Learning with Side Information through Modality Hallucination

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Outline

1. Introduction
2. Related work
3. Modality Hallucination Model
4. Experiments
5. Conclusion
6. Sources
Introduction

Use available paired RGB-d training data to learn to hallucinate mid-level convolutional features from a RGB image for **object detection** task.

**Figure**: Network Structure

1
Introduction

- Task: Object Detection
- Framework: Deep Learning (Convolutional Neuron Networks)
- What’s new: Additional ConvNets to extract depth features from RGB image (modality hallucination)
Results

RGB object detection:

34.0 mAP (this work) vs 29.9 mAP (Fast R-CNN)

Figure 4: Example Detections on the NYUD2 test set where our RGB hallucination network’s (green box) top scoring detection for the image is correct while the baseline RGB detector’s (red box) top scoring detection is incorrect.
Related Work

- Object detection using deep learning
  - RGB\cite{6}
  - RGB-d\cite{7}
- Transfer Learning\cite{8}\cite{9}
- Learning using side information\cite{10}
- Network distillation\cite{11}\cite{12}
Related Work

• Object detection using deep learning
  • RGB$^6$
  • RGB-d$^7$

• Transfer Learning$^8$$^9$

• Learning using side information$^{10}$

• Network distillation$^{11}$$^{12}$
Object Detection

- Extract region of interest (region proposal)
- Classification of this region
- Result: Region (bounding box coordinates) + Category
Figure 4: Example Detections on the NYUD2 test set where our RGB hallucination network’s (green box) top scoring detection for the image is correct while the baseline RGB detector’s (red box) top scoring detection is incorrect.
Object Detection Pipeline (Fast R-CNN[6])
Object Detection Pipeline (Fast R-CNN\textsuperscript{[6]})

Figure: F-RCNN Structure\textsuperscript{6}
State of the art

- Fast R-CNN (Mean Average Precision: 29.9%)\textsuperscript{[6]}
- RGB-d Fast R-CNN (Mean Average Precision: 44.4%)\textsuperscript{[7]}
Object detection can be improved significantly with **RBD-d images** (additional modality, complementary information).
Problem

Not all RBG images have corresponding depth information.
How about extracting depth features from RGB images?
Related Work

- Object detection using deep learning
  - RGB\textsuperscript{[6]}
  - RGB-d\textsuperscript{[7]}
- Transfer Learning\textsuperscript{[8][9]}
- Learning using side information\textsuperscript{[10]}
- Network distillation\textsuperscript{[11][12]}
Transfer Learning$^{[8][9]}$

- Transfer learning and domain adaptation which learns to share information from one task (Obj detection using depth features) to another (Obj detection with RGB features).
- Previous work used depth information at training time to inform RGB test time detection by learning transformations into a single representation for the joint modality space.
- This work focuses on learning an additional RGB representation, which is the hallucination network.
Learning algorithm has additional knowledge at training time, whether meta data or an \textit{additional modality}.

Use this extra information to inform training of a \textbf{stronger model} than could be produced otherwise, e.g. surface normals at training time could produce detection improvement.
Network distillation[^11][^12]

- **Network Distillation**: The output from one network (depth network) is used as the target probability distribution for a new network (hallucination network). Input can be different.

- This approach can also be seen as using distillation to learn representations on RGB images by **transferring supervision** from paired depth images, by employing joint training.
Hallucination Network (Training time)

Sharing depth modality information with RGB through hallucination network.

Figure: Network Structure

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1. Image Source
Hallucination Network (Test time)

Given only a RGB image and regions of interest, pass through both the RGB network and the hallucination network to produce two scores per category, per region, which we average and take the softmax to produce our final predictions.

Figure: Test Network Structure

\(^2\)
1. A convolutional neuron network (Hallucination network) whose input is a RGB image.

Figure: Network Structure
2. The **features maps** generated by this network is as identical as possible to the ones generated by depth ConvNets.

**Figure: Network Structure**

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1. Explanation
Explanation

3. A network whose input is RBG image generates depth features.

**Figure:** Network Structure\(^1\)
Explanation

4. Similar feature maps but different convolutional kernels (weights) because of different input modalities.

Figure: Network Structure

\(^1\)
Multi channels ConvNets:

- RGB Network
- Hallucination Network
- Depth Network

The base network structures can be AlexNet / VGG (to extract features).

Figure: Network Structure
Modality Hallucination Model

Training time

Testing time

Figure: Network Structure¹

Figure: Test Network Structure²
Training Pipeline

- Train RBG-N and Depth-N
- Initialize HalluN
- Joint optimization

Figure: Network Structure

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1. Network Structure
Training Pipeline

1. **Train RBG-N and Depth-N**
2. **Initialize HalluN**
3. **Joint optimization**

RGB and depth network are independently trained using the Fast R-CNN algorithm with the corresponding image input.
Training Pipeline

Train RGB-N and Depth-N

Initialize Hallu-N

Joint optimization

The hallucination network parameters are initialized with the learned depth network weights.
Training Pipeline

- Train RBG-N and Depth-N
- Initialize HalluN
- Joint optimization

Multi-task Optimization with hallucination loss.
Hallucination Loss

Activations after some layer, $l$, should be similar between the hallucination and depth networks.

Figure: Network Structure\textsuperscript{1}
Hallucination Loss

Euclidean loss: \[ L_{\text{hallucinate}}(l) = \| \sigma(A_l^{dNet}) - \sigma(A_l^{hNet}) \|_2^2 \]

where \( \sigma(x) = 1/(1 + \exp(-x)) \) (sigmoid function) and \( l = \text{layer} \)

Figure: Network Structure\(^1\)
Hallucination Loss

Asymmetric transfer of information: 0 learning rate lower than $l$

Figure: Network Structure

1
Hallucination Loss

1. Input image

Input: RGB / RGB-d

Regions of Interest: Image and Coordinates

Projection

2. Extract region proposals (~2k)

Extracting features of RoI

ConvNets: VGG / AlexNet

CNN features of whole image

RoI Pooling layers

RoI features

Classification

Bounding Box

Extracting features of whole image

Hallucination loss
Multi-task Optimization

11 total losses:

- 5 softmax cross-entropy losses for **classification**
- 5 smooth L1 losses for **bounding box** coordinates regression
- 1 hallucination loss
Multi-task Optimization

Figure: Network Structure

1
Multi-task Optimization

Figure: Network Structure

1
Multi-task Optimization

Figure: Network Structure

1
Multi-task Optimization

Figure: Network Structure

1
Balancing objectives

\[ \mathcal{L} = \gamma \mathcal{L}_{\text{hallucinate}} + \alpha \left[ \mathcal{L}_{\text{dNet}} + \mathcal{L}_{\text{rNet}} + \mathcal{L}_{\text{hNet}} + \mathcal{L}_{\text{rdNet}} + \mathcal{L}_{\text{rhNet}} \right] + \beta \left[ \mathcal{L}_{\text{cls}} + \mathcal{L}_{\text{rNet}} + \mathcal{L}_{\text{hNet}} + \mathcal{L}_{\text{rdNet}} + \mathcal{L}_{\text{rhNet}} \right] \]

\[ \alpha = 0.5, \beta = 1, \gamma = ? \]

\( \gamma \) is heuristically set to \( 10 \times \) the contribution of any of the other losses
Experiments

• Base Network: AlexNet, VGG
• Region Proposals: Multiscale Combinatorial Grouping (MCG)
• SGD Hyper-parameters: LR = 0.001, Momentum = 0.9, Weight decay = 0.0005, T = 10 (Threshold of gradient glipping)
NYUD2 Detection Evaluation

A - AlexNet, V - VGG

<table>
<thead>
<tr>
<th>method</th>
<th>btub</th>
<th>bed</th>
<th>bshelf</th>
<th>box</th>
<th>chair</th>
<th>counter</th>
<th>desk</th>
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<th>tv</th>
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<th>mAP</th>
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<tr>
<td>RGB only [10] (A)</td>
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<td>50.6</td>
<td>36.8</td>
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Figure: NYUD2 evaluation$^3$
NYUD2 Detection Evaluation

A - AlexNet, V - VGG

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Figure: NYUD2 evaluation
How to initialize the hallucination net?

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**Figure:** Initialization evaluation\(^4\)
How to initialize the hallucination net?

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*Figure: Initialization evaluation*
What did the hallucination net learn?

roi-pool5 activations from corresponding regions in the test image which have highest final detection scores

Figure: Activation of RoI Pool5

What did the hallucination net learn?

Figure 4: Example Detections on the NYUD2 test set where our RGB hallucination network’s (green box) top scoring detection for the image is correct while the baseline RGB detector’s (red box) top scoring detection is incorrect.
What did the hallucination net learn?
What did the hallucination net learn?
But it’s not perfect.

Figure 5: Example Detections on the NYUD2 test set where our RGB hallucination network’s (green box) top scoring detection for the image is a false positive while the baseline RGB detector’s (red box) top scoring detection is a true positive.
But it’s not perfect.
Conclusion

- A novel technique for extracting **unseen modality** features.
- Outperforms the corresponding Fast R-CNN RGB detection models on the NYUD2 dataset.
Sources

- [1][2][3][4][5]: J. Hoffman, S. Gupta, T. Darrell, Learning with Side Information through Modality Hallucination
- [6]: R. Girshick, Fast R-CNN
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Thanks.