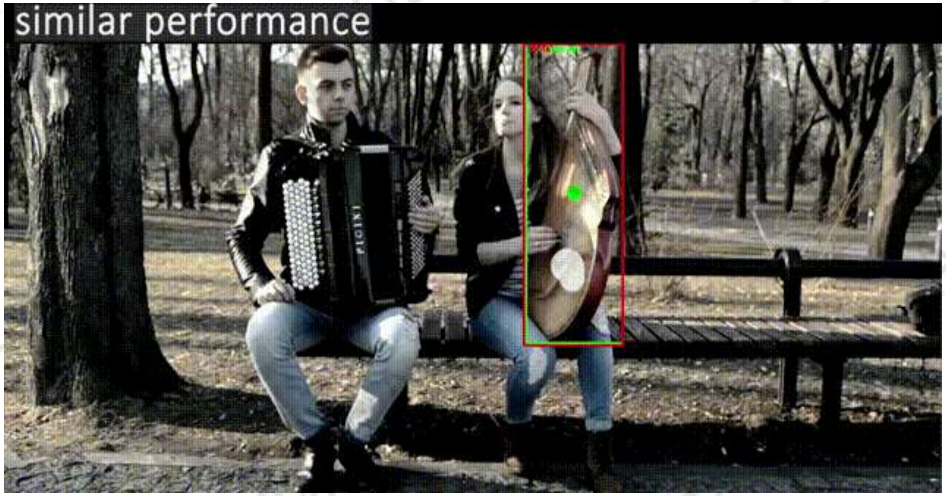
  - **For the first time**, human participants are introduced into the evaluation process of single object tracking tasks.

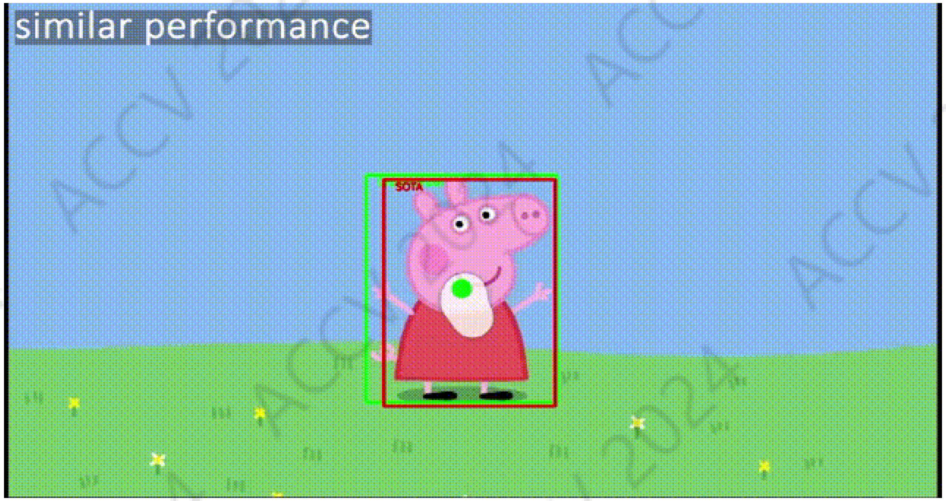
S. Hu, X. Zhao#, L. Huang, et al., "Global instance tracking: Locating target more like humans," IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), vol. 45, no. 1, pp. 576–592, 2023.

Human-to-Machine Evaluation

- **Example 3. Visual Turing Test in Global Instance Tracking**

➢ **When the target moves smoothly:** Humans and machines perform similarly



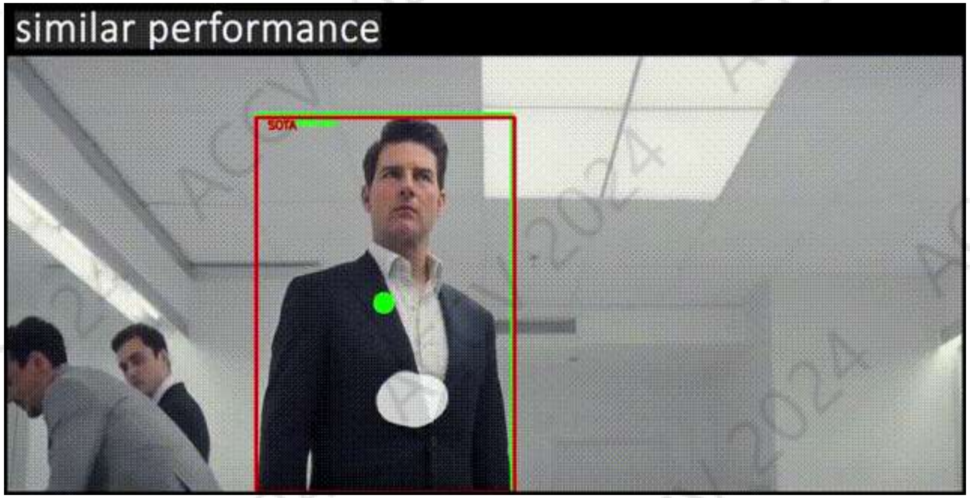


- **White semi-transparent dot:** human eye tracking result
- **Green rectangle:** target position
- **Green dot:** target center
- **Red rectangle:** SOTA algorithm tracking result

Human-to-Machine Evaluation

- **Example 3. Visual Turing Test in Global Instance Tracking**

➢ **A few challenging factors:** Humans are better than machines



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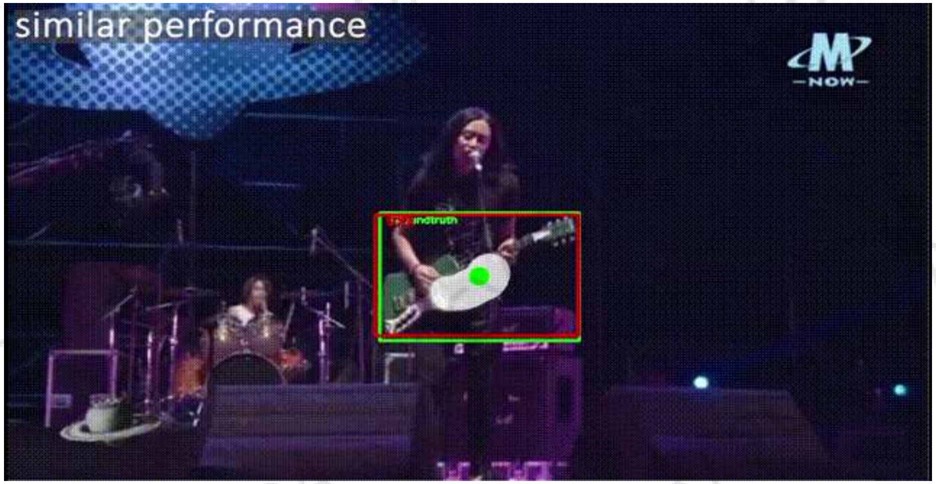
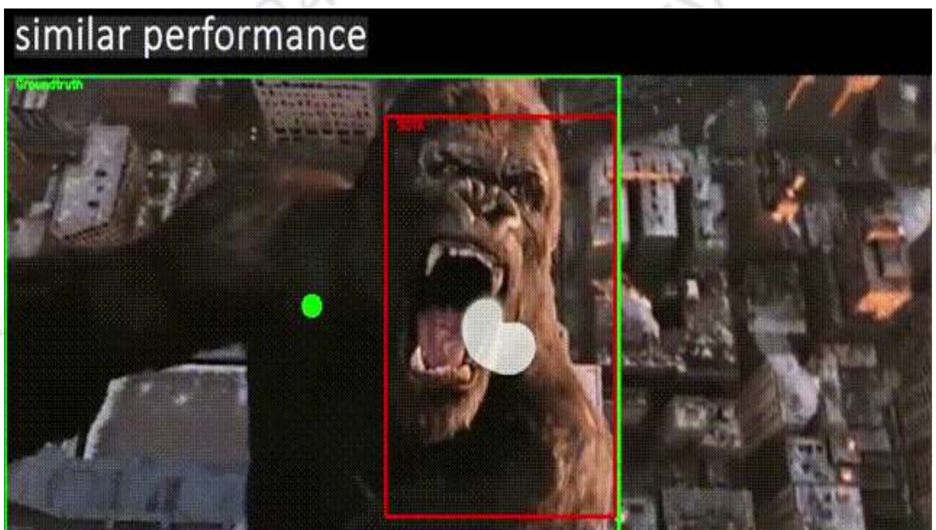
*S. Hu, X. Zhao#, L. Huang, et al., "Global instance tracking: Locating target more like humans," IEEE Transactions on Pattern Analysis and Machine Intelligence (**TPAMI**), vol. 45, no. 1, pp. 576–592, 2023.*

Human-to-Machine Evaluation

- **Example 3. Visual Turing Test in Global Instance Tracking**

➢ **Multiple challenging factors:** Both failed





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Human-to-Machine Evaluation

- **Core Steps in Visual Turing Test**
  - **Task Design:** Design identical visual tasks for both the machine and human participants.
  - **Result Collection:** Collect the results from both the machine and human participants on the same tasks.
  - **Result Comparison:** Use evaluation metrics such as similarity measures or success rates to compare machine and human performance.
  - **Judgment:** If the machine's results are indistinguishable from the human results, the machine is considered to have passed the Visual Turing Test.

Conclusion

➢ **Humans:**

- **Visual Theories**
  - Feature Integration Theory
  - Recognition-by-Components
  - Visual Computation
- **Visual Abilities**
  - Static Visual Ability
  - Dynamic Visual Ability
- **Insights for AI Development:** Understanding human visual theories and abilities, **provides foundational insights for enhancing algorithms**. By emulating these human mechanisms, machine vision systems can achieve **more accurate and adaptable tracking performance.**

Conclusion

➢ **Human-to-Machine Evaluation:**

- This approach **brings in human factors**, such as perception of occlusions, complex background differentiation, and rapid adjustments to changing conditions.
- By integrating human perspectives, human-to-machine evaluation enables **a more holistic understanding of a tracker's capabilities**, moving beyond traditional metrics to capture qualitative aspects of **intelligence and decision-making**.

ACCV

CONTENTS

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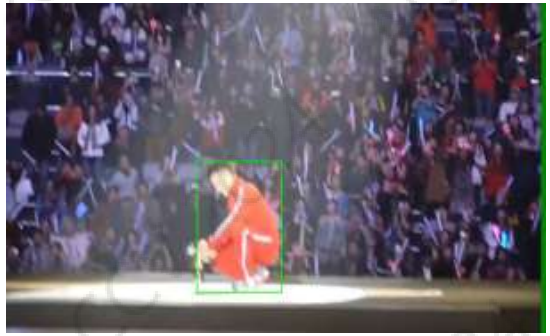
Trend 1. More Human-like Task Design

Trend 1. More Human-like Task Design

- What are the **abilities** of humans? → Designing more **human-like task** to model the dynamic vision ability.

Short-term tracking & Long-term tracking:
Methods utilize local search to locate the target near to its position in the previous frame.

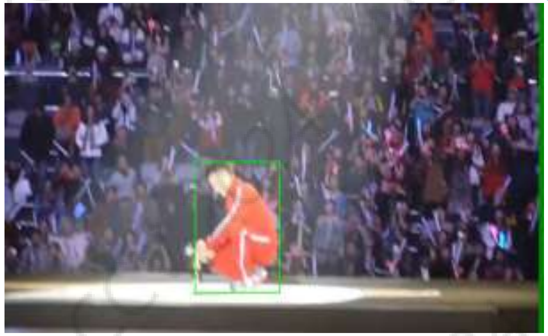
→ **perceptual level ability**

Global Instance Tracking:
Methods should remember the target and re-detect it in a new shot.
→ **cognitive level ability**

S. Hu, X. Zhao#, L. Huang, et al., "Global instance tracking: Locating target more like humans," IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), vol. 45, no. 1, pp. 576–592, 2023.

Trend 1. More Human-like Task Design

- **What are the abilities of humans? → Designing more human-like task to model the dynamic vision ability.**



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Methods utilize local search to locate the target near to its position in the previous frame.

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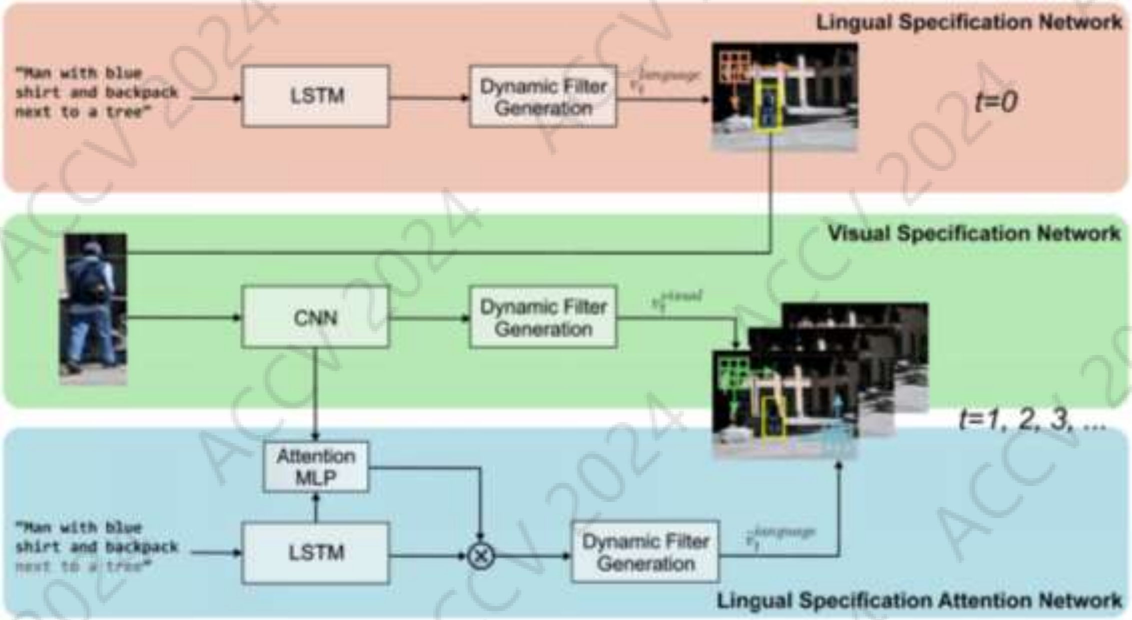
Visual Information (VOT) → *Add Semantic Information (VLT)*

Trend 1. More Human-like Task Design

- **Visual Language Tracking**



- **Type 1:** Tracking **using only textual information (Grounding)** without relying on visual data. The target is located and tracked purely through natural language descriptions.
- **Type 2:** The target is **initially located using textual descriptions**, and **then visual data is used** for single object tracking without further input from text.
- **Type 3: Both text and bounding boxes are used** for target initialization, and text continues to aid in object tracking throughout the process.

Li Z, Tao R, Gavves E, et al. Tracking by natural language specification, CVPR 2017

Trend 1. More Human-like Task Design

- **Visual Language Tracking**

➢ **Deep Learning-based Tracking Methods:** The **majority of deep learning-based object tracking methods belong to Type 3**, where both text and bounding box (BBox) are used for initialization, and text may or may not be used for further tracking. A **smaller portion of methods combine Type 2**, where text is only used during initialization, and further tracking relies solely on visual information.

Pre-training dataset

t=1

First frame: initialization
(semantic information and/or Bbox)

t=2,…,T

Video sequence: continuous tracking
(Use or not use semantic information)

OTB99-Lang (2017)

LaSOT (2019&2021)

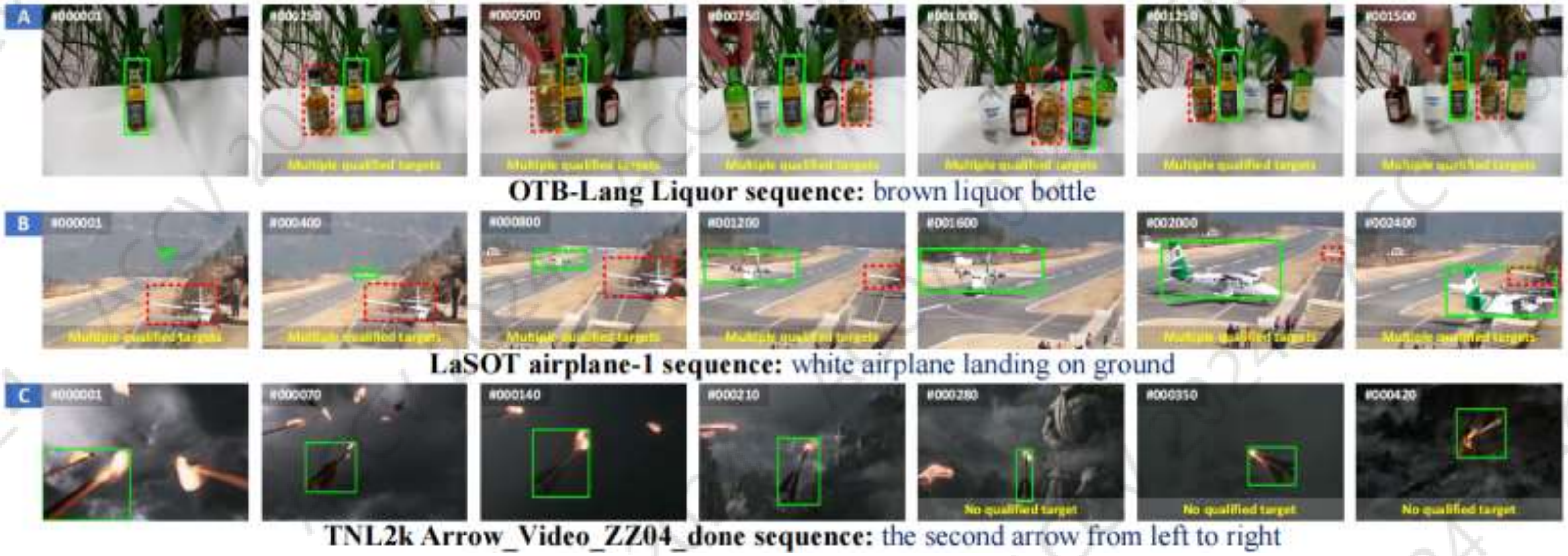
TNL2K (2021)

MGIT (2023)

Representative experimental environment

Trend 1. More Human-like Task Design

- **Example: Multimodal Global Instance Tracking (MGIT)**
  - **Motivation:** The VLT / VOT algorithm **performs poorly in complex scenes (long sequences & complex spatio-temporal causal relationships).** Some recent researches have considered studying from a multi-modal perspective:
    - **Limitations 1. Short sequence** (from hundreds of frames to thousands of frames) **→ Simple narrative content**
    - **Limitations 2. Inaccurate semantic annotation** (describing only the information of the first frame, and there may be multiple objects in the scene that fit the description) **→ Misguide algorithms**

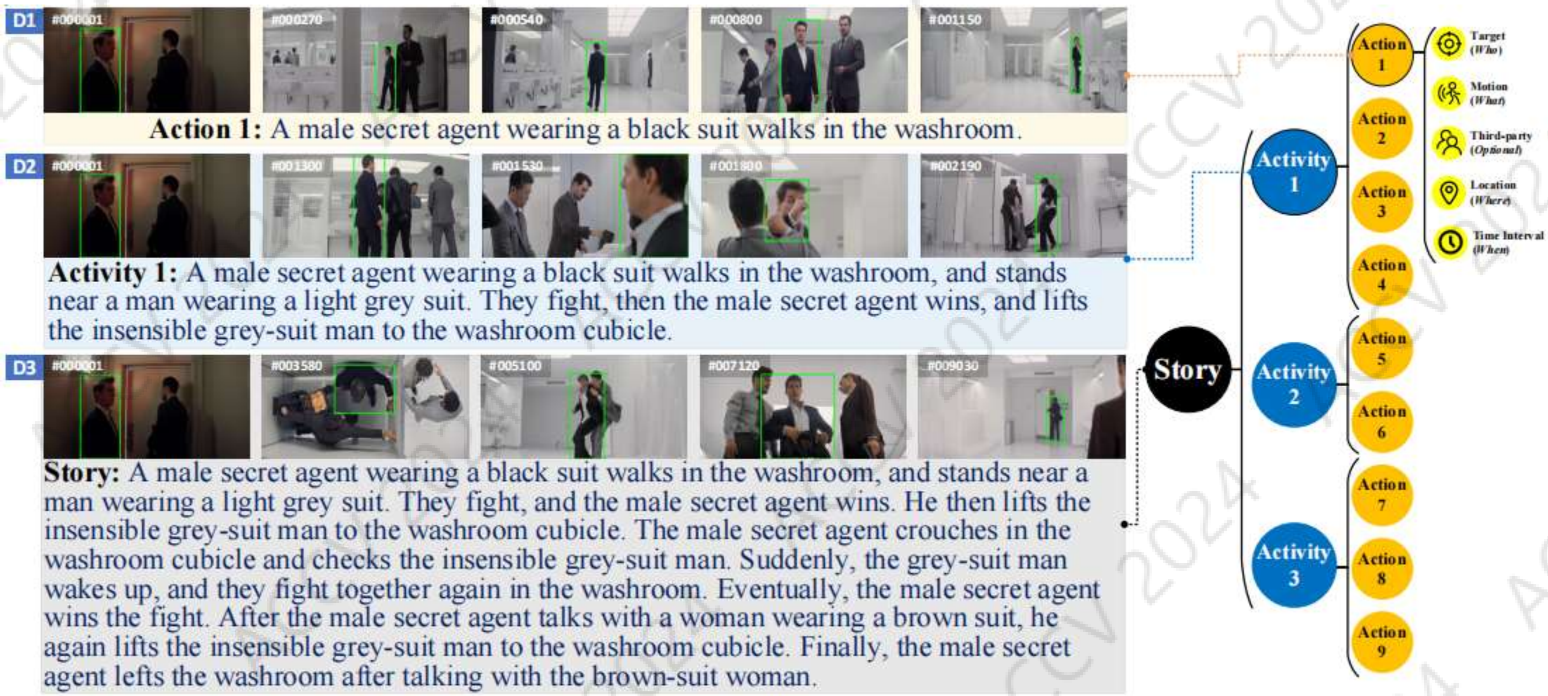


Limitations of existing works

S. Hu, D. Zhang, M. Wu, et al., "A multi-modal global instance tracking benchmark (mgit): Better locating target in complex spatio-temporal and causal relationship," in the 37th Conference on Neural Information Processing Systems (**NeurIPS**), 2023.

Trend 1. More Human-like Task Design

- **Example: Multimodal Global Instance Tracking (MGIT)**
  - **Limitations 1. Short sequence** (from hundreds of frames to thousands of frames) **→ Simple narrative content → Using longer sequences with more complex narratives**
  - **Limitations 2. Inaccurate semantic annotation** (describing only the information of the first frame, and there may be multiple objects in the scene that fit the description) **→ Misguide algorithms → Design a multi-granular annotation strategy to portray long videos**



Structure of MGIT

Trend 1. More Human-like Task Design

- **Example: Multimodal Global Instance Tracking (MGIT)**
  - ➢ **Rich subject matter →** Sufficiently covers the complex spatio-temporal causal relationships of long videos

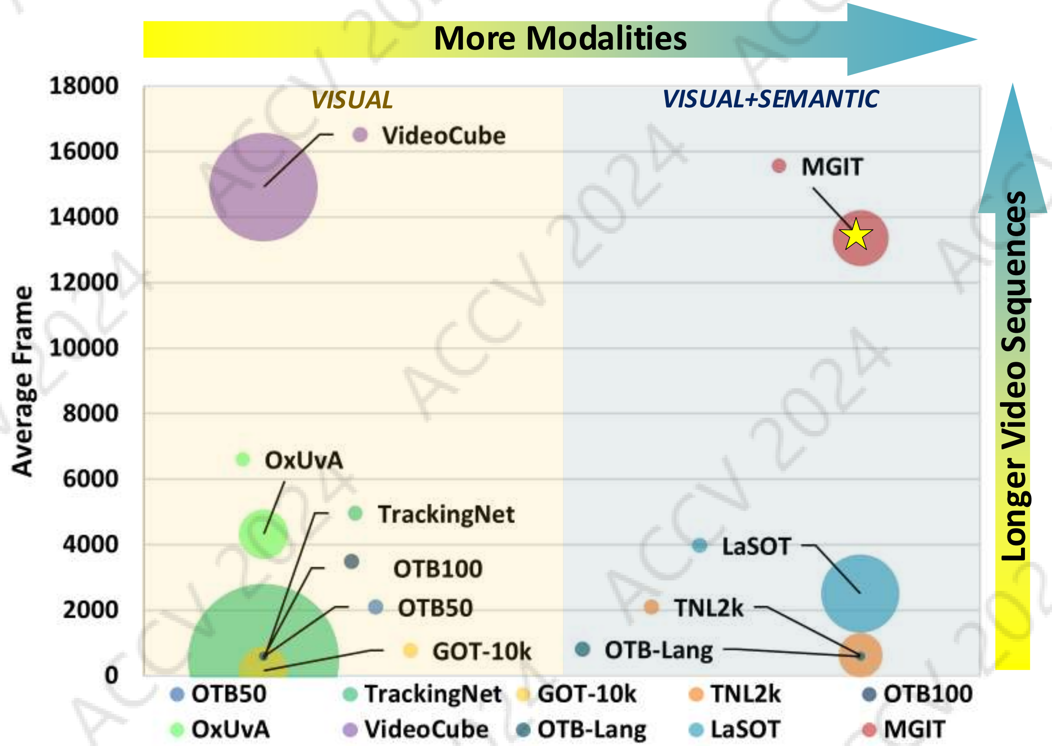
Several examples of MGIT

Trend 1. More Human-like Task Design

- **Example: Multimodal Global Instance Tracking (MGIT)**

➢ **Large-scale, Multi-modal**

- 150 long videos
- **2.03 million frames**
- The average length of a single video is **13,500 frames**



Comparison between MGIT with other VOT / VLT benchmarks

*S. Hu, D. Zhang, M. Wu, et al., "A multi-modal global instance tracking benchmark (mgit): Better locating target in complex spatio-temporal and causal relationship," in the 37th Conference on Neural Information Processing Systems (**NeurIPS**), 2023.*

Trend 1. More Human-like Task Design

- **Example: Multimodal Global Instance Tracking (MGIT)**

➢ Applying **hierarchical structure inspired by human cognition** for multi-granular annotation

- **Action :** Determining annotation dimensions from both **natural language grammar structure** and **video narrative content**
  - ☐ **Natural Language Grammar Structure :** Subject, Predicate, Object, Adverbial of time, Adverbial of place
  - ☐ **Video Narrative Content :** Time, Location, Character, Event

An example of action annotation

Trend 1. More Human-like Task Design

- **Example: Multimodal Global Instance Tracking (MGIT)**

➢ Applying **hierarchical structure inspired by human cognition** for multi-granular annotation

  - **Action :** Determining annotation dimensions from both **natural language grammar structure** and **video narrative content**
  - **Activity :** Using **causality** as a basis for classification

Action 5： more suitable as the ***Cause*** *for activity 2*

Action 4： more suitable as the ***Result*** *of activity 1*

Cause ➝ ***Result***

S. Hu, D. Zhang, M. Wu, et al., *"A multi-modal global instance tracking benchmark (mgit): Better locating target in complex spatio-temporal and causal relationship," in the 37th Conference on Neural Information Processing Systems (**NeurIPS**), 2023.*

Trend 1. More Human-like Task Design

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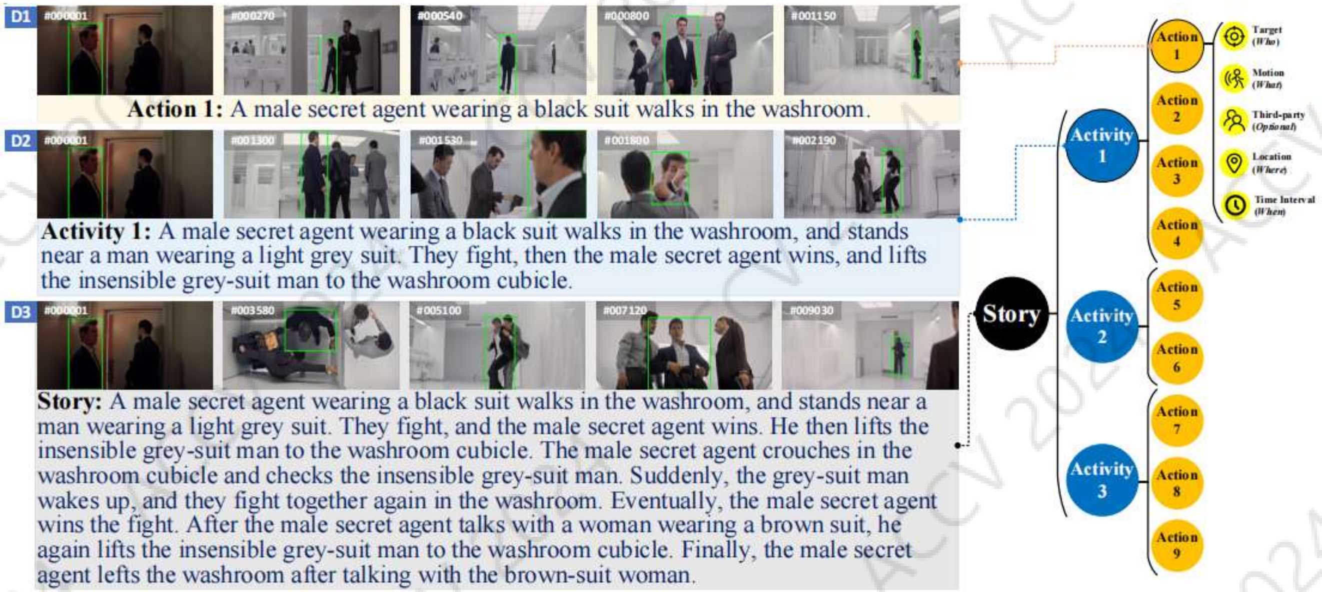
➢ Applying **hierarchical structure inspired by human cognition** for multi-granular annotation

- **Action :** Determining annotation dimensions from both **natural language grammar structure** and **video narrative content**
- **Activity :** Using **causality** as a basis for classification
- **Story :** To enhance **temporal and causal relationships**, guiding words such as "first, then, after that, finally," can be used on the basis of actions and activities



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Trend 1. More Human-like Task Design

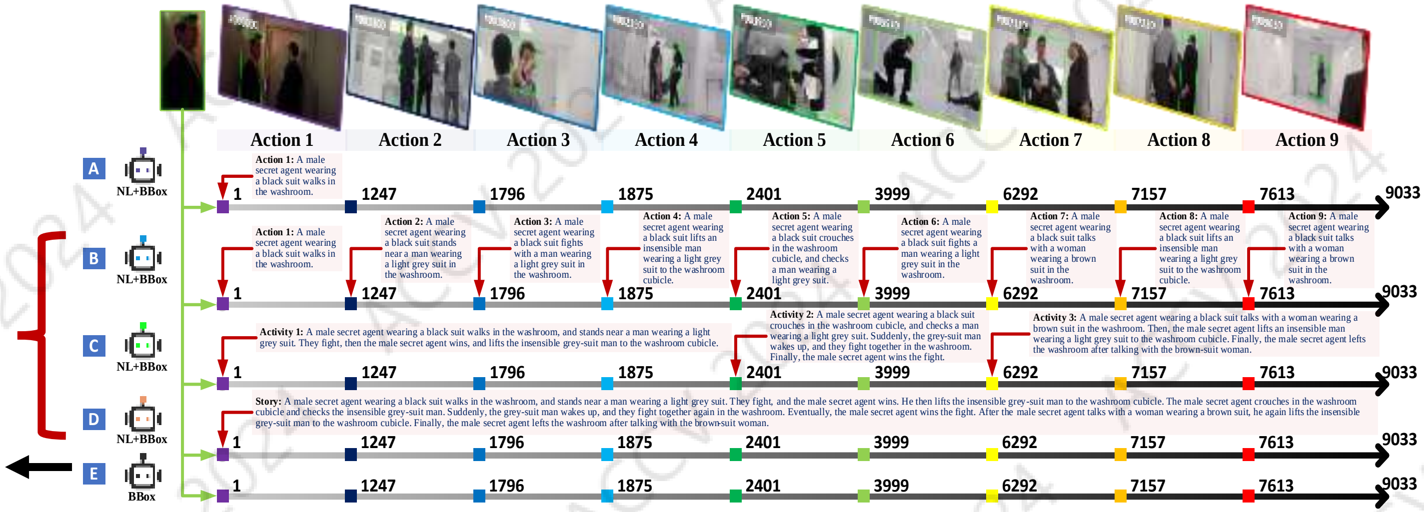
- **Example: Multimodal Global Instance Tracking (MGIT)**

➢ Expand the evaluation mechanism by conducting experiments under both **traditional evaluation mechanisms** (multi-modal single granularity, single visual modality) and **evaluation mechanisms adapted to this work** (multi-modal multi-granularity).

Multi-modal single granularity

Multi-modal multi-granularity

Single visual modality

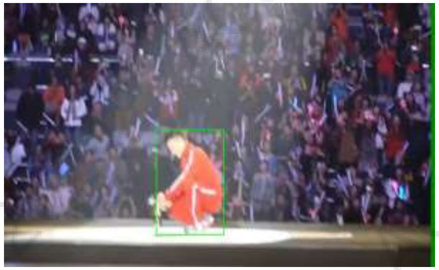


Adapted evaluation process for different task settings

Trend 1. More Human-like Task Design

- **Example: Multimodal Global Instance Tracking (MGIT)**

➢ Incorporate semantic information into the GIT task and introduced the Multi-modal GIT (MGIT) task → **Visual reasoning** in complex spatio-temporal causal relationships.



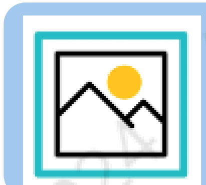
A long-term tracking demo

Short-term tracking & Long-term tracking

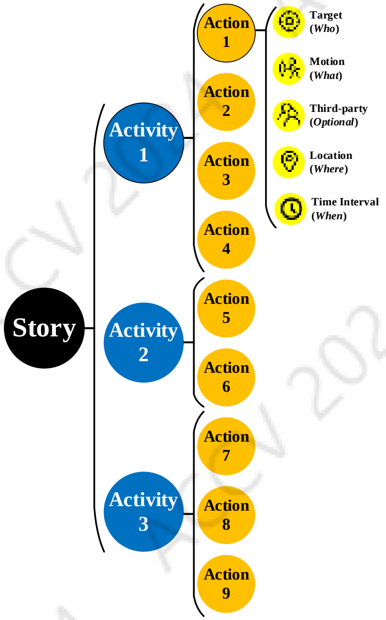
➢ Methods utilize local search to locate the target near to its position in the previous frame → **perceptual level**

Global Instance Tracking (GIT)

➢ Methods should remember the target and re-detect it in a new shot→ **cognitive level**



Visual Information



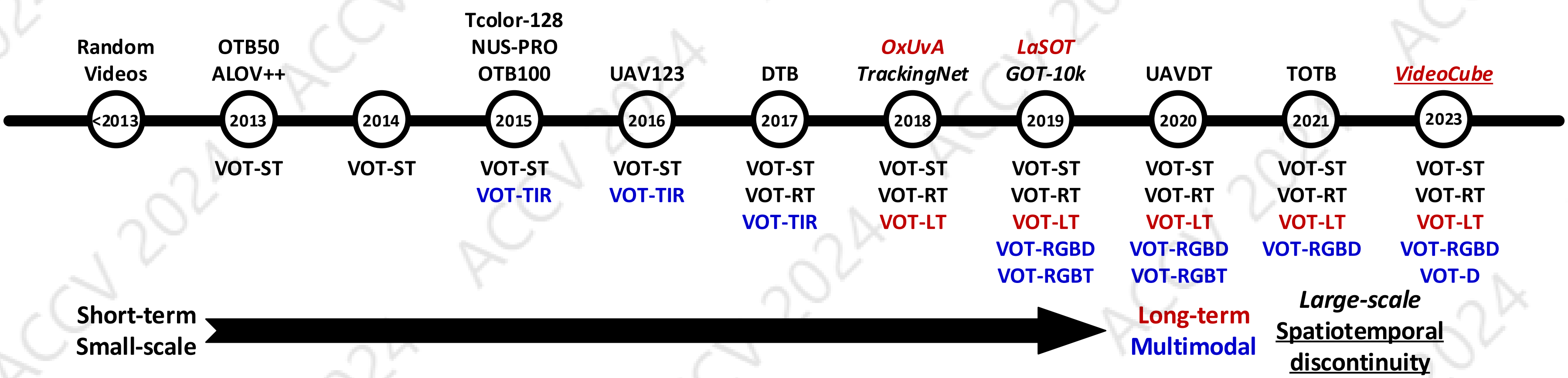
Semantic Information

S. Hu, D. Zhang, M. Wu, et al., "A multi-modal global instance tracking benchmark (mgit): Better locating target in complex spatio-temporal and causal relationship," in the 37th Conference on Neural Information Processing Systems (**NeurIPS**), 2023.

Trend 2. More Realistic Data Environment

Trend 2. More Realistic Data Environment

- **What are the living environments of humans? → Constructing more comprehensive and realistic datasets.**



- As computer vision technology advances, the need for evaluation environments that closely resemble the real world becomes more important. Realism in evaluation environments refers to **simulating the dynamic, diverse, and unpredictable nature of the real world** to assess the algorithm's performance in practical scenarios.

Trend 2. More Realistic Data Environment

- **From model-centric to data-centric**

nature machine intelligence

PERSPECTIVE

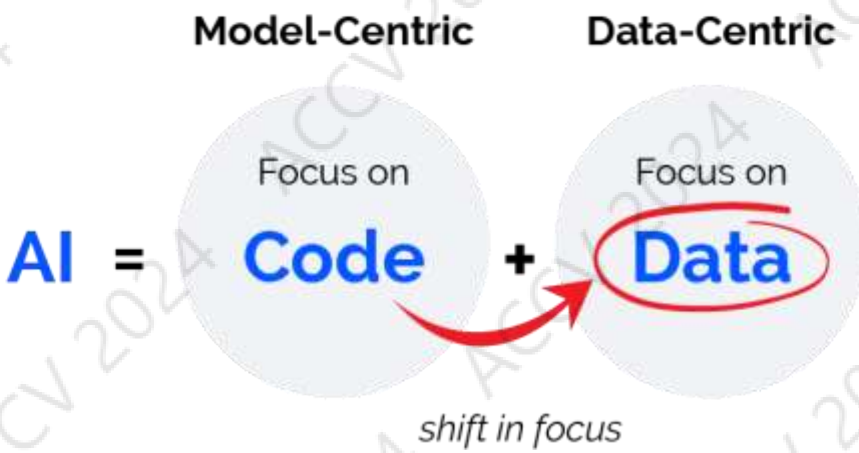
https://doi.org/10.1038/s42256-022-00516-1

Check for updates

Advances, challenges and opportunities in creating data for trustworthy AI

Weixin Liang[1], Girmaw Abebe Tadesse[2], Daniel Ho[3], Fei-Fei Li[1], Matei Zaharia[1], Ce Zhang[4] and James Zou[1,5]

[1]Department of Computer Science, Stanford University, Stanford, CA, USA. [2]IBM Research – Africa, Nairobi, Kenya. [3]Stanford Law School, Stanford University, Stanford, CA, USA. [4]Department of Computer Science, ETH Zurich, Zurich, Switzerland. [5]Department of Biomedical Data Science, Stanford University, Stanford, CA, USA. e-mail: jamesz@stanford.edu



➢ More attention needs to be placed on developing methods and standards to improve the **data-for-AI pipeline**.

Liang W, Tadesse G A, Ho D, et al. Advances, challenges and opportunities in creating data for trustworthy AI[J]. Nature Machine Intelligence, 2022, 4(8): 669-677.

Trend 2. More Realistic Data Environment

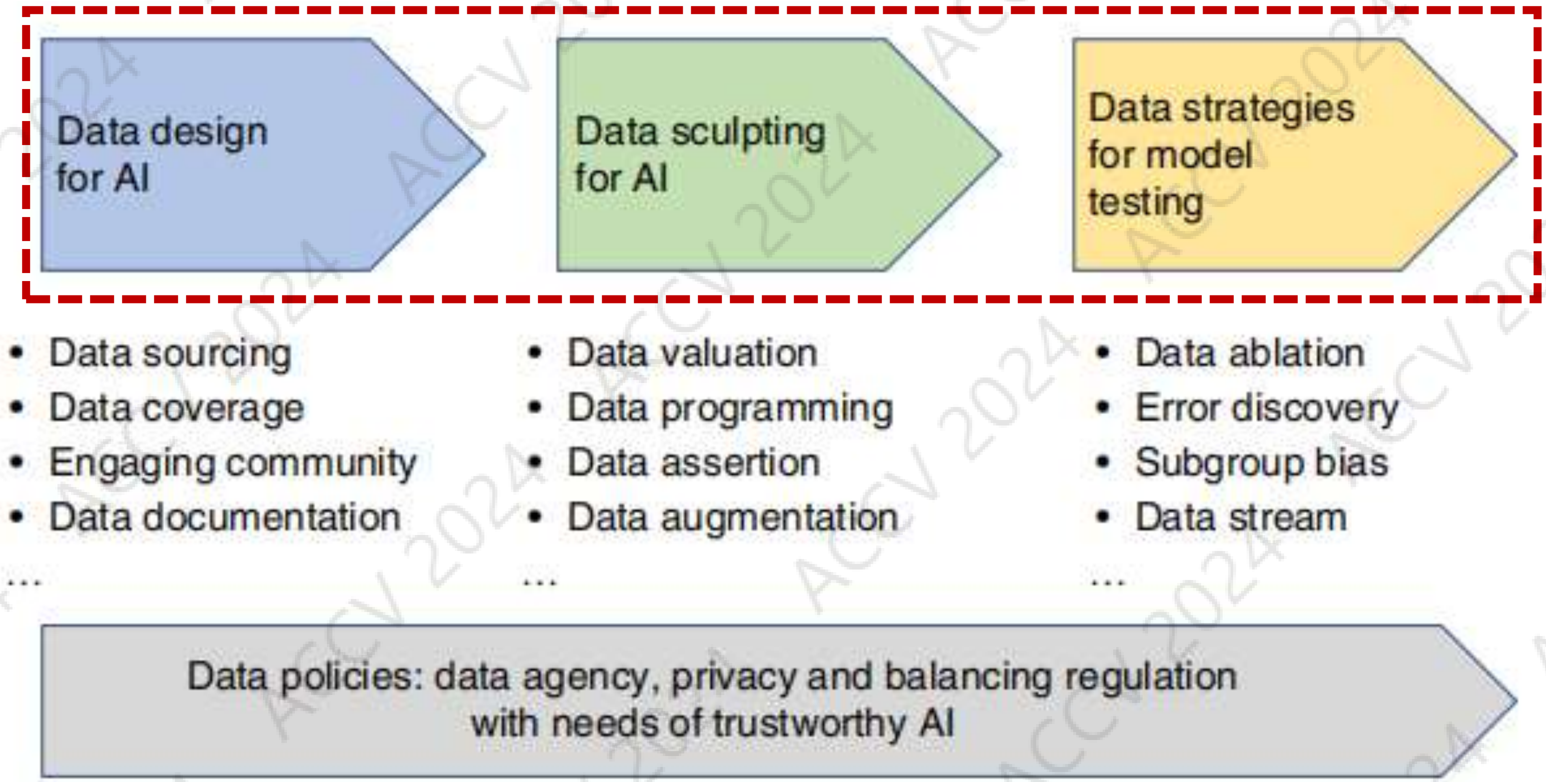
- **From model-centric to data-centric**

- **Model-centric** research typically considers data as given and focuses on improving the model architecture or optimization on this data.
- **Data-centric** research focuses on scalable methods to systematically **improve the data pipeline with data cleaning, selection, annotation and so on**.

Liang W, Tadesse G A, Ho D, et al. Advances, challenges and opportunities in creating data for trustworthy AI[J]. Nature Machine Intelligence, 2022, 4(8): 669-677.

Trend 2. More Realistic Data Environment

- **From model-centric to data-centric**
  - **Key Steps:**
    - Step 1. Dataset **design** for AI
    - Step 2. Data **sculpting** for AI
    - Step 3. Data strategies for **model testing**

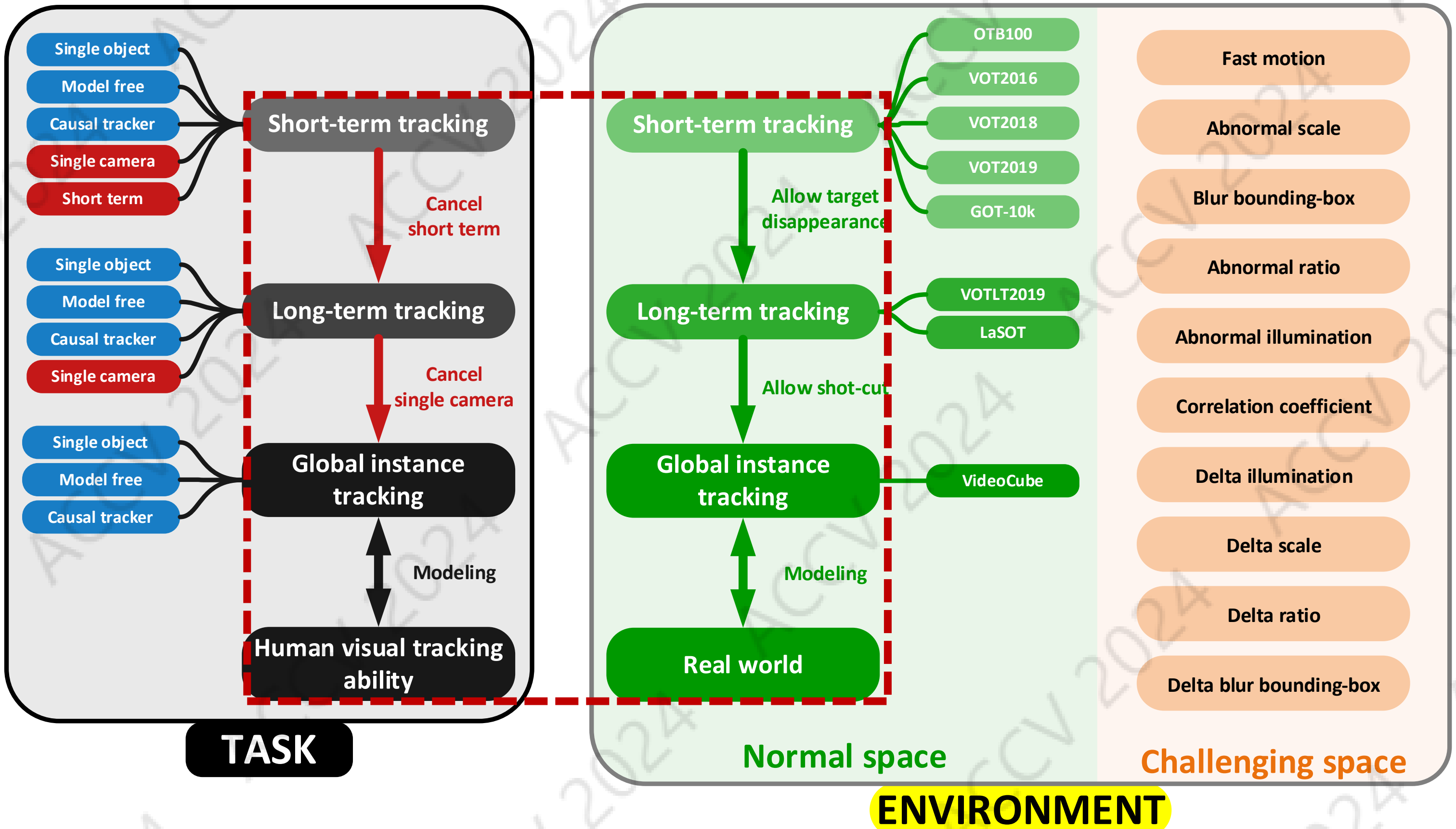


Liang W, Tadesse G A, Ho D, et al. Advances, challenges and opportunities in creating data for trustworthy AI[J]. Nature Machine Intelligence, 2022, 4(8): 669-677.

Trend 2. More Realistic Data Environment

- ## Step 1. Data design for AI

➢ Once an **AI application** has been identified, **designing the data**—namely identifying and documenting the sources of data—to develop the AI model is often one of the first considerations.



Trend 2. More Realistic Data Environment

- ## Step 1. Data design for AI

➢ Design should be an **iterative** process—it is often useful to have pilot data to develop an initial AI model and then **collect additional data** to patch the model's limitations.

GOT-10k

2017.11 ● **CVPR Submit**
1,000 videos

2018.10 ● **TPAMI Submit**
10,000 videos
Open-set evaluation
Generalization

VideoCube

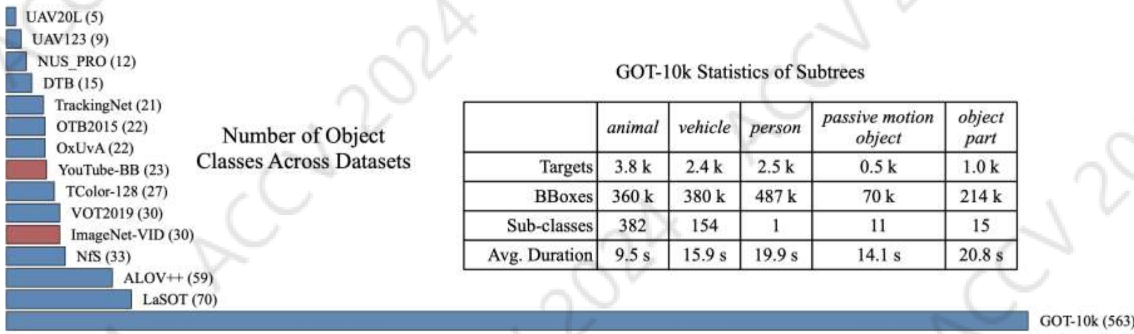
2020.03 ● **ECCV Submit**
GIT task
250 videos

2021.05 ● **TPAMI Submit**
GIT task
500 videos
Eye-tracking

Tiny version → Official version

Trend 2. More Realistic Data Environment

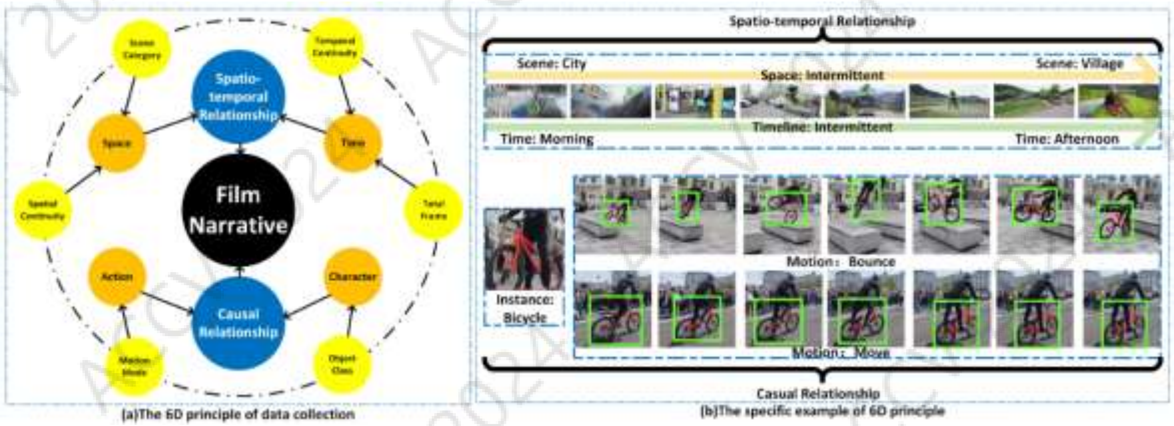
- **Step 1. Data design for AI**
  - ➢ A critical design criterion is to ensure that the data are appropriate for the task and have good **coverage to represent diverse users and scenarios** that the model can encounter in practice.



GOT-10k Statistics of Subtrees

	animal	*vehicle*	*person*	*passive motion object*	*object part*
Targets	3.8 k	2.4 k	2.5 k	0.5 k	1.0 k
BBoxes	360 k	380 k	487 k	70 k	214 k
Sub-classes	382	154	1	11	15
Avg. Duration	9.5 s	15.9 s	19.9 s	14.1 s	20.8 s

GOT-10K: 563 object classes, based on WordNet



(a)The 6D principle of data collection (b)The specific example of 6D principle

VideoCube: use 6D principle to model the real scenarios

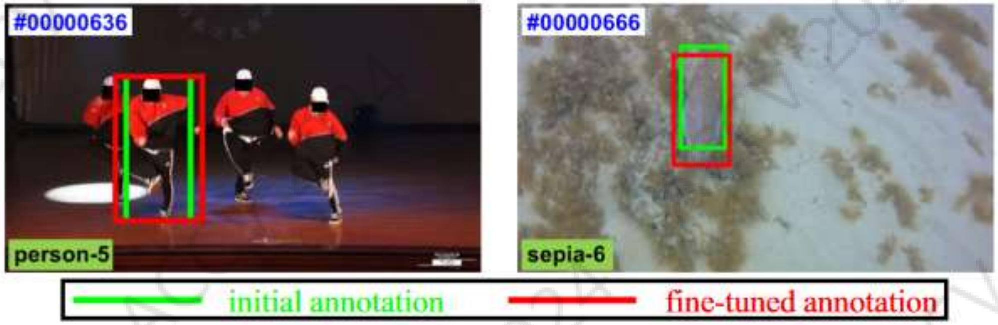
Trend 2. More Realistic Data Environment

- **Step 1. Data design for AI**
  - ➢ When representative data are hard to access, **synthetic data** can potentially fill some of the coverage gaps.

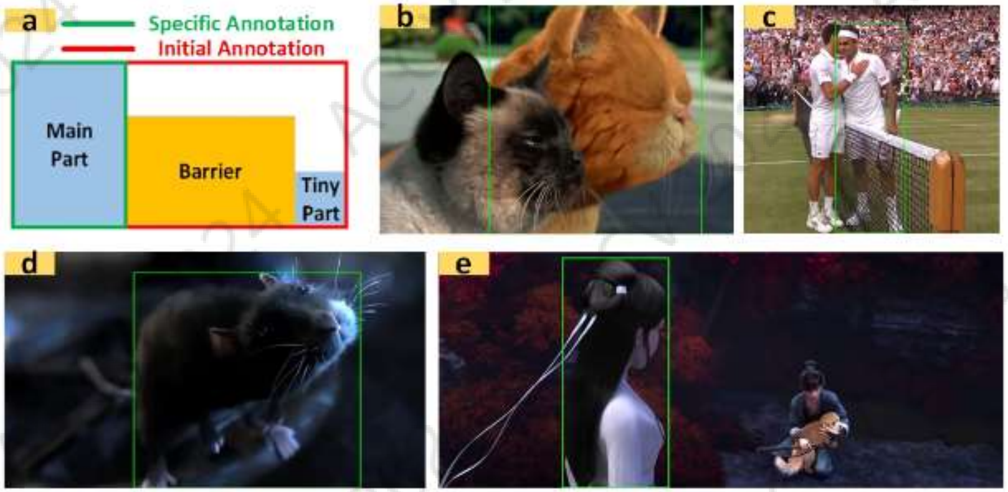
UAV123: Rotary-wing UAV (DJI S1000) + UAV simulator (UE4)

Trend 2. More Realistic Data Environment

- **Step 2. Data sculpting for AI**
  - Once an initial dataset is collected, a substantial amount of work is needed to **sculpt or refine** the data to make it **effective** for AI development.



LaSOT: fine-tuning initial annotations



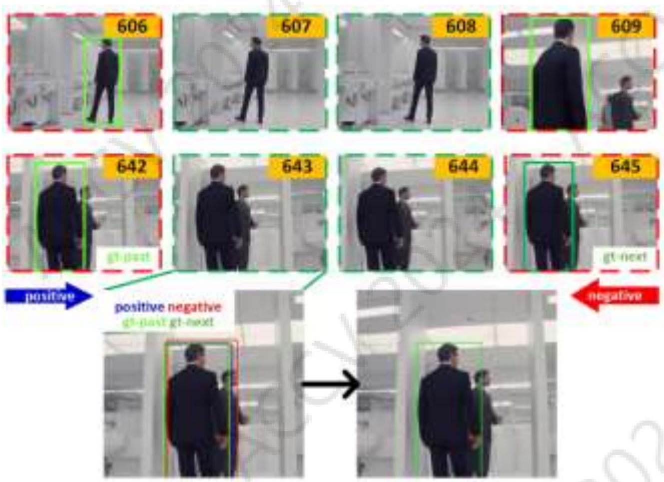
VideoCube: specific annotation rules

Trend 2. More Realistic Data Environment

- ## Step 2. Data sculpting for AI

  - A human-in-the-loop approach to reduce annotation costs is to prioritize the **most valuable data for humans to annotate**.

VideoCube: data verification process



VideoCube: automatic annotation

Algorithm 1: Framework of generate the automatic annotation

Input: P_{gt}: previous mannually labeled bounding-box; N_{gt}: next mannually labeled bounding-box; B_{pos}: bounding-box generated in forward order; B_{neg}: bounding-box generated in backward order

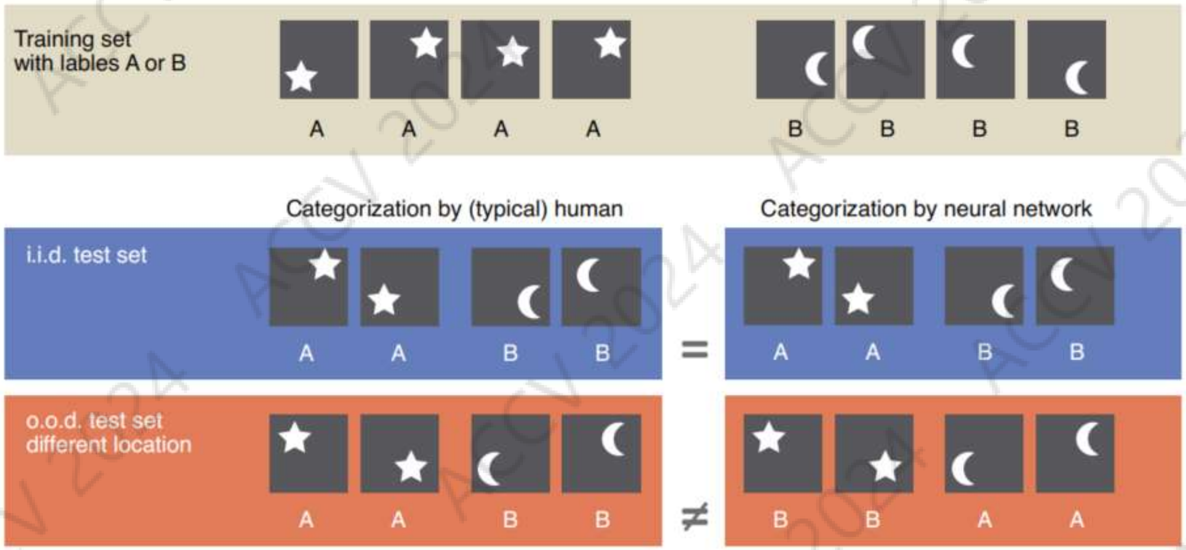
Output: B: bounding-box of present frame

calculate $D_1 = DIoU(P_{gt}, N_{gt})$
calculate $D_2 = DIoU(B_{pos}, B_{neg})$
/* Situation 1: a high value of D_1 indicates miniature movement, and the location can be directly calculated */
if $D_1 \geq \tau_1$ **then**
  $B = average(P_{gt}, N_{gt})$ return B
calculate $E_1 = Enclose(P_{gt}, N_{gt})$
/* Situation 2: a high value of D_2 indicates normal movement, and this is the most common situation. We assume that the motion range of instance in intermediate frame does not exceed E_1 */
if $D_2 \geq \tau_2$ **then**
  if *both* B_{pos} *and* B_{neg} *are enclosed by* E_1 **then**
    $B = average(B_{pos}, B_{neg})$
  else if B_{pos} *or* B_{neg} *is enclosed by* E_1 **then**
    $B = B_{pos}$ or $B = B_{neg}$
  else if *both* B_{pos} *and* B_{neg} *are outside* E_1 **then**
    $B = average(P_{gt}, N_{gt})$
  return B
/* Situation 3: the situation does not belong to the above two conditions indicates rapid movement or shot-switching */
if *presnet frame is the last two frame in a shot* **then**
  $B = average(B_{pos}, P_{gt})$
else if *presnet frame is the first two frame in a shot* **then**
  $B = average(B_{neg}, N_{gt})$
else
  calculate $D_3 = DIoU(P_{gt}, B_{pos})$
  calculate $D_4 = DIoU(N_{gt}, B_{neg})$
  if $D_3 \geq D_4$ **then**
    $B = Intersection(E_1, B_{pos})$
  else
    $B = Intersection(E_1, B_{neg})$
return B

Trend 2. More Realistic Data Environment

- **Step 3. Data strategies for model testing**

➢ An important aspect of evaluation is to verify that the AI models **do not use 'shortcut' strategies**.

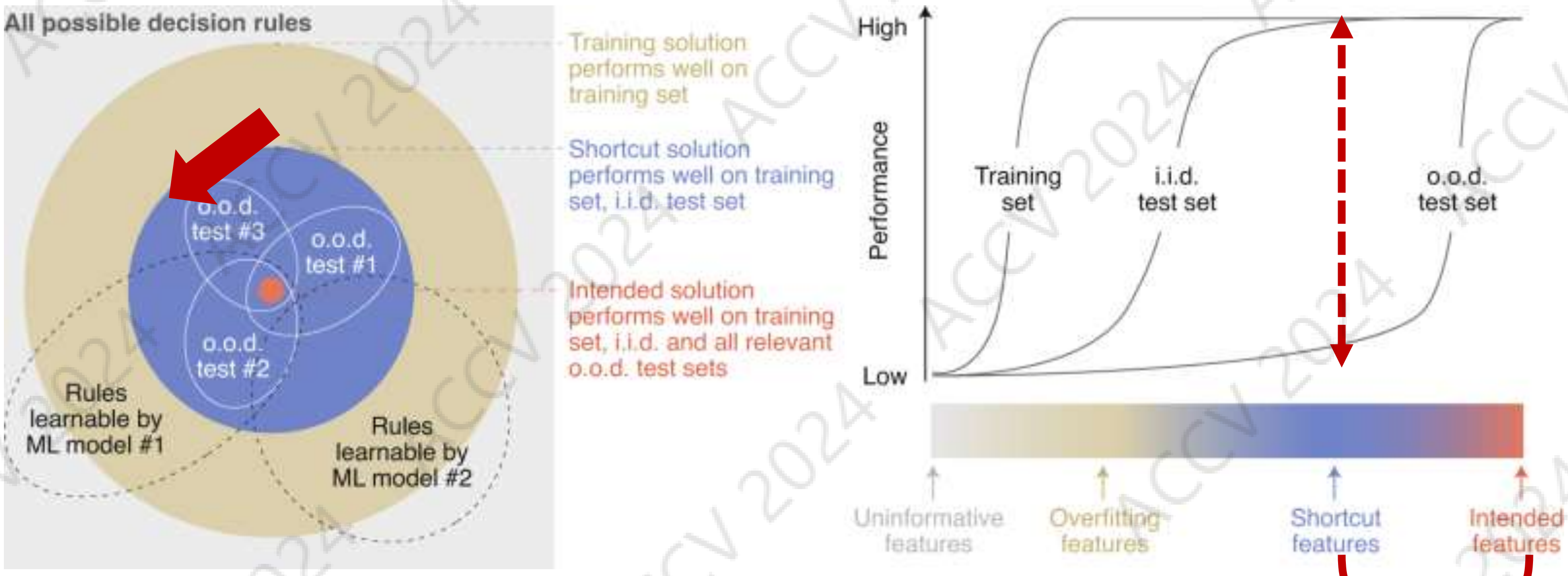


An example of shortcut

When trained on a simple dataset of stars and moons, a standard fully connected neural network learns a shortcut strategy: **classifying based on the location** (stars in the top right or bottom left; moons in the top left or bottom right) **rather than the shape of the objects.**

Trend 2. More Realistic Data Environment

- **Step 3. Data strategies for model testing**



➢ **I.i.d. test solutions, including shortcuts:** Decision rules that solve both the training and i.i.d. test set typically score high on standard benchmarks, but may fail in o.o.d test set.

- **By counting the number of white pixels (moons are smaller than stars)**
- **By location**
- **By shape**

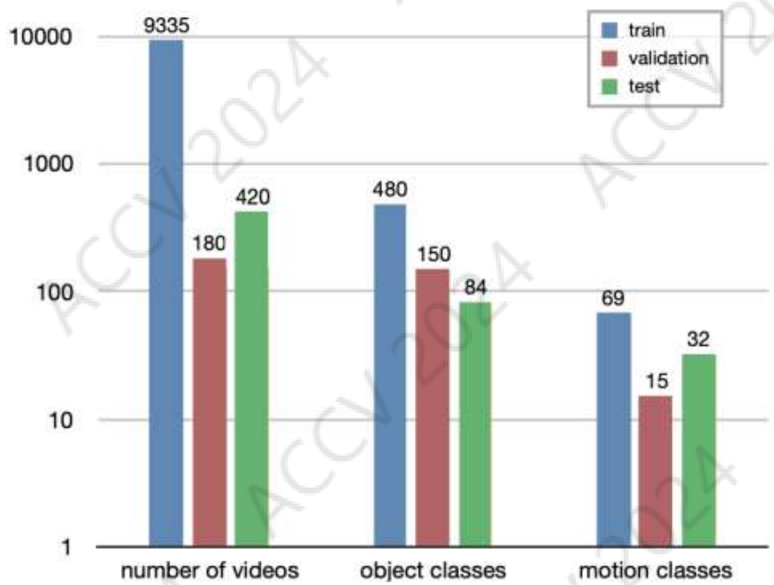
Shortcuts are decision rules that perform well on i.i.d. test data but fail on o.o.d. tests, revealing a mismatch between intended and learned solution.

Geirhos R, Jacobsen J H, Michaelis C, et al. Shortcut learning in deep neural networks[J]. Nature Machine Intelligence, 2020, 2(11): 665-673.

Trend 2. More Realistic Data Environment

• Step 3. Data strategies for model testing

- Towards **o.o.d. generalization** tests for detecting shortcuts:
  - If model performance is assessed only on i.i.d. test data, we cannot tell whether the model is actually acquiring the ability we think it is, since **exploiting shortcuts often leads to deceptively good results** on standard metrics.
  - **o.o.d. generalization tests should become a standard method for benchmarking models.**

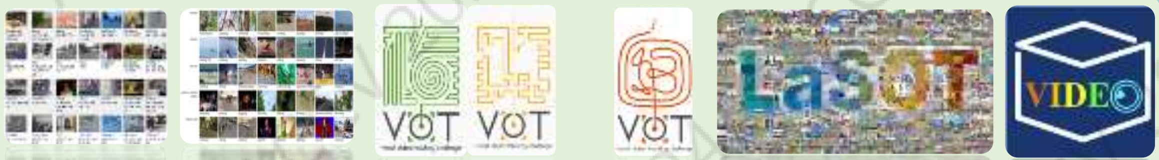


GOT-10k uses open-set evaluation (no overlap between training and testing categories) for generalization ability evaluation

Trend 2. More Realistic Data Environment

- **Example 1: SOTVerse (Dynamic and Open Task Space for VOT)**

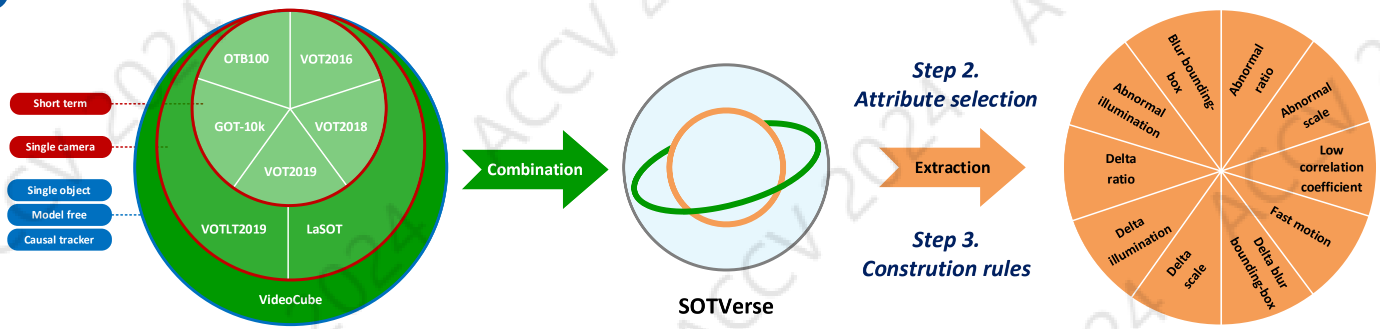
➢ **Motivation**



OTB-2013/2015 GOT-10k VOT2016&2018 VOTLT2019 LaSOT VideoCube

Existing datasets:

- **Static and closed** after construction
- **Ignore challenging factors**



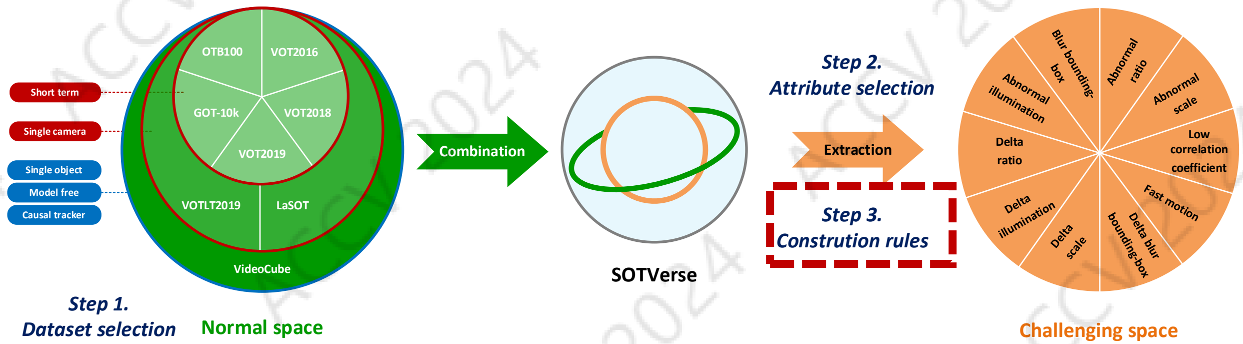
➢ Integrate diverse environments to create SOTVerse, a **dynamic and open task space** comprising 12.56 million frames.

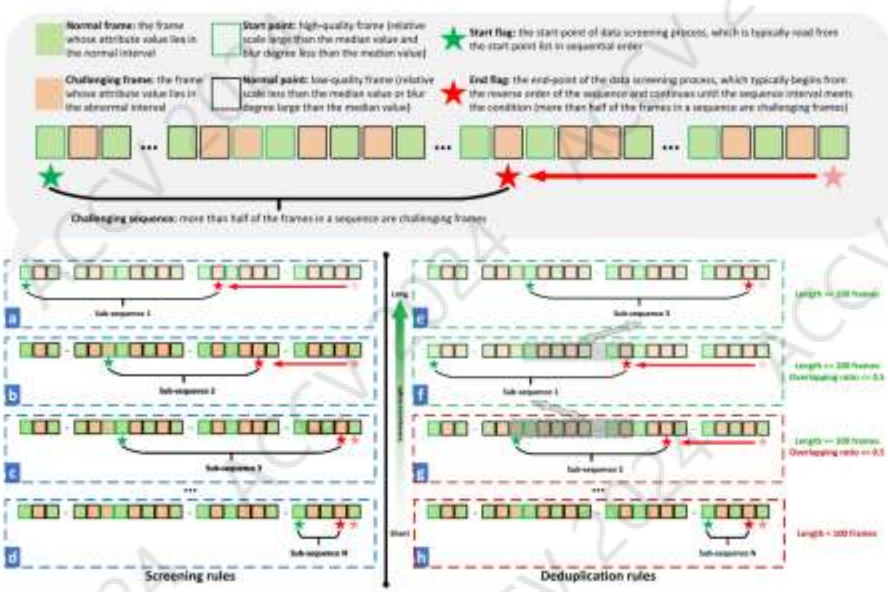
➢ Within this task space, researchers can efficiently construct different subspaces to train algorithms, thereby improving their **visual generalization** across various scenarios.

S. Hu, X. Zhao#, and K. Huang, "Sotverse: A user-defined task space of single object tracking," International Journal of Computer Vision (IJCV), 2024.

Trend 2. More Realistic Data Environment

- **Example 1: SOTVerse (Dynamic and Open Task Space for VOT)**
  - **Automatically mine challenging subsequences** that meet the requirements based on the research goal.





Algorithm 1 Framework of space construction.

Input: L: original sequence; $|\cdot|$: the cardinality; S: the list of start points in L, sorted by frame number in ascending order; C: the list of challenging frames in L, sorted by frame number in ascending order

Output: L_c: the set of challenging sub-sequences in L

```
/* Step 1: data screening */
screening set L_s = ∅
for i ← 0 to |S| − 1 do
    start flag α ← S[i]
    end flag β ← |L|
    while β > α do
        sub-sequence l ← L[α : β]
        if |l ∩ C| / |l| ≥ 0.5 then
            L_s ← L_s ∪ l
        else
            β ← β − 1
/* Step 2: data deduplication */
L_s ← DescendingSort(L_s)
extraction set L_l = ∅
for i ← 0 to |L_s| − 1 do
    sub-sequence l_i ← L_s[i]
    for j ← 0 to |L_s| − 1 do
        sub-sequence l_j ← L_s[j]
        if |l_i ∩ l_j| / |l_j| ≥ 0.5 then
        if (j == |L_s| − 1) ∧ (|L_s| ≥ 100) then
            L_l ← L_l ∪ l_i
return L_l
```

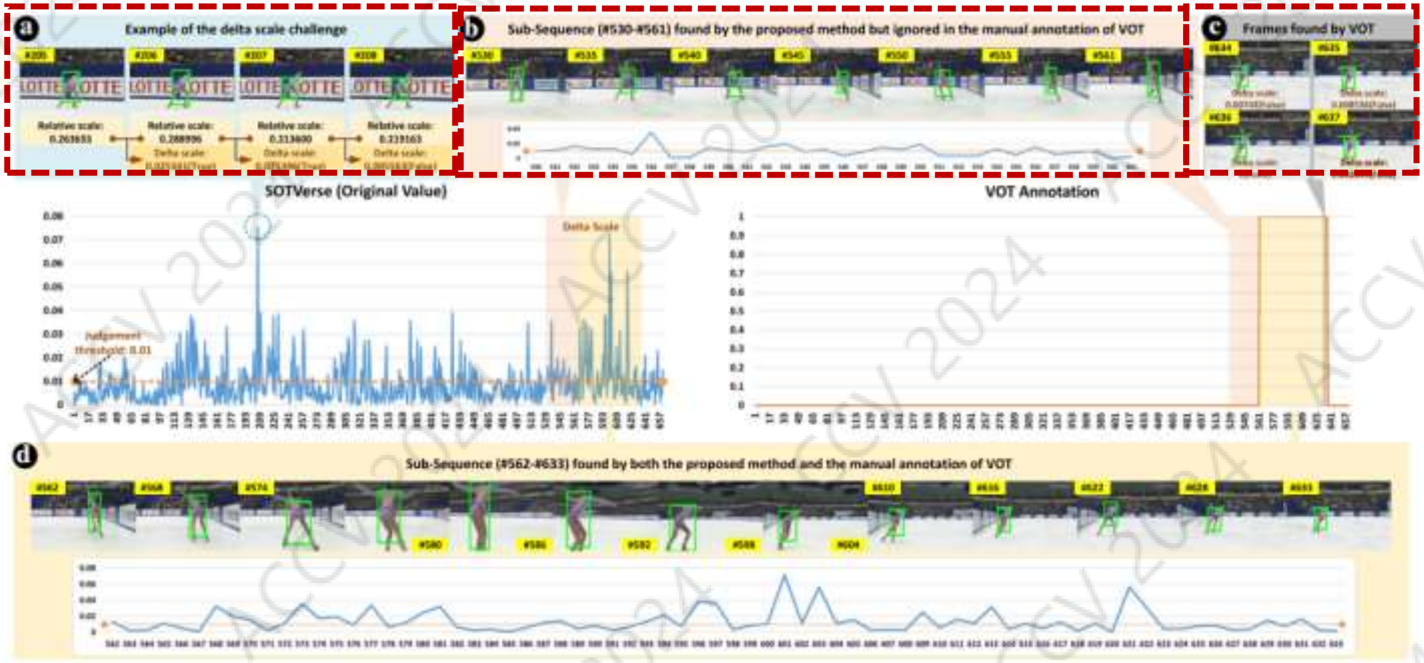
S. Hu, X. Zhao#, and K. Huang, "Sotverse: A user-defined task space of single object tracking," International Journal of Computer Vision (IJCV), 2024.

Trend 2. More Realistic Data Environment

- **Example 1: SOTVerse (Dynamic and Open Task Space for VOT)**

➢ **Comparison with human manual annotations**: Subspace construction strategy can effectively mine highly challenging sequences

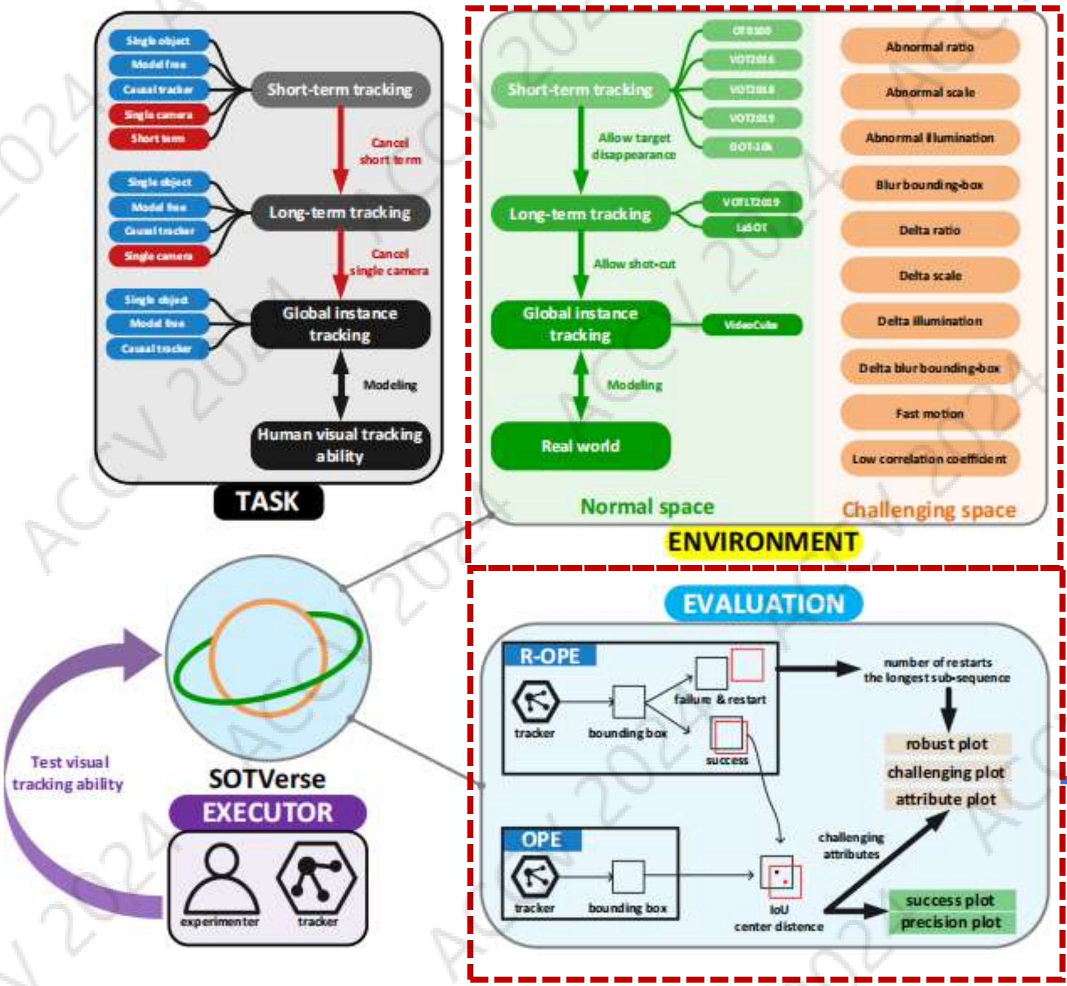
- Efficiently focus on **sparsely distributed** challenging video frames
- Effectively mine challenging sequences **ignored by human manual annotation**
- **More accurate judgment** on the starting and ending points of highly challenging sequences



S. Hu, X. Zhao#, and K. Huang, "Sotverse: A user-defined task space of single object tracking," International Journal of Computer Vision (IJCV), 2024.

Trend 2. More Realistic Data Environment

- **Example 1: SOTVerse (Dynamic and Open Task Space for VOT)**



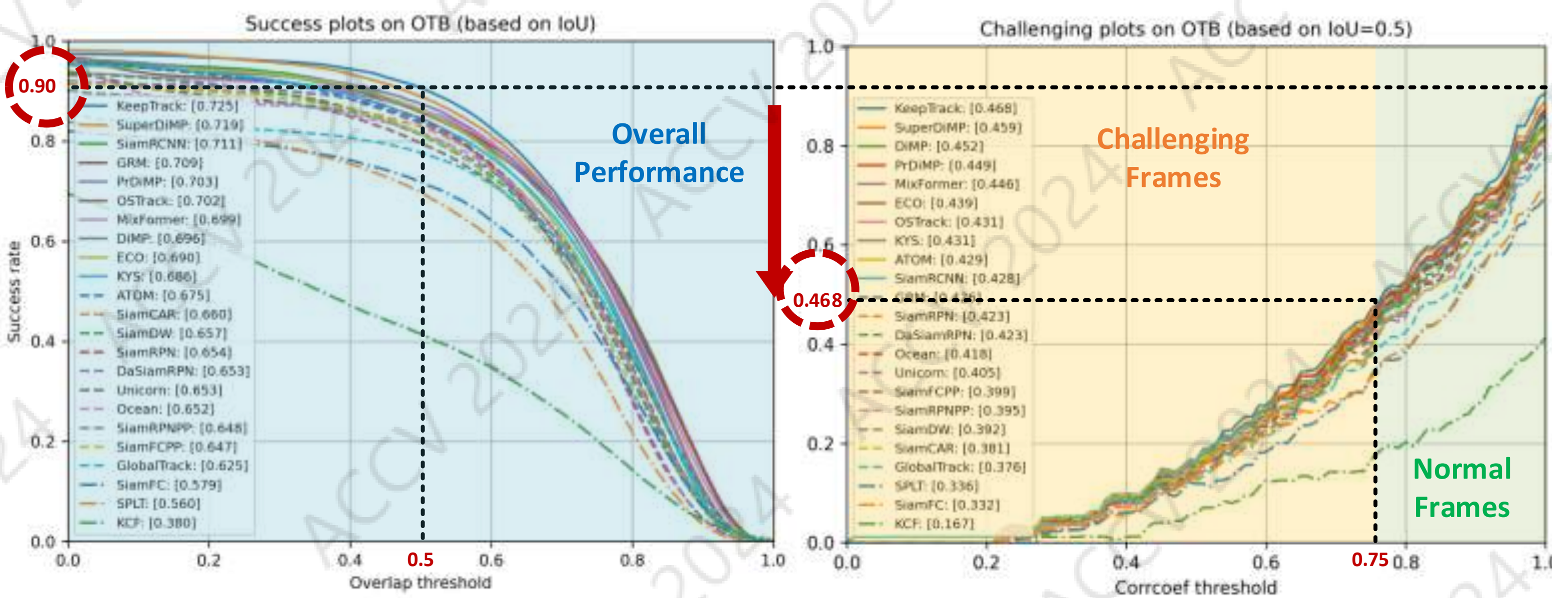
➢ **Some key issues that are masked by traditional evaluation methods:**
  - How does the SOTA algorithm perform when faced with difficult frames?
  - To which difficult challenges are algorithms more susceptible?
  - How well does the algorithm track over long sequences?

We **get nothing** by only focusing on scores under traditional evaluation methods.

Trend 2. More Realistic Data Environment

- **Example 1: SOTVerse (Dynamic and Open Task Space for VOT)**

➢ **Some key issues that are masked by traditional evaluation methods:** How does the SOTA algorithm perform when faced with difficult frames?
  - Difficult frame: correlation coefficient between two frames <0.75
  - **Challenge plot:** Calculates the success rate of the algorithm over all difficult frames
    - ☐ **The averaging form used in existing evaluation metrics will mask the bottleneck of the algorithm's ability on difficult frames.**



S. Hu, X. Zhao#, and K. Huang, "Sotverse: A user-defined task space of single object tracking," International Journal of Computer Vision (IJCV), 2024.

Trend 2. More Realistic Data Environment

- **Example 1: SOTVerse (Dynamic and Open Task Space for VOT)**

➢ **Some key issues that are masked by traditional evaluation methods:** To which difficult challenges are algorithms more susceptible?

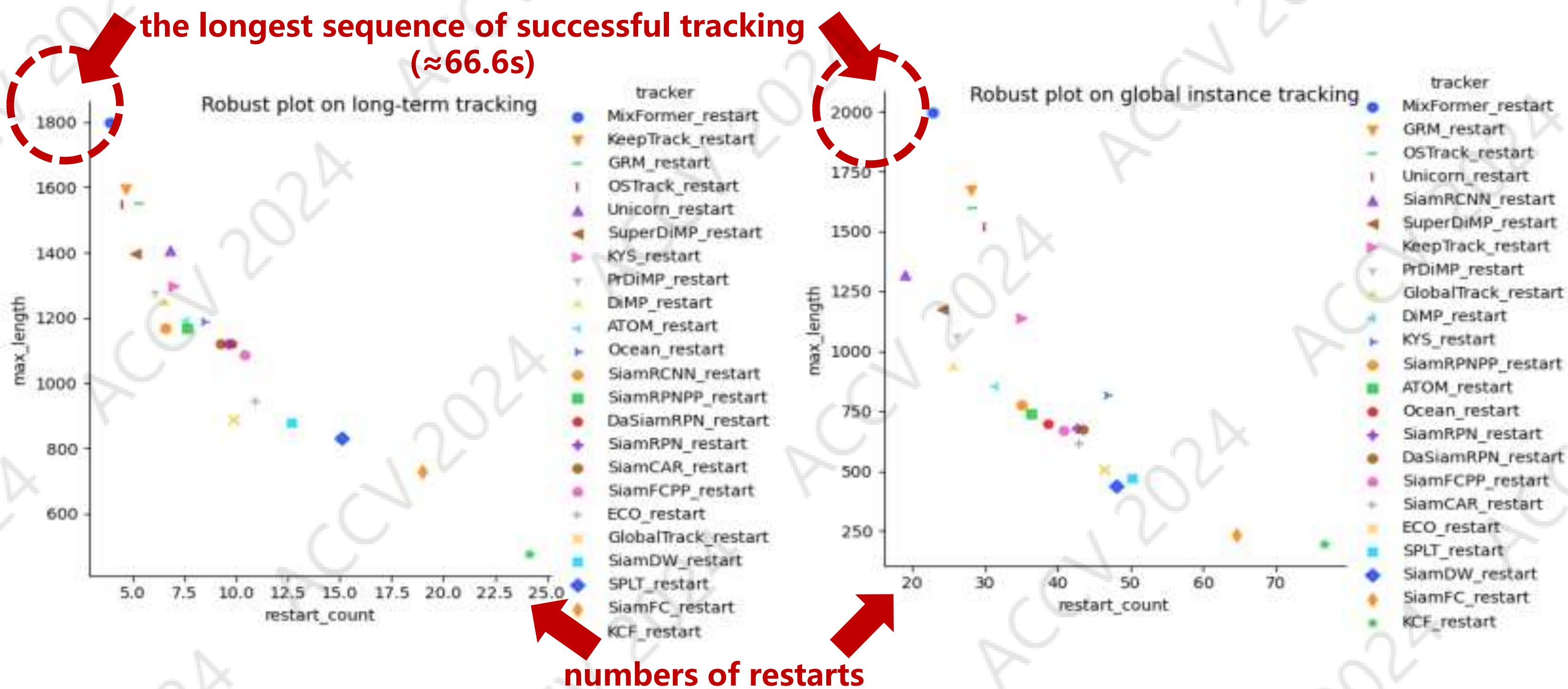
- Failure frame: frame where algorithm tracking fails (IoU<0.5)
- Successful frame: frame where the algorithm successfully tracks (IoU>=0.5)
- **Attribute plot:** Find the attribute with the largest difference between the failure frame and the success frame

Trend 2. More Realistic Data Environment

- **Example 1: SOTVerse (Dynamic and Open Task Space for VOT)**

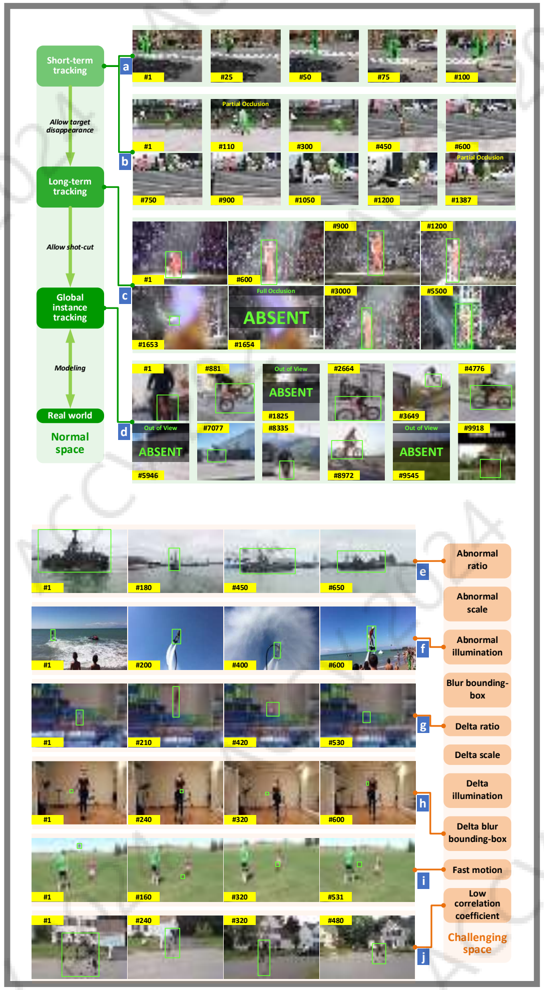
➢ **Some key issues that are masked by traditional evaluation methods:** How well does the algorithm track over long sequences?

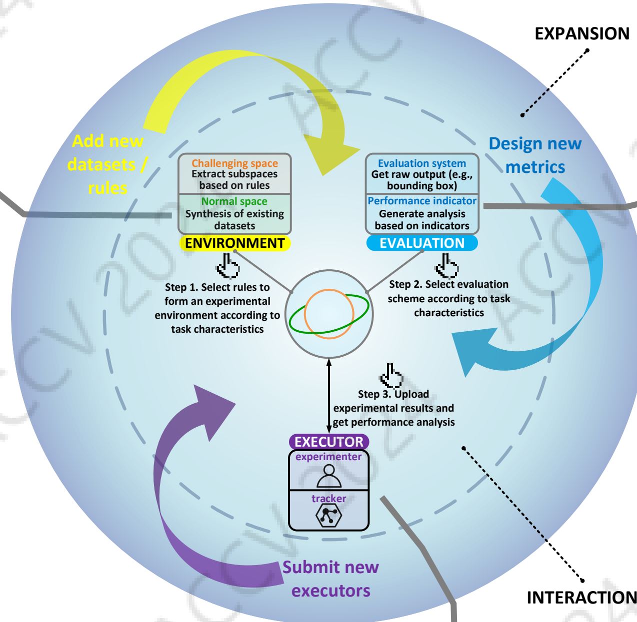
  - **Restart mechanism (R-OPE):** When an algorithm failure is detected, the algorithm is reinitialized at the nearest restart point.
  - **Robust plot:** measures the number of restarts of the algorithm, and the longest sequence of successful tracking.

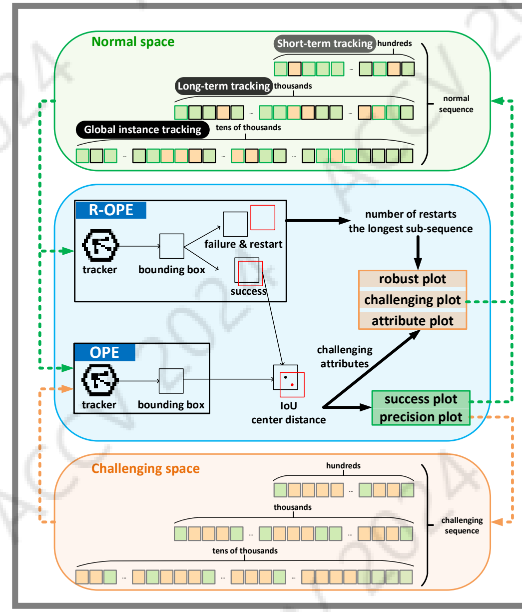


Trend 2. More Realistic Data Environment

- **Example 1: SOTVerse (Dynamic and Open Task Space for VOT)**







- Adapt to different experimental environments through multiple evaluation methods
- Comprehensive analysis of algorithms' bottlenecks

Trend 2. More Realistic Data Environment

- **Example 2: DTVLT (Diverse Multimodal Benchmark for VLT)**

➢ **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 :

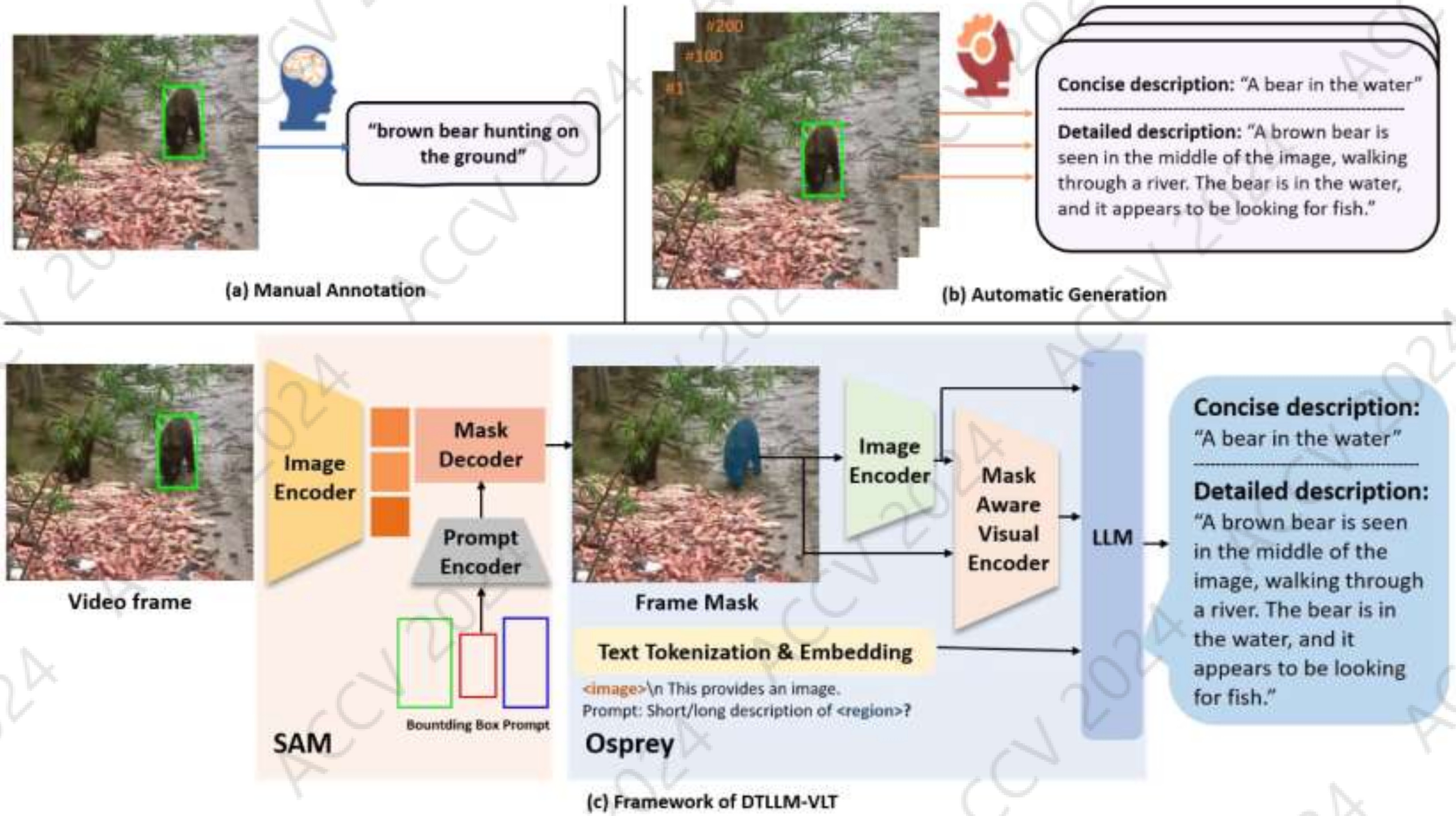
- **Limitations 1.** Semantic annotations in OTB99_Lang mainly describe **the first frame**, which may **misguide the algorithm**.
- **Limitations 2.** Sequence in MGIT has such **complex text** that they are **not conducive to algorithmic learning**.

➢ **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.

Li X, Hu S, Feng X, et al. DTVLT: A Multi-modal Diverse Text Benchmark for Visual Language Tracking Based on LLM[J]. arXiv preprint arXiv:2410.02492, 2024.

Trend 2. More Realistic Data Environment

- **Example 2: DTVLT (Diverse Multimodal Benchmark for VLT)**
  - **Diverse texts** matter → Integrating the **LLM** into the text generation process, offer a **diverse environment** conducive to VLT research.

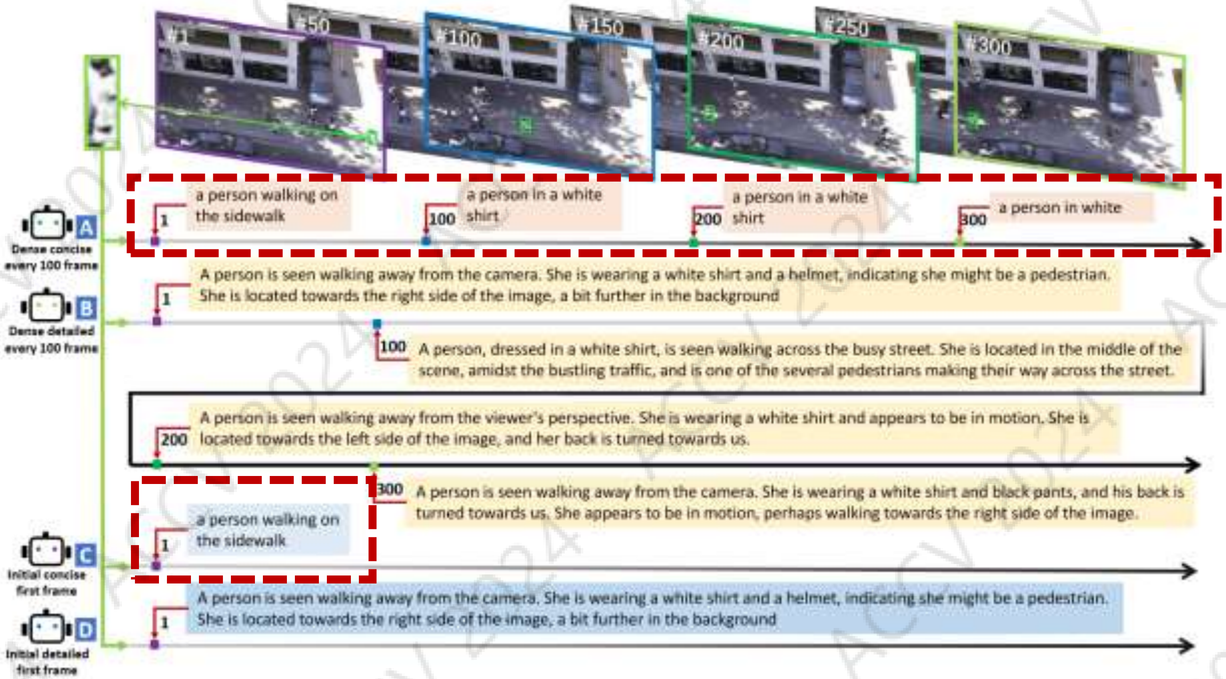


Trend 2. More Realistic Data Environment

- **Example 2: DTVLT (Diverse Multimodal Benchmark for VLT)**

➢ **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.

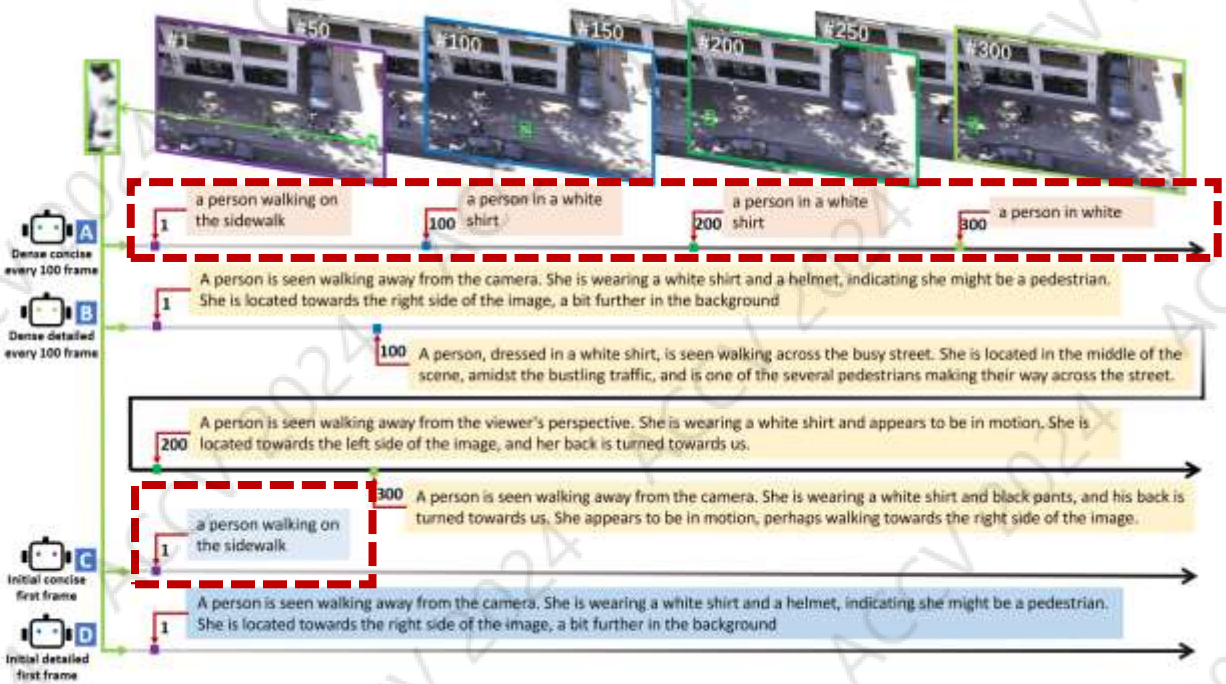


Trend 2. More Realistic Data Environment

- **Example 2: DTVLT (Diverse Multimodal Benchmark for VLT)**

➢ **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.
- **Dense 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.



Trend 2. More Realistic Data Environment

- **Example 2: DTVLT (Diverse Multimodal Benchmark for VLT)**
  - **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

(b) The word cloud of initial detailed texts

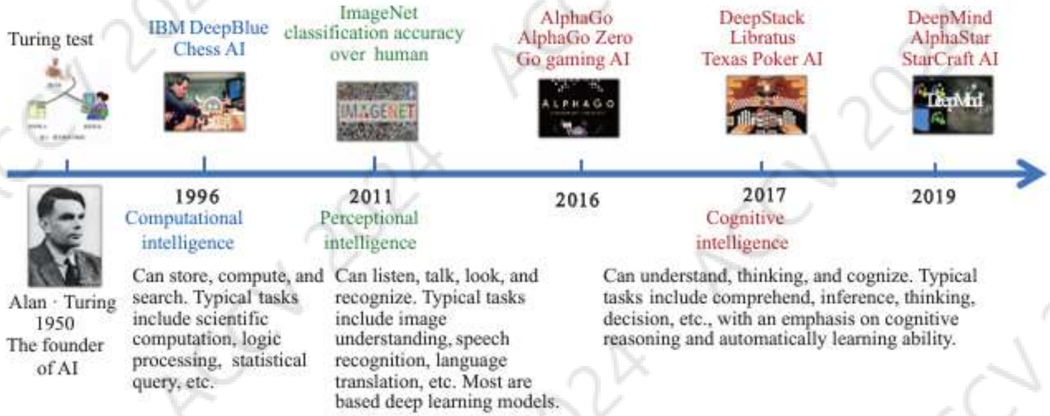
(c) The word cloud of dense concise texts

(d) The word cloud of dense detailed texts

Trend 3. More Human-like Executors

Trend 3. More Human-like Executors

- **Optimizing algorithms from the perspective of human-like modeling: understanding video content more like humans.**



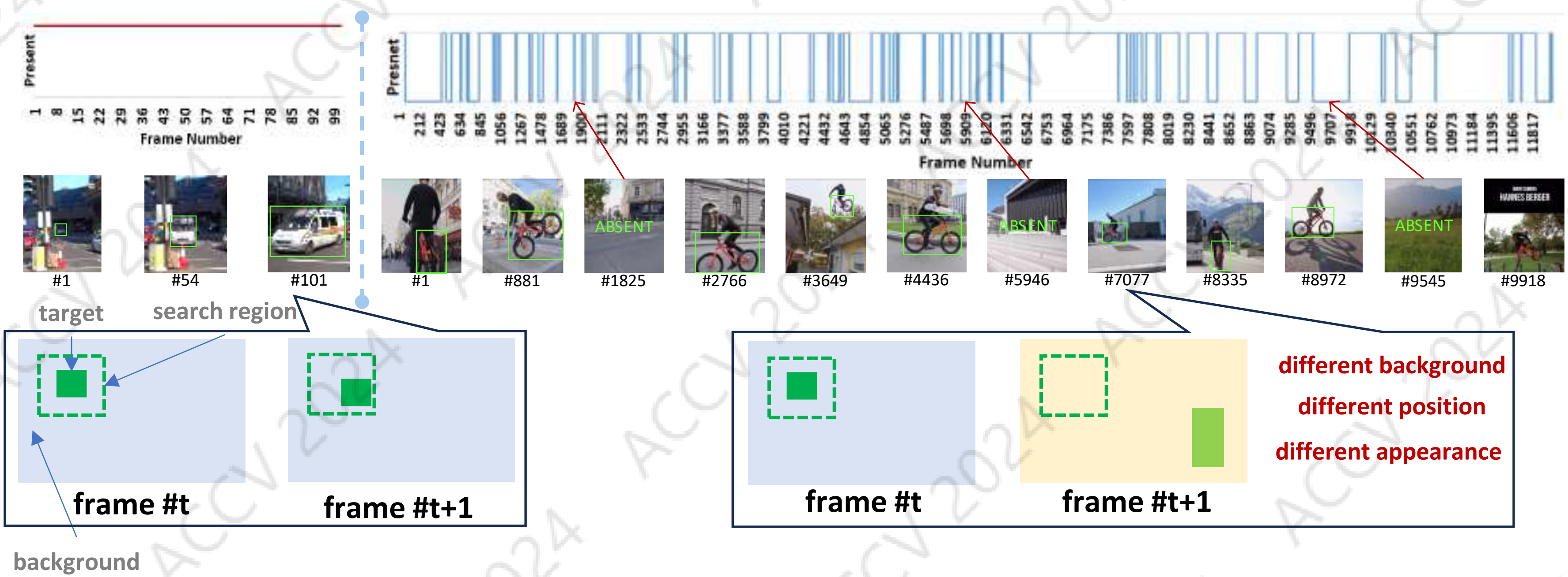
➢ **Goal of Computer Vision Research:** Equip machines with human-like visual intelligence. The goal is to achieve machine intelligence at multiple levels**.**

- **Computational Intelligence:** Responsible for signal processing, logical processing, and statistical calculations, serving as the foundation for higher intelligence levels.
- **Perceptual Intelligence:** Involves the ability to perceive and capture visual information from the environment, such as image recognition and object detection.
- **Cognitive Intelligence:** Includes memory, prediction, and reasoning capabilities, forming the basis for understanding and inferring future actions.

Huang K Q, Xing J L, Zhang J G, et al. Intelligent technologies of human-computer gaming (in Chinese). Sci Sin Inform, 2020, 50: 540–550, doi: 10.1360/N112019-00048

Trend 3. More Human-like Executors

- **Example 1. Human-like VOT via Visual Search Ability (Better Perceptual Intelligence)**

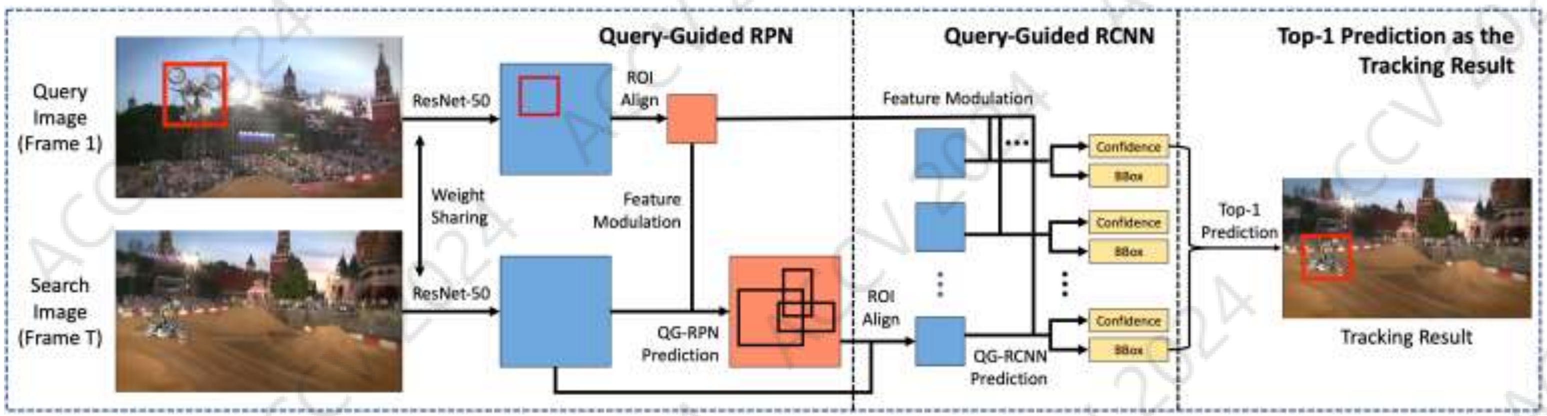


local search: applies **only to continuous motion assumption**

Trend 3. More Human-like Executors

- **Example 1. Human-like VOT via Visual Search Ability (Better Perceptual Intelligence)**

- **local search:** applies **only to continuous motion assumption**

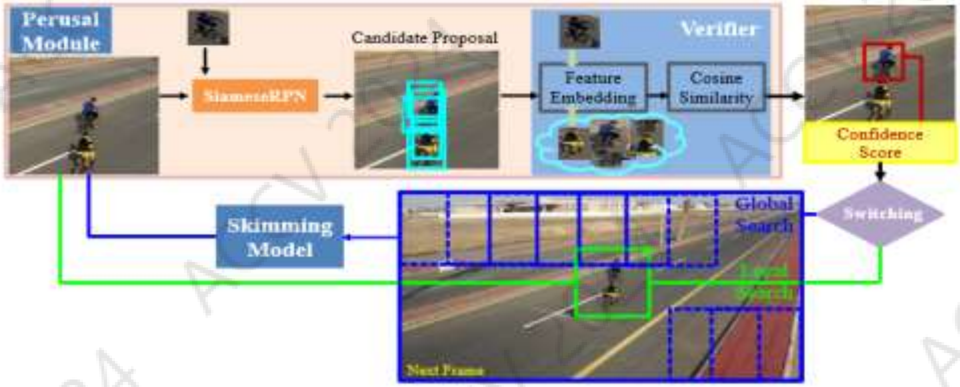


- **global search:** zero cumulative error, but it is **slow** and **easily interfered by background**

Trend 3. More Human-like Executors

- **Example 1. Human-like VOT via Visual Search Ability (Better Perceptual Intelligence)**

- **local search:** applies **only to continuous motion assumption**
- **global search:** zero cumulative error, but it is **slow** and **easily interfered by background**

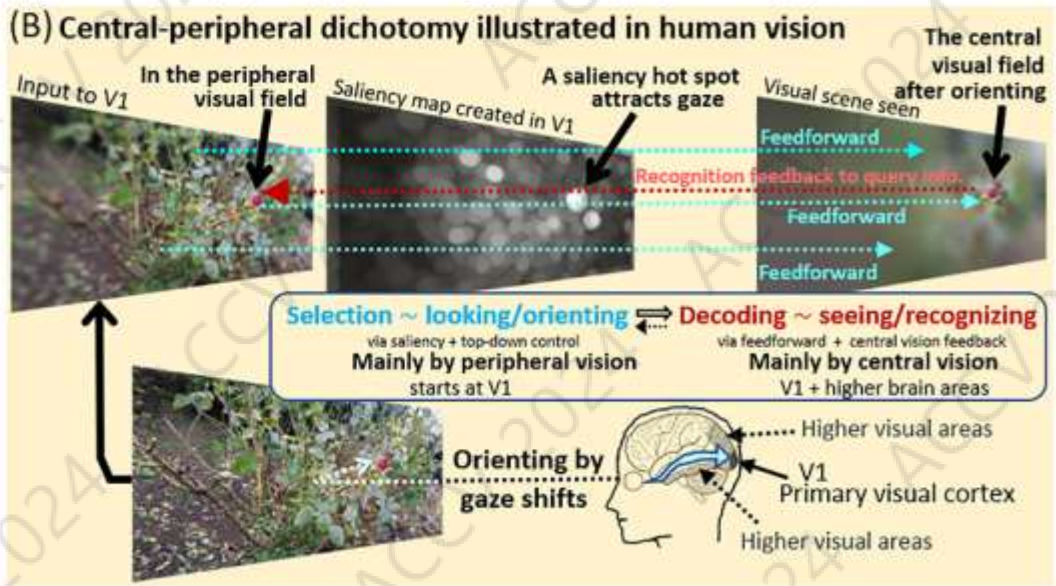


- **local search + global search:** good idea, but **the timing of the switch is difficult to determine**

How the human visual system accurately finds the target in a new frame?

Trend 3. More Human-like Executors

- **Example 1. Human-like VOT via Visual Search Ability (Better Perceptual Intelligence)**

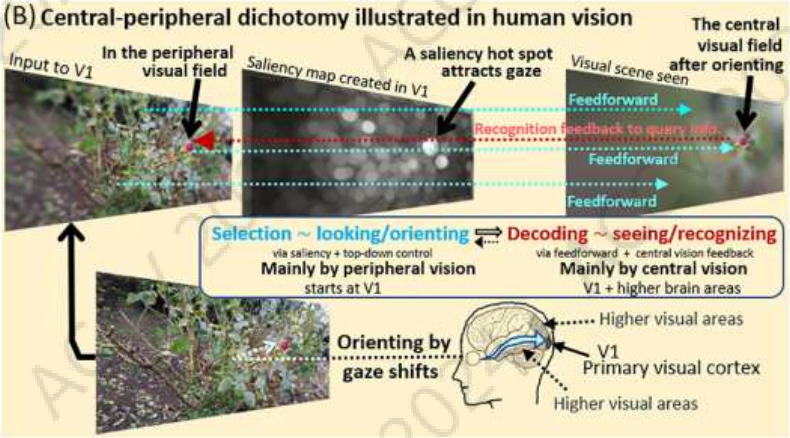


➢ **Central-Peripheral Dichotomy:** The human visual system is divided into central vision and peripheral vision, both playing distinct roles in the process of **visual perception.**

- **Peripheral Vision:** Responsible for detecting a wide visual field, mainly used for identifying salient areas in the environment.
- **Central Vision:** Responsible for fine visual processing, mainly used for target recognition and decoding.

Trend 3. More Human-like Executors

- **Example 1. Human-like VOT via Visual Search Ability (Better Perceptual Intelligence)**

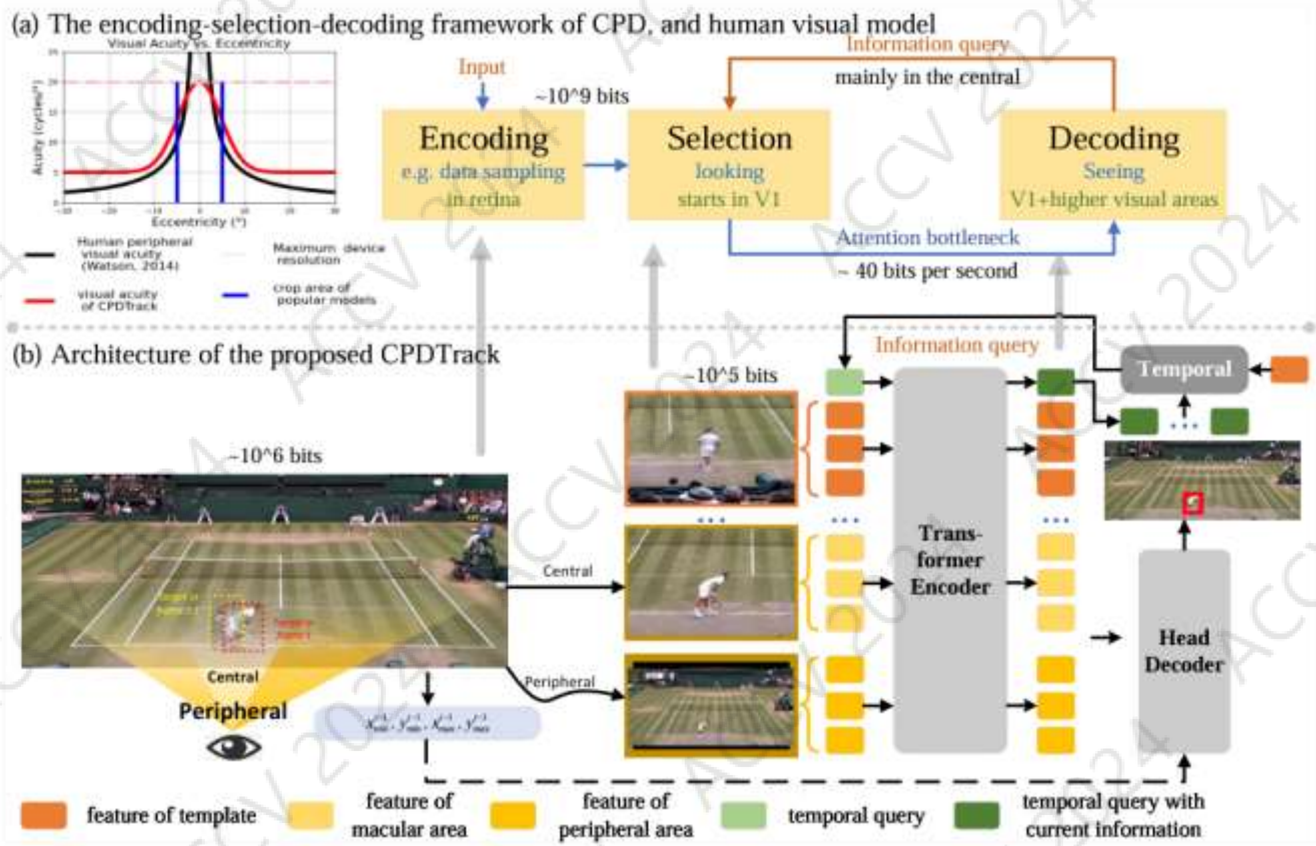


➢ **Process of Encoding, Selection, and Decoding:**
  - **Encoding:** Visual information from the peripheral field enters V1, generating a saliency hotspot map for further processing.
  - **Selection:** Peripheral vision uses saliency and top-down control to guide gaze shifts to areas of interest.
  - **Decoding:** Central vision decodes detailed information of the selected area through feedforward and feedback streams, enabling object recognition and scene understanding.

➢ Peripheral vision **scans the environment broadly** for potential targets, while central vision **focuses on high-precision visual decoding**.

Trend 3. More Human-like Executors

- **Example 1. Human-like VOT via Visual Search Ability (Better Perceptual Intelligence)**



➢ We constructed a model of the Central-Peripheral Dichotomy theory in cognitive science, utilizing the one-stream structure in visual object tracking.

D. Zhang, S. Hu, et al., "Beyond accuracy: Tracking more like human via visual search," in the 38th Conference on Neural Information Processing Systems (NeurIPS).

Trend 3. More Human-like Executors

- **Example 1. Human-like VOT via Visual Search Ability (Better Perceptual Intelligence)**

We study the discontinuity of the target state in space and time (i.e., *STDChallenge*), which comprises two challenges: **absent** and **shot-cut**.

Table 3: Representative Benchmarks in STT, LTT, GIT and *STDChallenge Benchmark*

Subtask	Benchmark	Videos	Min frame	Mean frame	Max frame	Total frame	*absent*	*shotcut*
STT	OTB2015[5]	100	71	590	3872	59K	✗	✗
	VOT2016[54]	60	41	357	1500	21K	✗	✗
	VOT2018[55]	60	41	356	1500	21K	✗	✗
	VOT2019[44]	60	41	332	1500	20K	✗	✗
	GOT-10k[17]	10000	29	149	1418	1.45M	✗	✗
LTT	VOTLT2019[44]	50	1389	4305	29700	215K	✓	✗
	LaSOT[7]	1400	1000	2502	11397	3.5M	✓	✗
GIT	VideoCube[3]	500	4008	14920	29834	7.46M	✓	✓
LTT+ GIT	*STDChallenge Benchamrk*	252	1000	5192	29700	1.3M	✓	✓

$$STD = \frac{(n_a + n_s) \cdot l_a}{l^2},$$

- We extracted sequences from LTT and GIT tasks that include the STDChallenge to form the **STDChallenge Benchmark**, aiming to suppress the bias of a single dataset.
- At the same time, we **quantified the difficulty of the STDChallenge**, taking into account the challenges of 'disappearance-reappearance' and 'shot switching' within the sequences.
- We divided the STDChallenge Benchmark into **three groups with different difficulty levels** based on the STD metric and selected five sequences from each group to form the STDChallenge Turing, which is used for the **Visual Turing Test.**

D. Zhang, S. Hu, et al., "Beyond accuracy: Tracking more like human via visual search," in the 38th Conference on Neural Information Processing Systems (NeurIPS).

Trend 3. More Human-like Executors

- **Example 1. Human-like VOT via Visual Search Ability (Better Perceptual Intelligence)**

D. Zhang, S. Hu, et al., "Beyond accuracy: Tracking more like human via visual search," in the 38th Conference on Neural Information Processing Systems (NeurIPS).

Trend 3. More Human-like Executors

- **Example 1. Human-like VOT via Visual Search Ability (Better Perceptual Intelligence)**

- Human results do not necessarily mean correctness, but **humans can usually quickly re-locate the target** after the STDChallenge.
- In the second image of the first row, **humans can recognize environmental factors closely related to the target.**
- In the second image of the second row, even when the target is absent, **humans are not distracted by the background.**
- In the fifth image, **humans are robust to occlusion**.

D. Zhang, S. Hu, et al., "Beyond accuracy: Tracking more like human via visual search," in the 38th Conference on Neural Information Processing Systems (NeurIPS).

Trend 3. More Human-like Executors

- **Example 2. Human-like VLT via Memory Modeling (Better Cognitive Intelligence)**

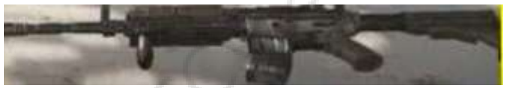
"The gun on the table"

➢ **Limitations of Static Cues:**
  - Text-template cues are **static and fixed**, whereas objects in the video are **dynamically changing**.
  - Static cues **cannot continuously provide reliable reference** for similarity matching.

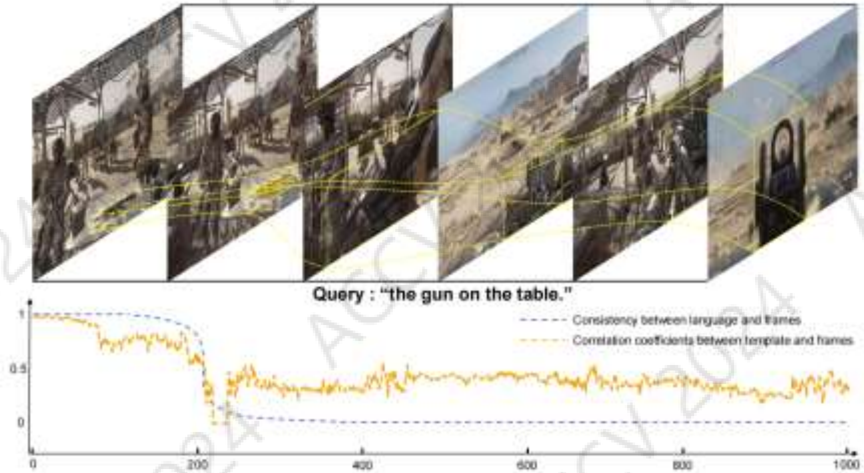
X. Feng, X. Li, S. Hu, et al., "Memvlt: Visual-language tracking with adaptive memory-based prompts," in the 38th Conference on Neural Information Processing Systems (NeurIPS).

Trend 3. More Human-like Executors

- **Example 2. Human-like VLT via Memory Modeling (Better Cognitive Intelligence)**



Template



➢ **Necessity of Introducing Temporal Information:**

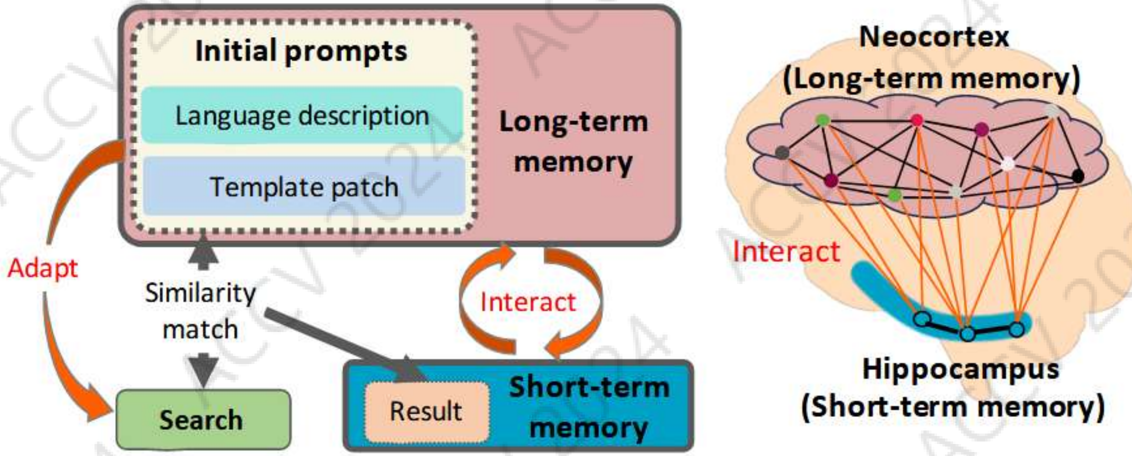
- **Dynamically Changing Targets:** The described scene in the text may **not align** with the actual target in the video, and the target **undergoes significant appearance changes** across frames, leading to lower matching accuracy with the image template.
- **Changing Environmental Factors**: In the video sequence, both the background and the state of the target are constantly changing, making it **difficult to handle these dynamics with static templates alone**.

➢ **Utilize Temporal Information to Provide Dynamic Cues:** By introducing temporal information, the tracking task can make use of frame-to-frame changes, enabling better target localization and tracking.

X. Feng, X. Li, S. Hu, et al., "Memvlt: Visual-language tracking with adaptive memory-based prompts," in the 38th Conference on Neural Information Processing Systems (NeurIPS).

Trend 3. More Human-like Executors

- **Example 2. Human-like VLT via Memory Modeling (Better Cognitive Intelligence)**

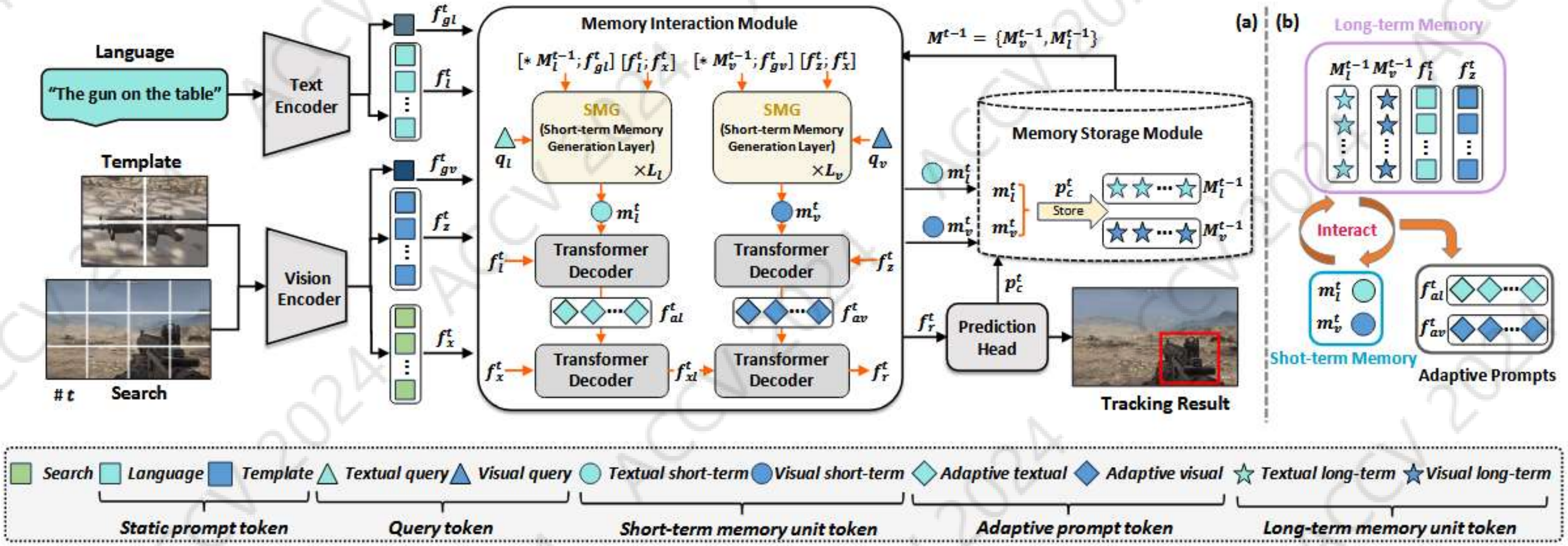


➢ **MemVLT:**
  - Aims to address the issue where static, fixed multimodal cues struggle to continuously guide tracking of dynamically changing targets.
  - Based on **complementary learning theory**, it models and stores dynamic changes in the target and adjusts the static template accordingly.
    - ☐ The human brain has two areas for storing memories: the **hippocampus for short-term memory** and the **neocortex for long-term memory.**
    - ☐ The **interaction between long and short-term memory** promotes human adaptation to different environments.

X. Feng, X. Li, S. Hu, et al., "Memvlt: Visual-language tracking with adaptive memory-based prompts," in the 38th Conference on Neural Information Processing Systems (NeurIPS).

Trend 3. More Human-like Executors

- **Example 2. Human-like VLT via Memory Modeling (Better Cognitive Intelligence)**



➢ **Core Design:**
- **Memory Interaction Module:** Models dynamic changes in the target and adjusts the static template.
- **Memory Storage Module:** Stores the dynamic features of the target.

X. Feng, X. Li, S. Hu, et al., "Memvlt: Visual-language tracking with adaptive memory-based prompts," in the 38th Conference on Neural Information Processing Systems (NeurIPS).

Trend 3. More Human-like Executors

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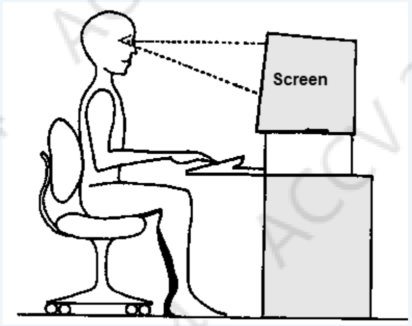
Trend 4. More Intelligent Evaluation

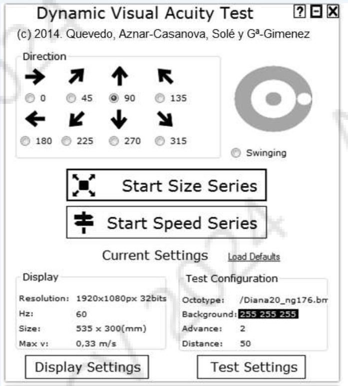
Trend 4. More Intelligent Evaluation

- **How to evaluate dynamic visual intelligence?**

Bernell's Rotator

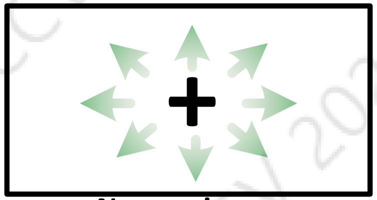
The dynamic visual acuity values are recorded as a combination of **visual acuity** and **speed** in rpm.





The DynVA is a computer software designed to assess DVA. The researcher can select the optotype to be presented in the two forms of the test: **(a)Size Series; (b) Speed Series**.

Human



Neuroscience: simple symbol on high-contrast background

Different

Machine

Computer vision: various targets in large-scale datasets

S. Hu, X. Zhao, Y. Wang, et al, "Nearing or surpassing: Overall evaluation of human-machine dynamic vision ability," Preprint, 2023.

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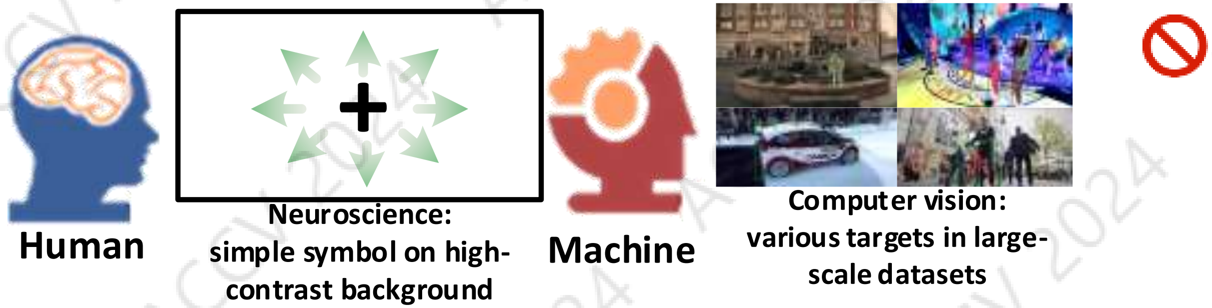
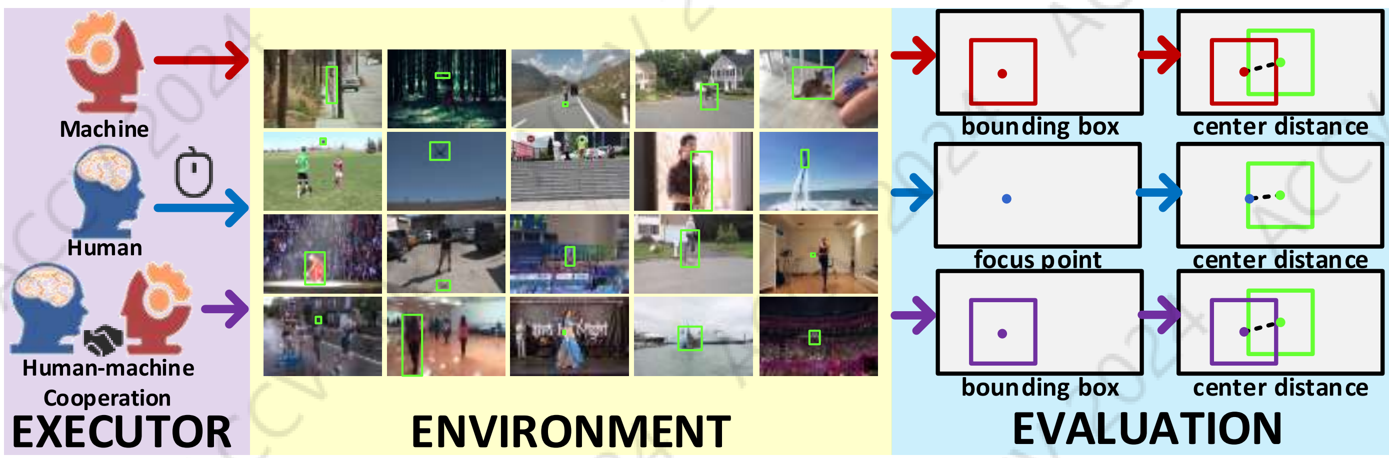
Trend 4. More Intelligent Evaluation

- **How to evaluate dynamic visual intelligence?**

➢ **Existing research**: Integrating human-machine evaluation into a unified framework for comparison and analysis is challenging due to **discrepancies across various research areas**.





➢ **Keypoint:** Designing a universal framework for evaluating dynamic visual abilities in humans and machines.

S. Hu, X. Zhao, Y. Wang, et al, "Nearing or surpassing: Overall evaluation of human-machine dynamic vision ability," Preprint, 2023.
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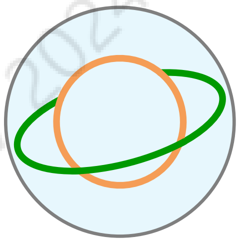
Trend 4. More Intelligent Evaluation

- **How to evaluate dynamic visual intelligence?**

➢ **Environment:**

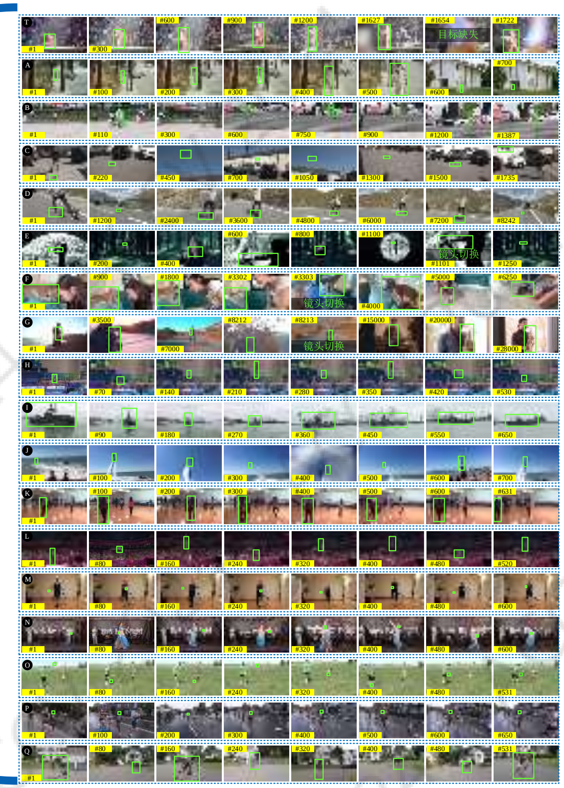
- Provide a thorough evaluation environment of the **perceptual, cognitive**, and **robust** tracking abilities of humans and machines.
  - ❑ **87 sequences, 17 themes, 245k frames**



quickly build a task space based on research goals

Table 1: Information on environment settings.

Task Settings			Characteristics: Target Absent	Characteristics: Shot-cut	Ability	Group	Frames
Short-term tracking (Target presents from beginning to end)			N	N	Perception	A	500-1,000
						B	1,000-2,000
Long-term tracking (Target may disappear and reappear in a single shot)			Y	N	Perception and cognition	C	1,000-2,000
						D	5,000-10,000
Global instance tracking (Target may disappear and reappear in multiple shots)			Y	Y		E	1,000-2,000
						F	5,000-10,000
						G	15,000-30,000
Short-term tracking with challenging factors (Target presents from beginning to end)	Challenging factors in single frame	Abnormal ratio	N	N	Perception and robustness	H	500-1,000
		Abnormal scale				I	
		Abnormal illumination				J	
		Blur bounding-box				K	
	Challenging factors between consecutive frames	Drastic ratio variation				L	
		Drastic scale variation				M	
		Drastic illumination variation				N	
		Drastic clarity variation				O	
		Fast motion				P	
		Low correlation coefficient				Q	



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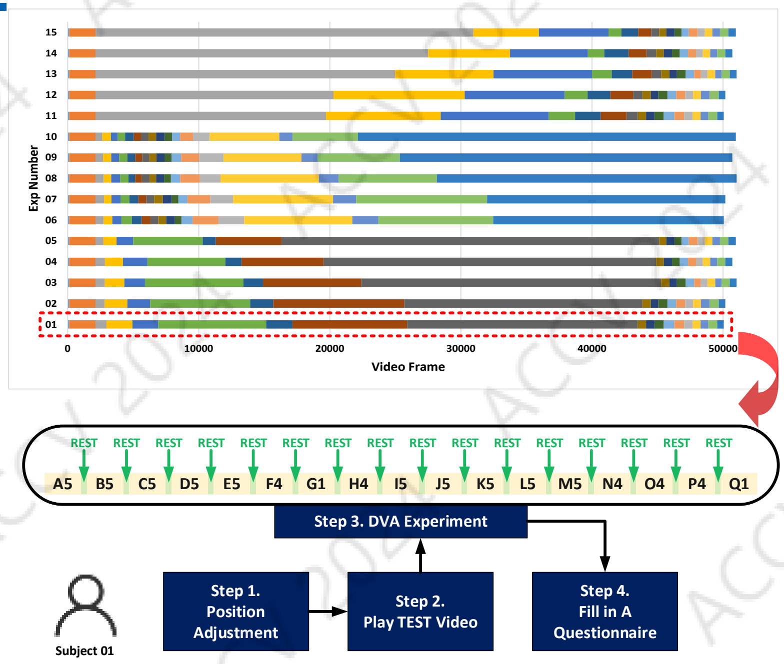
Trend 4. More Intelligent Evaluation

- **How to evaluate dynamic visual intelligence?**
  - **Executors:**
    - 20 representative algorithms (different architecture)
    - 15 human subjects were selected to participate in the visual tracking tasks, and their **behavior** was recorded (with a **self-developed program** by python)

Table 2: The performance (based on NP^{w}_{L3}) about human subjects and 20 representative models (SNN-Siamese Neural Network. CF-Correlation Filter. CNN-Convolutional Neural Network. Red, magenta and cyan represent the top-3 machines).

Executor	Ariticture	Characteristic	Score
Subject_Top	-	The best performance of subjects	0.891
Subject_Mean	-	The mean performance of subjects	0.853
Subject_Bottom	-	The worst performance of subjects	0.801
MixFormer (Cui et al. (2022))	Custom networks	Transformer-based framework	0.766
KYS (Bhat et al. (2020))	Custom networks	Scene information	0.528
GlobalTrack (Huang et al. (2019))	Custom networks	Zero cumulative error	0.645
KeepTrack (Mayer et al. (2021))	SNN+CF	Target candidate association	0.718
SuperDiMP (Danelljan et al. (2020))	SNN+CF	Probabilistic regression	0.701
PrDiMP (Danelljan et al. (2020))	SNN+CF	Probabilistic regression	0.683
DiMP (Bhat et al. (2019))	SNN+CF	Better discriminative ability	0.597
ATOM (Danelljan et al. (2018))	SNN+CF	Combine SNN with CF	0.506
SiamRCNN (Voigtlaender et al. (2020))	SNN	Re-detection mechanism	0.748
Ocean (Zhang & Peng (2020))	SNN	Anchor-free	0.635
SiamFC++ (Xu et al. (2020))	SNN	Anchor-free	0.512
SiamCAR (Guo et al. (2020))	SNN	Anchor-free	0.480
SiamDW (Zhang & Peng (2019))	SNN	Deeper and wider backbone	0.558
SPLT (Yan et al. (2019))	SNN	Local search and global search	0.610
SiamRPN++ (Li et al. (2018a))	SNN	Deeper backbone	0.662
DaSiamRPN (Zhu et al. (2018))	SNN	Data augmentation	0.528
SiamRPN (Li et al. (2018b))	SNN	Region proposal network	0.495
SiamFC (Bertinetto et al. (2016))	SNN	Originator of SNN-based trackers	0.285
ECO (Danelljan et al. (2017))	CNN+CF	Combine CNN with CF	0.377
KCF (Henriques et al. (2015))	CF	Representative CF-based method	0.270



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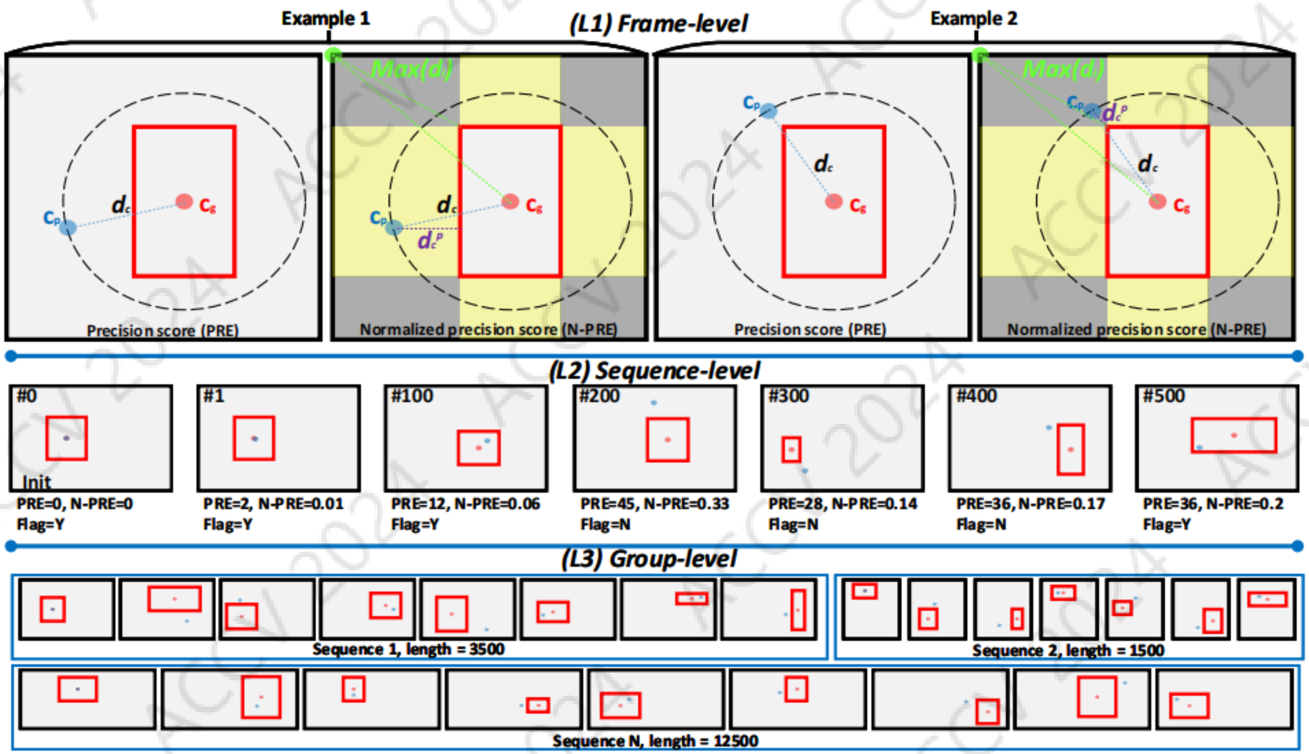
Trend 4. More Intelligent Evaluation

- **How to evaluate dynamic visual intelligence?**

➢ **Evaluation:**

- Provide **universal multi-granularity evaluation indicators** (frame → sequence → group) for humans and machines tailored to task characteristics.



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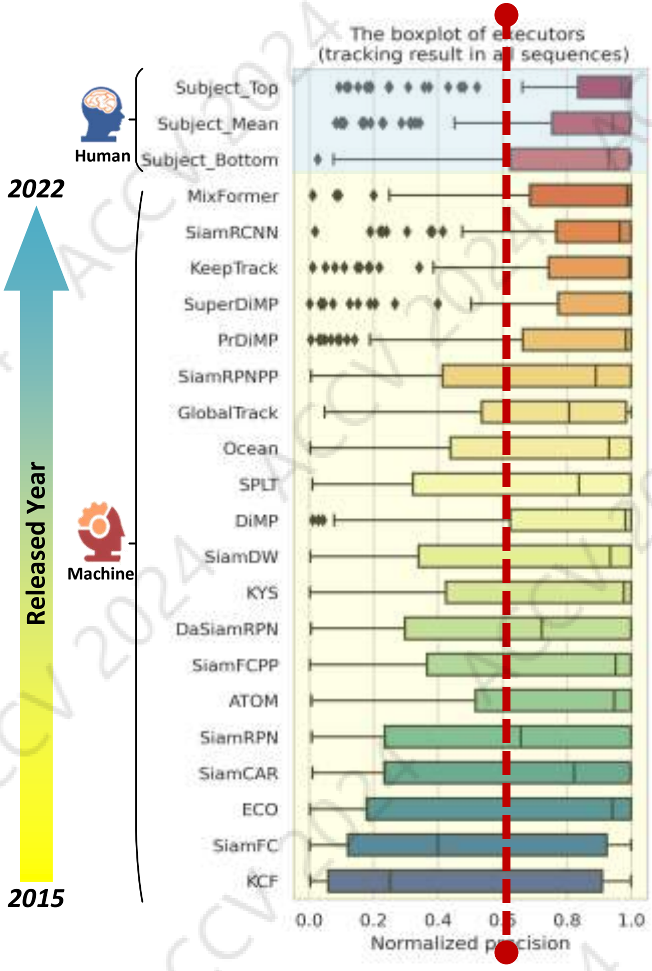
Trend 4. More Intelligent Evaluation

- **How to evaluate dynamic visual intelligence?**

➢ **Comprehensive comparison of human-machine dynamic vision capabilities:**

- Human dynamic vision ability is **overall better** than most algorithms.
- The current SOTA algorithm is close to the lower bound of human capabilities, and **the gap between the two is narrowing**.



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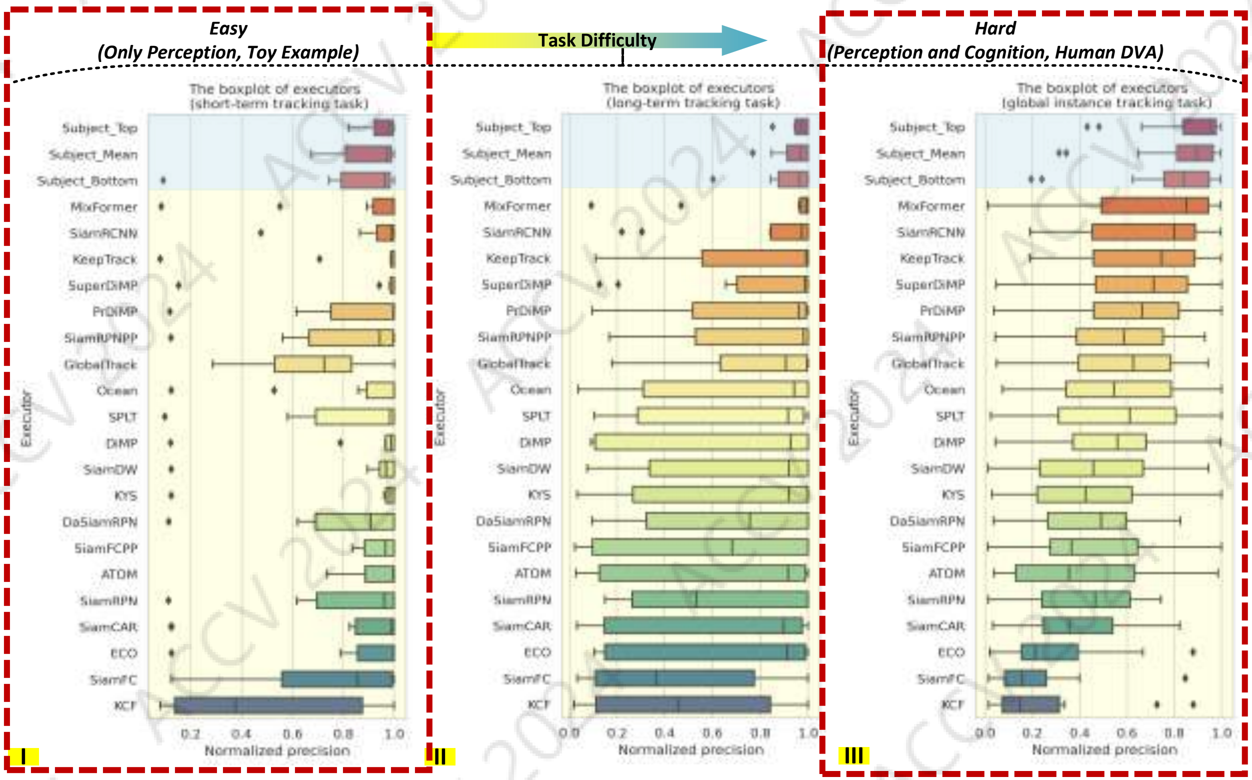
Trend 4. More Intelligent Evaluation

- **How to evaluate dynamic visual intelligence?**

  ➢ **Comprehensive comparison of human-machine dynamic vision capabilities:**
  - Algorithms are **similar in perception** to humans.
  - There is still **a certain gap in cognitive abilities** between algorithms and humans.



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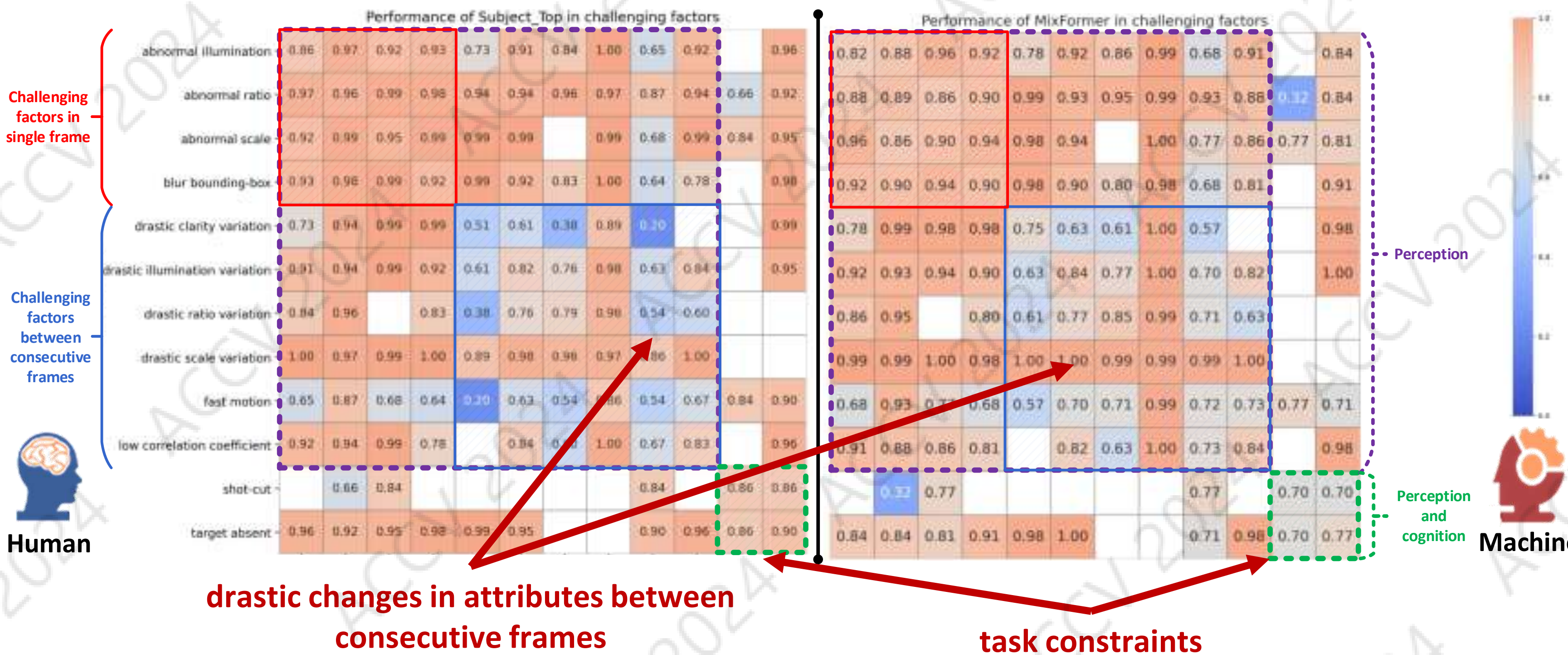
Trend 4. More Intelligent Evaluation

- **How to evaluate dynamic visual intelligence?**

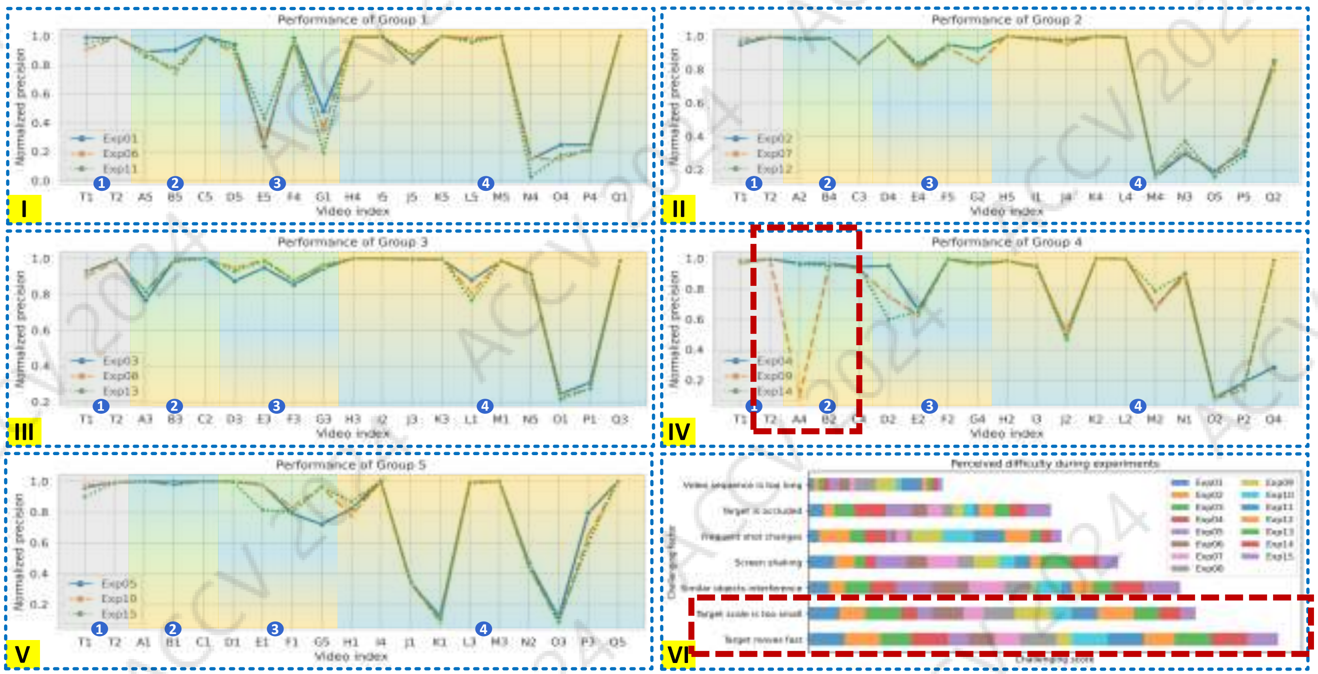
➢ **Comprehensive comparison of human-machine dynamic vision capabilities:**
  - **Task constraints (such as camera switching)** have a greater impact on the machine.
  - **Drastic changes in attributes between consecutive frames** (such as fast motion) are challenging for both humans and machines.



Trend 4. More Intelligent Evaluation

- ## How to evaluate dynamic visual intelligence?

  - **Human Subject Performance Analysis:**
    - Human subjects also **make careless mistakes**.
    - The questionnaire showed that most subjects found it **difficult to track fast-moving targets and small targets.**



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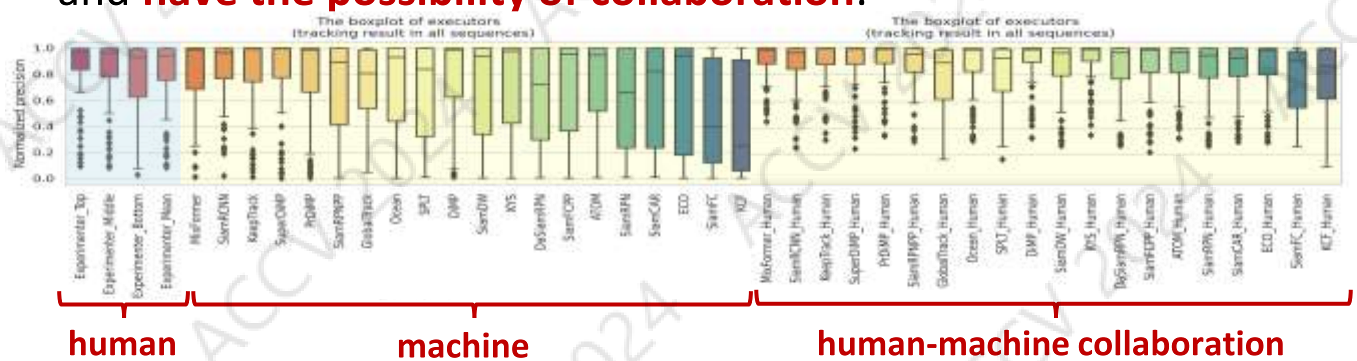
Trend 4. More Intelligent Evaluation

- **How to evaluate dynamic visual intelligence?**

➢ **A simple human-machine collaboration experiment:**

- A simple human-machine collaboration experiment shows that dynamic visual capabilities: **machine < human < human-machine collaboration**.
- In dynamic vision tasks, humans and machines each have their own strengths and **have the possibility of collaboration**.



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Future Work

Evaluation **Algorithm**

Decoupling visual capabilities:

- The visual object tracking task involves the coupling of multiple capabilities such as **observation, memory, and reasoning.**
- Therefore, the task can be further **decomposed**, and the intelligence of the algorithm can be more comprehensively analyzed and evaluated through a **fine-grained evaluation scheme**.

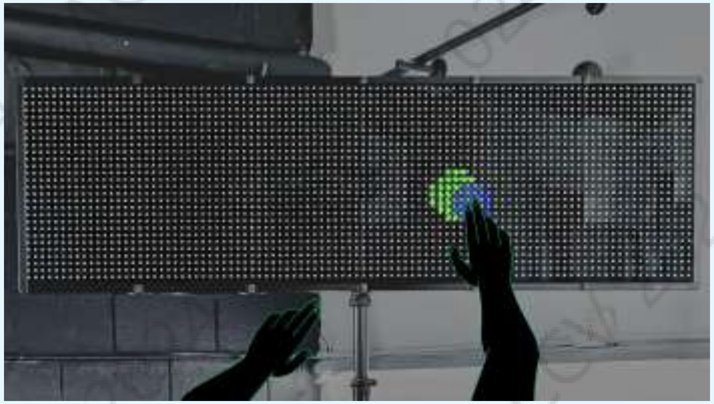
Future Work

Evaluation

Algorithm

Optimize the measurement method:

- Use a high-precision eye tracker and set up a rigorous eye movement experiment environment, or design a new human visual tracking ability measurement solution (such as conducting experiments based on a **mouse** or **touch screen**).



Future Work

Evaluation **Algorithm**

Exploring the characteristics of the subjects:

- Studies have shown that factors such as the subjects' **physiological characteristics, cognitive state, and personal traits** all have a certain impact on dynamic visual ability.
- How to select task objects based on the characteristics of the subjects to ensure that **the subject group is representative** is worthy of further analysis by researchers.

Future Work

Evaluation **Algorithm**

Visual modality target tracking algorithm:

- It can explore **a better mechanism for utilizing dynamic visual information** and strike a balance between the effective utilization of accumulated errors and temporal dependencies.

Future Work

Evaluation **Algorithm**

Multimodal target tracking algorithm:

- Mature basic models in the fields of natural language processing and static vision can be introduced to improve the limitations of the algorithm in **long text processing and multimodal information alignment**.

Future Work

Evaluation **Algorithm**

Expanding the human-machine collaboration mechanism:

- The human-machine collaboration mechanism can be further expanded to provide support for downstream tasks and practical applications. For example, **multiple rounds of human-machine interaction** experiments can be conducted during a single tracking process to observe whether the machine model's understanding of human intentions changes during the tracking process.

Thanks for listening!

2024.12.09 in Hanoi, Vietnam

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