Video Object Detection Method Using Single-Frame Detection and Motion Vector Tracking

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Introduction

- Increasing of video traffic on the Internet
- Growing demand for video analysis
- Demand for edge computing
  - Load balancing, bandwidth reduction, and network delay reduction
  - Computational resources are scarce, and high-performance GPUs are not always available
  - Network-transparent processing eliminates the need to change end-device and server configurations
    - Network-transparent : Add new services without changing network settings

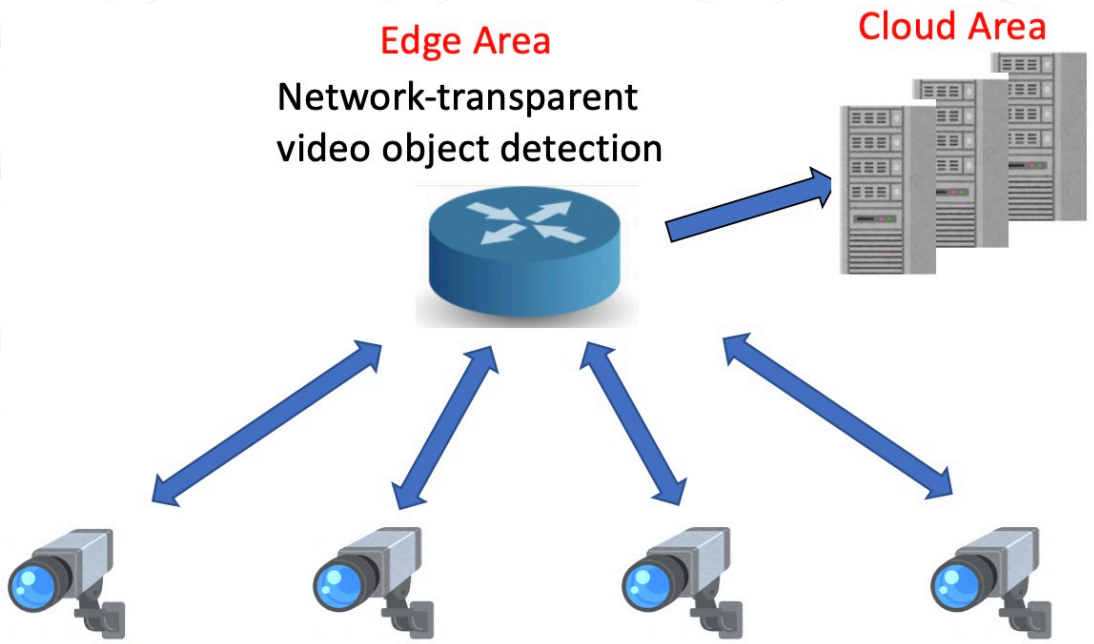
- High-throughput and memory-saving object detection method
- Network-transparent mechanism for acquiring video in edge area

Motion Compensation

- Compression technology used in every video codec
- Defines motion vectors for each macro blocks
- Three types of frame
  - I-frame : All information of the image
  - P-frame : Forward-predicted motion vectors
  - B-frame : Forward- and backward-predicted motion vectors

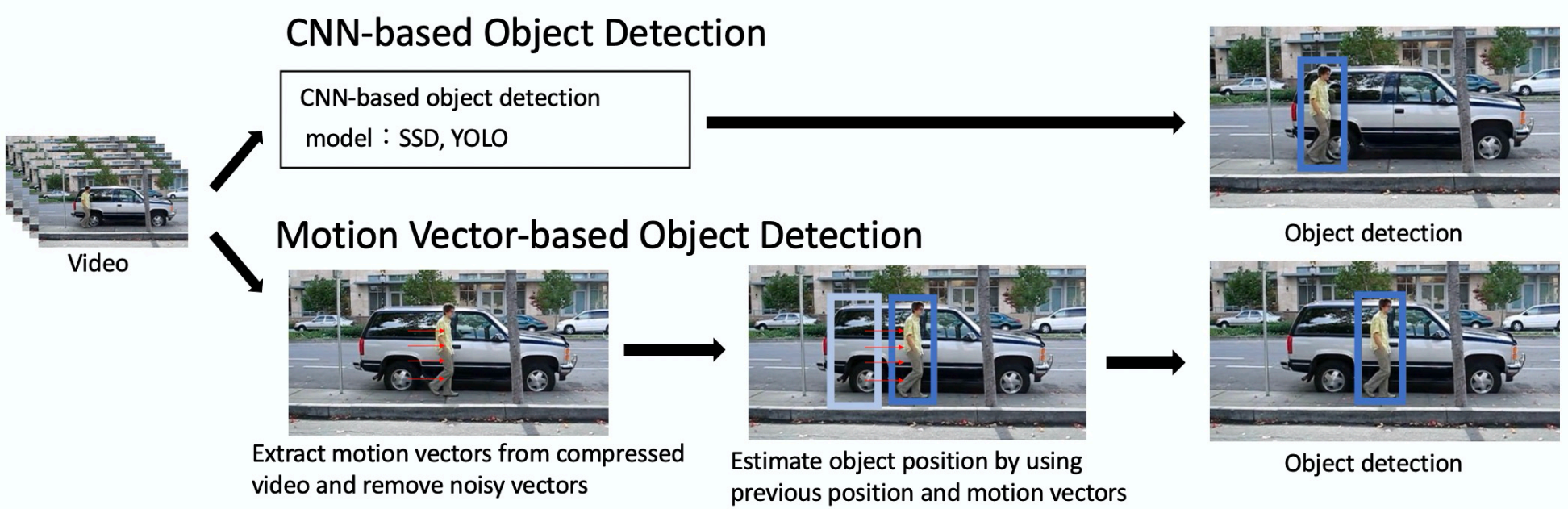
Assumed Environment

- Multiple surveillance cameras send video data to the cloud
  - Cameras for monitoring roads around residential areas
  - Cameras for monitoring production lines in a factory
- Network-transparent video object detection in edge area



Proposed Video Object Detection Method

- Different processes depending on frame types
  - I-frame
    - CNN-based object detection
  - P-frame, B-frame
    - CNN-based object detection
    - Motion vector-based object detection



Proposed Video Object Detection Method

- Reuse motion vectors in compressed video
  - No need to recalculate motion information
  - Motion vectors contain noisy vectors
- Remove noisy motion vectors
  - Apply median filter (filter size : 5 × 5 × 5) for maintaining spatiotemporal vector consistency

$$mv[x,y,t] = median\{mv[x',y',t'], x',y',t' \in w\} \quad (1)$$

x, y : position of the object
t : time axis
w : filter size

- Estimate next position of the object

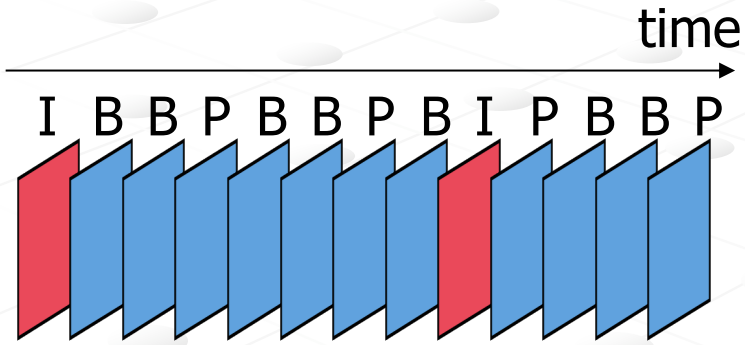
$$P_{now} = P_{previous} + \overline{mv} \quad (2)$$

$$\overline{mv} = average\{mv[w,h], w,h \in P_{previous}\} \quad (3)$$

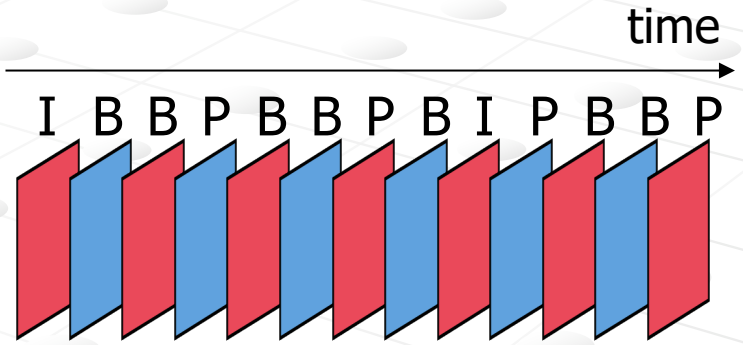
P_{now} : position of the object on current frame
$P_{previous}$: position of the object on previous frame

Trade-offs between Throughput and Accuracy

CNN-based object detection : Red
Motion vector-based object detection : Blue



- Throughput : High
- Accuracy : Low

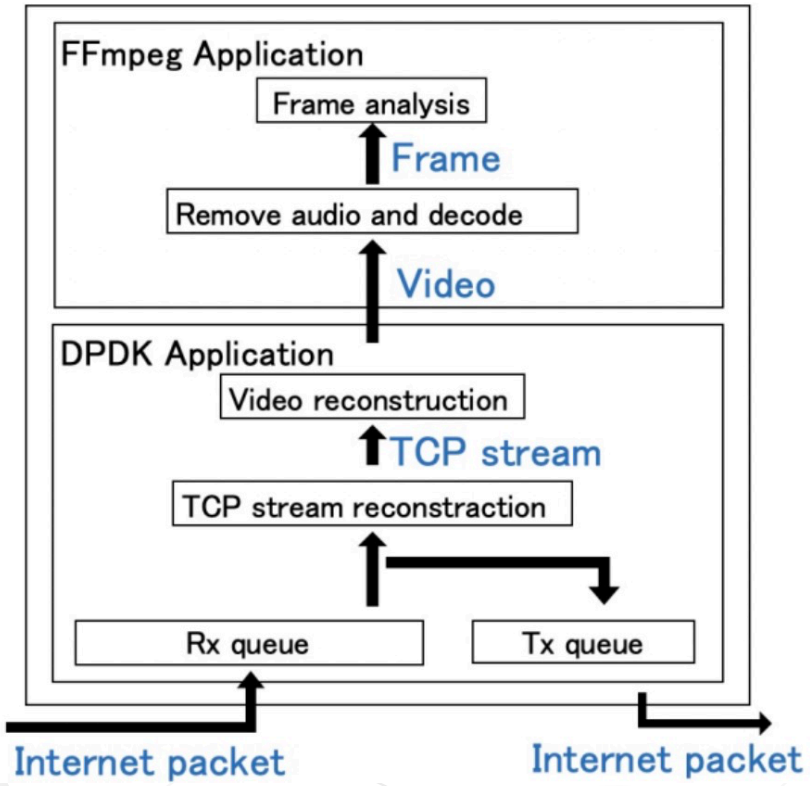


- Throughput : Low
- Accuracy : High

- The proposed method responds to various requirements in the trade-offs between throughput and accuracy

Implementation

- Used libraries
  - Data Plane Develop Kit (DPDK) : Set of libraries and drivers for fast packet processing using kernel bypass technology
  - FFmpeg : Complete cross-platform solution for recording, converting, and streaming audio and video
- DPDK Application
  - Reconstruct TCP stream
  - Reconstruct video
- FFmpeg Application
  - Remove audio data
  - Decode video data
  - Analyze frame data



Experimental Environment

- Video analysis device gets video network-transparently
- H.264 compressed video is used, which is captured by video distribution device

- Device Specifications
  - Small device for edge region was used

Device	Intel NUC	Shuttle DH310
OS	Ubuntu 18.04.1 LTS	Ubuntu 18.04.1 LTS
CPU	Intel(R) Core(TM) i3-6100U CPU@2.30GHz	Intel(R) Core(TM) i7–8700CPU@3.20GHz
Memory	8 G	32 G
Size	102 x 102 x 28 mm	190 x 165 x 43 mm

Experimental Results

Moving Object Detection


(a)


(b)


(c)


(d)


(e)


(f)

Video Object Detection

(a)

(b)

(c)

(d)

(e)

(f)

Evaluation : Accuracy and Throughput

- Comparison method
  - Video object detection : CNN-based object detection for all frames
- Accuracy (mean Average Precision 50 (mAP50))

	SSD	YOLOv3
CNN-based object detection for all frames (a)	0.796	0.774
Proposed method (b)	0.703	0.705
Accuracy ratio (b/a)	0.88	0.91

- Throughput (Frame Per Second (FPS))

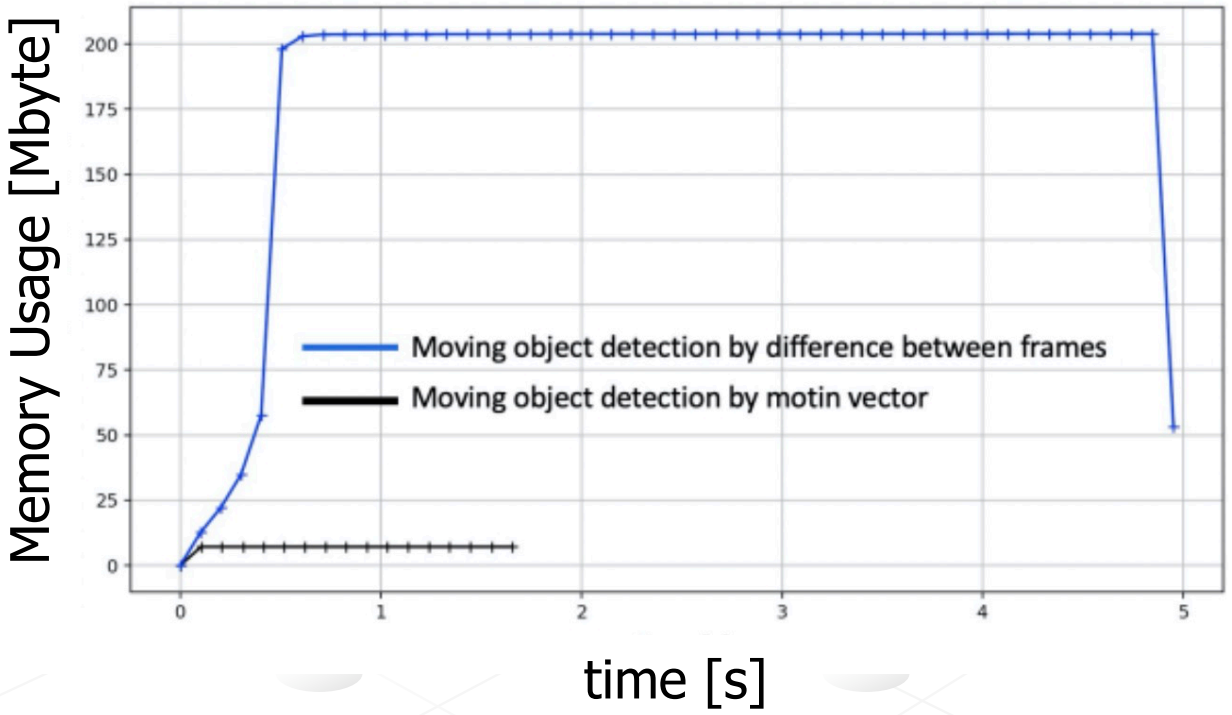
	SSD	YOLOv3
CNN-based object detection for all frames (a)	1.3	4.7
Proposed method (b)	58.3	75.5
Throughput ratio (b/a)	44.5	16.1

Throughput of 50 FPS or more is achieved by using motion vectors

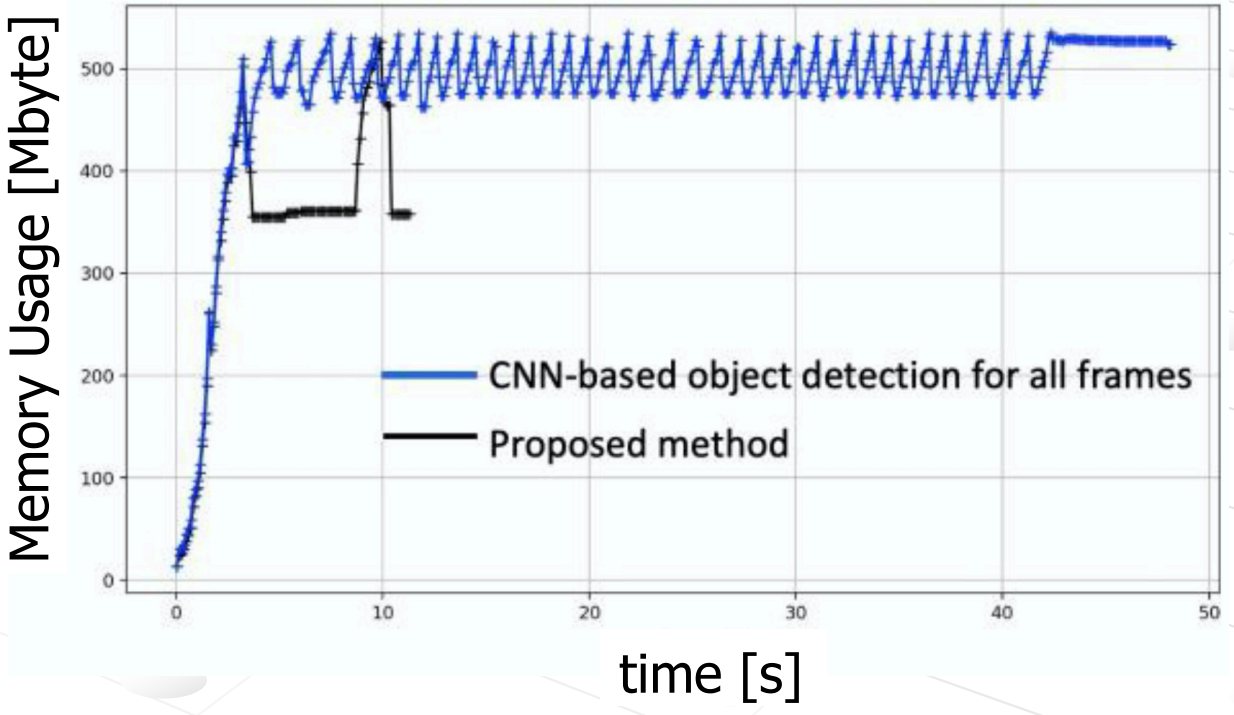
Evaluation : Memory Usage

- Time variation of memory usage

Moving object detection

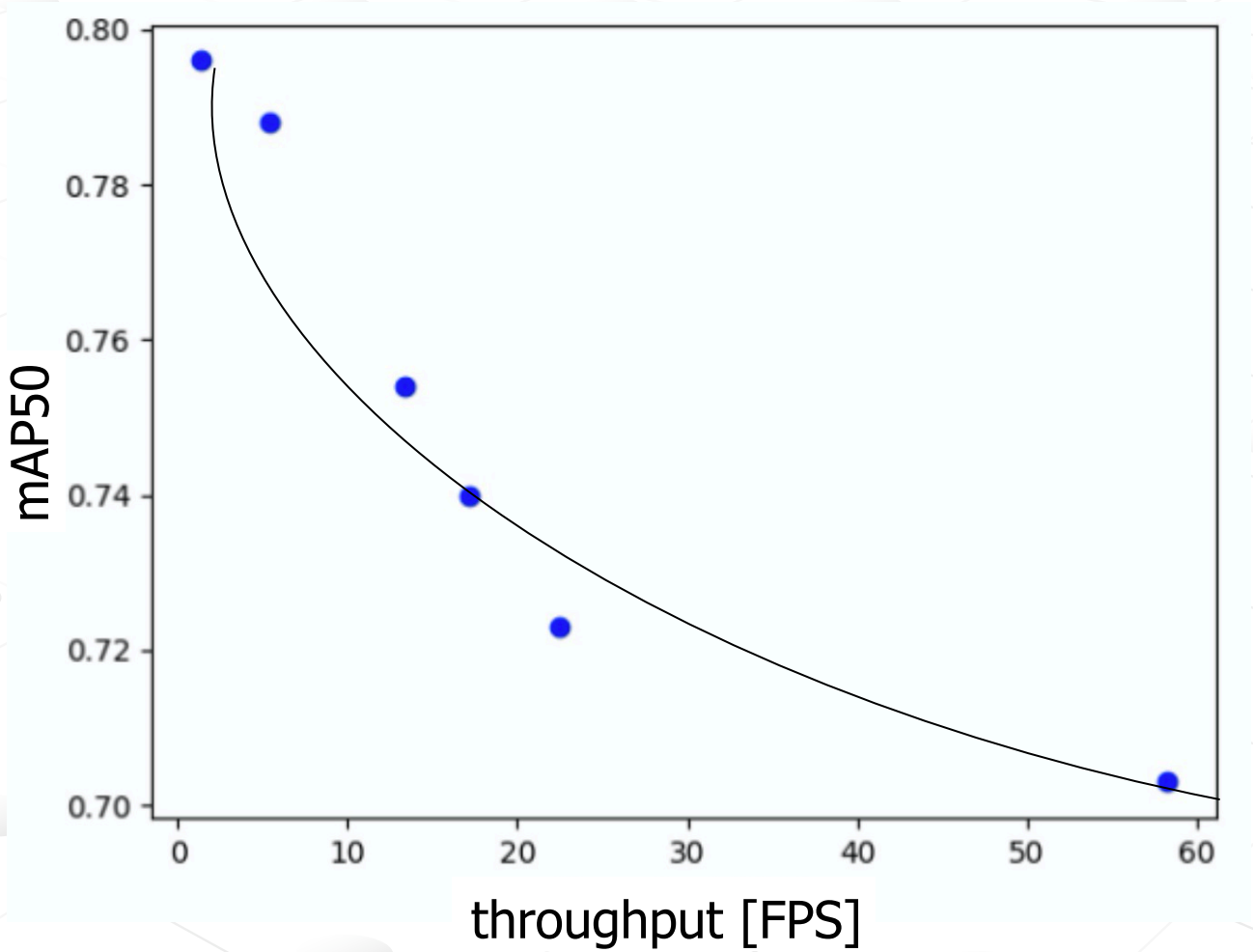


Video object detection



Trade-offs between Throughput and Accuracy

- Trade-offs between throughput and accuracy when using SSD



Conclusion

- A video object detection method was proposed for memory-saving and high-throughput analysis without the use of high-performance computing nodes like GPU

- A network-transparent mechanism for acquiring video was constructed in edge areas

- High-throughput and memory saving object detection in edge area where computational resources are scarce

Thank you for your attention

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Acknowledgements

- This work was supported by JST CREST Grant Number JPMJCR19K1, and the commissioned research by National Institute of Information and Communications Technology (NICT, Grant Number 22004) , JAPAN.