



AdaRadar: Rate Adaptive Spectral Compression for Radar-based Perception

Jinho Park¹, Se Young Chun², and Mingoo Seok¹

¹Columbia University

²Seoul National University

jp4327@columbia.edu, sychun@snu.ac.kr, ms4415@columbia.edu



VLSILab
@COLUMBIA UNIV



Table of Contents

- **Motivation**
- **Proposed methods**
 - Spectral pruning
 - Adaptive rate feedback
- **Experimental results**
 - Qualitative results
 - Rate-accuracy tradeoff
 - Compression performance against baseline work
- **Conclusion**



Table of Contents

- **Motivation**
- **Proposed methods**
 - Spectral pruning
 - Adaptive rate feedback
- **Experimental results**
 - Qualitative results
 - Rate-accuracy tradeoff
 - Compression performance against baseline work
- **Conclusion**



Radar Complements Camera & LiDAR

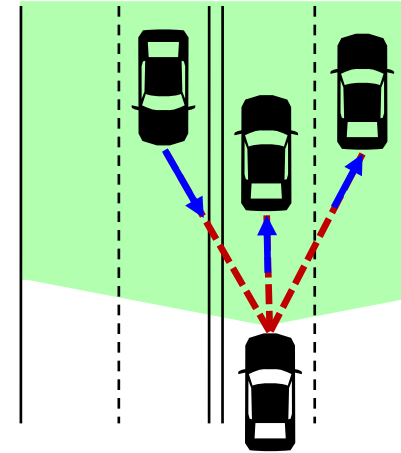
Vision is vulnerable to low-light and occlusion



LiDAR can be affected by scattering from rain & snow



--- Range
→ Doppler velocity



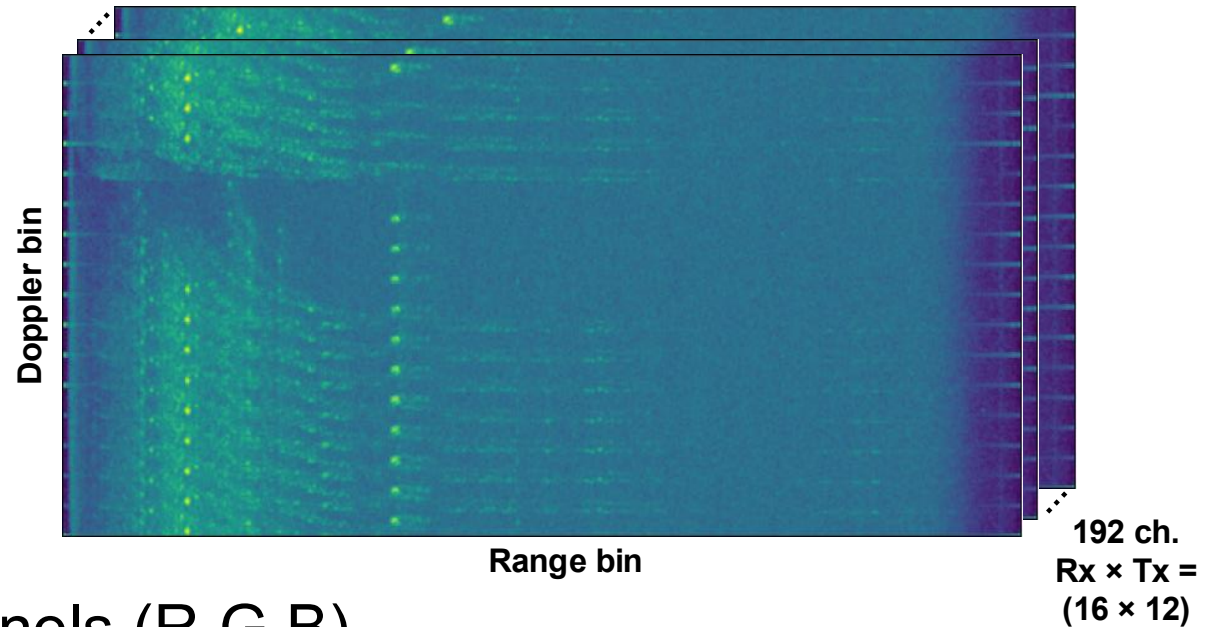
- Radar-based perception is a critical sensing modality in autonomous driving pipeline as it complements camera and LiDAR.
- Radar is robust to lighting and weather conditions.
- Its ability to measure relative range and Doppler velocity.

Radar Poses Bottleneck on Link BW

Image from KITTI

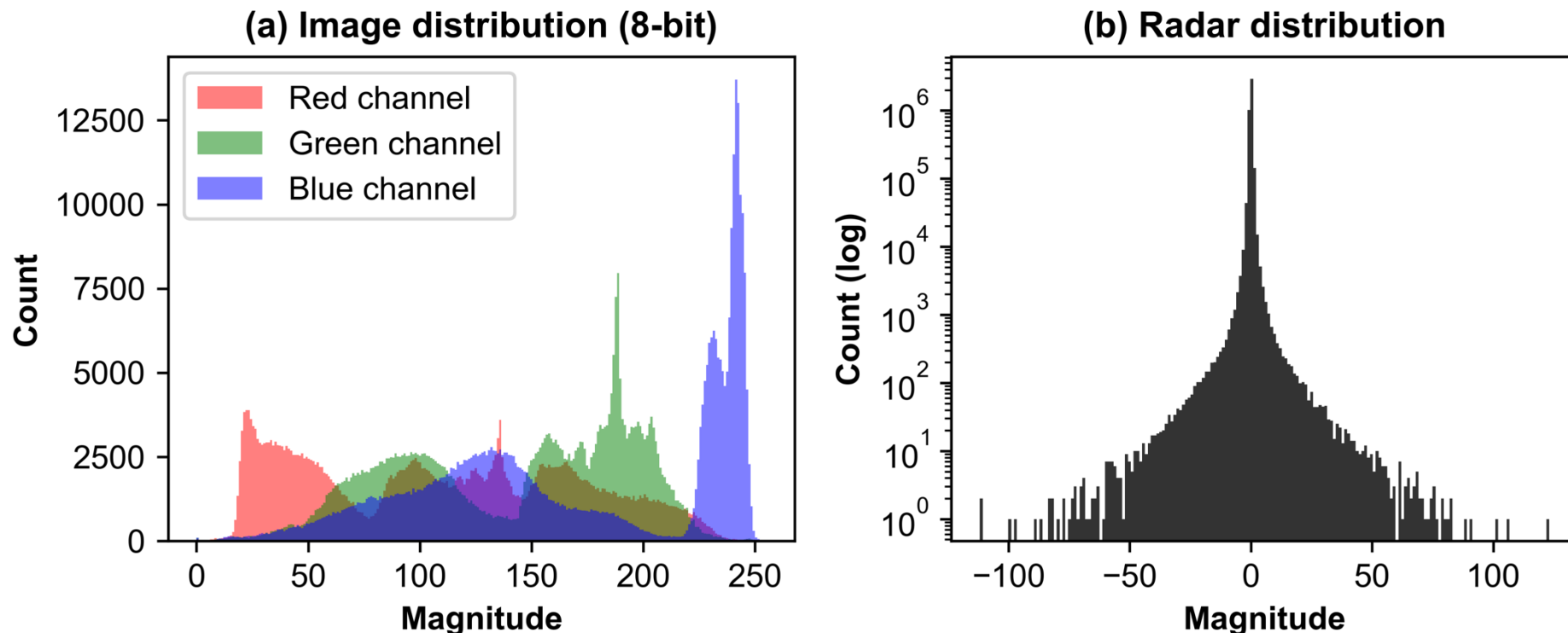


Radar from RADlal



- Unlike a camera, which only has 3 channels (R,G,B).
- Raw radar tensor has quadratically scaling channels to receiver (Rx) and transmitter (Tx) antennas.
- e.g., a single frame from a 16 x 12 cascaded MIMO radar system, configured with 512 range bins and 256 Doppler bins, amounts to roughly 100 MB.

Absence of Radar CODECs



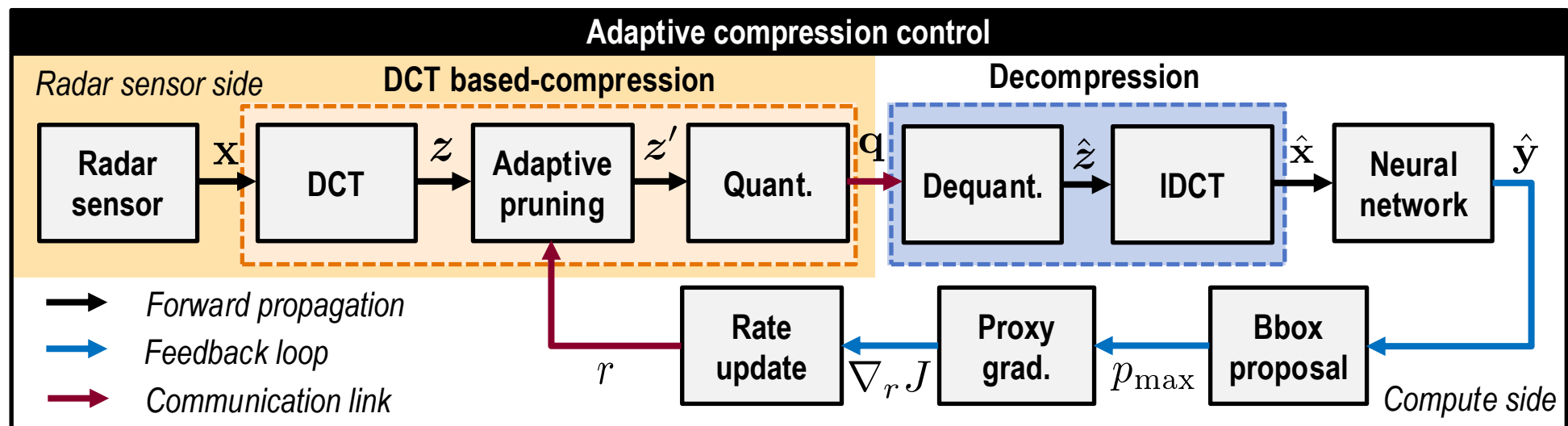
- a) Natural images span a broad dynamic range.
 - b) Radar signals exhibit extreme sparsity and a heavy-tailed profile (1st/99th percentiles at ± 1.74).
- Necessitating specialized compression beyond standard image-domain codecs.

Table of Contents

- Motivation
- **Proposed methods**
 - Spectral pruning
 - Adaptive rate feedback
- Experimental results
 - Qualitative results
 - Rate-accuracy tradeoff
 - Compression performance against baseline work
- Conclusion

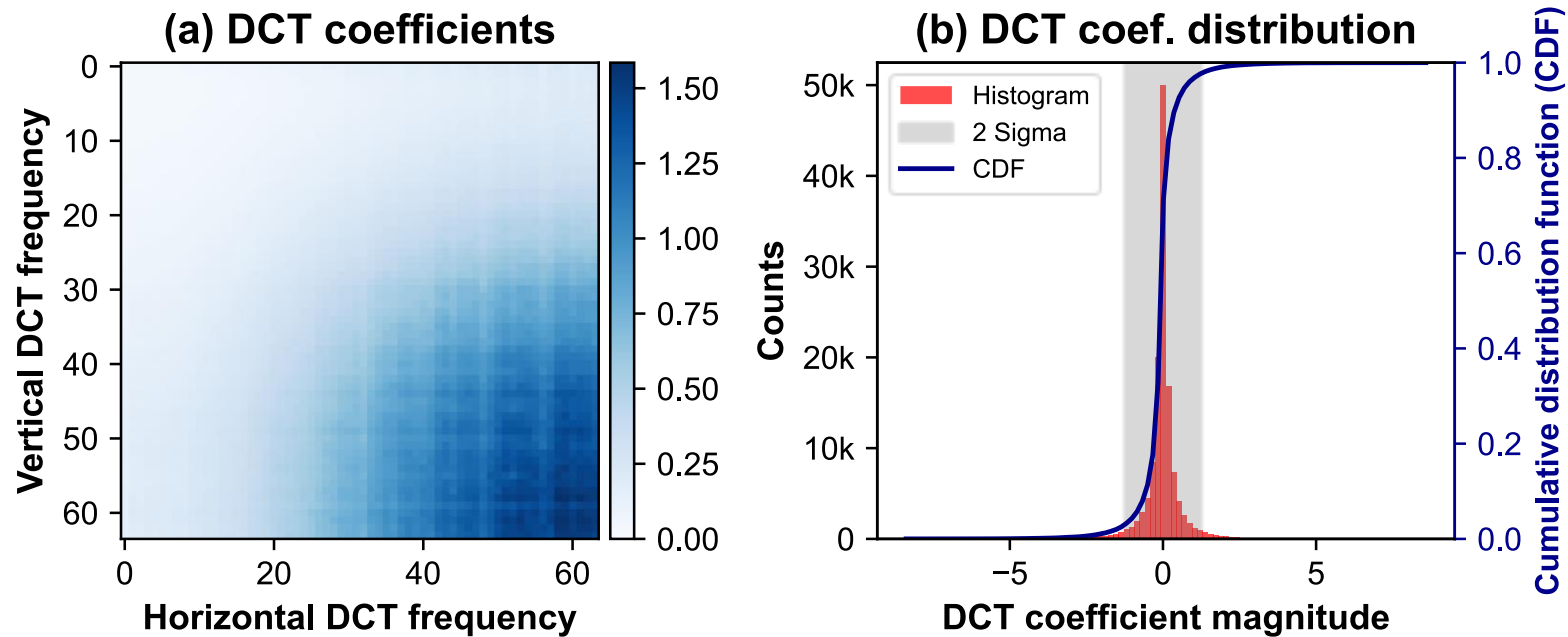


AdaRadar: Adaptive Compression Rate Control



- Our proposed method introduces a **feedback loop** in which the proxy gradient is computed from the detection outputs to update the compression ratio adaptively.
- This avoids the need for **backpropagation** through the communication channel.
- It involves DCT-based **compression** on the radar sensor-side and decompression on the compute side.

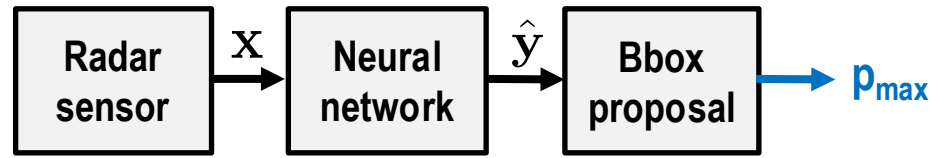
Propose Methods: (1) Spectral Compression



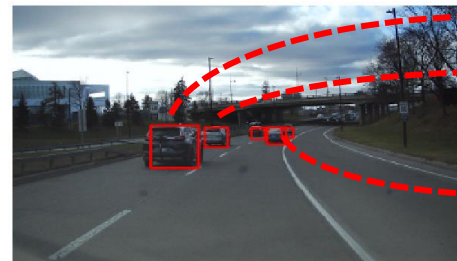
- a) The DCT coefficient **magnitudes** are clustered in the high-frequency bins.
 - b) Their histogram is sharply peaked, highlighting strong **sparsity** and clear opportunities for compression.
- Adaptive compression includes **spectral pruning** + **symmetric quantization**

Propose Methods: (2) Adaptive Feedback

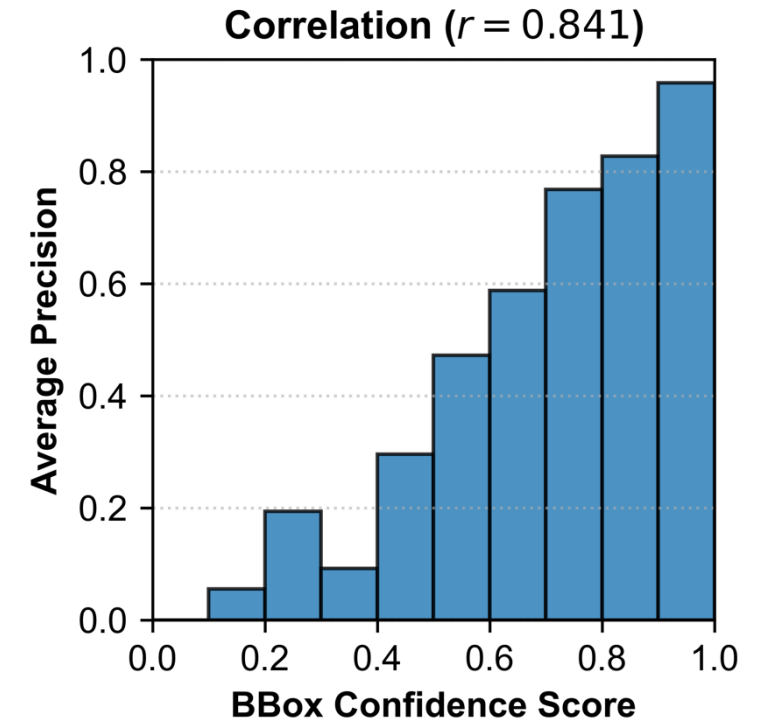
Processing chain for radar-based object detection



Bounding boxes (Bbox) in object detection:



$\begin{bmatrix} p_1 \\ p_2 \\ \dots \\ p_n \end{bmatrix}$
Associated Bbox probabilities



- We use the bounding box confidence as the **surrogate objective**.
- **Labels** are *not* available at test time to monitor the model performance.
- Bbox confidence shows great correlation with the ground truth label (if it were to exist).

Propose Methods: (2) Adaptive Feedback

Task objective:

$$\max_{\{r_t\}_{t=1}^T} \mathbb{E}[J_t(r_t)], \quad J_t(r_t) = h(\mathbf{x}_t, r_t) - \lambda \cdot B(r_t)$$

hyper-param to control accuracy-bandwidth trade-off
Instantaneous bit-rate

Gradient w.r.t rate (r):

$$\nabla_r J = \nabla_r h(\mathbf{x}, r) - \lambda \cdot B'(r)$$

Proxy gradient:

$$\nabla_r h(\mathbf{x}, r) \approx \frac{\overset{\text{Pass \#1}}{h(\mathbf{x}, r)} - \overset{\text{Pass \#2}}{h(\mathbf{x}, r - \epsilon)}}{\epsilon} = \frac{p - p^-}{\epsilon}$$

Algorithm 1: Adaptive rate control

Input: Radar sequence ($\{\mathbf{x}_t\}_{t=1}^T$), weight (Θ), initial pruning ratio (r_1), learning rate (η), perturbation (ϵ)

Output: Detection map ($\{\hat{\mathbf{y}}_t\}_{t=1}^T$)

```

1: for  $t := 1$  to  $T$  do
2:    $\mathbf{q}_t, \mathbf{Q}_t \leftarrow \text{Compression}(\mathbf{x}_t, r_t)$ ;
   // Transfer  $\{\mathbf{q}, \mathbf{Q}\}$  once
3:    $\hat{\mathbf{x}}_t \leftarrow \text{Decompression}(\mathbf{q}_t, \mathbf{Q}_t)$ ;
4:    $\hat{\mathbf{y}}_t \leftarrow f_{\Theta}(\hat{\mathbf{x}}_t)$ ; ←----- Network inference pass #1
5:    $\{(b_k, p_k)\}_{k=1}^K = \text{Propose}(\hat{\mathbf{y}}_t)$ ;
6:   if adaptive then
7:      $\mathbf{q}_t^- \leftarrow \text{Pruning}(\mathbf{q}_t, \epsilon)$ ;
8:      $\hat{\mathbf{x}}_t^- \leftarrow \text{Decompression}(\mathbf{q}_t^-, \mathbf{Q}_t)$ ;
9:      $\hat{\mathbf{y}}_t^- \leftarrow f_{\Theta}(\hat{\mathbf{x}}_t^-)$ ; ←----- Network inference pass #2
10:    if  $k > 0$  then
11:       $r_{t+1} \leftarrow r_t - \eta \hat{\nabla}_{r_t} J$ ;

```

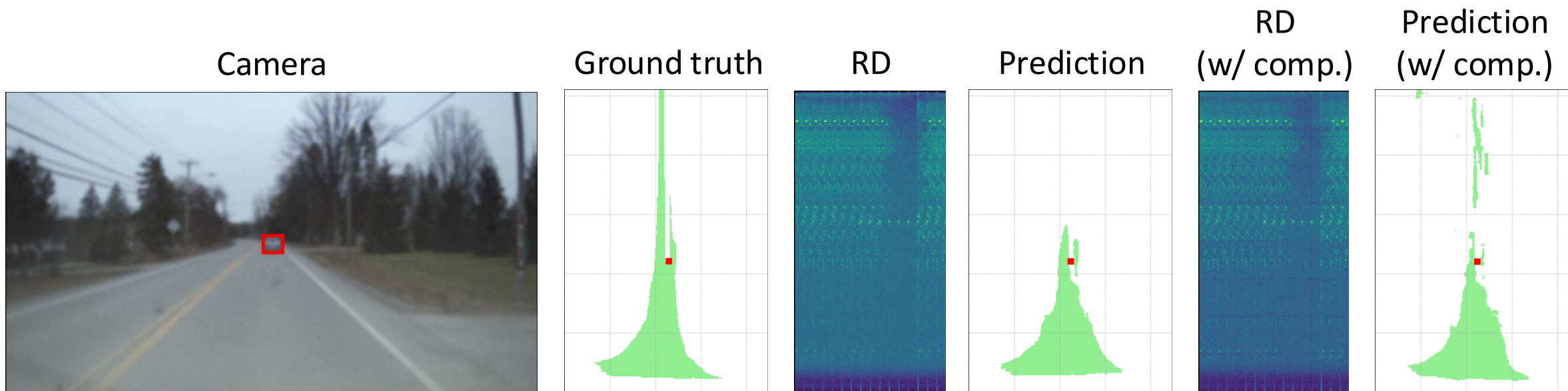
- Task objective: h encapsulates compression, decompression, forward inference, and Bbox proposal.
- Algorithm for adaptive rate control - compute the gradient with only two **forward** passes.

Table of Contents

- Motivation
- Proposed methods
 - Spectral pruning
 - Adaptive rate feedback
- **Experimental results**
 - **Qualitative results**
 - **Rate-accuracy tradeoff**
 - **Compression performance against baseline work**
- Conclusion

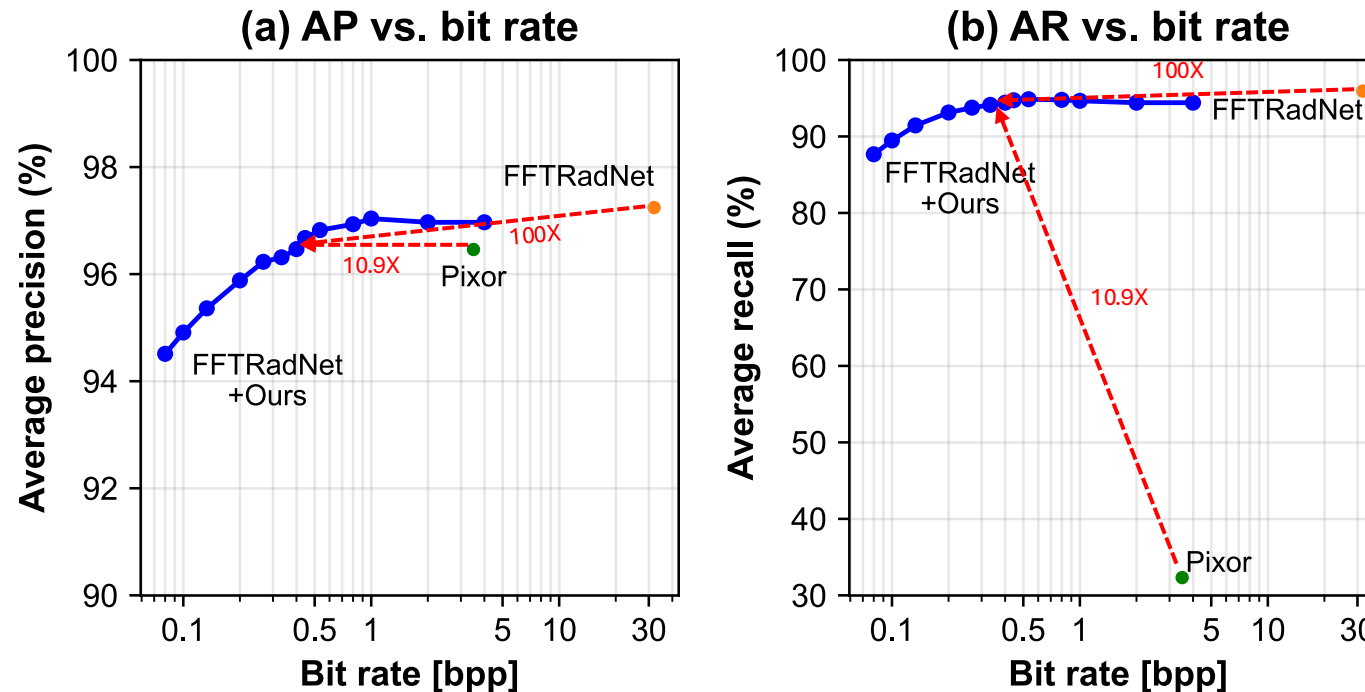


Qualitative Results



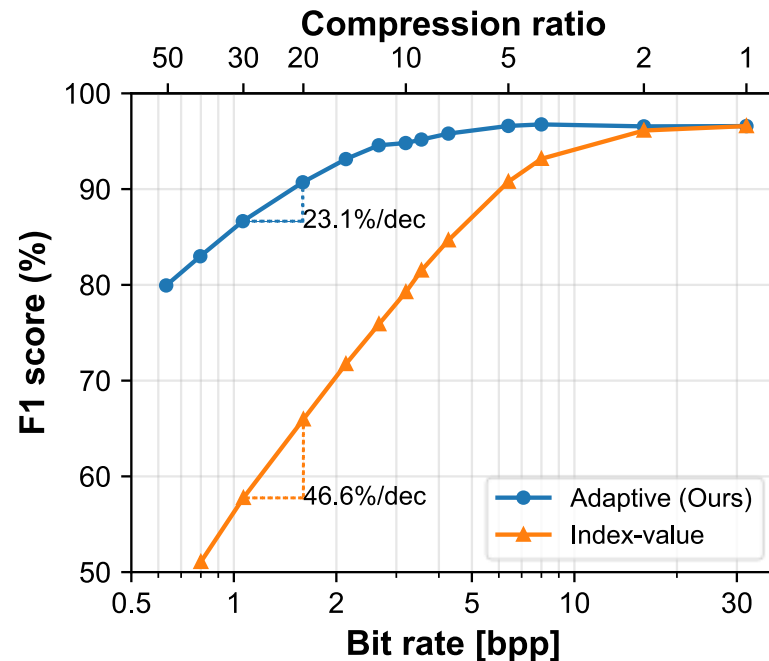
- **Camera images** provide contextual reference for the scene (not fed into network).
- The network predicts both **detection** and **segmentation** outputs.
- Compressed RD leads to **improved performance** compared to the uncompressed baseline.

Rate-accuracy Tradeoff



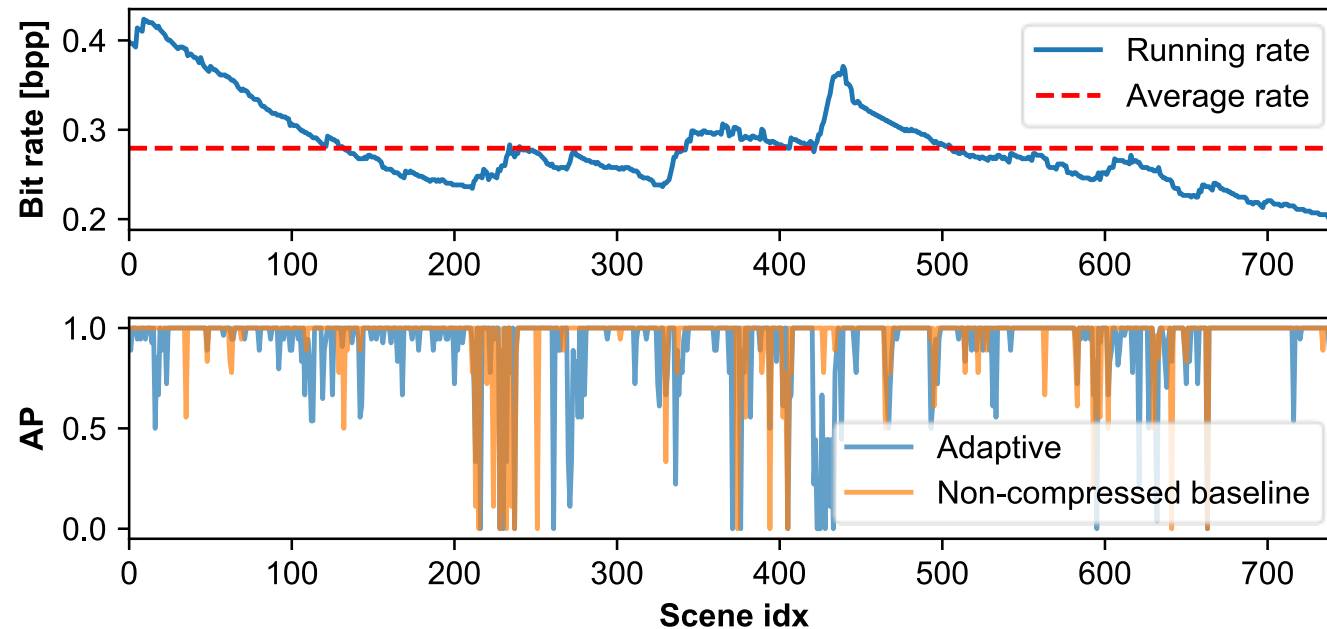
- It depicts the obvious **rate-accuracy tradeoff**.
- More importantly, our compression scheme achieves **100x** reduction in the radar feature map size while having a **1%p decrease** in the performance compared to the baseline.
- Against **Pixor**, our method achieves better precision and markedly better recall.

Against Index-value-based Method [NeurIPS'24]



- The **index-value based** compression selects Top- K elements in each $M \times M$ block according to the energy in the spatial domain.
- Our method remains **stable** until 5x compression whereas the performance roll-off begins immediately with the index-value pair-based method.
- The roll-off gradient of **23.1%/dec** is much more gentle for the spectral pruning-based compression vs. **46.6%/dec** of the counterpart.

Online Compression



- We **visualize** the online compression with bit rate and detection metric.
- Here, it is expected that the controller decreases the pruning ratio to **compensate** for the AR drop.
- It achieves an average bit rate of **0.279 bpp** with 8-bit quantization, yielding a **115x** compression with AR of **93.91%**.

Compression Results – RADial Dataset

RADial [CVPR'22]
Task: detection
& segmentation

Method	Bit	Prune ratio	Bit rate [bpp] ↓ (Comp. ratio ↑)	P (%) ↑	Detection R (%) ↑	F ₁ (%) ↑	Segment. mIoU (%) ↑
Baseline [2]	32	-	32 (1×)	97.24	95.93	96.58	75.97
+Index-value [11]	32	12×	2.67 (12×)	97.55	62.12	75.91	49.86
+Adaptive (Ours)	4	12.57×	0.32 (101×)	96.25	94.04	95.13	79.34

- An average pruning ratio of **12.57x** combined with **8x** gain from quantization, yields a bit rate of **0.32 bits per pixel** (bpp), corresponding to a **101x** compression ratio.
- On the segmentation task, ours improves the performance by **4%p**.
- Our method markedly **surpasses** index-value based method.



Compression Results – CARRADA, Radatron

CARRADA [ICPR'20]

Task: segmentation

Method	Bit	PR	BR [bpp] ↓	CR ↑	mIoU (%) ↑	mDice (%) ↑
Baseline [41]	32	-	32	1×	55.25	67.13
+Index-value [11]	32	29×	1.10	29×	38.96	46.90
+Adaptive (Ours)	8	29.28×	0.27	117×	54.03	65.87

Radatron [ECCV'22]

Task: detection

Method	Bit	PR	BR [bpp] ↓	CR ↑	mAP (%) ↑	AP ₅₀ (%) ↑	AP ₇₅ (%) ↑
Baseline [26]	32	-	32	1×	46.07	83.60	44.16
+Index-value [11]	32	7.5×	4.27	7.5×	45.72	80.44	47.54
+Adaptive (Ours)	8	7.5×	1.07	30×	48.46	83.69	49.07

CARRADA

- It allows even greater compression ratio of **117x** while maintaining the target metric close to the non-compressed baseline with **1%p drop**.

Radatron

- A range-azimuth heatmap is compressible by 30x with our compression method.
- Even at this compression rate, ours actually provides better performance than the non-compressed baseline -- up to **5%p** improvement in AP₇₅.

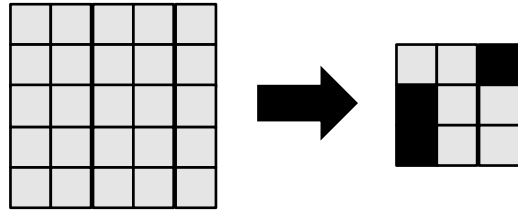


Table of Contents

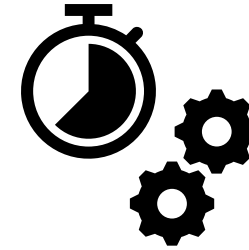
- Motivation
- Proposed methods
 - Spectral pruning
 - Adaptive rate feedback
- Experimental results
 - Qualitative results
 - Rate-accuracy tradeoff
 - Compression performance against baseline work
- **Conclusion**



Conclusion



**Spectral feature
compression**



Online rate adaptation

- We present **AdaRadar**, a rate-adaptive spectral-domain compression framework for radar-based object detection.
- Pruning and quantizing DCT coefficients shrink the range–Doppler cube by $>100x$, easing the sensor-to-compute bandwidth bottleneck while preserving accuracy at the lowest bit rate target.
- A lightweight test-time controller finely adjusts the compression ratio on the fly, making a judicious tradeoff between bandwidth and performance in real time.

Thank you for listening to our work on
AdaRadar:
Rate Adaptive Spectral Compression for
Radar-based Perception



Project page



Jinho Park¹



Se Young Chun²



Mingoo Seok¹

¹Columbia University

²Seoul National University

jp4327@columbia.edu, sychun@snu.ac.kr, ms4415@columbia.edu

Acknowledgements:

This work was supported in part by COGNISENSE, one of seven centers in JUMP 2.0, a Semiconductor Research Corporation (SRC) program sponsored by DARPA. The work of SY Chun was supported by IITP grants funded by the Korea government(MSIT) [No.RS-2021-II211343, Artificial Intelligence Graduate School Program (Seoul National University) / No.RS-2025-02314125, Effective Human-Machine Teaming With Multimodal Hazy Oracle Models].

