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Background

• The efficiency of "compressed" models are evaluated **without considering the practical hardware platform**, such as low-power FPGAs.













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- existing accelerators are evaluated on the ImageNet dataset with small input image sizes and do not scale to real-world High-Definition (HD) video frames.





Background

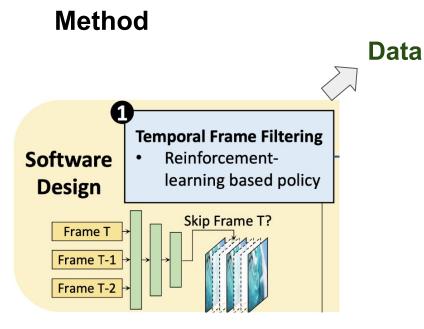
- The efficiency of "compressed" models are evaluated **without considering the practical hardware platform**, such as low-power FPGAs.
- existing accelerators are evaluated on the ImageNet dataset with small input image sizes and do not scale to real-world High-Definition (HD) video frames.
- Multi-Object Tracking (MOT) is the focus.





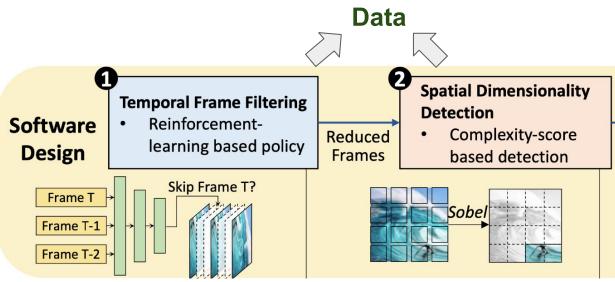












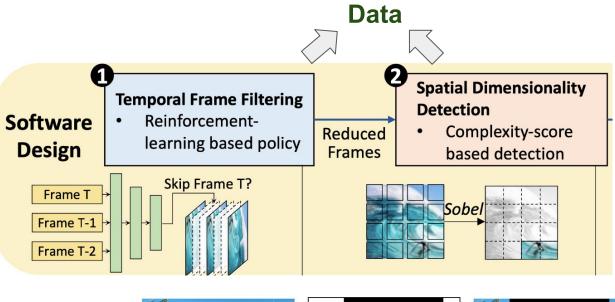




Method

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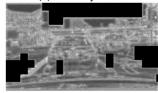
(a) Input frame



(e) FM(2,0)



(b) Saliency Mask



(f) FM(2,0) w/ Mask



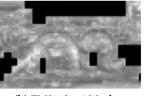
(c) Masked Input



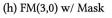
(g) FM(3,0)





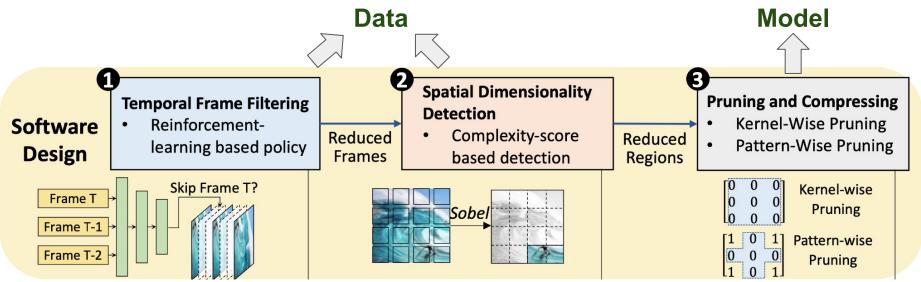








Patch Drop for Input Frame and intermediate features



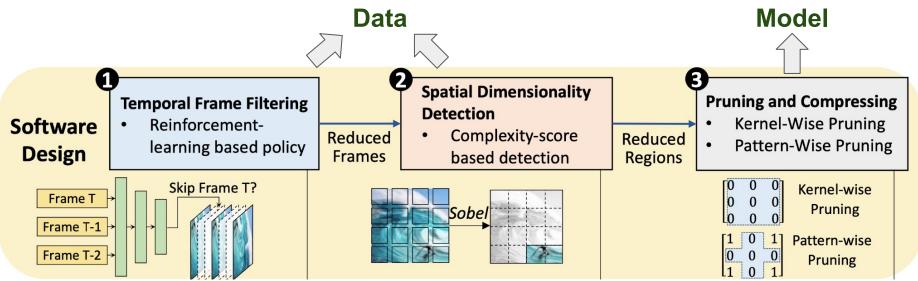


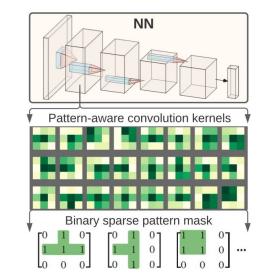


Method

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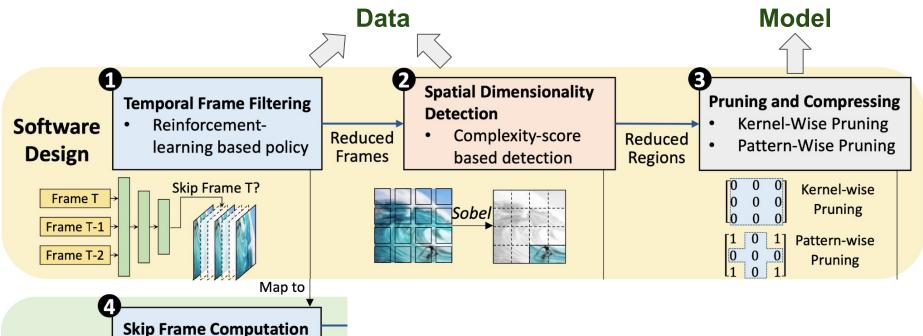




- **pre-define** irregular sparse patterns for 3 × 3 kernels
- leverage them to conduct irregular but pattern-aware weight pruning



Method





Frame 4

Backbone

Hardware

Design

Frame 2 dropped

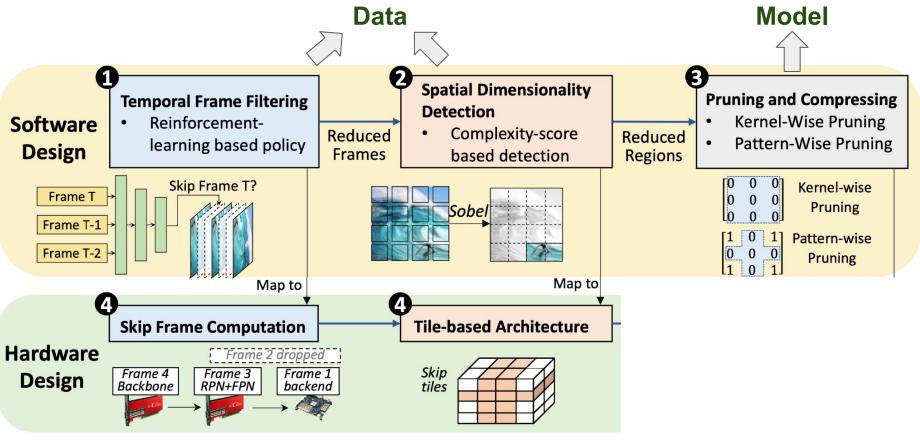
Frame 3

RPN+FPN

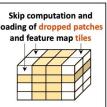
Frame 1

backend

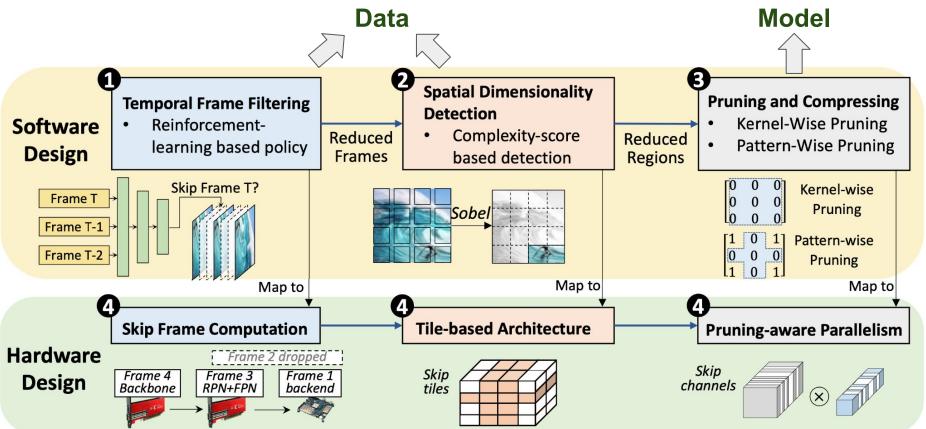
















= Methods	Data/model compression		Metrics					
	Data reduction	Pruning	IDF1 (†)	MOTA (↑)	Latency (\downarrow)	EFR (↑)	Power (\downarrow)	Energy Efficiency (\downarrow)
QDTrack (GPU baseline)	×	×	0.714	0.637	60.9	22.5	296 W	13.2 J/frame
QDTrack on FPGA	×	×	0.714	0.637	554.7	1.8	50.8 W	28.2 J/frame
Variant: Frame + patch drop	(40%, 20%)	×	0.71	0.628	443.8	2.3	50.8 W	22.0 J/frame
Tri-design (ours)	(40%, 20%)	90%	0.704	0.617	44.4	37.6	50.8 W	1.35 J/frame
Improv. over GPU baseline	—	_	-1.40%	-3.14%	1.37×	1.67 ×	5.83×	9.78×
Improv. over FPGA baseline	_	_	-1.40%	-3.14%	12.5×	20.9 ×	—	20.9 ×
			1.1070	5.11/0	12.07			20.77

Implementation Details

- 40% temporal **frame** dropping
- 20% spatial **patch** dropping
- 90% model pruning

Hardware Metrics given by on-board latency in the unit of millisecond

- effective frame rate (**EFR**) \rightarrow FPS
- power in the unit of Watt

Accuracy

- ID F1 Score (**IDF1**)
- Multi-Object Tracking Accuracy (MOTA)







