

CENTER FOR MACHINE PERCEPTION



CZECH TECHNICAL UNIVERSITY IN PRAGUE

# Two-view Matching with View Synthesis Revisited

### Dmytro Mishkin, Michal Perdoch, Jiri Matas

ducha.aiki{at}gmail.com,perdom1,matas {at}(cmp.felk.cvut.cz)

CTU-CMP-2013-15

October 29, 2018

**RESEARCH REPORT** 

The authors were supported by The Czech Science Foundation Project GACR P103/12/G084 and by the Technology Agency of the Czech Republic research program TE01020415 (V3C – Visual Computing Competence Center).

Research Reports of CMP, Czech Technical University in Prague, No. 15, 2013

Published by

Center for Machine Perception, Department of Cybernetics Faculty of Electrical Engineering, Czech Technical University Technická 2, 166 27 Prague 6, Czech Republic fax +420 2 2435 7385, phone +420 2 2435 7637, www: http://cmp.felk.cvut.cz

# Two-view Matching with View Synthesis Revisited

Dmytro Mishkin, Michal Perdoch, Jiri Matas

October 29, 2018

#### Abstract

Wide-baseline matching focussing on problems with extreme viewpoint change is considered. We introduce the use of view synthesis with affine-covariant detectors to solve such problems and show that matching with the Hessian-Affine or MSER detectors outperforms the state-of-the-art ASIFT [18].

To minimise the loss of speed caused by view synthesis, we propose the Matching On Demand with view Synthesis algorithm (MODS) that uses progressively more synthesized images and more (time-consuming) detectors until reliable estimation of geometry is possible. We show experimentally that the MODS algorithm solves problems beyond the state-of-the-art and yet is comparable in speed to standard wide-baseline matchers on simpler problems.

Minor contributions include an improved method for tentative correspondence selection, applicable both with and without view synthesis and a view synthesis setup greatly improving MSER robustness to blur and scale change that increase its running time by 10% only.

### **1** Introduction

The standard method for wide baseline matching involves detection of local features, calculation of descriptors, generation of tentative correspondences and their geometric verification using the homography or epipolar constraint.

It is well known [17, 8, 7] that performance of the pipeline decreases in the presence of viewpoint and scale changes, blur, compression artefacts, etc. Lepetit and Fua [12] showed that matching robustness is improved by synthesis of additional views given a single, fronto-parallel view of an object. Morel and Yu [18] combined viewpoint synthesis with the similarity-covariant Difference-of-Gaussians detector (DoG) and SIFT matching [14]. The resulting image matching method, called ASIFT, successfully matched challenging image pairs with significantly different viewing angles.

We develop the idea of view synthesis for wide baseline matching and propose a number of novelties that improve several stages of the matching pipeline. Some of the improvements are also applicable to two-view matching without synthesis. The proposed MODS wide-baseline matcher<sup>1</sup> outperforms ASIFT in terms of speed, the number and percentage of correct matches generated as well as in the precision of the estimated geometry. Performance was tested mainly on image pairs with extreme viewpoint changes, but viewpoint synthesis also improves matching results in the presence of phenomena like blur, occlusion and scale change. The following contributions are made: first, we show that the seemingly counter-intuitive synthesis of affine views for "affine-covariant" detectors greatly improves their performance in wide baseline matching. With suitable detector-specific configurations of synthesized viewpoints, found through extensive experimentation, both the Hessian-Affine [16] and MSER [15] detectors clearly outperform DoG [14].

Second, we generalize the "first-to-second-closest SIFT distance ratio" criterion for the selection of tentative correspondences. Depending on the image, the new criterion gives 5-20% more true matches than the standard at no extra computation cost. The proposed criterion improves even matching performance without synthesis, especially in images with local symmetries.

Third, we propose an adaptive algorithm for matching very challenging image pairs which follows the "do only as much as needed" principle. The MODS algorithm (Matching On Demand with view Synthesis)

<sup>&</sup>lt;sup>1</sup>Available at http://cmp.felk.cvut.cz/wbs/index.html

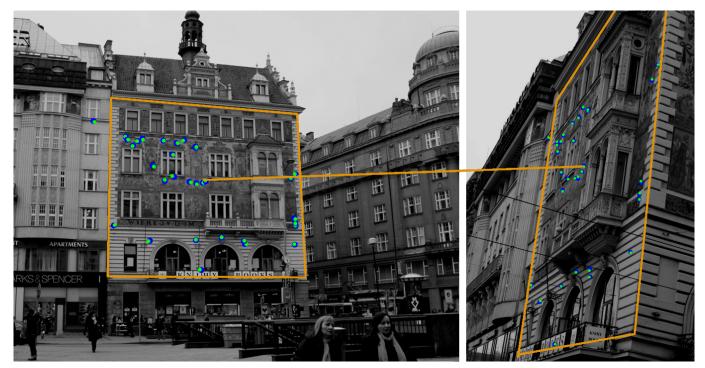


Figure 1. Homography estimation with extreme viewpoint change. The proposed MODS algorithm produces 32 matches, 25 are correct. The state-of-the-art ASIFT [18] outputs 41 matches, 3 are correct. Blue dots: centers of detected regions. Green dots: reprojected centers of corresponding regions showing good alignment.

uses progressively more detector types and more synthesized images until enough correspondences for reliable estimation of two-view geometry are found. MODS is fast on easy image pairs without compromising performance on the hardest problems.

### 1.1 Related work

The use of view synthesis for image matching is a recent development and the literature is limited and includes mainly modifications of the ASIFT algorithm. Liu *et al.* [13] synthesised perspective warps rather than affine. Pang *et al.* [20] replaced SIFT by SURF [3] in the ASIFT algorithm to reduce the computation time. Sadek *et al.* [22] present a new affine covariant descriptor based on SIFT which can be used with or without view synthesis. Detection of the MSERs on the scale space pyramid was proposed by Forssén and Lowe [9].

The rest of the paper is organised in a top-down manner. In Section 2, we introduce the adaptive MODS two-view matching algorithm. Section 3 studies view synthesis for affine-covariant detectors. Experiments are presented in Section 4. Full experimental data is in Appendix.

# 2 Matching with On Demand View Synthesis

The iterative MODS algorithm (see Alg. 1) repeats a sequences of two-view matching procedures, until a required minimum number of geometrically verified correspondences is found. In each iteration, a different detector is used and a different set of views generated. The adopted sequence is an outcome of extensive experimentation with the objective of solving the most challenging problems while keeping speed comparable to standard single-detector wide-baseline matchers for simple problems. For instance, the first iteration of the MODS algorithm runs the MSER detector with only a very coarse scale space pyramid which is 10% slower than standard MSER. Subsequent iterations run complementary detectors with a higher number of synthesized views. Details on the chose configuration and the selection process are given in Section 3. The rest of the section describes the steps employed in the iterations of the MODS algorithm.

```
Algorithm 1 MODS: Matching with On-Demand view Synthesis
Input: I_1, I_2 – two images; \theta_m – minimum required number of matches; S_{max} – maximum number of iterations.
Output: Fundamental of homography matrix F or H;
  list of corresponding points.
Variables: N_{\text{matches}} – detected correspondences, Iter – currect iteration.
  while (N_{\text{matches}} < \theta_m) and (\text{Iter} < S_{\text{max}}) do
     for I_1 and I_2 separately do
        1 Generate synthetic views according to the
          scale-tilt-rotation-detector setup for the Iter.
        2 Detect and describe local features.
       3 Reproject local features to original image.
          Add described features to general list.
     end for
     4 Generate tentative correspondences
        using the first geom. inconsistent rule.
     5 Filter duplicate matches.
     6 Geometrically verify tentative correspondences
        while estimating F or H.
```

end while

#### 2.1 Synthetic views generation

It is well known that a homography H can be approximated by an affine transformation A at a point using the first order Taylor expansion. Further, an affine transformation can be uniquely decomposed by SVD into a rotation, skew, scale and rotation around the optical axis [10]. Morel and Yu [18] proposed to decompose the affine transformation A as

$$A = H_{\lambda}R_{1}(\psi)T_{t}R_{2}(\phi) = = \lambda \begin{pmatrix} \cos\psi & -\sin\psi\\ \sin\psi & \cos\psi \end{pmatrix} \begin{pmatrix} t & 0\\ 0 & 1 \end{pmatrix} \begin{pmatrix} \cos\phi & -\sin\phi\\ \sin\phi & \cos\phi \end{pmatrix}$$
(1)

where  $\lambda > 0$ ,  $R_1$  and  $R_2$  are rotations, and  $T_t$  is a diagonal matrix with t > 1. Parameter t is called the absolute tilt,  $\phi \in \langle 0, \pi \rangle$  is the optical axis longitude and  $\psi \in \langle 0, 2\pi \rangle$  is the rotation of the camera around the optical axis. Each synthesised view is parametrised by the tilt, longitude and optionally the scale and represents a sample of the view-sphere resp. view-volume around the original image.

The view synthesis proceeds in the following steps: at first, scale synthesis is performed by building a Gaussian scale-space with Gaussian  $\sigma = \sigma_{\text{base}} \cdot S$  and downsampling factor S (S < 1). Second, each image in the scale-space is in-plane rotated by longitude  $\phi$  with step  $\Delta \phi = \Delta \phi_{\text{base}}/t$ . In the third step, all rotated images are convolved with a Gaussian filter with  $\sigma = \sigma_{\text{base}}$  along vertical direction and  $\sigma = t \cdot \sigma_{\text{base}}$  along horizontal direction to eliminate aliasing in the final tilting step. The tilt is applied by shrinking the image along the horizontal direction by factor t. The parameters of the synthesis are: the set of scales {S},  $\Delta \phi_{\text{base}}$  – the step of longitude samples at tilt t = 1, and a set of simulated tilts {t}.

#### 2.2 Local feature detection and description

The goal of the view synthesis procedure is to provide detectors with a sufficiently similar subset of all artificial views on the view-sphere that allows matching. For affine-covariant detectors, unlike the similaritycovariant DoG of ASIFT, the number of necessary view samples is significantly decreased while the performance for the most difficult image pairs gets improved. Moreover, it is known that different detectors are suitable for different types of images [17] and that some detectors are complementary in the feature points they detect [1]. Our experiments show (c.f. Section 4) that combining detectors improves the overall robustness and speed of the matching procedure.

MODS uses the state-of-the-art affine covariant detectors MSER and Hessian-Affine. The normalised patches are described by the recent modification of SIFT [14] – the RootSIFT [2]. The local feature frames



Figure 2. Comparison of the proposed *first to 1st inc. ratio* matching strategy and the standard *first to second closest ratio* matching strategy. Red regions are the second closest descriptors, yellow regions correspond to the closest geometrically inconsistent descriptors, green are the true corresponding regions. Upper pair – rotationally symmetric DoG regions, lower pair – affine covariant MSER regions.

computed on the synthesised views are backprojected to the coordinate system of the original image by a known affine matrix A and associated with the descriptor and the originating synthetic view.

### 2.3 Tentative correspondence generation

Different strategies for computation of the tentative correspondences in wide-baseline matching have been proposed. The standard method for matching SIFT(-like) descriptors is based on the distance ratio of the closest to the second closest descriptors in the other image [14]. Performance of this test in general very efficient method degrades when multiple observations of the same feature are present. In this case, the similar descriptors will lead to the first to second SIFT ratio to be close to 1 and the correspondences will "annihilate" each other, despite the fact they all represent the same geometric constraints and are therefore not mutually contradictory (see Figure 2). The problem of multiple detections is amplified in the matching by view synthesis since covariantly detected local features have often a response in multiple synthetic views. We propose to use, instead of comparing the first to the second closest descriptor distance, the distance of the first descriptor and the closest descriptor that is geometrically inconsistent with the first one (denoted 1st inc. in the following). We call descriptors in one image *geometrically inconsistent* if the Euclidean distance between centers of the regions is  $\geq 10$  pixels. The difference of the first-to-second closest ratio strategy and the closest-to-1st inc. strategy is illustrated in Figure 2.

The kd-tree algorithm from FLANN library [19] effectively finds the N-closest descriptors in the other image. The distance ratio thresholds of the closest to 1st inc. were experimentally selected based on the CDFs of matching and non-matching descriptors (see Appendix A). We recommend to use the same values for SIFT and RootSIFT descriptors, but different thresholds for the different local feature detectors:  $R_{\text{MSER}} = 0.85$ ,  $R_{\text{DoG}} = 0.85$  and  $R_{\text{HA}} = 0.8$ .

### 2.4 Duplicate filtering

The redetection of covariant features in synthetic views results in duplicates in tentative correspondences. The duplicate filtering is an optional step and prunes correspondences with close spatial distance of local features in both images. The number of pruned correspondences can be however used later for evaluating the quality (probability of being correct) in PROSAC-like [4] geometric verification.

### 2.5 Geometric verification

The LO-RANSAC [11] algorithm searches for the maximal set of geometrically consistent tentative correspondences. The model of the transformation is set either to homography or epipolar geometry, or automatically determined by a DegenSAC [5] procedure.

# **3** View synthesis for affine covariant detectors

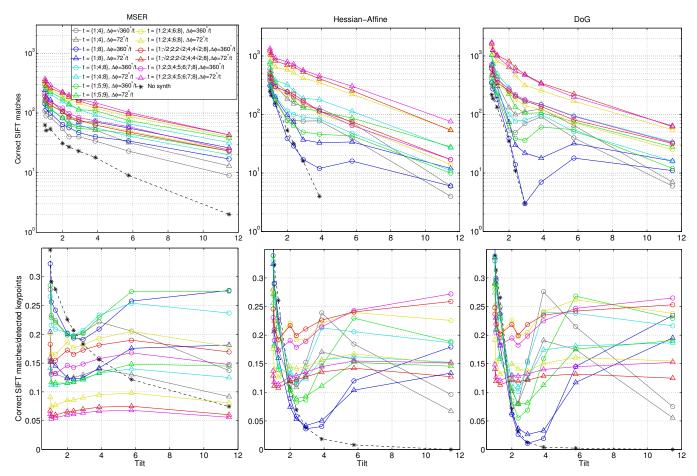


Figure 3. Comparison of view synthesis configurations on the synthetic dataset. First row: the number of correct SIFT matches a robust minimum (value 4% quantile) over 100 random images from [21]). Second row: the ratio of the number of correct matches to the number of detected regions; the mean over 100 random images. Only selected configurations are shown, full version in Appendix.

**Configurations.** The first two parameters of the view synthesis, tilt {t} sampling and latitude step  $\Delta \phi_{\text{base}}$ , were explored in the following synthetic experiment. For each of 100 random images from Oxford Building Dataset<sup>2</sup> [21], a set of simulated views with latitudes angles  $\theta = (0, 20, 40, 60, 65, 70, 75, 80, 85)^{\circ}$ , corresponding to tilt series  $t = (1.00, 1.06, 1.30, 2.00, 2.36, 2.92, 3.86, 5.75, 11.47)^3$  was generated. The ground truth affine matrix A was computed for each synthetic view using equation (1) and used in the final

<sup>&</sup>lt;sup>2</sup>available at http://www.robots.ox.ac.uk/~vgg/data/oxbuildings/

<sup>&</sup>lt;sup>3</sup>assuming that the original image is in the fronto-parallel view

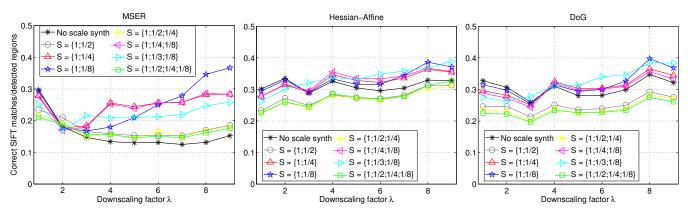


Figure 4. Estimation of the suitable scale synthesis configurations on the synthetic dataset. Ratio of the number of correct matches to the number of detected regions, mean over 100 random images from [21].

	Configu	urations
Detector	Sparse	DENSE
MSER	$ \{S\} = \{1; 0.25; 0.125\}, \{t\} = \{1; 5; 9\}, $ $ \Delta \phi = 360^{\circ}/t $	$ \{S\} = \{1; 0.25; 0.125\}, \{t\} = \{1; 2; 4; 6; 8\}, \\ \Delta \phi = 72^{\circ}/t $
HessAff	$ \{S\} = \{1\}, \{t\} = \{1; \sqrt{2}; 2; 2\sqrt{2}; 4; 4\sqrt{2}; 8\}, \\ \Delta \phi = 360^{\circ}/t $	$\{S\} = \{1\}, \{t\} = \{1; 2; 4; 6; 8\}, \Delta \phi = 72^{\circ}/t$
DoG	$\{S\} = \{1\}, \{t\} = \{1; 2; 4; 6; 8\}, \Delta \phi = 120^{\circ}/t$	$ \{S\} = \{1\}, \{t\} = \{1; \sqrt{2}; 2; 2\sqrt{2}; 4; 4\sqrt{2}; 8\}, \\ \Delta \phi = 72^{\circ}/t $

Table 1. View synthesis configurations based on the analysis of the algorithm on the synthetic dataset

verification step of the MODS algorithm. The various configurations of the view synthesis were tested and results for the selected configurations are shown in Figure 3. Note that the view synthesis significantly increases the matching performance, however after reaching some density of the view-sphere sampling additional views does not bring more correspondences. MSER and Hessian-Affine need sparser view-sphere sampling than DoG.

A similar experiment was performed to find the scale sampling set {S} of the view synthesis. Instead of tilting and rotating the images, a synthetic downsampling of the image by a factor  $\lambda = 1$  to 9 was employed (see Figure 4). It shows that MSER detector is prone to scale changes while the Hessian-Affine and DoG detectors perform well even without view synthesis with scale sampling. Consequently, the benefit of the scale sampling is higher for MSER than for Hessian-Affine and DoG detectors. Tilting and rotation parameters were not used in this experiment i.e. fixed to  $\{t\} = \{1\}$  and  $\Delta \phi_{\text{base}} = 180$ .

Two configurations, SPARSE and DENSE, were chosen for each detector (see Table 1) using the following criteria: efficiency – the ratio of correct matches per detected region, matching performance – the number of unique (non-duplicated) matches on the synthetic image pairs with 85° out of plane rotation. The SPARSE configuration is fast but still able to solve synthetic image pairs with up to 85° out of plane rotation. The DENSE configuration generates sufficient number of correspondences for the most image pairs in the EVD dataset for each detector.

**Image pre-smoothing.** Parameter  $\sigma_{\text{base}}$ , the amount of image smoothing prior to view synthesis was set experimentally; it affects matching performance significantly. Values too small fail to prevent aliasing, values too high oversmooth the image reducing the number of detected regions. Unlike MSER, the scale-space based detectors like DoG, Hessian-Affine apply pre-smoothing as an initial step. This leads to different optimal values for different detectors. We set  $\sigma_{\text{base}} = 0.8, 0.2$ , and 0.4 for the MSER, Hessian-Affine and DoG detectors, respectively.

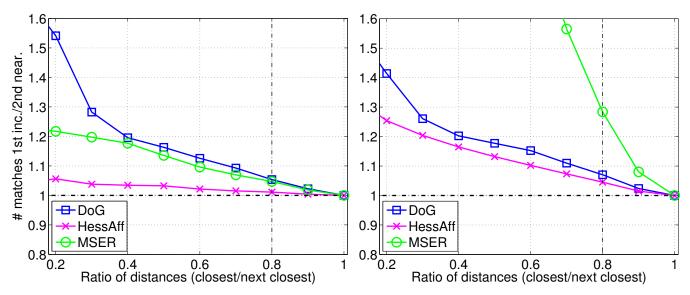


Figure 5. The ratio of the number of correct matches obtained by the 1st inconsistent and 2nd nearest method, without (left) and with (right) view synthesis. The black dashed line denotes the widely used distance ratio threshold = 0.8.

## 4 **Experiments**

### 4.1 1st geometrically inconsistent vs. 2nd nearest neighbour correspondence selection strategy

The *first to first geometrically inconsistent* strategy was evaluated on 50 image pairs of the publicly available datasets [17] and [6]. The cumulative distributions of the number of correct tentative correspondences as functions of the descriptor distance ratio are used for comparison. The new matching strategy improves the performance by up to 5% for the matching without view synthesis and up to 30% (see Figure 5) for matching with view synthesis at almost no additional computational costs.

### 4.2 Results on the Extreme Viewpoint Dataset

We introduce a two-view matching evaluation dataset<sup>4</sup> with extreme viewpoint changes, see Table 2. The dataset includes image pairs from publicly available datasets: ADAM and MAG [18], GRAF [17] and THERE [6]. The ground truth homography matrices were estimated by LO-RANSAC using correspondences from all three detectors in view synthesis configuration  $\{t\} = \{1; \sqrt{2}; 2; 2\sqrt{2}; 4; 4\sqrt{2}; 8\}, \Delta \phi = 72^{\circ}/t$ . The number of inliers for each image pair was  $\geq 50$  and the homographies were manually inspected. For the image pairs GRAF and THERE precise homographies are provided by Cordes *et al.* [6]. Transition tilts  $\tau$  were computed using equation (1) with SVD decomposition of the linearised homography at center of the first image of the pair (see Table 2).

The configurations evaluated are specified in Table 1. For comparison, ASIFT<sup>5</sup> results are added. Computations were performed on Intel i5 CPU @ 2.6GHz with 4Gb RAM; results for computation on one core are provided. Based on results of the different configuration, we have chosen the following configuration for MODS w.r.t increasing computation time and performance of the configurations – see Table 3. Please note that only views complementary to the previous iterations are synthesised.

The MODS algorithm allows to set the minimum desired number of inliers as a stopping criterion. The recommended value – 15 inliers to the homography, have a very low probability to be a random result, but are few enough to show the time gain from the algorithm. To maximize the number of inliers for each of the detectors, we recommend to use DENSE configuration as a single step. Figure 6 and Table 4 compare the different view synthesis configurations and the "affine-covariant" detectors – they generate more correct matches in a shorter time than the DoG detector. The DoG based matching and ASIFT matching cannot

<sup>&</sup>lt;sup>4</sup>Available at http://cmp.felk.cvut.cz/wbs/index.html

<sup>&</sup>lt;sup>5</sup>Reference code from http://demo.ipol.im/demo/my\_affine\_sift

2 5 7 9 10 12 14 15 3 4 6 8 1113 # THERE GRAF ADAM GRAND PKK FACE GIRL SHOP DUM INDEX CAFE FOX CAT VIN Name MAG EVD EVD EVD EVD EVD Source С Ox Μ Μ EVD EVD EVD EVD EVD EVD 6.3 6.9 6.9 11.9 22.5 49.8 au – transitional tilt 3.6 4.8 20 2.9 7.1 8.0 9.1 8.5 47 1536 600 600 1000 1000 1000 1000 1000 1000 1000 800 1000 1000 1000 800 Resolution x 1024 x 750 x 750 x 729 x 750 x 533 x 598 750 715 [pixels] 640 450 450 667 562 563 Image 1 Image 2 Image 1 Image 2 # Image 1 Image 2 # 11 7 12 8 13 9 15

Table 2. The Extreme View Dataset – EVD. Image sources: C – Cordes *et al.* [6], Ox – Mikolajczyk *et al.* [17], M – Morel and Yu [18].

Table 3. Configurations for MODS steps

Iter.	Setup
1	$MSER, \{S\} = \{1; 0.25; 0.125\}, \{t\} = \{1\}, \Delta \phi = 360^{\circ}/t$
2	$MSER, \{S\} = \{1; 0.25; 0.125\}, \{t\} = \{1; 5; 9\}, \Delta\phi = 360^{\circ}/t$
3	HessAff, $\{S\} = \{1\}, \{t\} = \{1; \sqrt{2}; 2; 2\sqrt{2}; 4; 4\sqrt{2}; 8\}, \Delta \phi = 360^{\circ}/t$
4	HessAff , $\{S\} = \{1\}, \{t\} = \{1; 2; 4; 6; 8\}, \Delta \phi = 72^{\circ}/t$

solve 3 resp. 9 out of the 15 image pairs. The ASIFT algorithm generates a lower number of correct inliers and works slower than our DoG DENSE configuration (which has the same tilt-rotation set). The main causes are elimination of "one-to-many", including correct, correspondences, the inferiority of the standard 2nd closest ratio and a simple bruteforce algorithm of matching used in ASIFT.

No single detector solved all image pairs. The Hessian-Affine with DENSE configuration successfully solved 14 out of 15 image pairs and outperformed other detectors and configurations in the number of inliers, however, at the expense of the highest computational cost. MSER with no synthesis and in the SPARSE configuration is the fastest and could solve 10 out of 15 image pairs. The MODS algorithm solves all image pairs and saves computational time on processing of the easy pairs at the cost of a small matching overhead on the hard cases. Also, MODS is the fastest algorithm in 7 cases, and in another 2 cases it is just  $\sim 10\%$  slower than the fastest configuration. The difference results of MODS step 2 and MSER SPARSE are caused by randomization in RANSAC and kd-tree building.

Fig. 7 shows the breakdown of the computational time. SIFT description with the dominant orientation estimation take 50% of the time. Note that the whole process is almost linear in the area of the synthesised views. The only super-linear part, matching, takes only 10% of the time.

### 4.3 MSER vs. blur and scale change

We have tested performance of recommended scale synthesis configuration for MSER on the image pairs most distorted by blur and scale change from the Oxford [17] dataset. To allow comparison with [17], the standard SIFT was used instead of RootSIFT in this experiment. Note that the results are not fully compatible as we use NN-distance ratio matching threshold = 0.8 (In [17] no ratio threshold has been

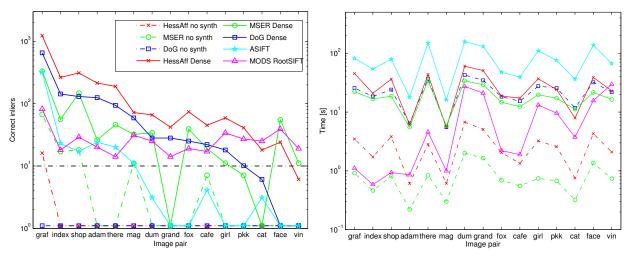


Figure 6. Performance of the selected view synthesis configurations defined in Table 1. MODS set to find  $\geq$  15 inliers. Left – the number of correct RANSAC inliers. The black dashed line marks the level of 10 correct inlier – a minimum for a reliable estimate of two-view geometry. Right – runtime (1 core).

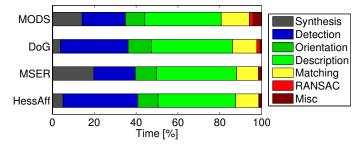


Figure 7. Percentage of time spent in the main stages of the matching with view synthesis process on a single core, DENSE configuration. SIFT description, i.e. the dominant gradient estimation and the descriptor computation is the most time-consuming part.

Table 4. A comparison of different view synthesis and detector configurations (with RootSIFT). Best results are highlighted by a grey background. MODS set to find  $\geq$  15 inliers. Results with less than 8 correct inliers are in red.

Image			Corre	ct inlier	s			,	Time, 1	core [s]					Correct i	nliers/se	c	
	MODS, $\theta_m = 15$	ASIFT	MSER SPARSE	HessAff SPARSE	HessAff DENSE	DoG DENSE	MODS, $\theta_m = 15$	ASIFT	MSER SPARSE	HessAff Sparse	HessAff DENSE	DoG DENSE	MODS, $\theta_m = 15$	ASIFT	MSER SPARSE	HessAff Sparse	HessAff DENSE	DoG DENSE
graf	82	322	165	375	1235	653	1.0	81.8	3.0	11.0	45.2	25.5	83.9	3.9	55	34.1	27.3	25.6
index	18	23	24	34	264	143	0.5	54.1	2.2	5.4	20.8	18.3	38.1	0.4	11.1	6.3	12.7	7.8
shop	29	17	73	133	311	130	0.8	79.5	2.5	10.1	36.2	24	35.2	0.2	28.7	13.2	8.6	5.4
adam	20	24	18	86	214	125	0.8	17.8	0.7	1.6	6.0	6.3	26.7	1.3	24.3	54.1	35.6	19.8
there	14	20	12	49	189	94	4.5	150.0	4.5	10.1	43.4	36.9	3.1	0.1	2.7	4.9	4.4	2.5
mag	31	11	28	54	72	59	0.8	16.1	0.8	1.6	5.3	5.4	37.3	0.7	34.4	33.5	13.5	10.9
dum	25	3	0	10	66	28	29.4	158.0	4.8	20.1	60.2	42.5	0.9	0.0	0.0	0.5	1.1	0.7
grand	14	0	9	0	42	28	21.9	131.0	4.2	14.8	50.8	34.6	0.6	0.0	2.1	0.0	0.8	0.8
fox	19	0	19	22	74	25	2.1	47.4	2.1	5.8	18.6	18.2	9.0	0.0	9.3	3.8	4	1.4
cafe	17	4	14	0	45	22	1.8	39.2	1.7	4.5	17.2	15.2	9.3	0.1	8.2	0.0	2.6	1.4
girl	34	0	0	14	59	18	13.1	110.0	2.7	10.0	36.7	27.5	2.6	0.0	0.0	1.4	1.6	0.7
pkk	27	0	6	12	41	10	9.5	75.9	2.4	6.8	24.1	25.5	2.8	0.0	2.5	1.8	1.7	0.4
cat	25	3	0	21	18	6	3.9	36.2	1.4	2.2	7.8	11.7	6.3	0.1	0.0	9.6	2.3	0.5
face	39	0	9	17	24	0	15.6	138.0	3.4	11.3	38.8	32.0	2.5	0.0	2.7	1.5	0.6	0.0
vin	19	0	0	0	6	0	30.3	66.9	2.3	6.3	22.8	21.7	0.6	0.0	0.0	0.0	0.3	0.0

used, so the absolute number of the matches differs a lot. But relative ratio between detectors performance remains the same). We have also performed the duplicate filtering procedure, which reduces the number of correspondences (c.f. Section 2).

Figure 8 shows that scale synthesis with 1st geom. inconsistent rule improves MSER performance by 60% to 1000%, solving the most common MSER problems – sensitivity to blur and scale change. The quality of tentative correspondences also increases with the proposed scale synthesis configuration (Figure 8, right). Table 6 shows the computation time.

Table 5. MODS ( $\theta_m = 15$ ) performance on the EVD dataset. The k-th iteration includes regions from all previous steps.

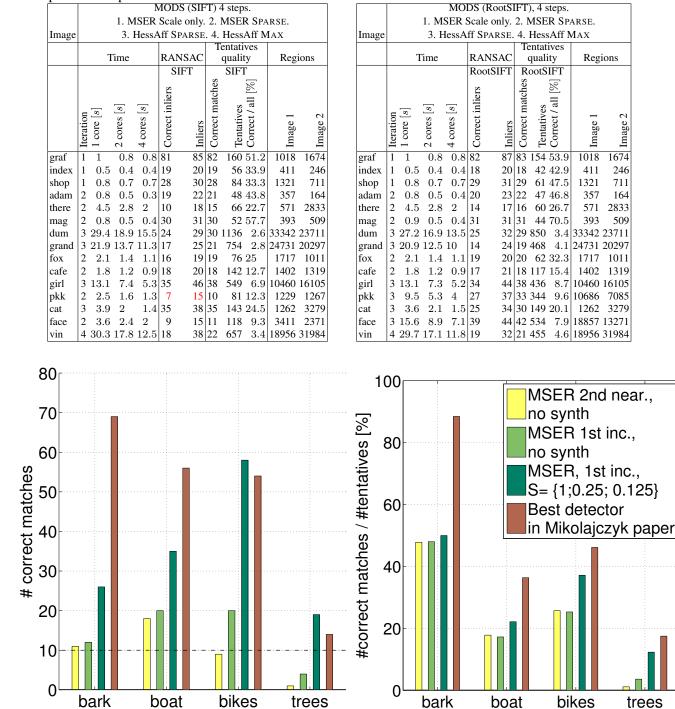


Figure 8. MSER performance with and w/o scale synthesis on the most distorted pairs (1-6) with scale change and blur from [17]. Left – the number of correct SIFT matches. Right – the proportion of correct matches within tentative correspondences. The best detectors from [17]: BARK, BOAT, TREES – Hessian-Affine, BIKES – IBR are shown for comparison.

# 5 Conclusions

We have introduced view synthesis to two-view wide-baseline matching with affine-covariant detectors and shown that matching with the Hessian-Affine or MSER detectors outperforms the state-of-the-art ASIFT.

· · ·		o mora [1	'
	scale synthesis setup	time [s]	
	$\{S\} = \{1\}$	56.6	1
	$\{S\} = \{1; 0.25; 0.125\}$	61.5	
			-

Table 6. MSER matcher runtime on Oxford [17] dataset

To address the robustness vs. speed trade-off, we have proposed the Matching On Demand with view Synthesis algorithm (MODS) that uses progressively more synthesized images and more (time-consuming) detectors until a reliable estimate of geometry is obtained. We show experimentally that the MODS algorithm solves matching problems beyond the state-of-the-art and yet is comparable in speed to standard wide-baseline matchers on simpler problems.

Minor contributions include an improved method for tentative correspondence selection, applicable both with and without view synthesis. A modification of the standard first to second nearest SIFT distance rule increases the number of correct matches by 5-20% at no additional computational cost. Finally, we found a simple view synthesis set up costing less than 10% of time that greatly improves MSER robustness to blur and scale change.

# References

- [1] H. Aanaes, A. Dahl, and K. Steenstrup Pedersen. Interesting interest points. IJCV, 97(1):18–35, 2012.
- [2] R. Arandjelović and A. Zisserman. Three things everyone should know to improve object retrieval. In CVPR, 2012.
- [3] H. Bay, T. Tuytelaars, and L. V. Gool. SURF: Speeded up robust features. In ECCV, 2006.
- [4] O. Chum and J. Matas. Matching with PROSAC progressive sample consensus. In CVPR, 2005.
- [5] O. Chum, T. Werner and J. Matas. Two-view geometry estimation unaffected by a dominant plane. In CVPR, 2005.
- [6] K. Cordes, B. Rosenhahn, and J. Ostermann. Increasing the accuracy of feature evaluation benchmarks using differential evolution. In *SSCI-Symposium on Differential Evolution*, 2011.
- [7] A. L. Dahl, H. Aanaes, and K. S. Pedersen. Finding the best feature detector-descriptor combination. 3DIMPVT, 2011.
- [8] F. Fraundorfer and H. Bischof. A novel performance evaluation method of local detectors on non-planar scenes. In CVPR'05 Workshops, 2005.
- [9] P.-E. Forssén and D. Lowe. Shape Descriptors for Maximally Stable Extremal Regions. In ICCV, 2007.
- [10] R. I. Hartley and A. Zisserman. Multiple View Geometry in Computer Vision, 2004.
- [11] K. Lebeda, J. Matas, and O. Chum. Fixing the Locally Optimized RANSAC. In BMVC, 2012.
- [12] V. Lepetit and P. Fua. Keypoint recognition using randomized trees. PAMI, 28(9):1465–1479,2006.
- [13] W. Liu, Y. Wang, J. Chen, J. Guo, and Y. Lu. A completely affine invariant image-matching method based on perspective projection. *MVA*, 23(2):231–242, 2012.
- [14] D. Lowe. Distinctive image features from scale-invariant keypoints. IJCV, 60(2):91–110, 2004.
- [15] J. Matas, O. Chum, M. Urban, and T. Pajdla. Robust wide-baseline stereo from maximally stable extremal regions. In BMVC, 2002.
- [16] K. Mikolajczyk and C. Schmid. Scale & affine invariant interest point detectors. IJCV, 60(1):63-86,2004.
- [17] K. Mikolajczyk, T. Tuytelaars, C. Schmid, A. Zisserman, J. Matas, F. Schaffalitzky, T. Kadir, and L. V. Gool. A comparison of affine region detectors. *IJCV*, 65(1-2):43–72, 2005.
- [18] J.-M. Morel and G. Yu. ASIFT: A new framework for fully affine invariant image comparison. SIIMS, 2(2):438–469, 2009.
- [19] M. Muja and D. G. Lowe. Fast approximate nearest neighbors with automatic algorithm configuration. In *VISSAPP'09*), 2009.
- [20] Y. Pang, W. Li, Y. Yuan, and J. Pan. Fully affine invariant SURF for image matching. *Neurocomputing*, 85(0):6–10, 2012.
- [21] J. Philbin, O. Chum, M. Isard, J. Sivic, and A. Zisserman. Object retrieval with large vocabularies and fast spatial matching. In CVPR, 2007.
- [22] R. Sadek, C. Constantinopoulos, E. Meinhardt, C. Ballester, and V. Caselles. On affine invariant descriptors related to SIFT. SIIMS, 5(2):652–687,2012.

# Appendix

## A Tuning view synthesis parameters

**Estimating threshold on the distance ratio.** The well known [14] matching strategy for SIFT descriptors is based on the distance ratio of the first to the second closest descriptor. The aim of this experiment is to set the threshold of the proposed modification – first to first geometrically inconsistent matching strategy.

To estimate the threshold we used 50 image pairs of the publicly available datasets [17] and [6], all pairs are provided with known homography transformation. The detectors – MSER, Hessian-Affine, DoG – were run on all pairs of images and distances between all descriptors in each pair computed. Then the closest, second closest and closest geometrically inconsistent descriptors were identified. The cumulative distributions of the number of correct and incorrect tentative correspondences as a function of the distance ratio were computed for both strategies using the ground truth homographies.

The results for both SIFT and RootSIFT descriptors are shown in Figure 9. We see that the DoG and MSER features are slightly less discriminative than Hessian-Affine. It is also clear from comparing the left and right columns in Figure 9, that the features detected using view synthesis are less distinctive. However, the distribution of incorrect matches does not change significantly, thus the thresholds for the new strategy with view synthesis can be kept on the value similar to the threshold without view synthesis. The results for the SIFT and RootSIFT descriptors are also very similar. Therefore, we propose to set the threshold of the first to first geometrically inconsistent distance ratio R for the local feature detectors as follows:  $R_{\text{MSER}} = 0.85$ ,  $R_{\text{DoG}} = 0.85$  and  $R_{\text{HA}} = 0.8$ .

Tilt set and latitude sampling step. The first two parameters of the view synthesis, tilt {t} sampling and latitude step  $\Delta \phi_{\text{base}}$ , were explored in the following synthetic experiment. For each of 100 random images from Oxford Building Dataset<sup>6</sup> [21], a set of simulated views with latitudes angles  $\theta = (0, 20, 40, 60, 65, 70, 75, 80, 85)^{\circ}$ , corresponding to tilt series  $t = (1.00, 1.06, 1.30, 2.00, 2.36, 2.92, 3.86, 5.75, 11.47)^7$  was generated. The reference image have been convolved with a Gaussian filter with  $\sigma_H = 0.8$ along horizontal direction and  $\sigma_V = 0.8t$  along vertical direction and finally shrunk in vertical direction by t. The ground truth affine matrix A was computed for each synthetic view using equation (1) and used in the final verification step of the MODS algorithm. The various configurations of the view synthesis were tested and results for the selected configurations are shown in Figures 10 – 12. Note that the view synthesis significantly increases the matching performance, however after reaching some density of the view-sphere sampling additional views does not bring more correspondences. MSER and Hessian-Affine need sparser view-sphere sampling than DoG.

Two configurations, SPARSE and DENSE, were chosen for each detector (see Table 1) using the following criteria: efficiency – the ratio of correct matches per detected region, matching performance – the number of unique (non-duplicated) matches on the synthetic image pairs with 85° out of plane rotation. The SPARSE configuration is fast but still able to solve synthetic image pairs with up to 85° out of plane rotation. The DENSE configuration generates sufficient number of correspondences for the most image pairs in the EVD dataset for each detector.

**Image pre-smoothing.** The early experiments with view synthesis, have shown that the amount of image smoothing  $\sigma_{\text{base}}$  prior to view synthesis affects matching performance significantly. Values too small fail to prevent aliasing, values too high oversmooth the image reducing the number of detected regions. Unlike MSER, the scale-space based detectors – DoG, Hessian-Affine apply pre-smoothing as the initial step of the scale-space pyramid.

This experiment measures the effect of the pre-smoothing parameter  $\sigma_{\text{base}}$  on the matching performance of different detectors. The range of values of the  $\sigma_{\text{base}}$  were used in matching of 35 image pairs of the publicly available datasets [17] and [6]. We have divided all pairs into two sets "Structured images" – scenes GRAF, GRACE, POSTERS, THERE, UNDERGROUND (25 image pairs in total) from [6] and "Images with repeated textures" – scenes WALL, COLORS (10 image pairs in total) [6], [17]. The DENSE configurations

<sup>&</sup>lt;sup>6</sup>available at http://www.robots.ox.ac.uk/~vgg/data/oxbuildings/

<sup>&</sup>lt;sup>7</sup>assuming that the original image is in the fronto-parallel view

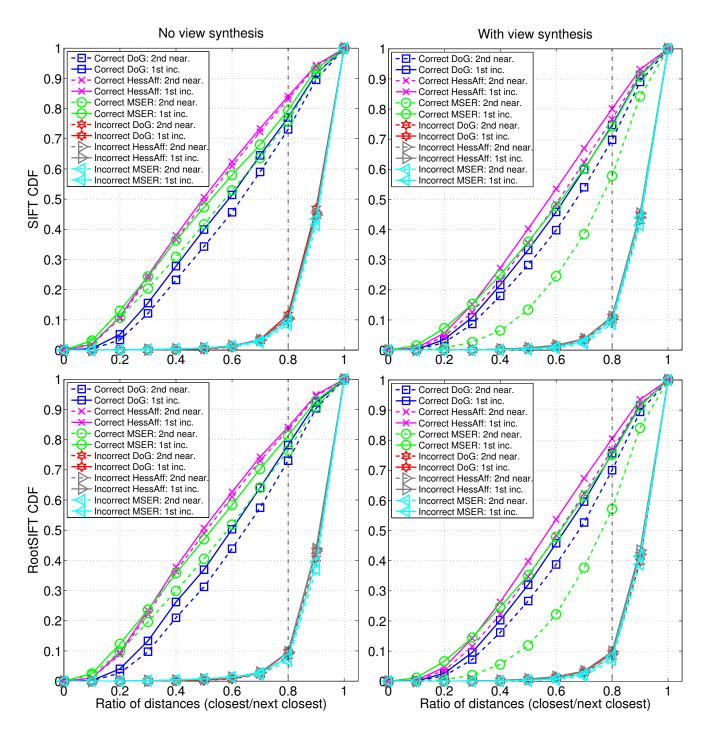


Figure 9. CDF. Columns: left – no view synthesis, right – with view synthesis. Rows: upper – SIFT, lower – RootSIFT. Average over 50 image pairs from Mikolajczyk *et al.* [17] and Cordes *et al.* [6] datasets. Black dashed line displays standard threshold = 0.8.

of the view synthesis were chosen for each of the detectors (see Table 1). Based on this experiment (see Figure 13), we have set following parameters for image pre-smoothing in the MODS algorithm:  $\sigma_{\text{base}} = 0.8, 0.2$ , and 0.4 for the MSER, Hessian-Affine and DoG detectors, respectively.

### **B** Full version of the experiments on the EVD dataset

The full version of experimental evaluation of the matching with view synthesis algorithm on EVD dataset is presented in this section. For this very challenging dataset it is hard to obtain ground truth homographies from the manually selected correspondences. Therefore, the ground truth homography matrices were estimated by running LO-RANSAC on correspondences of all three detectors with the view synthesis configuration  $\{t\} = \{1; \sqrt{2}; 2; 2\sqrt{2}; 4; 4\sqrt{2}; 8\}, \Delta \phi = 72^{\circ}/t$ . The number of inliers for each image pair was  $\geq$  50 and the homographies were manually inspected. For the image pairs GRAF and THERE precise homographies were provided by Cordes *et al.* [6]. The transition tilts were computed using equation (1) with SVD decomposition of the linearised homography at the center of the first image of the pair. The configurations of detectors evaluated are listed in Table 1, additionally, the performance of the MODS and MSER detector with scale synthesis were compared. The configuration for MODS algorithm is shown in Table 3. The MODS algorithm allows to set the minimum desired number of inliers as a stopping criterion. We set the threshold to 15 inliers, since fifteen inliers to a homography (with duplicate matches removed) have very low probability of being accidental and yet allow to demonstrate the speed gain of the algorithm.

The results for all configurations for all detectors are shown in Tables 7 - 19. For comparison, ASIFT<sup>8</sup> results were added. The timing measurements are reported for single, two and four cores of the Intel i5 CPU @ 2.6GHz processor with 4GB RAM.

<sup>&</sup>lt;sup>8</sup>Reference code from http://demo.ipol.im/demo/my\_affine\_sift

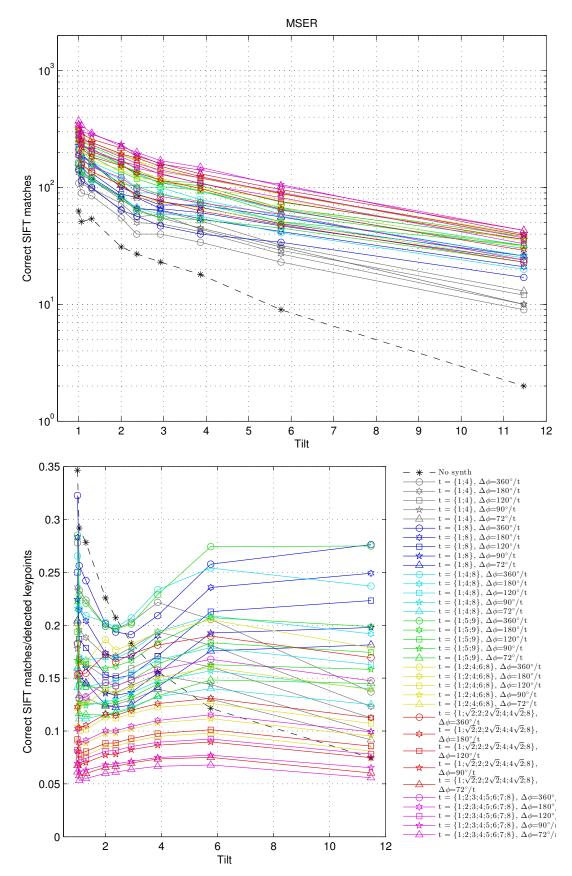


Figure 10. Comparison of MSER view synthesis configurations on the synthetic dataset. Upper graph – the number of correct SIFT matches a robust minimum (value 4% quantile) over 100 random images from [21]. Lower graph – the ratio of the number of correct matches to the number of detected regions; the mean over 100 random images.

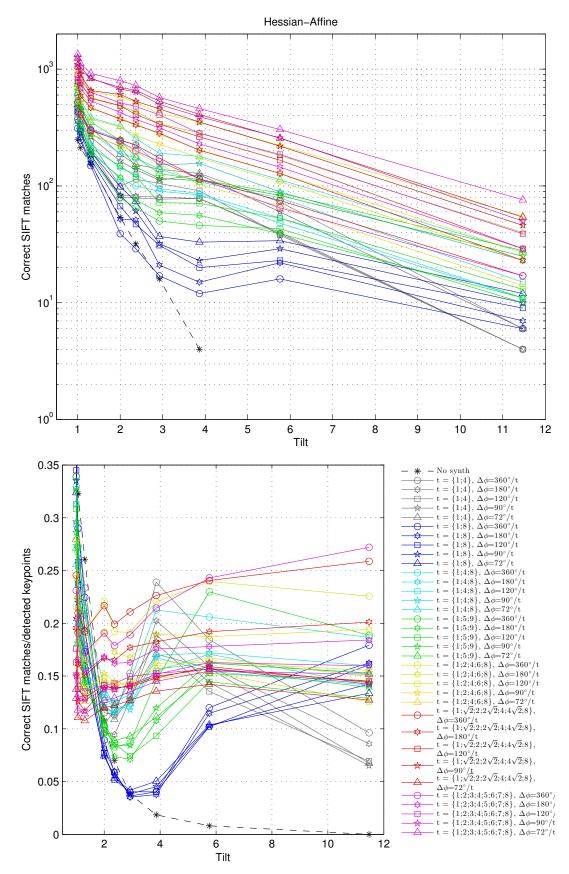


Figure 11. Comparison of Hessian-Affine view synthesis configurations on the synthetic dataset. Upper graph – the number of correct SIFT matches a robust minimum (value 4% quantile) over 100 random images from [21]. Lower graph – the ratio of the number of correct matches to the number of detected regions; the mean over 100 random images.

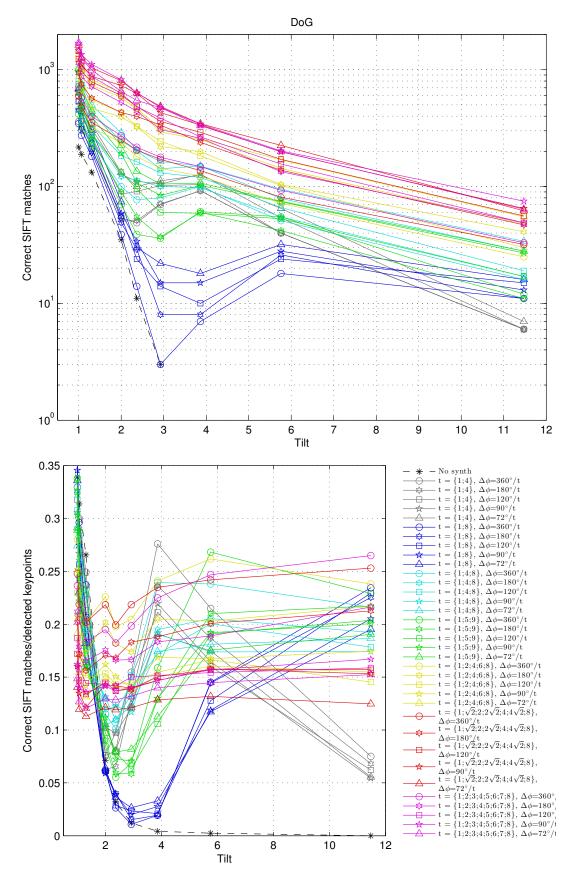


Figure 12. Comparison of DoG view synthesis configurations on the synthetic dataset. Upper graph – the number of correct SIFT matches a robust minimum (value 4% quantile) over 100 random images from [21]. Lower graph – the ratio of the number of correct matches to the number of detected regions; the mean over 100 random images.

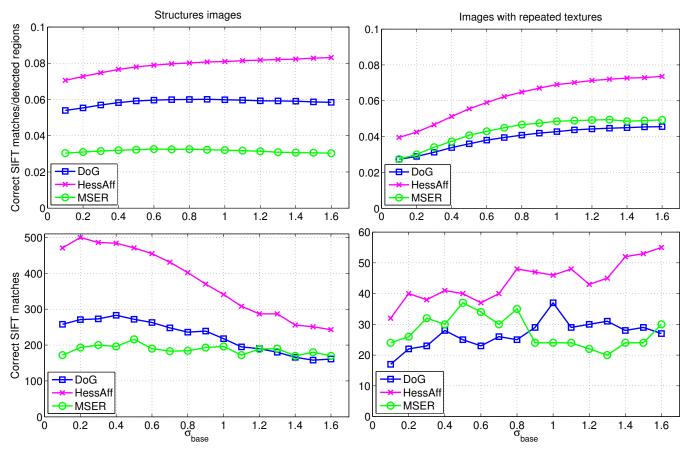


Figure 13. Matching with view synthesis (DENSE configuration) using different image pre-smoothing factor  $\sigma_{base}$ . Rows: upper – ratio of correct SIFT matches to number of detected regions, lower – number of correct SIFT matches – robust minimum (value 4% quantile). Columns: left – structured images, right – images with repeated patterns.

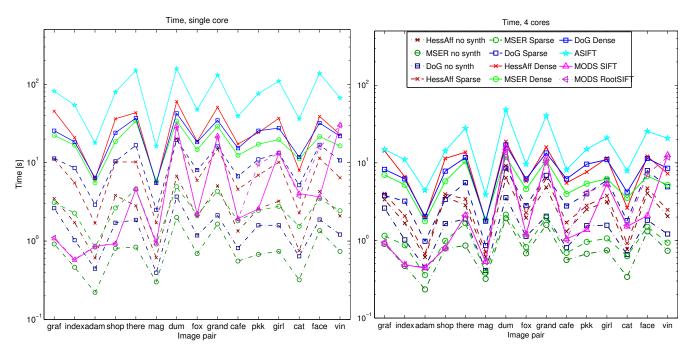


Figure 14. Running time of the different view synthesis configurations (Table 1). Left – 1 core, right – 4 cores.

Table 7. Performance on the EVD dataset. MSER, no view synthesis. Results with less than 8 correct inliers are in red.

Image								MSI	ER, no :	synt							
		Time				LO-RA	NS.	AC			Te	ntative	es qu	ıality		Reg	ions
					SI	T	R	oot	SIFT		SIF	Г		lootS	IFT		
	1 core $[s]$	2 cores $[s]$	4 cores $[s]$	Correct inliers	Inliers	Correct / all [%]	Correct inliers	Inliers	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Image 1	Image 2
graf	0.8	0.8	0.8	65	68	95.6	67	70	95.7	65	121	53.7	67	110	60.9	804	1432
index	0.4	0.4	0.4	18	19	94.7	17	18	94.4	18	44	40.9	17	36	47.2	291	172
shop	0.7	0.7	0.7	18	19	94.7	18	18	100	18	65	27.7	18	40	45	1131	646
adam	0.1	0.1	0.1	0	0	0	0	0	0	6	15	40	7	16	43.8	118	48
there	0.7	0.7	0.8	0	0	0	0	0	0	3	11	27.3	3	10	30	97	689
mag	0.2	0.2	0.2	11	11	100	11	11	100	11	20	55	11	20	55	203	306
dum	1.9	1.8	1.8	0	0	0	0	0	0	8	121	6.6	7	110	6.4	3108	1970
grand	1.6	1.5	1.5	0	0	0	0	0	0	4	51	7.8	5	36	13.9	2099	2598
fox	0.6	0.6	0.6	0	0	0	0	0	0	2	15	13.3	2	17	11.8	893	558
cafe	0.5	0.4	0.5	7	10	70	7	9	77.8	8	63	12.7	8	43	18.6	621	472
girl	0.6	0.6	0.6	0	0	0	0	0	0	3	21	14.3	2	22	9.1	566	816
pkk	0.6	0.6	0.6	0	0	0	0	0	0	1	36	2.8	1	25	4	661	343
cat	0.2	0.2	0.2	0	0	0	0	0	0	1	4	25	1	6	16.7	48	93
face	1.3	1.2	1.2	0	0	0	0	0	0	0	56	0	0	41	0	2323	747
vin	0.6	0.6	0.6	0	0	0	0	0	0	0	11	0	0	8	0	597	899

Table 8. Performance on the EVD dataset. MSER, scale view synthesis only. Results with less than 8 correct inliers are in red.

Image					<b>R</b> , 2				otal ima	ige a							
		Time				LO-RA						ntative	es qu	ality		Reg	ions
					SIF	FΤ	R	loot	SIFT		SIF	Г		ootS	IFT		
	1 core $[s]$	2 cores $[s]$	4 cores $[s]$	Correct inliers	Inliers	Correct / all [%]	Correct inliers	Inliers	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Image 1	Image 2
graf	1	0.8	0.8	81	85	95.3	82	87	94.3	82	160	51.2	83	154	53.9	1018	1674
index	0.5	0.4	0.4	19	20	95	18	20	90	19	56	33.9	18	42	42.9	411	246
shop	0.8	0.7	0.7	28	30	93.3	29	31	93.5	28	84	33.3	29	61	47.5	1321	711
adam	0.2	0.1	0.1	0	0	0	8	8	100	8	18	44.4	9	19	47.4	135	62
there	0.9	0.7	0.8	0	0	0	0	0	0	6	19	31.6	6	17	35.3	160	947
mag	0.2	0.2	0.2	13	13	100	12	12	100	13	22	59.1	12	18	66.7	223	330
dum	2.1	1.9	1.9	0	0	0	0	0	0	8	134	6	9	129	$\overline{7}$	3367	2247
grand	1.9	1.7	1.7	0	0	0	0	0	0	4	70	5.7	4	46	8.7	2362	2763
fox	0.7	0.6	0.6	0	0	0	0	0	0	2	19	10.5	2	12	16.7	967	605
cafe	0.6	0.5	0.5	0	0	0	8	8	100	8	65	12.3	8	54	14.8	715	561
girl	0.8	0.6	0.7	0	0	0	0	0	0	6	32	18.8	5	24	20.8	675	949
pkk	0.7	0.6	0.6	0	0	0	0	0	0	2	44	4.6	4	29	13.8	729	437
cat	0.3	0.2	0.2	0	0	0	0	0	0	1	5	20	1	6	16.7	59	138
face	1.4	1.2	1.2	0	0	0	0	0	0	2	57	3.5	2	43	4.7	2442	911
vin	0.7	0.6	0.6	0	0	0	0	0	0	0	12	0	0	12	0	642	1012

Image			11000		015				Aff, no	) syn	ths.						
		Time			L	.O-RA	NS	AC			Ten	tatives	s qu	ality		Reg	ions
					SIF	Т	R	ootS	IFT		SIF	Г		ootS	IFT		
	1 core $[s]$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$			Inliers	Correct / all [%]	Correct inliers	Inliers	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Image 1	Image 2
graf			3.3	14	17	82.4	16	19	84.2	15	141	10.6	19	97	19.6	3630	4614
index	1.6	1.6	1.6	0	0	0	0	0	0	0	114	0	1	79	1.3	2188	874
shop	3.7	3.6	3.5	0	0	0	0	0	0	0	78	0	0	39	0	5675	2657
adam	0.5	0.6	0.5	0	0	0	0	0	0	2	24	8.3	2	19	10.5	812	208
there	2.7	2.7	2.7	0	0	0	0	0	0	0	8	0	0	9	0	467	3659
mag	0.5	0.5	0.5	0	0	0	0	0	0	0	12	0	0	7	0	502	784
dum	6.6	6.5	6.3	0	0	0	0	8	0	6	147	4.1	3	76	4	9248	6666
grand	5	4.8	4.8	0	0	0	0	0	0	3	62	4.8	3	34	8.8	6364	6555
fox	2	1.9	1.9	0	0	0	0	0	0	0	17	0	0	8	0	3324	1393
cafe	1.2	1.2	1.2	0	10	0	0	11	0	2	58	3.5	1	42	2.4	1510	1184
girl	3.1	3.1	3	0	0	0	0	0	0	0	29	0	0	20	0	2808	4306
pkk	2.5	2.4	2.4	0	0	0	0	0	0	0	39	0	0	16	0	3832	1568
cat	0.7	0.7	0.7	0	0	0	0	0	0	1	18	5.6	0	13	0	388	581
face	4.2	4	4	0	0	0	0	0	0	0	21	0	0	21	0	6283	3638
vin	2	1.9	2	0	0	0	0	0	0	0	25	0	0	20	0	1759	2913

Table 9. Performance on the EVD dataset.Hessian-Affine, no view synthesis. Results with less than 8 correct inliers are in red.

Table 10. Performance on the EVD dataset. DoG, no view synthesis. Results with less than 8 correct inliers are in red.

Image								Do	G, no	syn	ths.						
		Time			L	O-RA	NS	AC			Ten	tative	s qu	alit	у	Reg	ions
					SIF	Т	R	oot	SIFT		SIF	Т		oot	SIFT		
	$1 \operatorname{core} [s]$	2 cores $[s]$	4 cores $[s]$	Correct inliers	Inliers	Correct / all [%]	Correct inliers	Inliers	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Image 1	Image 2
graf	2.5	2.5	2.5	0	0	0	0	0	0	3	120	2.5	4	83	4.8	1682	2419
index	0.9	0.9	0.9	0	0	0	0	0	0	0	106	0	0	80	0	1171	516
shop	1.6	1.6	1.6	0	0	0	0	0	0	0	93	0	0	83	0	2570	1238
adam	0.3	0.3	0.3	0	0	0	0	0	0	0	31	0	0	29	0	495	132
there	1.8	1.9	1.8	0	0	0	0	0	0	0	49	0	0	30	0	541	2476
mag	0.3	0.3	0.3	0	0	0	0	0	0	0	17	0	0	15	0	252	370
dum	3.6	3.5	3.5	0	0	0	0	0	0	0	144	0	0	89	0	4242	2791
grand	2	2	2	0	0	0	0	0	0	0	66	0	1	47	2.1	2754	2956
fox	1.1	1.1	1	0	0	0	0	0	0	0	42	0	0	22	0	1764	817
cafe	0.7	0.7	0.7	0	10	0	0	8	0	1	60	1.7	0	46	0	847	813
girl	1.5	1.5	1.5	0	0	0	0	0	0	0	60	0	0	39	0	1217	2190
pkk	1.5	1.5	1.5	0	0	0	0	0	0	0	40	0	0	26	0	2091	1487
cat	0.5	0.5	0.6	0	0	0	0	0	0	0	30	0	0	19	0	262	519
face	1.8	1.8	1.7	0	0	0	0	0	0	0	34	0	0	39	0	2406	2457
vin	1.1	1.2	1.1	0	0	0	0	0	0	0	48	0	0	32	0	876	1661

		aren	i icu.	M	SFR	6 tilt	synth	s x (1	+ 2 sca	le sv	nth)	$\Delta \phi -$	360°	)/t			
Imaga				111			•							/ ',			
Image		<b>T</b> '							nage ar	$ea A_i$			0	1.4		D	
		Time				LO-R						ntative	-	· ·		Reg	ions
					SIFT		R	ootS			SIFT			ootSI	FΓ		
				s		8	8		[%]	he		[%]	he		[%]		
				lie		TI I	lie		II	atc		II	atc		II		
	$\overline{s}$	$[\infty]$	[s]	Ei		1	t in		t/ 8	E I	ves	t / 8	E I	ves	[ / 5		3
	core	cores	cores	Correct inliers	SIS	Correct / all [%]	Correct inliers	SIS	Correct / all	Correct matches	Tentatives	Correct / all	Correct matches	Tentatives	Correct / all	e e	
	3		3	LIO	Inliers	ЦQ		Inliers	LIO	LO LO	ent	lo	LO LO	ent	ЦQ	Image	Image
		0	4				-		-	-	-	-	-		-		
graf	3	1.6	1.1	167	173	96.5	165	169	97.6	175	340	51.5	170	339	50.1	2780	3782
index	2.2	1.2	0.8	23	32	71.9	24	35	68.6	25	106	23.6	27	103	26.2	1204	736
shop	2.5	1.4	0.9	67	69	97.1	73	74	98.6	67	172	39	73	163	44.8	2899	1474
adam	0.7	0.4	0.3	18	20	90	18	21	85.7	20	48	41.7	20	42	47.6	357	164
there	4.5	2.5	1.6	12	19	63.2	12	18	66.7	15	65	23.1	17	61	27.9	571	2833
mag	0.8	0.5	0.3	25	27	92.6	28	28	100	26	47	55.3	28	40	70	393	509
dum	4.8	2.7	2.1	0	0	0	0	0	0	12	229	5.2	14	173	8.1	6276	4579
grand	4.2	2.4	1.9	0	0	0	9	14	64.3	10	163	6.1	9	105	8.6	4840	4346
fox	2.1	1.1	0.7	12	17	70.6	19	20	95	16	68	23.5	20	61	32.8	1717	1011
cafe	1.7	1	0.6	13	20	65	14	20	70	15	117	12.8	16	104	15.4	1402	1319
girl	2.7	1.5	1	10	15	66.7	0	0	0	11	82	13.4	10	61	16.4	1479	2208
pkk	2.4	1.3	0.9	4	14	28.6	6	10	60	7	68	10.3	8	45	17.8	1229	1267
cat	1.4	0.8	0.5	0	0	0	0	0	0	2	13	15.4	2	13	15.4	144	440
face	3.4	1.9	1.4	0	0	0	9	14	64.3	11	93	11.8	10	86	11.6	3411	2371
vin	2.3	1.3	0.8	0	0	0	0	0	0	4	24	16.7	4	21	19	1106	1881

Table 11. Performance on the EVD dataset.MSER, SPARSE configuration. Results with less than 8 correct inliers are in red.

Table 12. Performance on the EVD dataset.Hessian-Affine, SPARSE configuration. Results with less than 8 correct inliers are in red.

			<u>15 arc</u>			Н	essAf	f, 10	synths	s. $\Delta \phi$	=30	$50^{\circ}/t$ ,					
Image			1	$t = \{1;$	$\sqrt{2};$	$2; 2\sqrt{2}$	$\overline{2};4;4$	$\sqrt{2}; 8$	8}. To	tal in					orig		
		Time			Ι	LO-RA	NSA	C			Te	ntative	es qua	lity		Reg	ions
					SIFT	•	R	ootSI	FT		SIFT			ootSI	FT		
	1 core $[s]$	2 cores $[s]$	4 cores $[s]$	Correct inliers	Inliers	Correct / all [%]	Correct inliers	Inliers	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Image 1	Image 2
graf	11	5.9	3.9	371	379	97.9	375	383	97.9	375	799	46.9	384	765	50.2	12519	14144
index	5.4	3	2	23	40	57.5	34	52	65.4	34	412	8.3	44	284	15.5	7967	3139
shop	10.1	5.4	3.9	134	143	93.7	133	141	94.3	138	341	40.5	135	257	52.5	16326	8549
adam	1.6	0.8	0.6	86	93	92.5	86	99	86.9	88	157	56.1	88	151	58.3	2486	635
there	10.1	5.3	3.3	58	66	87.9	49	56	87.5	64	223	28.7	52	163	31.9	2702	15991
mag	1.6	0.9	0.6	55	60	91.7	54	59	91.5	57	95	60	57	93	61.3	1664	2162
dum	20.1	11.7	9.1	0	0	0	10	12	83.3	10	254	3.9	11	150	7.3	27066	19132
grand	14.8	8.1	6.2	0	0	0	0	0	0	8	152	5.3	5	65	7.7	19891	15951
fox	5.8	3.1	2.2	27	34	79.4	22	32	68.8	30	99	30.3	27	72	37.5	10227	3798
cafe	4.5	2.4	1.6	0	14	0	0	14	0	9	135	6.7	7	112	6.3	4642	5349
girl	10	5.3	3.7	16	25	64	14	23	60.9	18	170	10.6	17	120	14.2	8981	13897
pkk	6.8	3.7	2.7	21	25	84	12	19	63.2	25	105	23.8	17	84	20.2	9457	5818
cat	2.2	1.2	0.8	24	26	92.3	21	29	72.4	24	75	32	23	67	34.3	1118	2839
face	11.3	6	4.6	35	39	89.7	17	20	85	38	139	27.3	18	93	19.4	15446	10900
vin	6.3	3.4	2.4	0	0	0	0	0	0	0	46	0	0	31	0	5656	8401

correct	miner	saic	mitte				D	7 20		<b>A</b> /	1000	2/1					
						<i>C</i> .			synths.			'					
Image									`otal im	age a	rea $A_{to}$	$_{otal} =$	$7A_{or}$	$\cdot ig$			
		Time			]	LO-RA	ANSA	AC			Te	ntative	es qua	lity		Reg	ions
					SIFT	1	R	lootS	IFT		SIFT			ootSII	T		
	1 core $[s]$	2 cores $[s]$	4 cores $[s]$	Correct inliers	Inliers	Correct / all [%]	Correct inliers	Inliers	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Image 1	Image 2
graf	11.2	6	3.7	354	368	96.2	363	376	96.5	368	1121	32.8	379	1019	37.2	12708	17175
index	8.5	4.8	3.1	52	67	77.6	51	73	69.9	63	930	6.8	67	692	9.7	7986	4770
shop	10.3	5.5	3.3	62	65	95.4	66	72	91.7	63	575	11	69	374	18.4	15747	7873
adam	2.8	1.5	0.9	70	72	97.2	69	79	87.3	74	283	26.1	75	241	31.1	3181	899
there	16.6	9	5.5	37	51	72.5	25	42	59.5	43	533	8.1	33	365	9	5389	21491
mag	2.4	1.3	0.8	37	39	94.9	38	38	100	38	110	34.5	40	94	42.6	1467	1678
dum	19.4	12	8.5	13	20	65	16	22	72.7	15	646	2.3	17	455	3.7	23607	19402
grand	16	9.7	6.8	0	0	0	16	19	84.2	11	447	2.5	16	256	6.3	18270	15387
fox	8	4.4	2.7	14	21	66.7	11	21	52.4	15	278	5.4	12	157	7.6	10026	4999
cafe	6.6	3.9	2.7	11	17	64.7	13	19	68.4	12	271	4.4	15	207	7.3	5153	6541
girl	13.1	8.2	5.9	0	0	0	0	0	0	6	370	1.6	7	226	3.1	7745	14677
pkk	10.9	6.1	3.9	0	0	0	0	0	0	8	358	2.2	7	238	2.9	9934	10704
cat	5.1	2.8	1.7	0	0	0	2	9	22.2	2	119	1.7	4	79	5.1	1815	3750
face	16.8	10.6	7.8	0	0	0	0	0	0	11	584	1.9	5	396	1.3	17217	14204
vin	10.6	6.7	4.8	0	0	0	0	0	0	6	250	2.4	2	131	1.5	6470	9861

Table 13. Performance on the EVD dataset.DoG, SPARSE configuration. Results with less than 8 correct inliers are in red.

Table 14. Performance on the EVD dataset. MSER, DENSE configuration. Results with less than 8 correct inliers are in red.

correct	mmer	s are	III IEU														
				]			-				synth			,			
Image									image	e area	$A_{tota}$	l = 4.	$2A_{ori}$				
		Time			Ι	O-RA	NSA	C			Te	ntative	es qua	lity		Reg	ions
					SIFT		R	ootSI	FT		SIFT		R	ootSII	Τ		
	$\operatorname{core}[s]$	cores [s]	cores [s]	Correct inliers	Inliers	Correct / all [%]	Correct inliers	Inliers	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Image 1	Image 2
graf	- 22.2	∾ 11.7	<del>4</del>	330	361	91.4	332	353	94.1	339	1061	$\frac{0}{32}$	342	1014	33.7	20454	26177
index	16.6	8.8	5.1	51	65	78.5	56	76	73.7	60	390	15.4	66	391	16.9	9087	5733
shop	18.5	9.7	5.7	139	152	91.4	147	161	91.3	145	530	27.4	150	446	33.6	19560	9905
adam	5.4	2.8	1.7	36	41	87.8	26	38	68.4	38	114		34	104	32.7	2161	1201
there	34.1	18	10.4	43	68	63.2	46	69	66.7	59	243	24.3	61	247	24.7	4405	20824
mag	5.7	3	1.8	30	36	83.3	32	39	82.1	35	114	30.7	35	105	33.3	2123	2836
dum	33.9	18.7	11.8	42	47	89.4	34	39	87.2	43	867	5	38	653	5.8	38881	29687
grand	29.1	16.5	10.6	0	0	0	0	0	0	15	540	2.8	12	349	3.4	29894	23431
fox	14.6	7.6	4.5	37	41	90.2	39	43	90.7	42	241	17.4	41	209	19.6	10731	5960
cafe	12.3	6.5	3.9	17	30	56.7	19	32	59.4	20	287	7	22	263	8.4	8932	8805
girl	19.6	10.4	6.1	9	25	36	11	21	52.4	23	237	9.7	16	192	8.3	9313	15567
pkk	17.1	9.1	5.3	2	25	8	7	29	24.1	12	182	6.6	18	194	9.3	6922	9210
cat	11.1	5.9	3.4	0	0	0	0	0	0	4	31	12.9	3	41	7.3	1084	3333
face	21.5	11.3	6.6	52	68	76.5	55	70	78.6	56	438	12.8	64	358	17.9	13733	17135
vin	16.3	8.6	5.1	10	15	66.7	11	17	64.7	10	125	8	11	101	10.9	6423	10539

	HessAff, 50 synths. $\Delta \phi = 72^{\circ}/t$ ,																
Image					t =	$\{1; 2\}$	; 4; 6; 8	}. Tot	al ima	ge area	$A_{tota}$	l = 11	$A_{orig}$				
	Time LO-RANSAC										Ter		Regions				
					SIFT		R	ootSIF	Т		SIFT			ootSIF			
	1 core $[s]$	2 cores $[s]$	4 cores $[s]$	Correct inliers	Inliers	Correct / all [%]	Correct inliers	Inliers	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Image 1	Image 2
graf	45.2	23.8	14.2	1214	1260	96.3	1235	1274	96.9	1249	2958	42.2	1267	2887	43.9	46997	58020
index	20.8	10.9	6.5	270	297	90.9	264	302	87.4	312		18.4	326	1297	25.1	27910	11497
shop	36.2	19.2	11.3	303	315	96.2	311	322		311	847	36.7	326	676	48.2	55508	25538
adam	6	3.1	1.9	205	239	85.8	214	231		242	525	46.1	239	497	48.1	7616	2310
there	43.4	23	13.6	211	274	77	189	234	80.8	240	905	26.5	212	680	31.2	11784	61930
mag	5.3	2.8	1.7	71	79	89.9	72	76	94.7	74	184	40.2	73	151	48.3	4362	6296
dum	60.2	31.6	18.7	61	68	89.7	66	74	89.2	63	617	10.2	68	419	16.2	79499	64321
grand	50.8	26.6	15.8	54	61	88.5	42	54	77.8	56	525	10.7	46	276	16.7	63962	52899
fox	18.6	9.7	5.8	75	86	87.2	74	84	88.1	79	258	30.6	76	205	37.1	26946	12327
cafe	17.2	9.2	5.4	34	45	75.6	45	53	84.9	39	437	8.9	48	409	11.7	16538	18329
girl	36.7	19.3	11.4	55	65	84.6	59	69	85.5	64	452	14.2	65	291	22.3	26776	49353
pkk	24.1	12.7	7.5	40	73	54.8	41	73	56.2	52	349	14.9	52	247	21.1	25266	22414
cat	7.8	4.2	2.5	21	38	55.3	18	34	52.9	37	147	25.2	29	115	25.2	3645	7267
face	38.8	20.5	12	52	55	94.5	24	25	96	56	417	13.4	26	277	9.4	42689	38507
vin	22.8	12.2	7.2	8	16	50	6	12	50	10	147	6.8	7	94	7.5	16608	28275

Table 15. Performance on the EVD dataset. Hessian-Affine, DENSE configuration. Results with less than 8 correct inliers are in red.

Table 16. Performance on the EVD dataset. DoG,DENSE configuration. Results with less than 8 correct inliers are in red.

		DoG, 59 synths. $\Delta \phi = 72^{\circ}/t$ ,															
Image				t ={1	$;\sqrt{2};$	2; 2	(2;4;4)	$4\sqrt{2};$	8}. To	otal ir	nage a	rea $A_t$	otal =	= 16 <i>A</i> ,	orig		
	Time LO-RANSAC										Te	0	Regions				
					SIFT		R	ootSI	FT		SIFT		R	lootSII	T		
	1 core $[s]$	2 cores $[s]$	4 cores $[s]$	Correct inliers	Inliers	Correct / all [%]	Correct inliers	Inliers	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Image 1	Image 2
graf	25.5	13.9	8.1	637	659	96.7	653	675	96.7	665	2284	29.1	675	2041	33.1	28836	38361
index	18.3	9.9	6.1	138	167	82.6	143	164	87.2	161	1901	8.5	157	1385	11.3	18477	10549
shop	24	12.8	7.7	118	122	96.7	130	134	97	124	1238	10	132	845	15.6	37205	18541
adam	6.3	3.3	1.9	129	135	95.6	125	138	90.6	136	549	24.8	145	434	33.4	7462	2062
there	36.9	19.6	11.6	98	125	78.4	94	112	83.9	119	1129	10.5	108	817	13.2	12041	47887
mag	5.4	2.8	1.7	52	57	91.2	59	62	95.2	54	209	25.8	59	178	33.1	3522	3952
dum	42.5	24.9	16.9	31	36	86.1	28	35	80	36	1440	2.5	31	966	3.2	54700	43809
grand	34.6	20	13.3	26	34	76.5	28	38	73.7	30	943	3.2	32	595	5.4	42032	35904
fox	18.2	10	6.1	27	40	67.5	25	39	64.1	33	614	5.4	28	370	7.6	24039	11336
cafe	15.2	9	6.1	22	28	78.6	22	28	78.6	25	558	4.5	23	415	5.5	12310	14829
girl	27.5	16	10.9	11	20	55	18	24	75	18	759	2.4	21	496	4.2	17867	33840
pkk	25.5	14.8	9.5	13	41	31.7	10	28	35.7	23	763	3	22	473	4.7	23470	24826
cat	11.7	6.5	4.1	0	0	0	6	16	37.5	5	215	2.3	11	153	7.2	4266	8714
face	32	17.8	11.3	0	0	0	0	0	0	33	1205	2.7	6	980	0.6	38334	32892
vin	21.7	12.6	8.4	0	0	0	0	0	0	7	491	1.4	5	270	1.9	14223	23069

				ASIF	T, 59	synth	s. $\Delta q$	$\phi = 7$	$2^{\circ}/t$ ,						
Image	t ={1	$t = \{1; \sqrt{2}; 2; 2\sqrt{2}; 4; 4\sqrt{2}; 8\}$ . Total image area $A_{total} = 16A_{orig}$													
		Time		(	ORS	4	Tent	atives	quality	Regions					
					SIFT	1		SIF	Т						
	[s]	S [ <i>S</i> ]	S [ <i>S</i> ]	Correct inliers		Correct / all [%]	Correct matches	ives	Correct / all [%]	_	5				
	1 core [s]	2 cores	4 cores $[s]$	Correc	Inliers	Correc	Correc	Tentatives	Correc	Image	Image				
graf	81.8	26.5	14.8	322	531	60.6	325	582	55.8	31199	38677				
index	54.1	18.3	10.9	23	94	24.5	23	178	12.9	20349	10115				
shop	79.5	25	14.1	17	34	50	18	76	23.6	41984	25270				
adam	17.8	6	4.3	24	63	38.1	25	92	27.1	7572	3295				
there	150	48.4	27.8	20	72	27.8	21	365	5.8	26901	52334				
mag	16.1	5.5	3.8	11	25	44	12	54	22.2	4204	6399				
dum	158	50.8	48.3	3	39	7.7	3	64	4.7	66380	48622				
grand	131	41.8	40.4	0	0	0	1	81	1.2	54350	43713				
fox	47.4	15.7	9.5	0	0	0	4	32	12.5	22300	13502				
cafe	39.2	12.9	8	4	74	5.4	4	109	3.6	16088	16245				
girl	110	35.6	20.8	0	0	0	12	199	6	35834	46892				
pkk	75.9	25.1	14.9	0	0	0	6	107	5.6	33229	22352				
cat	36.2	12.6	7.8	3	37	8.1	6	42	14.3	4979	10142				
face	138	44.1	25.4	0	0	0	6	136	4.4	59278	41859				
vin	66.9	21.3	20.6	0	0	0	0	49	0	17127	31329				

 Table 17. Performance on the EVD dataset.ASIFT. Results with less

 than 8 correct inliers are in red.

Table 18. Performance on the EVD dataset. MODS ( $\theta_m = 15$ ), SIFT. Results with less than 8 correct inliers are in red.

					<u>15 u</u>	M	IODS, 4	ste	ps.					
	1. MSER Scale only. 2. MSER SPARSE.													
Image	3. HessAff Sparse. 4. HessAff Dense													
		TimeLO-RANSACTentatives qualityRegions												
						SI	T		SIFT	•				
	Step	1 core $[s]$	2 cores $[s]$	4 cores $[s]$	Correct inliers	Inliers	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Image 1	Image 2		
graf	1	1	0.8	0.8	81	85	95.3	82	160	51.2	1018	1674		
index	1	0.5	0.4	0.4	19	20	95	19	56	33.9	411	246		
shop	1	0.8	0.7	0.7	28	30	93.3	28	84	33.3	1321	711		
adam	2	0.8	0.5	0.3	19	22	86.4	21	48	43.8	357	164		
there	2	4.5	2.8	2	10	18	55.6	15	66	22.7	571	2833		
mag	2	0.8	0.5	0.4	30	31	96.8	30	52	57.7	393	509		
dum	3	29.4	18.9	15.5	24	29	82.8	30	1136	2.6	33342	23711		
grand	3	21.9	13.7	11.3	17	25	68	21	754	2.8	24731	20297		
fox	2	2.1	1.4	1.1	16	19	84.2	19	76	25	1717	1011		
cafe	2	1.8	1.2	0.9	18	20	90	18	142	12.7	1402	1319		
girl	3	13.1	7.4	5.3	35	46	76.1	38	549	6.9	10460	16105		
pkk	2	2.5	1.6	1.3	7	15	46.7	10	81	12.3	1229	1267		
cat	3	3.9	2	1.4	35	38	92.1	35	143	24.5	1262	3279		
face	2	3.6	2.4	2	9	15	60	11	118	9.3	3411	2371		
vin	4	30.3	17.8	12.5	18	38	47.4	22	657	3.4	18956	31984		

	MODS, 4 steps.														
		1. MSER Scale only. 2. MSER SPARSE.													
Image		3. HessAff Sparse. 4. HessAff Dense													
		Time LO-RANSAC Tentatives quality Regions													
							SIFT			SIFT	C				
	Step	1 core $[s]$	2 cores $[s]$	4 cores $[s]$	Correct inliers	Inliers	Correct / all [%]	Correct matches	Tentatives	Correct / all [%]	Image 1	Image 2			
graf	1	1	0.8	0.8	82	87	94.3	83	154	53.9	1018	1674			
index	1	0.5	0.4	0.4	18	20	90	18	42	42.9	411	246			
shop	1	0.8	0.7	0.7	29	31	93.5	29	61	47.5	1321	711			
adam	2	0.8	0.5	0.4	20	23	87	22	47	46.8	357	164			
there	2	4.5	2.8	2	14	17	82.4	16	60	26.7	571	2833			
mag	2	0.9	0.5	0.4	31	31	100	31	44	70.5	393	509			
dum	3	27.2	16.9	13.5	25	32	78.1	29	850	3.4	33342	23711			
grand	3	20.9	12.5	10	14	24	58.3	19	468	4.1	24731	20297			
fox	2	2.1	1.4	1.1	19	20	95	20	62	32.3	1717	1011			
cafe	2	1.8	1.2	0.9	17	21	81	18	117	15.4	1402	1319			
girl	3	13.1	7.3	5.2	34	44	77.3	38	436	8.7	10460	16105			
pkk	3	9.5	5.3	4	27	37	73	33	344	9.6	10686	7085			
cat	3	3.6	2.1	1.5	25	34	73.5	30	149	20.1	1262	3279			
face	3	15.6	8.9	7.1	39	44	88.6	42	534	7.9	18857	13271			
vin	4	29.7	17.1	11.8	19	32	59.4	21	455	4.6	18956	31984			

Table 19. Performance on the EVD dataset.MODS ( $\theta_m = 15$ ), Root-SIFT. Results with less than 8 correct inliers are in red.