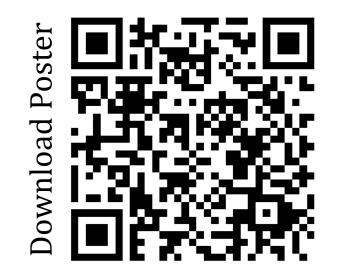


# **WxBS: Wide Baseline Stereo Generalizations**

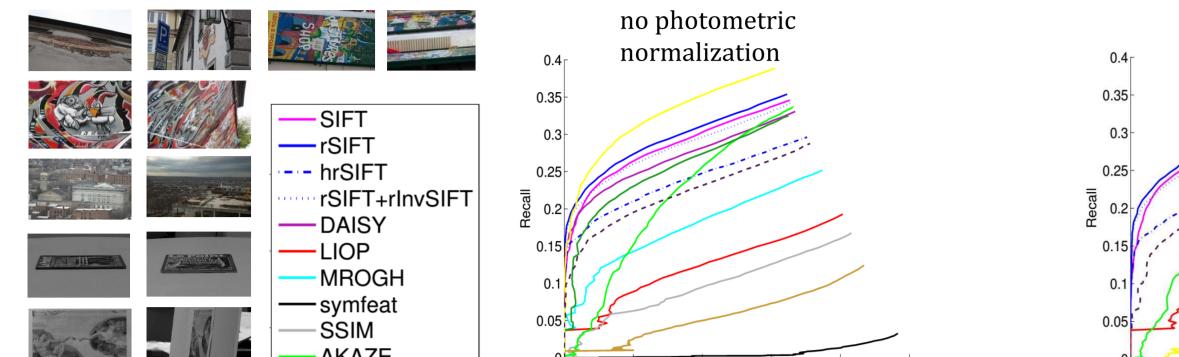
Dmytro Mishkin<sup>1</sup>, Jiri Matas<sup>1</sup>, Michal Perdoch<sup>2</sup>, Karel Lenc<sup>3</sup> <sup>1</sup>Center for Machine Perception, Czech Technical University in Prague; <sup>2</sup>Computer Vision Laboratory, ETH Zurich, Switzerland; <sup>3</sup>Department of Engineering Science, University of Oxford, UK

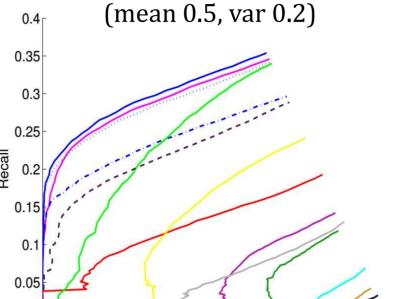


# Abstract

- **Generalization of the wide baseline two-view matching problem WxBS** x stands for different subsets of "wide baselines" in acquisition conditions.
- **Novel dataset** of ground-truthed image pairs which include multiple "wide baselines"
- We show that state-of-the art matchers fail on almost all image pairs.
- WxBS-M a novel matching algorithm for the WxBS problem is introduced. We show experimentally that the WxBS-M matcher dominates the state-of-the-art methods both on the new and existing datasets

# WGBS – Wide Geometry Baseline Stereo





with photo normalization

0.8

# **WxBS-Matcher**

**Input**: *I*<sub>1</sub>, *I*<sub>2</sub>- two images,  $\Theta_m$ - minimum required number of matches,  $S_{max}$ - maximum number of iterations **Output**: Fundamental or homography matrix **F** or **H**; a list of corresponding local features while  $(N_{matches} < \Theta_m)$  and  $(Iter < S_{max})$  do for *I*<sub>1</sub> and *I*<sub>2</sub> separately do

**1 Generate synthetic views** according to the scale-tilt-rotation-detector setup for Iter

**2 Detect local features** using adaptive thresholding

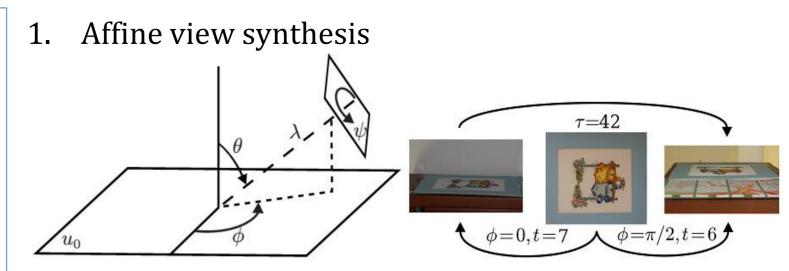
**3** Extract rotation invariant descriptors with: **3a RootSIFT** and **3b HalfRootSIFT** 4 Reproject local features to I<sub>1</sub>, I<sub>2</sub> end for

5 Generate tentative correspondences based on

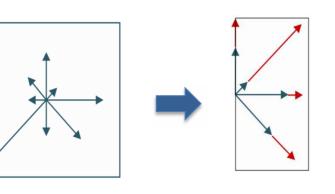
1<sup>st</sup> geom. Inconsistent rule for RootSIFT and HalfRootSIFT separately using kD-tree

**6** Filter duplicates

**7 Geometric verification** of all TC with modified DEGENSAC estimating F or H



2. Adaptive thresholding: if #HesAffs <  $\theta_{HesAff}$ , lower the detection threshold 3. HalfRootSIFT: HalfSIFT bin SIFT bin



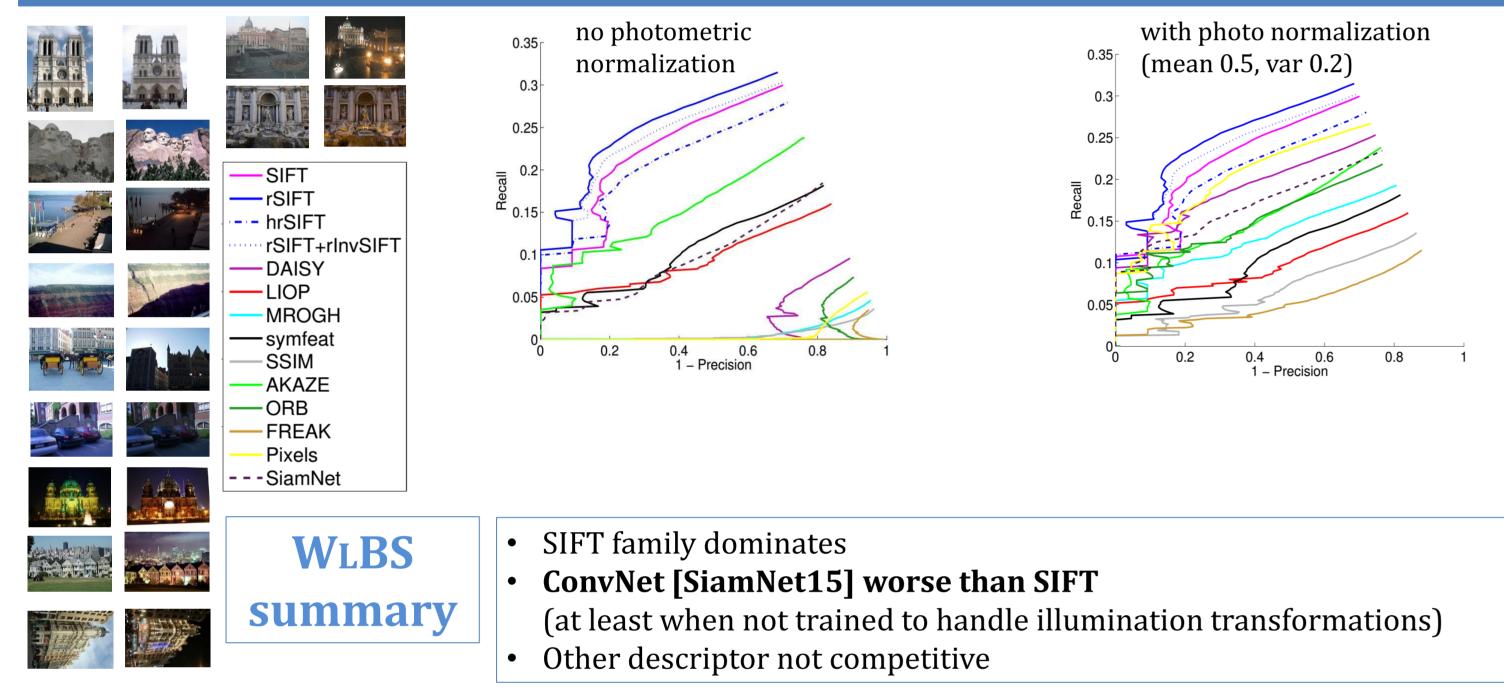
5. 1<sup>st</sup> geom. Inconsistent rule: use for second nearest distance ratio only patches, which are inconsistent with closest one (yellow, not red)



	0 0.2 0.4 0.6 0.8 1 1 – Precision 0 0.2 0.4 0.6 1 – Precision 1 – Precision
WGBS summary	<ul> <li>SIFT family dominates</li> <li>Photo-L2 normalized pixel intensities is a strong descriptor</li> <li>ConvNet [SiamNet15] worse than SIFT (at least when not trained to handle large transformations)</li> <li>Other descriptor not competitive</li> </ul>

\*Images from Extreme View (EVD) and Oxford-Affine(OxAff) Datasets

#### WLBS – Wide illumination Baseline Stereo

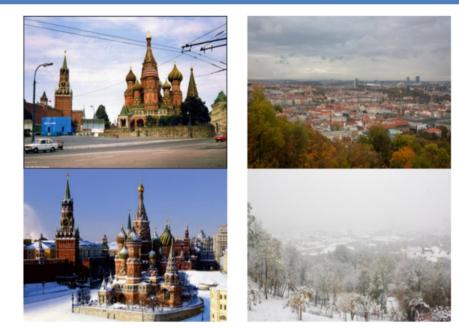


\*Images from SymBench, GDBootstrap, EgdeFoci (EF) datasets

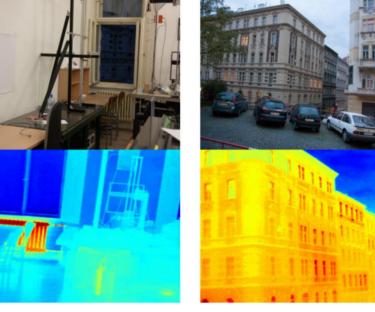
8 Check geometric consistency of the local affine features with est. F or H end while

6. Filter duplicates: discard redetections (red patches)

# WxBS: Multiple Wide Baselines

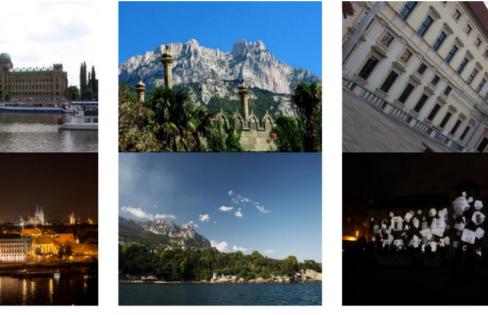


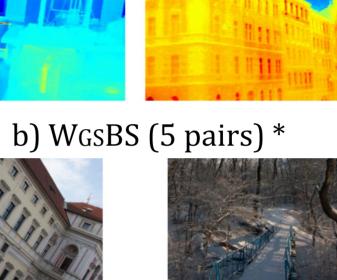
Alg.





a) WGABS (5 pairs)







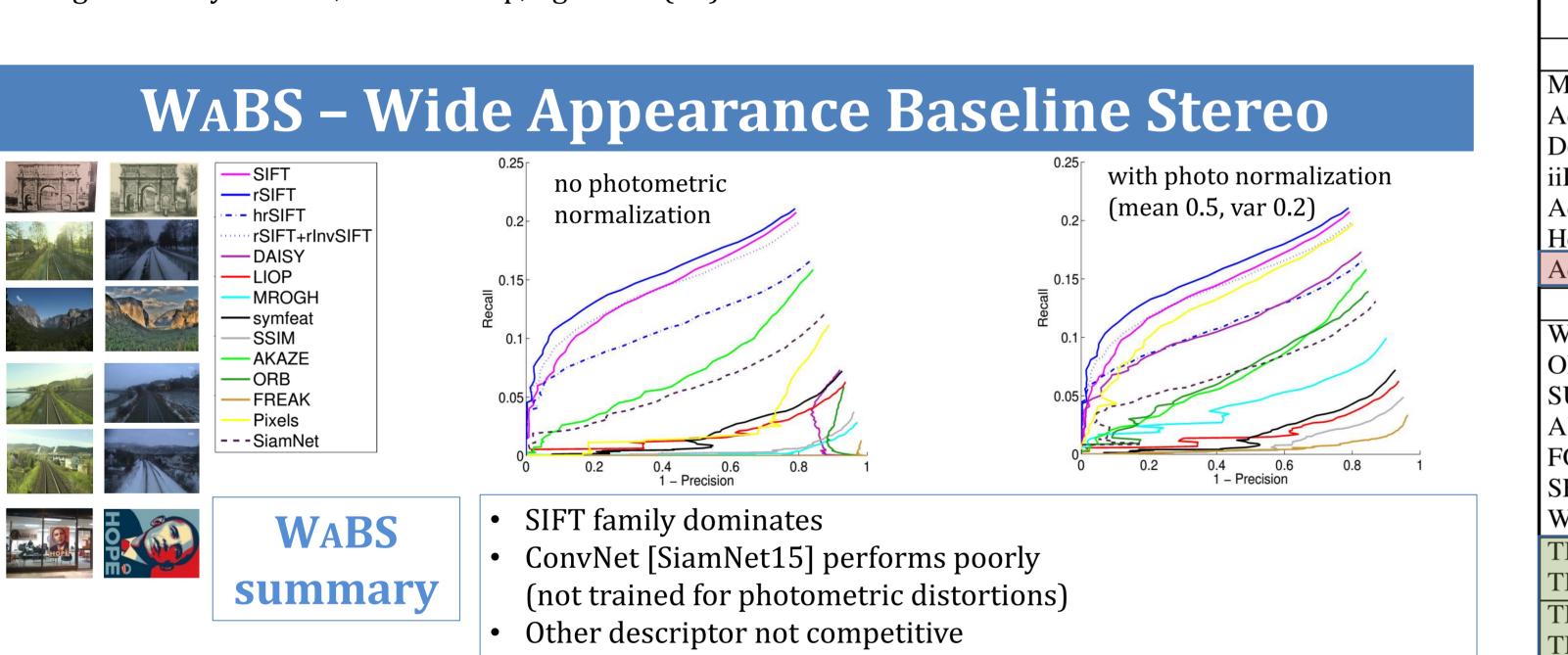
e) WGALBS (8 pairs)



d) WGLBS (9 pairs) \*WGSBS contains image pairs of thermal camera vs visible

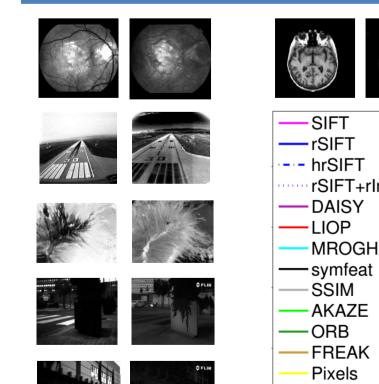
### **Detector and matcher comparison**

•	]	EF	E	VD	MMS		WGABS		WGALBS		WGLBS		WGSBS		WLABS		Past		OxAff		SymB		G	DB	
	#	time	#	time	#	time		time		time		time		time		time		time			<b>#</b>	time	#	time	
	22	r ı	15	ГЛ	100	ГI	5	гл	0	ГI	0	гэ	5	гı	1	гл	170	r ı	40	гı I	16	гл	22	гι	1

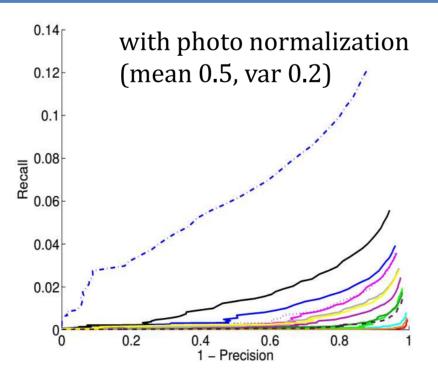


\*Images from SymBench, VPRiCE 2015, EgdeFoci (EF) datasets

#### WSBS – Wide Sensor Baseline Stereo



#### no photometric normalization 0.12 rSIFT+rInvSIFT L 0.06 0.04 0.4 0.6 0.8 1 - Precision



	33	[ <i>s</i> ]	15	[ <i>s</i> ]	100	<b>[</b> <i>S</i> <b>]</b>	5	<b>[</b> <i>S</i> <b>]</b>	8	[ <i>s</i> ]	9	[ <i>s</i> ]	5	<b>[</b> <i>S</i> <b>]</b>	4	<b>[</b> <i>S</i> <b>]</b>	172	[s]	40	<b>[</b> <i>S</i> <b>]</b>	46	[s]	22	[2
										Threshold	ad	aptation	n											
MSER	16	1.4	3	1.4	1	0.3	0	2.0	0	1.3	0	1.3	0	0.8	1	1.2	8	1.3	40	3.5	23	2.4	9	
AdMSER	25	3.4	8	4.0	6	1.0	0	4.0	0	3.2	0	3.3	0	1.4	1	2.6	11	2.9	40	5.7	26	4.6	13	(
DoG	29	2.3	0	2.8	10	0.8	0	2.7	0	2.3	0	2.1	0	1.0	1	2.4	13	2.0	38	4.8	29	2.7	12	
iiDoG	29	3.1	0	3.0	11	1.2	0	3.2	0	2.9	0	2.8	0	1.2	1	2.5	13	2.2	38	8.0	29	2.9	12	
AdDoG	29	2.6	0	3.4	11	1.2	0	3.3	0	3.0	0	3.0	0	1.5	1	2.7	13	2.7	38	4.1	30	3.0	12	
HesAf	32	4.6	1	5.2	15	1.2	0	5.5	0	3.8	0	4.2	0	2.0	1	3.6	24	4.0	40	11	35	5.8	17	
AdHesAf	33	5.7	2	7.6	35	2.9	0	7.2	1	6.5	0	6.0	0	3.2	1	4.9	25	5.4	40	10	35	7.2	18	
										Other c	lete	ectors												
WαSH	0	1.8	0	5.4	0	0.6	0	2.8	0	2.5		1.4	0	1.8	0	1.2	0	1.9	24	4.1	3	2.8	3	
ORB	3	4.1	0	3.6	1	0.8	0	2.8		2.7		3.6	0	1.6		2.8	1	2.3	28	8.7	5	3.0	3	
SURF	27	2.3	0	2.4	7	1.0	0	2.5	0	1.9		2.1	•	0.9		1.4	10	1.9	38	5.8	31	2.9	15	
AKAZE	28	4.3	0	3.6	10	0.8	1			3.4		4.0		1.3	1	2.7	25		38		35	5.6	17	
FOCI	29	12	0	39	14	11	1	32	1	29		29		20		29	21		38		35	27	17	
SFOP	25	11	0	16	12	4.7	0	12	1	10	0	10	0	9.2		7.5	11		36	15	24	11	8	
WADE	16	14	0	20	0	3.4	0	58	-	11		14		7.9	1	8.3	20	23	34		34	46	13	
TILDE-StL-ns	22	3.7	0	6.6	20	2.8	0	5.0		4.5		5.0		4.6		4.2	-	-		5.5		4.6	8	
TILDE-StL	27	18.	0	32.	31	13.	0	22.		20.		21.		17.	1	21.	-	-		24.		22.	9	
TILDE-Cha	26	16	0	30		11	0	21	0		0	20	0	16	1	21	13	19	38	25	30	22	8	
TILDE-Cou	28	18	0	30	42	13		23		22	0	24		17	1	21	18		37		31	22	8	
TILDE-Fra	23	18	1	32	33	13		22			0	23		17	1	23	14		37		31	22	9	
TILDE-Mex	24	17	0	29	5	12		23		23		23		18		21	13		36			22	8	
TILDE-Pan	29	18	0	30	42	13	0	26		24		23		18	1	23	15	20	36	26	32	21	11	
										State-of-a														
ASIFT	23	27	5	12	18	3.2		52		32		35		12		30		32		102		14		
MODS	33	4.8		11	27	11	$\left  2 \right $	41				46		17		26			40		42	18		
DBstrap	31	26	0	18	79	9.3	0	11	0	13	-	13	0	4.7	0	15	16	28	36	24	38	21	16	
	0.0	]								Propose			0						10		10	1.0		
WXBS-M	33	4.7	15	14	82	12	3	40	3	63	3	61	0	26	3	28	107	42	40	5.1	43	18	22	

TILDE detector results are post-CR deadline

Best results among single detectors (AdHesAf) and view-synth based matchers (WxBS-M)

Take away



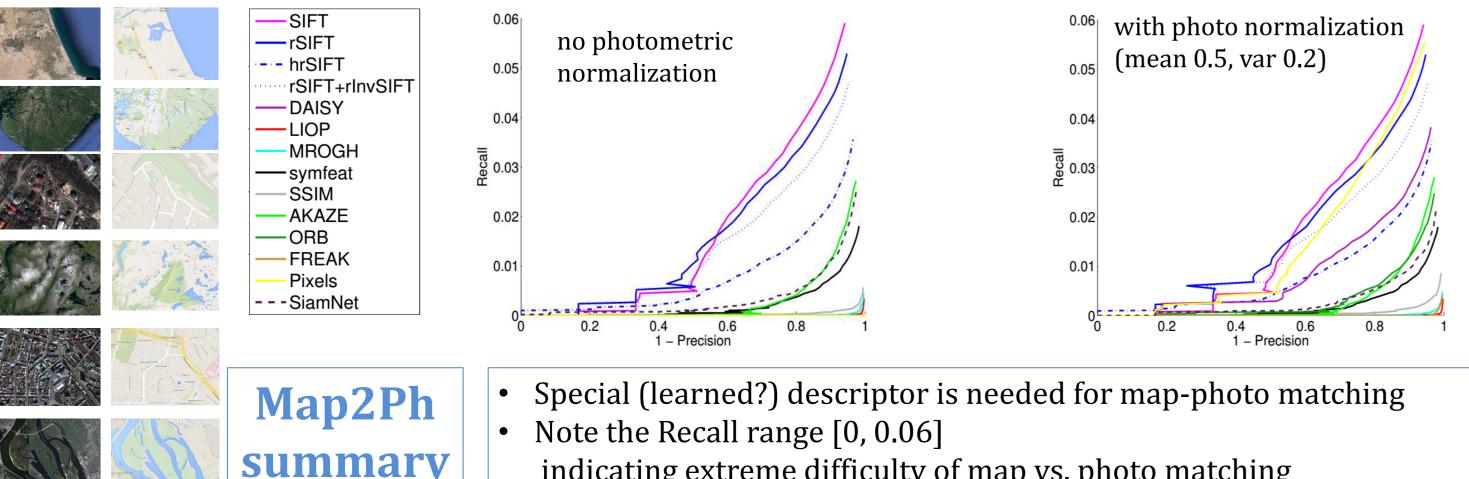




- No descriptor performance acceptable
- Only gradient folding in HalfSIFT works (poorly) Note the Recall range [0, 0.14] indicating high difficulty

\*Images from GDBstrap and MMS datasets

#### Map2Photo: WABS special case



indicating extreme difficulty of map vs. photo matching

- SIFT family is still the best local descriptor, outperforms novel CNN [SiamNet2015] approaches.
- (adaptive) Hessian-Affine is the best detector with broad applicability
- Affine view synthesis greatly helps for non-geometrical problems.
- Datasets and WxBS-Matcher available <a href="http://cmp.felk.cvut.cz/wbs/">http://cmp.felk.cvut.cz/wbs/</a>
- We need more diverse datasets for learning local descriptors than Yosemite and Liberty

#### References

- [SiamNet15] S. Zagoruyko, N. Komodakis. Learning to Compare Image Patches via **Convolutional Neural Networks. In CVPR 2015**
- [HalfSIFT10] J. Chen, J. Tian, N. Lee, J. Zheng, R. Smith, and A. Laine. A partial intensity invariant feature descriptor for multimodal retinal image registration. Biomedical Engineering, IEEE Transactions on, 2010.
- [MODS15] D. Mishkin and J. Matas and M. Perdoch. MODS: Fast and Robust Method for Two-View Matching. Accepted to CVIU, 2015.
- [DEGENSAC05] O.Chum, T. Werner, J. Matas. Two-view Geometry Estimation Unaffected by a Dominant Plane. In CVPR 2005