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Frequency-aware Feature Fusion for Dense Image Prediction

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Linwei Chen 陈林蔚 Ph.D

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Supervisor: Prof. Ying Fu（付莹）

Team and collaborators

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Research Team

Team Leader: Prof. Jun Zhang（张军）

Academician of the Chinese Academy of Engineering, Distinguished Professor of the Ministry of Education, National-level Leading Talent, and Deputy Secretary of the Party Committee of the Council of the Chinese Institute of Electronics.

Supervisor: Prof. Ying Fu（付莹）

Professor and Ph.D. advisor, National-level high-caliber young talent and a recipient of the Shi Qingyun Award for Women Scientists from the China Society of Image and Graphics.

Collaborators

- YOU Shaodi
  Associate Professor, Universit…
- Kaixuan Wei
  KAUST
- Lin Gu
  Research Scientist, RIKEN AI…
- Felix Heide
  Princeton University | Torc Ro…
- Chenggang Yan
  Hangzhou Dianzi University
- Tatsuya Harada
  The University of Tokyo
- Gao Huang （黄高）
  Associate Professor, Tsinghua…

- Felix Heide - Princeton University
- Tatsuya Harada - The University of Tokyo
- Lin Gu - The University of Tokyo / RIKEN AIP
- Shaodi You - University of Amsterdam
- Gao Huang - Tsinghua University
- Chenggang Yan - Hangzhou Dianzi University
- Kaixuan Wei - King Abdullah University of Science and Technology

Academic profile

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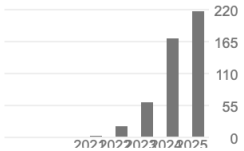

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- Lin Gu, Research Scientist, RI…
- YOU Shaodi, Associate Professor, U…
- Kaixuan Wei, KAUST
- Chenggang Yan, Hangzhou Dianzi Univ…
- Felix Heide, Princeton University | T…
- Tatsuya Harada, The University of Tokyo
- Gao Huang （黄高）, Associate Professor, T…

- Published 10+ papers, including 8 first-author papers in top-tier journals and CCF-A conferences like TPAMIx2, IJCV, ICLR, CVPR Highlight (Top 2.8%), CVPR, ICCV and ISPRS.
- 5 pending national patents, with 2 already granted.
- CVPR 2024 PBDL Low-Light Detection and Segmentation Challenge: 2nd Place.
- PLA Rocket Force Intelligent Fire Eye National Competition: Excellence Award.
- Best Reviewer at BMVC 2024.

Highlight: TPAMI FreqFusion

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Journals & Magazines > IEEE Transactions on Pattern ... > Volume: 46 Issue: 12

Frequency–Aware Feature Fusion for Dense Image Prediction

Publisher: IEEE Cite This PDF

Linwei Chen ; Ying Fu ; Lin Gu ; Chenggang Yan ; Tatsuya Harada ; Gao Huang **All Authors**

19 Cites in Papers

3870 Full Text Views

Abstract

Document Sections

I. Introduction

II. Related Work

III. Feature Similarity Analysis Metrics

IV. Frequency–Aware Feature Fusion

V. Experimental Results

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Metrics

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Abstract:
Dense image prediction tasks demand features with strong category information and precise spatial boundary details at high resolution. To achieve this, modern hierarchical models often utilize feature fusion, directly adding upsampled coarse features from deep layers and high–resolution features from lower levels. In this paper, we observe rapid variations in fused feature values within objects, resulting in intra–category inconsistency due to disturbed high–frequency features. Additionally, blurred boundaries in fused features lack accurate high frequency, leading to boundary displacement. Building upon these observations, we propose Frequency–Aware Feature Fusion (FreqFusion), integrating an Adaptive Low–Pass Filter (ALPF) generator, an offset generator, and an Adaptive High–Pass Filter (AHPF) generator. The ALPF generator predicts spatially–variant low–pass filters to attenuate high–frequency components within objects, reducing intra–class inconsistency during upsampling. The offset generator refines large inconsistent features and thin boundaries by replacing inconsistent features with more consistent ones through resampling, while the AHPF generator enhances high–frequency detailed boundary information lost during downsampling. Comprehensive visualization and quantitative analysis demonstrate that FreqFusion effectively improves feature consistency and sharpens object boundaries. Extensive experiments across various dense prediction tasks confirm its effectiveness.

Published in: IEEE Transactions on Pattern Analysis and Machine Intelligence (Volume: 46 , Issue: 12, December 2024)

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FreqFusion Public

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README

FreqFusion

TPAMI 2024：Frequency-aware Feature Fusion for Dense Image Prediction

The preliminary official implementation of our TPAMI 2024 paper "Frequency-aware Feature Fusion for Dense Image Prediction" (IEEE arxiv) , which is also available at https://github.com/ying-fu/FreqFusion.

Interested readers are also referred to an insightful Note about this work in Zhihu (TODO).

About

TPAMI：Frequency-aware Feature Fusion for Dense Image Prediction

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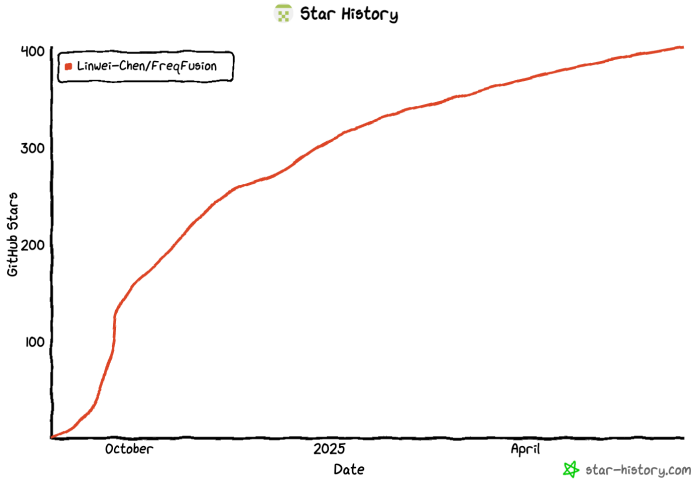

Highlight: TPAMI FreqFusion

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- **Citation count reached the Top ~1.3%, Google Scholar: Cited 63**
- **Influencing subsequent research in the field.**

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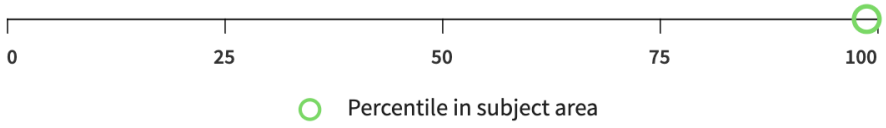

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Highlight: TPAMI FreqFusion

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TPAMI 2024 FreqFusion

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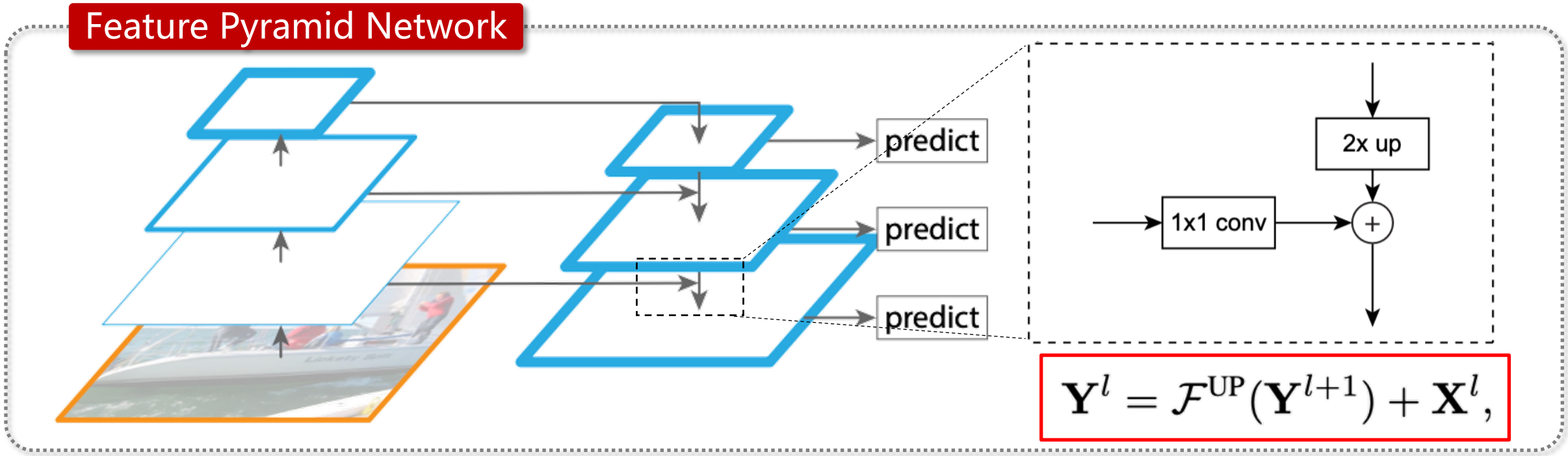
Research Background

- Feature fusion is fundamental and widely-used in modern vision models
- It integrates low-level details and high-level semantic, such as **FPN**



$$\mathbf{Y}^l = \mathcal{F}^{\mathrm{UP}}(\mathbf{Y}^{l+1}) + \mathbf{X}^l,$$

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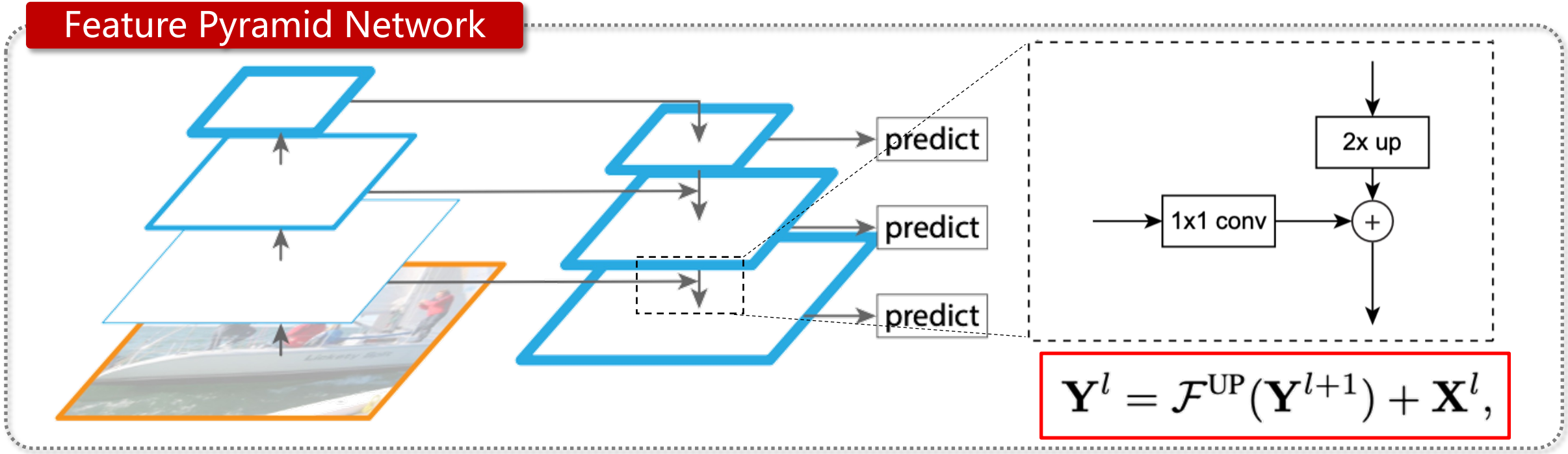
Research Background

- It involves two main steps: Upsampling and Element-wise Add/Concat
- The upsampling ensure the low&high level feature have the same size



$$\mathbf{Y}^l = \mathcal{F}^{\mathrm{UP}}(\mathbf{Y}^{l+1}) + \mathbf{X}^l,$$

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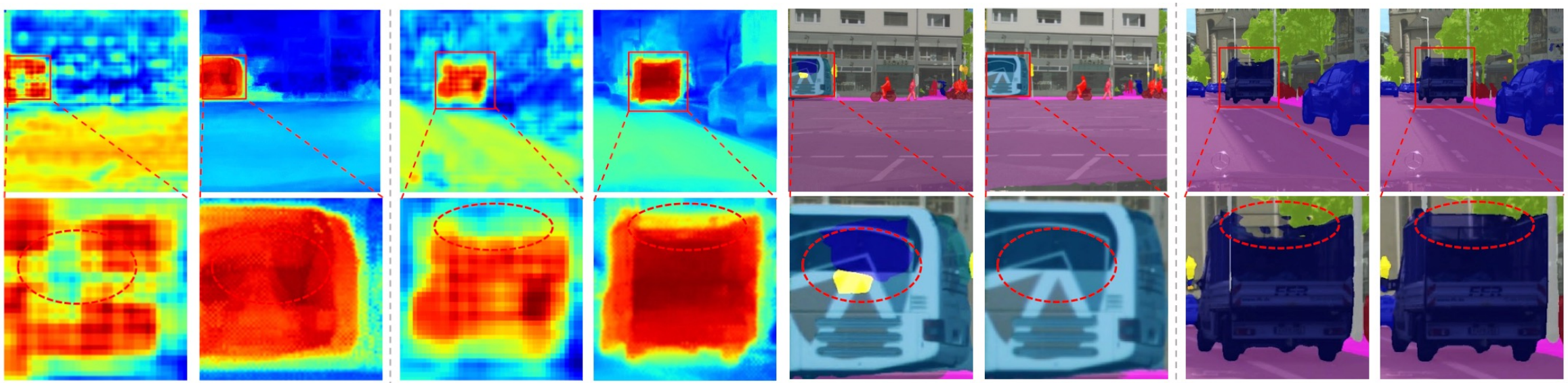
Scientific Question

- Details from low-level and semantic info from high-level are crucial
- Directly fusion leads to intra-class inconsistency&boundary displacement

Feature Visualization



Standard fusion FreqFusion Standard fusion FreqFusion Standard fusion FreqFusion Standard fusion FreqFusion

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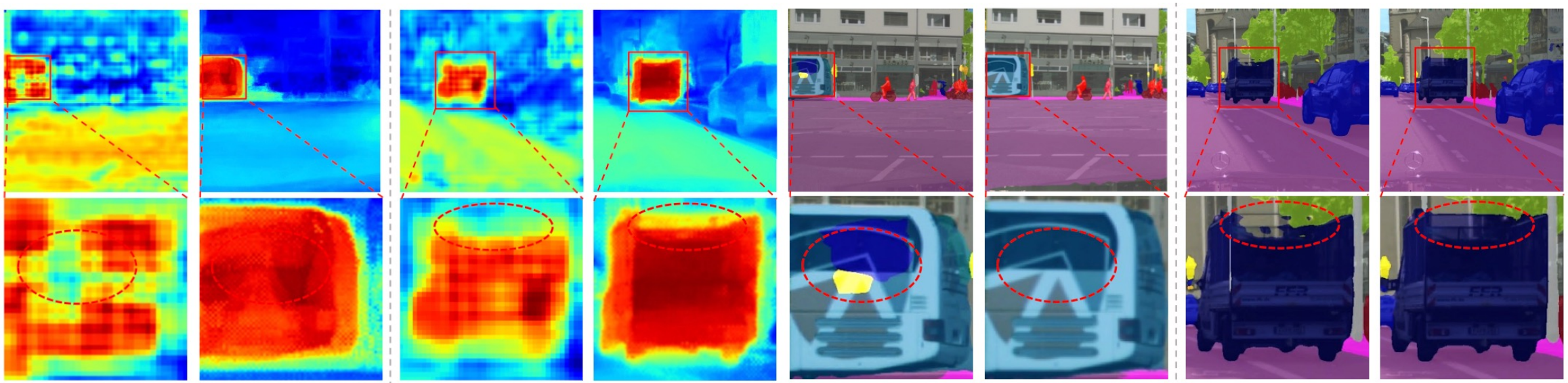
Scientific Question

- **Intra-class inconsistency** occurs when features belonging to the same object are not uniform. Inside the car, the features are noisy and contain unnecessary high-frequency components, leading to inconsistency.

Feature Visualization



Standard fusion FreqFusion Standard fusion FreqFusion Standard fusion FreqFusion Standard fusion FreqFusion

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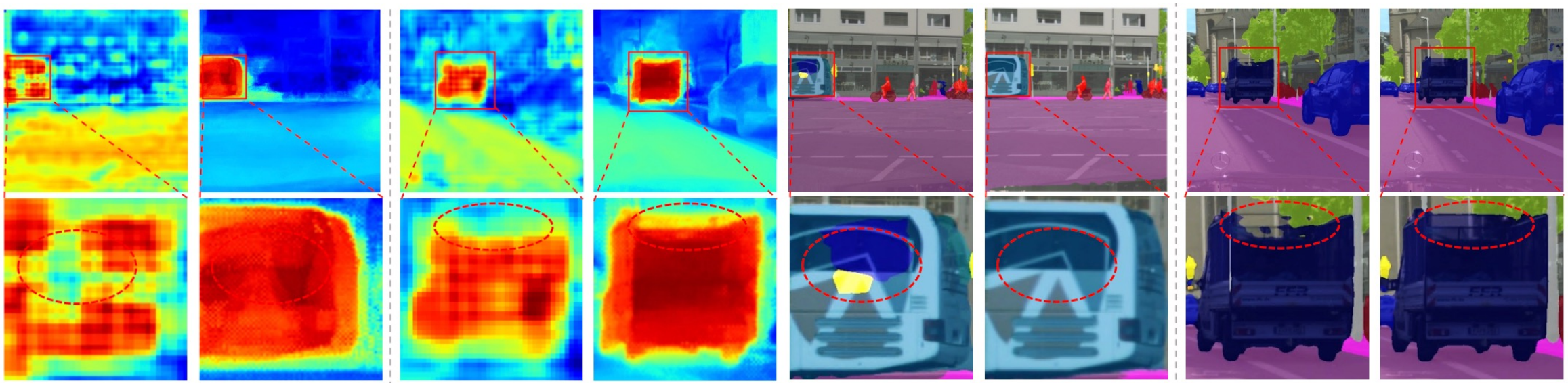
Scientific Question

- **Boundary displacement** occurs when object edges blur and are inaccurately localized, reflecting a lack of the high-frequency components necessary for precise prediction.

Feature Visualization



Standard fusion FreqFusion Standard fusion FreqFusion Standard fusion FreqFusion Standard fusion FreqFusion

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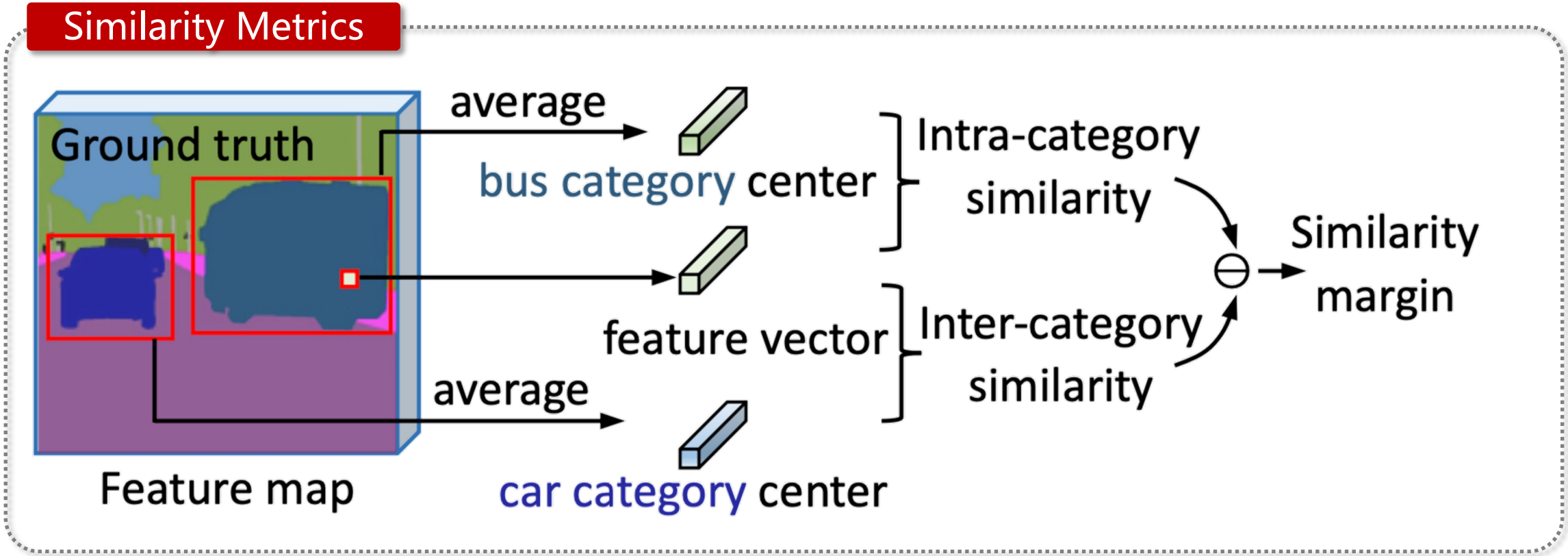
How to quantify inconsistency & displacement?

- We develope a set of similarity metrics
- Including Intra-category/Inter-category Similarity, Similarity Margin



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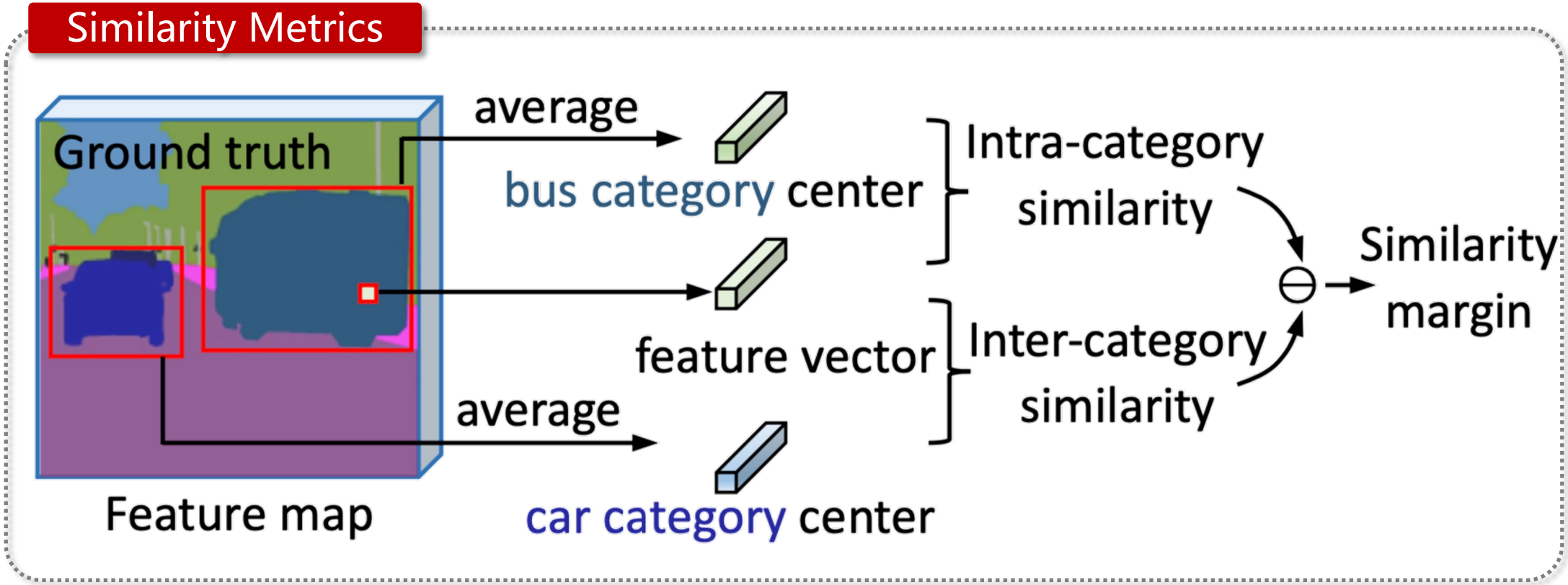
How to quantify inconsistency & displacement?

- IntraSim measures how similar a feature is to its own category
- Category center is the the average feature of its own class



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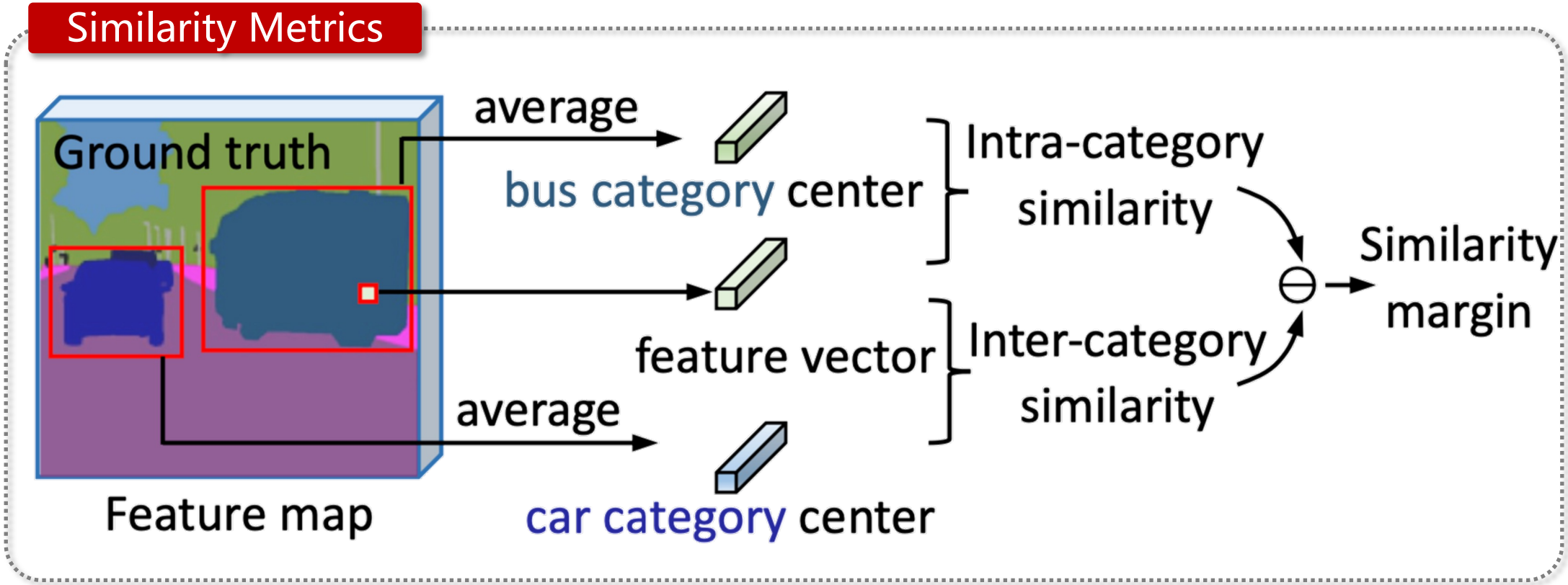
How to quantify inconsistency & displacement?

- InterSim measures how similar a feature is to different category
- The difference between these two gives us the Similarity Margin



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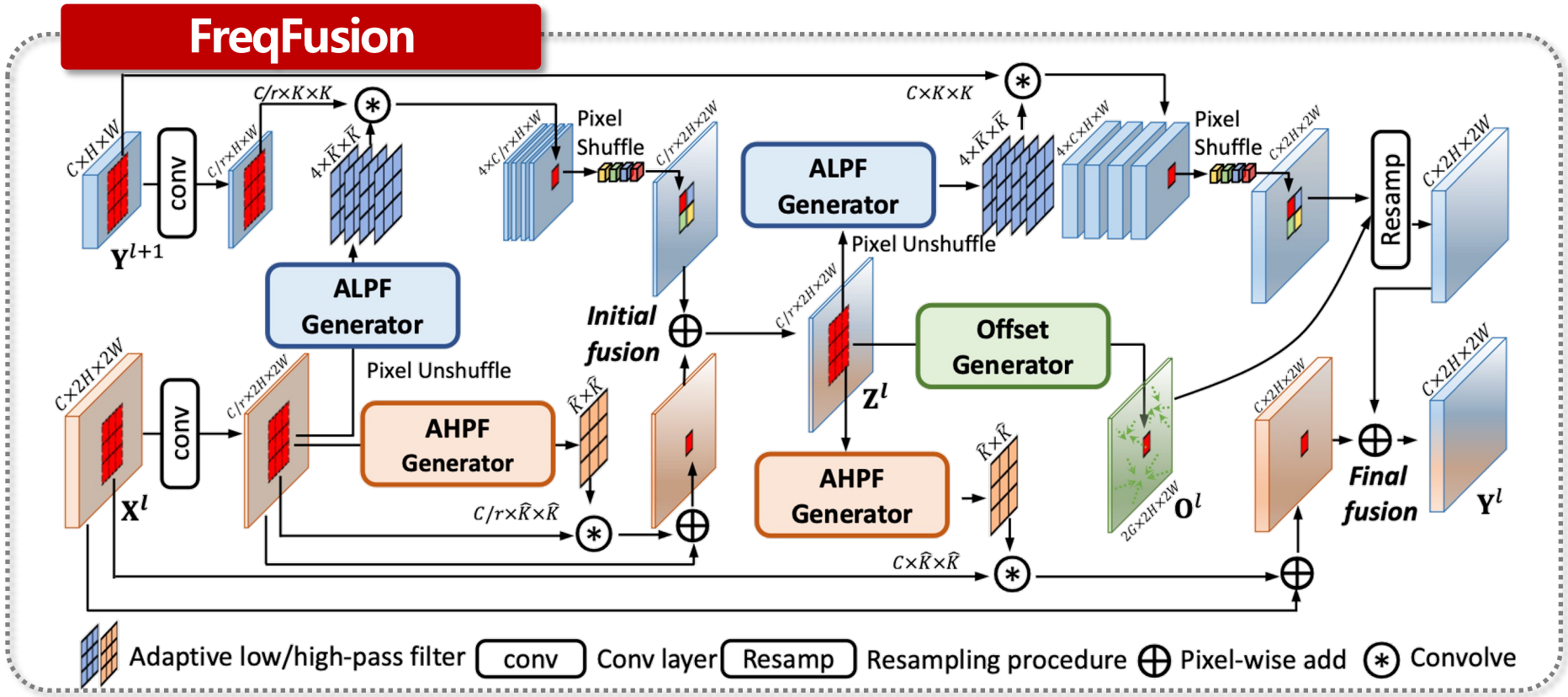
Proposed Method: FreqFusion

- To solve inconsistency and displacement, we propose FreqFusion
- It is a **light-weight**, **pretrain-free**, **pulg-in** module (*one line code*)



3 key components

1. Adaptive Low-Pass Filter (ALPF) Generator
2. Offset Generator
3. Adaptive High-Pass Filter (AHPF) Generator

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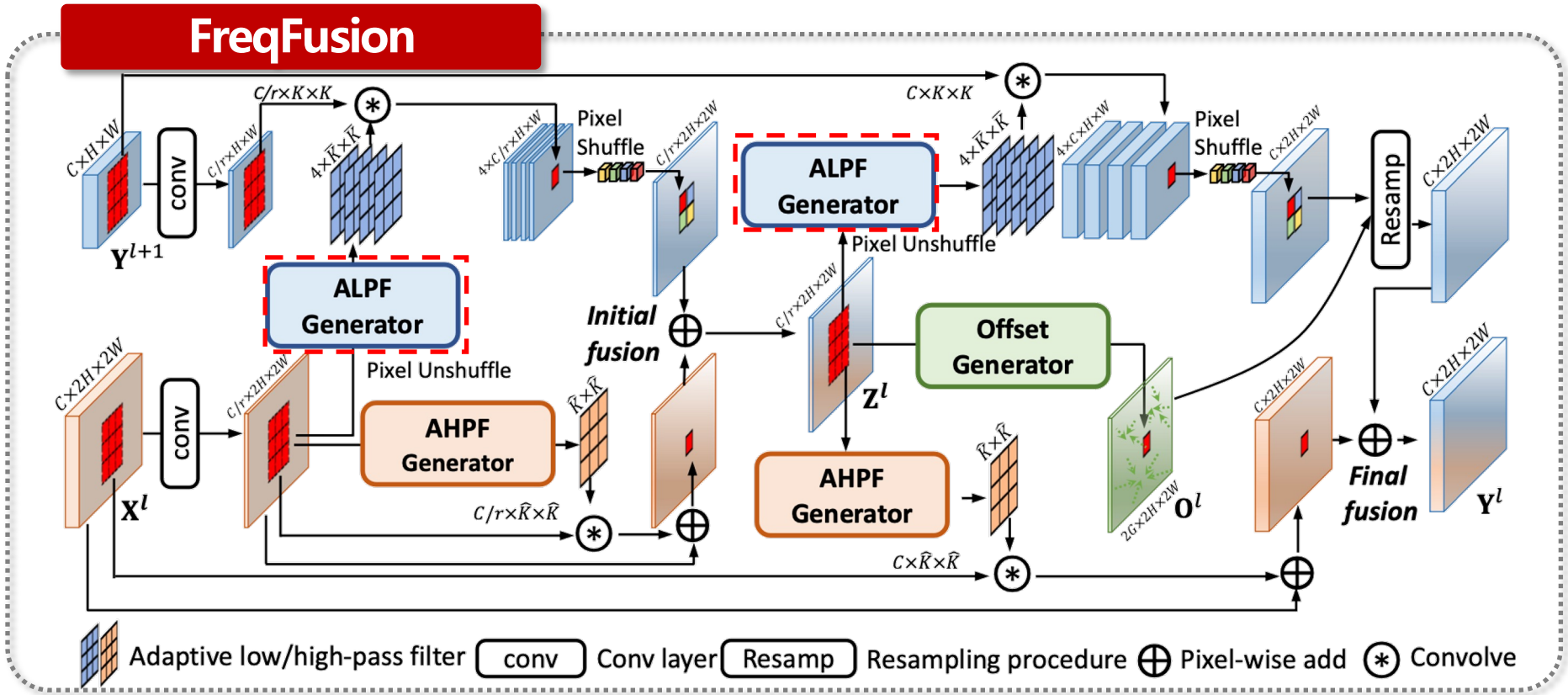
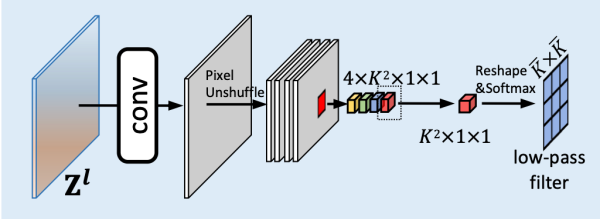
Adaptive Low-Pass Filter (ALPF) Generator

- We observed that intra-class inconsistency often appears as unnecessary high-frequency componets within an object's feature representation



Generation of ALPF:



$$\bar{\mathbf{V}}^l = \mathrm{Conv}_{3\times3}(\mathbf{Z}^l),$$

$$\bar{\mathbf{W}}^{l,p,q}_{i,j} = \mathrm{Softmax}(\bar{\mathbf{V}}^l_{i,j}) = \frac{\exp(\bar{\mathbf{V}}^{l,p,q}_{i,j})}{\sum_{p,q\in\Omega}\exp(\bar{\mathbf{V}}^{l,p,q}_{i,j})},$$

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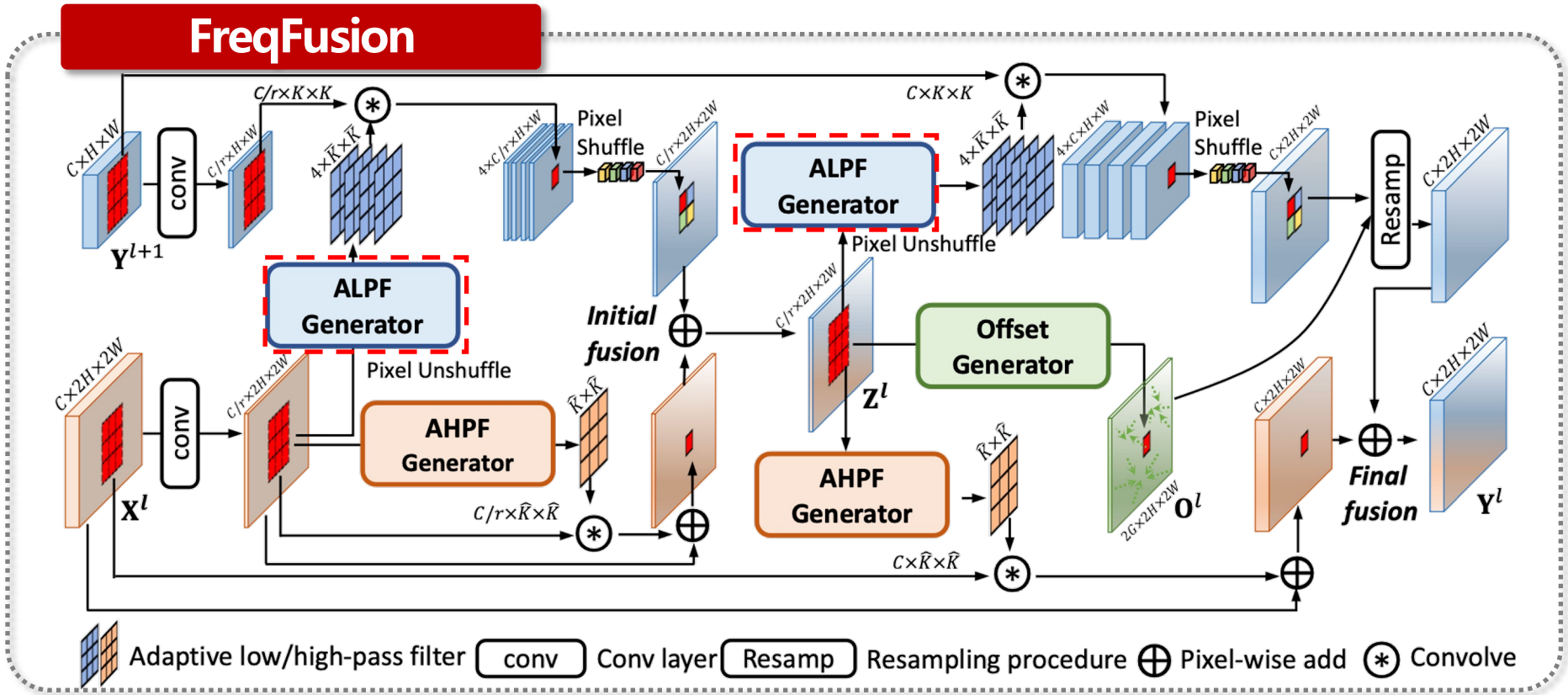
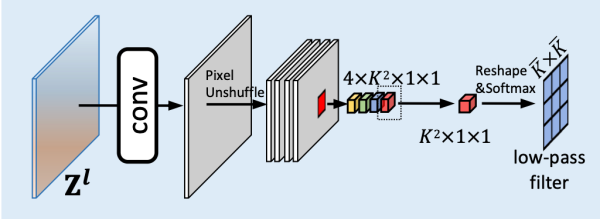
Adaptive Low-Pass Filter (ALPF) Generator

- ALPF Generator produces spatially-variant low-pass filters to attenuates the unnecessary high-frequency components, leading to much more uniform and consistent features within each object



Generation of ALPF:



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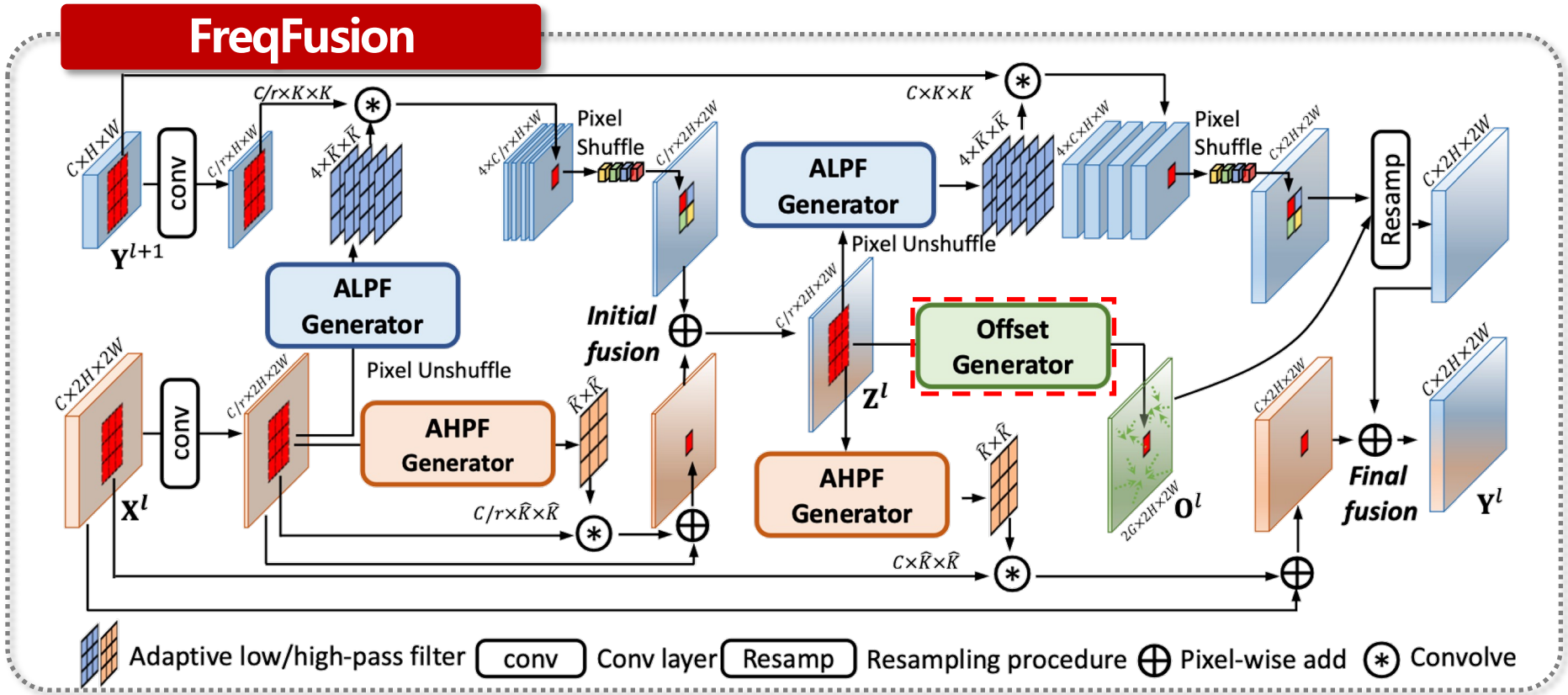
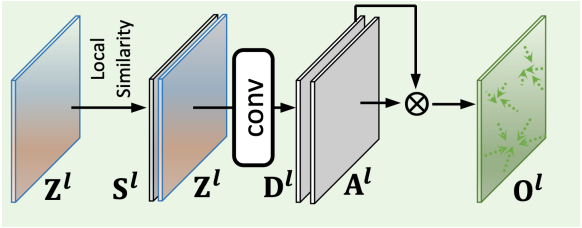
Offset Generator

- ALPF cannot fix both thin (prefer small filters) and large (prefer large filters) inconsistent regions. Regions with inconsistent features are often surrounded by regions with highly consistent features



Generation of offset:



$$\mathbf{O}^l = \mathbf{D}^l \cdot \mathbf{A}^l,$$
$$\mathbf{D}^l = \mathrm{Conv3} \times 3(\mathrm{Concat}(\mathbf{Z}^l, \mathbf{S}^l)),$$
$$\mathbf{A}^l = \mathrm{Sigmoid}(\mathrm{Conv3} \times 3(\mathrm{Concat}(\mathbf{Z}^l, \mathbf{S}^l))),$$

$$\mathbf{S}^{l,p,q}_{i,j} = \frac{\sum_{c=1}^{C} \mathbf{Z}^l_{c,i,j} \cdot \mathbf{Z}^l_{c,i+p,j+q}}{\sqrt{\sum_{c=1}^{C} (\mathbf{Z}^l_{c,i,j})^2} \sqrt{\sum_{c=1}^{C} (\mathbf{Z}^l_{c,i+p,j+q})^2}},$$

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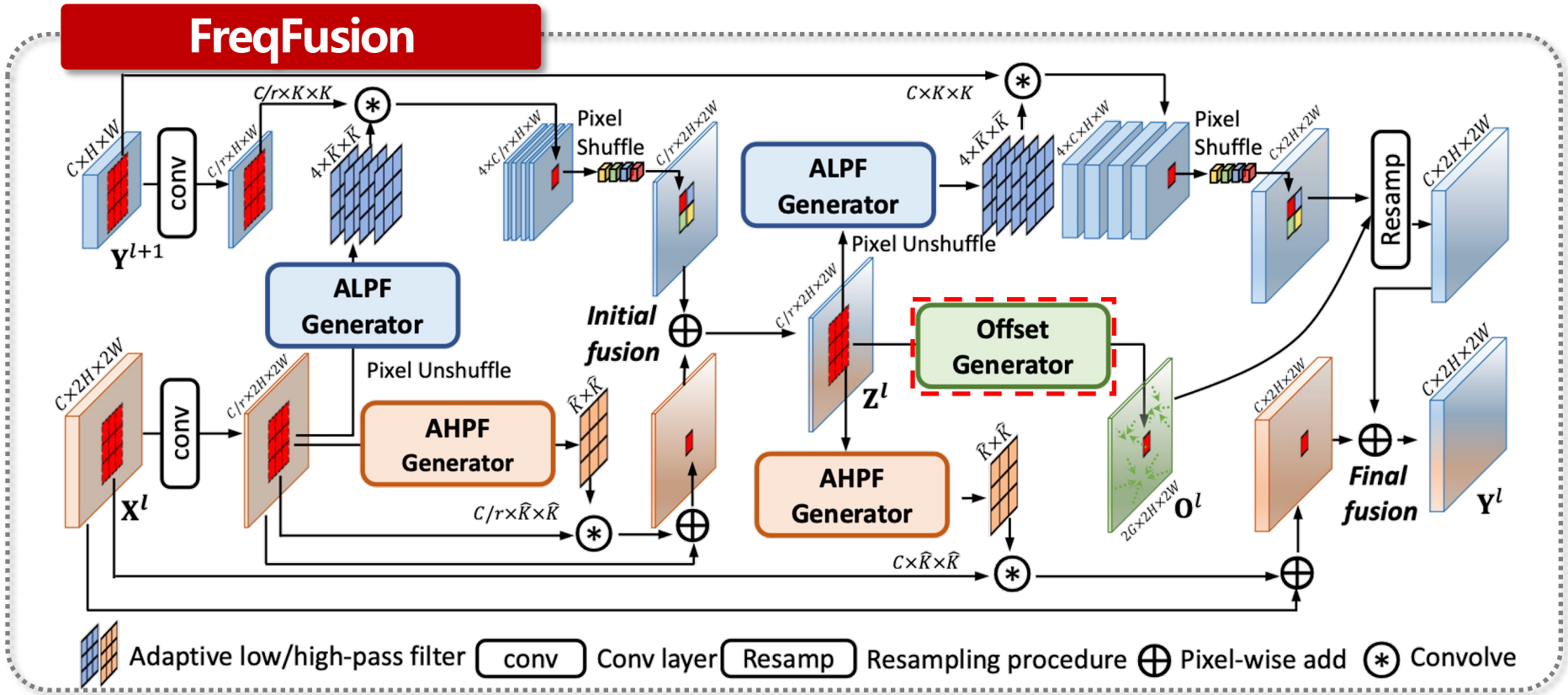
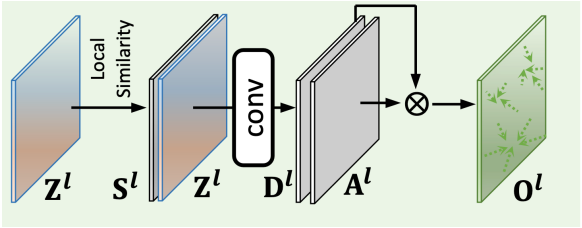
Proposed Method: FreqFusion

- The Offset Generator learns to resample features. It replaces inconsistent features with more consistent ones from the local neighborhood, which improves intra-class consistency for both large areas and thin boundaries.



Generation of offset:



$$\mathbf{O}^l = \mathbf{D}^l \cdot \mathbf{A}^l,$$
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$$\mathbf{A}^l = \mathrm{Sigmoid}(\mathrm{Conv3} \times 3(\mathrm{Concat}(\mathbf{Z}^l, \mathbf{S}^l))),$$

$$\mathbf{S}^{l,p,q}_{i,j} = \frac{\sum_{c=1}^{C} \mathbf{Z}^l_{c,i,j} \cdot \mathbf{Z}^l_{c,i+p,j+q}}{\sqrt{\sum_{c=1}^{C} (\mathbf{Z}^l_{c,i,j})^2} \sqrt{\sum_{c=1}^{C} (\mathbf{Z}^l_{c,i+p,j+q})^2}},$$

TPAMI 2024 FreqFusion

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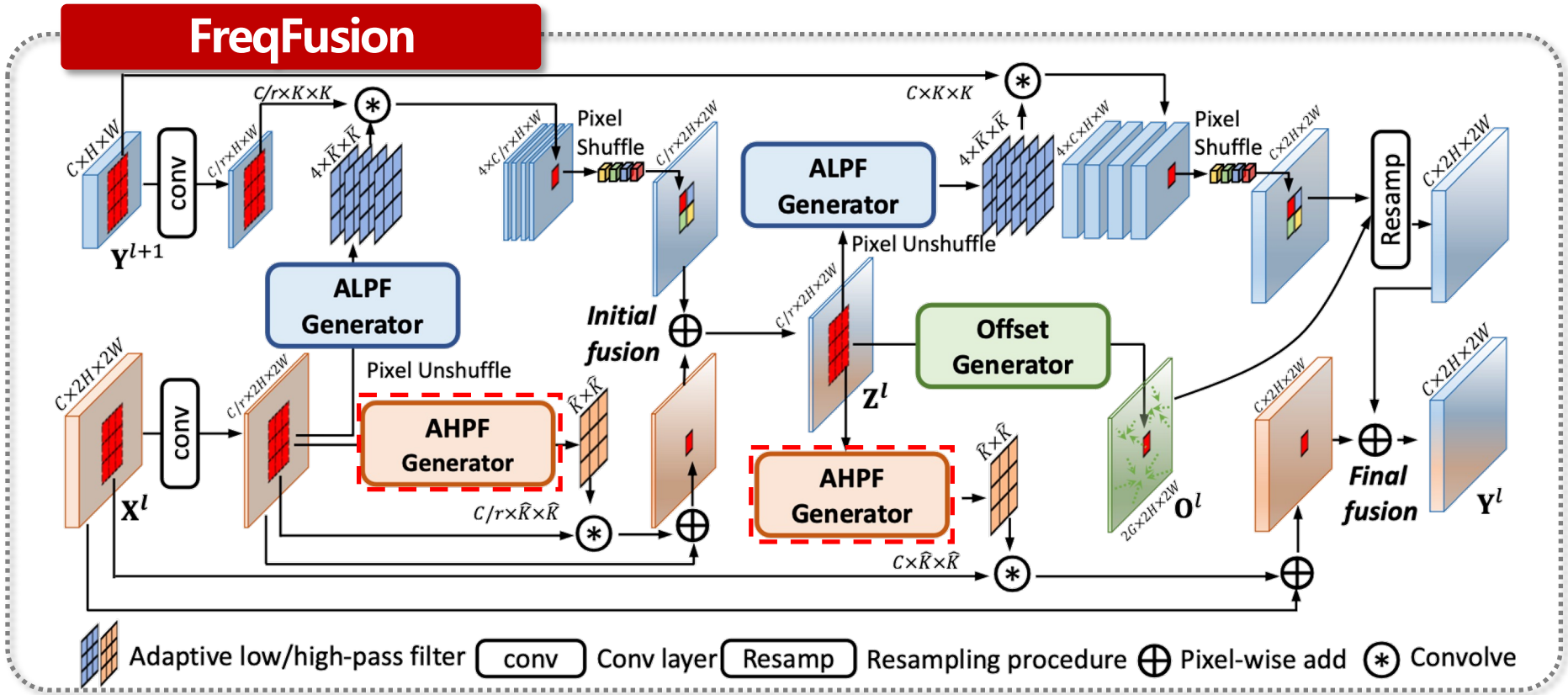
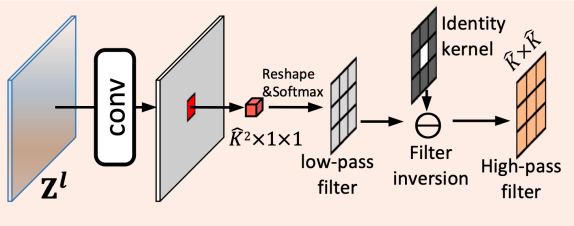
Adaptive High-Pass Filter (AHPF) Generator

- Boundary blur is caused by the loss of high-frequency information during the downsampling stages in the network backbone



Generation of AHPF:



$$\hat{\mathbf{V}}^l = \mathrm{Conv}_{3\times3}(\mathbf{Z}^l),$$

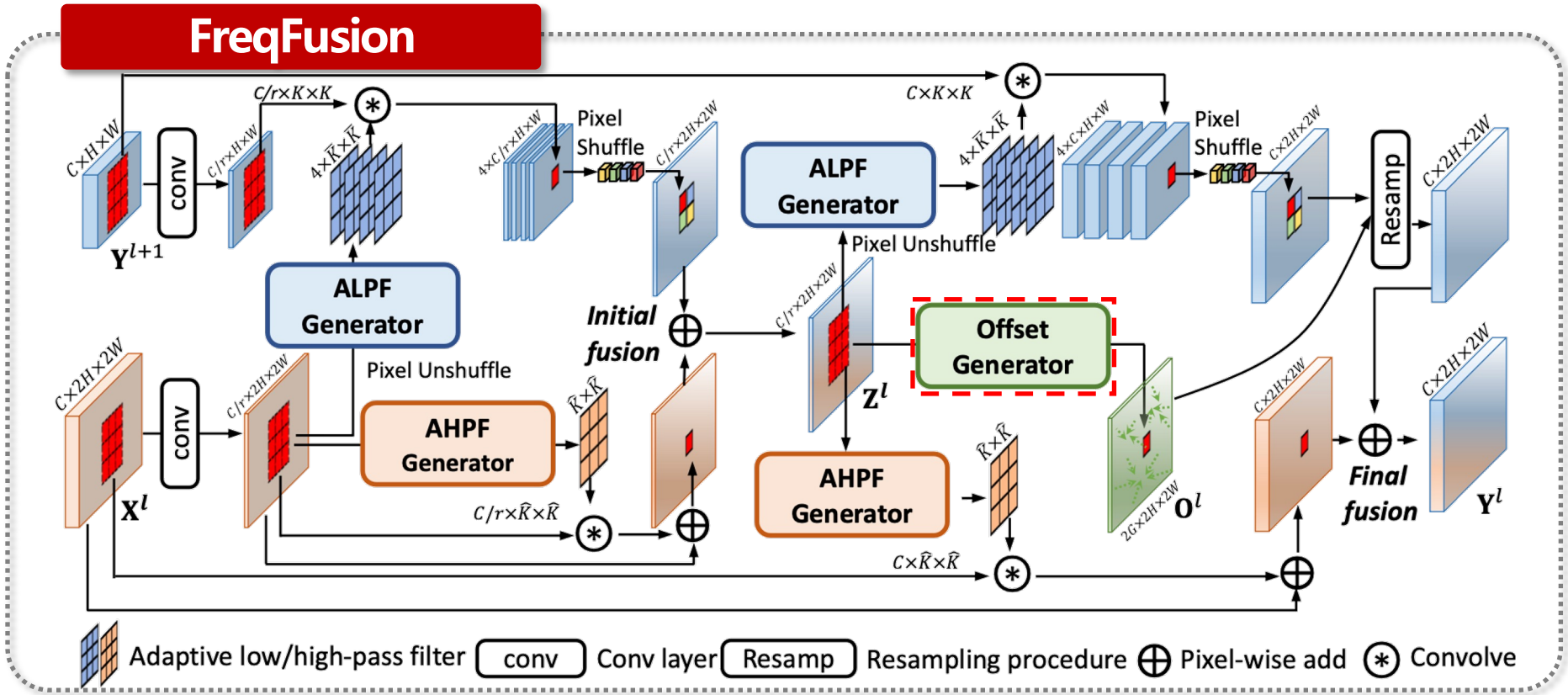
$$\hat{\mathbf{W}}^{l,p,q}_{i,j} = \mathbf{E} - \mathrm{Softmax}(\hat{\mathbf{V}}^l_{i,j}) = \mathbf{E}^{p,q} - \frac{\exp(\hat{\mathbf{V}}^{l,p,q}_{i,j})}{\sum_{p,q\in\Omega}\exp(\hat{\mathbf{V}}^{l,p,q}_{i,j})},$$

$$\tilde{\mathbf{X}}^l_{i,j} = \mathbf{X}^l_{i,j} + \sum_{p,q\in\Omega} \hat{\mathbf{W}}^{l,p,q}_{i,j} \cdot \mathbf{X}^l_{i,j}.$$

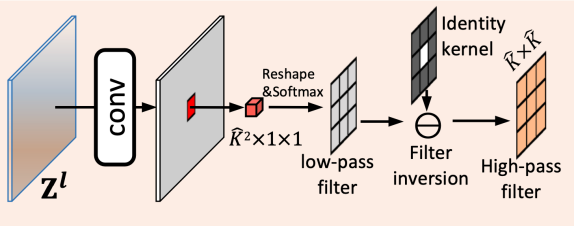
TPAMI 2024 FreqFusion

Proposed Method: FreqFusion

- The Adaptive High-Pass Filter (AHPF) Generator enhances the final fusion. It strengthens the detailed high-frequency boundary information, resulting in sharper and more accurate object boundaries.



Generation of AHPF:



$$\hat{\mathbf{V}}^l = \mathrm{Conv}_{3\times3}(\mathbf{Z}^l),$$

$$\hat{\mathbf{W}}^{l,p,q}_{i,j} = \mathbf{E} - \mathrm{Softmax}(\hat{\mathbf{V}}^l_{i,j}) = \mathbf{E}^{p,q} - \frac{\exp(\hat{\mathbf{V}}^{l,p,q}_{i,j})}{\sum_{p,q\in\Omega}\exp(\hat{\mathbf{V}}^{l,p,q}_{i,j})},$$

$$\tilde{\mathbf{X}}^l_{i,j} = \mathbf{X}^l_{i,j} + \sum_{p,q\in\Omega} \hat{\mathbf{W}}^{l,p,q}_{i,j} \cdot \mathbf{X}^l_{i,j}.$$

TPAMI 2024 FreqFusion

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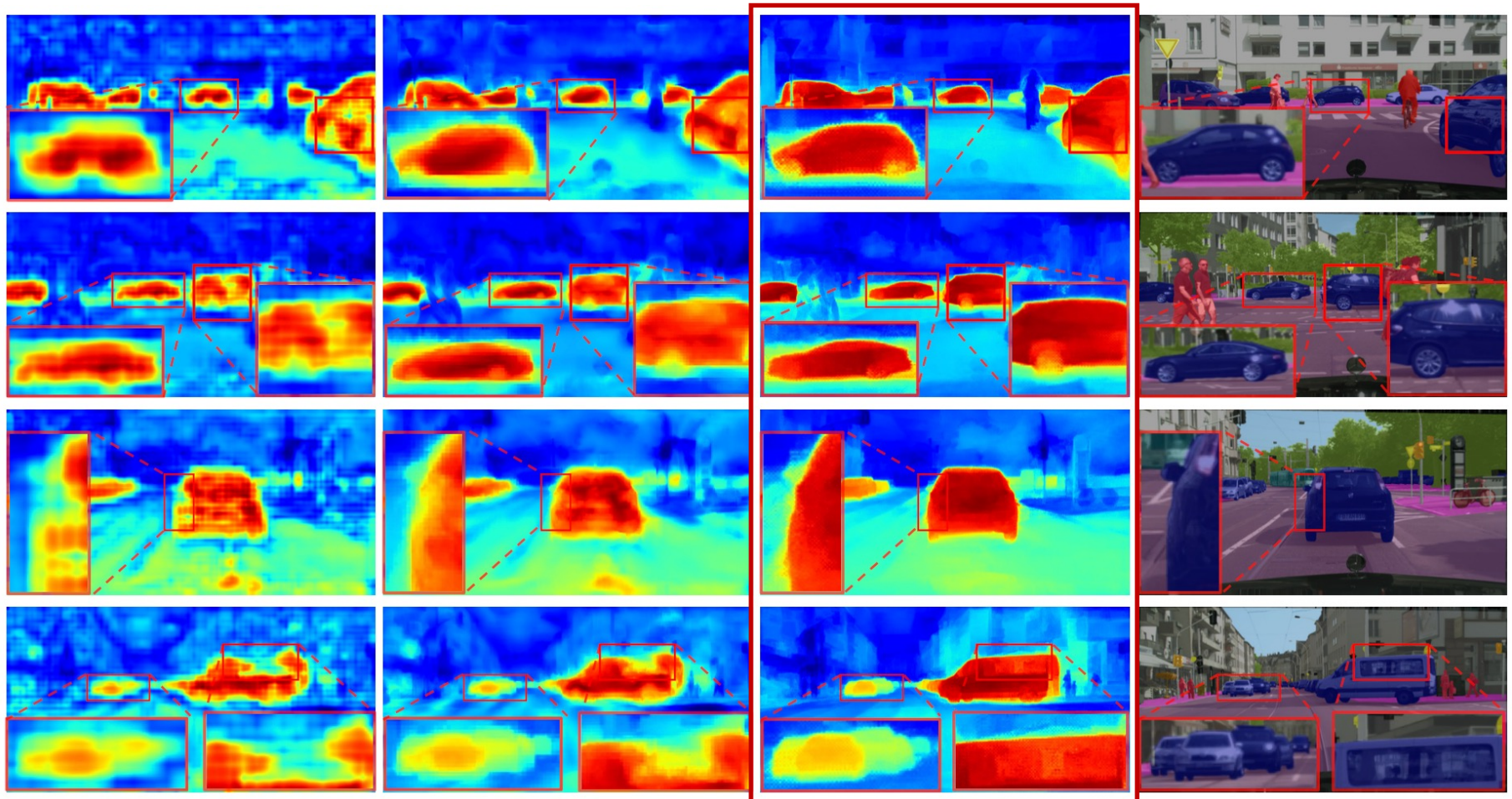
Feature Visualization

ALPF (b) and Offset generators (c) significantly improves feature consistency compared to standard fusion (a)



(a) Standard feature fusion (b) +ALPF generator (c) +ALPF generator +Offset generator (d) Ground truth

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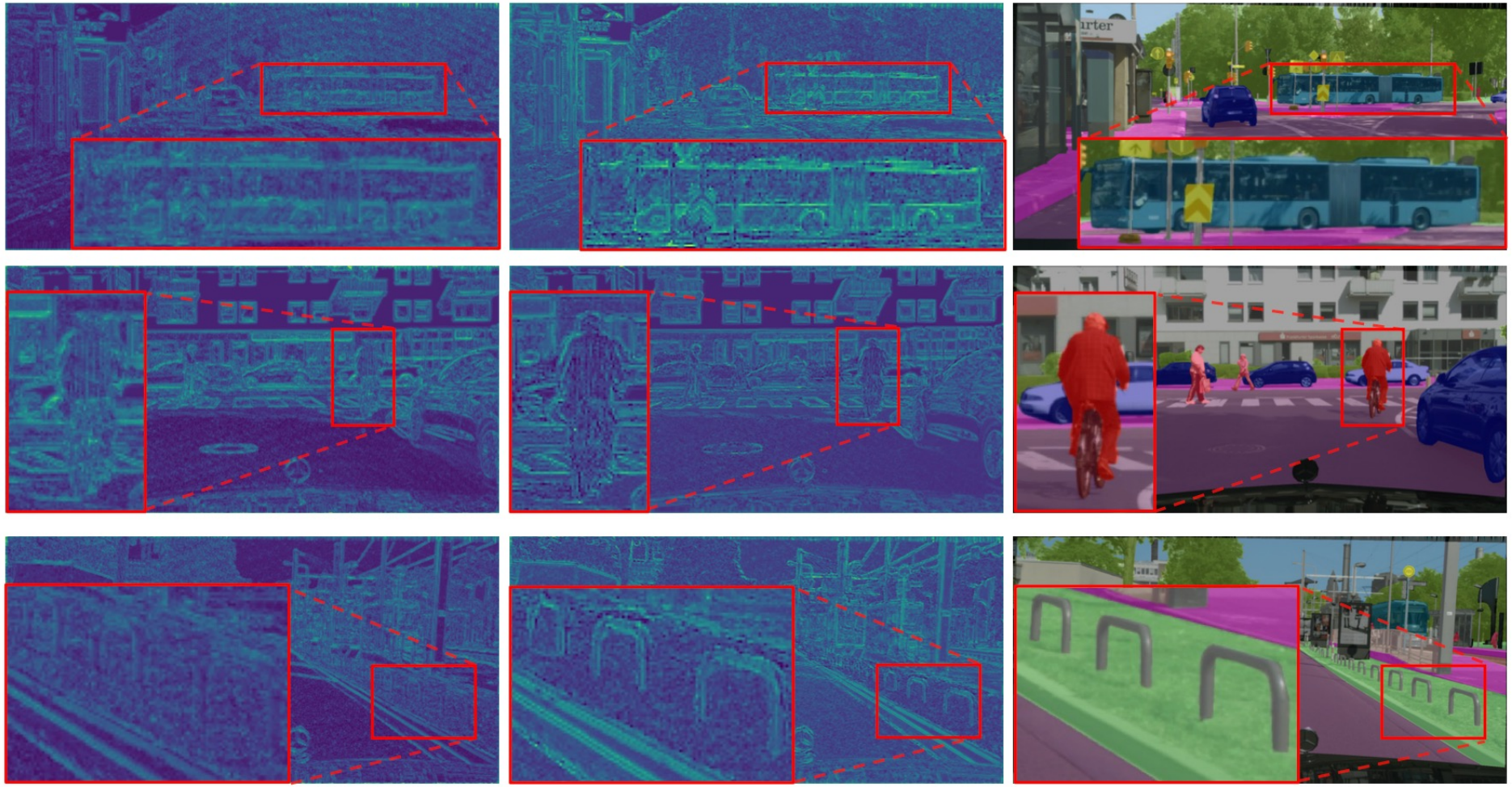
Feature Visualization

The AHPF component strengthens fine details in low-level features, making object contours clearer and more complete.



(a) Low-level feature (b) +AHPF generator (c) Ground truth

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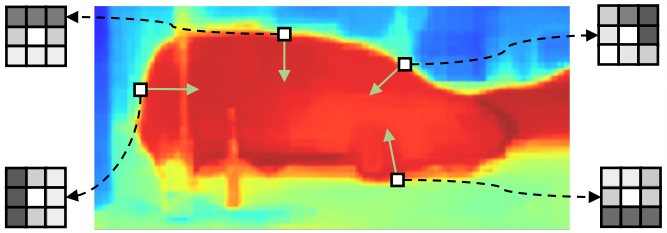
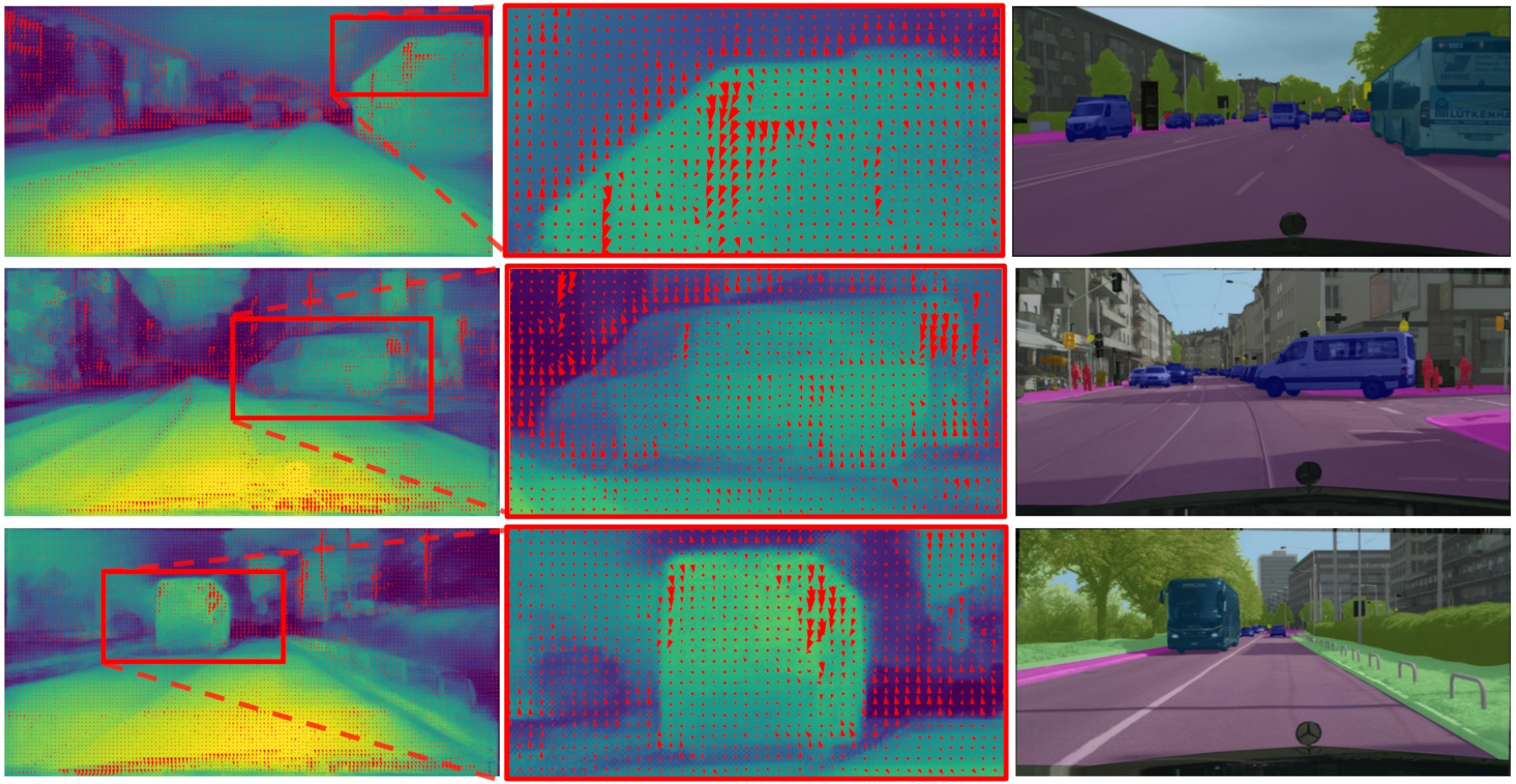
Feature Visualization

The Offset Generator learns to sample from more consistent feature regions to correct inconsistent areas nearby.





Resampling offsets | Zoom in | Ground truth

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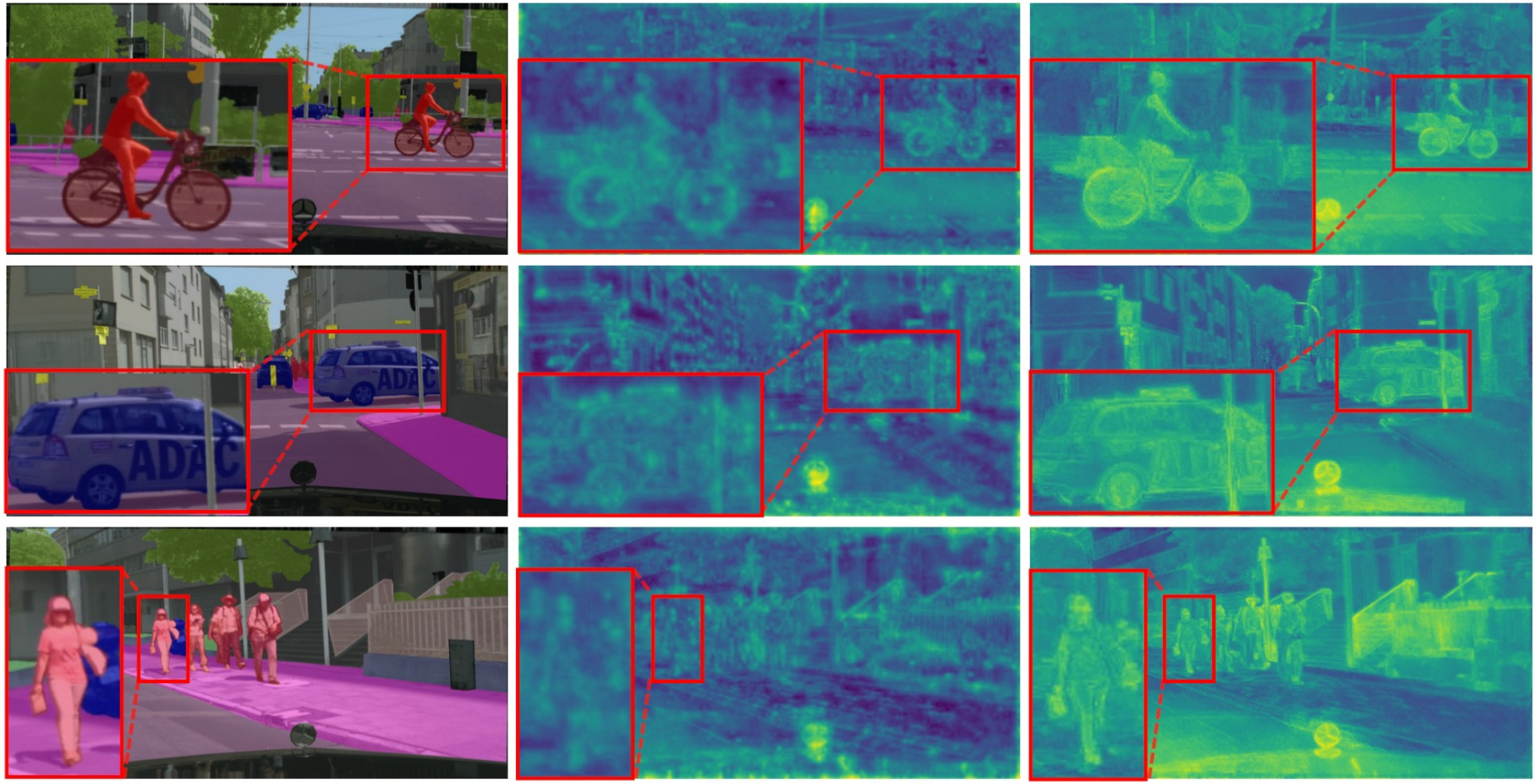
Feature Visualization

The features generated by FreqFusion are visibly superior to those from standard feature fusion, with less internal noise and sharper boundaries.



Ground truth | Standard feature fusion | FreqFusion (Ours)

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Quantitative Feature Analysis

- The proposed FreqFusion significantly improves the overall feature quality, including IntraSim, SimMargin, SimAcc

Method	IntraSim↑	SimMargin↑	SimAcc↑	Boundary IntraSim↑	Boundary SimMargin↑	Boundary SimAcc↑
Standard feature fusion	0.697	0.255	0.907	0.584	0.202	0.632
FreqFusion	**0.799**	**0.297**	**0.941**	**0.694**	**0.239**	**0.728**
w/o ALPF Generator (Initial fusion)	0.792	0.288	0.929	0.687	0.230	0.725
w/o AHPF Generator (Initial fusion)	0.798	0.296	0.940	0.690	0.232	0.726
w/o ALPF Generator (Final fusion)	0.727	0.245	0.918	0.610	0.229	0.724
w/o Offset Generator (Final fusion)	0.760	0.295	0.925	0.648	0.235	0.720
w/o AHPF Generator (Final fusion)	0.796	0.295	0.938	0.688	0.228	0.718

TPAMI 2024 FreqFusion

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Quantitative Results on Downstream Tasks

- The improvements in feature quality translate directly to better performance on various dense prediction tasks, including Semantic/ Instance/Panoptic Segmentation, Object Detection

Mask2Former[CVPR2022] [32]	Backbone	mIoU
Bilinear	Swin-B†	53.9
FreqFusion (Ours)	Swin-B†	**55.3 (+1.4)**
Bilinear	Swin-L†	56.1
FreqFusion (Ours)	Swin-L†	**56.8 (+0.7)**

Method	Params (M)	FLOPs (G)	mIoU	bIoU
Segformer-B1 [NeurIPS2021] [29]	13.74	15.91	41.7	27.8
+ Deconv[CVPR2010] [79]	+3.5	+34.4	40.7	25.9
+ PixelShuffle[CVPR2016] [41]	+14.2	+34.4	41.5	26.6
+ CARAFE[ICCV2019] [43]	+0.44	+1.45	42.8	29.8
+ IndexNet[TPAMI2020] [44]	+12.6	+30.65	41.5	28.3
+ A2U[CVPR2021] [45]	+0.12	+0.41	41.5	27.3
+ FADE[ECCV2022] [22]	+0.29	+2.65	43.1	31.7
+ SAPA-B[NeurIPS2022] [21]	+0.1	+1.0	43.2	31.0
+ Dysample-S+[ICCV2023] [50]	+0.01	+0.3	43.6	29.9
+ Dysample+[ICCV2023] [50]	+0.1	+0.4	43.3	29.2
+ FreqFusion (Ours)	+0.34	+2.35	**44.5**	**32.8**

Method	Backbone	Param.	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
Nearest	R50	46.8M	37.5	58.2	40.8	21.3	41.1	48.9
Deconv	R50	+2.4M	37.3	57.8	40.3	21.3	41.1	48.0
PixelShuffle[CVPR2016] [41]	R50	+9.4M	37.5	58.5	40.4	21.5	41.5	48.3
CARAFE[ICCV2019] [43]	R50	+0.3M	38.6	59.9	42.2	23.3	42.2	49.7
IndexNet[TPAMI2020] [44]	R50	+8.4M	37.6	58.4	40.9	21.5	41.3	49.2
A2U[CVPR2021] [45]	R50	+38.9K	37.3	58.7	40.0	21.7	41.1	48.5
FADE[ECCV2022] [22]	R50	+0.2M	38.5	59.6	41.8	23.1	42.2	49.3
SAPA-B[NeurIPS2022] [21]	R50	+0.1M	37.8	59.2	40.6	22.4	41.4	49.1
DySample-S+[ICCV2023] [50]	R50	+8.2K	38.6	59.8	42.1	22.5	42.1	50.0
DySample+[ICCV2023] [50]	R50	+65.5K	38.7	60.0	42.2	22.5	42.4	50.2
FreqFusion (Ours)	R50	+0.3M	**39.4**	**60.9**	**42.7**	**23.0**	**43.3**	**50.9**
Nearest	R101	65.8M	39.4	60.1	43.1	22.4	43.7	51.1
DySample+[ICCV2023] [50]	R101	+65.5K	40.5	61.6	43.8	24.2	44.5	52.3
FreqFusion (Ours)	R101	+0.3M	**41.0**	**62.2**	**44.9**	**24.7**	**45.0**	**53.4**

Method	Backbone	Params	PQ	PQ^{th}	PQ^{st}	SQ	RQ
Nearest	R50	46.0M	40.2	47.8	28.9	77.8	49.3
Deconv	R50	+1.8M	39.6	47.0	28.4	77.1	48.5
PixelShuffle[CVPR2016] [41]	R50	+7.1M	40.0	47.4	28.8	77.1	49.1
CARAFE[ICCV2019] [43]	R50	+0.2M	40.8	47.7	30.4	78.2	50.0
IndexNet[TPAMI2020] [44]	R50	+6.3M	40.2	47.6	28.9	77.1	49.3
A2U[CVPR2021] [45]	R50	+29.2K	40.1	47.6	28.7	77.3	48.0
FADE[ECCV2022] [22]	R50	+0.1M	40.9	48.0	30.3	78.1	50.1
SAPA-B[NeurIPS2022] [21]	R50	+0.1M	40.6	47.7	29.8	78.0	49.6
DySample-S+[ICCV2023] [50]	R50	+6.2K	41.1	48.1	30.5	78.2	50.2
DySample+[ICCV2023] [50]	R50	+49.2K	41.5	48.5	30.8	78.3	50.7
FreqFusion	R50	+0.3M	**42.7**	**49.3**	**32.7**	**79.0**	**51.9**
Nearest	R101	65.0M	42.2	50.1	30.3	78.3	51.4
DySample+[ICCV2023] [50]	R101	+49.2K	43.0	50.2	32.1	78.6	52.4
FreqFusion	R101	+0.3M	**44.0**	**50.8**	**33.7**	**79.4**	**53.4**

Method	Backbone	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
Nearest	R50	38.3	58.7	42	21.9	41.8	50.2
Deconv	R50	37.9	58.5	41.0	22.0	41.6	49.0
PixelShuffle[CVPR2016] [41]	R50	38.5	59.4	41.9	22.0	42.3	49.8
CARAFE[ICCV2019] [43]	R50	39.2	60.0	43.0	23.0	42.8	50.8
IndexNet[TPAMI2020] [44]	R50	38.4	59.2	41.7	22.1	41.7	50.3
A2U[CVPR2021] [45]	R50	38.2	59.2	41.4	22.3	41.7	49.6
FADE[ECCV2022] [22]	R50	39.1	60.3	42.4	23.6	42.3	51.0
SAPA-B[NeurIPS2022] [21]	R50	38.7	59.7	42.2	23.1	41.8	49.9
DySample-S+[ICCV2023] [50]	R50	39.3	60.3	42.8	23.2	42.7	50.8
DySample+[ICCV2023] [50]	R50	39.6	60.4	43.5	23.4	42.9	**51.7**
FreqFusion	R50	**40.0**	**61.2**	**43.5**	**24.3**	**43.9**	51.5
Nearest	R101	40.0	60.4	43.7	22.8	43.7	52.0
DySample+[ICCV2023] [50]	R101	41.0	61.9	44.9	24.3	45.0	53.5
FreqFusion	R101	**41.6**	**62.4**	**45.7**	**25.0**	**45.6**	**54.2**
Instance Segmentation Mask Results							
Nearest	R50	34.7	55.8	37.2	16.1	37.3	50.8
Deconv	R50	34.5	55.5	36.8	16.4	37.0	49.5
PixelShuffle[CVPR2016] [41]	R50	34.8	56.0	37.3	16.3	37.5	50.4
CARAFE[ICCV2019] [43]	R50	35.4	56.7	37.6	16.9	38.1	51.3
IndexNet[TPAMI2020] [44]	R50	34.7	55.9	37.1	16.0	37.0	51.1
A2U[CVPR2021] [45]	R50	34.6	56.0	36.8	16.1	37.4	50.3
FADE[ECCV2022] [22]	R50	35.1	56.7	37.2	16.7	37.5	51.4
SAPA-B[NeurIPS2022] [21]	R50	35.1	56.5	37.4	16.7	37.6	50.6
DySample-S+[ICCV2023] [50]	R50	35.5	56.8	37.8	17.0	37.9	51.9
DySample+[ICCV2023] [50]	R50	35.7	57.3	38.2	17.3	38.2	51.8
FreqFusion	R50	**36.0**	**57.9**	**38.1**	**17.9**	**39.0**	**52.3**
Nearest	R101	36.0	57.6	38.5	16.5	39.3	52.2
DySample+[ICCV2023] [50]	R101	36.8	58.7	39.5	17.5	40.0	53.8
FreqFusion	R101	**37.4**	**59.6**	**39.9**	**18.4**	**40.6**	**54.3**

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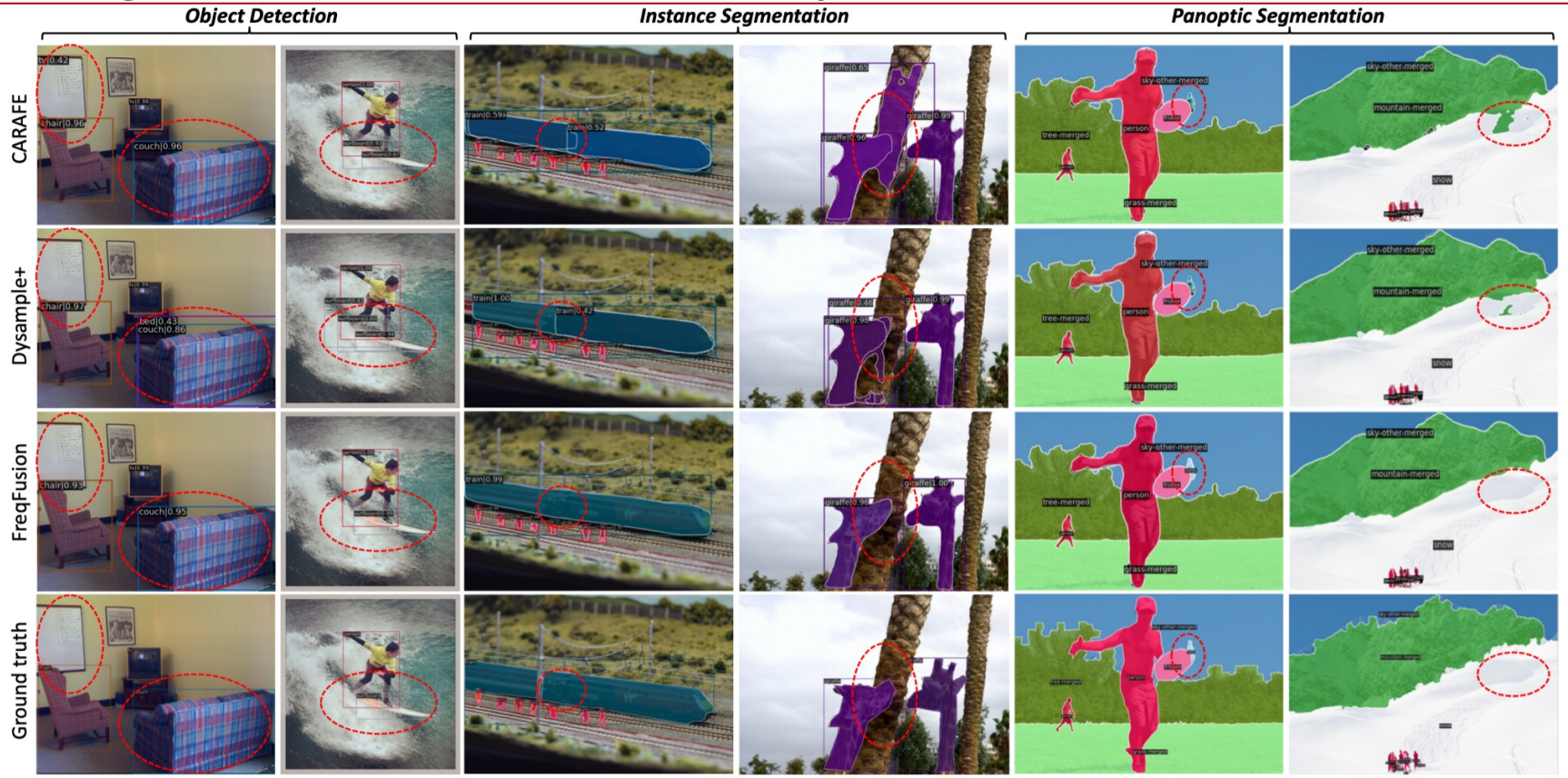
Qualitative Results on Downstream Tasks

- The visual results show that models enhanced with FreqFusion produce more detailed and accurate predictions. This is especially evident at object edges and for small, thin objects.



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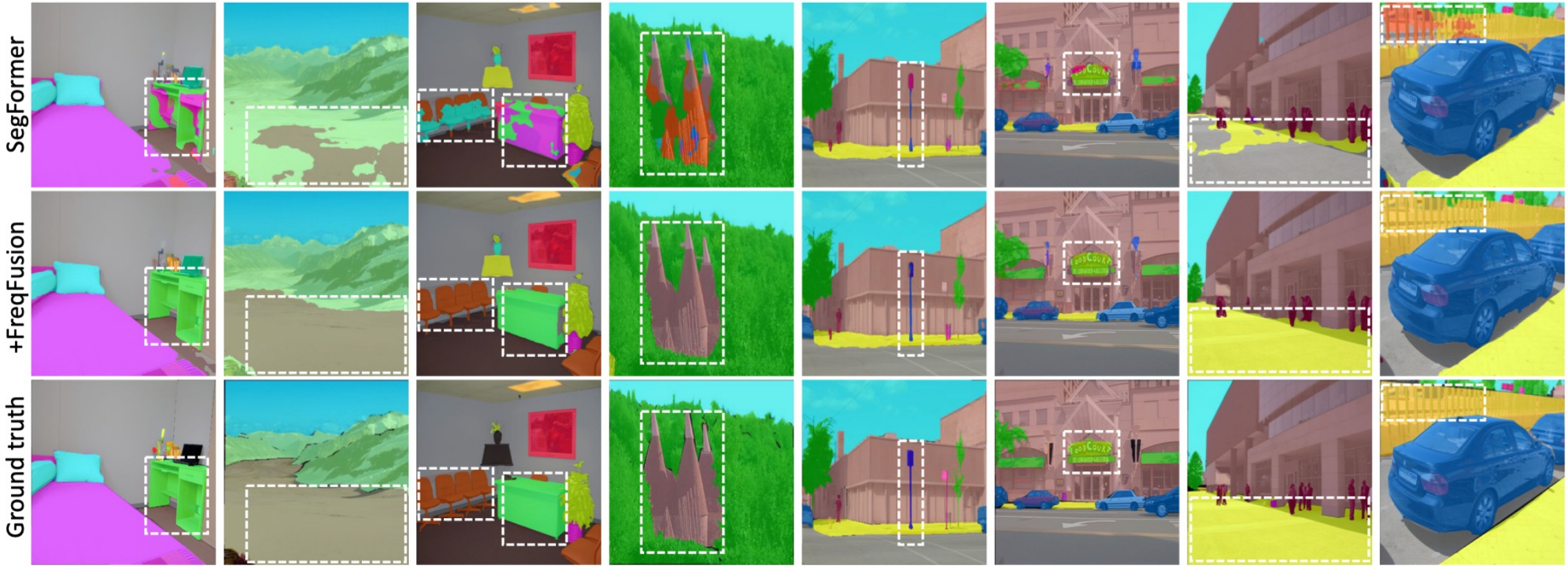
Qualitative Results on Downstream Tasks

- The predictions are cleaner, with fewer misclassified pixels and more precise segmentation masks



Conclusion & Future Work

- Conclusion
  - This paper addresses the key challenges of intra-class inconsistency and boundary displacement in dense image prediction tasks.
  - We proposed FreqFusion, a novel module that uses frequency-aware principles and feature similarity analysis to resolve these issues, leading to significant performance gains.
- Future Work
  - We plan to explore improving computational efficiency and real-time applicability for deployment in resource-constrained environments.
  - We will also investigate extending FreqFusion to handle different data modalities, such as video, to address feature fusion for dynamic scenes.

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Frequency-aware Feature Fusion for Dense Image Prediction

Code Paper Github Google Scholar

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Team member

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ISP Lab：https://ying-fu.github.io/

Prof. Ying Fu

Beijing Insitute of Technology

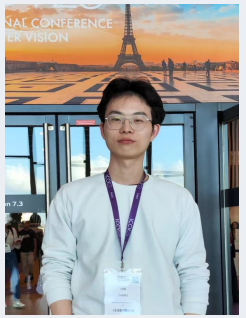
- National High-Level Talent Program in 2017.
- Best Paper Awards: ICML 2020, PRCV 2019.

Yunhao Zou-Ph.D

- Denoising, HDR,

Linwei Chen-Ph.D

- Segmentation, Detection



Fan Zhang-Ph.D

- Image enhancement

Yingping Liang

- 3D Vision

Yingping Liang

- Super-resolution

Lab Website