PeakConv: Learning Peak Receptive Field for Radar Semantic Segmentation

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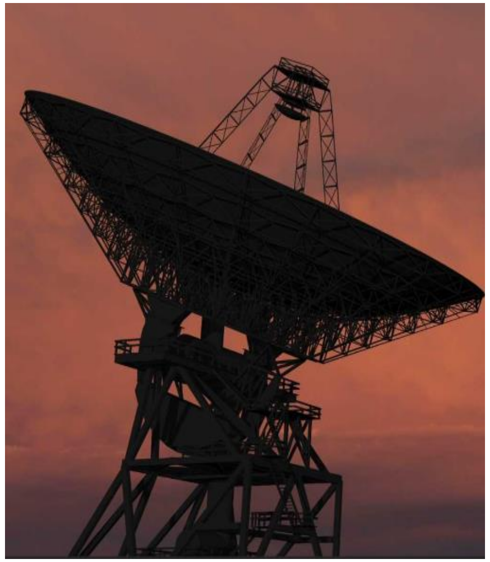
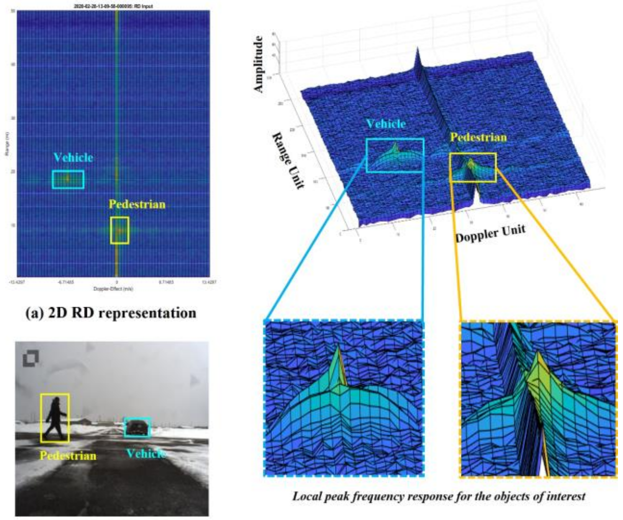
I. Background

Radar Semantic Segmentation (RSS)



- Remote sensor
- Robust to extreme weather, dim light condition and sun glare
- RSS can provide more refined and detailed information in radar scene understanding

Radar Object Signature



(a) 2D RD representation

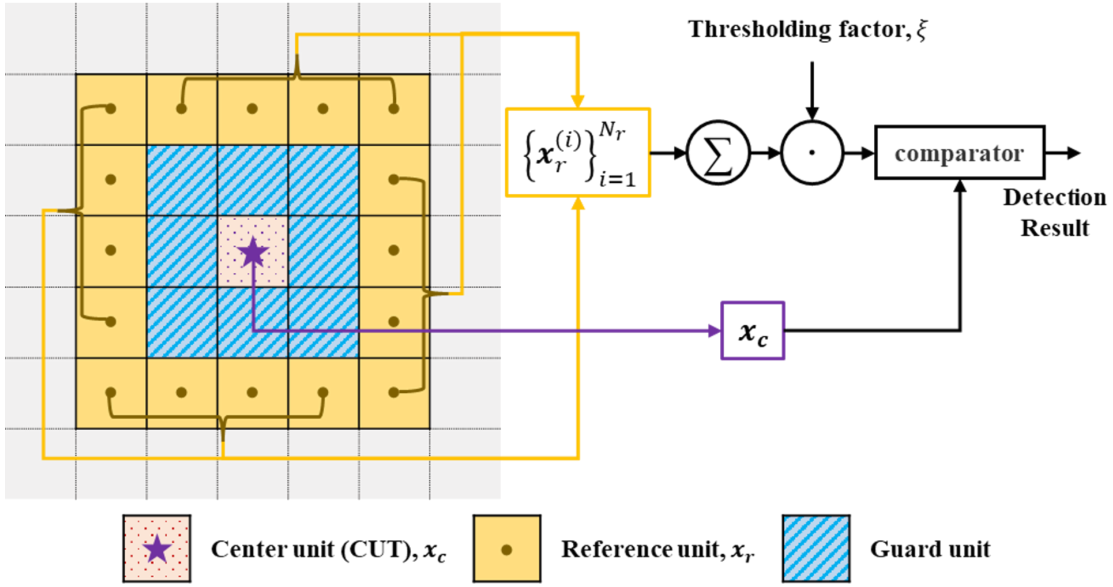
(c) Synchronized camera image

(b) RD-amplitude 3D representation

- Not as intuitively understood as the optical images
- Less intuitive priors of human vision
- Local peak frequence response

I. Background

■ Constant False Alarm Rate Detection （CFAR）



Averaging aggregation from reference cells $\{x_r^{(i)}\}_{\{i=1\}}^{N}$

Threshold computing: $\theta = \xi \cdot \frac{1}{N}\sum_{i=1}^{N} x_r^{(i)}$

Decision-making by comparing x_c and θ

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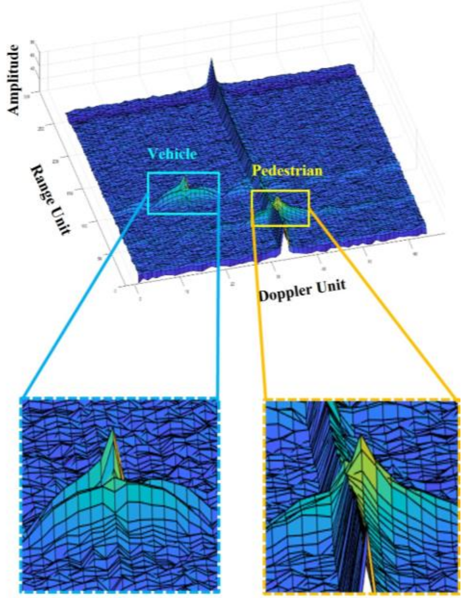
II. Motivation

- **Defects of Existed Radar object detection Methods**
  - Classic CFAR-based radar object detection methods:
    - Effects rely on manually fine-tune hyper-parameters
    - Lack of semantic information of objects
  - Deep learning-based RSS methods:
    - Mechanically apply methods which are designed for optical images specifically
    - Inefficient learning on radar signal



Local peak frequency response for the objects of interest

Radar-specific Semantic Segmentation Method is necessary!

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III. Methodology

- Peak Receptive Field (PRF)：

$$\mathcal{R} = \left\{x_c, \{x_r^{(i)}\}_{i=1}^{N_r}\right\}, \quad (1)$$

$$s.t. |\boldsymbol{b}_G| < \left|\boldsymbol{p}_r^{(i)} - \boldsymbol{p}_c\right| \leq |\boldsymbol{b}_R + \boldsymbol{b}_G|$$

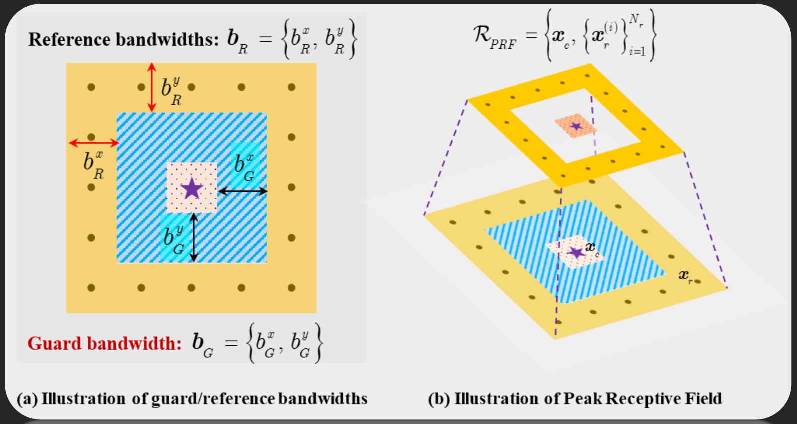


Fig.1 Guard/reference bandwidths and PRF

Learning from PRF

- Vanilla-PKC: $PKC(\mathcal{R};W) \in \mathbb{R}^{C_{\text{in}} \times N_r \times C_{\text{out}}}: \mathbb{R}^{C_{\text{in}}} \to \mathbb{R}^{C_{\text{out}}}$

$$PKC(\mathcal{R};W) = x_c - Vec\left(\left\{\textstyle\sum_{i=1}^{N_r} w_j^{(i)} * x_r^{(i)}\right\}_{j=1}^{C_{\text{out}}}\right), \quad (2)$$

$$w_j^{(i)} \in \mathbb{R}^{C_{\text{in}}}(j = 1, \ldots, C_{\text{out}})\ \&\ C_{\text{in}} = C_{\text{out}}.$$

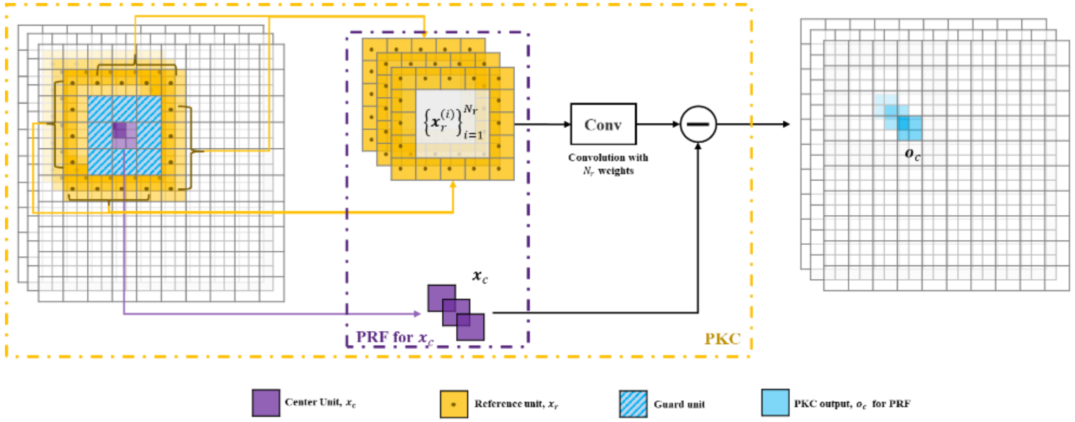


Fig.2 The the whole process for a PeakConv layer

- ReDA-PKC: $PKC^*(\mathcal{R};\boldsymbol{W}) \in \mathbb{R}^{C_{\text{in}} \times N_r \times C_{\text{out}}}: \mathbb{R}^{C_{\text{in}}} \to \mathbb{R}^{C_{\text{out}}}$

$$PKC^*(\mathcal{R};W) = Vec\left(\left\{\textstyle\sum_{i=1}^{N_r} w_j^{(i)} * \left(x_c - x_r^{(i)}\right)\right\}_{j=1}^{C_{\text{out}}}\right), \quad (3)$$

$$w_j^{(i)} \in R^{C_{\text{i}}}\sim(j = 1, \cdots, C_{\text{out}}).$$

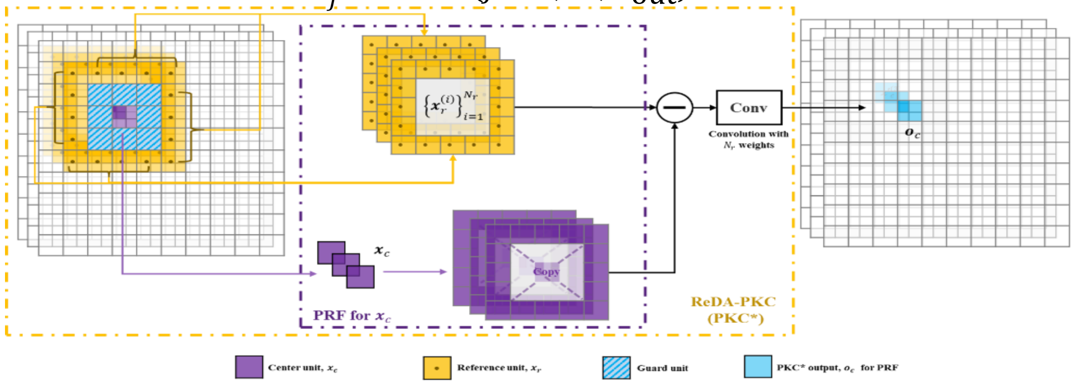
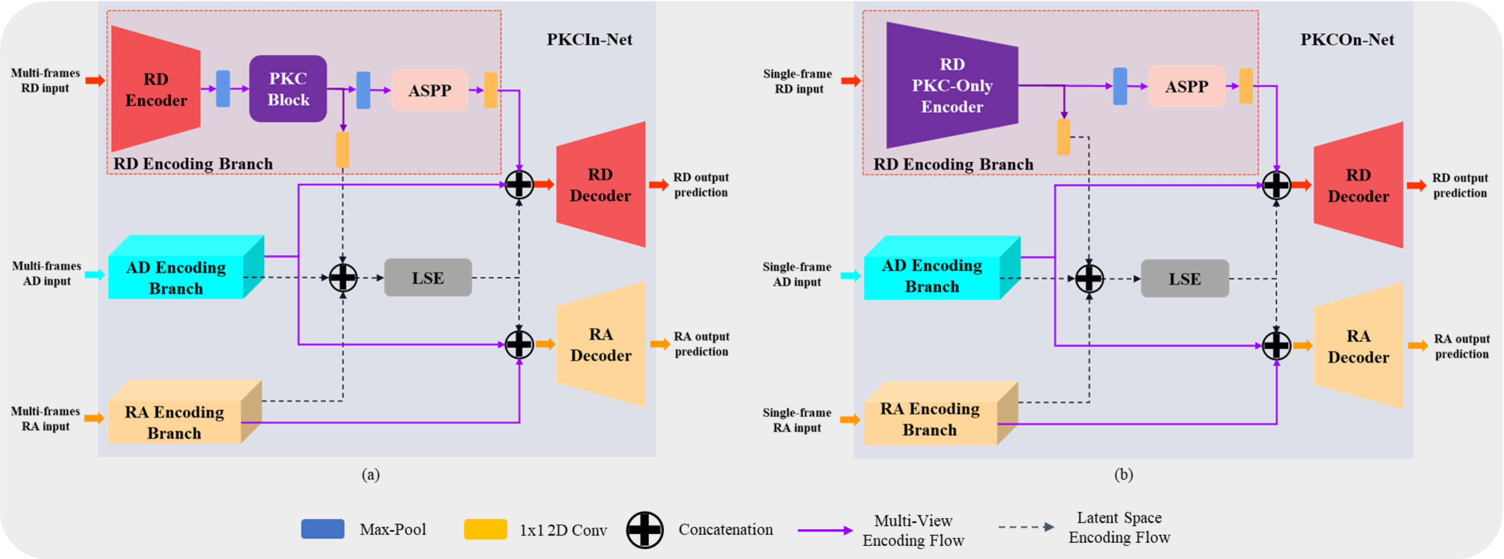


Fig.3 The the whole process for a ReDA-PKC layer

III. Methodology

- PeakConv-based RSS Network: PKCIn-Net & PKCOn-Net



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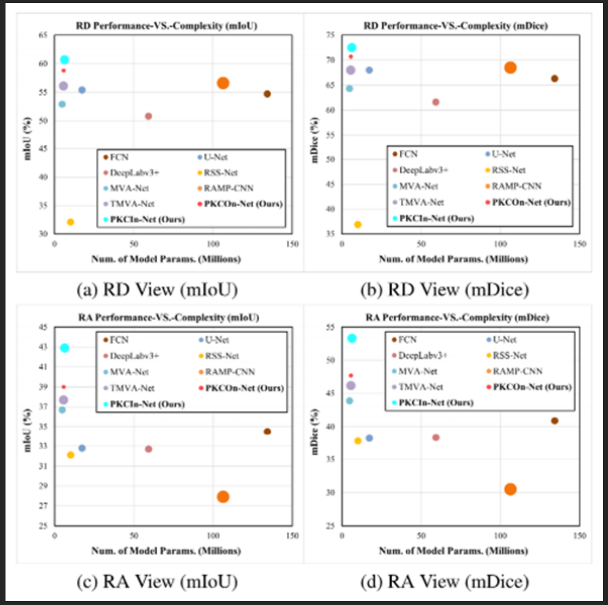
IV. Experiments & Results

- PKCOn-Net + Vanilla PKC->PKCOn
- PKCOn-Net + ReDA-PKC -> PKCOn*
- PKCIn-Net + Vanilla PKC -> PKCIn
- PKCIn-Net + ReDA-PKC -> PKCIn*



(a) RD View (mIoU) (b) RD View (mDice)
(c) RA View (mIoU) (d) RA View (mDice)

Ablation Experiments & SoTA Comparison

Table 1. The effectiveness of guard bandwidths

Frameworks	B_G	#Params	RD View mIoU	RD View mDice	RA View mIoU	RA View mDice
PKCOn	{0, 0, 0}	4.5M	57.2%	68.9%	36.9%	44.7%
	{1, 1, 1}	5.7M	58.8%	**70.7%**	39.0%	47.7%
	{2, 2, 2}	6.9M	58.8%	70.5%	39.8%	48.5%
PKCOn*	{0, 0, 0}	4.5M	58.2%	69.7%	35.4%	42.5%
	{1, 1, 1}	5.7M	58.2%	70.1%	37.9%	46.3%
	{2, 2, 2}	6.9M	**59.1%**	70.3%	**40.2%**	**49.7%**
PKCIn	{0, 0, 0}	5.5M	58.7%	70.6%	40.4%	49.7%
	{1, 1, 1}	6.3M	60.0%	71.9%	42.5%	52.9%
	{2, 2, 2}	7.1M	60.3%	72.3%	42.7%	53.4%
PKCIn*	{0, 0, 0}	5.5M	59.2%	71.0%	41.1%	50.9%
	{1, 1, 1}	6.3M	60.7%	72.5%	42.9%	53.3%
	{2, 2, 2}	7.1M	**61.1%**	**72.9%**	**43.3%**	**53.5%**

Table 3. Comprehensive RSS performance comparison.

Frameworks	#Params @Frames	RD View mIoU	RD View mDice	RA View mIoU	RA View mDice
FCN	134.3M@3	54.7%	66.3%	34.5%	40.9%
U-Net	17.3M@3	55.4%	68.0%	32.8%	38.2%
DeepLabv3+	59.3M@3	50.8%	61.6%	32.7%	38.3%
RSS-Net	10.1M@3	32.1%	36.9%	32.1%	37.8%
MVA-Net	4.8M@3	53.5%	65.3%	37.1%	44.8%
RAMP-CNN	106.4M@9	56.6%	68.5%	27.9%	30.5%
TMVA-Net	5.6M@5	56.1%	68.0%	37.7%	46.2%
PKCOn	5.7M@1	58.8%	70.7%	39.0%	47.7%
PKCOn*	5.7M@1	59.4%	71.2%	38.6%	47.3%
PKCIn	6.3M@5	60.0%	71.9%	42.5%	52.9%
PKCIn*	6.3M@5	**60.7%**	**72.5%**	**42.9%**	**53.3%**

*Please note that $B_G = \{b_G^{RD}, b_G^{AD}, b_G^{RA}\}$, where $b_G^x = b_G^y$ by default.

Table 2. Exploration of various convolutions.

Conv Type		Conv				DefConv				DefConvV2				DilConv				PeakConv		PeakConv*	
Kernel Size		3 × 3		5 × 5		3 × 3		5 × 5		3 × 3		5 × 5		3 × 3		5 × 5		16		16	
Frameworks		SF	MF	SF	MF	SF	MF	SF	MF	SF	MF	SF	MF	SF	MF	SF	MF	SF	MF	SF	MF
#Params		4.7M	5.6M	7.1M	7.2M	4.9M	5.7M	8.1M	8.2M	4.9M	5.8M	8.5M	8.6M	4.7M	5.6M	7.1M	7.2M	5.7M	6.3M	5.7M	6.3M
RD View	mIoU	54.0%	56.1%	55.6%	57.4%	55.5%	58.0%	55.8%	58.3%	55.4%	58.8%	56.1%	59.1%	57.1%	58.4%	57.9%	59.9%	58.8%	60.0%	**59.4%**	**60.7%**
	mDice	65.3%	68.0%	67.1%	69.2%	67.3%	69.8%	68.0%	70.2%	67.0%	70.6%	68.2%	70.8%	69.1%	70.4%	69.8%	71.9%	70.7%	71.9%	**71.2%**	**72.5%**
RA View	mIoU	36.4%	37.7%	36.4%	37.7%	38.2%	39.1%	38.4%	39.2%	38.3%	39.3%	38.6%	39.3%	37.4%	39.1%	37.7%	39.7%	**39.0%**	42.5%	38.6%	**42.9%**
	mDice	43.9%	46.2%	44.0%	46.4%	47.2%	48.1%	47.6%	48.2%	47.3%	48.6%	**47.8%**	48.6%	45.6%	48.1%	46.2%	49.3%	47.7%	52.9%	47.3%	**53.3%**

*SF denotes network with single-frame input, which has the same structure with PKCOn-Net; MF denotes network with multi-frames input, which has the same structure with PKCIn-Net. Dilation step = 2 for all DilConvs.

Conclusions

In this paper, we propose a **novel convolution operation**, **PeakConv**, to highlight object signature from interference such as clutters/noises. PeakConv is **designed specifically for radar data-related learning tasks**. According to the role of center unit in interference estimation, there are two kinds of implements for PeakConv, vanilla- and ReDA-PKC. Comparing with existing RSS models, PeakConv-based networks achieve an outstanding trade-off between performance and complexity, in which PKCIn-Net achieves **SoTA RSS performance** and PKCOn-Net becomes suboptimal one without additional temporal clues, i.e., with single-frame input. It is obvious that the ability of PKCon-Net to capture peak response would be further improved by introducing temporal information. Besides, **in-depth optimization of PeakConv through auto-adaptive guard bandwidth is also one of our future research priorities**.

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Question and cooperation please connect with lwzhang9161@126.com
PeakConv Project: https://github.com/zlw9161/PKC
CARRADA-RAC Project: https://github.com/zlw9161/CARRADA-RAC

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Thanks!
Q&A