Image Matching and Visual Search

large scale methods and applications

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outline

1. local features and bag-of-words
2. local feature detection
3. visual vocabularies
4. spatial matching and re-ranking
5. geometry indexing
6. feature selection
7. clustering of photo collections
8. location and landmark recognition
9. implementation: `ivl` library

outline

image matching

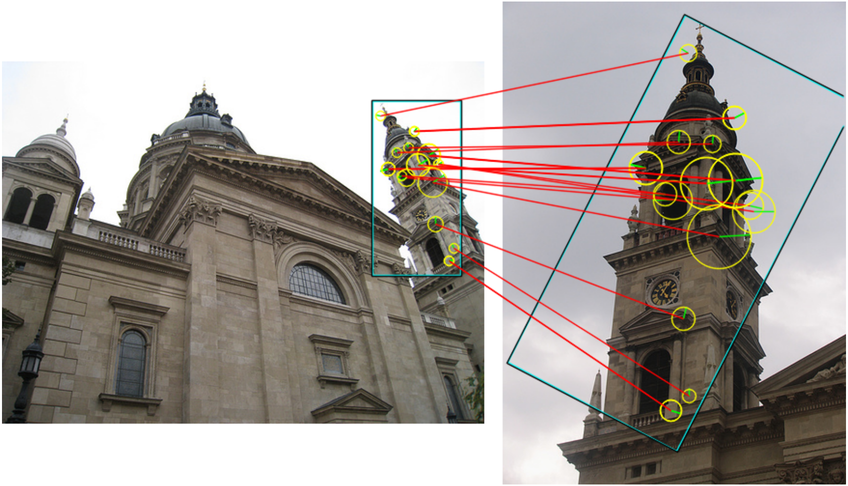
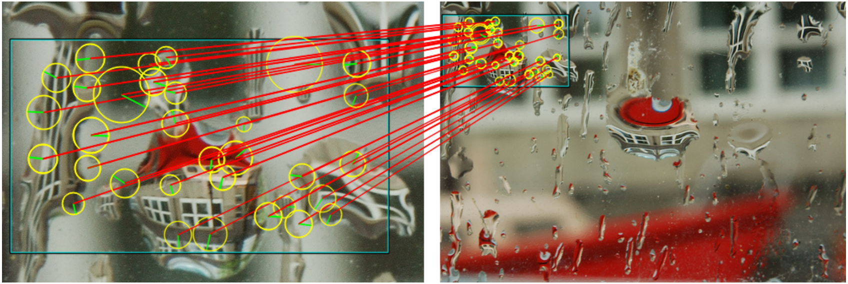
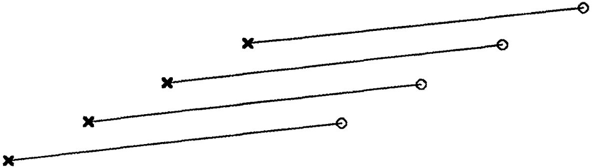


image matching



matching local feature points

[Scott and Longuet-Higgins, RSL 1991]



- given two sets of points $a_i, i = 1, \ldots, m$ and $b_j, j = 1, \ldots, n$ on the same plane, let d_{ij} be the distance between a_i and b_j
- following earlier theories of Ullman and Marr, the problem is to associate points a_i and b_j in a one-to-one correspondence such that the sum of squared distances between corresponding points is minimized

a spectral approach

1. construct the $m \times n$ proximity matrix G with elements

$$g_{ij} = \exp(-d_{ij}^2/2\sigma^2)$$

2. perform singular value decomposition of G

$$G = USV^{\mathrm{T}}$$

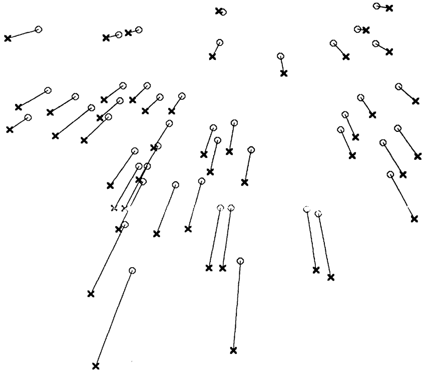
   where U, V are orthogonal matrices of dimension m, n and S is a non-negative diagonal $m \times n$ matrix

3. replace each diagonal element s_{ij} of S by 1 and reconstruct

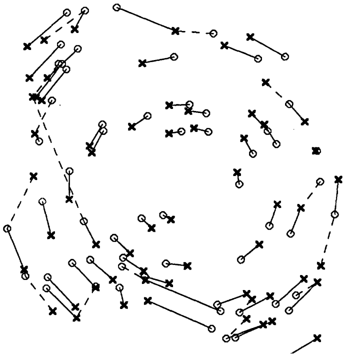
$$P = UEV^{\mathrm{T}}$$

4. finally, associate points a_i and b_j if element p_{ij} of P is the greatest element in its row and its column

a spectral approach



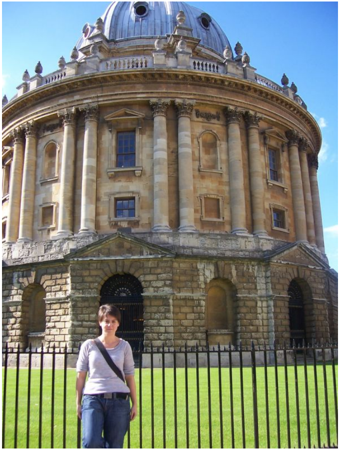
scale, translation



rotation

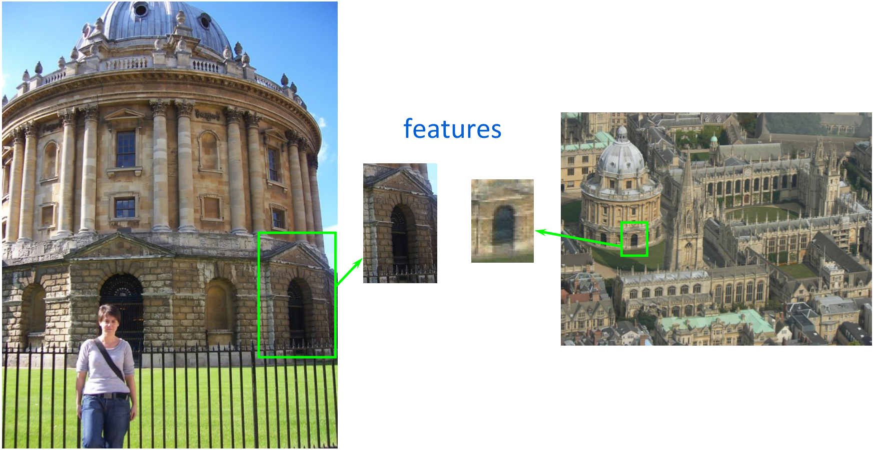
matching discriminative local features

[Lowe, ICCV 1999]



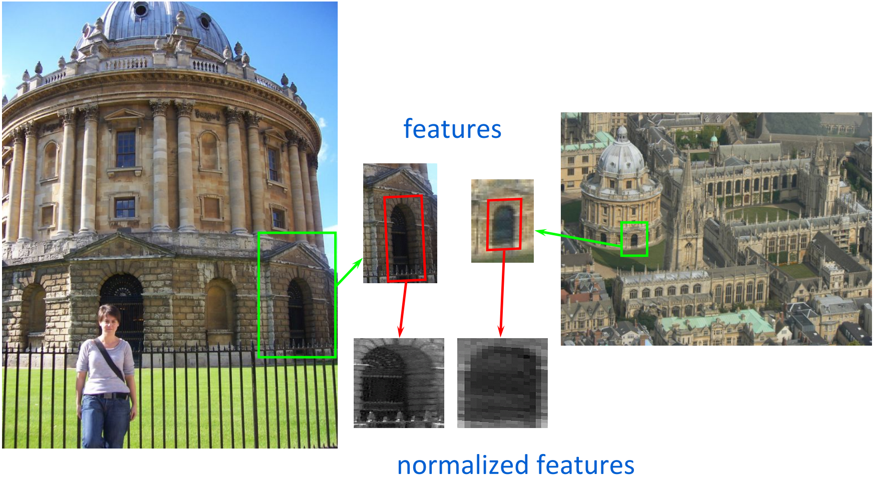
matching discriminative local features

[Lowe, ICCV 1999]



matching discriminative local features

[Lowe, ICCV 1999]

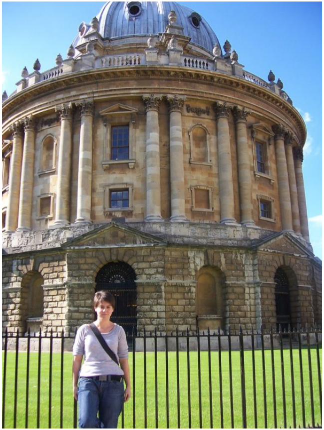


forget about geometry: bag-of-words

[Sivic and Zisserman, ICCV 2003]

Object → Bag of 'words'

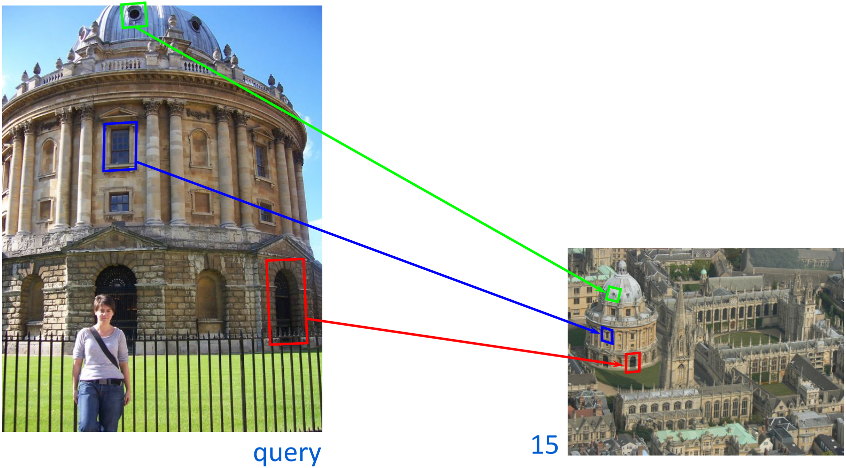
vector quantization $\rightarrow$ visual words



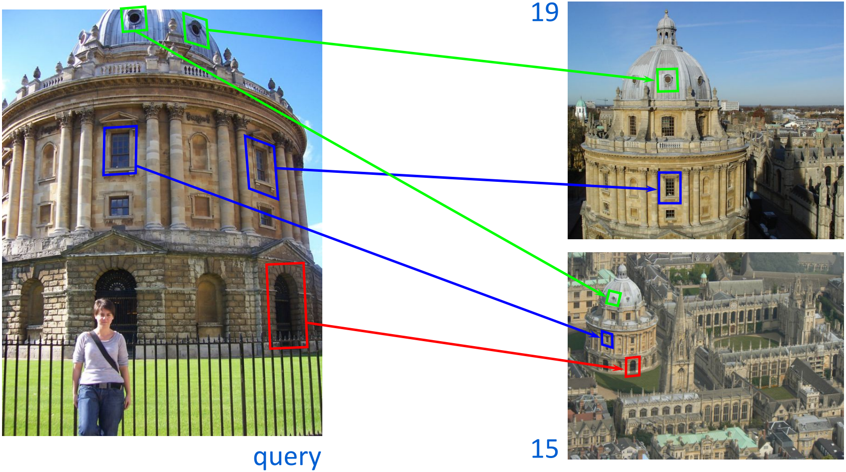
query

15

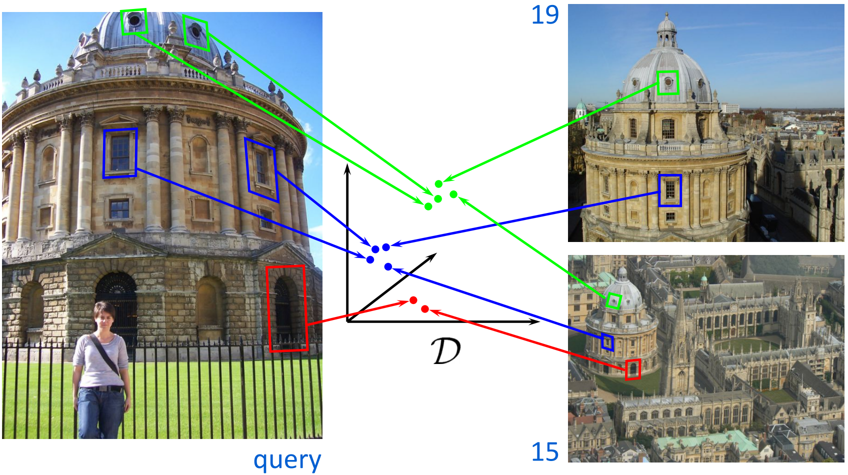
vector quantization → visual words



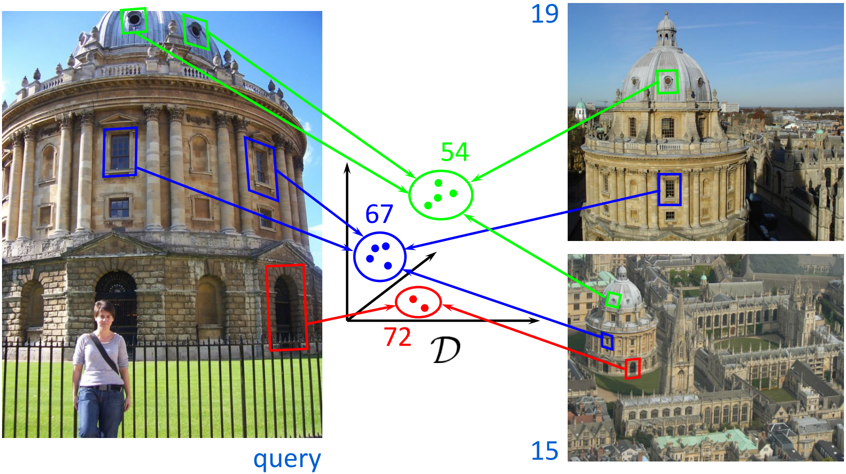
vector quantization $\rightarrow$ visual words



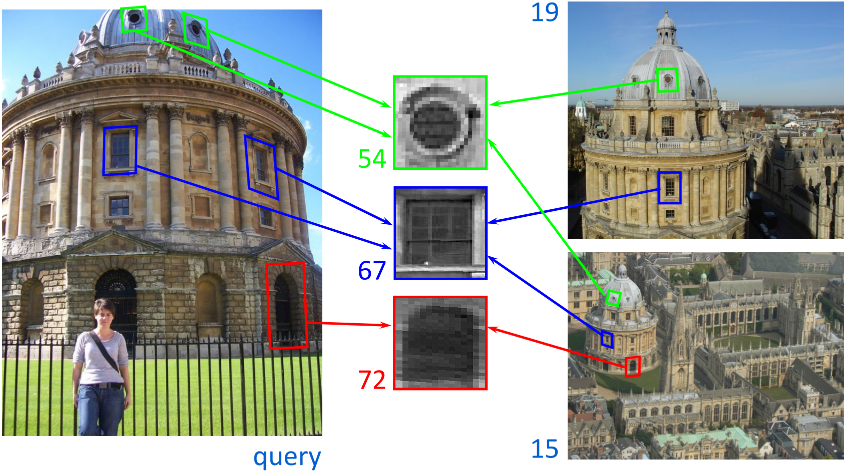
vector quantization → visual words



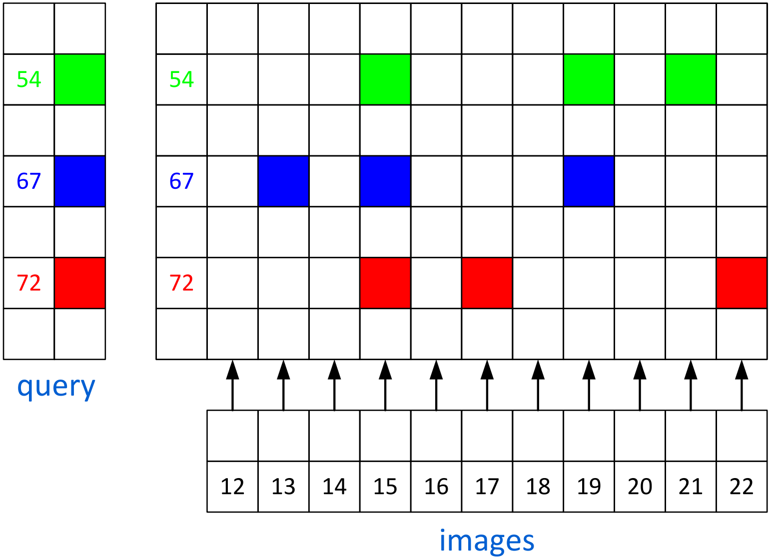
vector quantization → visual words



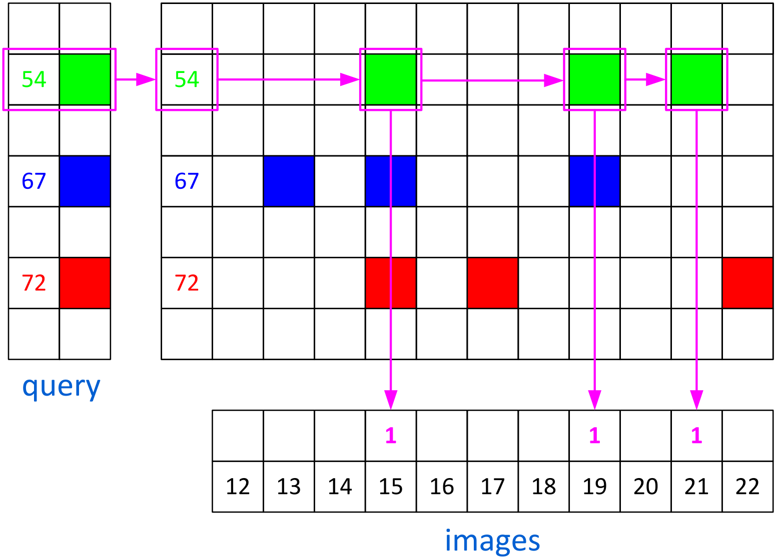
vector quantization → visual words



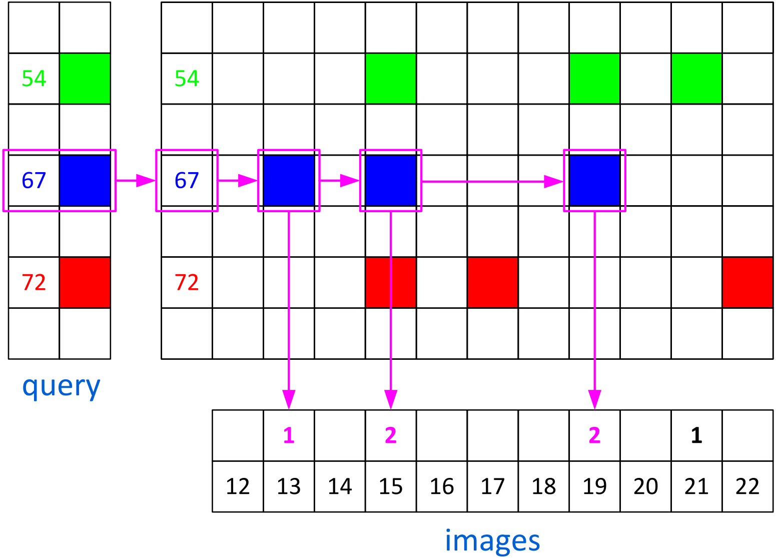
inverted file indexing



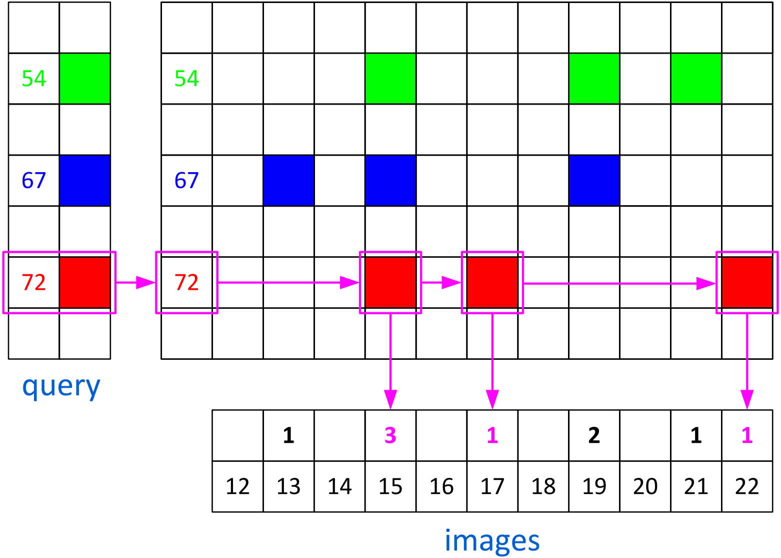
inverted file indexing



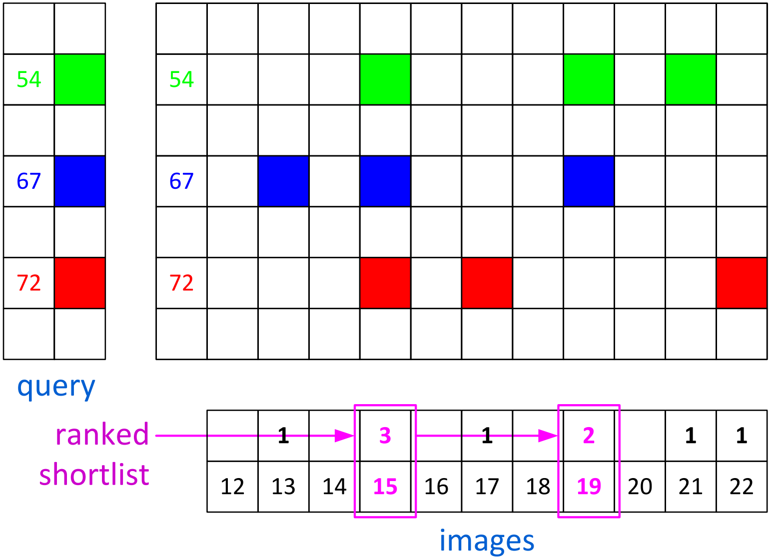
inverted file indexing



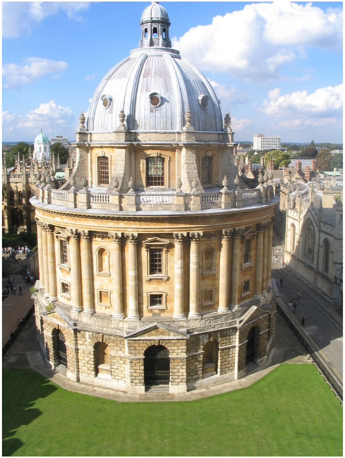
inverted file indexing

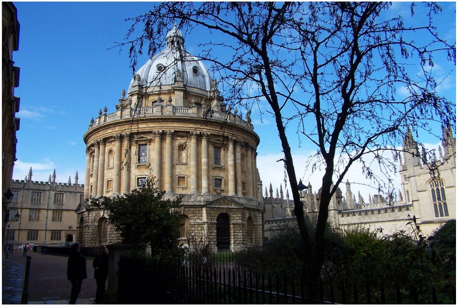


inverted file indexing



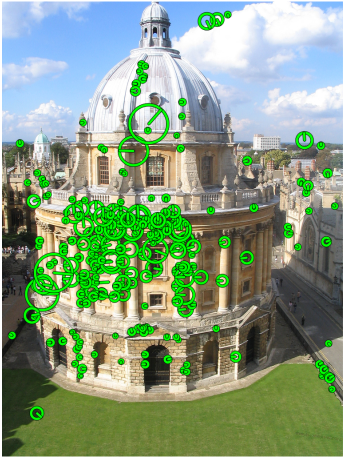
back to geometry: re-ranking





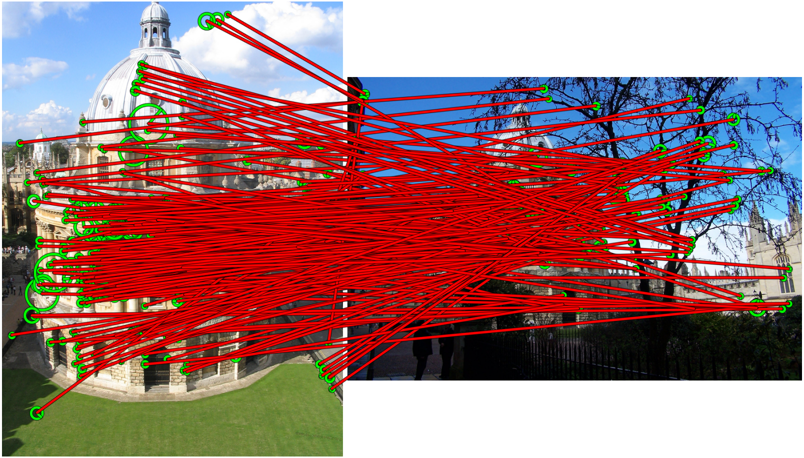
original images

back to geometry: re-ranking



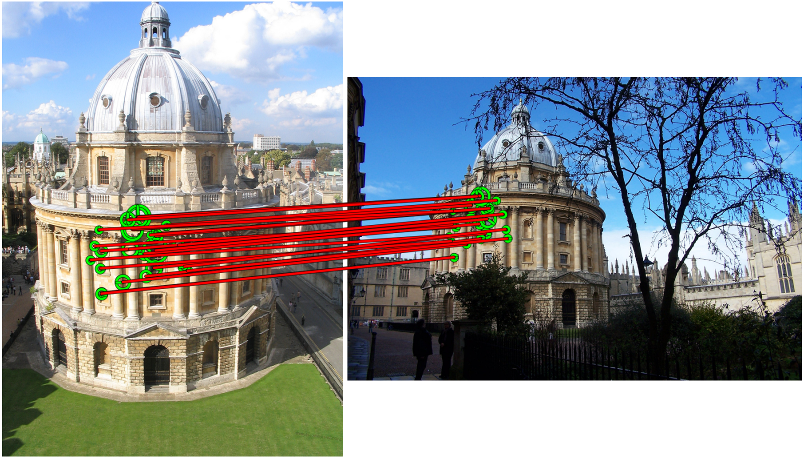

local features

back to geometry: re-ranking



tentative correspondences

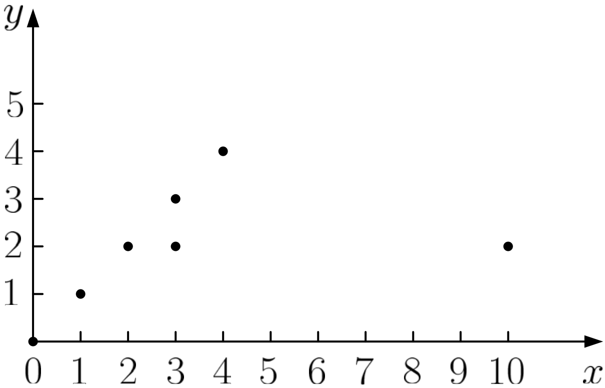
back to geometry: re-ranking



RANSAC inliers

RANSAC

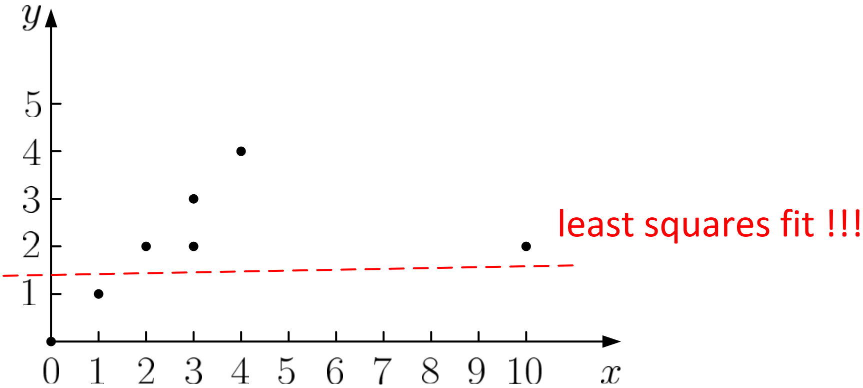
[Fischler and Bolles, CACM 1981]



problem: fit line to data

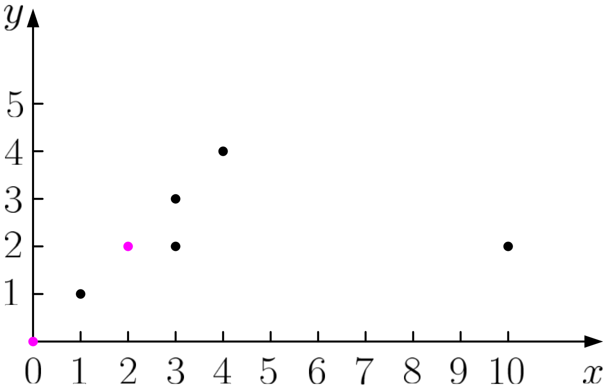
RANSAC

[Fischler and Bolles, CACM 1981]



RANSAC

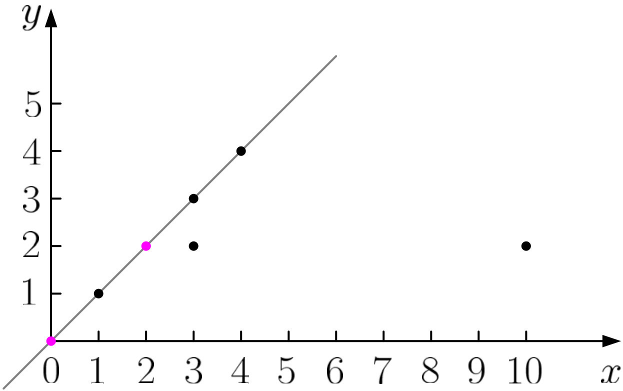
[Fischler and Bolles, CACM 1981]



solution: choose 2 random points ...

RANSAC

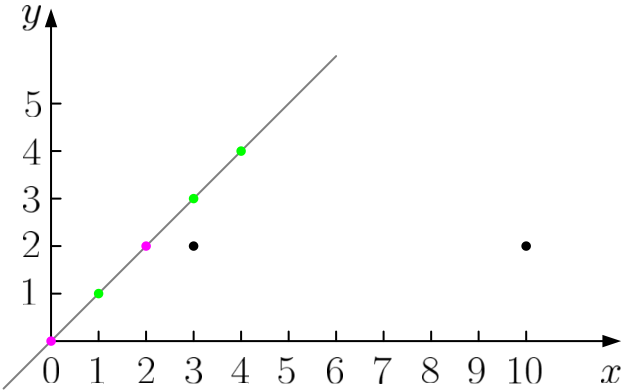
[Fischler and Bolles, CACM 1981]



... fit line to them ...

RANSAC

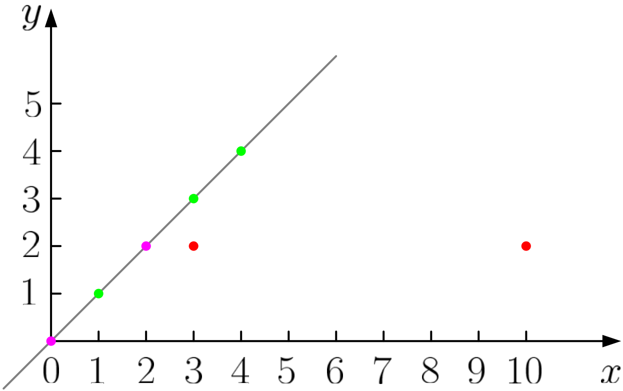
[Fischler and Bolles, CACM 1981]



... classify remaining points to inliers ...

RANSAC

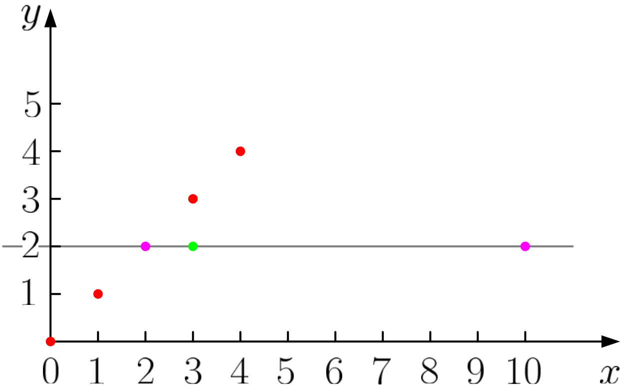
[Fischler and Bolles, CACM 1981]



... and outliers

RANSAC

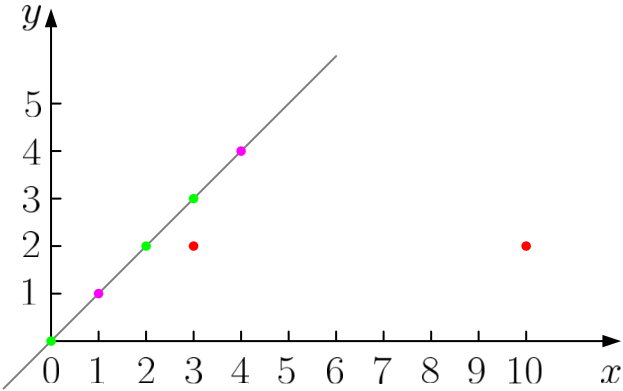
[Fischler and Bolles, CACM 1981]



repeat ...

RANSAC

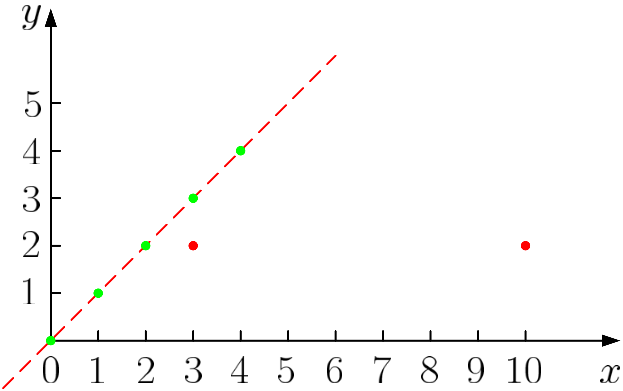
[Fischler and Bolles, CACM 1981]



... and repeat

RANSAC

[Fischler and Bolles, CACM 1981]



finally: maximum inliers

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2. **local feature detection**
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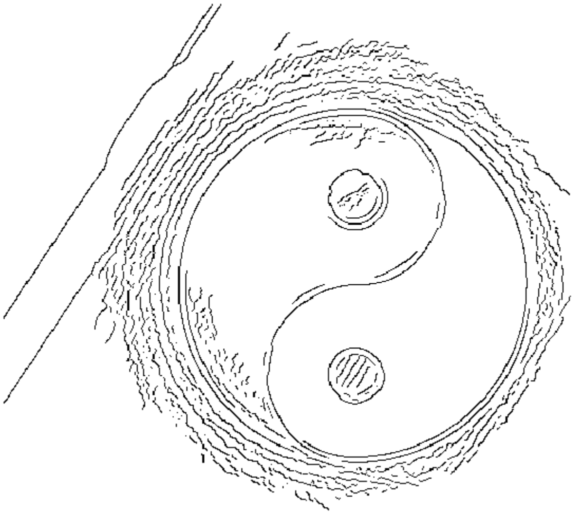
edge-based feature detection

[Rapantzikos and Avrithis, ECCVW 2010]

- blob-like regions starting from single-scale edges
- local maxima of Euclidean distance transform expected to lie in region interior or close to ridges
- greedily merge maxima guided by edge strength, to reproduce the effect of smoothing in scale-space evolution
- regions of arbitrary shape and scale, unaffected by spurious or disconnected edges

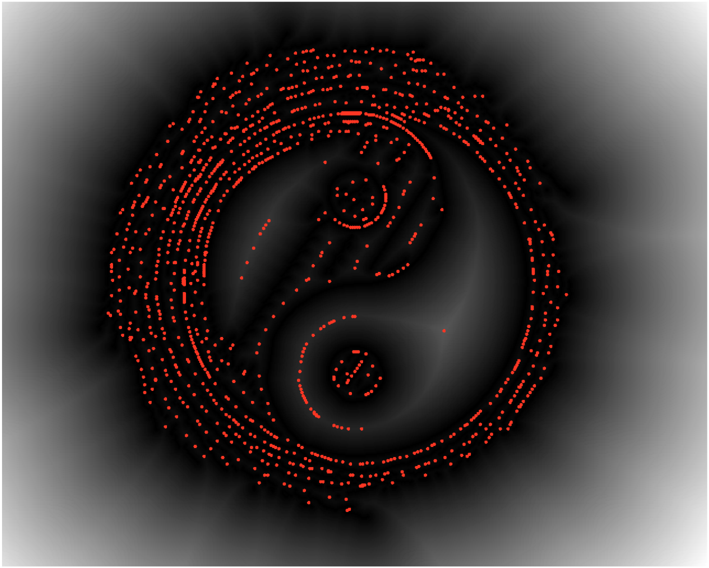
original image

binary edge map

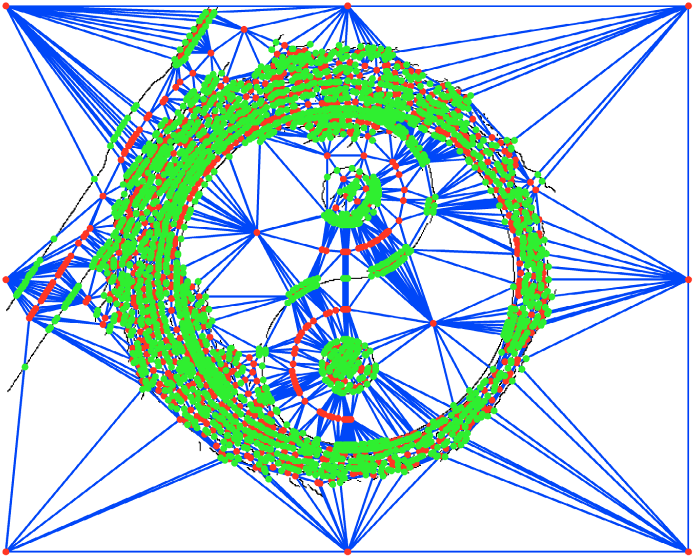


binary distance map

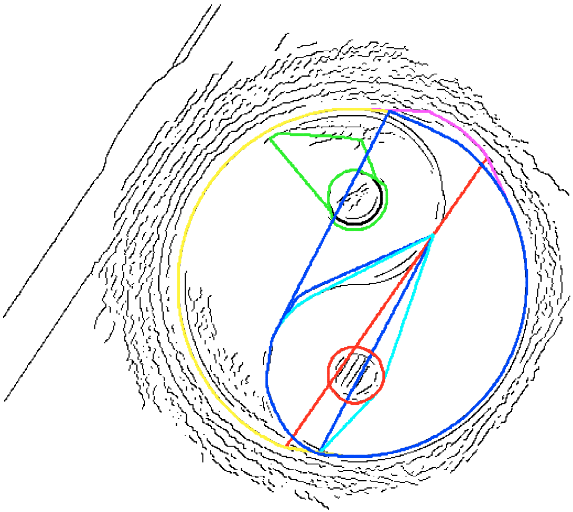
distance map + local maxima



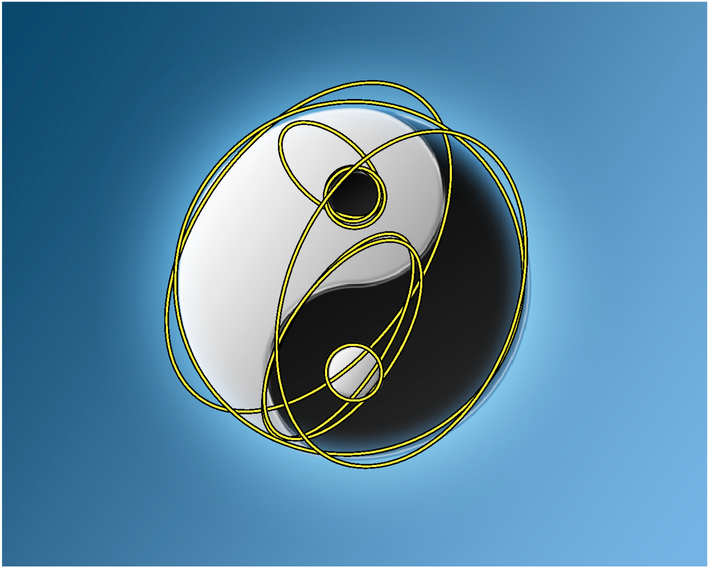
Delaunay triangulation



convex hulls of selected regions



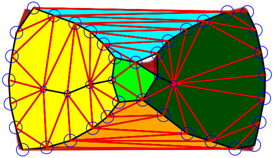
original image + features



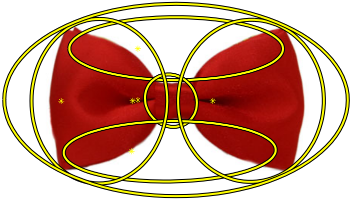
weighted α-shapes

[Varytimidis et al., submitted to ECCV 2012]

input



triangulation



α-detector

MSER

medial features

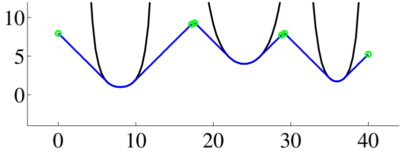
[Avrithis and Rapantzikos, ICCV 2011]

- additively weighted distance map directly from image gradient, computed exactly in linear time

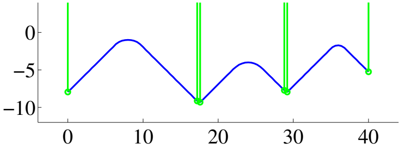
$$\mathcal{D}_d(f)(x) = \min_{y \in X}\{d(x,y) + f(y)\}, \quad x \in X$$

- weighted medial capturing region structure and topology
- region/boundary duality and image partition

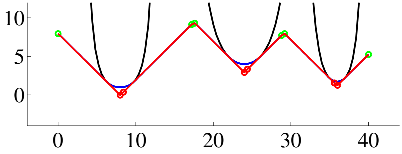
region/boundary duality



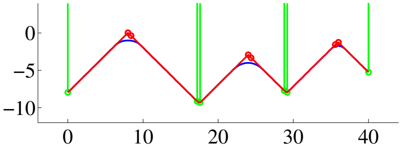
distance propagation



negated distance & medial

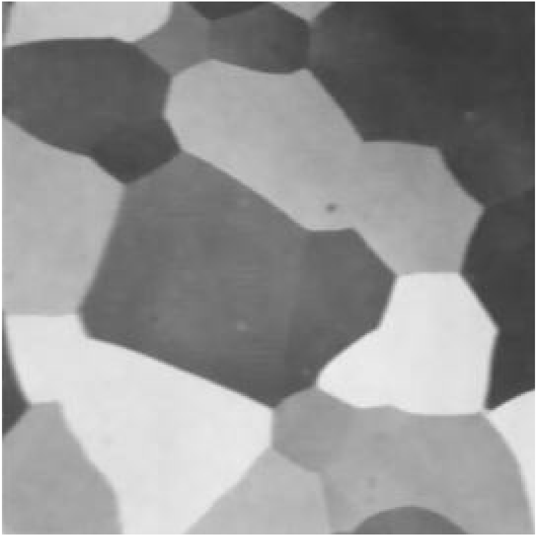


partition

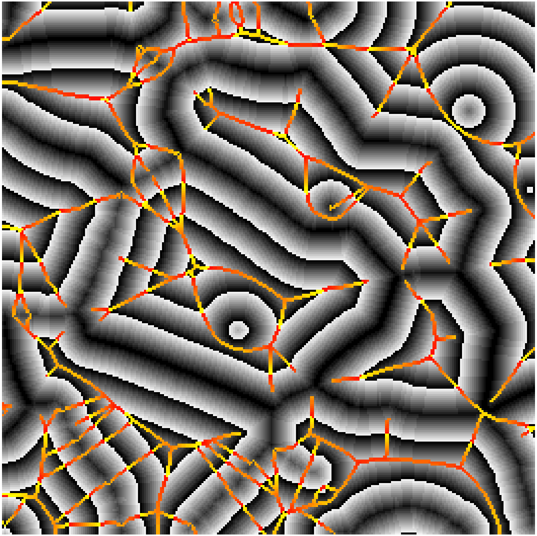


backpropagation

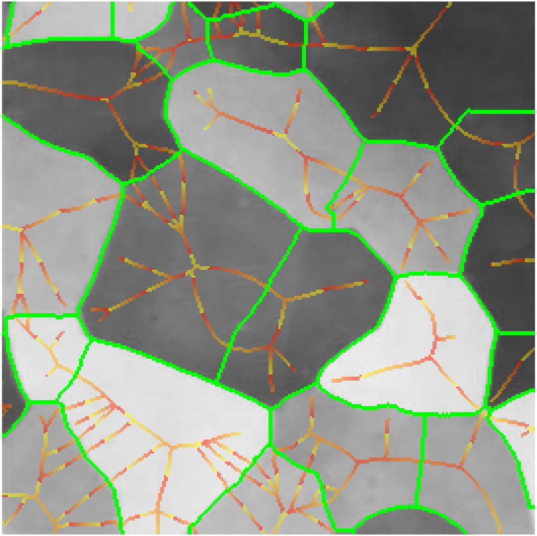
original image



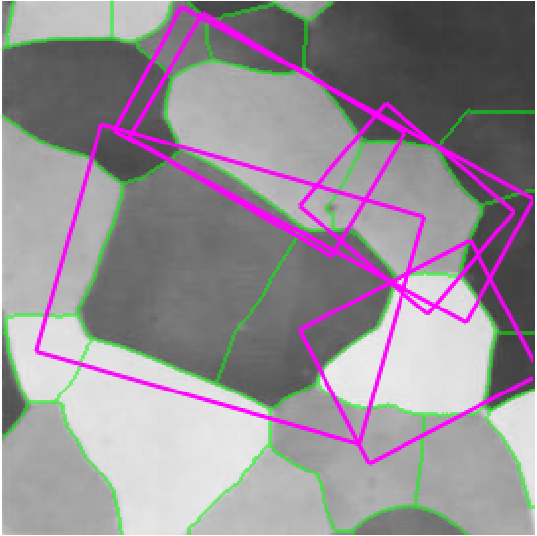
weighted distance map and medial



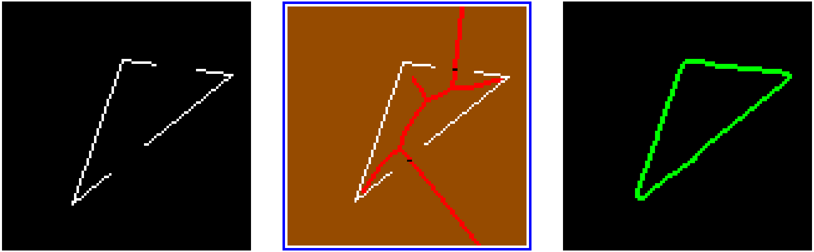
region/boundary duality



original image + features



fragmentation factor

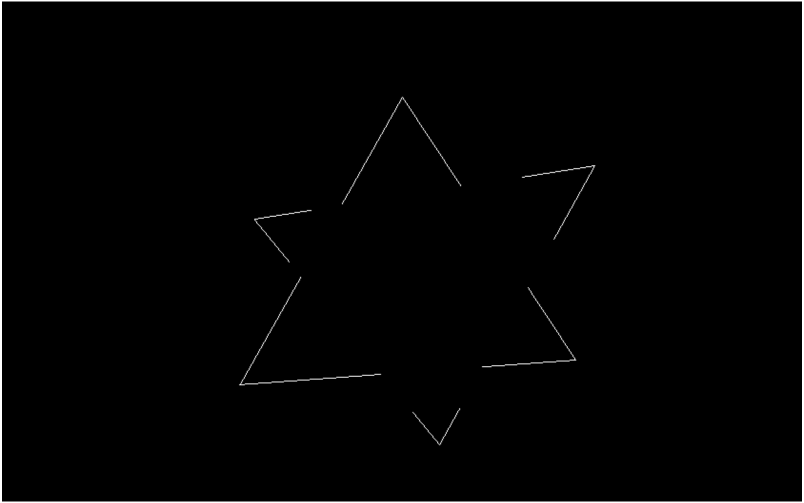


binary input | point labels | image partition

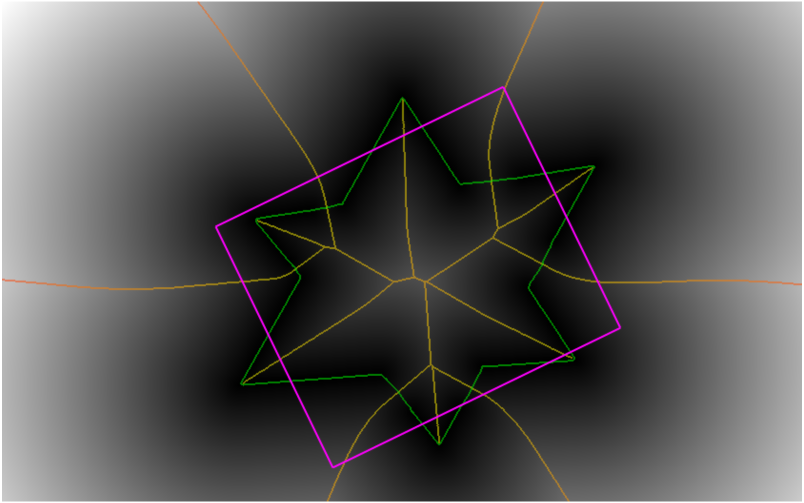
$$\phi(\kappa) = \frac{1}{a(\kappa)} \sum_{e \in E(\kappa)} w^2(x(e))$$

- simple selection criterion: is a region well-enclosed by boundaries?
- arbitrary shape and scale, without explicit scale-space construction

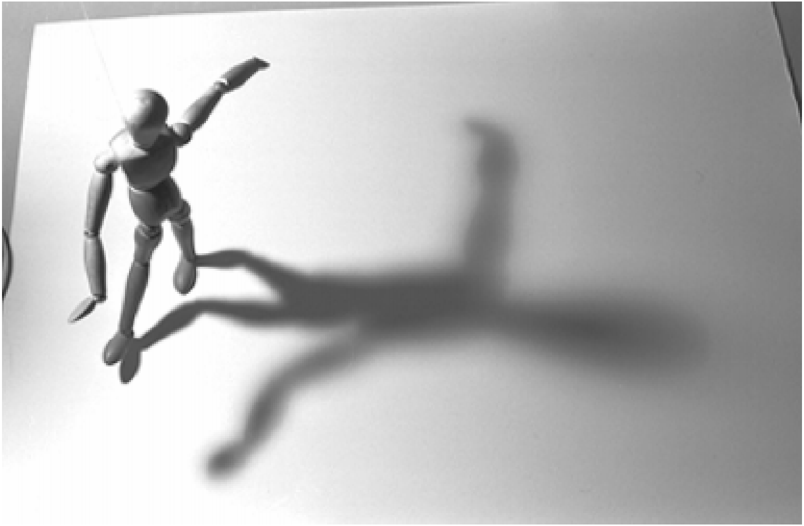
the challenge of shape



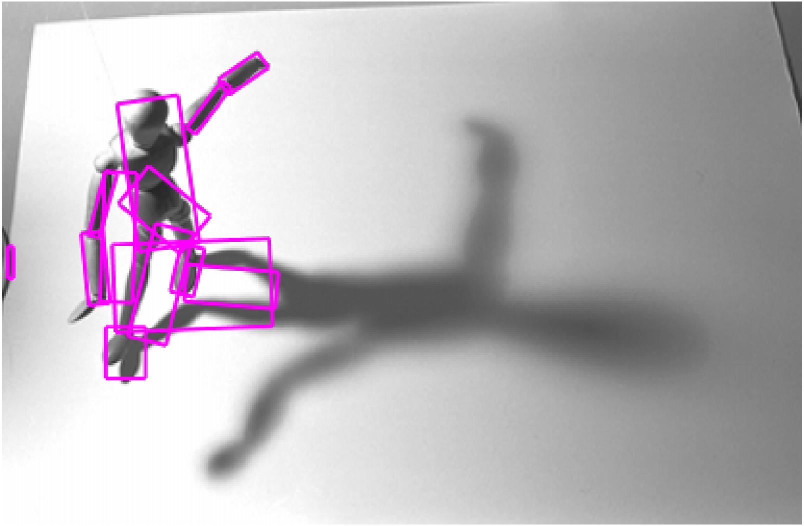
the challenge of shape



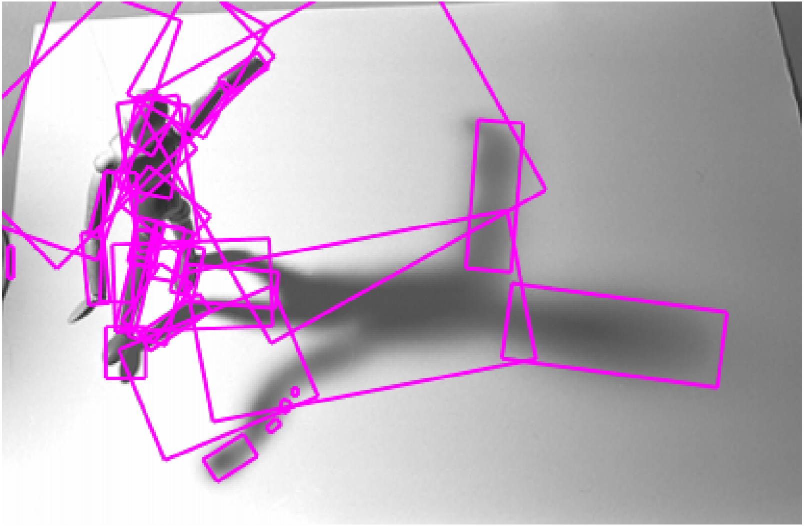
the challenge of scale



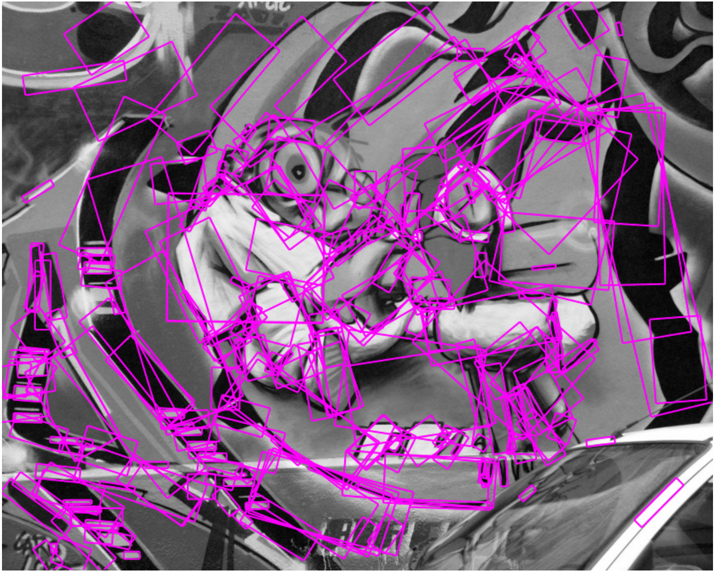
the challenge of scale



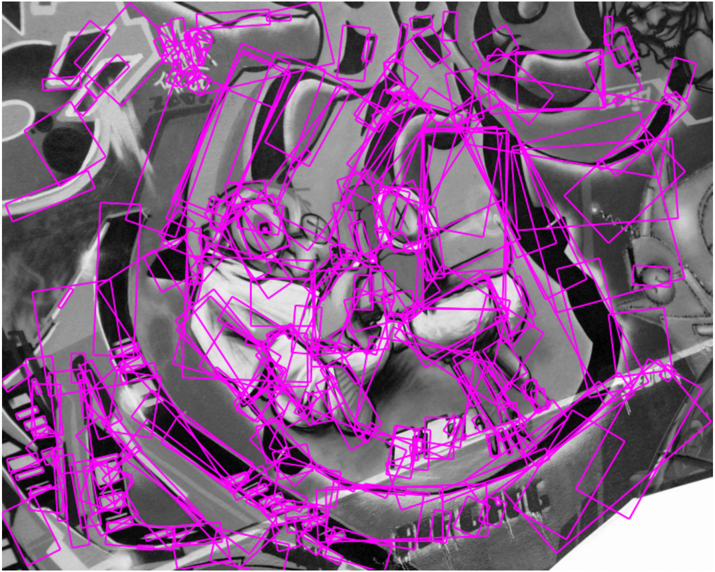
the challenge of scale



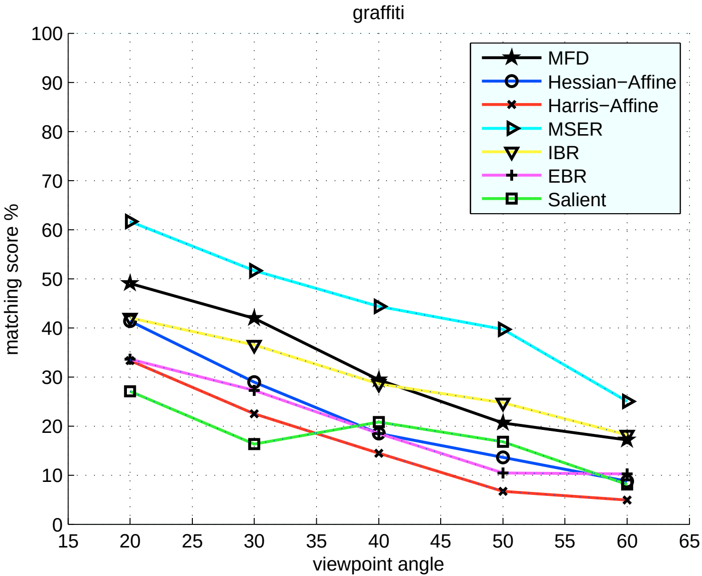
viewpoint: graffiti scene



viewpoint: `graffiti` scene



viewpoint: `graffiti` scene



scale + rotation: `boat` scene

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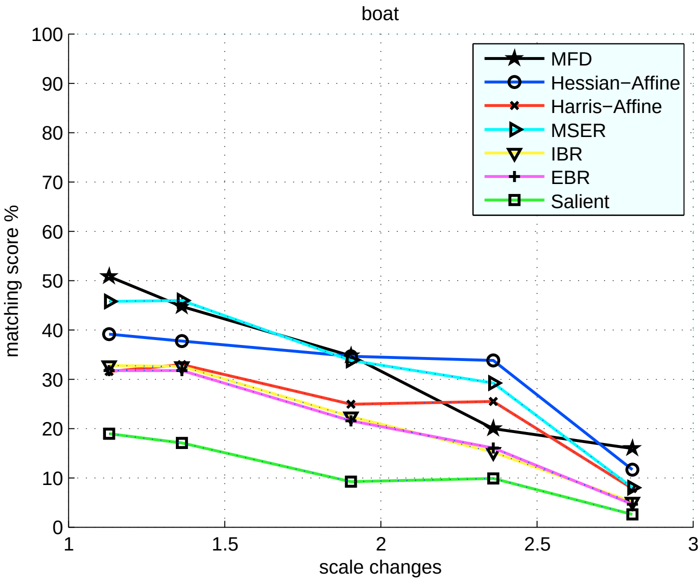

blur: `bikes` scene

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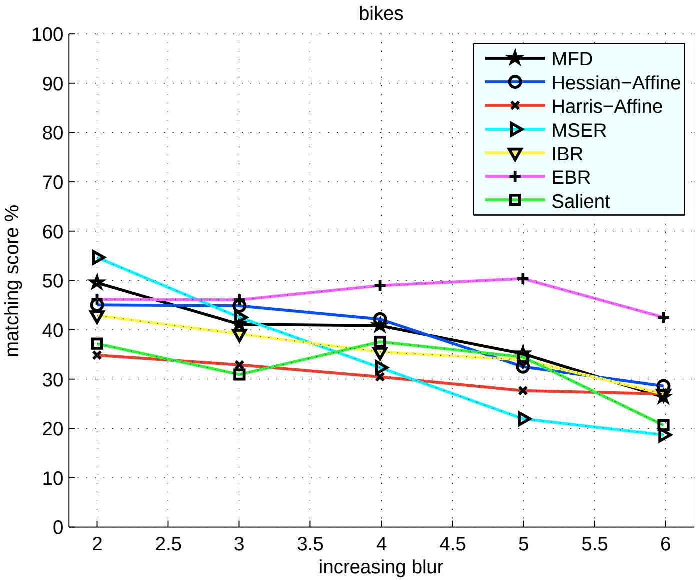
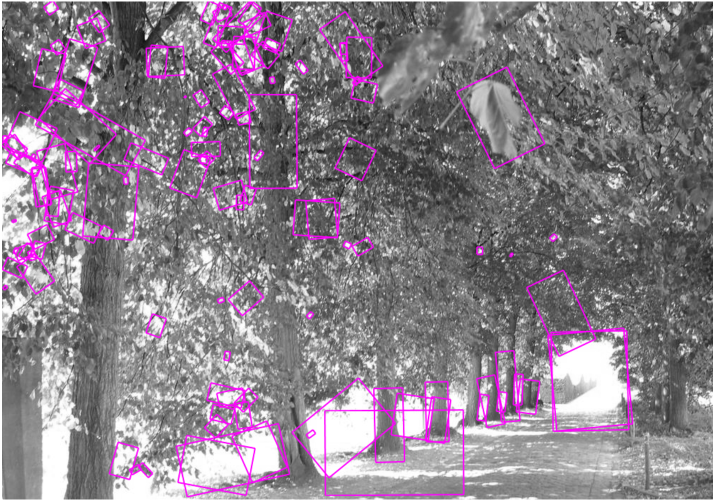
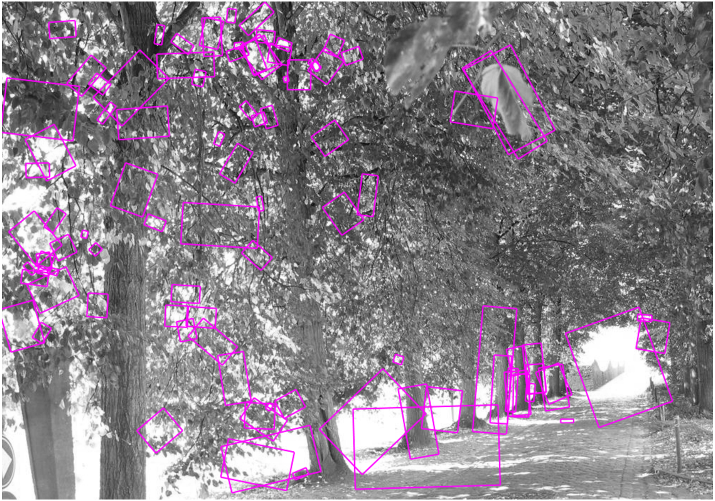


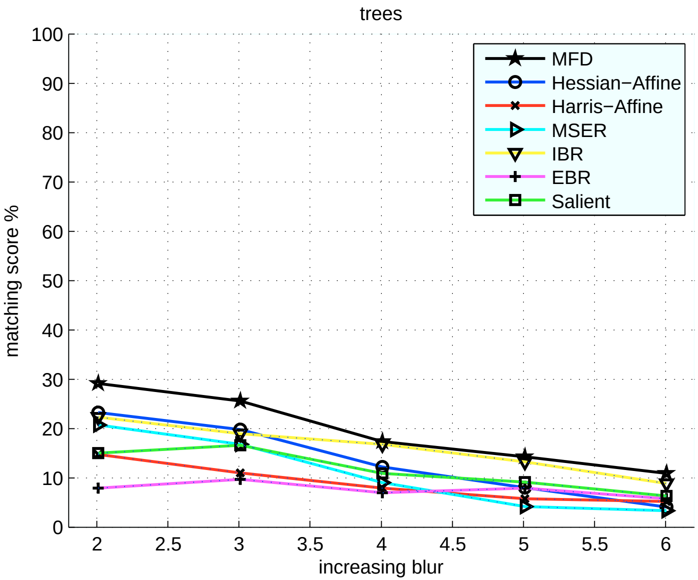
texture + blur: `trees` scene



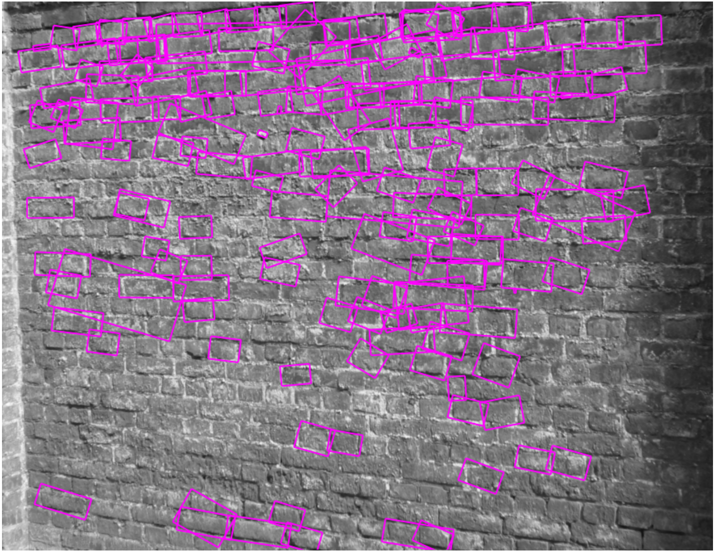
texture + blur: `trees` scene



texture + blur: `trees` scene



viewpoint: `wall` scene



viewpoint: `wall` scene

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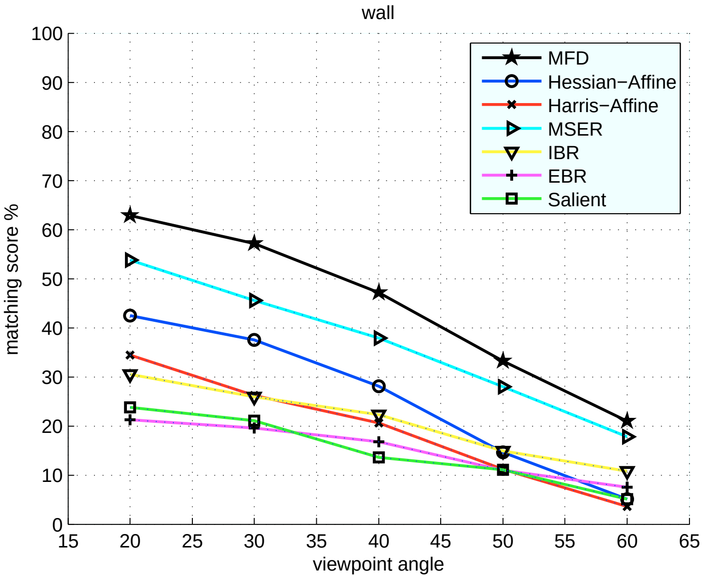
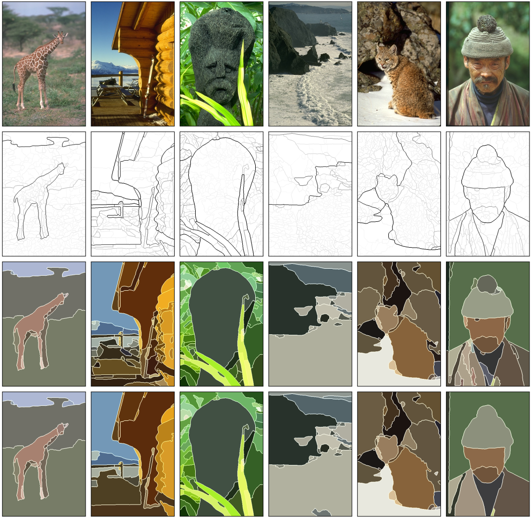


application to segmentation

[Avrithis and Leonardos, unpublished 2012]



application to segmentation

[Avrithis and Leonardos, unpublished 2012]

	BSDS500						
	Covering			PRI		VI	
	ODS	OIS	Best	ODS	OIS	ODS	OIS
Human	0.72	0.72	–	0.88	0.88	1.17	1.17
gPb-owt-ucm[3]	**0.59**	**0.65**	**0.74**	**0.83**	**0.86**	1.69	1.48
gPb-mad-ucm$_g$	0.58	0.64	**0.74**	**0.83**	**0.86**	**1.62**	**1.39**
gPb-mad-esm$_c$	0.55	0.62	0.71	0.82	**0.86**	1.83	1.51
Mean Shift [15]	0.54	0.58	0.66	0.79	0.81	1.85	1.64
Felz-Hutt [18]	0.52	0.57	0.69	0.80	0.82	2.21	1.87
gPb-mad-sfm	0.52	0.56	0.62	0.79	0.82	1.83	1.70
gPb-mad-esm$_a$	0.51	0.54	0.60	0.79	0.80	1.86	1.82
Canny-owt-ucm [3]	0.49	0.55	0.66	0.79	0.83	2.19	1.89
myCanny-mad-ucm$_g$	0.48	0.55	0.65	0.79	0.83	2.10	1.77
gPb-mad-ucm$_\phi$	0.46	0.54	0.63	0.77	0.80	2.07	1.81
NCuts [16]	0.45	0.53	0.67	0.78	0.80	2.23	1.89
gCanny-mad-esm$_c$	0.45	0.53	0.63	0.78	0.83	2.31	1.91
gCanny-mad-sfm	0.42	0.49	0.58	0.77	0.80	2.18	1.95
gCanny-mad-esm$_a$	0.40	0.47	0.53	0.76	0.77	2.41	2.27
gCanny-mad-ucm$_\phi$	0.35	0.42	0.50	0.74	0.77	2.43	2.29
Quad-Tree	0.32	0.37	0.46	0.73	0.74	2.46	2.32

outline

1. local features and bag-of-words
2. local feature detection
3. **visual vocabularies**
4. spatial matching and re-ranking
5. geometry indexing
6. feature selection
7. clustering of photo collections
8. location and landmark recognition
9. implementation: `ivl` library

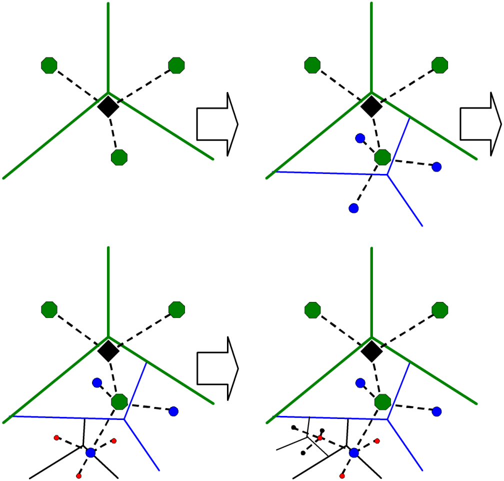
hierarchical k-means

[Nister and Stewenius, CVPR 2006]

- large scale clustering: $n = 10^7$ data points into $k = 10^6$ clusters, in $d = 10^2$ dimensions!
- complexity of k-means per iteration is $O(ndk)$: not practical!
- build a vocabulary tree by hierarchical k-means
- *e.g.* with a branching factor of $b = 10$, one needs only $l = \log_b k = 6$ levels, of complexity $O(ndb)$ each
- the same tree is used for nearest neighbor search and scoring

hierarchical k-means

[Nister and Stewenius, CVPR 2006]



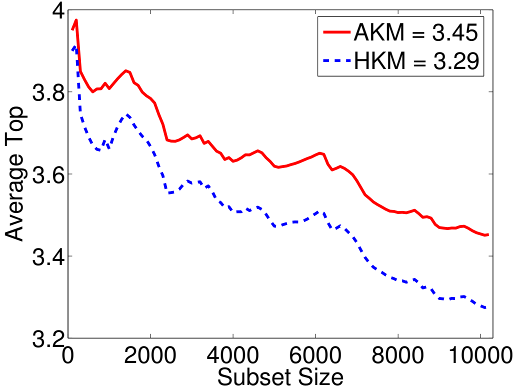
approximate k-means

[Philbin et al., CVPR 2007]

- in k-means, most computation is spent on searching for nearest neighbors between points and cluster centers
- replace exact search by an approximate nearest neighbor (ANN) search, implemented by randomized k-d trees
- now a single level of complexity $O(ndt)$ is needed, where t is a fixed number of tests, *e.g.* $t = 100$
- more flexible than hierarchical k-means!

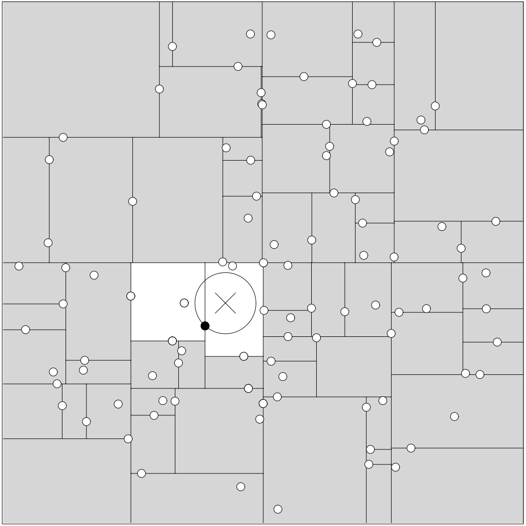
approximate k-means

[Philbin et al., CVPR 2007]



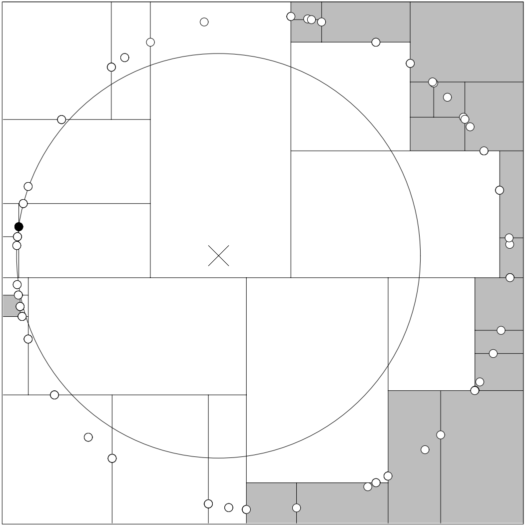
exact nearest neighbors: k-d tree

[Bentley, ACM 1975]



exact nearest neighbors: k-d tree

[Bentley, ACM 1975]



approximate NN: randomized k-d trees

[Silpa-Anan and Hartley, CVPR 2008]

indexing

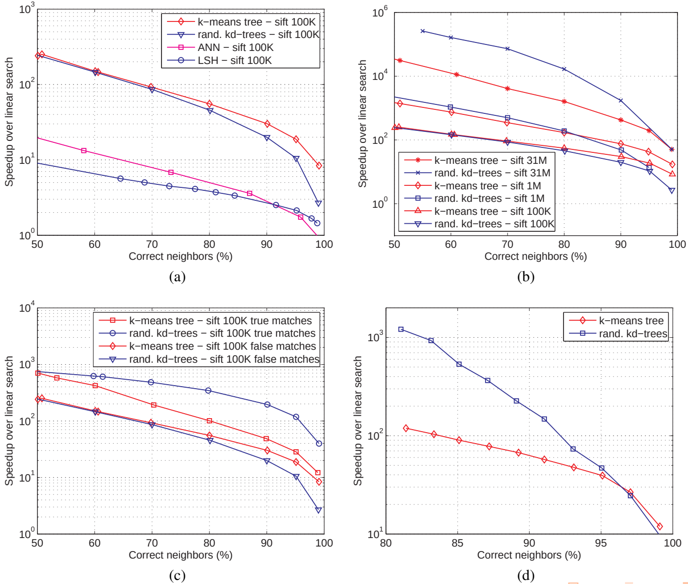
- build m different k-d trees, each with a different structure
- use a random *e.g.* splitting plane, rotation, or projection for each tree

search

- parallel search among all m trees, with a limit of t nodes in total
- traverse all trees once, then use a shared priority queue

FLANN implementation

[Muja and Lowe, VISAPP 2009]



Gaussian mixtures

- each cluster j represented by component p_j with

$$p_j(\cdot) = \pi_j \mathcal{N}(\cdot | \boldsymbol{\mu}_j, \sigma_j \mathbf{I}),$$

  modeling its population π_j, position $\boldsymbol{\mu}_j$ and scale σ_j
- responsibility of component p_j for data point $\mathbf{x}_i$

$$\gamma_{ij} = \frac{p_j(\mathbf{x}_i)}{\sum_\ell p_\ell(\mathbf{x}_i)}$$

- maximum likelihood estimates of parameters $\pi_j, \boldsymbol{\mu}_j, \sigma_j$ obtained as weighted averages over data, with responsibilities as weights
- iteratively compute responsibilities and parameters by expectation maximization (EM)

approximate Gaussian mixtures

[Avrithis and Kalantidis, submitted to ECCV 2012]

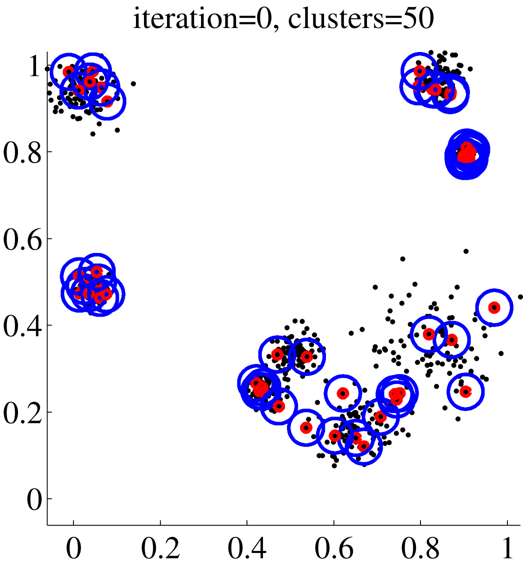
incremental search

- keep all t nearest neighbors found for each data point, not just the best
- use them across iterations, limiting the effort spent in new search
- limit responsibilities to this approximate nearest neighbor set: complexity is still $O(ndt)$

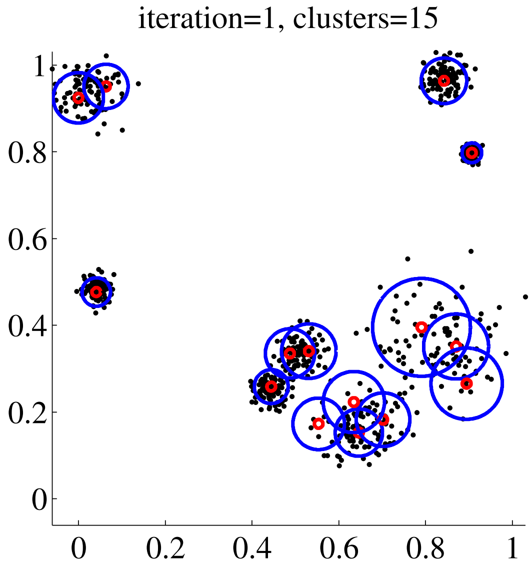
dynamic estimation of k

- start with all data points as components
- purge overlapping clusters and expand remaining ones at each iteration

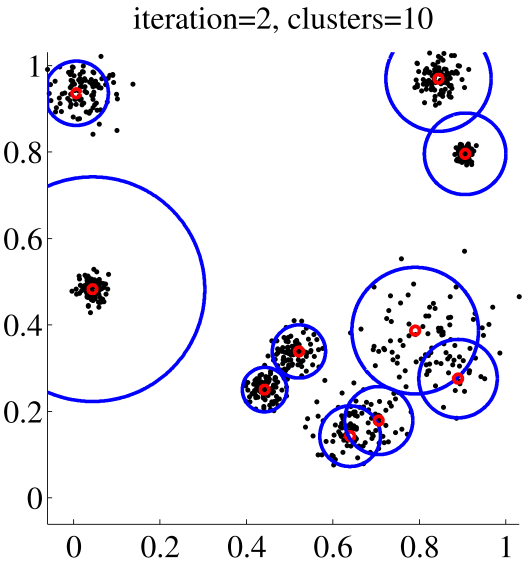
approximate Gaussian mixtures—2d example



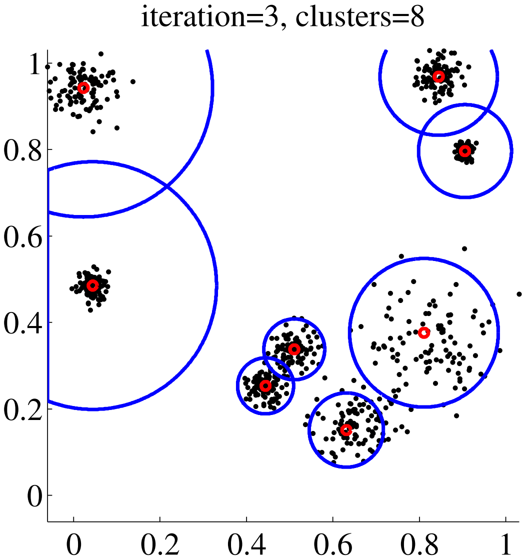
approximate Gaussian mixtures—2d example



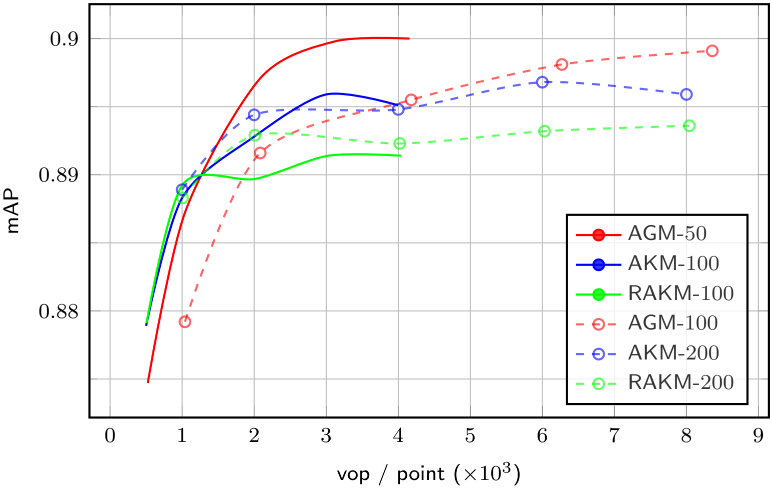
approximate Gaussian mixtures—2d example



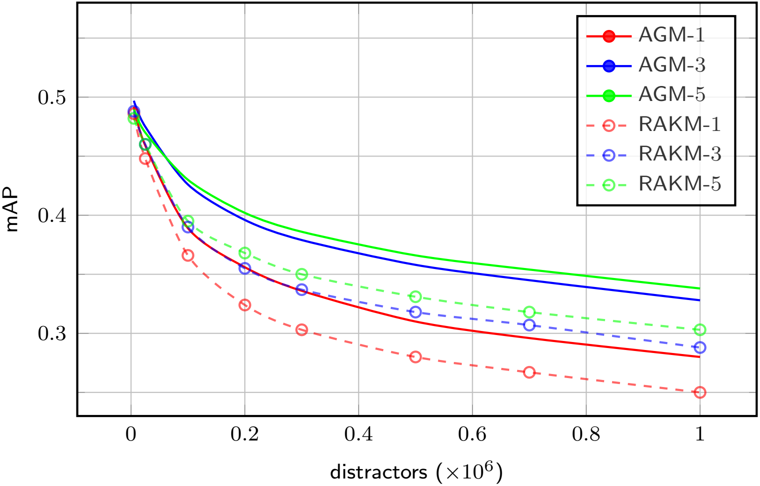
approximate Gaussian mixtures—2d example



approximate Gaussian mixtures—learning



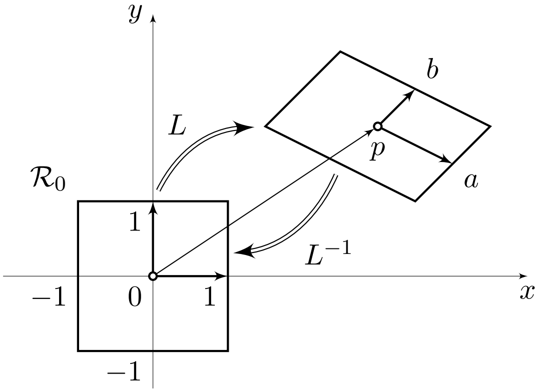
approximate Gaussian mixtures—distractors



outline

local patches

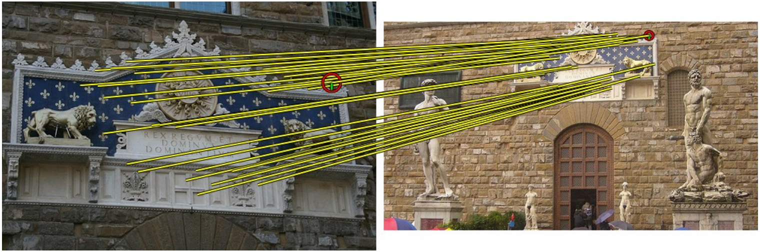
- each local feature is associated with an image patch L, which also represents an affine transform
- the rectified patch $\mathcal{R}_0$ is transformed to the patch via L
- the patch is rectified back to $\mathcal{R}_0$ via L^{-1}



fast spatial matching (FSM)

[Philbin et al., CVPR 2007]

- single patch correspondence $L \leftrightarrow R$
- the transformation from one patch to the other is RL^{-1}
- each correspondence provides a transformation hypothesis
- hypotheses are now $O(n)$; we can try them all for inliers
- overall complexity is $O(n^2)$

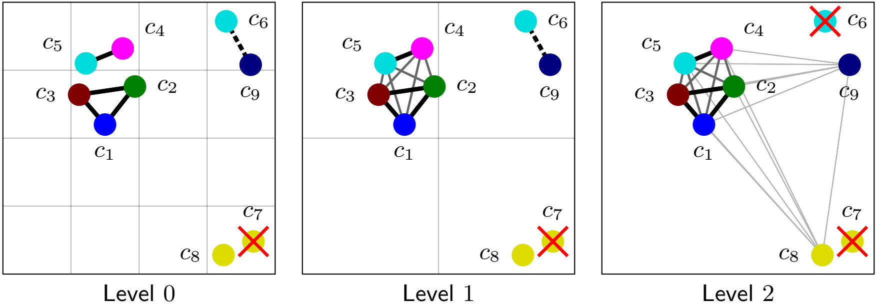


relaxed spatial matching

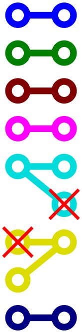
[Tolias and Avrithis, ICCV 2011]

- do not seek for inliers
- rather, look for hypotheses that agree with each other
- how? build a hierarchical partition of 4d transformation space and count hypotheses that fall in the same bin
- inspired by Hough voting—hence Hough pyramid matching (HPM)
- for ℓ levels (*e.g.* $\ell = 5$), complexity drops from $O(n^2)$ to $O(n\ell)$!

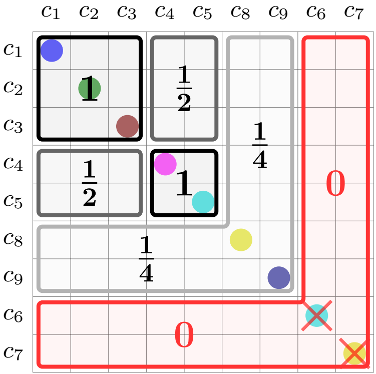
toy example—Hough pyramid



toy example—correspondences, strengths

	$p \quad q$	strength
c_1		$(2 + \frac{1}{2}2 + \frac{1}{4}2)w(c_1)$
c_2		$(2 + \frac{1}{2}2 + \frac{1}{4}2)w(c_2)$
c_3		$(2 + \frac{1}{2}2 + \frac{1}{4}2)w(c_3)$
c_4		$(1 + \frac{1}{2}3 + \frac{1}{4}2)w(c_4)$
c_5		$(1 + \frac{1}{2}3 + \frac{1}{4}2)w(c_5)$
c_6		0
c_7		0
c_8		$\frac{1}{4}6w(c_8)$
c_9		$\frac{1}{4}6w(c_9)$

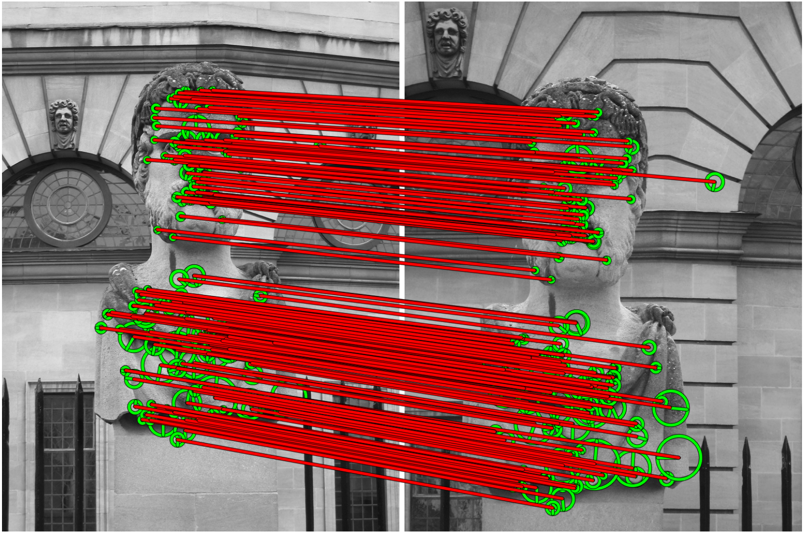
toy example—affinity matrix



relaxed spatial matching ...

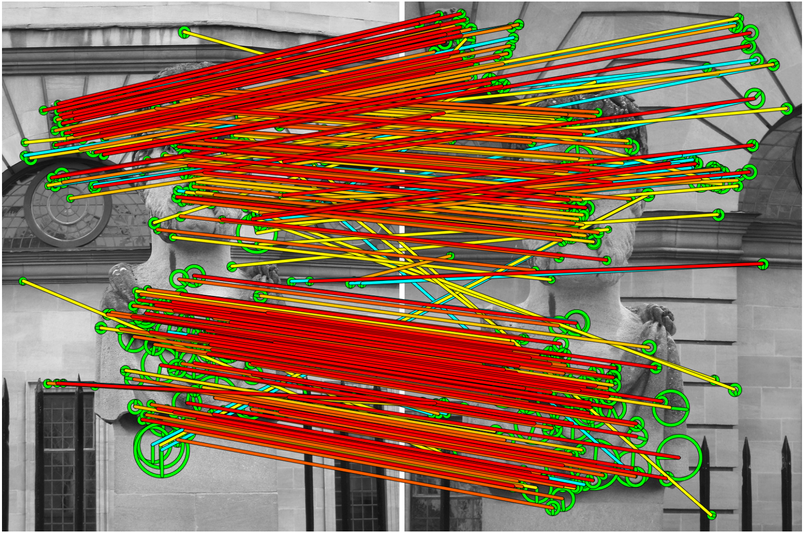
- is invariant to similarity transformations
- is flexible, allowing non-rigid motion and multiple matching surfaces or objects
- imposes one-to-one mapping

relaxed spatial matching—examples



fast spatial matching

relaxed spatial matching—examples



relaxed spatial matching

relaxed spatial matching—examples

fast spatial matching

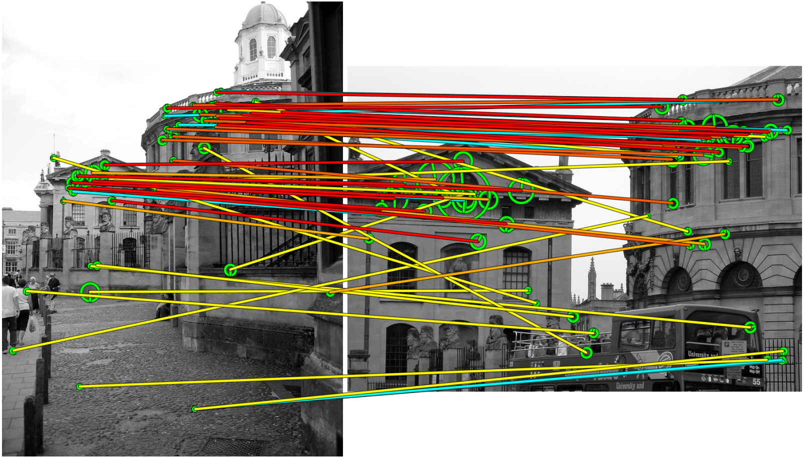
relaxed spatial matching—examples

relaxed spatial matching

relaxed spatial matching—examples

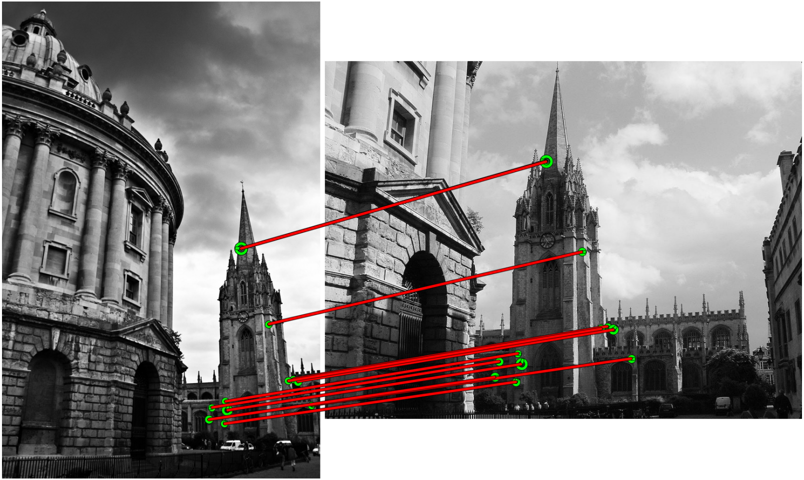
fast spatial matching

relaxed spatial matching—examples



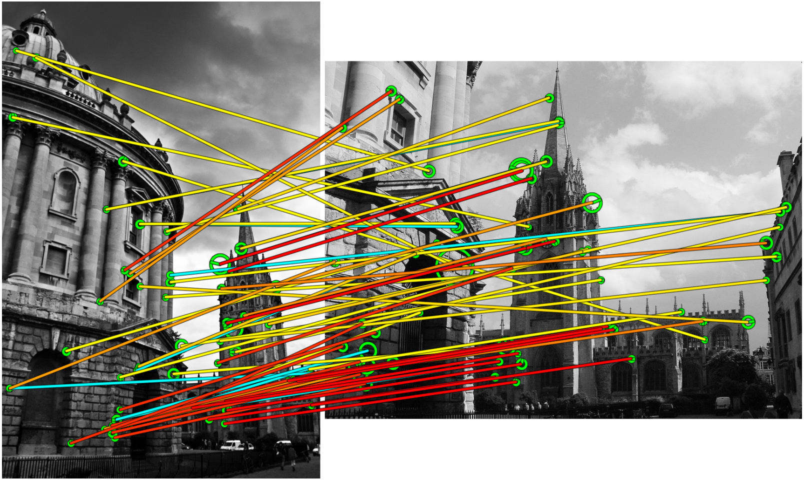
relaxed spatial matching

relaxed spatial matching—examples



fast spatial matching

relaxed spatial matching—examples

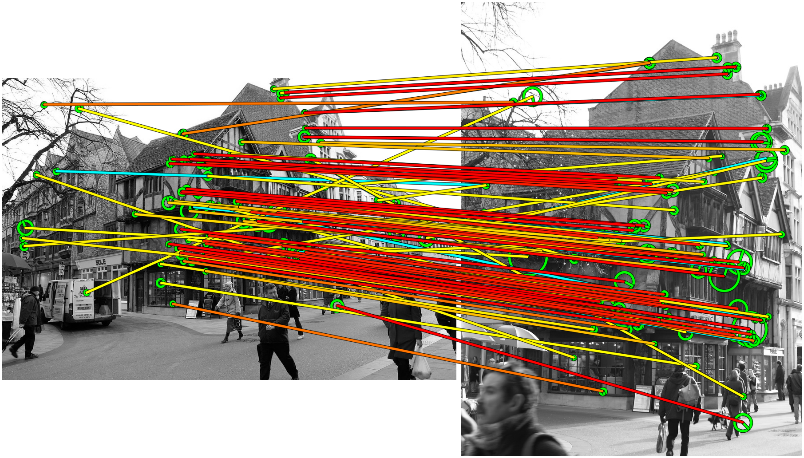


relaxed spatial matching

relaxed spatial matching—examples

fast spatial matching

relaxed spatial matching—examples



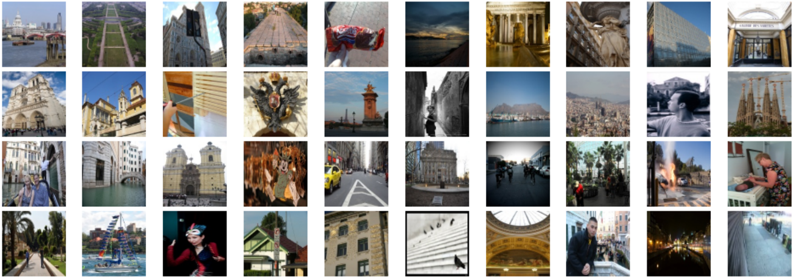
relaxed spatial matching

world cities dataset

- 927 annotated images
- 17 groups of photos, each from a landmark scene in Barcelona
- 5 queries from each group

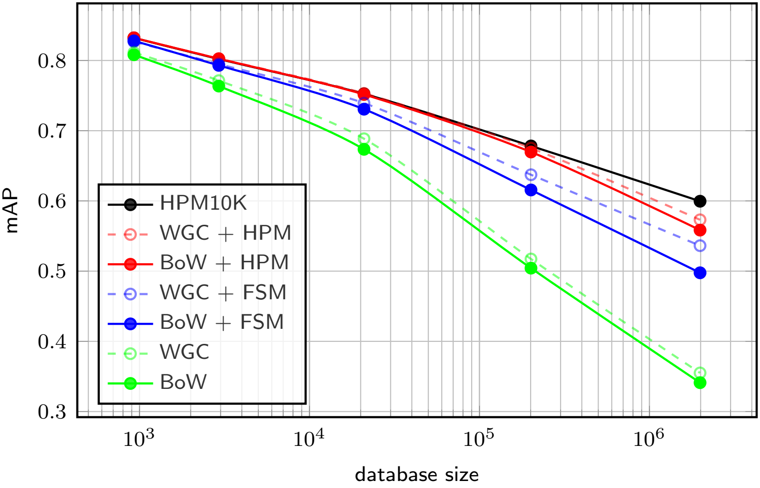
world cities dataset

- 927 annotated images
- 17 groups of photos, each from a landmark scene in Barcelona
- 5 queries from each group
- $2,226,414$ distractor images from 40 cities
- most depict urban scenery like the ground-truth



publicly available: `http://image.ntua.gr/iva/datasets/wc/`

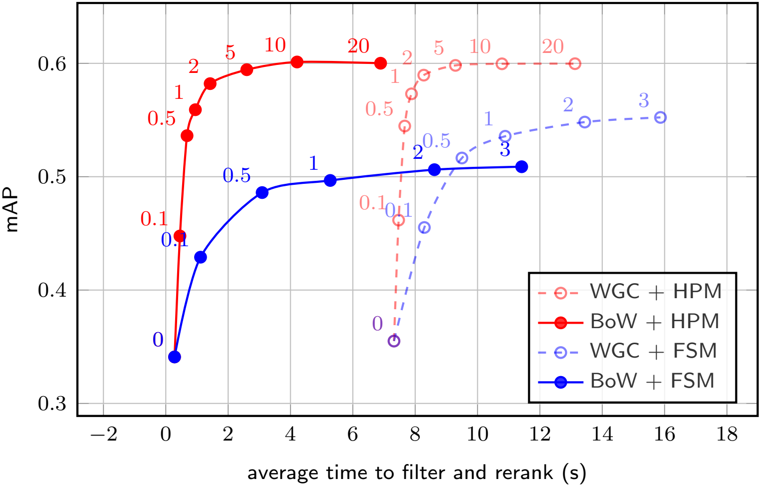
relaxed spatial matching—distractors



relaxed spatial matching . . .

- is non-iterative, and linear in the number of correspondences
- in a given query time, can re-rank one order of magnitude more images than the state of the art
- needs less than one millisecond to match a pair of images, on average

relaxed spatial matching—timing



this work is becoming part of...

OpenCV

http://opencv.willowgarage.com/

outline

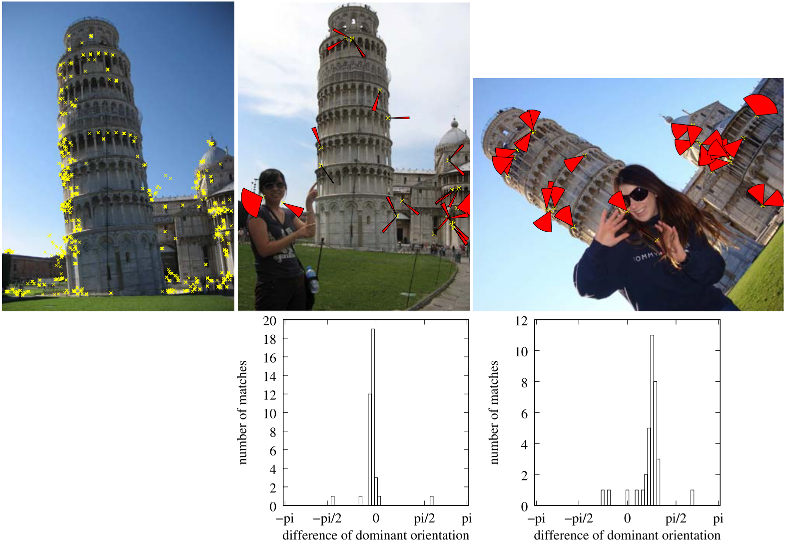
weak geometric consistency (WGC)

[Jegou et al., ECCV 2008]

- when an image undergoes rotation or scaling, the orientation and scale of local features is consistently modified
- quantize orientation and scale differences between feature pairs
- maintain several scores for each image, one for each difference bin
- this is not enough to recover a full transformation, but does improve ranking

weak geometric consistency (WGC)

[Jegou et al., ECCV 2008]



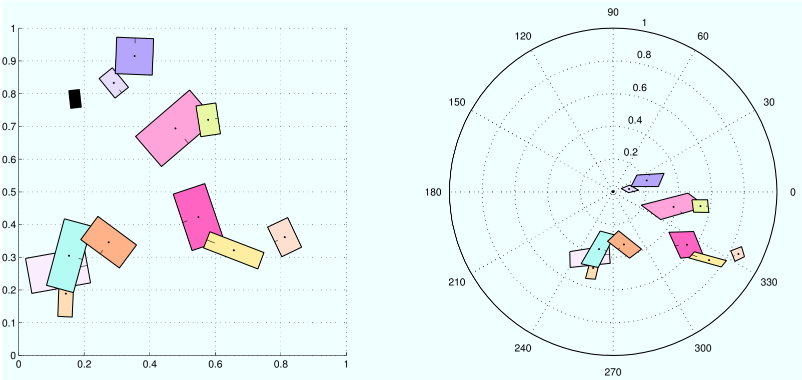
feature map hashing

[Avrithis et al., ACM-MM 2010]

- estimate image alignment via single correspondence
- for each feature, construct a feature map encoding normalized positions and appearance of all remaining features
- represent an image by a collection of such feature maps
- RANSAC-like matching is reduced to a number of set intersections

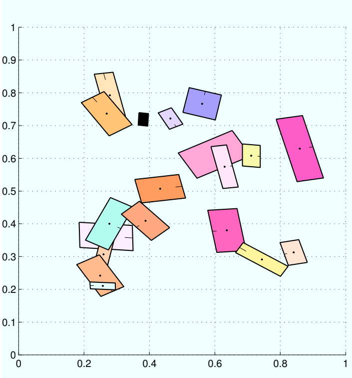
feature maps—example

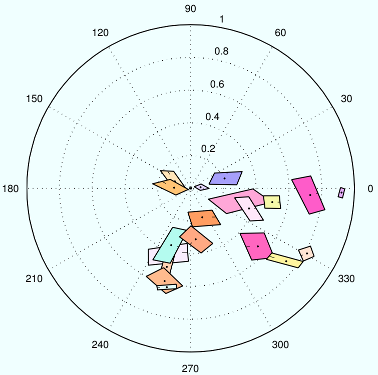
- well aligned feature sets are likely to have maps with a high degree of overlap



feature maps—example

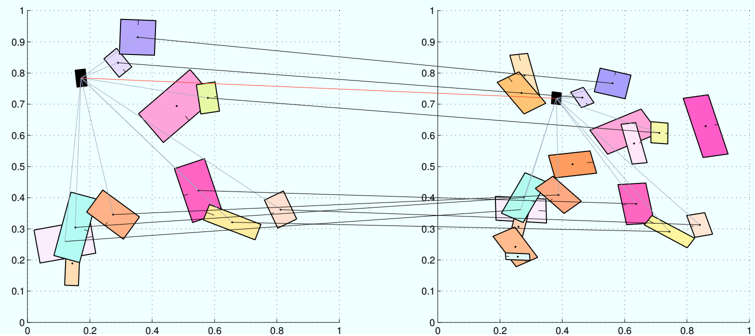
- well aligned feature sets are likely to have maps with a high degree of overlap





feature map similarity

$$S_F(P,Q) = \max_{v \in V(P,Q)} \max_{\substack{\hat{x} \in H_v(P) \\ \hat{y} \in H_v(Q)}} f_P^{\mathrm{T}}(\hat{x}) \;\; f_Q(\hat{y})$$



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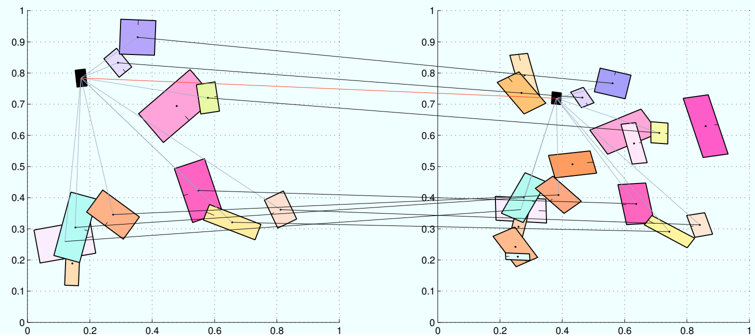
feature map of image P wrt origin $\hat{x}$



feature map similarity

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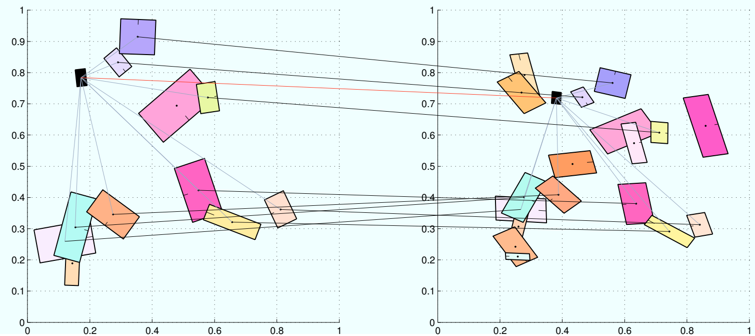
feature map of image P wrt origin $\hat{x}$

feature map of image Q wrt origin $\hat{y}$



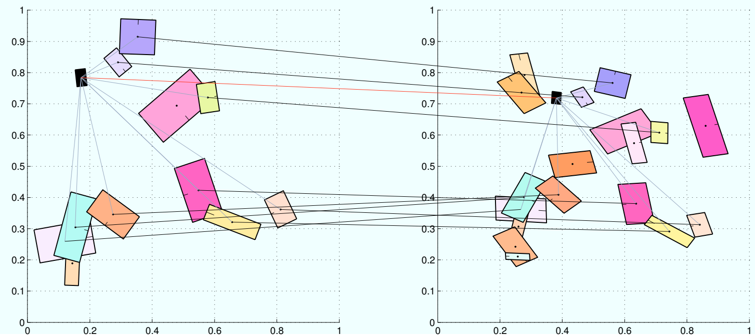
feature map similarity

over all origins mapped to visual word v

$$S_F(P,Q) = \max_{v \in V(P,Q)} \max_{\substack{\hat{x} \in H_v(P) \\ \hat{y} \in H_v(Q)}} f_P^{\mathrm{T}}(\hat{x}) \; f_Q(\hat{y})$$

feature map of image P wrt origin $\hat{x}$

feature map of image Q wrt origin $\hat{y}$



feature map similarity

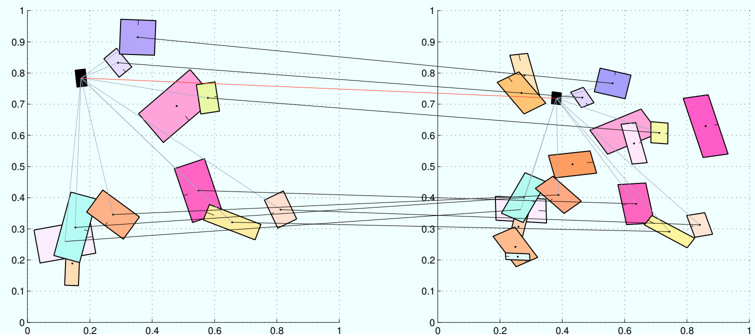
over all visual words that P, Q have in common

over all origins mapped to visual word v

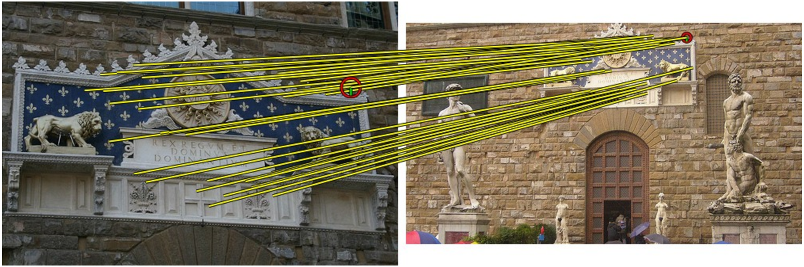
$$S_F(P,Q) = \max_{v \in V(P,Q)} \max_{\substack{\hat{x} \in H_v(P) \\ \hat{y} \in H_v(Q)}} f_P^{\mathrm{T}}(\hat{x}) \; f_Q(\hat{y})$$

feature map of image P wrt origin $\hat{x}$

feature map of image Q wrt origin $\hat{y}$

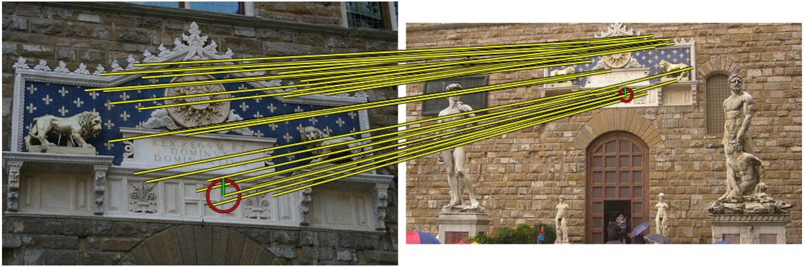


feature map similarity—example



fast spatial matching (35 inliers)

feature map similarity—example



feature map similarity (32 inliers)

towards indexing

with min-wise independent permutations [Broder, CCS 2000]

- FMS is a fast way of matching 2 images, but still not enough for indexing
- a feature map is an extremely sparse histogram; bin count typically takes values in $\{0, 1\}$
- each feature map f is represented by a set $\bar{f}$ of non-empty bins
- then, use min-wise independent permutations a.k.a. min-hashing as an equivalent to random sampling

an example

[Chum et al. 2007]

a	b	c	d	e	f	$\{a,b,c\}$	$\{b,c,d\}$	$\{a,e,f\}$
permutations						hash values		
3	6	2	5	4	1	2	2	1
1	2	6	3	5	4	1	2	1
3	2	1	6	4	5	1	1	3
4	3	5	6	1	2	3	3	1

an example

[Chum et al. 2007]

a	b	c	d	e	f	$\{a, b, c\}$	$\{b, c, d\}$	$\{a, e, f\}$
permutations						hash values		
3	6	2	5	4	1	2	2	1
1	2	6	3	5	4	1	2	1
3	2	1	6	4	5	1	1	3
4	3	5	6	1	2	3	3	1

an example

[Chum et al. 2007]

a	b	c	d	e	f	$\{a,b,c\}$	$\{b,c,d\}$	$\{a,e,f\}$
permutations						hash values		
3	6	2	5	4	1	2	2	1
1	2	6	3	5	4	1	2	1
3	2	1	6	4	5	1	1	3
4	3	5	6	1	2	3	3	1

an example

[Chum et al. 2007]

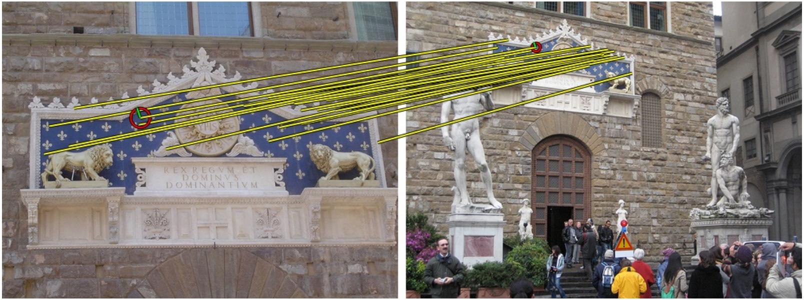
a	b	c	d	e	f	$\{a,b,c\}$	$\{b,c,d\}$	$\{a,e,f\}$
permutations						hash values		
3	6	2	5	4	1	2	2	1
1	2	6	3	5	4	1	2	1
3	2	1	6	4	5	1	1	3
4	3	5	6	1	2	3	3	1

an example

[Chum et al. 2007]

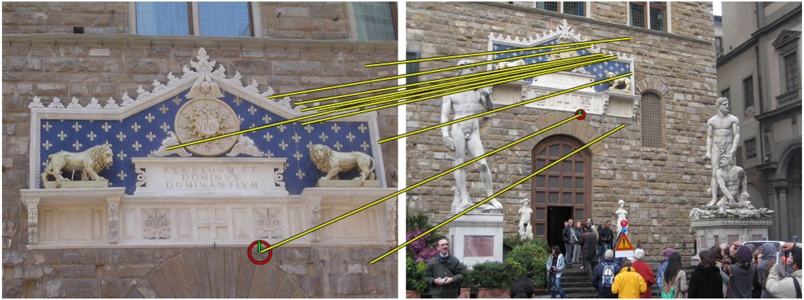
a	b	c	d	e	f	$\{a,b,c\}$	$\{b,c,d\}$	$\{a,e,f\}$
permutations						hash values		
3	6	2	5	4	1	2	2	1
1	2	6	3	5	4	1	2	1
3	2	1	6	4	5	1	1	3
4	3	5	6	1	2	3	3	1

matching maps



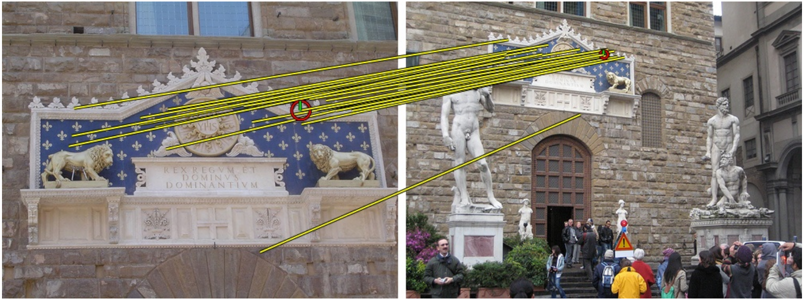
multiple matching pairs of feature maps

matching maps



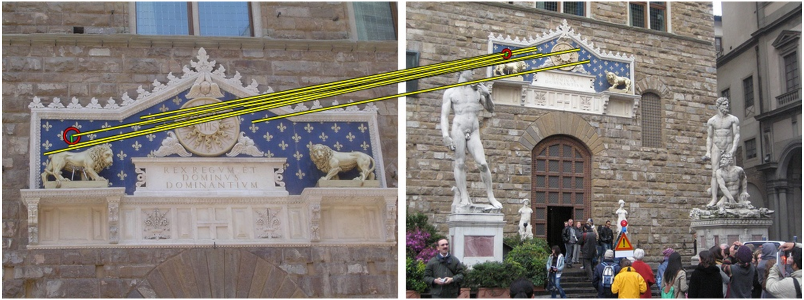
multiple matching pairs of feature maps

matching maps



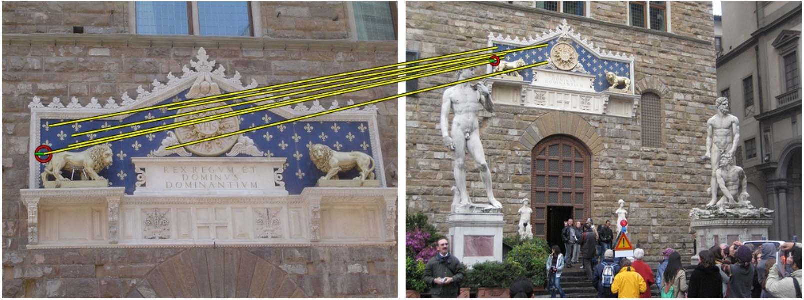
multiple matching pairs of feature maps

matching maps



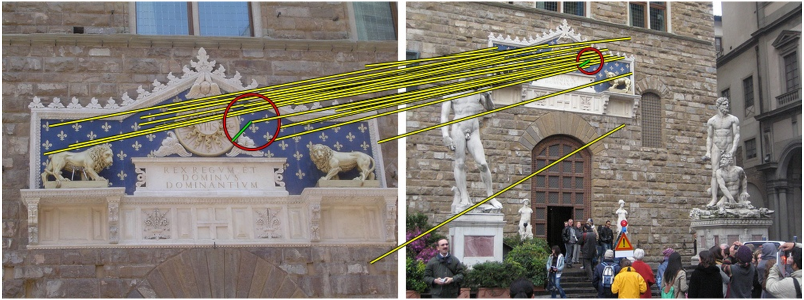
multiple matching pairs of feature maps

matching maps



multiple matching pairs of feature maps

matching maps



multiple matching pairs of feature maps

retrieval

indexing

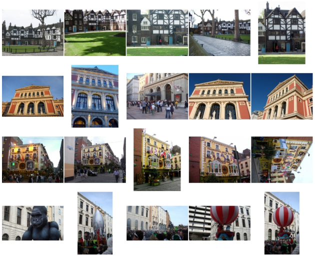
- construct inverted file of triplets $(\hat{v}, w, \pi)$ (origin, hash value, permutation)
- memory requirements $10\times$ a typical baseline system

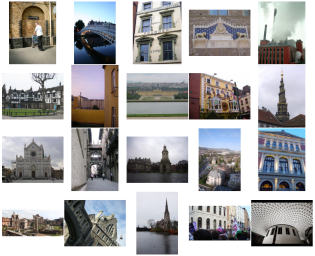
query

- retrieve images by triplets $(\hat{v}, w, \pi)$ of query image
- re-estimate transformation parameters using LO-RANSAC
- re-ranking is an order of magnitude faster than FastSM, because an initial estimate is already available

European cities dataset 50K (EC50K)

- 778 annotated images
- 20 groups of photos
- 5 queries from each group

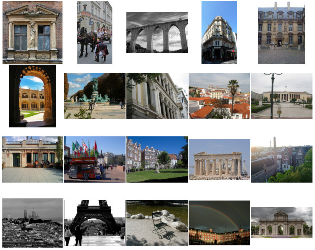


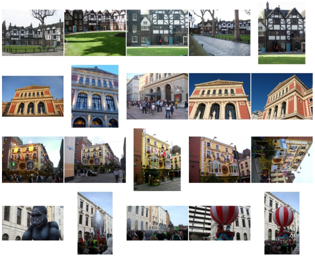


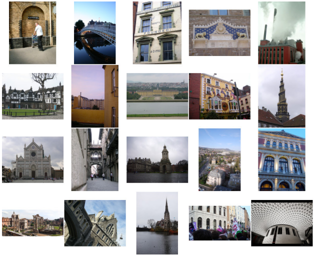
publicly available: `http://image.ntua.gr/iva/datasets/ec50k`

European cities dataset 50K (EC50K)

- 778 annotated images
- 20 groups of photos
- 5 queries from each group
- 50,000 distractor images

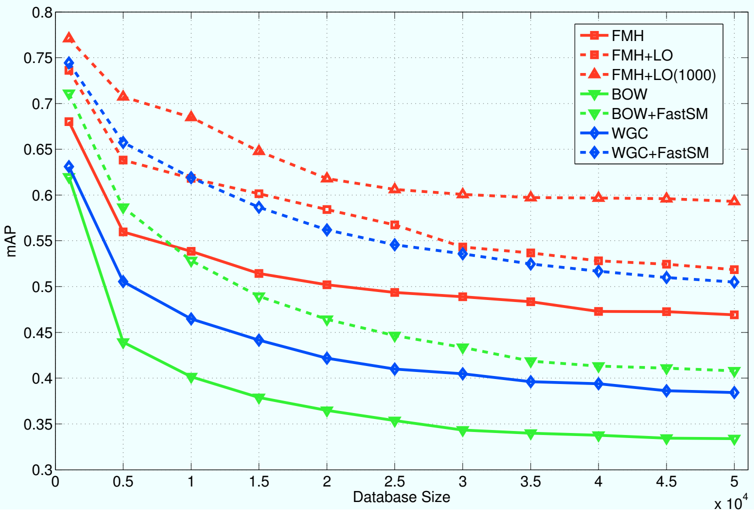






publicly available: `http://image.ntua.gr/iva/datasets/ec50k`

feature map hashing—results EC50K



outline

selecting useful features

[Turcot and Lowe, ICCV 2009]

- index space is now the bottleneck in going to large scale, not speed
- select features by matching across multiple views of the same object or scene
- for each image in the database, find similar views, perform spatial matching, and select features appearing as inliers

selecting useful features

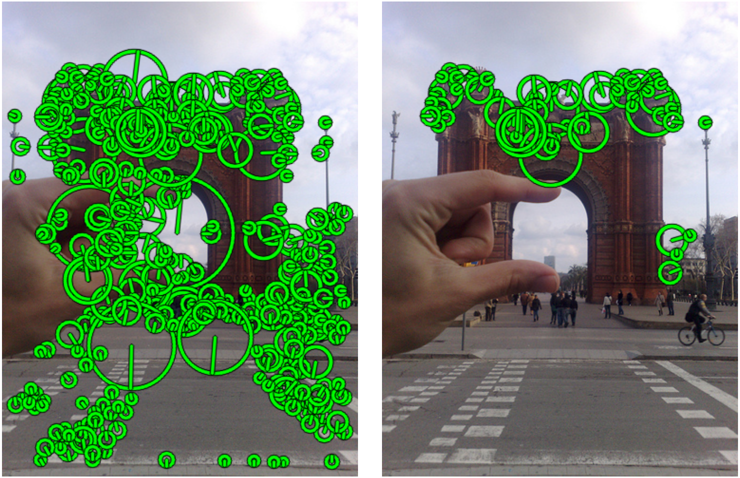
[Turcot and Lowe, ICCV 2009]

large scale geometry indexing

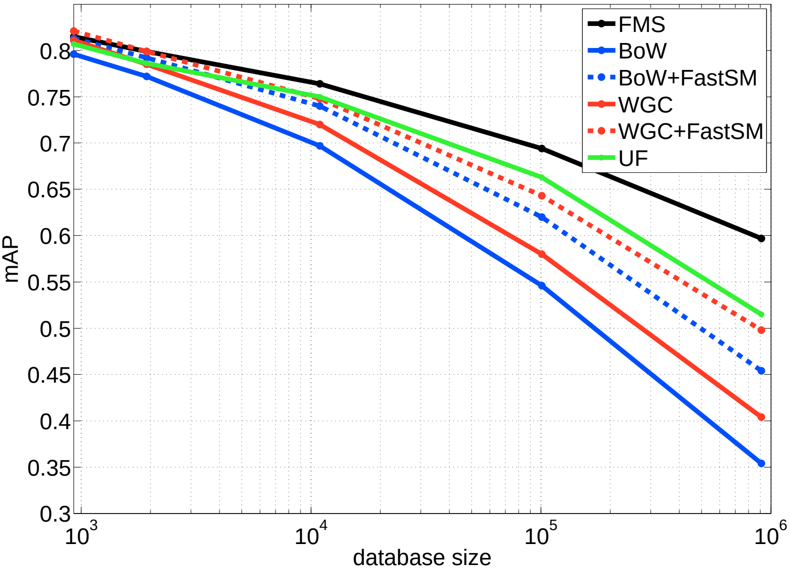
[Tolias et al., submitted to CVIU, 2012]

- feature map hashing implies random selection
- instead, select robust features, again by matching across similar views in dataset
- individual selection criteria for origins and inlier features
- dramatic reduction in index size

feature selection



results EC1M

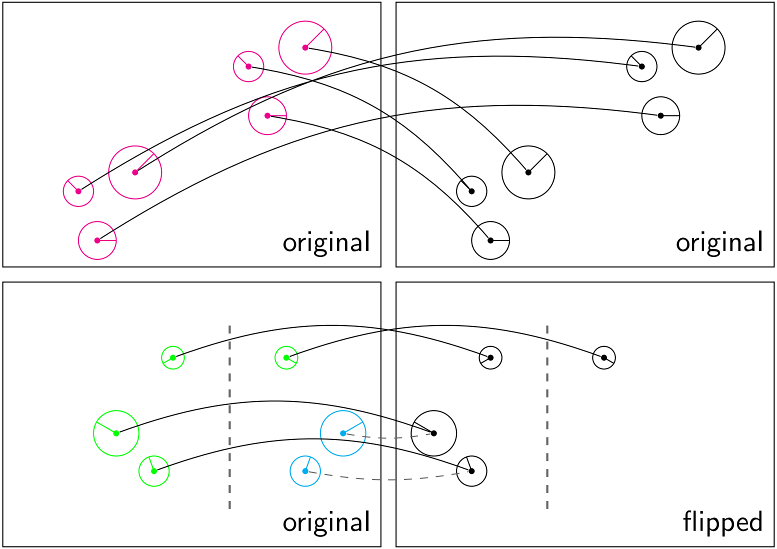


feature selection by symmetry

[Tolias et al., submitted to ACM-MM 2012]

- feature selection so far relies on multiple views
- how about unique views of an object or scene?
- in fact, most images in a dataset are unique
- exploit self-similarities, repeating patterns and symmetries

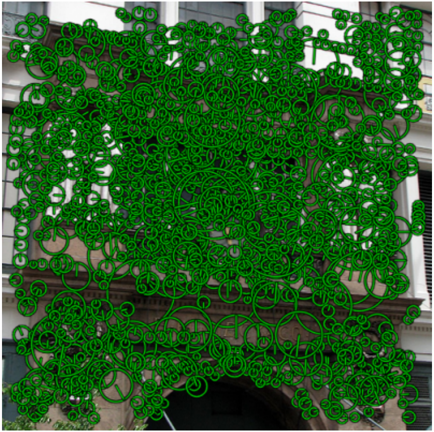
matching scheme



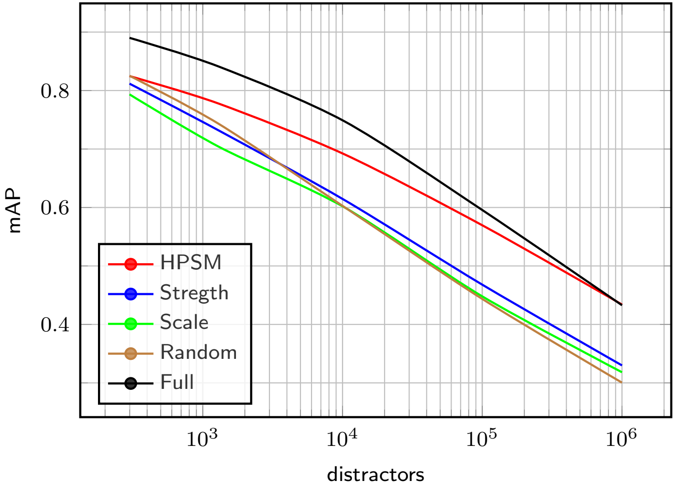
direct matching

flipped matching

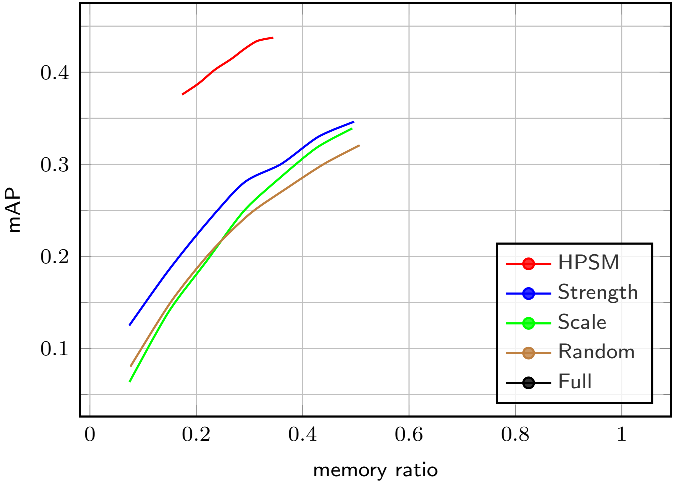
selected features



precision vs distractors



precision vs memory



outline

community photo collections

clustering / landmark recognition

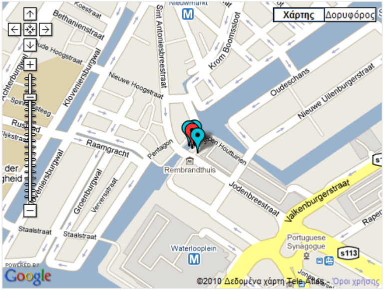
- focus on popular subsets
- applications: browsing, 3D reconstruction

[Crandall *et al.*, ICCV 2009]

community photo collections

retrieval / location recognition

- include all images, has not yet scaled enough
- applications: automatic geo-tagging, camera pose estimation



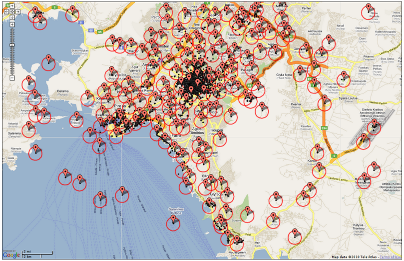
Estimated Location, Similar Image, Incorrectly geo-tagged, Unavailable

Suggested tags: Sint Antoniesbreestraat, Zwanenburgwal, Amsterdam
Frequent user tags: Anthoniesluis, sluijswacht, krom, stare, Skirt

view clustering

[Avrithis et al., ACM-MM 2010]

- identify images that potentially depict views of the same scene
- geo clustering: according to location
- visual clustering: according to visual similarity



- use sub-linear indexing in the clustering process

kernel vector quantization (KVQ)

[Tipping and Schölkopf, AIS 2001]

properties

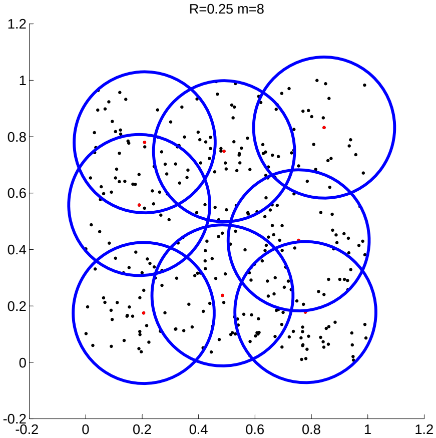
- codebook vectors are points of the original dataset: $Q(D) \subseteq D$
- distortion upper bounded by r: for all $x \in Q(D)$

$$\max_{y \in C(x)} d(x, y) < r$$

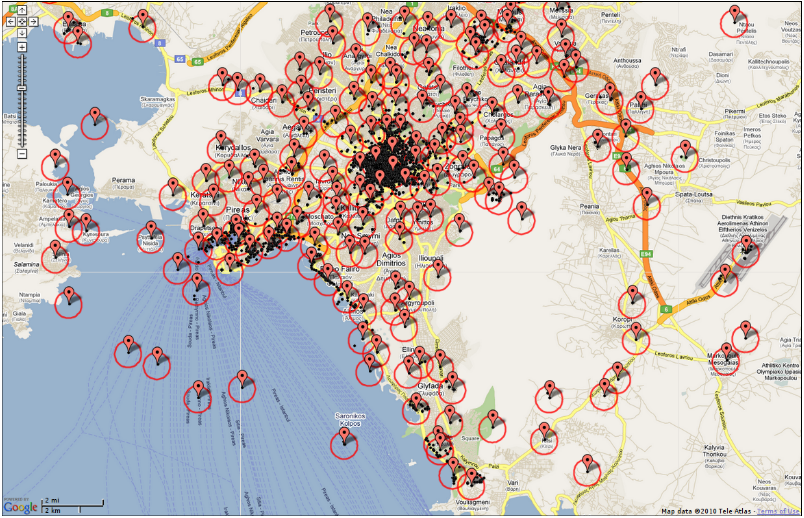
- the cluster collection

$$\mathcal{C}(D) = \{C(x) : x \in Q(D)\}$$

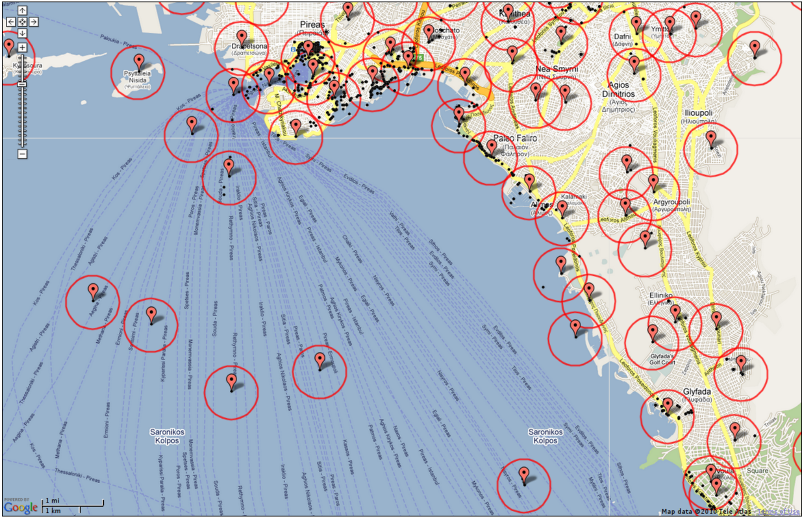
  is a cover for D
- clusters are overlapping



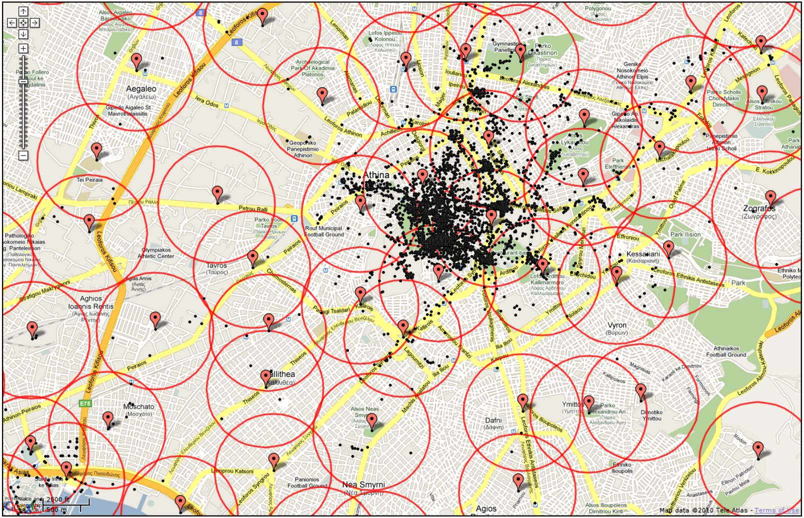
geo-clustering—example



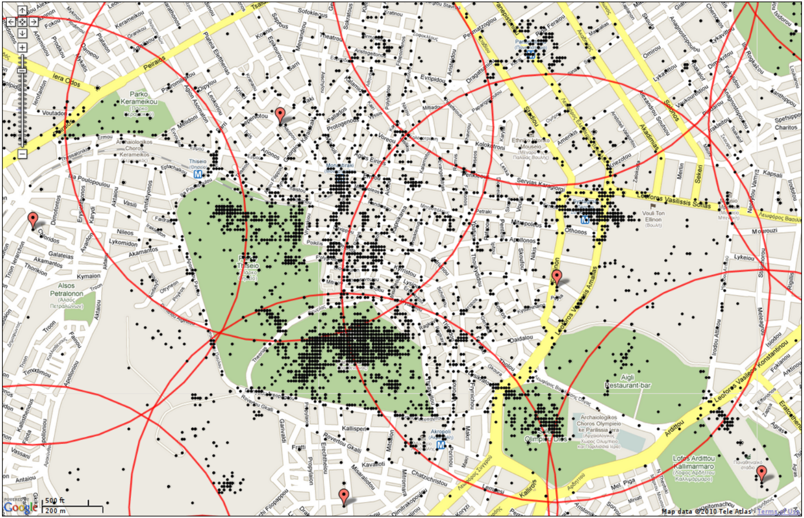
geo-clustering—example



geo-clustering—example



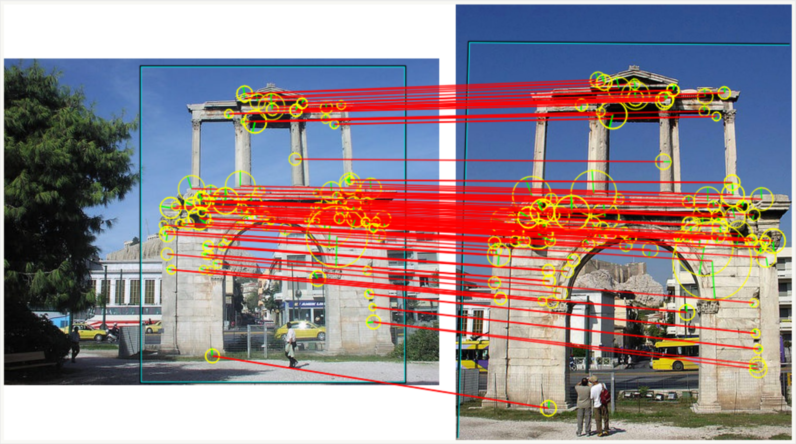
geo-clustering—example



visual clustering

visual similarity measure

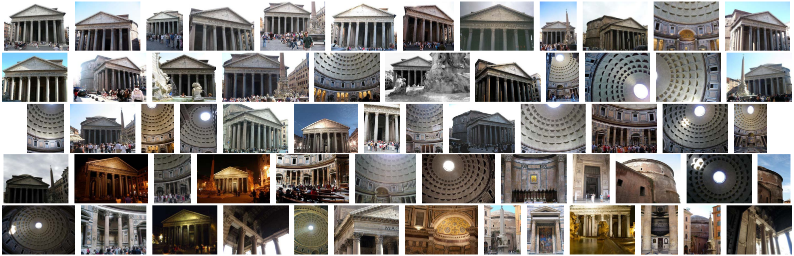
- $I(F_p, F_q)$: number of inliers between visual feature sets F_p, F_q of photos p, q respectively



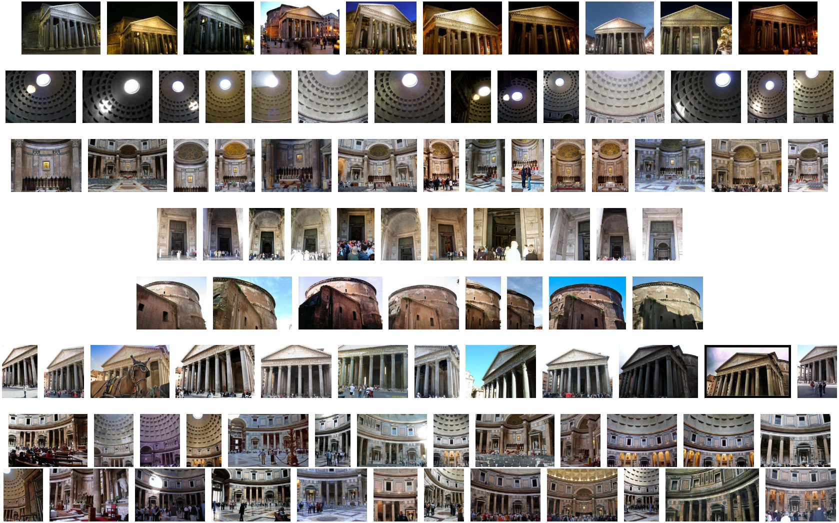
visual clustering—example

$1,146$ **geo-tagged Flickr images of Pantheon, Rome**

- 258 resulting visual clusters
- 30 images at each visual cluster on average
- an image belongs to 4 visual clusters on average



visual clustering—example



scene maps

[Avrithis et al., ACM-MM 2010]

- the image associated to the center of a view cluster shares at least one rigid object with all other images in the cluster
- treat this image as a reference for the cluster and align all other images to it
- initial estimates available from the view clustering stage—only local optimization needed
- construct a 2D scene map by grouping similar local features
- extend index, retrieval, and spatial matching for scene maps

view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—input images

view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—input images

view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—input images

view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—input images

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view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—input images

view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—input images

view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—input images

view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—aligned images

view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—aligned images

view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—aligned images




view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—aligned images





view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—aligned images

view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—aligned images

view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—aligned images

view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—aligned images

view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—aligned images

view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—aligned images

view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—aligned images

view cluster alignment—example

Palau Nacional, Montjuic, Barcelona—aligned images

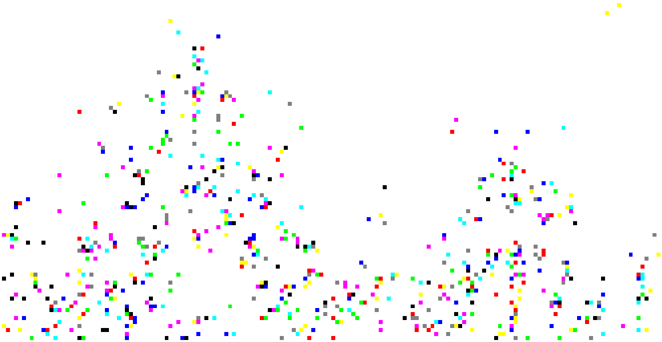
scene map construction—example

visual cluster containing 30 images of Palau Nacional, Montjuic

scene map construction—example

before vector quantization

scene map construction—example



after vector quantization

scene map indexing

index construction

- scene maps and images have the same representation—sets of features
- index all scene maps by visual word in an inverted file

query

- re-rank using the single correspondence assumption [Philbin et al. 2007]
- whenever a scene map $S(p)$ is found relevant, all images $q \in C_v(p)$ are retrieved as well

European cities 1M dataset (EC1M)

- $1,081$ images in Barcelona, annotated into 35 groups
- 5 queries from each group
- all geo-tagged Flickr images

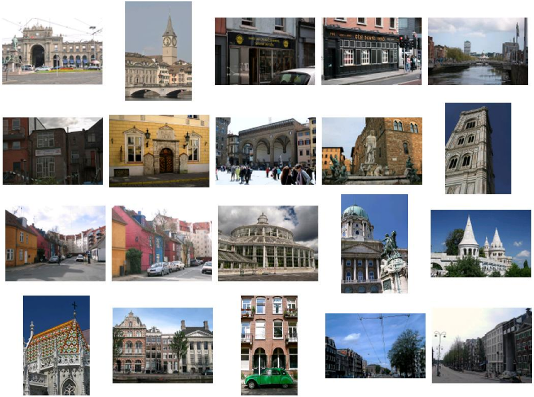
17 landmark groups

18 non-landmark groups

publicly available: `http://image.ntua.gr/iva/datasets/ec1m/`

European cities 1M dataset (EC1M)

- $908,859$ distractor images from 21 European cities, excluding Barcelona
- most depict urban scenery like the ground-truth



publicly available: `http://image.ntua.gr/iva/datasets/ec1m/`

mining statistics—scene maps

- 1M images, 58 hours, single machine (8GB RAM), landmarks and non-landmarks

mining statistics—related work

- [Chum *et al.*, PAMI 2010] web-scale clustering: 5M images, 28 hours, single machine (64GB RAM), popular subsets only
- [Agarwal *et al.*, ICCV 2009] building Rome in a day: 150K images, 24 hours, 500 cores
- [Frahm *et al.*, ECCV 2010] building Rome in a cloudless day: 3M images, 24 hours, GPU
- [Heath *et al.*, CVPR 2010] image webs: 200K images, 4,5 hours, 500 cores

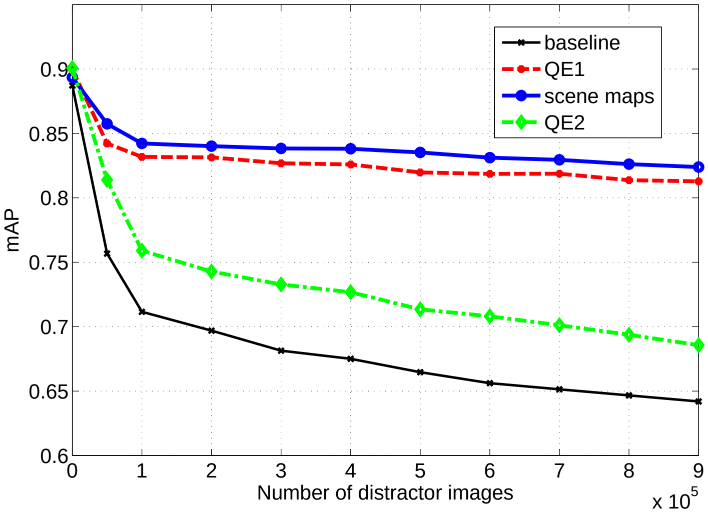
retrieval comparisons

- baseline: bag-of-words with fast spatial matching [Philbin et al. 2007]
- QE1: iterative query expansion, re-query using the retrieved images and merge results, 3 times iteratively
- QE2: create a scene map using the initial query's result and re-query once
- both QE schemes similar to total recall [Chum *et al.*, 2007]

query timing

Method	time	mAP
Baseline BoW	**1.03s**	0.642
QE1	20.30s	0.813
QE2	2.51s	0.686
Scene maps	1.29s	**0.824**

retrieval statistics



outline

location and landmark recognition

[Y. Kalantidis et al., MTAP 2011]

- assume that a subset of similar photos are correctly geo-tagged, and not too far apart
- recognize the location where the query photo is taken, as the centroid of the most populated spatial (geo) cluster
- cross-validate locations and text (title, tags) of similar images with Geonames entries and geo-referenced Wikipedia articles
- link to known landmarks or points of interest

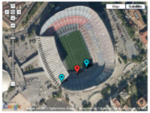
location recognition—examples



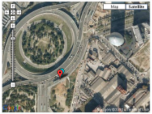










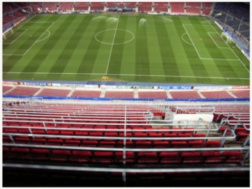



landmark recognition—examples

Suggested tags: Park Güell, Barcelona
Frequent user tags: Best of, me, Palau Güell

Suggested tags: La Barceloneta, Barcelona
Frequent user tags: honeymoon, wedding, straße

Suggested tags: Triumphal arch, Arc de Triomf, Barcelona
Frequent user tags: Sant Pere, Santa Caterina i La Ribera, macba, Passeig de Lluís Companys, lluis companys, Sant Beltra



Suggested tags: FC Barcelona Museum, Camp Nou, Barcelona
Frequent user tags: champions league, vfb, vfb stuttgart, Zoo de Barcelona, Camp Nou

Suggested tags: Montjuïc circuit, Museu Nacional d'Art de Catalunya, Barcelona
Frequent user tags: Montjuic, castellers, Travelling Pooh, architecture, mnac

Suggested tags: Sagrada Familia, Sagrada Família, Barcelona
Frequent user tags: gaudi, Sagrada Familia, sagrada, familia, expiatorio

http://viral.image.ntua.gr

query

results

Estimated Location Similar Image, Incorrectly geo-tagged Unavailable

Suggested tags: Buxton Memorial Fountain, Victoria Tower Gardens, London
Frequent user tags: Victoria Tower Gardens, Buxton Memorial Fountain, Winchester Palace, Architecture, Victorian gothic

Similar Images

Similarity: 0.619
Details Original

Similarity: 0.491
Details Original

Similarity: 0.397
Details Original

Similarity: 0.385
Details Original

similar of similar

Original

Original

Original

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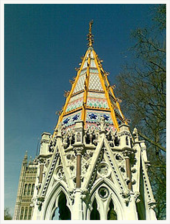
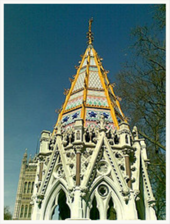


Original



Original

Original

similar of similar


Original


Original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Original


Original


Original


Original

suggested tags

Suggested tags: Buxton Memorial Fountain, Victoria Tower Gardens, London
Frequent user tags: Victoria Tower Gardens, Buxton Memorial Fountain, Winchester Palace, Architecture, Victorian gothic

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Buxton Memorial Fountain

From Wikipedia, the free encyclopedia


The Buxton Memorial Fountain, designed by Samuel Sanders Teulon, celebrating the emancipation of slaves in the British Empire in 1834, in Victoria Tower Gardens, Millbank,

The **Buxton Memorial Fountain** is a memorial and drinking fountain in London, the United Kingdom, that commemorates the emancipation of slaves in the British Empire in 1834.

It was commissioned by Charles Buxton MP, and was dedicated to his father Thomas Fowell Buxton along with William Wilberforce, Thomas Clarkson, Thomas Babington Macaulay, Henry Brougham and Stephen Lushington, all of whom were involved in the abolition. It was designed by Gothic architect Samuel Sanders Teulon (1812–1873) in 1865 coincidently with the passing of the Thirteenth Amendment to the United States Constitution, which effectively ended the western slave-trade.[1]

It was originally constructed in Parliament Square, erected at a cost of £1,200. As part of the postwar redesign of the square it was removed in 1949 and not reinstated in its present position in Victoria Tower Gardens until 1957.[2] There were eight decorative figures of British rulers on it, but four were stolen in 1960 and four in 1971. They were replaced by fibreglass figures in 1980. By 2005 these were missing, and the fountain was no longer working. Between autumn 2006 and February 2007 restoration works were carried out. The restored fountain was unveiled on 27 March 2007 as part of the commemoration of the 200th anniversary of the act to abolish the slave trade [3].

A memorial plaque commemorating the 150th anniversary of the Anti-Slavery Society was added in 1989.

Description [edit]

The base is octagonal, about twelve feet in diameter, having open arches on the eight sides, supported on clustered shafts of polished Devonshire marble around a large central shaft, with four massive granite basins. Surmounting the pinnacles at the angles of the octagon are eight figures of bronze, representing the different rulers of England; the Britons represented by Caractacus, the Romans by Constantine, the Danes by Canute, the Saxons by Alfred, the Normans by William the Conqueror, and so on, ending with Queen Victoria. The fountain bears an inscription to the effect that it is "intended as a memorial of those members of Parliament who, with Mr. Wilberforce, advocated the abolition of the British slave-trade, achieved in 1807; and of those members of Parliament who, with Sir T.

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Victoria Tower Gardens

From Wikipedia, the free encyclopedia

Coordinates: 51°29′49.0″N 0°7′30.0″W

Victoria Tower Gardens is a public park along the north bank of the River Thames in London. As its name suggests, it is adjacent to the Victoria Tower, the south-western corner of the Palace of Westminster. The park, which extends southwards from the Palace to Lambeth Bridge, sandwiched between Millbank and the river, also forms part of the Thames Embankment.

Victoria Tower Gardens, 2005, with the Buxton Memorial Fountain at the front and the Palace of Westminster in the background

Contents [hide]

Features [edit]

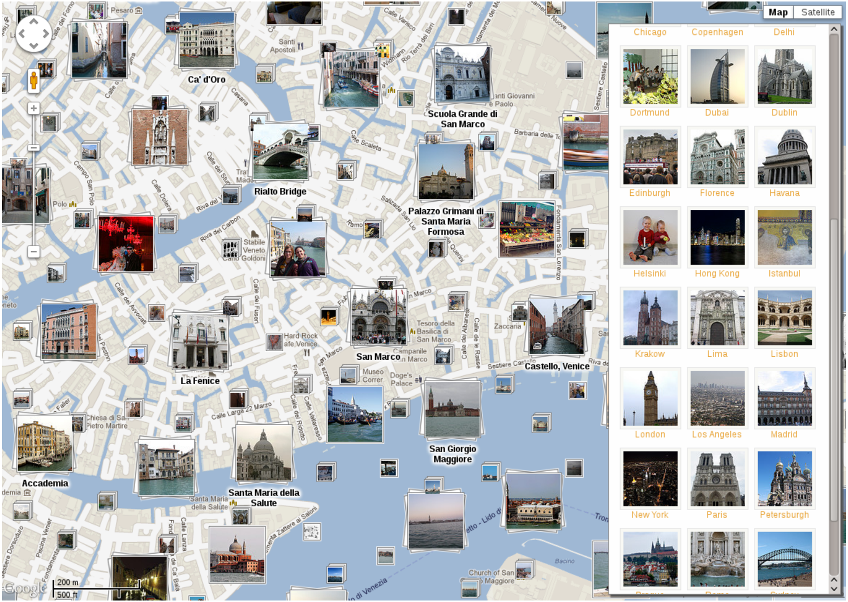
The park features:

- A reproduction of the sculpture *The Burghers of Calais* by Auguste Rodin, purchased by the British Government in 1911 and positioned in the Gardens in 1915.
- A 1930 statue of the suffragette Emmeline Pankhurst, by A.G. Walker.
- The Buxton Memorial Fountain – originally constructed in Parliament Square, this was removed in 1940 and placed in its present position in 1957. It was commissioned by Charles Buxton MP to commemorate the emancipation of slaves in 1834, dedicated to his father Thomas Fowell Buxton, and designed by Gothic architect Samuel Sanders Teulon (1812–1873) in 1865.
- A stone wall with two modern-style goats with kids – situated at the southern end of the Gardens.

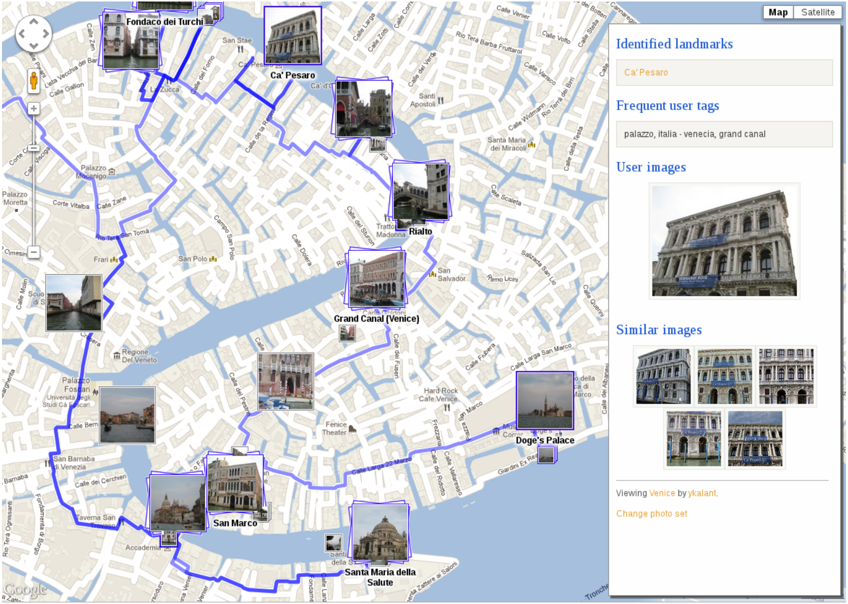
Transport [edit]

VIRaL explore

VIRaL explore



VIRaL routes



outline

recall feature point matching

1. construct the $m \times n$ proximity matrix G with elements

$$g_{ij} = \exp(-d_{ij}^2 / 2\sigma^2)$$

2. perform singular value decomposition of G

$$G = USV^{\mathrm{T}}$$

   where U, V are orthogonal matrices of dimension m, n and S is a non-negative diagonal $m \times n$ matrix

3. replace each diagonal element s_{ij} of S by 1 and reconstruct

$$P = UEV^{\mathrm{T}}$$

4. finally, associate points a_i and b_j if element p_{ij} of P is the greatest element in its row and its column

Matlab code

```
function [m1, m2] =
match(                  x1,                   y1,
                        x2,                   y2, F s)


    [Ax1, Ax2] = meshgrid  (x1, x2);
    [Ay1, Ay2] = meshgrid  (y1, y2);

                D = sqrt((Ax1 - Ax2)  .^ 2 + (Ay1 - Ay2)  .^ 2);
                G = exp(-D  .^ 2 ./ (2 *   s    ^ 2));

    [U, S, V] = svd  (G);
                E = S > 0;
                P = U   * E   * V'   ;


    [tmp, c] = max  (P, [], 2);
    [tmp, r] = max  (P, [], 1);

                match = r(c) ==    (1 :  length(c)   );
       m1 = find(match);
       m2 = c(match)';
```

ivl C++ code

```
template<class F>   ret<array<F>, array<F> >
match(const array<F>& x1, const array<F>& y1,
      const array<F>& x2, const array<F>& y2, F s)
{
   array_2d<F> Ax1, Ax2, Ay1, Ay2, U, S, V, tmp;
   _(Ax1, Ax2) = meshgrid++(x1, x2);
   _(Ay1, Ay2) = meshgrid++(y1, y2);

   array_2d<F> D = sqrt((Ax1 - Ax2) ->* 2 + (Ay1 - Ay2) ->* 2);
   array_2d<F> G = exp(-D ->* 2  / (2 * _[s] ->* 2));

   _(U, S, V) = svd++(G);
   array_2d<F> E = S > 0;
   array_2d<F> P = U ()* E ()* V(!_);

   array<int> c, r;
   _(tmp, c) = max++(P, _ , 2);
   _(tmp, r) = max++(P, _ , 1);

   array<bool> match = r[c] == rng(0, c.length() - 1);
   return _(find(match),
            c[match]);
}
```

ivl library

[Kontosis and Avrithis, expected 2012]

- C++ template library, compatible to STL
- supports most types, syntax and built-in operations of Matlab language
- fully optimized: minimal overhead/temporaries/copying; all array expressions boil down to a single `for` loop
- uses multiple CPU cores
- integrated with basic image functionalities of OpenCV
- integrated with most common LAPACK routines

plans

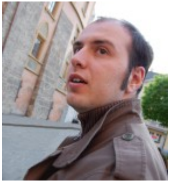
- integration with QT to support visualization
- CUDA massively parallel implementation on GPU

Credits

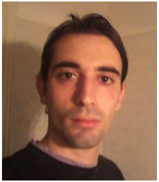
Spyros Leonardos

Yannis Kalantidis

Giorgos Tolias



Christos Varitimidis



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Yannis Avrithis

project pages

http://image.ntua.gr/iva/research

VIRaL

http://viral.image.ntua.gr

datasets

http://image.ntua.gr/iva/datasets

thank you!