Foundations for Summarizing and Learning Latent Structure in Video

Presenter: Kevin Pitstick, MTS – Engineer

PI: Ed Morris, MTS – Senior Engineer

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Problem

DoD Operational Deficiency

- Volume of streaming and archived surveillance video is outpacing the ability of analysts to manually monitor and view it
- Our collaborators, Darrell Lochtefeld and Daniel Zelik from AFRL's Human-Centered ISR Division, confirmed there is a lack of automated tools to assist Processing, Exploitation, and Dissemination (PED) analysts in monitoring real-time video or analyzing archived video
- First task of Project Maven, an initiative to provide computer algorithms and artificial intelligence to warfighter, is to provide computer vision algorithms to assist PED analysts

Solution

Background: Video Summarization

- Computer vision task to condense a long video into a shorter “trailer” which contains the key or unique segments
- Various techniques: (1) key frames, (2) key frame sub-shots, (3) key objects

Key Object-Motion Clip Video Summarization

We propose a new video summarization task that aims to generate video summaries based on the key objects in motion

The summaries should answer the following questions:

1. What are the representative objects residing in the video?
2. What key actions of these objects are occurring in the video?

Approach

Object-Level Video Summarization via Online Motion Auto-Encoder

Design and prototype a novel unsupervised video summarization pipeline which functions on extracted clips of objects in motion

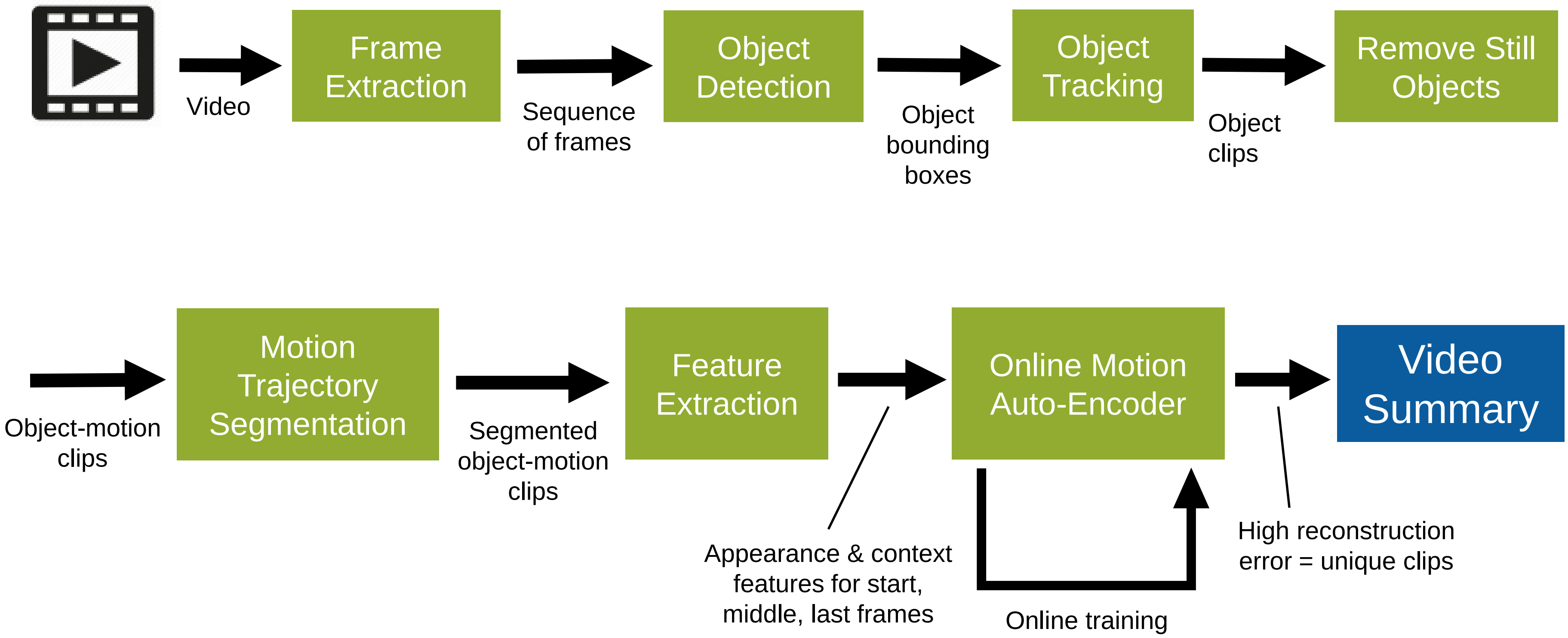
1. Extract clips of objects in motion from video
   - Object detection, object tracking, and object clip segmentation
2. Feed each object clips' features through auto-encoder
   - Auto-encoder attempts to reconstruct the input
3. Clips with highest reconstruction error (adjustable threshold) become the summary
   - All clips are used as online training to the auto-encoder to learn "on the fly"

Key Contributions

1. Utilizing key object motion clips to depict whole video and generate video summaries
2. Unsupervised online motion auto-encoder model – encode and learn object motion patterns

CMU Machine Learning Dept. Collaborators: Xiaodan Liang and Eric Xing

Video Summarization Pipeline



Experiments

- **Datasets:** Orangeville (new), Base Jumping, SumMe, TVSum
- **Key Metrics:** Area under ROC curve (AUC), Average Precision (AP), F-measure (at threshold = 0.5)
- **Object-level:** Orangeville, **Subshot-level:** Base Jumping, SumMe, TVSum

Original: 100 seconds

From “Orangeville” dataset (described in paper submission)

Summary: ~17 seconds

Demonstration Summary Video

Orangeville Results

Quantitative - Table 1

- Ground-truth annotated manually for key clips (fast moving cars, people crossing road, cars turning)
- Comparison with competing unsupervised, online approaches: sparse coding, alternate auto-encoders

	Sparse Coding	Stacked Sparse Auto-encoder	Stacked LSTM Auto-encoder	Stacked Sparse LSTM Auto-encoder (OURS)
AUC score	0.4252	0.4354	0.5680	**0.5908**
AP score	0.1542	0.1705	0.2638	**0.2850**
F-measure	0.1284	0.1662	0.2795	**0.2901**

Table 1: Object-level summarization results between competing approaches on **Orangeville** dataset

Qualitative – Figure 1

- 15 subjects watching original at 3x speed followed by summary
- Assign rating from 1 to 10

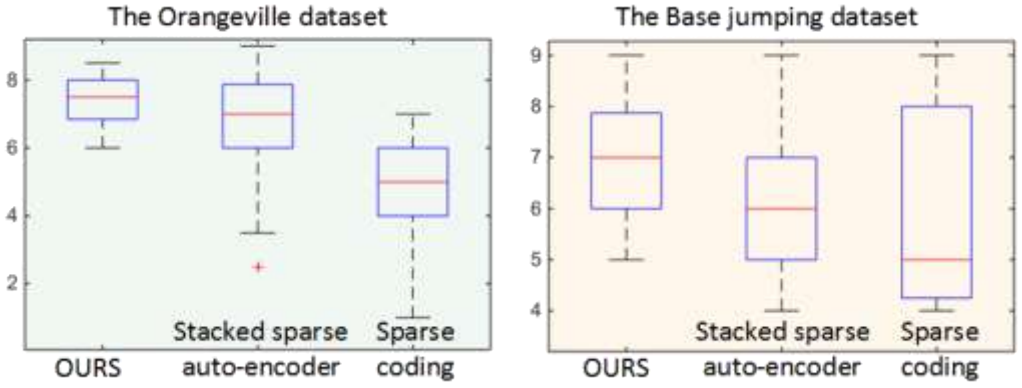


Figure 1: User study evaluation scores between competing approaches on **Orangeville** and **Base Jumping** datasets

SumMe and TVSum Results

- Adapt pipeline for subshot-level summarization to compare our auto-encoder against subshot-level approaches (e.g., TVSum, LiveLight, etc)

Method	F-measure
Video MMR	0.266
TVSum	0.266
$VSUMM_1$	0.328
$VSUMM_2$	0.337
Stacked GRU Auto-Encoder	0.354
Online Motion AE (OURS)	**0.377**

Table 1: Subshot-level summarization results on **SumMe** dataset

Method	F-measure
Web Image Prior	0.360
LiveLight	0.460
TVSum	0.500
Stacked GRU Auto-Encoder	0.510
Online Motion AE (OURS)	**0.515**

Table 2: Subshot-level summarization results on **TVSum** dataset

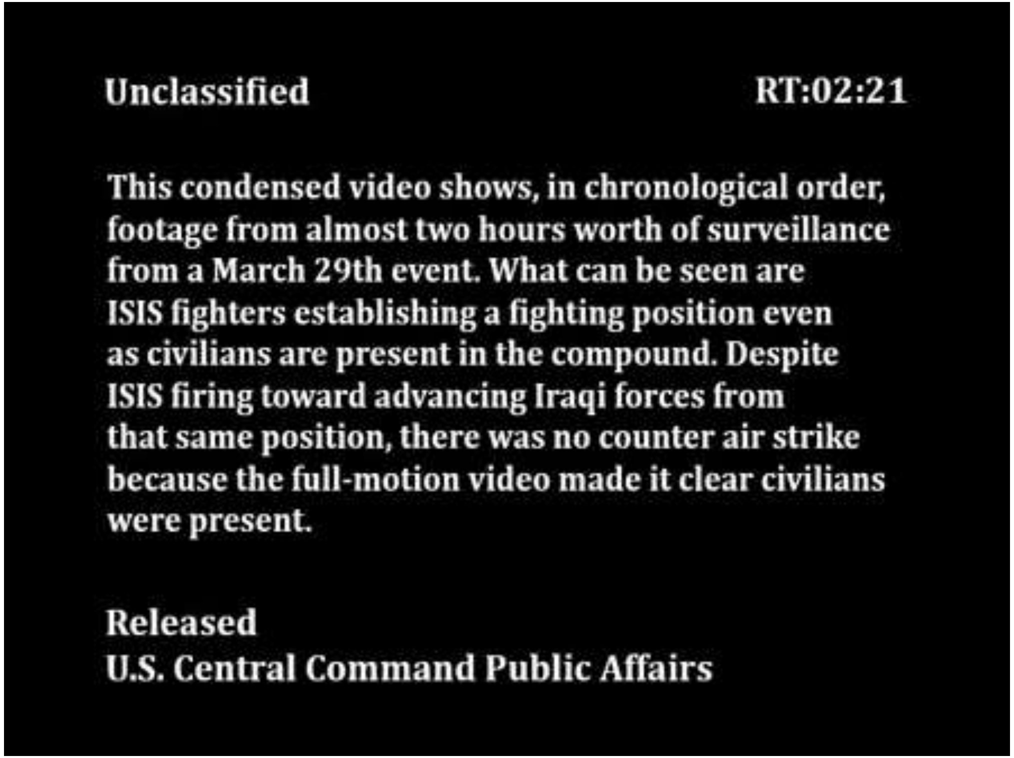
Analyzing DoD Full Motion Video (FMV)

While results are promising, DoD full motion video (FMV) differs from ground surveillance

- Infra-red (IR) vs electro-optical (EO) switches
- Moving camera vs. stationary camera
- Aerial viewpoint vs. ground viewpoint
- Changing zoom levels and rapid panning

AFRL Human-Centered ISR Division Collaboration

Darrell Lochtefeld and Daniel Zelik

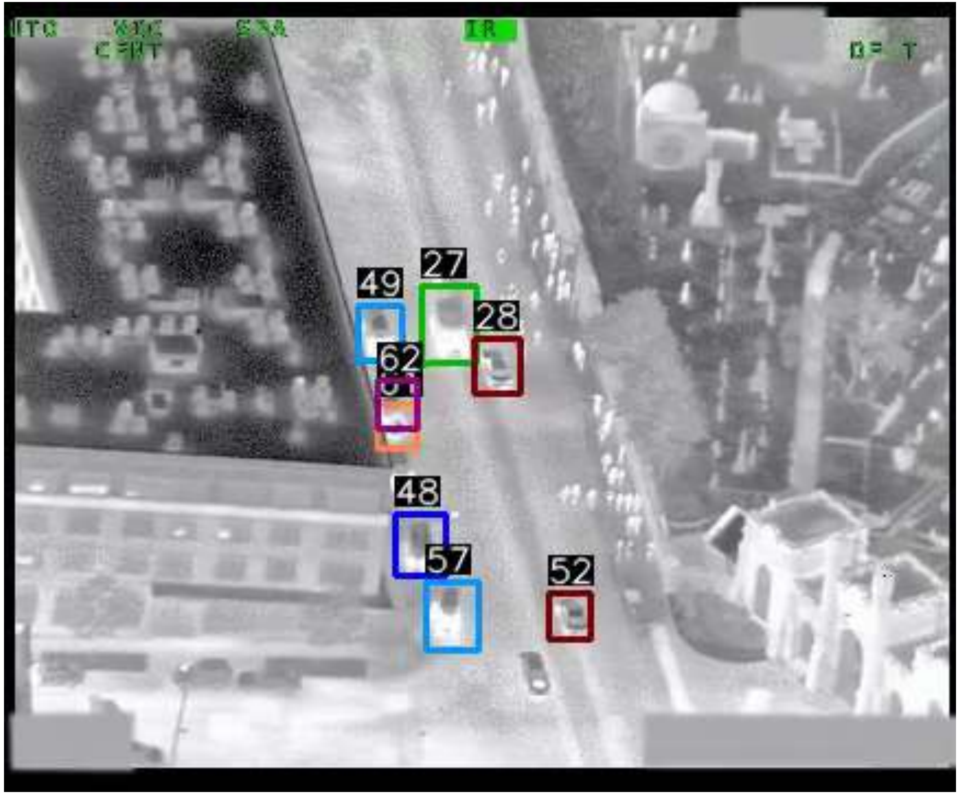


Publicly released by U.S. Central Command Public Affairs on CENTCOM’s website - http://www.centcom.mil/MEDIA/VIDEO-AND-IMAGERY/VIDEOS/videoid/520438/

FBI Surveillance Video

Using FBI video of protests in Baltimore as first aerial surveillance dataset

- Labeled ~300 images with ground-truth vehicle annotations
- “Fine-tune” ImageNet object detection model to detect IR vehicles
  - Replace classifier layer and retrain it with 300 labeled images
- Detection model’s average precision: **0.89**



“Protests in Baltimore, Maryland 2015, Aerial Surveillance Footage.” FBI Records: The Vault. https://vault.fbi.gov/protests-in-baltimore-maryland-2015/unedited-versions-of-video-surveillance-footage

Project Artifacts

- **Software**
  - Prototype utilizing the pipeline for unsupervised, online, object-level video summarization
  - Video Markup Tool for annotating spatial-temporal object clips within video
- **Paper**
  - Submission to IEEE Transactions on Cybernetics: “Unsupervised Object-Level Video Summarization with Online Motion Auto-Encoder”
- **Dataset**
  - “Orangeville” benchmark for object-level summarization – dataset and annotations
  - Annotations and model for detecting vehicles in infra-red (IR) surveillance data released by FBI

Conclusion

Summary

- *Problem:* Lack of automated tools to assist analysts in processing the increasing volume of DoD surveillance video
- *Goal:* Utilize video summarization techniques to reduce video to consequential clips
- *Results:* Object-level video summarization pipeline which identifies key clips occurring in video & meets or exceeds competing algorithms on benchmark datasets

Future Work – FY18 Project: Summarizing and Searching Video

- Apply current pipeline to summarization of FMV aerial datasets
- Detect and search for specific actions/activities in video
- AFRL collaboration to explore applying analysis techniques to existing DoD problems
  - e.g. Nothing Significant to Report (NSTR) task

Contact Information

Presenter
Kevin Pitstick
MTS – Engineer
Email: kapitstick@sei.cmu.edu

Primary Investigator
Ed Morris
MTS – Senior Engineer
Email: ejm@sei.cmu.edu

SEI Team

- Jeffery Hansen
- Mark Klein
- Mike Konrad
- Keegan Williams
- Javier Vazquez-Trejo

CMU Machine Learning Department Collaborators

- Eric Xing, Professor
- Xiaodan Liang, Postdoctoral

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- Darrell Lochtefeld
- Daniel Zelik