NII team: Query-adaptive asymmetrical dissimilarities for instance search

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Outline

- Asymmetrical method
 - -Instance search is inherently asymmetric.
 - Query-adaptive asymmetrical dissimilarities.
- INS2013 submission
 - Experimental settings.
 - Performance.

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Behind this method

- A joint work between NII and Dr. Hervé Jégou at INRIA.
- Accepted to ICCV2013.

The problem

• Instance search is inherently asymmetric

 the query object is mostly included in the database video, while the converse is not necessarily true.

- However, existing BoW approaches mostly compare query ROIs and database videos with symmetrical measures
 - L1 and L2 distance metrics are mostly used, while they are symmetrical.



Fig. 1: A toy example comparing the standard scoring method in the second row $(\ell_1(\mathbf{Q}, \mathbf{T}_1) = 1, \ell_1(\mathbf{Q}, \mathbf{T}_2) = 1.2)$ with our asymmetrical dissimilarity in the third row $(\delta_1(\mathbf{Q}, \mathbf{T}_1, \infty) = 1, \delta_1(\mathbf{Q}, \mathbf{T}_2, \infty) = 0).$



INS2011

INS2012

Fig. 2: Examples visualizing the asymmetrical inlier/outlier ratio on the query and database side on each benchmark.

Table 1: Symmetrical ℓ_1 vs. (query-adaptive) asymmetrical δ_1 . Note the asymmetrical methods are compatible with an inverted index.

Symmetrical
$$\begin{aligned} & \left\{ \ell_1(\mathbf{Q}_i, \mathbf{T}_j) = \left\| \frac{\mathbf{Q}_i}{\|\mathbf{Q}_i\|_1} - \frac{\mathbf{T}_j}{\|\mathbf{T}_j\|_1} \right\|_1 \\ & \text{Asymmetrical} \\ & \left\{ \delta_1(\mathbf{Q}_i, \mathbf{T}_j, w) = \|\mathbf{T}_j\|_1 - w \|\min(\mathbf{Q}_i, \mathbf{T}_j)\|_1 \\ & \left\{ \delta_1(\mathbf{Q}_i, \mathbf{T}_j, a) = \|\mathbf{T}_j\|_1 - \left\{ \frac{\sum_{j=1}^N \|\mathbf{T}_j\|_1}{\sum_{j=1}^N \|\min(\mathbf{Q}_i, \mathbf{T}_j)\|_1} \right\| \min(\mathbf{Q}_i, \mathbf{T}_j) \right\|_1 \end{aligned}$$



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Table 2: Performance obtained with different parameter w and α .

Configurations	Oxford105K	$Oxford105K^*$	INS2011	INS2012
$\delta_1(\mathbf{Q},\mathbf{T},0)$	0.3	0.3	0.02	0
$\delta_1({f Q},{f T},1)$	2.79	2.78	0.02	0
$\delta_1({f Q},{f T},\infty)$	65.29	38.85	44.88	19.51
$\delta_1(\mathbf{Q},\mathbf{T},w_{ ext{opt}})$	75.38	55.81	47.38	20.88
$\delta_1(\mathbf{Q},\mathbf{T},lpha_{ ext{opt}})$	78.14	61.05	48.50	21.73
$\ell_1(\mathbf{Q},\mathbf{T})$	73.88	54.47	45.16	19.83



Fig. 3: Impact of the parameter α (horizontal axis) on the performance (vertical axis) of the δ_1 asymmetrical dissimilarity.

More details please refer to our recent paper:

C.-Z. Zhu, H. Jégou, and S. Satoh. Query-adaptive asymmetrical dissimilarities for visual object retrieval. Accepted to ICCV, 2013.

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INS2013 dataset

- 469,539 shots from 243 videos (~433.5 hours after the shot0_* being excluded)
 - Recall that 20,982 and 76,751 shots are in the INS2011 and INS2012, respectively.
- 30 query topics, 4 images each.

1+4 non-rigid objects



• 25 rigid objects

– 8 'big' objects



— 7 logos



- 10 other 'small' objects



Our submission

- Experimental settings
 - Sample 5 frames/sec.
 - SIFT only
 - 3 detectors: Hessian-affine, Harris-Laplace and MSER.
 - 2 descriptors: Root-SIFT and color SIFT.
- Three BoW based submissions
 - LO-RANSAC re-rank, Hessian-affine Root-SIFT only.
 - Asymmetrical $\delta 1$ dissimilarity with multiple SIFTs.
 - Baseline L1 distance with multiple SIFTs.

Performance table list

We are ranked 1st, 3rd and 4th, among 74 submissions.



Performance per topic of the best run

• In total we won 12 topics out of 30, in which the spatial re-ranking method contributes two



Run score (dot) versus median (---) versus best (box) by topic



α vs. infAP on INS2013



Thank you!