Predicting Good Features for Image Geo-Localization Using Per-Bundle VLAD

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Motivation

Are all features useful for geo-localization?

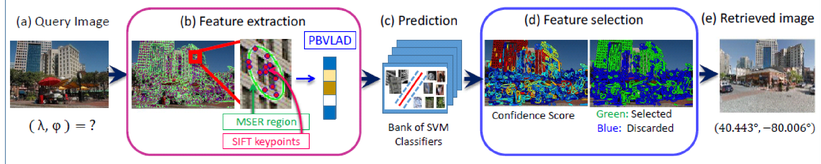
Selecting features intelligently would Allow us to achieve better performance while reducing the number of features.

Contributions

(1) We offer a way to predict features that are good in a data-driven sense. We show that by selecting features based on predictions from learned classifiers, geo-localization performance can be improved.

(2) We propose per-bundle vector of locally aggregated descriptors (PBVLAD) as a novel representation for bundled local features that is effective for both learning to predict features and image retrieval.

Overview



We discover features that are useful for recognizing a place in a data-driven manner, and use this knowledge to predict useful features in a query image prior to the geo-localization process.

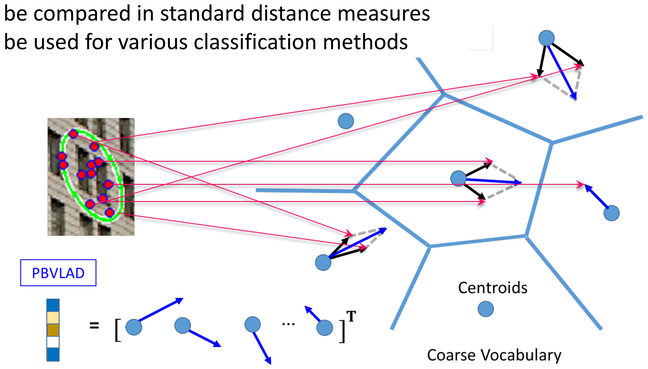
Feature Representation

Per-Bundle VLAD (PBVLAD)

MSER is described by a vector of locally aggregated descriptors (VLAD) on multiple scale-invariant features detected within the region.

Advantages:

- Robust to photometric and geometric changes
- Compact representation with fixed-size
- Can be compared in standard distance measures
- Can be used for various classification methods



$$p_a^w = \sum_{d_i : NN(d_i)=w, d_i \in B_a} \frac{d_i - c^w}{\|d_i - c^w\|} \qquad p_a = [p_a^1, p_a^2, ..., p_a^{|W|}]$$

Image Similarity

Matching score of feature to image: $f(p_q, I_r) = \max_{p_r \in I_r} M(p_q, p_r),$

Similarity between two images: $Sim(I_q, I_r) = \sum_{p_q \in I_q} f(p_q, I_r)$

Predicting Features for Geo-Localization

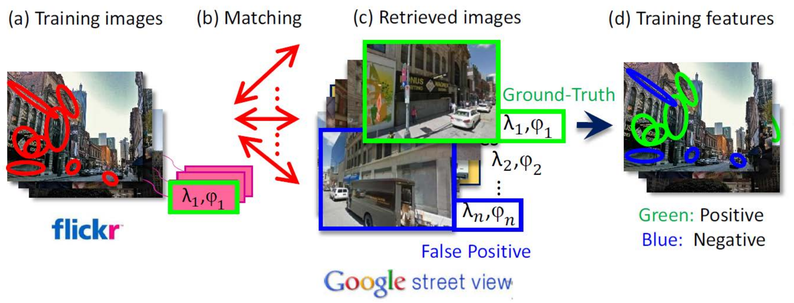
Automatic Training Data Generation

Utilize GPS-tagged images on the web to generate training data.

(1) Perform image geo-localization to get false positive images
- False positive images: Images in the shortlist whose GPS location is far away
- Ground-truth images: Spatially verified images near given GPS location

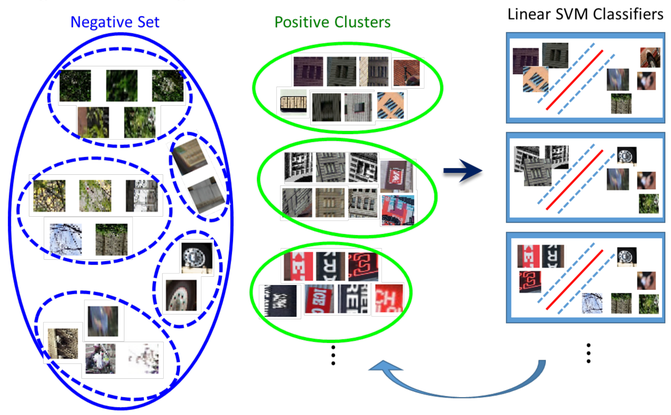
(2) Generate training data (features) comparing its matching score in ground-truth and false positives

- Positive: $f(p_t, I_{GT}) - f(p_t, I_{FP}) > m$
- Negative: $f(p_t, I_{GT}) - f(p_t, I_{FP}) < -m$



Closed-Loop Training of SVM Classifiers

Due to label conflicts and high intra-class variation, perform bottom-up clustering while training SVM on each cluster.

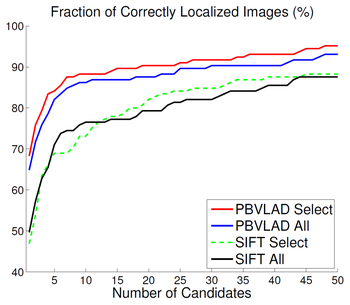


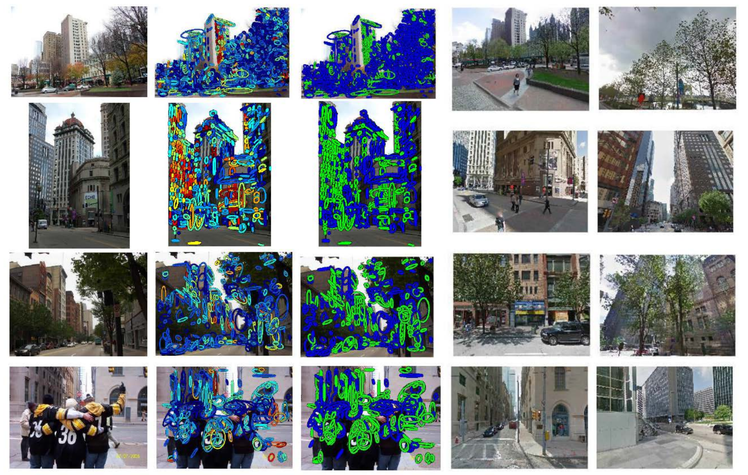
Experiments

Image Geolocalization in Pittsburgh, PA

Query Images: Unconstrained photos from photo sharing websites. [1]
Database Images: Google Streetview with 16 reprojcted images from each panorama

Method	% Correct
PBVLAD All	64.83
PBVLAD Select	**68.28**
PBVLAD Random	33.38
PBVLAD Select^C	19.31
SIFT All [1]	49.66
SIFT Select	46.90
Chance	0.20





Oxford Buildings Dataset

	Full	Dim Reduced		
Dim	16384	8192	4096	2048
mAP	**0.369**	0.364	0.334	0.264

Affect of dimension reduction

Descriptor	# Vocabulary	mAP
BoW	200,000	0.364
BoW	20,000	0.319
Fisher	64	0.317
VLAD	128	0.339
PBVLAD	128	**0.369**

Reference

[1] A. R. Zamir and M. Shah. Accurate image localization based on google maps street view. ECCV 2010

[2] Z. Wu, Q. Ke, M. Isard, and J. Sun. Bundling features for large scale partial-duplicate web image search. CVPR 2009

Acknowledgement

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