Visual Instance Search based-on Pretrained Network

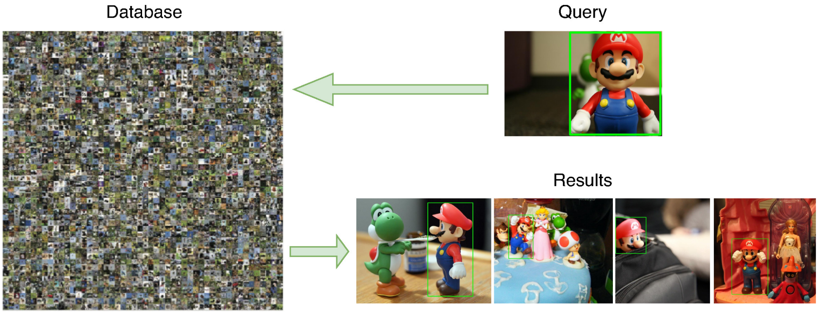
Dr. Wan-Lei *Zhao*

Jul. 21 2020

Contact: wlzhao@xmu.edu.cn

Outline

Instance Search: the problem



- Instance search is widely used in various multimedia applications
  - video editing, image hyperlink and online shopping, etc.
  - Instance: any semantically meaningful visual subject

Existing Solutions and Challenges (1)

- Image-search based solutions
  - Features are aggregated from several local regions into a global feature
  - Several weighting strategies are employed to highlight instances
  - e.g., R-MAC, CroW, CAM, BLCF-SalGAN, and Regional Attention
- Advantages
  - Only pre-trained models are required
- Challenges
  - Features are not discriminative for instance search
  - The instance localization are unfeasible

Existing Solutions and Challenges (2)

- Instance-level solutions
  - Instances are localized using object detection or segmentation framework
  - For instance, DeepVision, FCIS+XD and PCL*+SPN
- Advantages
  - Instance-level localizations and features are obtained
- Challenges
  - The training conditions are demanding
  - Generalization to the unseen categories is nearly impossible

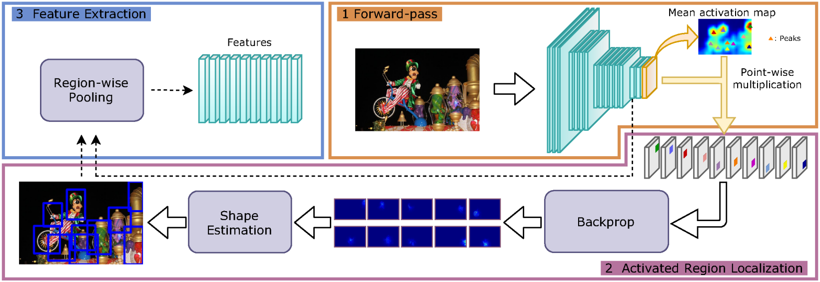
The Aim of our Design

1. Class-agonistic
2. Instance localization
3. High discriminative of the instance level feature

Motivation: the idea

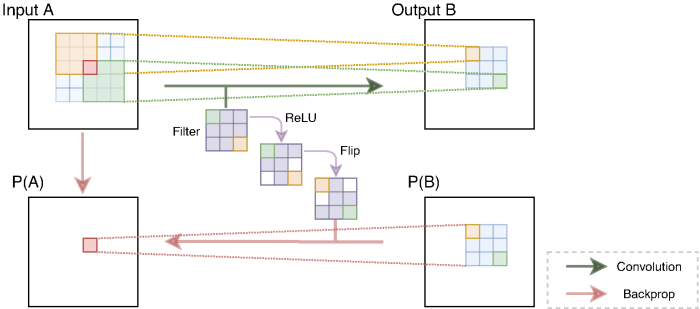
- The last convolution layer preserves class-agnostic clues for latent instances
  - They are not suppressed in the prediction layer yet

The Framework



- Peaks in the forward-pass indicate the latent instances (of both known and unknown)
- A back-propagation process is leveraged to highlight instance regions
- Instance-level features are extracted with localization results

Back-propagation in One Layer in Detail

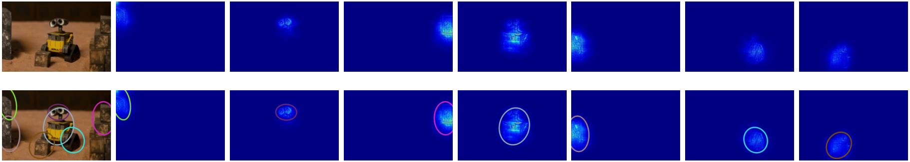


$$P(A_{x,y}) = \sum_{i=x-\frac{W_f}{2}}^{x+\frac{W_f}{2}} \sum_{j=y-\frac{H_f}{2}}^{y+\frac{H_f}{2}} P(A_{x,y}|B_{i,j})P(B_{i,j}) \tag{1}$$

$$P(A_{x,y}|B_{i,j}) = \begin{cases} Z_{i,j}A_{x,y}F_{x-i,y-j}, & \text{if } F_{x-i,y-j} > 0 \\ 0, & otherwise. \end{cases} \tag{2}$$

- A top-down probability model is introduced

Instance Localization with Second Moment Matrix



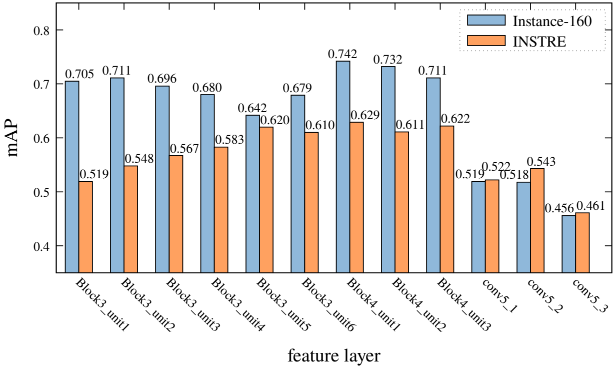
$$\sum_{r(x,y)\geq\tau} \begin{bmatrix} x^2 & x\cdot y \\ x\cdot y & y^2 \end{bmatrix} \tag{3}$$

- The second moment matrix is employed to estimate the instance shape
- The final localizations are the circumscribed rectangles of the estimated ellipses

More Salient region: DASR*

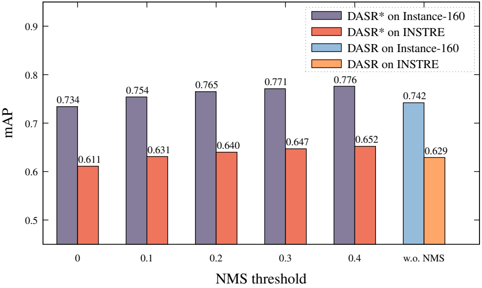
- Remaining issues
  - Different instances share one latent response peak
  - Different peaks indicate nearly the same region
- Solutions
  - More pixels are back-propagated
  - Non-maximum suppression (NMS) is employed to reduce the representation redundancy and select out the most salient regions

Ablation Study (1): layer for feature-pooling



- Experiments are conducted with ResNet-50 and Vgg-16
- Features derived from ResNet-50 are much distinctive

Ablation Study (2): DASR vs. DASR*



- DASR* outperforms DASR when $\beta > 0.1$
- The larger overlapping rate β leads to better performance

How about Back-propagating from the Last Layer

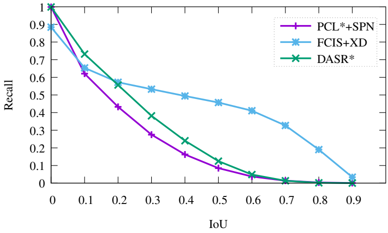
- Comparing with the approaches back-propagated from the last layer, DASR enables to localize class-agnostic instances with bounding boxes.

Instance Search Results on Two Benchmarks

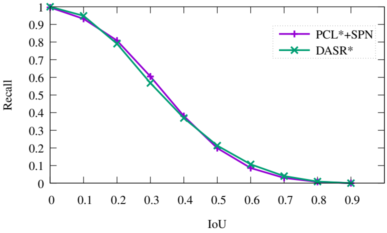
Approach	Model-Type	Loc.	Dim.	Instance-335			INSTRE
				Top-50	Top-100	All	
R-MAC	pre-trained	image	512	0.234	0.315	0.375	0.523
CroW	pre-trained	image	512	0.159	0.225	0.321	0.416
CAM	pre-trained	image	512	0.194	0.263	0.347	0.320
BLCF	pre-trained	image	336	0.246	0.358	0.483	0.636
BLCF-SalGAN	pre-trained	image	336	0.245	0.350	0.469	**0.698**
Regional Attention	pre-trained	image	2,048	0.242	0.351	0.488	0.542
DeepVision	strong	region	512	0.402	0.521	0.620	0.197
FCIS+XD	strong	pixel	1,536	0.403	0.500	0.593	0.067
PCL*+SPN	weak	region	1,024	0.380	0.475	0.580	0.575
DASR	pre-trained	region	2,048	0.419	0.558	0.699	0.629
DASR*	pre-trained	region	2,048	**0.433**	**0.580**	**0.724**	0.647
DASR-m	pre-trained	region	2,048	0.411	0.533	0.662	0.671
DASR-m*	pre-trained	region	2,048	0.428	0.560	0.694	0.692

- DASR outperforms many weakly supervised approaches
- The only pre-trained model that achieves region level localization

Localization Accuracy



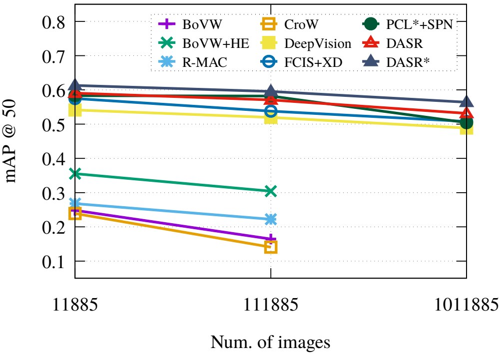
(a) Instance-335



(b) INSTRE

- DASR* shows superior performance compared to weakly supervised model PCL*+SPN

Instance Search Results in Large-scale



- DASR* outperforms all the approaches, including FCIS+XD based on a fully supervised model

Instance Search Samples

- It is meaningful even for false-positive samples
- DASR fails when the object is in small-scale ($< 32\times32$ pixels)

DASR for Image Search: the idea

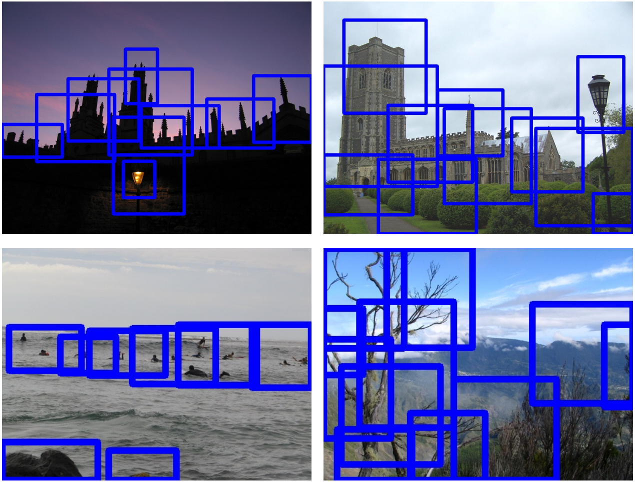
- DASR features are considered as instance level features
- DASR features could be aggregated into image level feature via VLAD

Image Search Results

Method	Dim.	Holidays	Oxford5k	Paris6k
BoVW+HE	65,536	0.742	0.503	0.501
SIFT+VLAD*	8,192	0.664	0.359	0.391
R-MAC	512	-	0.669	0.830
CroW	512	0.851	0.708	0.797
CAM	512	0.785	0.712	0.805
BLCF	336	0.854	0.722	0.798
BLCF-SalGAN	336	0.835	0.746	0.812
Regional Attention	2,048	-	**0.768**	**0.875**
DeepVision	512	-	0.710	0.798
DASR+VLAD	8,192	0.834	0.594	0.690
DASR*+VLAD	8,192	**0.873**	0.613	0.744

- It is competitive to features specfically designed for image-level search
- It becomes possible to integrate instance-level and image-level search under one framework

How DASRs are Distributed in a Natural Image



Summary

- Advantages
  - No additional training data or training stage is required
  - Localization of latent foreground instances is feasible
  - The pipeline can be carried out using any CNN classification network

Q & A

Thanks for your attention!