Superpixel-based Refinement for Object Proposal Generation

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Motivation	Method	Conclusion

Object Proposal Generation (OPG)

Problems of Segmentations in OPG

Proposed Idea



Result w/o our refinement



Motivation	Method	Conclusion

Object Proposal Generation (OPG)

- Localize and segment all objects in an image
- Class-agnostic proposals in contrast to instance segmentation

Problems of Segmentations in OPG

Proposed Idea



Result w/o our refinement



Motivation	Method	Conclusion

Object Proposal Generation (OPG)

Problems of Segmentations in OPG

- State-of-the-art systems segment proposals on coarse resolution (e.g. 10×10 pixels)
- Hundreds of proposals per image

Proposed Idea



Result w/o our refinement



Motivation	Method	Conclusion

Object Proposal Generation (OPG)

Problems of Segmentations in OPG

- State-of-the-art systems segment proposals on coarse resolution (e.g. 10×10 pixels)
- Hundreds of proposals per image

Proposed Idea

- Combine coarse DL-based proposals and fine-grained superpixels
- Classify superpixels as foreground or background



Result w/o our refinement



Motivation ○	Method ●○	Conclusion
System Overview		



Motivation O	Method ●○	Evaluation	Conclusion
System Overview			



Generate coarse object proposals with state-of-the-art AttentionMask [Wilms and Frintrop, ACCV'18].

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Motivation O	Method ●○	Evaluation	Conclusion
System Overview			



Generate detailed superpixel segmentations [Felzenszwalb and Huttenlocher, IJCV'04] for object proposals of different scales.

Motivation O	Method ●○	Evaluation	Conclusion
System Overview			



Extract features from the backbone network for object proposals of different scales.

Motivation o	Method ●○	Conclusion
System Overview		



Combine coarse proposals with extracted features using superpixel pooling and classify the superpixels.

Motivation ⊙	Method ○●	Evaluation 00	Conclusion
Simplified Example	9		
Superpixel Segmentation	AttentionMask	Superpixel Refinement (per	Proposal)
Extracted Features			

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Motivation O	Method ○●		Conclusion
Simplified Example			
Superpixel V Segmentation	AttentionMask Proposal	Superpixel Refinement (per Propos	sal)



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Upsample

• Upsample coarse object proposal mask

from AttentionMask

Motivation O	Method ○●	Conclusion
Simplified Example		
Supernixel	AttentionMask	



Segmentation



Superpixel Refinement (per Proposal)

• Upsample coarse object proposal mask from AttentionMask



Motivation O	Method ○●	Conclusion



Superpixel Refinement (per Proposal)

- Upsample coarse object proposal mask from AttentionMask
- Superpixel avg. pooling on upsampled results → mask prior: superpixel rather foreground or background

Features

Motivation O	Method ○●	Conclusion
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- Upsample coarse object proposal mask from AttentionMask
- Superpixel avg. pooling on upsampled results → mask prior: superpixel rather foreground or background

Motivation O	Method ○●	Conclusion



- Upsample coarse object proposal mask from AttentionMask
- Superpixel avg. pooling on upsampled results → mask prior: superpixel rather foreground or background
- Superpixel avg. pooling on extracted features → feature vector per superpixel

Motivation O	Method ⊙●	Conclusion



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Motivation O	Method ⊙●	Conclusion



- Upsample coarse object proposal mask from AttentionMask
- Superpixel avg. pooling on upsampled results → mask prior: superpixel rather foreground or background
- Superpixel avg. pooling on extracted features → feature vector per superpixel
- Classify each superpixel based on mask prior and feature vector as foreground or background

Motivation O	Method ⊙●	Conclusion



- Upsample coarse object proposal mask from AttentionMask
- Superpixel avg. pooling on upsampled results → mask prior: superpixel rather foreground or background
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- Classify each superpixel based on mask prior and feature vector as foreground or background

Motivation	Method	Evaluation	Conclusion
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Quantitative Results on LVIS Dataset

Method	AR@10	AR@100
DeepMask [Pinheiro et al., NIPS'15]	0.069	0.147
SharpMask [Pinheiro et al., ECCV'16]	0.073	0.154
FastMask [Hu et al., CVPR'17]	0.069	0.161
AttentionMask [Wilms and Frintrop, ACCV'18]	0.073	0.189
Ours	0.092	0.206

- LVIS has COCO images with more precise annotations
- AR@N: Average Recall for N proposals

Motivation Method	Evaluation	Conclusion
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Quantitative Results on LVIS Dataset

Method	AR@10	AR@100
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Method	BR↑	UE↓
DeepMask	0.488	0.087
SharpMask	0.561	0.080
FastMask	0.510	0.084
AttentionMask	0.568	0.070
Ours	0.681	0.068

- LVIS has COCO images with more precise annotations
- AR@N: Average Recall for N proposals
- BR: Boundary Recall
- UE: Undersegmentation Error

Motivation	Method	Evaluation	Conclusion
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Qualitative Results on LVIS Dataset





 ${\sf Attention} {\sf Mask}$





Ground Truth

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Ours

Motivation	Method	Evaluation	Conclusion
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Qualitative Results on LVIS Dataset



AttentionMask

Ours

Ground Truth

Motivation	Method	Conclusion
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Summarv		

- Object proposals mostly have only coarse segmentations
- Superpixel-based refinement
- Combination of coarse masks, DL features and superpixels
- Improvement in general object proposal results
- Better adherence to object boundaries

Conclusion

Superpixels can be helpful in combination with DL!



Result w/o our refinement



Motivation	Method	Conclusion
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Thank you for your att	ontion	

Thank you for your attention!

Visit our poster in session **PS T5.6** on **Thursday**, 14 January

LA 07:00 am New York 10:00 am CET 04:00 pm Beijing 11:00 pm Sydney 02:00 am



Web page with **Code and Paper** www.inf.uni-hamburg.de/ spxrefinement