Matching of interest point groups with pairwise spatial constraints

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Scope

Why are accurate correspondences important?

- Accurate correspondences are required in various computer vision tasks (e.g. detection, classification)
- Performance of these algorithms degrades under various conditions (e.g. occlusion, viewpoint change)
- We focus on the use of interest points (e.g. DoG) and descriptors (eg. SIFT) here to establish correspondences [1]

[1] Lowe, *Distinctive image features from scale-invariant keypoints*, IJCV 2004

Main motivation

- Matching of features using appearance alone is insufficient
- We consider the use of spatial information as well
- Spatial information used are in the form of pairwise spatial constraints between features
- The aim is to use spatial information to produce robust correspondences

Matching techniques

- Spatial information has been used previously for matching:
  - Graph matching [2]
  - Optimisation with geometric models [3]
  - Spatial pyramids [4]
- The proposed algorithm has similarities to techniques based on graph matching and optimisation with geometric models

[2] M. Leordeanu and M. Hebert, *A spectral technique for correspondence problems using pairwise constraints*, ICCV 2007

[3] D. Lowe, *Distinctive image features from scale-invariant keypoints*, IJCV 2004

[4] K. Grauman and T. Darrell, *The pyramid match kernel: Discriminative classification with sets of image features*, ICCV 2005

Pairwise relationships between a pair of interest points

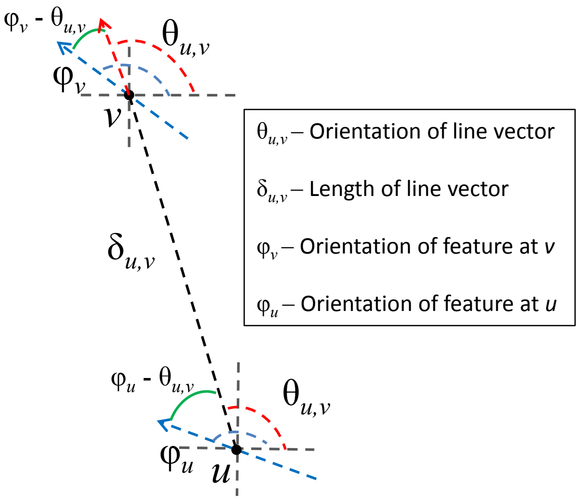


Figure: Pairwise spatial relationships used for a pair of interest points u, v

Pairwise relationships

- Consider interest points u, v in an image X:

$$\hat{x} = \delta_{u,v} \exp(j\theta_{u,v}) \tag{1}$$

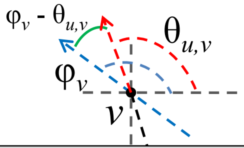
- We define 2 sets of pairwise relationships between u, v:

$$A_1(u,v) = \begin{pmatrix} \phi_u - \theta_{u,v} \\ \phi_v - \theta_{u,v} \end{pmatrix} \tag{2}$$

$$A_2(u,v) = \begin{pmatrix} f_u \\ f_v \end{pmatrix} \tag{3}$$

- where ϕ_u and ϕ_v are feature orientations, f_u, f_v are feature descriptors

Pairwise relationships between a pair of interest points



$\varphi_v - \theta_{u,v}$ and $\varphi_u - \theta_{u,v}$ are spatial relationships collected for a pair of interest points in an image

They should remain fairly consistent for a pair of matching interest points in another image

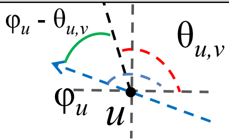


Figure: Pairwise spatial relationships used for a pair of interest points u, v

Pairwise relationships

- Likewise, we consider p, q in an image Y:

$$\hat{y} = \delta_{p,q} \exp(j\theta_{p,q}) \tag{4}$$

- We collect the pairwise relationships $A_1(p, q)$ and $A_2(p, q)$ between p, q as defined previously
- The log-ratio of line vectors $(\ln \frac{\hat{x}}{\hat{y}})$ defines a pairwise relationship between interest point pairs u, v and p, q

Pairwise relationships

$$\begin{aligned} \kappa + j\rho &= \ln \left(\frac{\delta_{u,v} \exp(j\theta_{u,v})}{\delta_{p,q} \exp(j\theta_{p,q})} \right) \\ &= \ln \frac{\delta_{u,v}}{\delta_{p,q}} + j(\theta_{u,v} - \theta_{p,q}) \end{aligned} \tag{5}$$

- ρ - difference in orientation of vectors
- κ - log-ratio of vector lengths
- Scale change (κ) and rotation (ρ) of interest point pairs

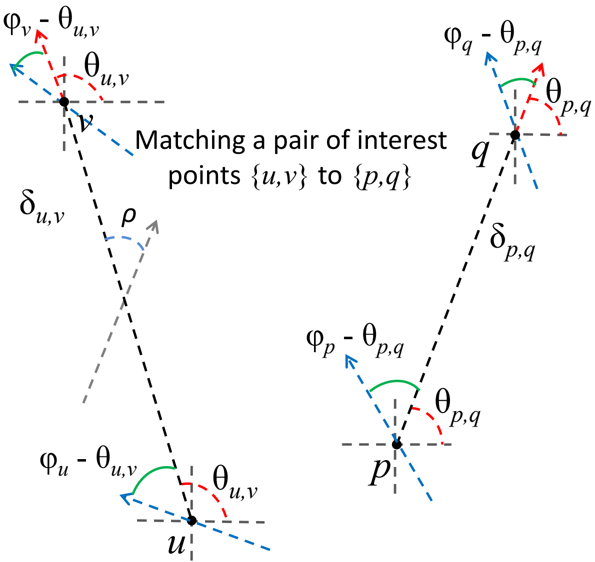


Figure: Matching a pair of interest points u, v to a second pair p, q.

Pairwise spatial matching

- Define a similarity space $\mathcal{S}(\kappa, \rho)$
- $\mathcal{S}$ measures consistency of orientation and scale change
- Consider matching u, p
- Define orientation consistency of interest point pairs as:

$$\chi_{u,p} = \frac{\cos(\phi_u - \theta_{u,v} - \phi_p + \theta_{p,q}) + 1}{2} \tag{6}$$

- Note: The cos function has a fairly broad maximum

Pairwise spatial matching

- We define the feature similarity of interest point pairs as:

$$\gamma_{u,p} = \exp\left(-\|f_u - f_p\|^2 / 2\sigma^2\right) \tag{7}$$

- The similarity of interest point pairs depends on orientation consistency and feature similarity
- Likewise, we define $\gamma_{v,q}$ and $\chi_{v,q}$ for v, q
- The pairwise similarity can then be expressed as:

$$\psi_{\{(u,p),(v,q)\}} = \frac{\chi_{u,p}\gamma_{u,p} + \chi_{v,q}\gamma_{v,q}}{2} \tag{8}$$

- γ and χ measure orientation consistency and feature similarity respectively

Pairwise spatial matching

- The similarity score $\psi_{\{(u,p),(v,q)\}}$ is calculated for pairwise combinations of interest points
- These scores are collected in $\mathcal{S}(\kappa, \rho)$
- Matches can then be found by searching for peaks in $\mathcal{S}$
- For example, using the maxima of histogram or mean shift mode estimator [5]

[5] D. Comaniciu and P. Meer, *Mean shift: A robust approach towards feature space analysis*, PAMI 2002

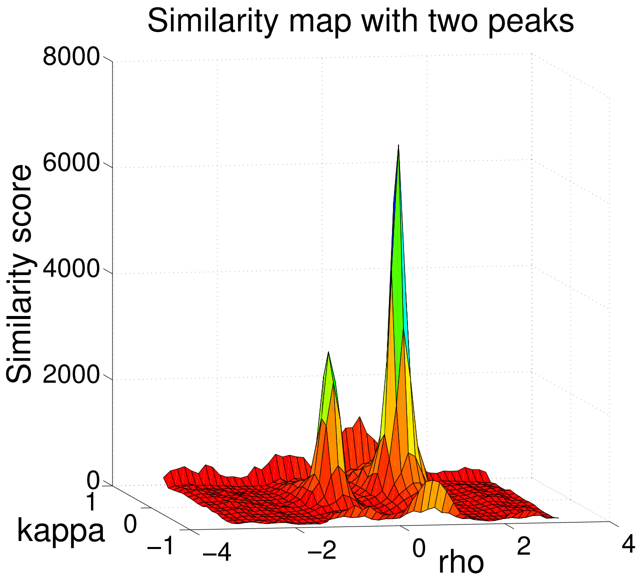


Figure: An example of the similarity space for matching two images

Proposed algorithm

- Spatial constraints are weak for interest points that are far apart
- Thus, we choose to employ spatial constraints over a local neighbourhood
- Consider adjacent square windows having 50% area overlap in an image
- Windows are chosen to be a certain fraction of image area (typically chosen to be 1/25 of image area)
- We used interest points from the Difference of Gaussians detector, along with SIFT descriptors

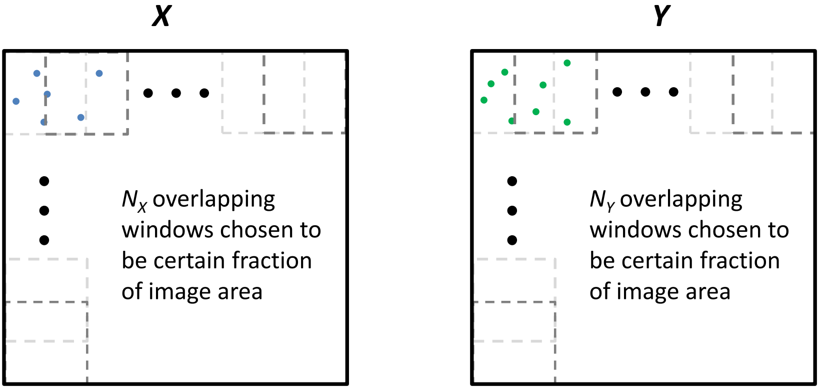


Figure: Summary of matching algorithm

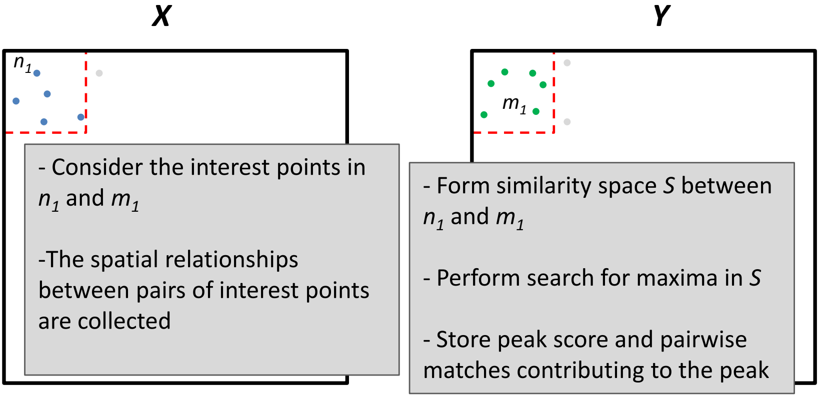
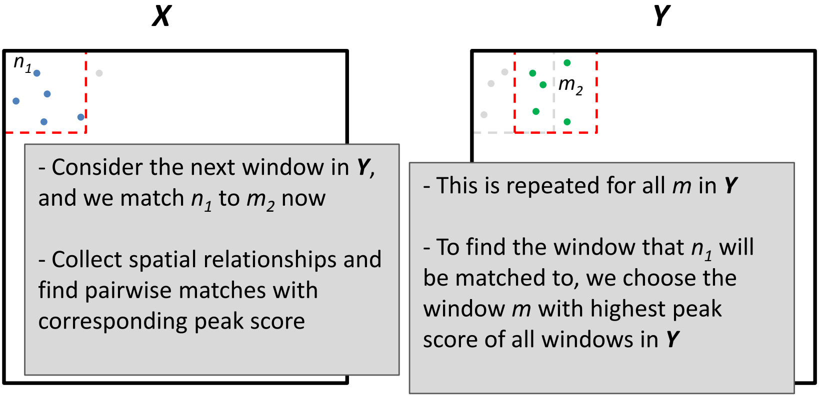


Figure: Summary of matching algorithm



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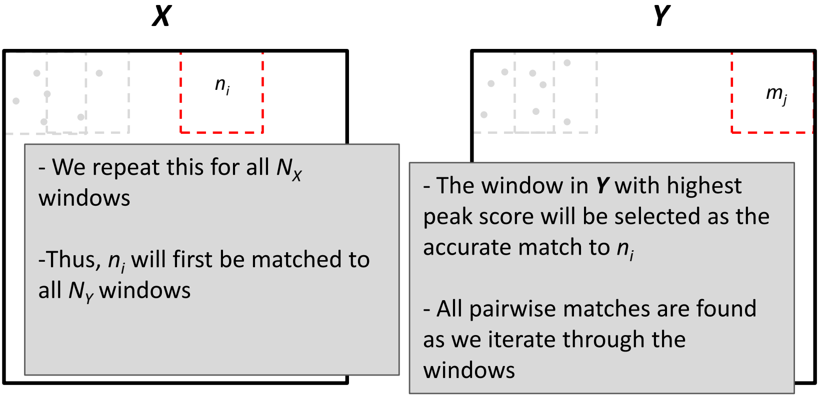

Figure: Summary of matching algorithm

Reducing the computational cost

- The computational cost is high when we consider all possible pairwise combinations of interest points
- We do not need to consider all possible combinations
- An initial set of matches can be first selected
- Initial matches are selected using the ratio of nearest neighbours threshold [6]
- In our tests, we set this threshold to be 0.4, with the unconstrained SIFT initial matches as the baseline
- Spatial relationships are only considered between these initial matches

[6] D. Lowe, *Distinctive image features from scale-invariant keypoints*, IJCV 2004

Reducing the computational cost

- In addition, the similarity score $\psi_{\{(u,p),(v,q)\}}$ for each interest point pairs considered must be $> \tau$ to be stored in $\mathcal{S}$
- This reduces the number of pairs we consider when collecting $\mathcal{S}$
- τ is typically set to 0.7 here

Evaluation framework

- We compared four algorithms
  - Unconstrained baseline SIFT using ratio of nearest neighbours threshold (*uc-sift*)
  - Spectral matching (*sp-match*) [7]
  - *uc-sift* followed by a Hough transform for fitting the matches to a geometric affine model (*hough-sift*) [8]
  - Proposed algorithm (*pw-match*)
- We adopted an evaluation framework which used epipolar constraints to validate actual correspondences [9]

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[7] M. Leordeanu and M. Hebert, *A spectral technique for correspondence problems using pairwise constraints*, ICCV 2007

[8] D. Lowe, *Distinctive image features from scale-invariant keypoints*, IJCV 2004

[9] P. Moreels and P. Perona, *Evaluation of feature detectors and descriptors based on 3D objects*, IJCV 2007

Evaluation framework

- 25 objects were tested
- Test views of the framework consist of each object being rotated on a turntable at intervals of 5°, and matched to a ground truth view of the object
- We repeat the tests 3 times for each object, at ground truth views of $-30^\circ, 0^\circ, 30^\circ$, with viewpoint change of -45° to 45° at intervals of 5° relative to each ground truth view
- We compared the average correspondence ratios of the algorithms

$$\text{correspondence ratio} = \frac{\sum \text{correct matches}}{\sum \text{total matches}} \tag{9}$$

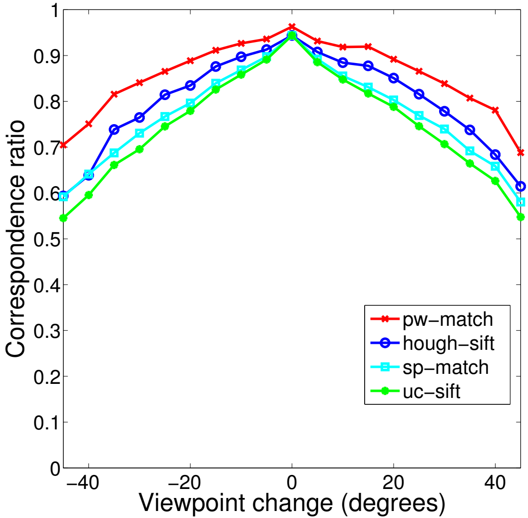


Figure: Results for viewpoint change

Results

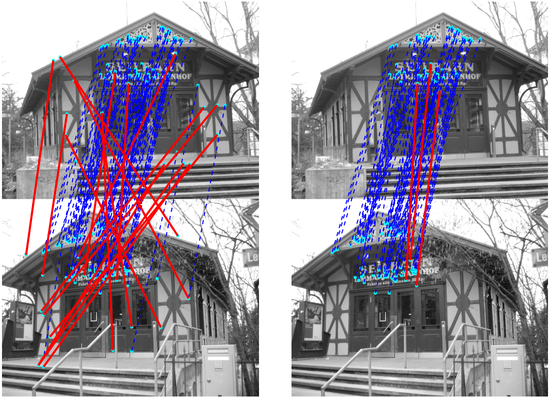
- *pw-match* produced higher correspondence ratios across all viewpoints
- This is followed by *hough-sift*, which performs better than *sp-match* and *uc-sift*
- *uc-sift* has the lowest correspondence ratio, since no spatial information is being considered

Results

- The improvement in correspondence ratio for *pw-match* is higher at larger viewpoint changes
- This implies that the use of spatial constraints have produced matches that are more robust to viewpoint change
- The proposed algorithm has approximately 25% higher computational time compared to *uc-sift*

Results

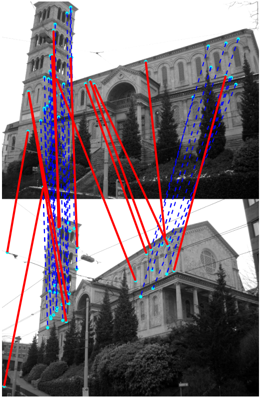
- We also performed tests on the ZuBud building database
- 15 pairs of building images were selected from the database
- Since the ground truth is unavailable, we labelled the false matches by hand



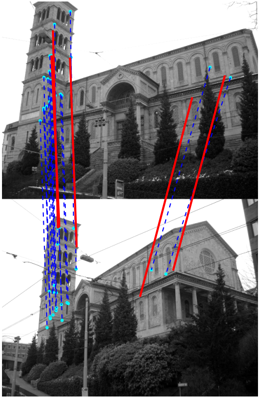
91 correct matches,
16 false matches
(a) *uc-sift*

72 correct matches,
3 false matches
(b) *pw-match*

Figure: Results for ZuBud database



35 correct matches,
13 false matches
(a) *uc-sift*



16 correct matches,
5 false matches
(b) *pw-match*

Figure: Results for ZuBud database

Table: Matching results for 15 buildings in ZuBud database

Results	*uc-sift*	*sp-match*	*pw-match*
Total matches	2199	2033	1483
Correct matches	1913	1830	1421
False matches	286	203	62
Correspondence ratio	0.870	0.900	0.958

Summary

- The proposed algorithm can account for the structure and layout of features by using pairwise constraints
- The pairwise similarity of interest point pairs are defined based on orientation consistency and feature similarity
- Our experiments suggest that the matching algorithm produces robust matches even under large changes in viewpoints
- Future work: Extension to classification and detection of objects with matches produced

End

Thank you

http://www-sigproc.eng.cam.ac.uk/˜esn21