Point correspondence and repeated patterns: *Beyond the curse of perceptual aliasing*

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Repeated patterns are everywhere! (1)

Hôtel de Ville de Paris.

Repeated patterns are everywhere! (2)

Yellow cabs.

Repeated patterns are everywhere! (3)

Think different.

Repeated patterns in the point correspondence problem

Example: point matching for Structure from Motion.

Roberts et al. CVPR 2011:

"When image pairs containing different instances are matched based on visual similarity, the pairwise geometric relations as well as the correspondences inferred from such pairs are erroneous, which can lead to catastrophic failures in the reconstruction."

Interest points and repeated patterns

Many Computer Vision applications (e.g. SfM) require solving the **Point correspondence problem**.
$\longrightarrow$ find pairs of Interest Points in two images that correspond to the same physical point.

A **descriptor** D_i encodes a similarity / affine invariant patch around an **Interest Point** x_i.

This talk focuses on specific difficulties with **repeated patterns**.

A popular matching algorithm

Data: two images I and I', invariant features (x_i, D_i), (x'_j, D'_j)

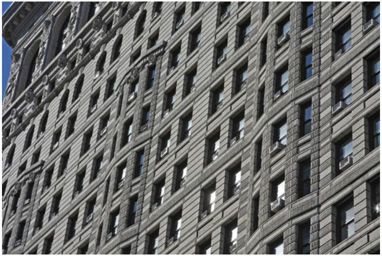
Standard matching method, two independent steps:

1. Build set of corresp. (x_i, x'_j) based on descriptor similarity:
x_i matches x'_j if D'_j is the nearest neighbour to D_i in I'
(except if "ambiguity")
Called here NN' matching.

2. Prune this set by Ransac to ensure consistency to epipolar geometry or homography (or. . .)
(See J. Matas' talk about state-of-the-art Ransac).

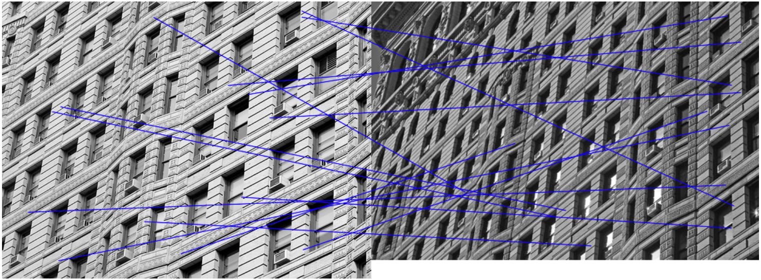
$\longrightarrow$ used in Lowe's Sift, Snavely's Bundler (for SfM), etc.

Example (1)



Flatiron Building, NYC ,1902

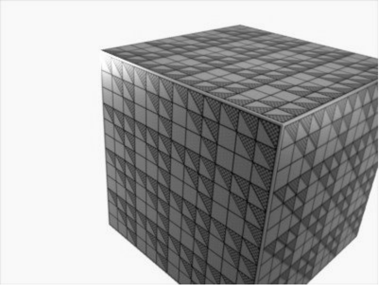
Example (1)

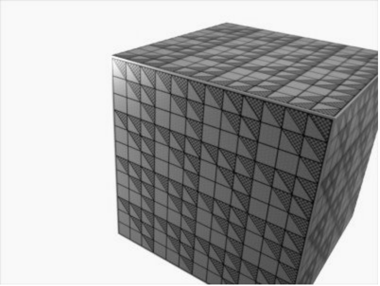


NN' matching.

$\longrightarrow$ no way to extract a set of consistent correspondences.

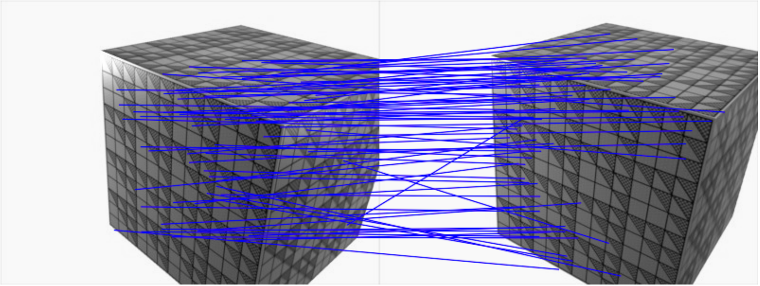
Example (2)





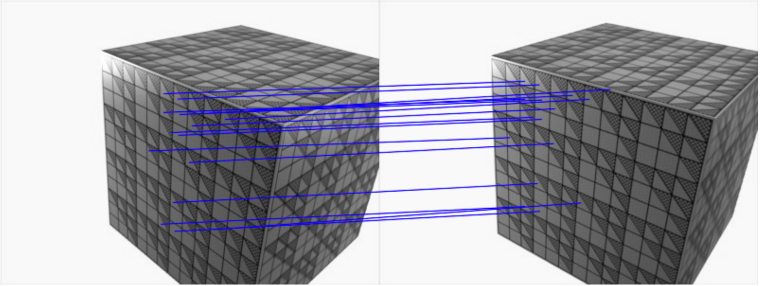
Synthetic cube

Example (2)



NN' matching

Example (2)



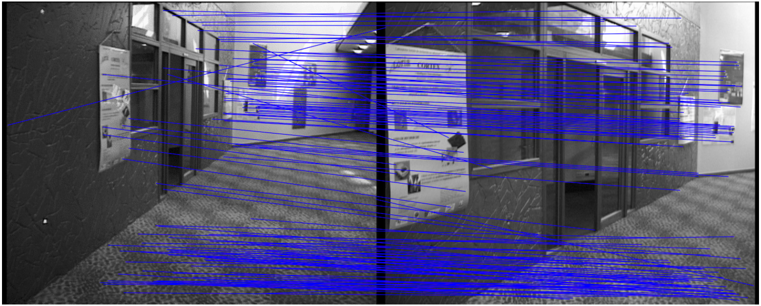
NN' matching + Homography RANSAC

⟶ shifted set of correspondences.

Example (3)

LORIA *lab corridor*

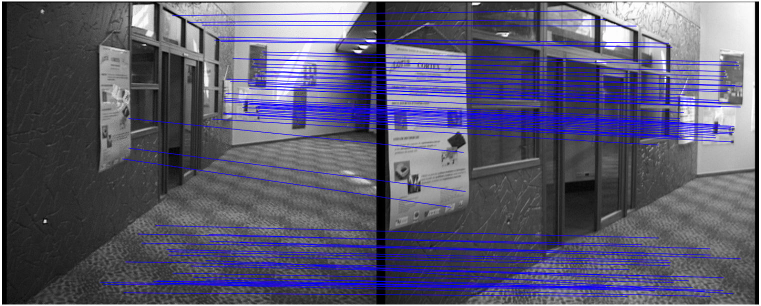
Example (3)



NN' matching.

⟶ NN tends to associate points of similar scale (in pixels).
(scale invariance *vs* limited resolution)

Example (3)



NN' matching + Fundamental matrix RANSAC

⟶ correspondences correctly selected, except for the repetitive texture.

Outline of the talk

Deliberately focused on "what does not work".

1. The curse of **perceptual aliasing**
   $\longrightarrow$ a concept from robotics which helps formalizing problems with repeated patterns.
2. **Beyond the Nearest Neighbour**
   $\longrightarrow$ the NN matching is not well adapted to scenes with repeated patterns.
3. The curse of **double nail illusion**
   $\longrightarrow$ some situations cannot be disambiguated from two views.

The perceptual aliasing problem

Context: robotics, control of systems.

Definition (Whitehead & Ballard 1991)

Perceptual Aliasing = "*a state in the world, depending upon the configuration of the sensorymotor subsystem, may map to several internal states; [and] conversely, a single internal state may represent multiple world states.*"

Robot kidnapping
"Where am I?"

Aliasing from Latin *alias* ("at another place").

Perceptual aliasing and feature matching

For feature-based computer vision:
state in the world = a 3D point
internal state = "invariant" descriptor.

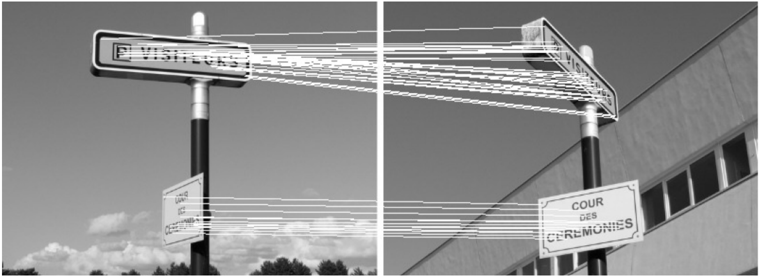
Source of **problematic perceptual aliasing**:

1. the same 3D small patch seen from different positions maps to too different descriptors
   $\longrightarrow$ when **viewpoint change is too large** and the descriptor is not invariant enough.

2. a set of close descriptors corresponds to actually different objects
   $\longrightarrow$ when **repeated patterns** are present.

A blessing or a curse. . . (Whitehead and Ballard 1991)

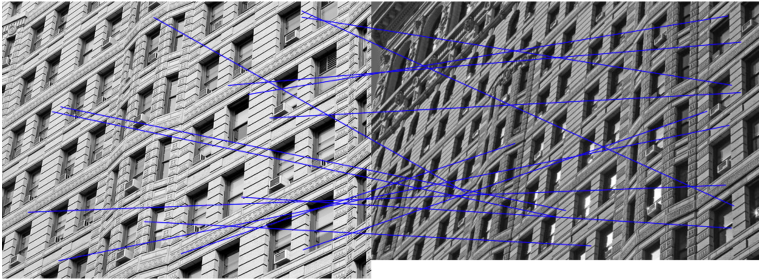
"Perceptual aliasing can be a blessing or a curse. If the mapping between the external world and the internal representation is chosen correctly, a potentially huge state space (with all its irrelevant variation) collapses into a small simple internal state space. Ideally, this projection will group world situations that are the same with respect to the task at hand."



For the point correspondence problem: a blessing. . .

A blessing or a curse. . . (Whitehead and Ballard 1991)

" But, if the mapping is not chosen carefully, inconsistencies will arise and prevent the system from learning an adequate control strategy."



. . . **and** a curse!

A matching method flawed with repeated patterns

The guilty one: *nearest neighbour matching*.

Data: two images I and I', invariant features (x_i, D_i), (x'_j, D'_j),

Standard matching method, two independent steps:

1. Build set of corresp. (x_i, x'_j) based on descriptor similarity
Rule of thumb: x_i matches x'_j if D'_j is the nearest neighbour to D_i in I' provided that $d(D_i, D'_j)/d(D_i, D'_k) < 0.6/0.8$
(D'_k: second nearest neighbour).

2. Prune this set by RANSAC to ensure consistency to epipolar geometry or homography (or. . .)

Specific problems with *repeated patterns*. . .

$\longrightarrow$ first idea: relax the correspondences and go *beyond the NN*.

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Standard RANSAC (RANdom SAmple Consensus)

Aim: prune a set $\mathcal{S}$ of putative correspondences $\{(x, y)\}$ by restricting to those consistent with a geometric mapping A.

Hypothesis: each x has a unique putative correspondence y.

Iterate:

1. draw from $\mathcal{S}$ a sample of minimum size to estimate A
   4 corresp. for homography, 7 or 8 corresp. for fundamental matrix.
2. define the consensus set:

$$S_A^\delta = \{(x, y) \in \mathcal{S} \text{ s.t. } d(A(x), y) < \delta\}$$

Return the largest consensus set.

Generalized RANSAC (inspired by Zhang-Kosecka 2006)

Hypothesis: each x has $K(x)$ putative corresp. $y_1 \dots y_{K(x)}$

Iterate:

1. draw from $\mathcal{S}$ a sample of minimum size s to estimate A (associate x to a single one of the y_i)
2. define an association rule between x and $y(x)$, one of the y_i. (knowing A)
3. define the consensus set:

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Return the largest consensus set.
(here: $\delta \simeq 1$ pix.)

Zhang & Kosecka suggest to select randomly in steps 1 and 2.
Problem: the larger K, the less probable it is to find a large consensus set.

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Generalized RANSAC: computational load

Here: $K(x) = K$ is the same for all x.

Instead of randomly drawing the $y(x)$, we decide:

- in *step 1*: estimate A based on IP associated w.r.t. NN between descriptors
- in *step 2*: associate with $y(x) = \text{argmin } d(A(x), y_i)$.

Motivations: – most correct correspondences are among NN,
– for a point-point constraint, the correct y_i is likely to be the closest to $A(x)$.

Additional computational load w.r.t. standard RANSAC:
$K \cdot |S|$ times more computations at each iteration. (find the argmin)
(just a bit less costly than Zhang & Kosecka.)

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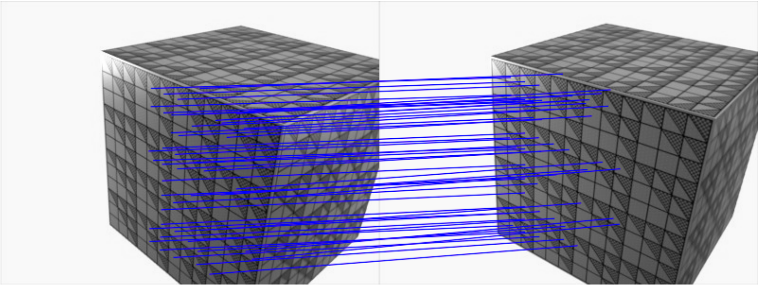
Experiment: synthetic cube (1)

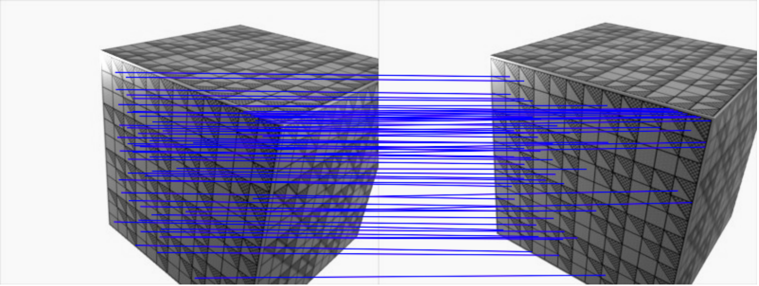
NN (no condition on the ratio) + Homography Ransac



Still large shifted consensus sets (here 49 matches)

Experiment: synthetic cube (2)

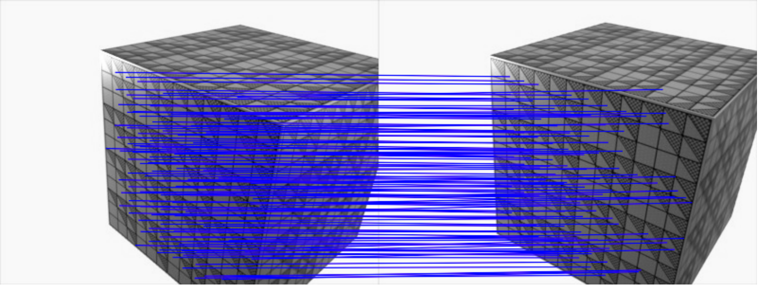
NN (no condition on the ratio) + Homography Ransac
Being careful with the number of iterations:
($\simeq 31,000$ iterations for beating perceptual aliasing)



Here: 60 matches (among $\simeq 800$ IP).

Experiment: synthetic cube (3)

5 NN + Homography Generalized Ransac



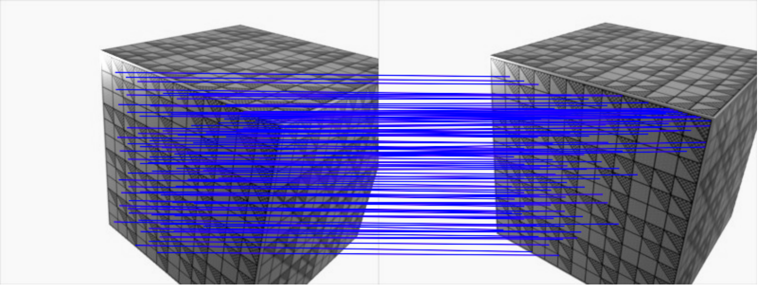
Here: 113 correspondences.

($\simeq 13,000$ iterations for beating perceptual aliasing)

Rank	1	2	3	4	5
Nr of corresp.	**43**	25	24	14	7

Experiment: synthetic cube (4)

10 NN + Homography Generalized Ransac



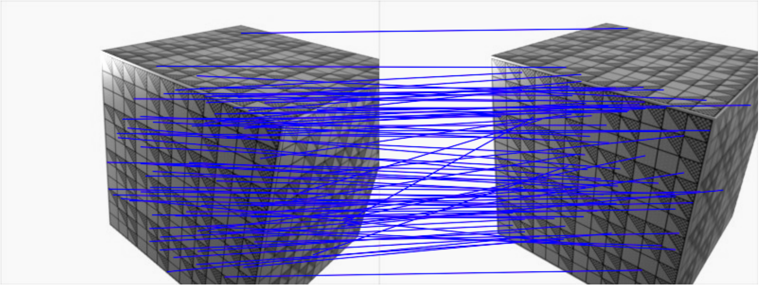
102 correspondences.

($\simeq 6,000$ iterations for beating perceptual aliasing)

Rank	1	2	3	4	5	6	7	8	9	10
Nr of corresp.	**45**	16	18	9	6	4	1	1	0	2

Experiment: synthetic cube (5)

10 NN + **Fundamental matrix** Generalized Ransac



⟶ define $y(x) = \text{argmin}\ d(A(x), y_i)$ cannot work properly with **point/line** constraints.

⟶ next section.

Contextual dissimilarity measure

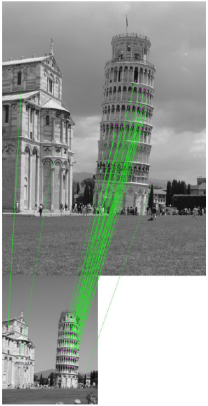
Problem: K NN not well adapted
$\longrightarrow$ K should vary according to the "amount of repeatability".

Naïve idea: threshold over the distance between descriptors
$\longrightarrow$ Does not work : the space of descriptors is not homogeneous.

Better: build a *contextual dissimilarity measure*.
E.g. a-contrario model (Rabin et al. 2008) :

$$N_1 N_2 \Pr(d(D_1, D_2) \leq \delta) \leq \varepsilon$$

where $\Pr(d(D_1, \cdot))$ is *empirically estimated* over all possible correspondences D_2.



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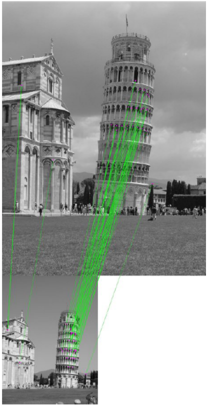
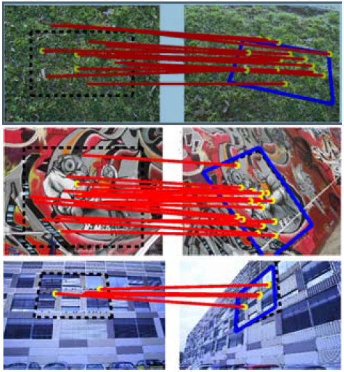


Mixing photometry and geometry

Problem when photometry and geometry independent in matching.



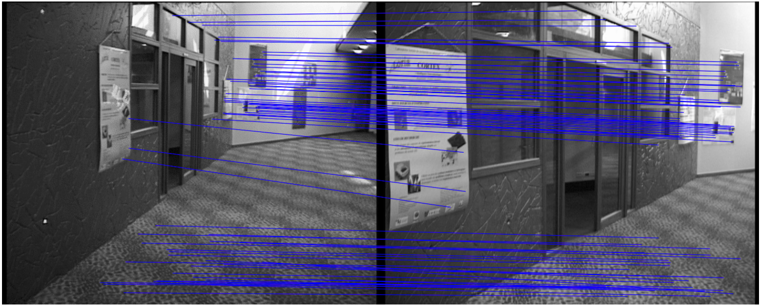
⟶ simultaneously take account of geometric and photometric cues in point matching and go beyond the NN. e.g. Serradell et al. 2010 (illustration), Hsiao et al. 2010.

Remark: Guided MLESAC (Tordoff-Murray 2005) mention the possibility of relaxing photometric matching step by incorporating the photometric information (NCC) in the prior.
⟶ "no benefit w.r.t. re-evaluation of matches".

Repeated patterns and two-view geometry

Summary: going beyond the NN helps planar IP matching. . .

However in two-view geometry:



Remember: NN' + Fundamental matrix RANSAC.
⟶ repeated patterns / textures present specific problems.

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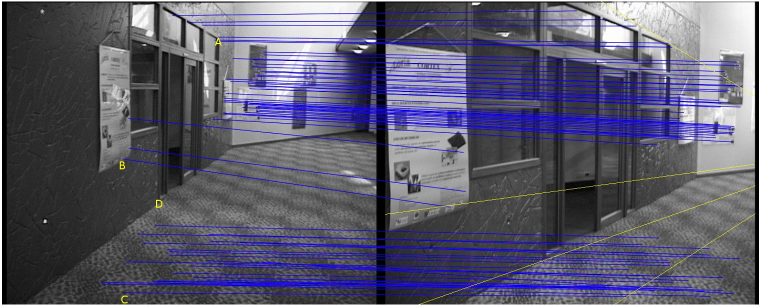
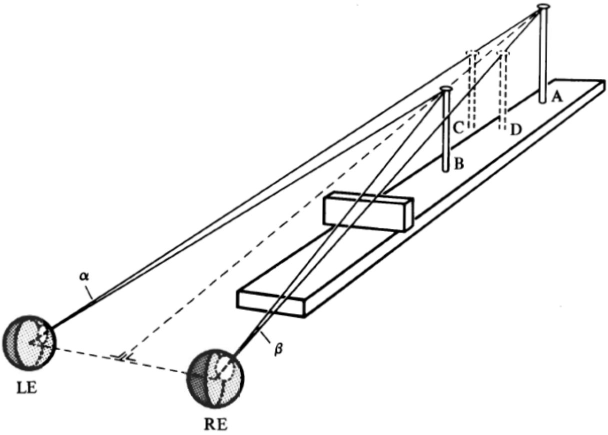


⟶ even with a correct geometry (D is mapped to the correct epipolar line), some repeated patterns (e.g. C) fall "by chance" on the associated epipolar line and give false correspondences. . .

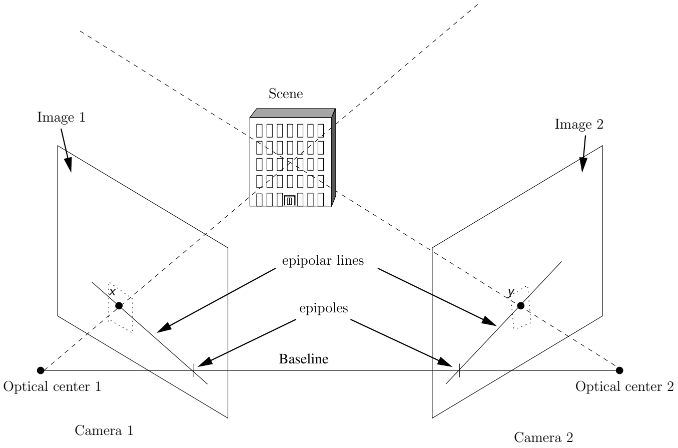
Another curse: the double nail illusion



From Krol and van den Grind 1980.

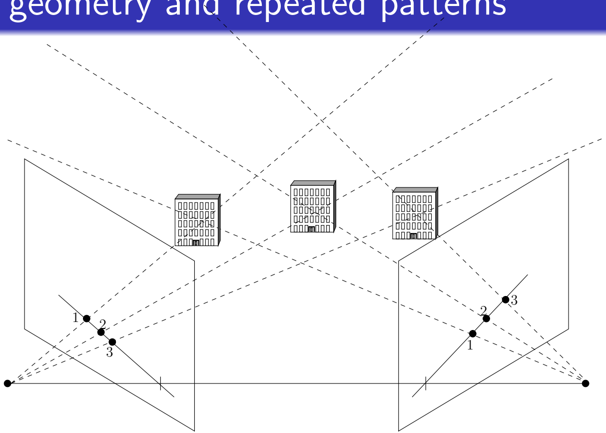
Try it yourself :-)

Two-view geometry: vocabulary



Interest Points x and y are in correspondence.
Descriptors of x and y are similar by design.

Two-view geometry and repeated patterns



If the repeated patterns and the baseline lie on the same plane...

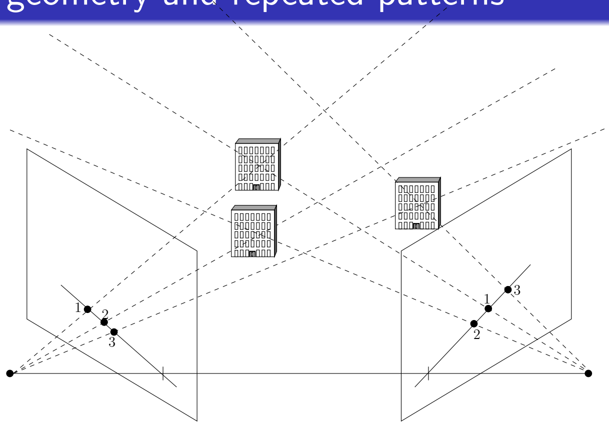
⟶ **several possibilities** (here 6) consistent with:

– *photometry*: scale-invariant descriptor (also holds for human vision according to Krol and van den Grind)

– *geometry*: all keypoints are on the same epipolar line!

⟶ only **one is real**.

Two-view geometry and repeated patterns



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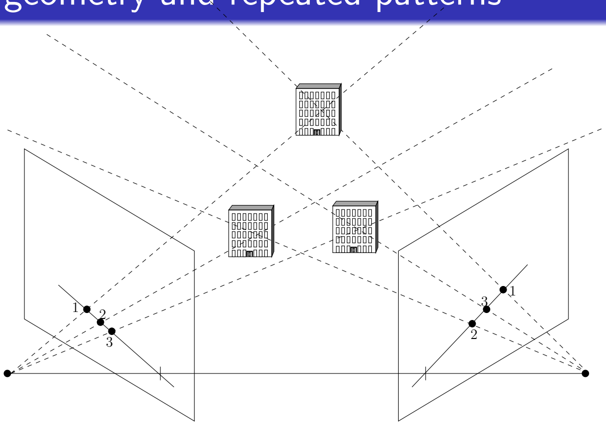

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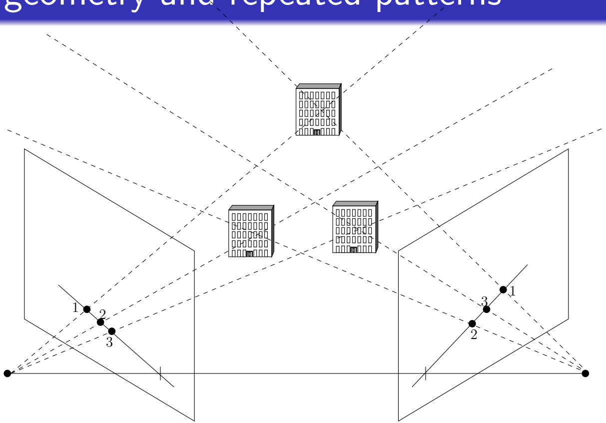

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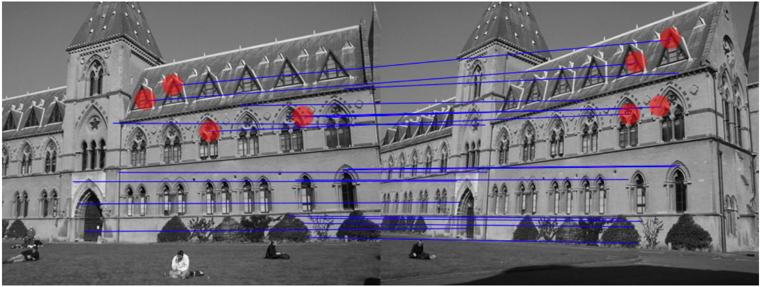
The double nail illusion: experiment



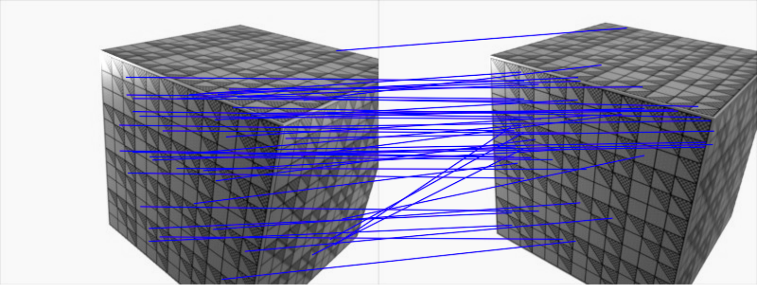
Pitt Rivers Museum, Oxford.

NN + Fundamental Ransac
15 correspondences randomly drawn out of 197: 4 are not correct.

Remark: one is due to symmetry.

Trapped by the double nail illusion

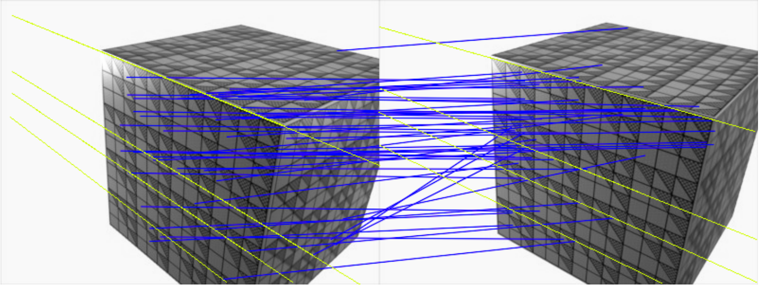
NN + Fundamental Ransac



20 correspondences randomly drawn out of 60.

Trapped by the double nail illusion

NN + Fundamental Ransac



20 correspondences randomly drawn out of 60.

$\longrightarrow$ trapped by the repeated patterns:
the epipolar pencil degenerates to the set of vanishing lines.

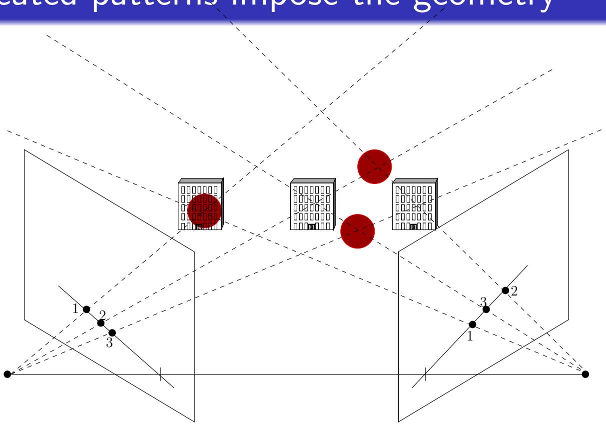
Repeated patterns and vanishing lines

Summary: if the geometry is correct, then the repeated patterns in a epipolar plane can match (falsely).

However, if "multiple nail" illusion is overwhelming, then the **largest set** found by RANSAC is likely to be consistent with a **geometry imposed by the aligned repeated patterns**.

Illustration...

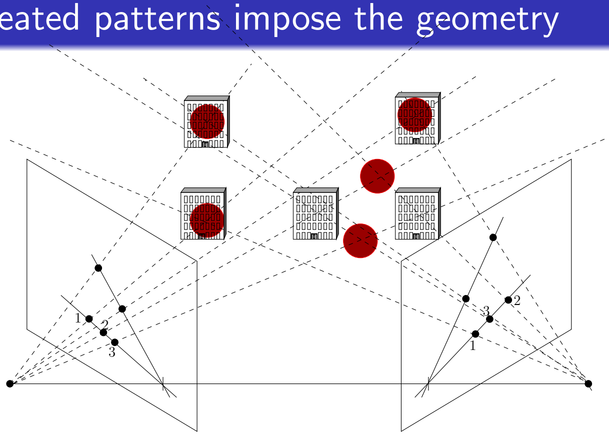
When repeated patterns impose the geometry



Working hypothesis: repeated patterns lie on a vertical plane.
In red: 3D position inferred from both images.

⟶ IP actually on the same plane are not seen as vertically planar.

When repeated patterns impose the geometry

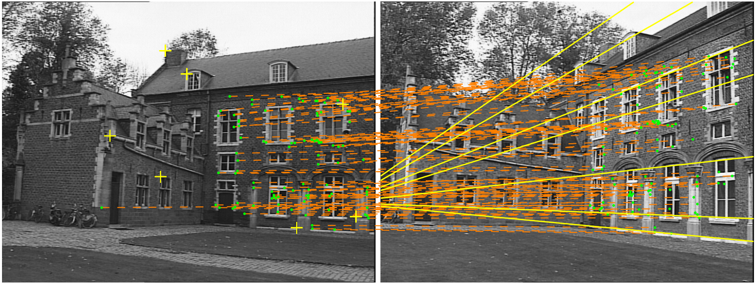


Here, mismatched repeated patterns on a 3D plane are seen as points in a general position. (no ambiguity on F)

Conclusion: epipolar lines = images of the longest parallel 3D lines on which repeated patterns are aligned.

$\longrightarrow$ geometry fitted to the "multiple" nail illusion.

Trapped by the double nail illusion: another example

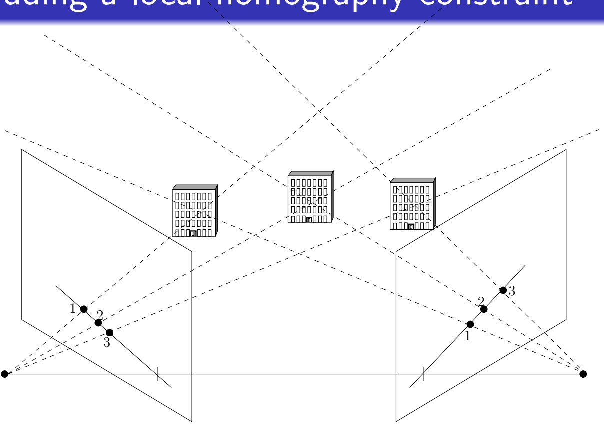


Images from Pollefeys' Leuven Castle sequence.

$\longrightarrow$ trapped by the repeated patterns (over the dominant plane): the epipolar pencil degenerates to vanishing lines.

Points outside the dominant plane are seen as outliers.

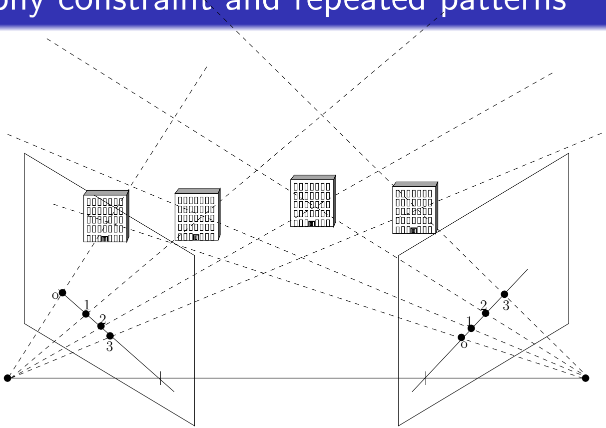
Remark: adding a local homography constraint



⟶ adding local homography constraints impose relative positioning.
⟶ a *single* solution would be selected.

Other possibility: Triggs-Bendale 2010 (constraints on descriptor scale).
⟶ likely to help solving the *vergency trap* of double nail illusion.

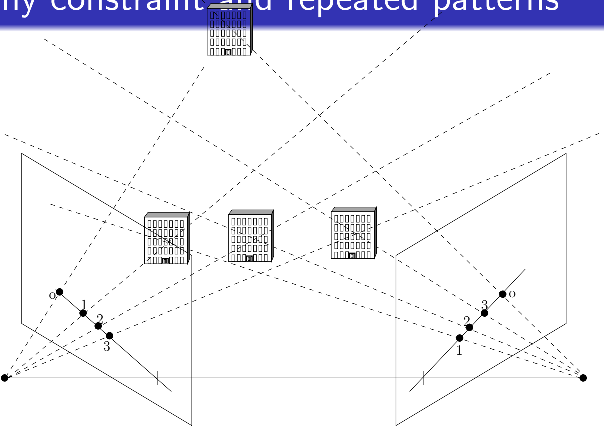
Homography constraint and repeated patterns



Shifting phenomenon still possible in spite of the homography constraint. . . (o=outlier)

But can be disambiguated with external “anchors”.
(homography adds shape/interest point context)

Homography constraint and repeated patterns



Shifting phenomenon still possible in spite of the homography constraint... (o=outlier)

But can be disambiguated with external "anchors".
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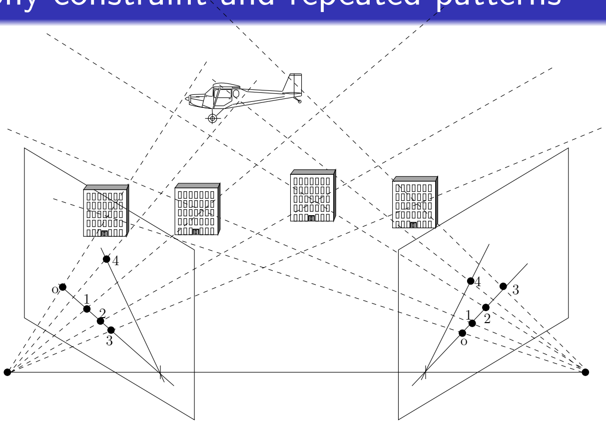
Homography constraint and repeated patterns

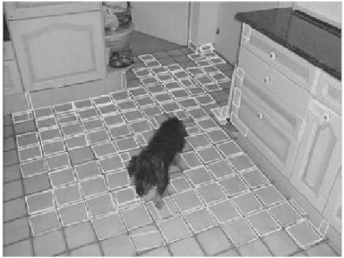


Shifting phenomenon still possible in spite of the homography constraint. . . (o=outlier)

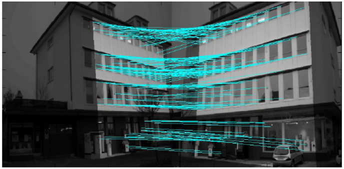
But can be disambiguated with external "anchors".
(homography adds shape/interest point context)

How to recover from the double nail illusion ? (1)

Grouping process:
detect repeated structures
e.g. Wu et al. 2010, Tuytelaars et al. 2003 (illustration), Schaffalitzky 1998
then enforce the homography constraint.



Lee et al. 2009 for building façades:
Search the largest group of points (Harris) consistent with homographies built on edges of a building.



Roberts et al. 2011: use $N > 2$ views in SfM context.

How to recover from the double nail illusion ? (2)

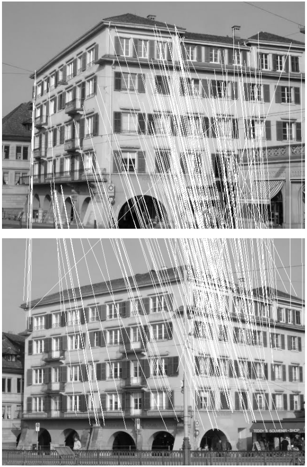
Back to ASIFT

(Morel and Yu 2009)

ASIFT based on NN matching.
Epipolar constraint enforced by final RANSAC.

⟶ subject to the curse of double nail illusion.

Idea to improve ASIFT:
enforce local homographies.



(from ZUBUD database)

ASIFT, 184 matches

Improving ASIFT w.r.t. repeated patterns

Data: two images I and I'.

1. Generate the $I_{t,\phi}$ and $I'_{t',\phi'}$.

2. Extract SIFT features from all generated images.

3. Match SIFT features: for each pair from step 1, match each feature from $I_{t,\phi}$ to its nearest neighbour in $I'_{t',\phi'}$ (with distance ratio condition).

4. Keep only the matched SIFT keypoints from the $I_{t,\phi}$'s and $I'_{t',\phi'}$'s, among the N largest set of correspondences.

5. Discard possible false correspondences: epipolar RANSAC.

Output: a set of corresponding points of interest.

Improving ASIFT w.r.t. repeated patterns

Data: two images I and I'.

1. Generate the $I_{t,\phi}$ and $I'_{t',\phi'}$.

2. Extract SIFT features from all generated images.

$\longrightarrow$ **3.** Match SIFT features: for each pair from step 1, match each feature from $I_{t,\phi}$ to its nearest neighbour in $I'_{t',\phi'}$ (with distance ratio condition).

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Improving ASIFT w.r.t. repeated patterns

Data: two images I and I'.

1. Generate the $I_{t,\phi}$ and $I'_{t',\phi'}$.

2. Extract SIFT features from all generated images.

$\longrightarrow$**3.** Match SIFT features: for each pair from step 1, extract a group of correspondences with generalized Homography-RANSAC.

4. Keep only the matched SIFT keypoints from the $I_{t,\phi}$'s and $I'_{t',\phi'}$'s, among the N largest set of correspondences.

5. Discard possible false correspondences: epipolar RANSAC.

Output: a set of corresponding points of interest.

Reason: affine mapping = local homography
enforce a coplanarity constraint.

Improving ASIFT w.r.t. repeated patterns

Data: two images I and I'.

1. Generate the $I_{t,\phi}$ and $I'_{t',\phi'}$.

2. Extract SIFT features from all generated images.

3. Match SIFT features: for each pair from step 1, extract a group of correspondences with generalized Homography-RANSAC.

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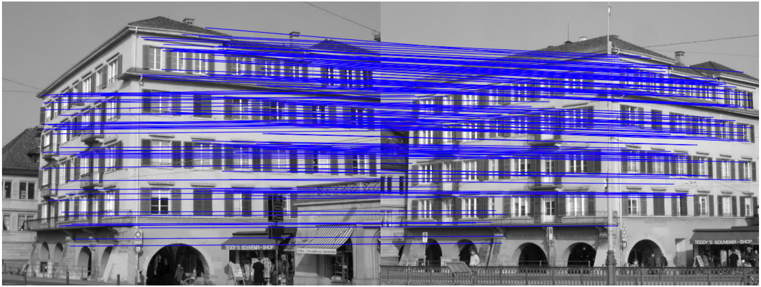
5. Discard possible false correspondences: epipolar RANSAC.

Output: a set of corresponding points of interest.

$\longrightarrow$ *Improved-ASIFT*.
(**Noury et al. 2010**, see also **Le Brese et al. 2010**)

Experiment: large viewpoint change and repeated patterns

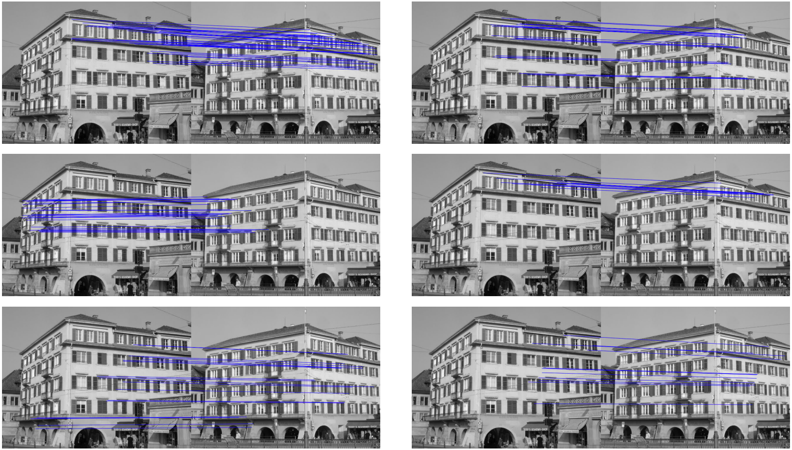


Improved ASIFT: 151 correspondences.

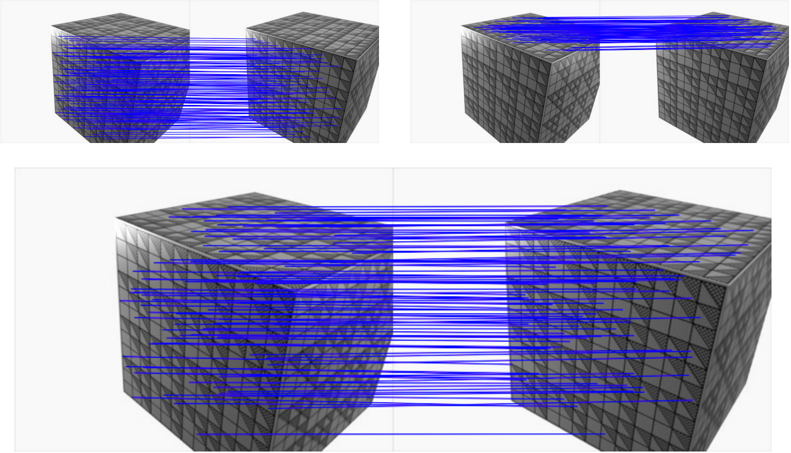
Rank	1	2	3	4	5
Nr of corresp.	**89**	27	19	9	7

Experiment: large viewpoint change and repeated patterns

The six largest correspondence sets from different pairs of simulated views:



Experiment: synthetic cube

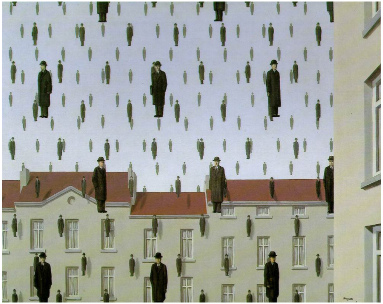


324 correspondences with Improved-ASIFT (only 142 are NN).
($\simeq$ 100 are shown, randomly selected)

Conclusion

Repeated patterns endanger the point correspondence problem:

- may necessitate to go beyond the nearest neighbour,
- double nail illusion is untractable just from IP matching.



René Magritte - *Golconde* - 1953

How to beat the curse of perceptual aliasing?

$\longrightarrow$ current **line of research**, may depend on the application.

Selected references (1)

The double nail illusion:

– J. Krol, W. van der Grind, *The double nail illusion: experiments on binocular vision with nails, needles, and pins*. Perception, 9, pp 651–659, 1980

Encorporating scale information in IP matching:

– B. Triggs, P. Bendale, *Epipolar constraints for multiscale matching*. Proc. of the British Machine Vision Conference, 2010.

An a-contrario contextual dissimilarity measure:

– J. Rabin, J. Delon, Y. Gousseau, *A statistical approach to the matching of local features*. SIAM Journal on Imaging Science 2(3), pp. 931–958, 2008.

Generalized RANSAC:

– W. Zhang, J. Kosecka, *Generalized RANSAC framework for relaxed correspondence problems*, Proc. of the Int. Symposium on 3D Data Processing, Visualization, and Transmission, 2006.

Selected references (2)

Detecting repetitive patterns:

– C. Wu, J.-M. Frahm, M. Pollefeys, *Detecting large repetitive structures with salient boundaries*. Proc. of the European Conference on Computer Vision, 2010.

– F. Schaffalitzky, A. Zisserman, *Geometric grouping of repeated elements within Images*. Proc. of the British Machine Vision Conference, 1998.

– T. Tuytelaars, A. Turina, L. Van Gool, *Noncombinatorial detection of regular repetitions under perspective skew*. Trans. on Pattern Analysis and Machine Intelligence, 25(4) pp. 418–432, 2003.

– J.A. Lee, K.-C. Yow, and A. Y.-S. Chia, *Robust matching of building facades under large viewpoint changes*, proc. of Int. Conference on Computer Vision, pp 1258–1264, 2009.

Selected references (3)

Combining geometric and photometric cues in a unified measure:

– E. Serradell, M. Özuysal, V. Lepetit, P. Fua, F. Moreno-Noguer, *Combining geometric and appearance priors for robust homography estimation*. Proc. of the European Conference on Computer Vision, 2010.

– E. Hsiao, A. Collet, M. Hebert, *Making specific features less discriminative to improve point-based 3D object recognition.* Int. Conference on Computer Vision and Pattern Recognition, 2010.

– R. Roberts, S.N. Sinha, R. Szeliski, D. Steedly, *Structure from motion for scenes with large duplicate structures*, Proc. of the Int. Conference on Computer Vision and Pattern Recognition 2011.

– B.J. Tordoff and D.W. Murray, *Guided-MLESAC: Faster image transform estimation by using matching priors*. Trans. on Pattern Analysis and Machine Intelligence, 27(10) pp 1523 - 1535, 2005.

Selected references (4)

Improving ASIFT:

– J.-M. Morel, G.Yu, *ASIFT, A new framework for fully affine invariant image comparison*. SIAM Journal on Imaging Sciences, 2(2): pp. 438–469, 2009.

– N. Noury, F. Sur, M.-O. Berger, *How to overcome perceptual aliasing in ASIFT?*. Proc. of the Int. Symposium on Visual Computing, LNCS 6453 pp. 231–242, 2010.

– C. Le Brese, J.J. Zou, B. Uy, *An improved ASIFT algorithm for matching repeated patterns*. Proc. of the Int. Conference on Image Processing 2010.

Database:

– Zurich Building Image Database:
`http://www.vision.ee.ethz.ch/showroom/zubud/`