



# Depth Privileged Object Detection in Indoor Scenes via Deformation Hallucination

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# Motivations

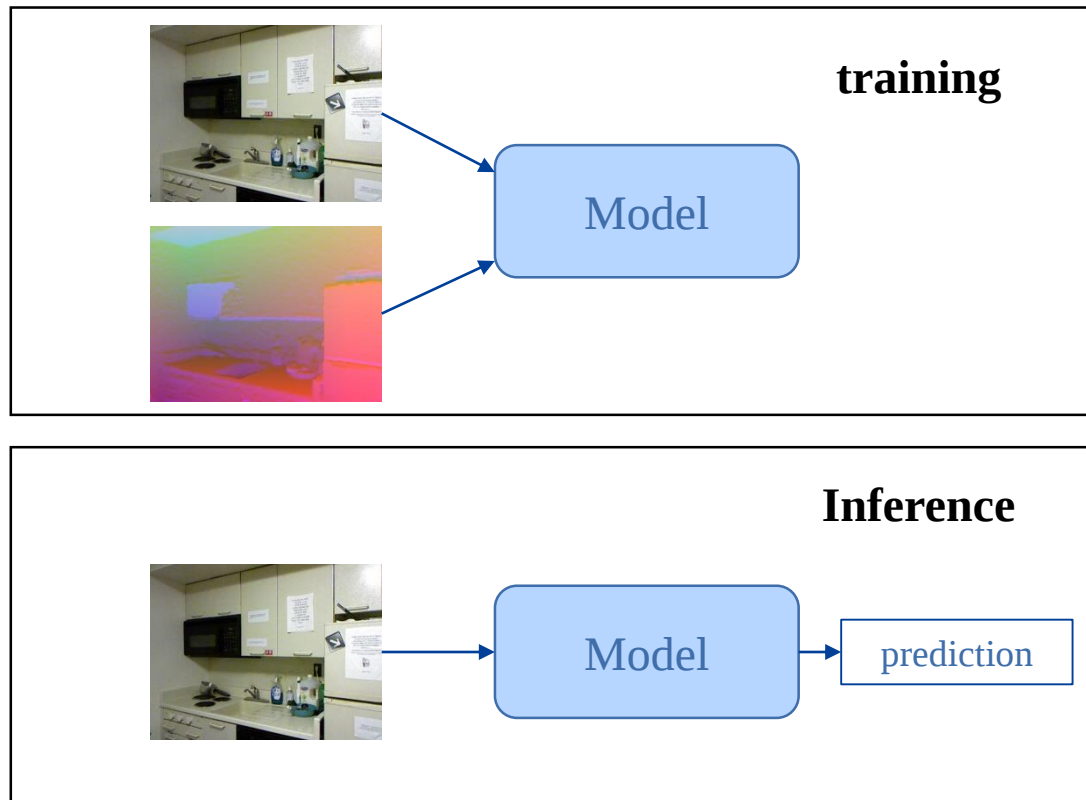


- Cluttered objects remain difficult to be detected due to the large variations (e.g., occlusion and illumination)
- Depth information can provide additional geometric cues to complement RGB image
- While RGB image capturing devices are pervasive, depth capturing devices are much less prevalent.

# Learning Using Privileged Information



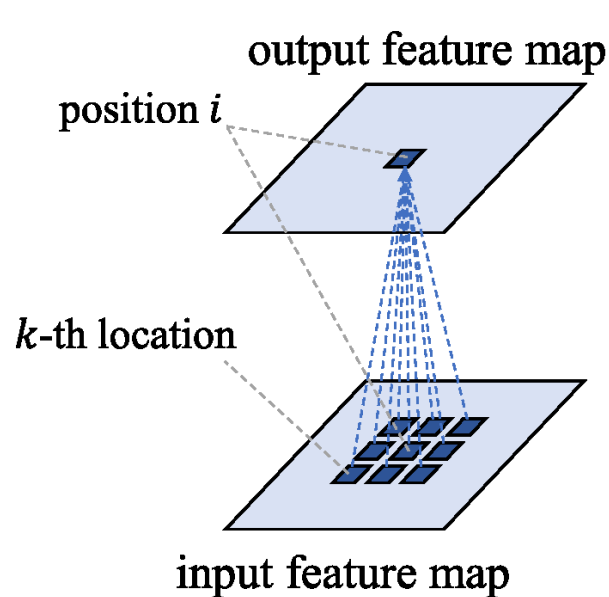
- Privileged information: can be accessed in training stage while be not available in inference stage.



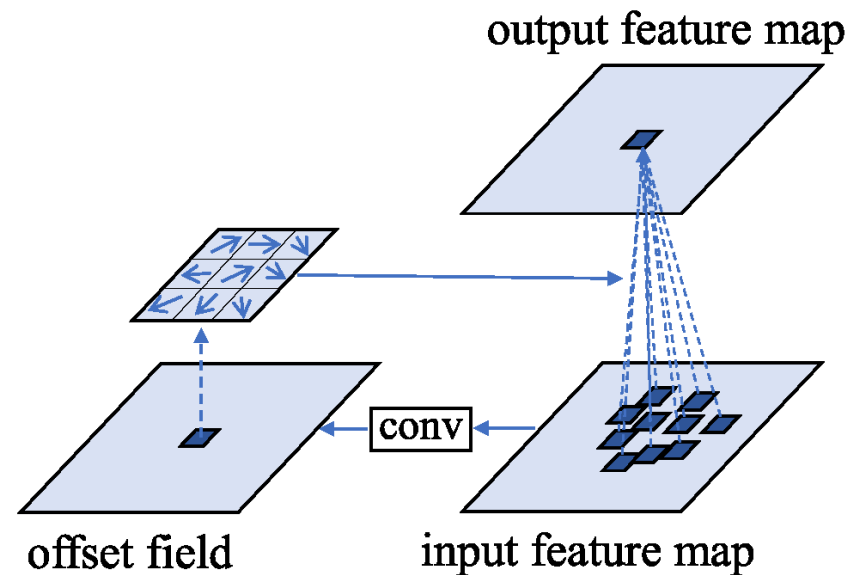
# Deformable Convolutional Networks



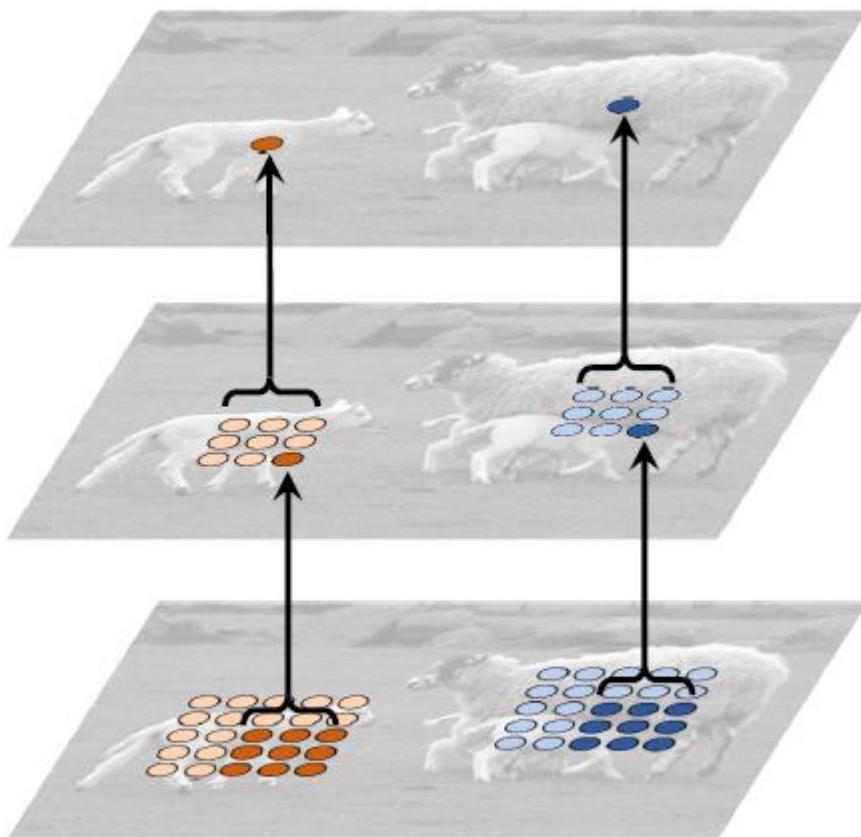
## Standard Convolution



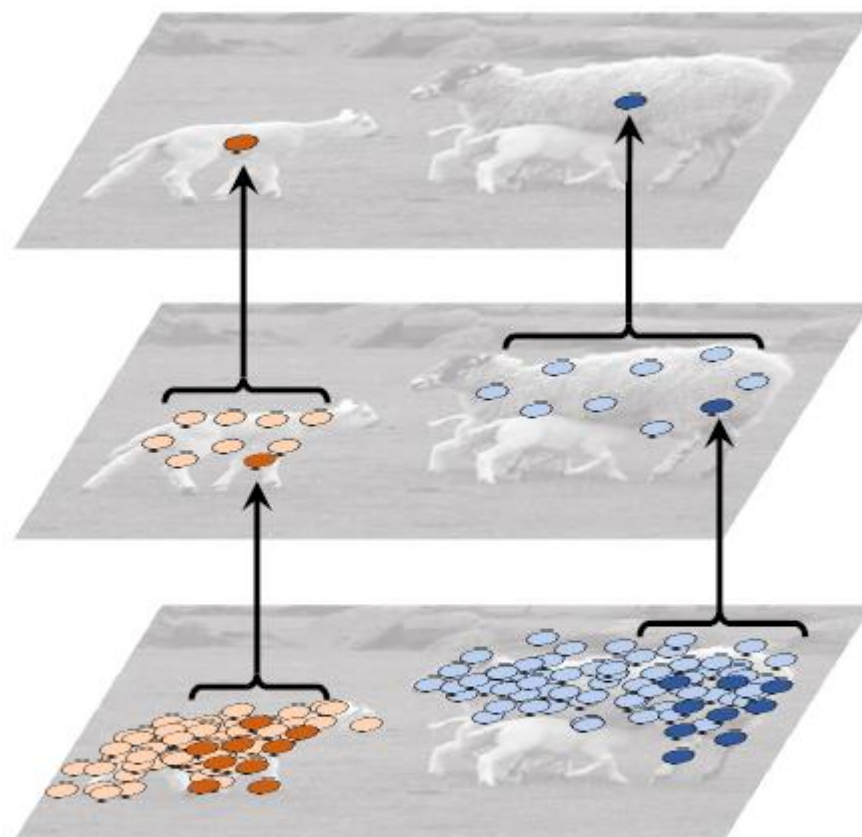
## Deformable Convolution



# Deformable Convolutional Networks

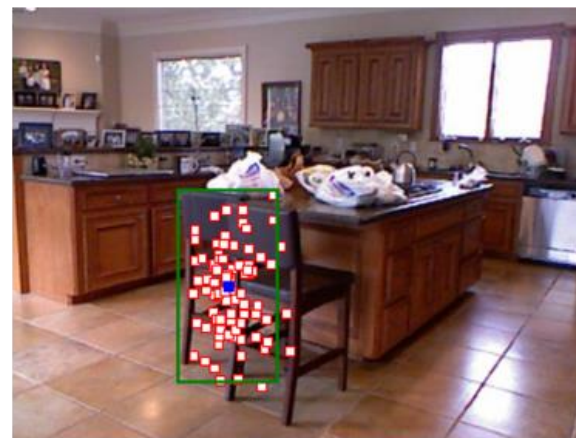
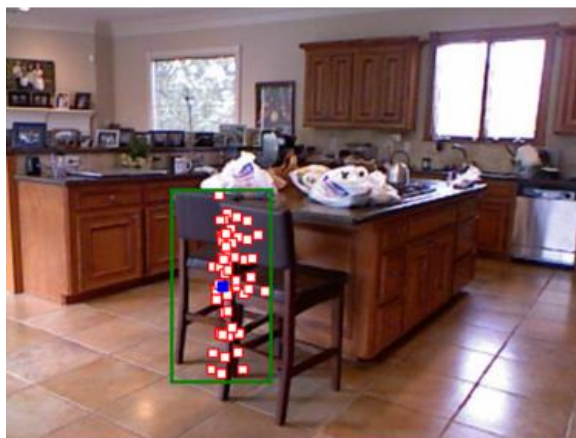


(a) standard convolution



(b) deformable convolution

# Deformation in Different Modalities



(a) RGB Deformation

(b) Depth Deformation

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**Experiments**

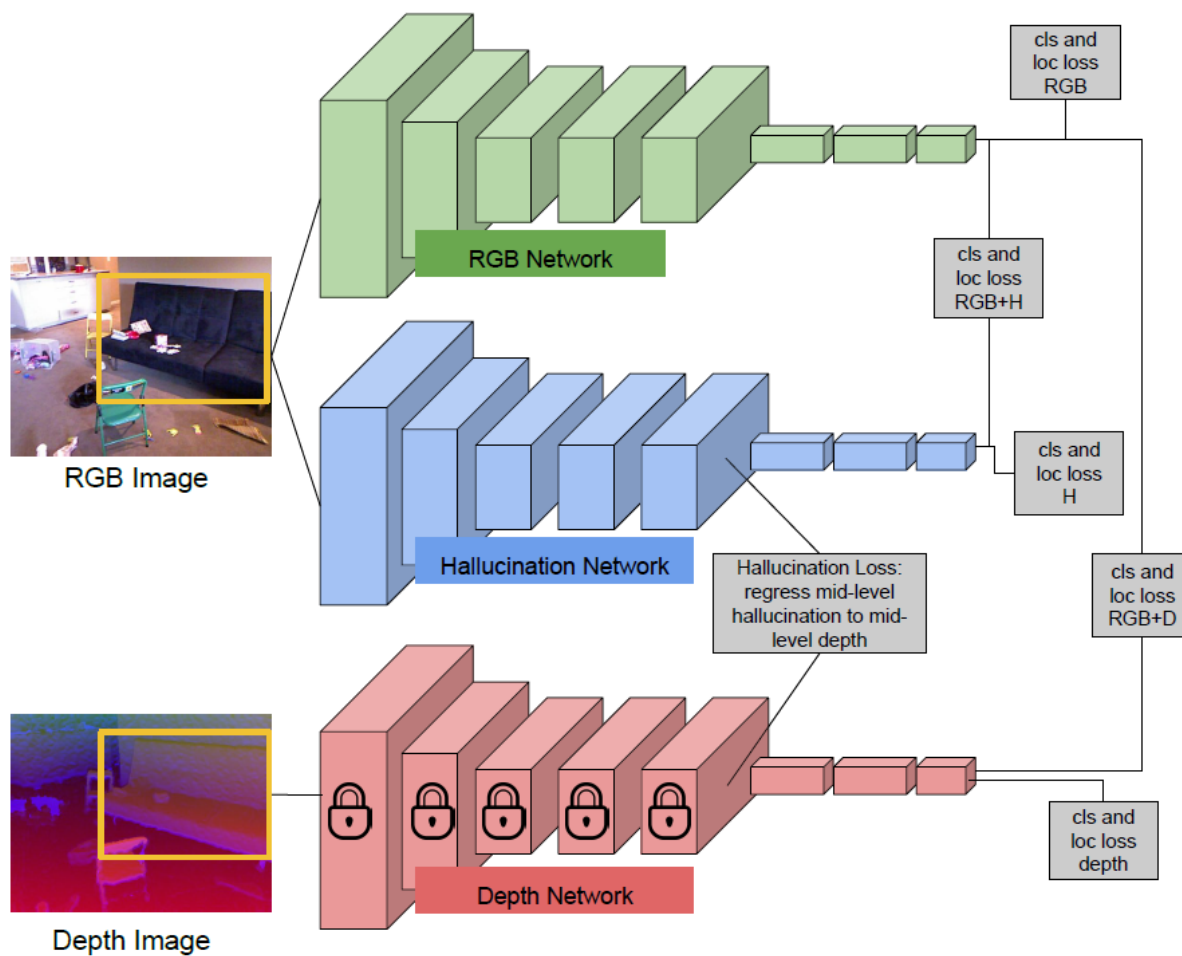


# Depth Privileged Object Detection

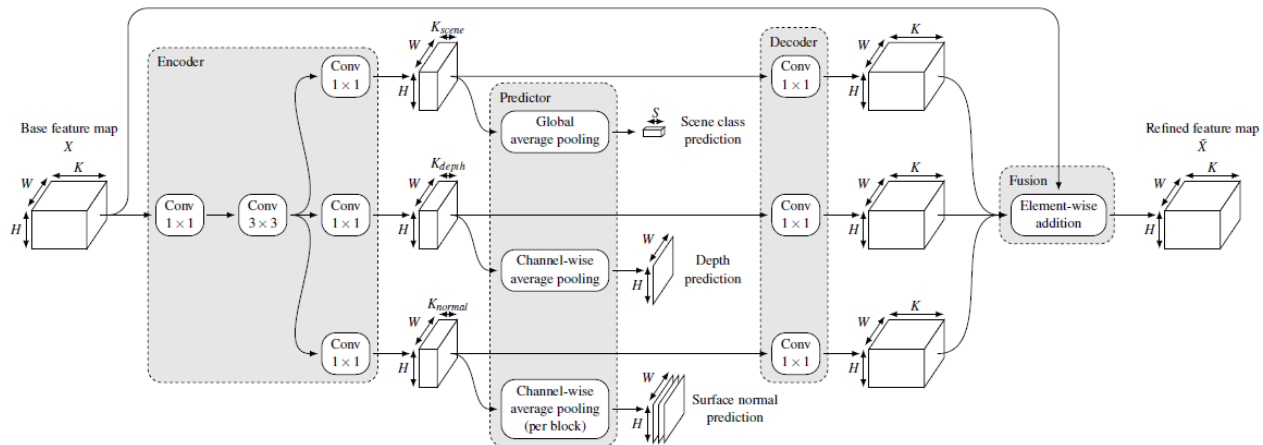
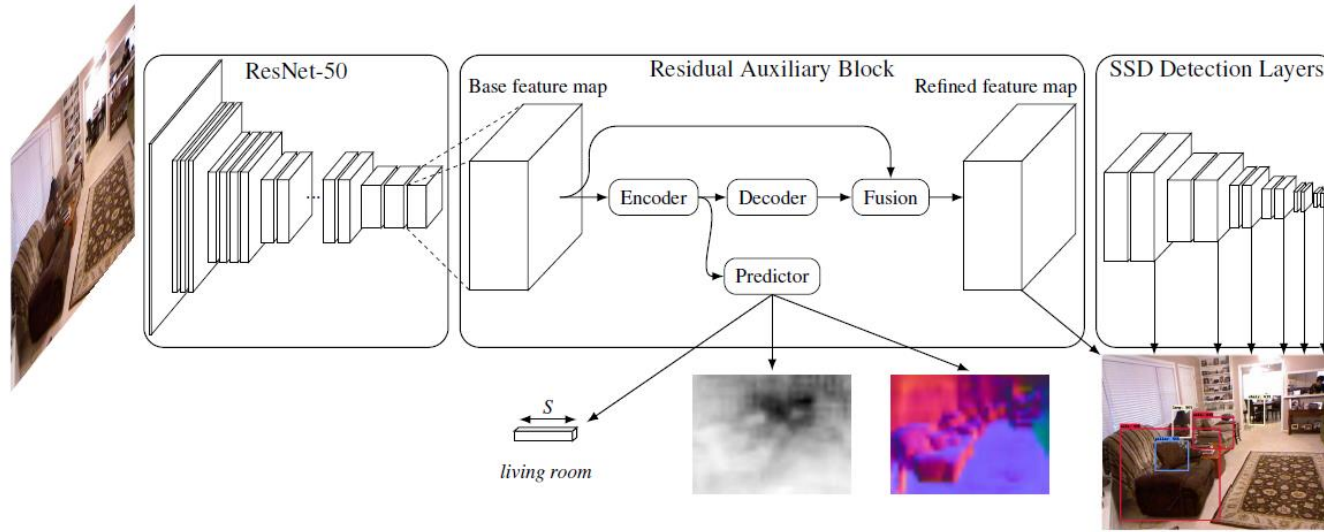


- Research lines:
  - Modality hallucination: HallucitansionNet , Cao et al. (2016)
  - Multi-task learning: ROCK

# HallucinationNet



# ROCK



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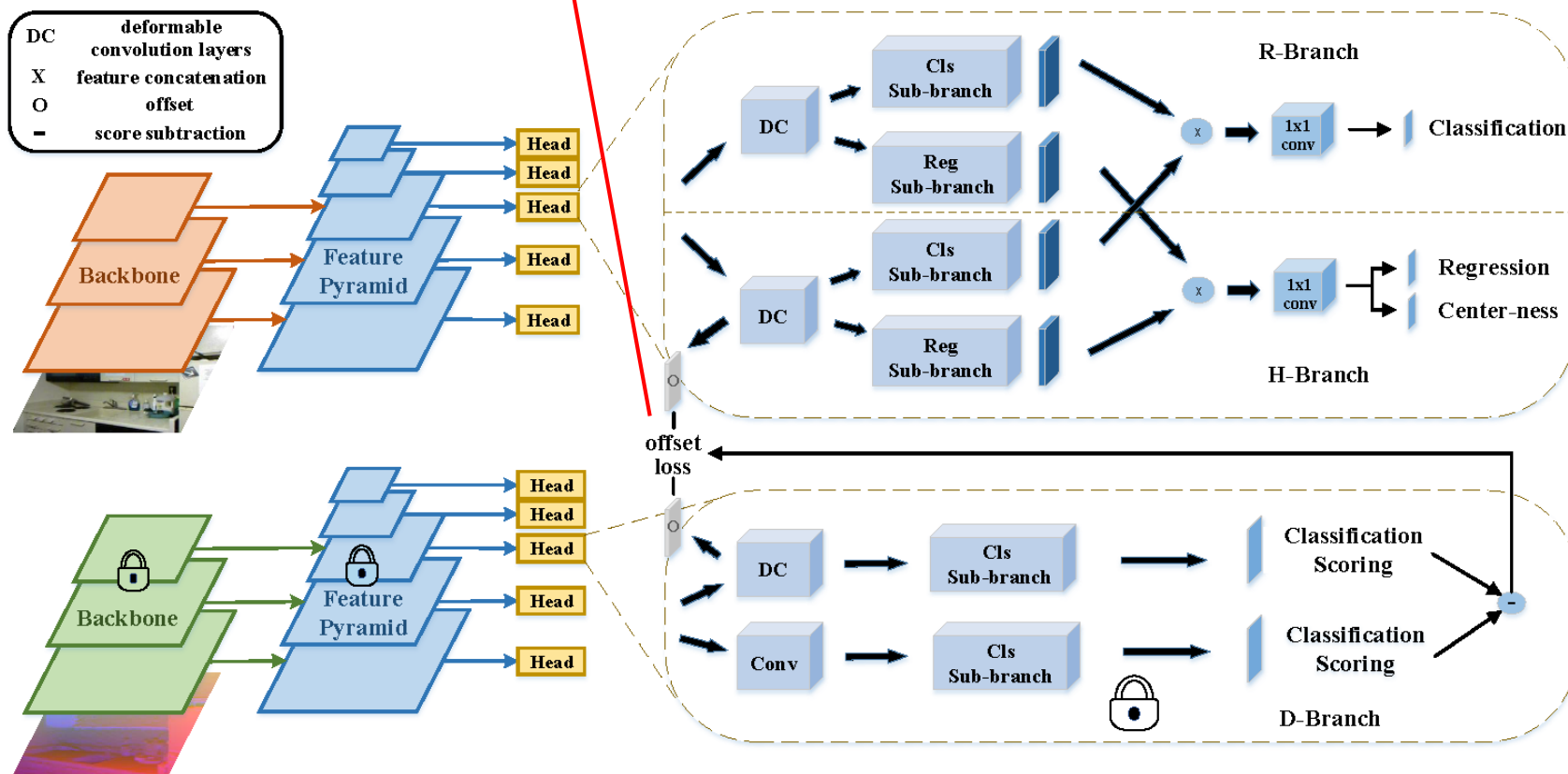
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**Experiments**



# Framework

$$L_o = \sum_{s=1}^S \sum_{m=1}^M \sum_{i=1}^{h_s \times w_s} \sum_{k=1}^{K^2} \|\Delta l_{s,m,i,k}^D - \Delta l_{s,m,i,k}^H\|_2^2$$



# Positive Position Transfer



- The depth deformation is not always reliable, transferring noisy deformation is likely to degrade the performance.
- Positive samples, which are determined by ATSS algorithm, has a major influence on the results (classification, regression)

$$L_o^p = \sum_{s=1}^S \sum_{m=1}^M \sum_{i=1}^{h_s * w_s} \sum_{k=1}^{K^2} P_{s,m,i} \|\Delta l_{s,m,i,k}^D - \Delta l_{s,m,i,k}^H\|_2^2$$

# Avoid Negative Transfer



- Classification scores (with/without dcn) can reflect the quality of deformation
- we calculate the loss weights at different positions in previous DeformConvs by tracking their contributions to the classification score improvement.

$$w_{s,m,i} = \exp(\delta \cdot (f_{s,i}^{(w)} - f_{s,i}^{(w/o)}))$$

$$L_o^{pw} = \sum_{s=1}^S \sum_{m=1}^M \sum_{i=1}^{h_s \cdot w_s} \sum_{k=1}^{K^2} w_{s,m,i} P_{s,m,i} \|\Delta l_{s,m,i,k}^D - \Delta l_{s,m,i,k}^H\|_2^2$$

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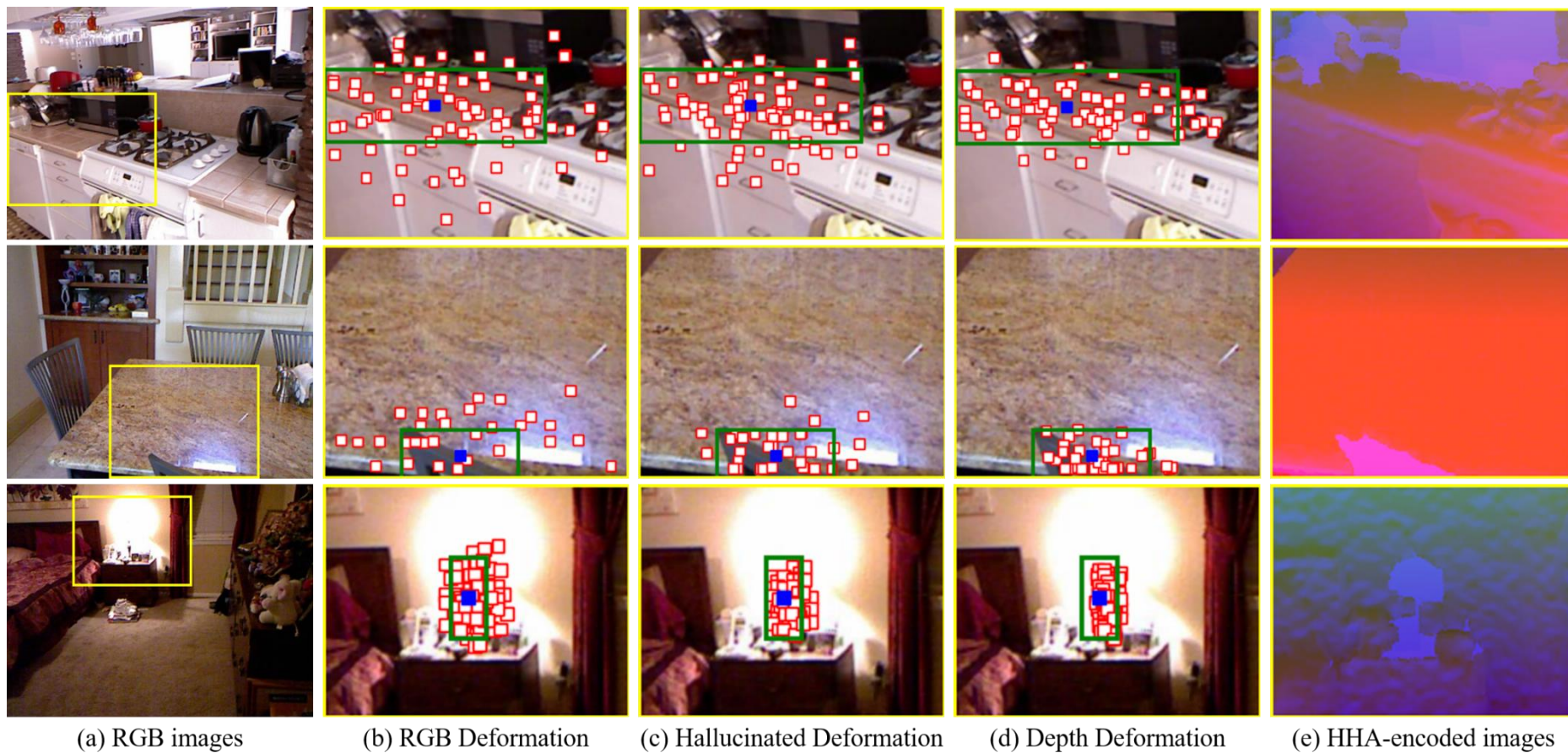
**Deformation Hallucination**

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**Experiments**



# Visualization Results



# Compared with SOTA Methods



| $L_d$ | $L_o$ | $L_o^p$ | $L_o^{pw}$ | mAP(%) |           |
|-------|-------|---------|------------|--------|-----------|
|       |       |         |            | NYUDv2 | SUN RGB-D |
| √     |       |         |            | 44.01  | 53.93     |
| √     | √     |         |            | 46.26  | 56.15     |
| √     |       | √       |            | 46.50  | 56.47     |
| √     |       |         | √          | 46.88  | 56.84     |

| Method           | mAP(%) |           |
|------------------|--------|-----------|
|                  | NYUDv2 | SUN RGB-D |
| FCOS+ATSS        | 42.73  | 52.94     |
| HallucinationNet | 45.22  | 55.35     |
| ROCK             | 44.89  | 55.14     |
| Cao et al.(2016) | 44.96  | 55.27     |
| Ours             | 46.88  | 56.84     |

# Ablation Study



## Configuration of DeformConvs

| Configuration | mAP(%) |                 |
|---------------|--------|-----------------|
|               | $L_d$  | $L_d + \mu L_o$ |
| $B_1$         | 43.66  | 45.34           |
| $B_2$         | 44.17  | 45.93           |
| $B_3$         | 44.43  | 46.19           |
| $H_1$         | 43.35  | 45.36           |
| $H_2$         | 44.04  | 46.26           |
| $H_3$         | 44.21  | 46.30           |
| $B_3 + H_2$   | 44.25  | 46.32           |

## Fusion Strategy Analyses

| mAP(%)        | After DeformConvs | After sub-branch |
|---------------|-------------------|------------------|
| Concatenation | 46.32             | 46.88            |
| Addition      | 45.79             | 46.15            |

## Evaluation on RGB-only dataset

| Model        | mAP(%) |
|--------------|--------|
| RGB-only     | 38.96  |
| Ours         | 40.68  |
| RGB-only(ft) | 81.01  |
| Ours(ft)     | 82.57  |

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**Thanks For Watching!**



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