Context-Aware Cascade Network for Semantic Labeling in VHR Image

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Outline

1 Introduction

2 Related work

3 CAC-NET

4 Future work

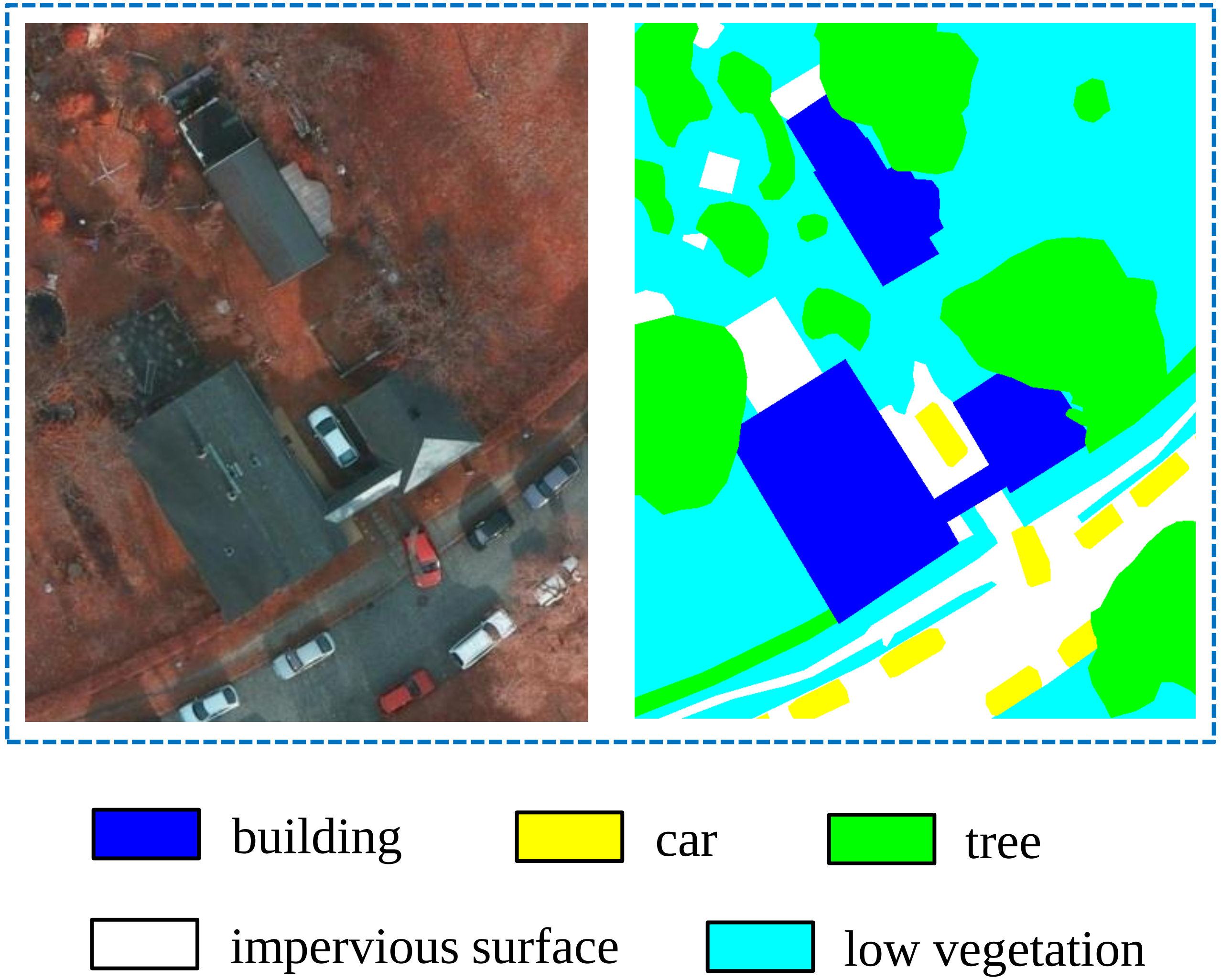
Introduction

Semantic labeling :

Assign each pixel in a given image to a semantic object class

Important application :

- Infrastructure planning
- Urban change detection
- Disaster exploration ……



Introduction

Challenges :

(1) Complex man-made objects

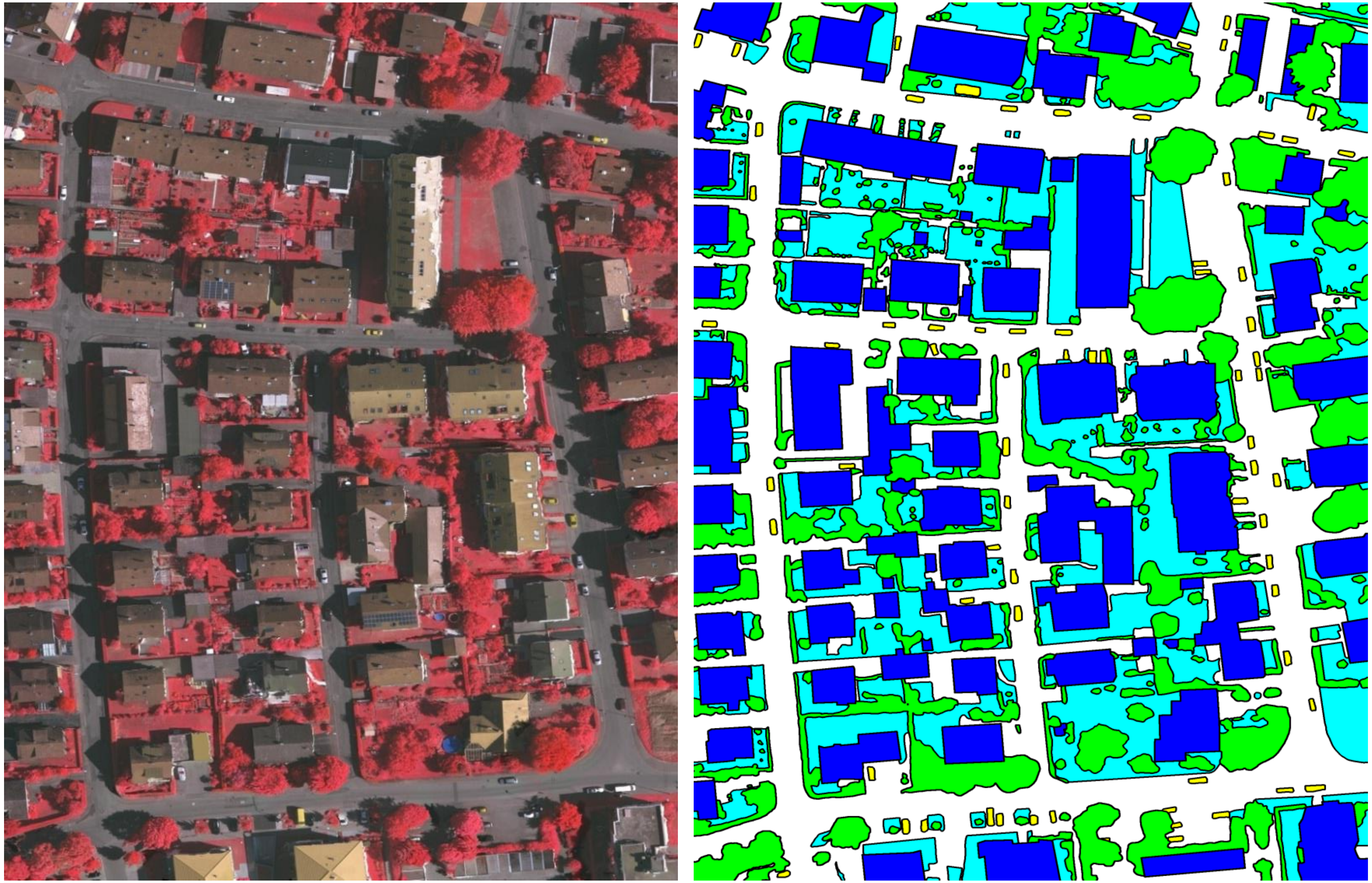
- high intra-class variance
- low inter-class variance

(2) Fine-structured objects

- small or threadlike
- locate together
- occlusions and cast shadows

(3) Additional challenge

- different solutions

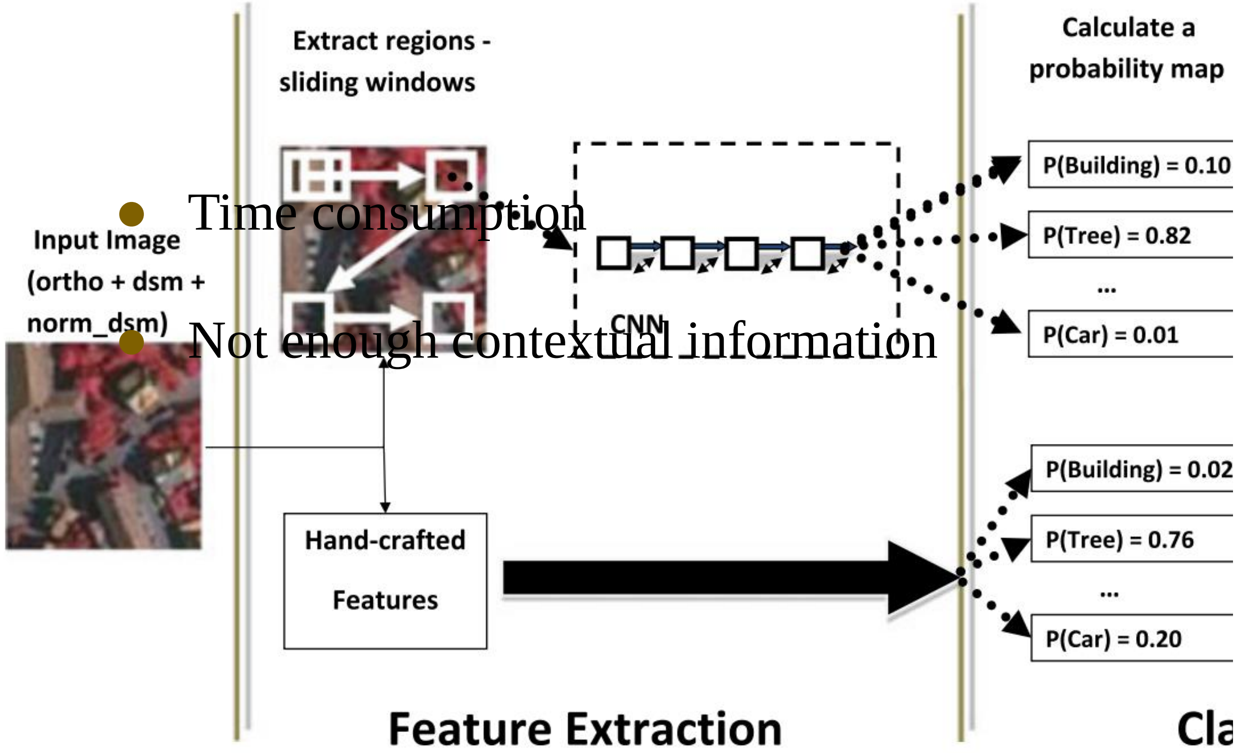


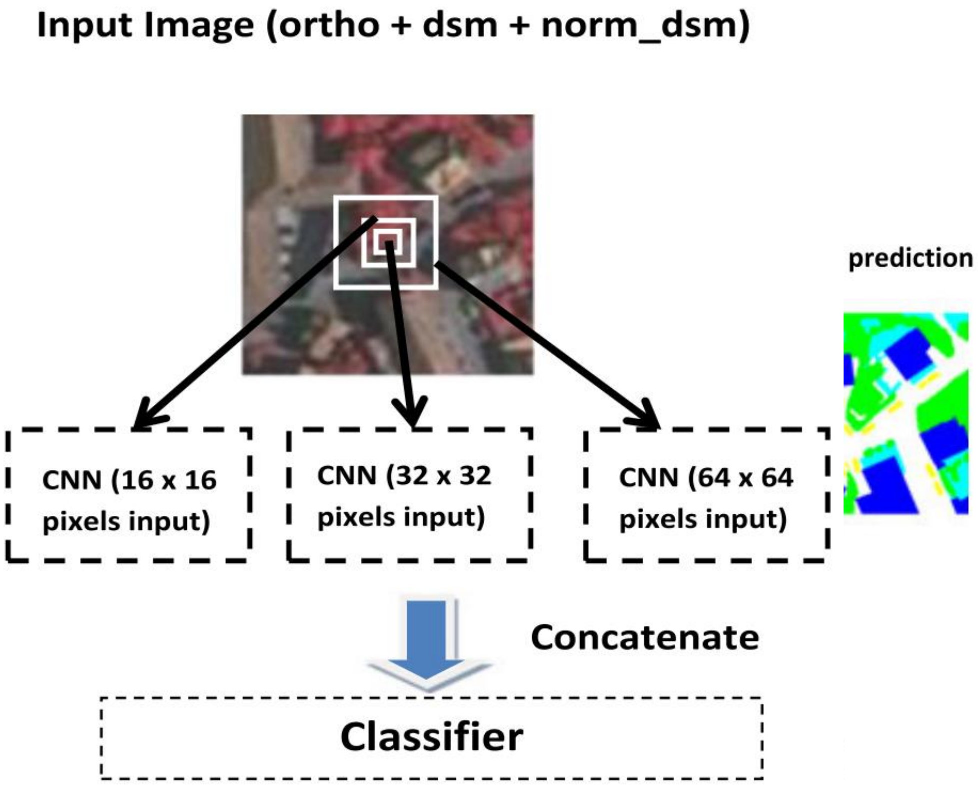
Related work

1) Patch-based methods

2016, Paisitkriangkrai et al.

- Time consumption
- Not enough contextual information

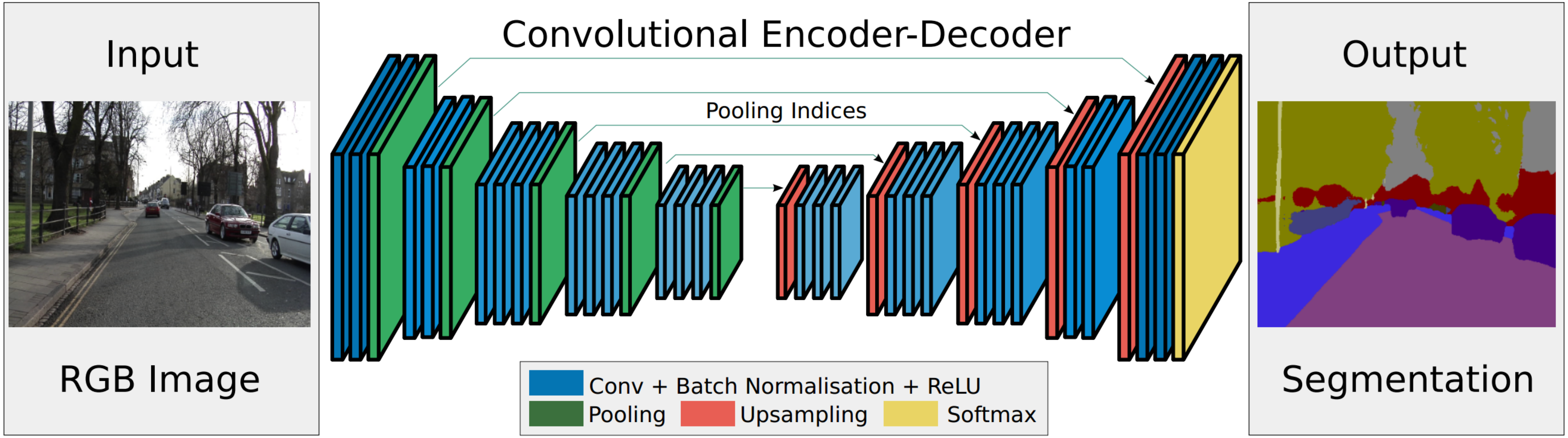




Related work

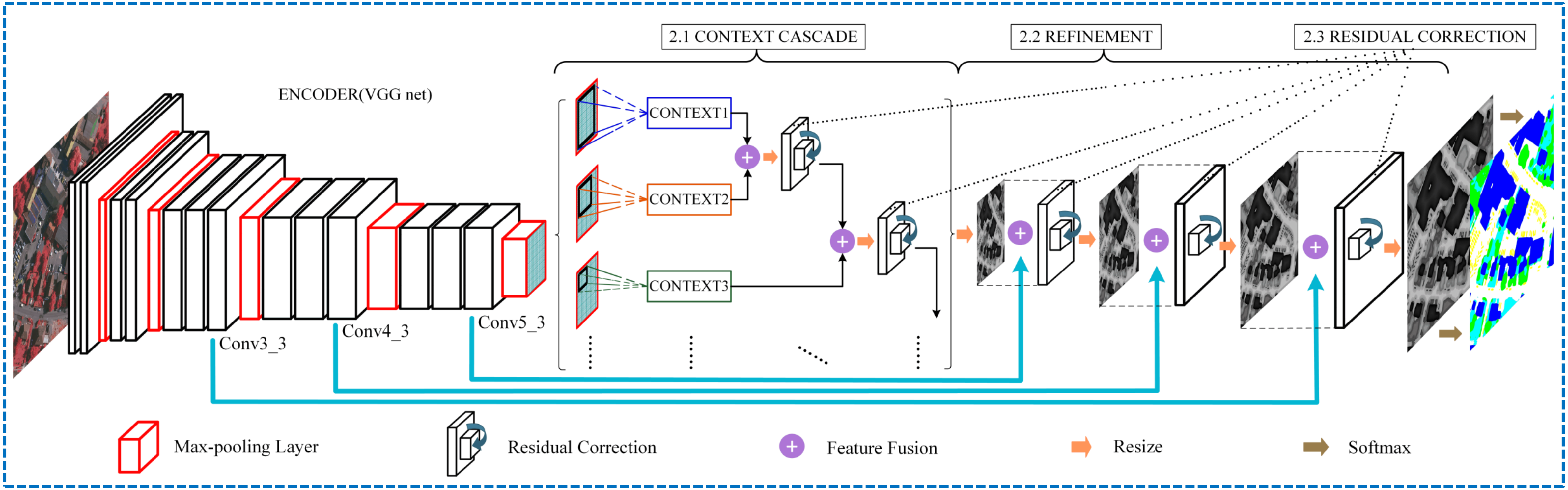
2) Fully convolutional methods

2015, Badrinarayanan et al. (Segnet)



CAC-NET

Context-Aware Cascade Network



- ✓ **Encoder** : extract features of different levels
- ✓ **Context Cascade**: capture contextual information for complex objects
- ✓ **Refinement**: refine the coarse labeling of fine-structured objects
- ✓ **Residual correction**: improve the fusion of different-level features

CAC-NET: context cascade

Contextual information

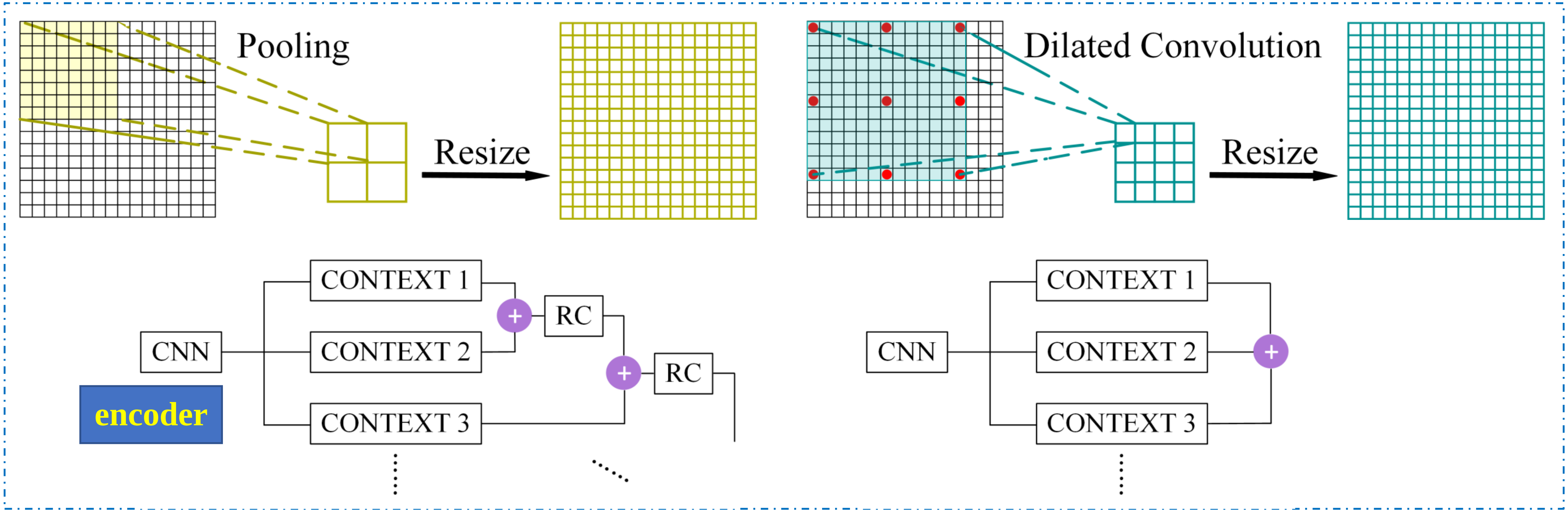
Latent dependencies between an object and its surroundings.

How did we do ?

- Multi-scale images
- Multi-size convolutional kernel

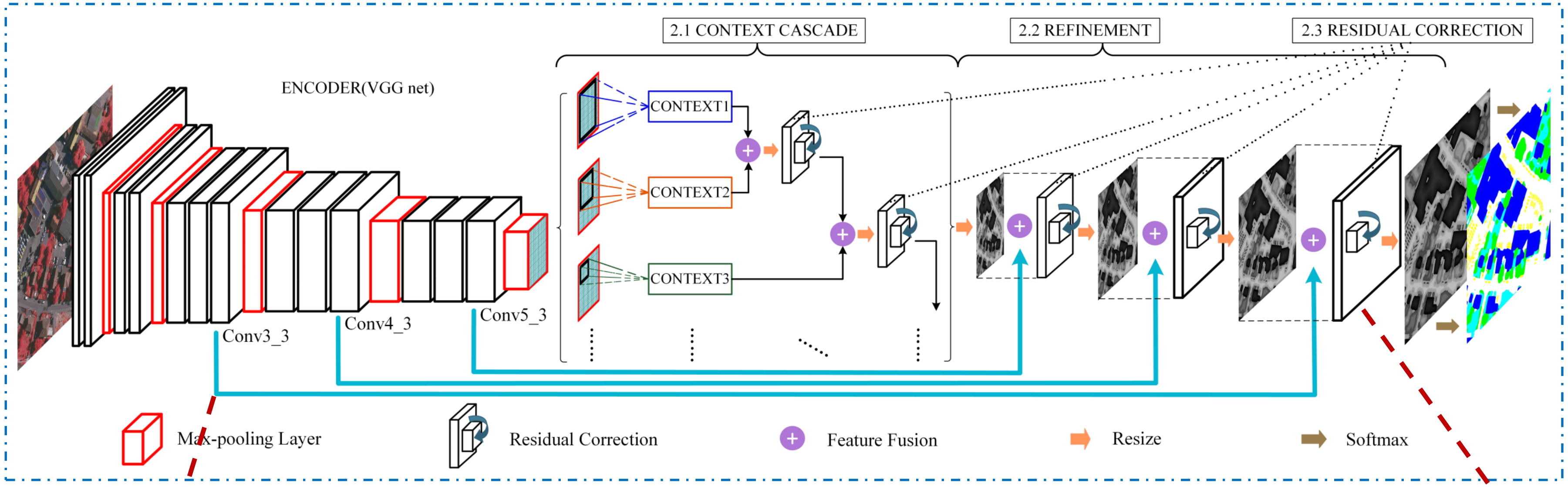
EFFECTIVE and EFFICIENT ?

CAC-NET: context cascade



- ✓ **Context capturing** : multi-kernel pooling and dilated convolution
- ✓ **Context aggregating**: **from global to local** in a sequentially cascaded manner
- ✓ **Residual correction**: improve the fusion of **different-level context**

CAC-NET: refinement



Local details

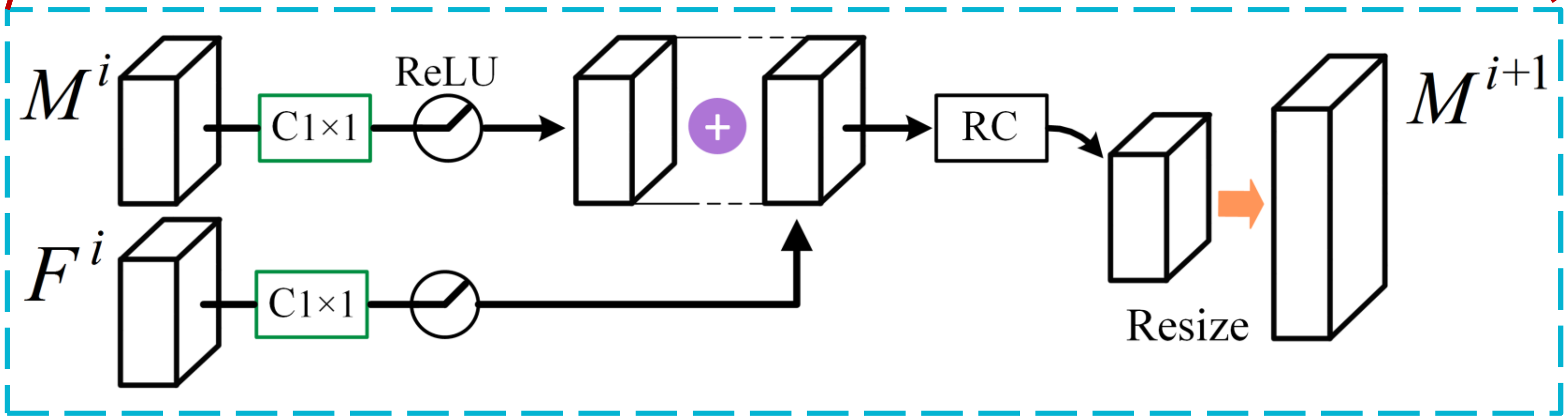
long-span connection

progressively introduced

Residual correction

improve different-level

features fusion



CAC-NET: residual correction

different-level context

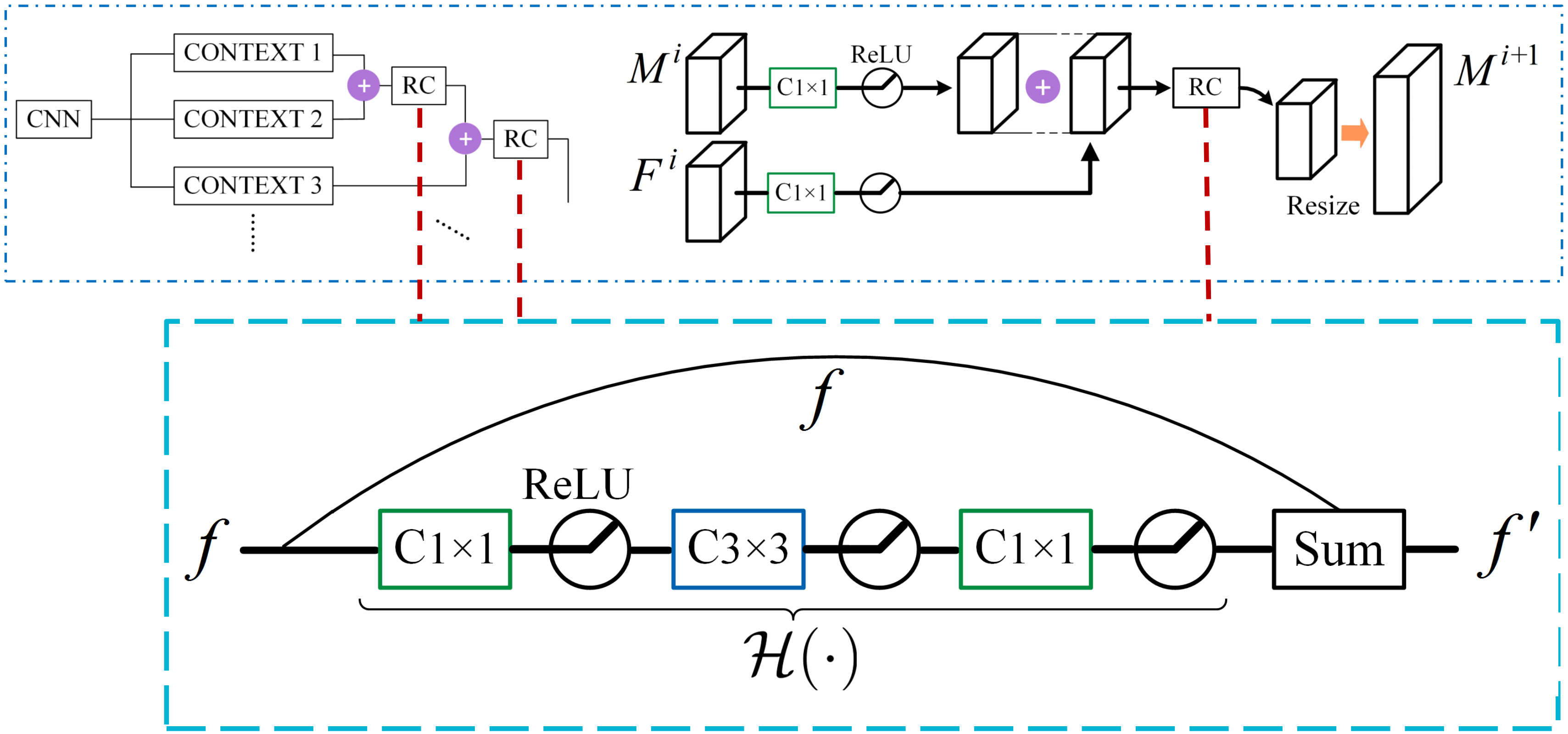
different-level features

semantic gap

sum fusion: information loss

remedy

residual correction scheme



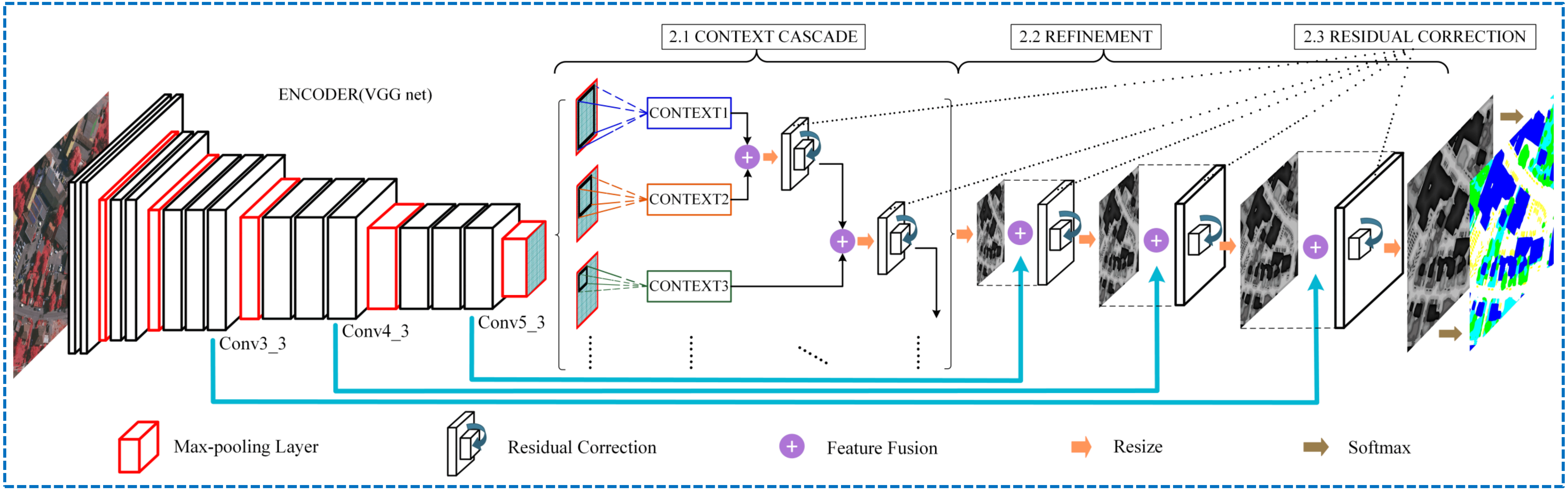
f : fused features

f' : underlying desired fusion

$$\mathcal{H}(\cdot) = f' - f \longrightarrow f' = f + \mathcal{H}(\cdot)$$

CAC-NET

Context-Aware Cascade Network



global to local

coarse to fine

end-to-end

CAC-NET: experiment

Dataset:

ISPRS Vaihingen 2D semantic labeling Challenge

Image: IRRG (infrared red green) ✓ ONLY

Elevation data: DSM (digital surface model)

NDSM (normalized ~)

Training: crop patches (400 * 400)

data augmentation

Source: http://www2.isprs.org/commissions/comm3/wg4/semantic-labeling.html

CAC-NET: experiment

Evaluation metric:

Intersection over Union (IoU)

$$IoU(P_m, P_{gt}) = \frac{|P_m \cap P_{gt}|}{|P_m \cup P_{gt}|}$$

P_{gt} : ground truth

P_m : prediction

Table1: comparison with excellent deep models

Table2: ablation experiment

Table 1: Comparison with the state-of-the-art models(%). surf: impervious surface (roads), veg: low vegtation.

Method	surf	roof	veg	tree	car	Mean
Segnet [5]	66.9	76.1	44.6	69.7	62.4	63.9
FCN-8s [1]	75.2	80.4	65.6	70.5	45.8	67.5
Deeplab-vgg [16]	80.0	87.9	70.0	75.4	36.1	69.9
Ours(vgg)	**81.3**	**89.3**	**70.3**	**75.5**	**66.4**	**76.6**
Deeplab-res101	81.6	90.7	71.4	**76.7**	58.9	75.9
Ours(res101)	**84.0**	**90.9**	**72.1**	76.6	**75.3**	**79.8**

Table 2: Ablation Experiment(%). MPD: multiple average pooling and dilation, MCC: multi-context cascade, RC: residual correction.

Method	surf	roof	veg	tree	car	Mean
Ours(Deeplab_13)	76.7	82.3	67.8	72.6	40.7	68.0
+ MPD	79.7	86.5	68.3	74.6	47.2	71.3
+ Refinement	80.1	87.1	68.0	74.6	55.5	73.1
+ MCC	80.3	88.1	69.5	76.5	60.0	74.9
+ RC	81.3	89.3	70.3	75.5	66.4	76.6

CAC-NET: experiment

Online evaluation metric:

F1 score and *Overall Accuracy*

$$F1 = 2\frac{pre \times rec}{pre + rec} \text{ and } rec = \frac{tp}{C}, pre = \frac{tp}{P}$$

Table3: ISPRS 2D semantic labeling challenge results

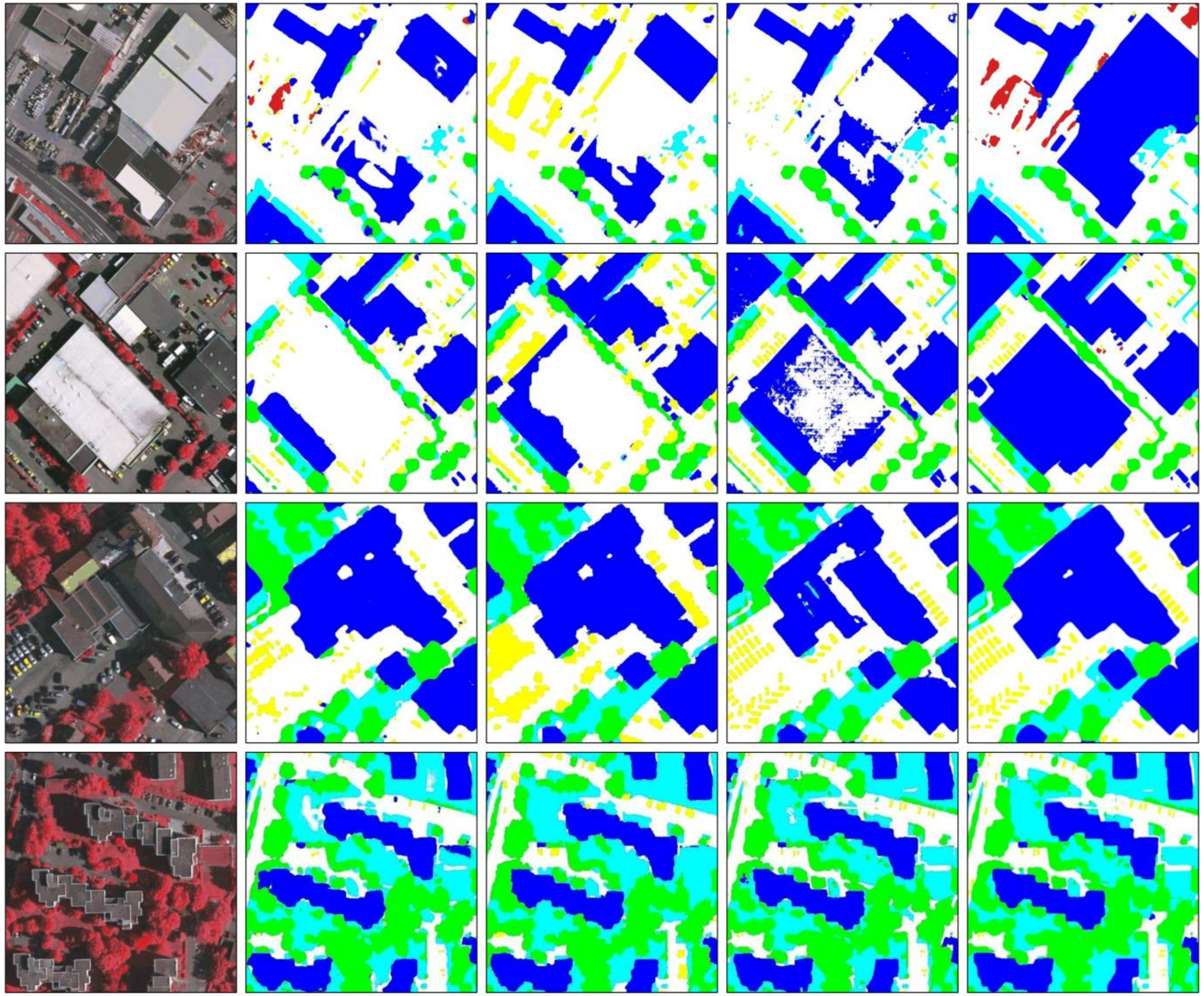
Table 3: *ISPRS 2D Semantic Labeling Challenge* results(%). OA: Overall Accuracy, DSM: Digital Surface Model

Method	surf	roof	veg	tree	car	OA
FCN+DSM('UZ_1')	89.2	92.5	81.6	86.9	57.3	87.3
CNN+RF+CRF+DSM [3]	89.5	93.2	82.3	88.2	63.3	88.0
FCN+RF+CRF [2]	90.5	93.7	83.4	89.2	72.6	89.1
FCN+Edge+DSM [10]	90.4	93.6	83.9	89.7	76.9	89.2
Segnet+DSM [19]	91.0	94.5	**84.4**	**89.9**	77.8	89.8
Ours(res101)	**92.7**	**95.3**	84.3	89.6	**80.8**	**90.6**

Source: http://www2.isprs.org/vaihingen-2d-semantic-labeling-contest.html

CAC-NET: experiment

Qualitative comparison



IRRG data | FCN+DSM 'UZ_1' | CNN+RF+ CRF+DSM [3] | Segnet+ DSM [17] | Ours

Source: *http://www2.isprs.org/vaihingen-2d-semantic-labeling-contest.html*

Future work

Instance labeling

Thank you for your attention !