# Coherent Temporal Synthesis for Incremental Action Segmentation

CVPR2024

Guodong Ding, Hans Golong and Angela Yao

National University of Singapore





## Extensively studied in image domain

- Image classification,
- Object detection,
- Semantic segmentation, etc.

## Extensively studied in image domain

- Image classification,
- Object detection,
- Semantic segmentation, etc.

## Underexplored in video domain

- Action recognition,
- $\cdot$  ... (more to come)

## Fundamental Categories of IL algorithms

• Replay/Rehersal

replay a few of the data samples previously seen tasks (exemplar, generative)

• Regularization [1]

consolidates the past knowledge, controlling the network weights updates

• Architectural

dynamically changes the model's architecture, isolating task-specific parameters

### **Procedural Videos**

Series of actions performed in some **constrained but non-unique order** to achieve some intended high-level goal.

## **Procedural Videos**



Series of actions performed in some **constrained but non-unique order** to achieve some intended high-level goal.

Make coffee



## **Procedural Videos**



Series of actions performed in some **constrained but non-unique order** to achieve some intended high-level goal.

Make coffee



## Video Replay

- (Symbolic) Action sequence
  - take cup pour coffee add milk add sugar stir coffee SIL
- $\cdot$  Action duration
  - 180 150 90 140 160 100
- (Segmental) Action features

## **Temporally Coherent Action Model**

## Action Modeling via Conditional VAE

### The Encoder takes as input

- $\cdot x$  frame feature
- *a* action label
- *c* coherence variable
  - relative temporal progression of a frame within the action [0-1]



### The Decoder

- samples a latent variable
- outputs the reconstruction of the original feature

## Action Synthesis with Decoder

#### Frames in the same segment have

- consistent action label
- identical sampled latent variable
- varying coherence variable
  - in accordance to their temporal location



#### Generated segments are concatenated in time to form the replay video.

### Whenever new task data comes

#### Action Segmentation

- construct replay data with generators from previous tasks
- $\cdot$  learn segmentation with both incoming data and replay data

### Whenever new task data comes

#### Action Segmentation

- construct replay data with generators from previous tasks
- $\cdot$  learn segmentation with both incoming data and replay data

### Video Replay

- train new generator with incoming data
- cache generator in task stask

### **Incremental Training**

### Whenever new task data comes

#### Action Segmentation

- $\cdot$  construct replay data with generators from previous tasks
- $\cdot$  learn segmentation with both incoming data and replay data

#### Video Replay

- train new generator with incoming data
- cache generator in task stask



Iterate between Action Segmentation and Video Replay.

### Main Result

### Effectiveness on two benchmarks with two backbones

#### Improvement

- significant improvements over standard finetune approach without data replay
- improvements compared to exemplar-saving counterpart

#### Gaps

• large performance gap compared to using original frame features

# Tasks			MSTCN					ASFormer			
		Acc	Edit	F1 @ {10, 25, 50}			Acc	Edit	F1 @	F1 @ {10, 25, 50}	
			Breakfast								
10	Finetune Exemplar Ours Original	7.4 16.1 <b>29.4</b> 43.1	7.2 13.3 <b>25.9</b> 41.1	7.5 13.8 <b>26.3</b> 41.2	7.0 12.5 <b>23.5</b> 37.6	5.4 9.5 <b>17.7</b> 29.5	9.9 12.4 <b>34.2</b> 48.1	9.8 11.2 <b>32.4</b> 45.2	10.3 11.7 <b>33.1</b> 45.9	9.4 10.7 <b>30.1</b> 42.4	7.5 8.5 <b>23.4</b> 34.2
5	Finetune Exemplar Ours Original	15.4 32.5 <b>54.5</b> 60.4	15.8 28.9 <b>49.4</b> 59.1	16.6 30.8 <b>51.1</b> 60.3	15.8 28.5 <b>46.9</b> 56.1	12.7 22.9 <b>37.7</b> 46.0	15.7 29.5 <b>57.2</b> 65.1	16.1 27.5 <b>56.8</b> 64.2	16.9 28.7 <b>58.3</b> 65.6	15.8 26.7 <b>54.0</b> 61.5	13.2 22.0 <b>43.6</b> 51.0
		YouTube Instructional									
5	Finetune Exemplar Ours Original	13.6 <b>30.8</b> 30.2 55.9	2.8 19.7 <b>25.0</b> 39.4	3.6 19.8 <b>21.9</b> 38.1	2.7 16.0 <b>18.5</b> 32.2	0.6 9.3 <b>11.1</b> 19.1	13.9 22.1 <b>25.2</b> 59.2	11.5 18.9 <b>20.9</b> 51.1	11.1 17.7 <b>20.1</b> 45.4	9.8 15.3 <b>17.5</b> 39.1	6.3 10.0 11.4 25.5

### **Temporal Coherence**

	SD	FD	TC	Acc	Edit	F1 @ {10, 25, 50}		
Exemplar	1	×	X	27.8	35.6	36.1	31.7	24.3
Ours <sub>random</sub>	$\checkmark$	$\checkmark$	×	32.9	38.9	40.0	35.6	27.2
Ours <sub>static</sub>	$\checkmark$	×	×	37.9	42.9	43.8	38.9	29.0
Ours	$\checkmark$	$\checkmark$	$\checkmark$	41.8	45.0	47.0	41.5	32.0

SD - segment-level diversity FD - frame-level diversity TC - tempo

TC - temporal coherence

- Without temporal coherence, static segmnet works better than random
- All factors considered together achieves the best performance

## **Replay Size**

М	Acc	Edit	F1 @	{10, 25	5, 50}
30	34.0	39.6	41.0	34.8	24.7
60	35.4	41.2	42.3	36.0	25.6
90	36.2	42.3	43.9	37.3	26.8
120	38.0	42.3	44.0	37.1	26.2

- A larger replay size leads to better performance
- saturates and no further gain with replay size

## TCA Training data

	$\mathcal{T}(\%)$	Acc	Edit	F1 @ {10, 25, 50}		
Exemplar	-	22.6	34.8	36.0	32.4	25.2
	25	41.7	43.2	46.1	40.9	31.5
Ourc	50	42.1	43.3	45.1	40.5	31.5
Ours	75	45.3	45.9	47.8	43.7	34.7
	100	47.4	46.9	48.2	42.8	33.4

Access to more real data helps build the generative ability

### Take aways

- · Generative replay approaches are better desired for procedural videos
- Temporal coherence is essential for video replay
- This is an underexplored area full of research possibilities

# Thank you!