A Comparison of Feature Detectors and Descriptors for Visual Object Class Matching

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***Abstract*—Solid protocols to benchmark local feature detectors and descriptors were introduced in Mikolajczyk et al. 2005 [1] and Mikolajczyk and Schmid 2005 [2]. The detectors and descriptors are popular tools in visual object classification, but the original benchmarks are for the wide baseline setting which poorly corresponds to object classification where appearance variation can be large. In this work, we extend the original intuitive and quantitative benchmarks to the case of visual object class matching.**

In the experimental part, we evaluate the state-of-the-art detectors and descriptors and provide the following important findings: 1) detectors generally perform well, but descriptors' ability to match regions over class instances collapse; 2) using multiple, even a few, matches instead of the best match only has significant effect on the performance; 3) dense sampling outperforms interest point detectors; 4) the original SIFT is superior to all recent fast descriptors; 5) implementation matters - OpenCV SIFT outperforms VLFeat SIFT by a clear margin; 6) object pose variation (rotation) makes dense sampling collapse while the best detector (Hessian-affine) is unaffected. These findings expose new interesting research problems related to interest point/region detectors and descriptors, and our benchmark provides a solid development framework.

***Index Terms*—interest point, region, local part, detector, descriptor, SIFT, SURF, BRIEF, BRISK, ORB, FREAK.**

I. Introduction

IMAGE feature detectors and descriptors are useful methods in computer vision problems where point or region correspondences between images are needed. Ideally, they should tolerate pose variation, illumination changes, motion blur and other typical scene changes and distortions. That is the case, for example, in wide baseline matching [3], robot localisation [4] and panorama image stitching [5]. In all these cases, the feature correspondences are needed to match several views of a same scene and therefore the well-known detector and descriptor evaluations by Mikolajczyk and Schmid 2005 [1] and Mikolajczyk et al. 2005 [2] aid in finding the most suitable method. Another important application of feature-based matching is visual object classification and detection, where instances of various object classes must be identified and localised in input images. In that case, the visual appearance variation can be very large as compared to fixed scenes in the wide baseline setting, and thus, the original evaluations are not directly applicable.

Various methods have been proposed for detecting interest points/regions and to construct descriptors from them, most of which are designed with a different application in mind. [1] and [2] evaluated and compared the most popular detectors and descriptors. The detectors were evaluated by their repeatability ratios and total number of correspondences over several views of scenes and with various imaging distortion types. The descriptors were evaluated by their matching rates for the same views. Comparisons concerning object classification tasks were reported in [6] and [7], but in these works the evaluation was tied to a single methodological approach, namely visual Bag-of-Words (BoW). Moreover, many fast descriptors have been proposed recently: SURF [8], FREAK [9], ORB [10], BRISK [11], BRIEF [12]. Our main contributions are:

- We introduce novel intuitive and quantitative detector and descriptor benchmarks by
  - extending the detector repeatability evaluation in [1] to intra-class repeatibility of visual object classes and
  - extending the descriptor matching evaluation in [2] to the case of object classes.
- We compare the recent and most popular detectors and descriptors and their various implementations in our novel intra-class detector and descriptor evaluation settings.
- We also investigate the effect of using K multiple best feature matches ($K = 1, 2, \ldots$) and introduce an alternative performance measure: *match coverage*.

By these contributions and the experimental results, we arrive at the following important findings:

- Detectors generally perform well, but the ability of descriptors to match regions over visual class examples collapses.
- Using multiple—even a few—best matches instead of the single best match provides significant performance improvement and the collapse can be avoided.
- Dense grid sampling outperforms all interest point detectors.
- The original SIFT is superior to all recent fast descriptors.
- Implementation matters, for example, OpenCV SIFT outperforms VLFeat SIFT.
- Object pose variation severely affects dense sampling while the best detector (Hessian-affine) is unaffected.

Matlab source code, evaluation scripts, and data to repeat the experiments will be made public[1].

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[1] https://bitbucket.org/kamarain/descriptor_vocbenchmark

A. Previous work

We believe that the general evaluation principles in [1], [2] also hold in the context of visual object classes: 1) *detectors which return the same object regions for class examples are good detectors* – detection repeatability; 2) *descriptors which match the same object regions between class examples are good descriptors* – match count/ratio. We refer to these repeating and matching regions as "category-specific landmarks". A qualitative measure to visualise descriptors ("HOGgles") was recently proposed by Vondrick et al. [13], but its main use is in image-wise debugging of existing methods. More quantitative evaluations were reported by Zhang et al. [6] and Mikolajczyk et al. [7], but these were quite heuristic and tied to a single methodology, the visual Bag-of-Words (BoW) [14], [15]. In this work, we show that the original evaluation principles can be adopted to obtain similar quantitative performance measures in the general, comparable and intuitive forms used in the original works of Mikolajczyk et al., and not tied to any specific approach.

II. Comparing Detectors

A good feature detector should detect local points or regions at the same locations of class examples to make it possible to match corresponding "parts". This criterion differs from [1], where detectors are evaluated over views of the same scene corresponding to a single object. On the other hand, in part-based object class detection, which has been adopted in the state-of-the-art approaches [16], the descriptors (parts) should match despite substantial variance in class visual appearance.

A. Data

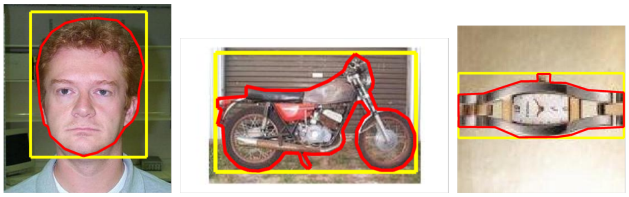


Figure 1. Caltech-101 examples with annotated ground truth (bounding boxes and the foreground region).

The experiments were conducted with the popular Caltech-101 [17] data set. We preferred Caltech-101 over the more recent data sets, such as Caltech-256 [18], Pascal VOC [19] and ImageNet [20], since they contain substantial 3D view point changes (e.g. car frontal vs. car side) which are not expected to be solved on the local feature level. The foreground masks available in the data set were used to remove features detected in the background (Fig. 1). Affine correspondence between category examples were established by manually annotating 5-12 landmarks per category and estimating the pair-wise image transformations using the direct linear transform [21]. Examples with annotated landmarks are shown in Fig. 2. For this experiment we used repeatedly 25 random pairs of images from each category.

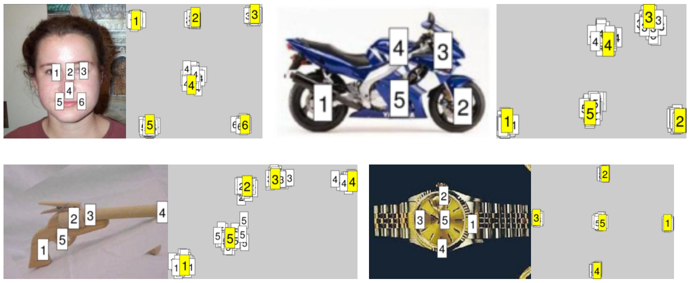


Figure 2. Object class examples with annotated landmarks (leftmost in each image pair) and 50 examples (affine) projected into a single space (denoted by the yellow tags). The image diagonal normalised (resolution independent) two standard deviations are 0.0158, 0.0297, 0.0486 and 0.0177, respectively. The part variances imply class specific spatial variance of object parts.

B. Region detectors

In our preliminary work we evaluated the following nine detectors [22]:

1) Two implementations of the difference of Gaussian: *sift* and *dog-vireo*
2) Harris-Laplace: *harlap-vireo*
3) Laplacian of Gaussian (log): *log-vireo*
4) Three implementations of the Hessian-affine: *hessaff*, *hessaff-alt* and *hesslap-vireo*
5) Speeded-up robust features: *surf*
6) Maximally stable extramal regions: *mser*

The detectors are publicly available: **-vireo* implementations in Zhao's Lip-vireo toolkit (http://code.google.com/p/lip-vireo), *hessaff* and *hessaff-alt* (by Mikolajczyk) at http://featurespace.org, *surf* at the authors' [8] web site and *mser* and *sift* in the popular VLFeat toolbox (http://vlfeat.org).

The best achieved average repeatability was 33.7% (*dog-vireo*) and the largest average number of corresponding regions 57.4 (*hesslap-vireo*). The best three detectors based on both repeatability and number of regions were *hesslap-vireo* (30.6%, 57.4), *hessaff* (25.3%, 47.8) and log-vireo (26.3%, 46.5). For comparison, the hessaff and the VLFeat SIFT descriptors were also included here.

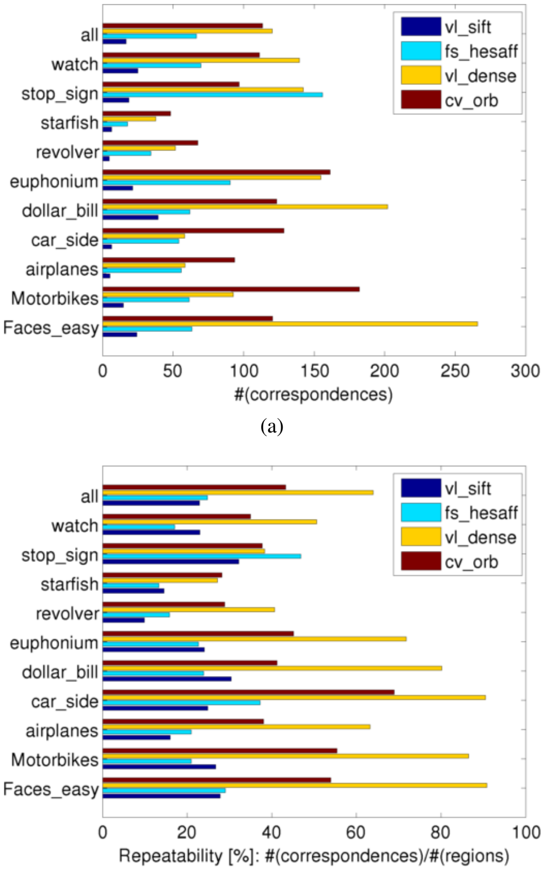
To bring our experiments up-to-date, we tested the recently proposed keypoint detectors: BRIEF [12], BRISK [11], ORB [10] and FREAK [9]. The best results were obtained with ORB included in the OpenCV library (http://opencv.org) and it was selected in this work (*orb*). Moreover, dense sampling has replaced detectors in the top methods (see, e.g., the results of Pascal VOC 2011 [23]) and lately also dense interest points have been proposed [24]. Therefore we added the dense SIFT in VLFeat (http://vlfeat.org) to our evaluation (*dense*).

C. Performance measures and evaluation

For the detector performance evaluation, we adopted the test protocol in [1]. Interest points are first extracted from images. The interest points detected inside the object area (Caltech-101 foreground) are selected for the evaluation. For each image pair, points from the first image are projected onto the second image by the affine transformation estimated using the annotated landmarks. The landmarks projected on a randomly selected example of each category are demonstrated in Fig. 2 with the two standard deviations corresponding to the 95% error distributions. Interest regions are described by 2D ellipses and a sufficient spatial overlap of two normalised ellipses within the image pair under consideration is accepted as a correct correspondence. We thus have a *corresponding region*, or simply a *correspondence*. The number and rate of correspondences for each detector is of interest. A detector performs well if the total number is large and also reliably if the ratio of correct matches is high. We used the parameter settings from [1]: 40% overlap error threshold and normalisation of the ellipses to the radius of 30 pixels.

The reported performance numbers are the average number of corresponding regions between image pairs and the repeatability rate, i.e. the ratio between the corresponding regions and the total number of detected regions.

D. Results



(a)

(b)

Detector	Avg # of corr.	Avg. rep. rate
vl_sift	16.7	22.9%
fs_hessaff	66.5	24.8%
cv_orb	113.4	43.3%
vl_dense	120.4	64.0%

(c)

Figure 3. Benchmarking detectors for visual object class matching: (a) average number of corresponding regions, (b) repeatability rates, and (d) the overall results table.

The results of the detector experiment are shown in Fig. 3. The main difference as compared to our preliminary work [22] is that the best of recently proposed detectors, ORB, and the simple dense sampling are clearly superior to the earlier winner, the Hessian-affine detector by Mikolajczyk. The difference to the original detector by Lowe is almost by order of magnitude better in terms of the number of correspondences. Clearly, with ORB or dense sampling there are much more regions to match (> 100 on average). Some less favourable properties of dense sampling are discussed in Sec. IV-C.

III. Comparison of Local Region Descriptors

A good region descriptor for the object classification problem should be discriminative to match only correct regions, and also tolerate small appearance variation between category examples. These requirements are general for feature extraction in computer vision and image processing. The descriptor performances were obtained in the original work [2] by computing statistics of the correct and false matches. In the case of classification, the descriptor matches are expected to be weaker due to increased variance in the visual appearance of regions. For example, scooters and road bikes are both in the Caltech-101 motorbikes category, but their pair-wise similarity is much weaker than between two scooters or two road bikes.

A. Available descriptors

In our preliminary work we evaluated the following six combinations [22]:

1) Hessian-affine and SIFT
2) Hessian-affine and linear filters
3) Alternative (Vireo) implementation of Hessian-affine and SIFT
4) Original SIFT detector and SIFT descriptor
5) Alternative (Vireo) implementation of SIFT and SIFT
6) SURF and SURF

The combinations 1) and 2) utilising Mikolajczyk's implementation of Hessian-affine detector were clearly superior to other methods. The Hessian-affine and SIFT achieved the average number of matches 66.1 and median 46.0.

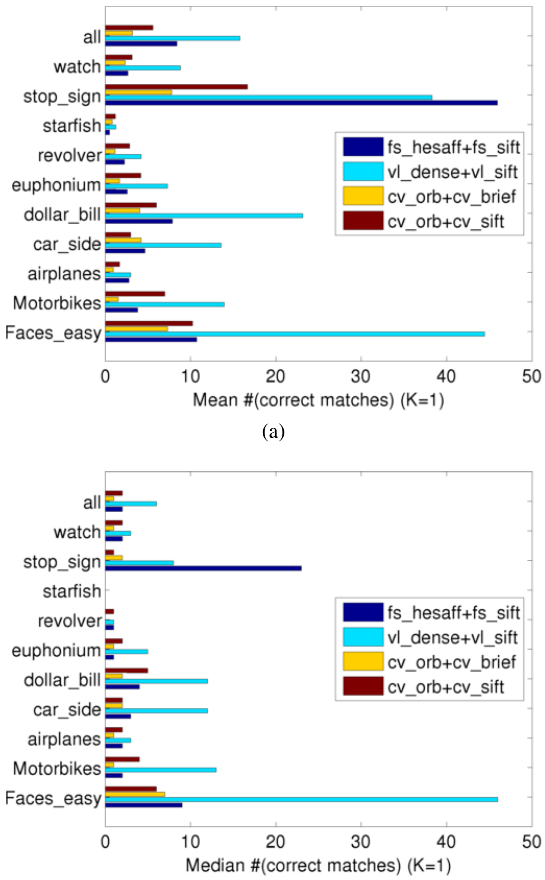
To complete the previous experiments, we here include the dense sampling and the best of the fast detectors (ORB) and descriptors (BRIEF). The following combinations will be reported: *fs_hessaff+fs_sift* (FeatureSpace implementation), *cv_orb+cv_brief* (OpenCV implementation), *cv_orb+cv_sift* (OpenCV, to compare SIFT and BRIEF), *vl_dense+vl_sift* (VLFeat implementation).

B. Performance measures and evaluation

In the experiments for this article, it turned out that the simplified version of Mikolajczyk's descriptor performance measure proposed in [22] produces overly optimistic results. Therefore in this work, we revert back to the original measure with an ellipse overlap threshold and using the nearest neighbour (without the descriptor matching threshold) [2]. At first, descriptors are computed for all detected regions (foreground only). Images are processed pair-wise and best matches for each region is selected from full distance matrices. It is worth noting that the rule proposed in [25] for discarding "bad regions" (ratio between the first and the second best is less than 1.5) must not be used with object classes since it would produce virtually no matches at all. This can be explained by the fact that matches are never as good as in the wide baseline setting. We used the maximum ellipse overlap error 50% from [2] for finding detector correspondences.

Our performance numbers are the average number of matches and median number of matches. The median is used to suppress the effect of several too well matching pairs (same person, identical stop signs, etc.)

C. Results



(a)

(b)

Detector+descriptor	Avg #	Med #
fs_hessaff+fs_sift	8.4	2
vl_dense+vl_sift	15.8	6
cv_orb+cv_brief	3.2	1
cv_orb+cv_sift	5.6	2

(c)

Figure 4. Descriptor evaluation: (a) average number of matches per class, (b) median, (c) colour coding of the method names, and (d) overall results table.

The average and median number of matches for the descriptor evaluation are shown in Fig. 4. For many classes, the mean and median numbers are very low and clearly descriptors sampled on the dense grid are superior for almost all classes, achieving the average of 15.8 and median of 6 matches. The only exception is the stop signs category for which the Hessian-affine outperforms dense sampling.

The best results were obtained for the stop signs, dollar bills and faces, but the overall performance is poor. The best discriminative methods could still learn to detect these categories, but it is difficult to imagine naturally emerging "common codes" for other classes except the stop signs, faces and dollar bills. It is surprising that the best detectors, Hessian-affine and dense sampling, were able to provide 66 and 120, repeatable regions on average, but only roughly 10% of these match in the descriptor space. The main conclusion of these results is that all descriptors perform poorly in matching similar regions between class examples. Fortunately, intra-class matching based on descriptors can be improved, as we will describe in the following section.

IV. Advanced Analysis

In this section, we address the open questions raised during the detector and descriptors comparisons in Section II and III. The important questions are: why only a few matches are found between different class examples and what can be done to improve that? Why dense sampling outperforms all interest point detectors and does it have any drawbacks?

A. Beyond single best match

It is obvious that descriptors match better between two images of a same scene than two different examples of a same object class. However, it can be assumed that on average two descriptors describing the same object part should match better than two distant parts. To test this assumption, every descriptor can be assigned to multiple best matches. Our next experiment was motivated by soft assignment, where a single descriptor contributes more than a single codeword. This approach has been found successful in visual classification [26], [27], [28]. In order to measure the effect of multiple assignments, we establish a new performance measure: *coverage*. Coverage corresponds to the number of image pairs for which at least N matches have been found (*coverage-N*). We tested the multiple assignment procedure by accumulating matches over $n = 1, 2, \ldots, K$ best matches. The corresponding coverages for $K = 1, 5, 10$ are shown in Fig. 5. Obviously, more image pairs contains at least $N = 5$ than $N = 10$ matches. With $K = 1$ (only the best match) the best method, VLFeat dense SIFT, finds at least $N = 5$ matches in 14 out of 25 image pairs and for $N = 10$ 10 matches. When the number of best matches is increased to $K = 5$, the same numbers are 19 and 17, respectively, showing clear improvement. Beyond $K = 5$ the positive effect diminishes, but it is clearly beneficial to use more than one best match of each region.

B. Two implementations of the dense SIFT

During the course of work, we noticed that different implementations of the same method provided different results. Since there are two popular implementations of dense sampling with the SIFT descriptor, OpenCV and VLFeat, we decided to compare the two distinct implementations. The results corresponding to the previous experiments in Sections II

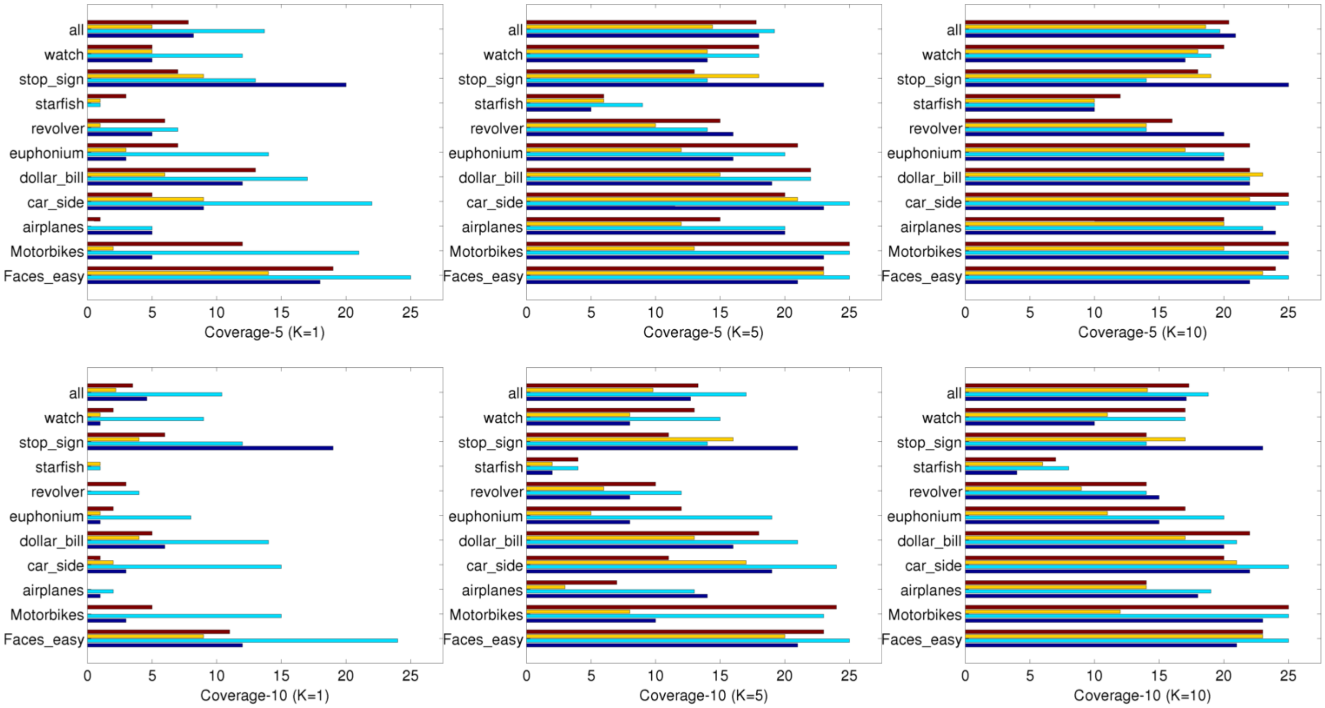


Figure 5. Descriptor evaluation results using K best matches. From left to right: $K = 1, 5, 10$, respectively. From top down: coverage-5, coverage-10.

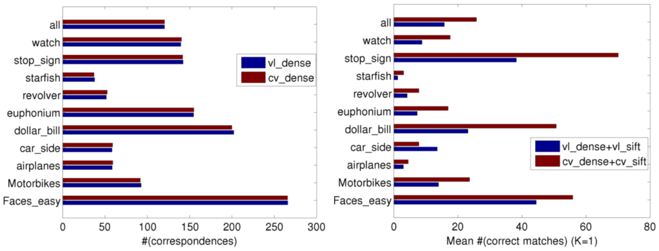


Figure 6. OpenCV dense SIFT vs. VLFeat dense SIFT - detector (left) and descriptor (right) comparison.

and III are shown in Fig. 6. The striking result is that in the OpenCV implementation the SIFT descriptors match better than in the VLFeat implementation (OpenCV average 25.8 and median 8 and for VLFeat 15.8 and 6). For only one class (car side) the VLFeat implementation is better, but on average OpenCV implementation is better by a clear margin.

C. Challenging dense sampling: r-caltech-101

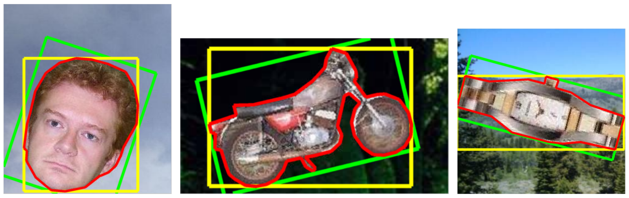


Figure 7. The r-Caltech-101 versions of the original Caltech-101 images in Fig. 1 (original bounding box shown by green).

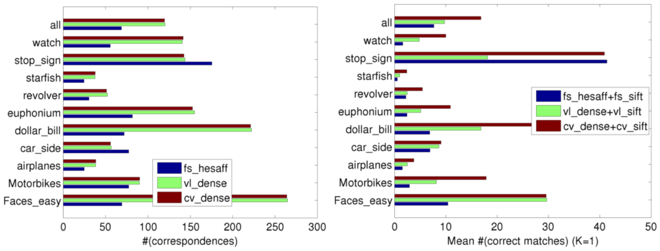


Figure 8. Benchmarks for r-Caltech-101: detector (left) and descriptor (right). The detector results are almost equivalent to Fig. 3. In the descriptor benchmark (right, cf. with Fig. 4) the Hessian-affine is almost unaffected (mean: $8.4 \rightarrow 7.7$) while both dense implementations, VLFeat ($15.8 \rightarrow 9.7$) and OpenCV ($25.8 \rightarrow 16.8$) are severely affected.

With dense sampling we are concerned with its robustness to changes in scale and, in particular, orientation, since these are not estimated similar to interest point detection methods. In this experiment, we replicated the previous experiments with the two dense sampling methods and the best interest point detection method using the randomised version of the Caltech-101 data set, r-Caltech-101 [29]. R-Caltech-101 contains the same objects (foreground), but with varying random Google backgrounds and the objects have been translated, rotated and scaled randomly (Fig. 7).

The detector and descriptor results of this experiment are shown in Fig. 8 Now it is clear that artificial rotations affect the dense descriptors while Hessian-affine is almost unaffected. It is noteworthy that the generated pose changes in r-Caltech-101 are rather small ($[-20°, +20°]$) and the performance drop could be more dramatic with larger variation. The obvious research direction would be better scale- and rotation-invariant dense interest points.

V. Discussion

Interest points and regions have been the low-level features in visual object detection and classification for a decade [14]. Recently, supervised low-level features, such as trained convolution filters in deep neural networks [30], have gained momentum, but we believe that the unsupervised interest point detector-descriptor approach can be developed further by identifying its weaknesses and bottlenecks. In this work, we took a step to this direction by introducing an evaluation framework of visual class part detectors and descriptors which provides intuitive and comparable quantitative results similar to the seminal works of Mikolajczyk et al. [1], [2].

With the proposed framework we identified the following important findings: 1) Detectors generally perform well, but descriptors' ability to match regions over visual class examples collapse. 2) Using multiple, even a few, best matches instead of the single best match provides significant performance improvement. 3) Dense grid sampling is clearly superior to all interest point detectors. 4) The original SIFT is superior to all recent fast descriptors. 5) Implementation matters, for example, OpenCV SIFT outperforms VLFeat SIFT. 6) Object pose variation severely affects dense sampling while the best detector (Hessian-affine) is unaffected.

The findings advocate new research on i) better object descriptors, ii) dense scale- and rotation-invariant interest point sampling and iii) alternative matching methods. Some results already exist. For example, BoW codebook descriptors can be enhanced by merging descriptors based on co-location and co-activation clustering [31], dense interest points have been proposed [24], and soft-assignment has been shown to improve BoW codebook matching [26]. Moreover, the success of the standard SIFT in our experiments justifies further development of better descriptors, not only faster descriptors. In the new research directions, our evaluation framework it a useful tool.

Acknowledgment

The authors would like to thank...

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