Real-time Referred Video Object Segmentation (RVOS)-based Video Summarization using Multimodal Transformers

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Outline

Project at a Glance

- **Goal:** Create short, relevant video summaries.
- **Problem with Old Methods:** Often generic, don't understand user interest.
- **Our Approach:** Use Referring Video Object Segmentation (RVOS).
  - User describes an object in text (e.g., "person playing guitar").
  - System (MTTR model) finds and highlights this object.
- **Summarization:**
  - Use these highlighted segments to create the summary.
  - Two methods: simple uniform sampling, and advanced feature-based analysis.
- **Outcome:** System that generates query-focused video summaries.

The Challenge: Video Overload

- We have too much video content to watch.
- Video summarization creates short versions to save time.
- **Key Question:** What is "important" information in a video?
  - This is subjective and depends on the user's needs.
- Traditional methods often use basic visual cues (motion, scene cuts).
  - They might miss the actual meaning or user-specific interests.

A Smarter Way: Referring Video Object Segmentation (RVOS)

- RVOS lets users guide the summarization:
  - Describe an object/action in text (e.g., "the dog catching the frisbee").
  - The RVOS system finds and highlights (segments) that object.
- This enables summaries directly related to user interest.
- Powerful AI models like MTTR (Multimodal Tracking Transformer) [1] excel at this task.

Our Project's Aim: The "RVOS-Summarizer"

- We built a system using RVOS (with MTTR) for video summarization.
- **How it works:**
  1. **Input:** A long video + text query (e.g., "car turning left").
  2. **RVOS:** MTTR segments the queried object in frames.
  3. **Summarization:** A module processes these segments to create a short summary video.
- This query-based method produces highly relevant summaries.
- We explored two summarization techniques:
  - Uniform sampling (basic).
  - Feature-based analysis (advanced).

Key Steps in Our Project (1/2)

Our project involved several main development stages:

- **MTTR Model Setup:**
  - Prepared the Multimodal Tracking Transformer (MTTR).
  - Installed necessary tools and loaded a pre-trained version.
- **Video Processing Pipeline:**
  - Created an automated system (using Python tools like ‘yt_dlp‘, ‘MoviePy‘).
  - This system can:
    - Download YouTube videos.
    - Trim them to desired lengths.
    - Prepare them for the MTTR model.

Key Steps in Our Project (2/2)

Continuing with our development stages:

- **RVOS Inference:**
  - Used the pre-trained MTTR model.
  - It segments objects in videos based on text queries.
  - This process outputs "masks" that highlight the target objects.
- **Summarization Modules:**
  - Implemented two distinct methods to create summaries:
    - **Uniform Sampler:** A simple approach; picks frames at regular intervals.
    - **Feature-based Analyzer:** More advanced; calculates video features (like motion, scene changes, object size, audio events) and uses these features to create summaries and informative plots.
- **Integration:**
  - Combined all components into an end-to-end system.
  - It takes a video URL and query, then outputs: an annotated video, a summary clip, and analytical plots.

Our System's Two-Stage Process

Our RVOS-Summarizer uses a two-stage approach:

1. **RVOS with MTTR:**
   - The MTTR model first identifies and segments (highlights) the object described in your text query throughout the video.
2. **Video Summarization Module:**
   - The output from MTTR (video frames with the object highlighted) is then used to create a summary.

Stage 1: Finding Objects with MTTR

- We use the Multimodal Tracking Transformer (MTTR) [1].
- MTTR understands both video (visuals) and text (language query).
- **Simplified MTTR Process:**
  - Takes video frames + text query as input.
  - Processes visual and text features separately.
  - Fuses these features using a multimodal Transformer.
  - Outputs segmentation masks showing the queried object over time.
- We use a pre-trained MTTR model (no re-training in this project).

MTTR Architecture Overview

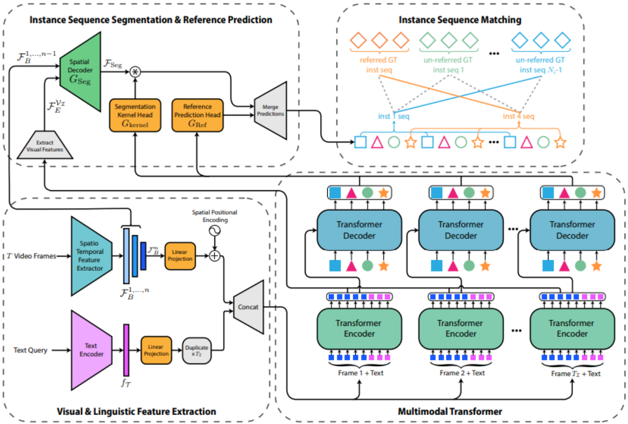


Figure 1: Architecture of MTTR [1]: Uses encoders for video/text, then a Transformer to combine them for segmentation.

Image Source: Botach et al. (2022) [1]

Stage 2: Making Summaries - Two Ways

After MTTR creates an annotated video (frames + object masks), we use one of two summarization methods:

1. **Uniform Sampling Summarizer (Simple Baseline)**
   - Opens the annotated video from MTTR.
   - User specifies summary length (e.g., 50
   - Calculates a sampling interval (N).
   - Picks every Nth frame for the summary.
   - *Result:* A shorter version of the annotated video. Can miss quick events.

Stage 2: Feature-based Analyzer (Advanced)

2. **Feature-based Analyzer**

- Aims for more content-aware summaries.
- Calculates key video features frame-by-frame:
  - Optical Flow (motion)
  - Scene Change Scores
  - Mask Coverage (object size/prominence)
  - Frame Shannon Entropy (visual complexity)
  - Audio Onset Strength (sound events)
- **Uses these features to select keyframes and create a summary video.**
- Summary length is user-controllable (default: 50
- *Result:* Analytical plots of features AND a content-aware summary video.

Feature-based Analyzer: The Process

Algorithm 1 Feature-based Analysis Summarization (Conceptual)

Require: Annotated Video V_{ann} (Frames F_i, Masks M_i), Audio A, Target Summary Percent P_{sum}
Ensure: Feature plots, Summarized Video V_{sum}

Initialize feature lists (motion, scene, mask, entropy, audio)
Process A for $Feat_{audio}$
for each frame F_i in V_{ann} **do**
    Calculate c_i (Mask Coverage); Add to $Feat_{mask}$
    Calculate e_i (Entropy); Add to $Feat_{entropy}$
    if $i > 1$ **then**
        Calculate Optical Flow magnitude m_i; Add to $Feat_{motion}$
        Calculate Scene Change d_i; Add to $Feat_{scene}$
    end if
end for
Generate plots from feature lists.
Analyze features to score/select keyframes to meet P_{sum}.
Assemble V_{sum} from selected keyframes.

This provides rich data and creates a more meaningful summary.

Overall System Flow

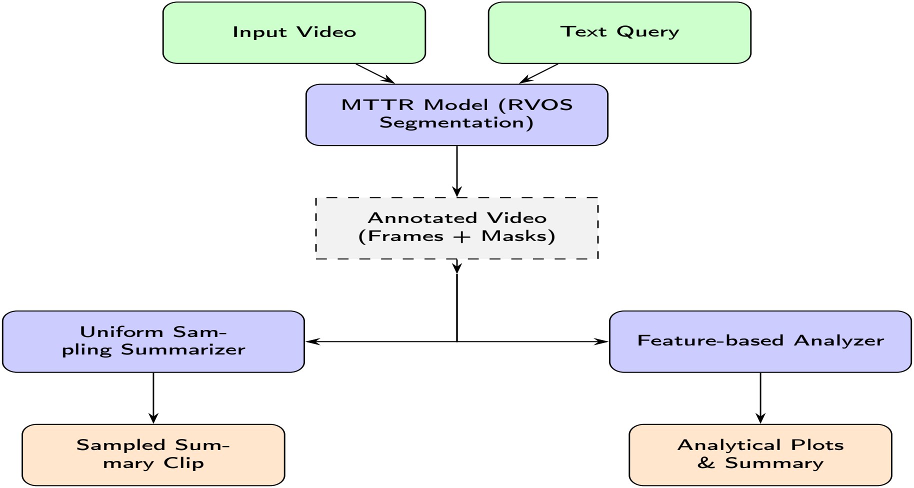


Figure 2: Our RVOS-Summarizer: Processes video and text, MTTR segments objects, then two paths for summarization/analysis.

Key Observations

From our work, we noticed:

- **MTTR Effectiveness:** Very good at finding and highlighting the queried object, even in complex scenes. This is vital.
- **Query Specificity:** Clear, specific text queries give the best results. Vague queries can cause errors.
- **Uniform Sampling Limits:** Simple and fast, but can easily miss short, important events if they fall between samples.
- **Feature Analysis Insights:** The generated plots (motion, object size, etc.) are very informative. They show great potential for guiding smarter summary creation.
- **Computational Cost:** RVOS with MTTR is computationally heavy. Feature analysis (especially optical flow) also adds to processing time.

Limitations of Current Approaches

Traditional video summarization often struggles with:

- **Semantic Understanding:** Difficulty prioritizing content by meaning or specific user interest if relying only on low-level features.
- **Generic Summaries:** Unsupervised methods often create general summaries, not tailored to individual needs.
- **RVOS Complexity:** Some older RVOS methods use complex, multi-stage pipelines, hard to integrate.

Our RVOS-based approach also has limitations:

- **Depends on MTTR:** The quality of the summary is highly dependent on MTTR's segmentation accuracy. Errors propagate.
- **Computational Cost:** As noted, the process is resource-intensive.

Results: MTTR's RVOS Performance

- The MTTR model itself is highly capable.
- It performs well on standard benchmarks like A2D-Sentences.
- The table (from original MTTR paper [1]) shows its strong performance compared to other methods.

Table 1: MTTR performance on A2D-Sentences benchmark [2, 1].

	Precision @ K					**IoU**		
Method	50%	60%	70%	80%	90%	Overall	Mean	mAP
MTTR ($w = 8$)	72.1	68.4	60.7	45.6	16.4	70.2	61.8	44.7
MTTR ($w = 10$)	75.4	71.2	63.8	48.5	16.9	72.0	64.0	46.1

Higher "Precision", "IoU", and "mAP" scores are better.

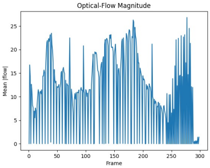
Query: **"a guy riding a bicycle"**

(a) Input video frame

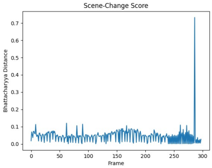
(b) Output frame with RVOS mask

Figure 3: The system successfully segmented the "guy riding a bicycle".

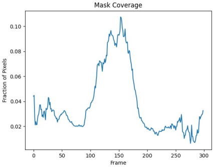
Results: Feature Analysis Plots (Set 1 of 2)



(a) (a) Mean Optical Flow (Motion)



(b) (b) Scene Change Score

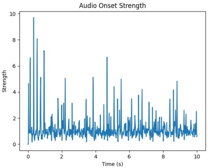


(c) (c) Mask (Object) Coverage

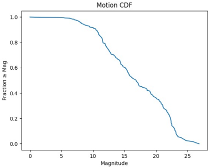
Figure 4: Example plots from Feature Analyzer (1/2): Motion, scene changes, object prominence.

Results: Feature Analysis Plots (Set 2 of 2)

(a) (a) Frame Shannon Entropy



(b) (b) Audio Onset Strength



(c) (c) Motion Distribution Hist.

Figure 5: More analytical plots (2/2): Frame complexity, audio events, motion patterns.

Conclusion

In Summary:

- Successfully built an RVOS-based video summarizer using MTTR.
- It performs query-specific object segmentation, then summarization.
- Two summarization methods explored:
  - Basic uniform sampling.
  - Advanced feature-based analysis (provides insights and summary).
- Demonstrates promise of RVOS for semantic, query-relevant summaries.

Future Work Ideas

- **Smarter Keyframe Selection:** Further develop algorithms using the extracted features for even better summary frame selection.
- **Efficiency Improvements:** Optimize the pipeline for faster processing, aiming towards real-time capabilities (e.g., model distillation).
- **User Studies:** Conduct studies to evaluate the perceptual quality and usefulness of the generated summaries from a user perspective.
- **Explore Different RVOS Models:** Test with newer or alternative RVOS architectures as they emerge.
- **Broader Applications:** Investigate use in other areas like video search or content moderation.

Demo

References I

Botach, A., Zheltonozhskii, E., & Baskin, C. (2022). *End-to-End Referring Video Object Segmentation with Multimodal Transformers*. arXiv preprint arXiv:2111.14821.

Gavrilyuk, K., Ghodrati, A., Li, Z., & Snoek, C. G. M. (2018). *Actor and action video segmentation from a sentence*. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 8166-8175.

Thank You! Questions?