

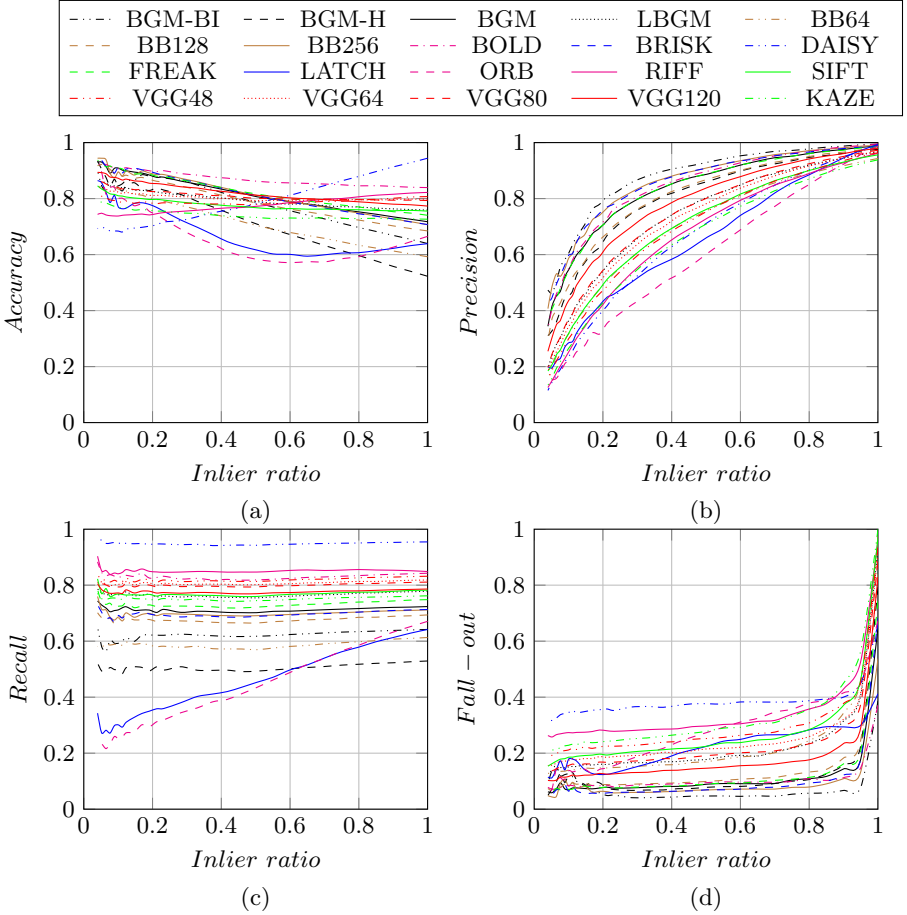
# Evaluations on Matching Quality for 20 Different Descriptors and KAZE Keypoints over Various Inlier Ratios

Josef Maier<sup>1</sup>, Martin Humenberger<sup>1</sup>, Oliver Zendel<sup>1</sup>, and Markus Vincze<sup>2</sup>

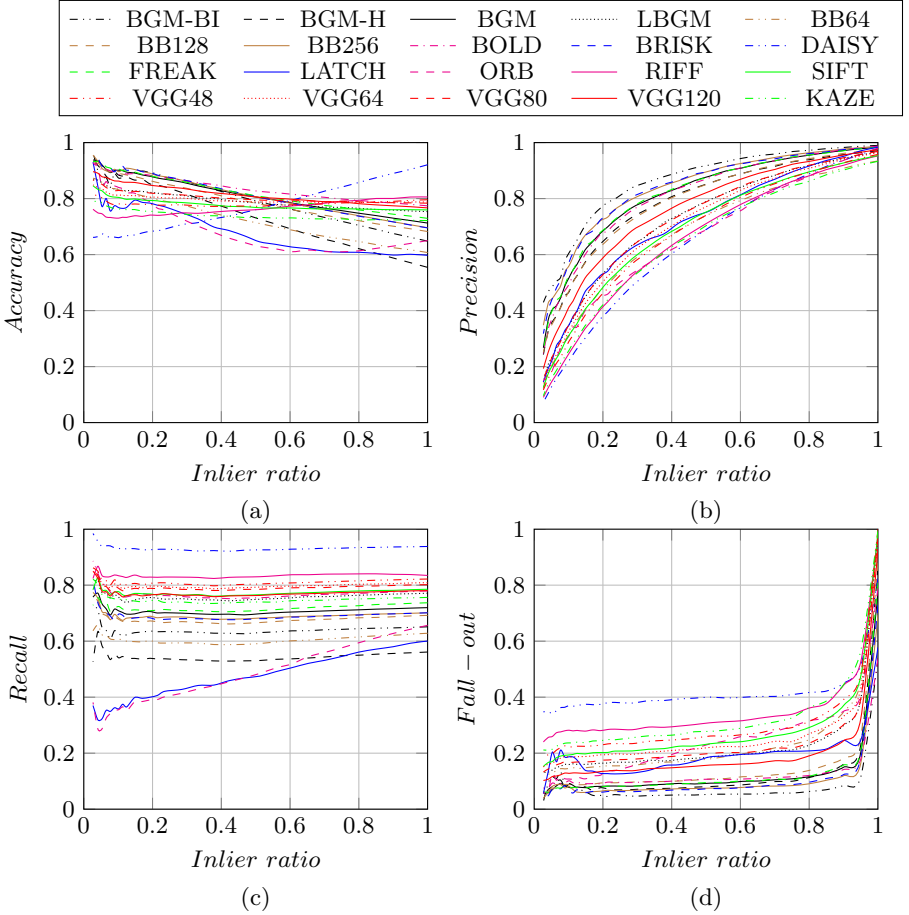
<sup>1</sup> AIT Austrian Institute of Technology  
{josef.maier.fl, martin.humenberger,  
oliver.zendel}@ait.ac.at

<sup>2</sup> Vienna University of Technology  
vincze@acin.tuwien.ac.at

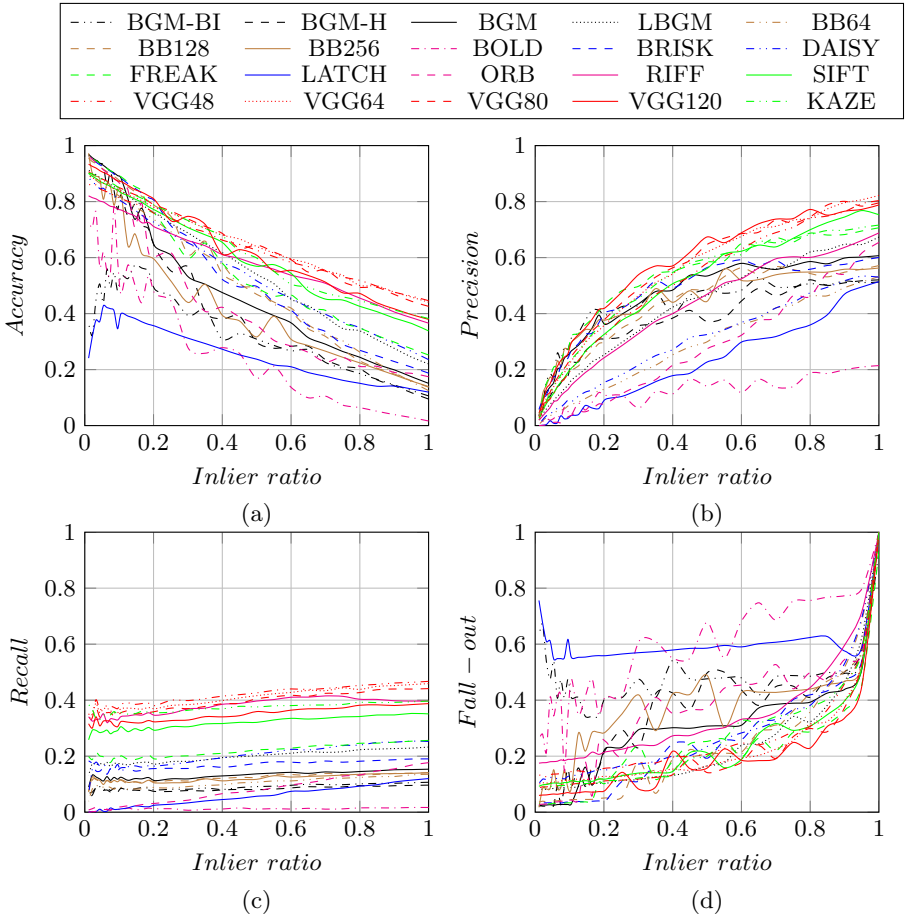
**Abstract.** In this document, we present additional results on the mean accuracy, precision, recall, and fall-out over various inlier ratios. The evaluations are performed on numerous datasets for different descriptors using KAZE [1] keypoints.



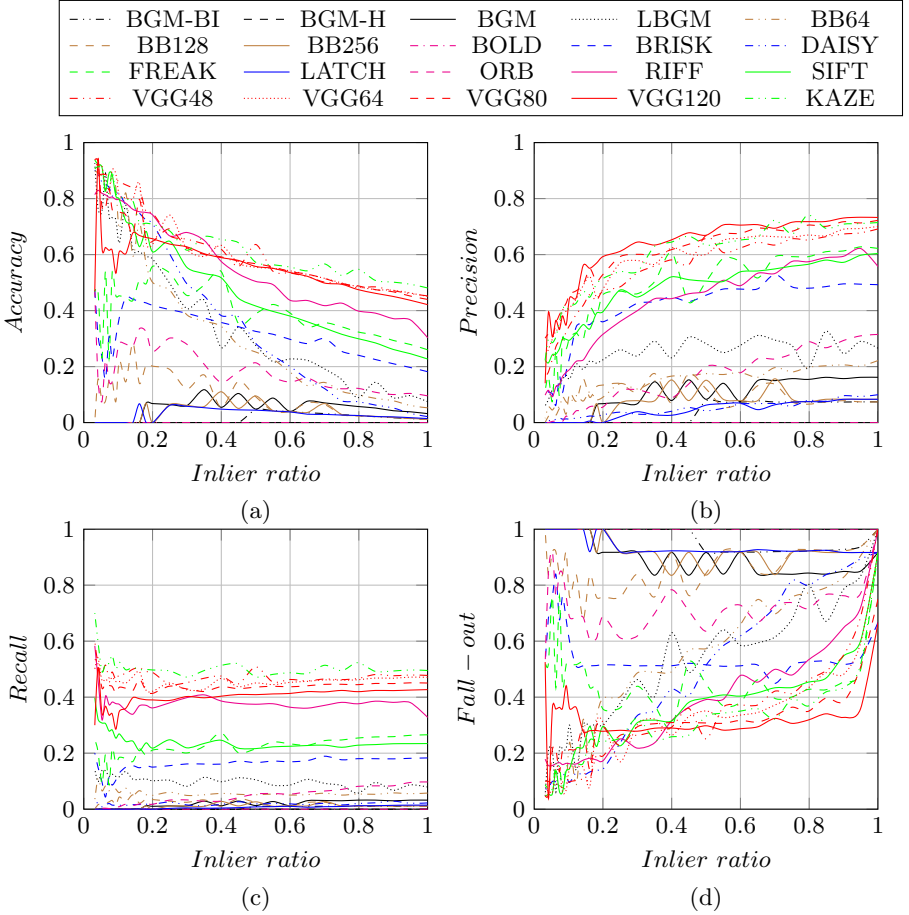
**Fig. 1.** Varying inlier ratio compared to mean (a) accuracy, (b) precision, (c) recall, and (d) fall-out using KAZE keypoints for the entire **KITTI disparity dataset** from Menze and Geiger [2]. For comparison, the following descriptors were used: KAZE [1], BOLD [3], BRISK [4], DAISY [5], FREAK [6], LATCH [7], ORB [8], RIFF [9], SIFT [10], BGM-Bilinear (BGM-BI) [11], BGM-Hard (BGM-H) [11], BGM [11], LBGM [11], BinBoost [12, 13] with a descriptor size of 64 bits (BB64), 128 bits (BB128), and 256 bits (BB256), in addition to the VGG descriptor [14] with a descriptor size of 48 bits (VGG48), 64 bits (VGG64), 80 bits (VGG80), and 120 bits (VGG120). On the results of all algorithms, a ratio test was performed.



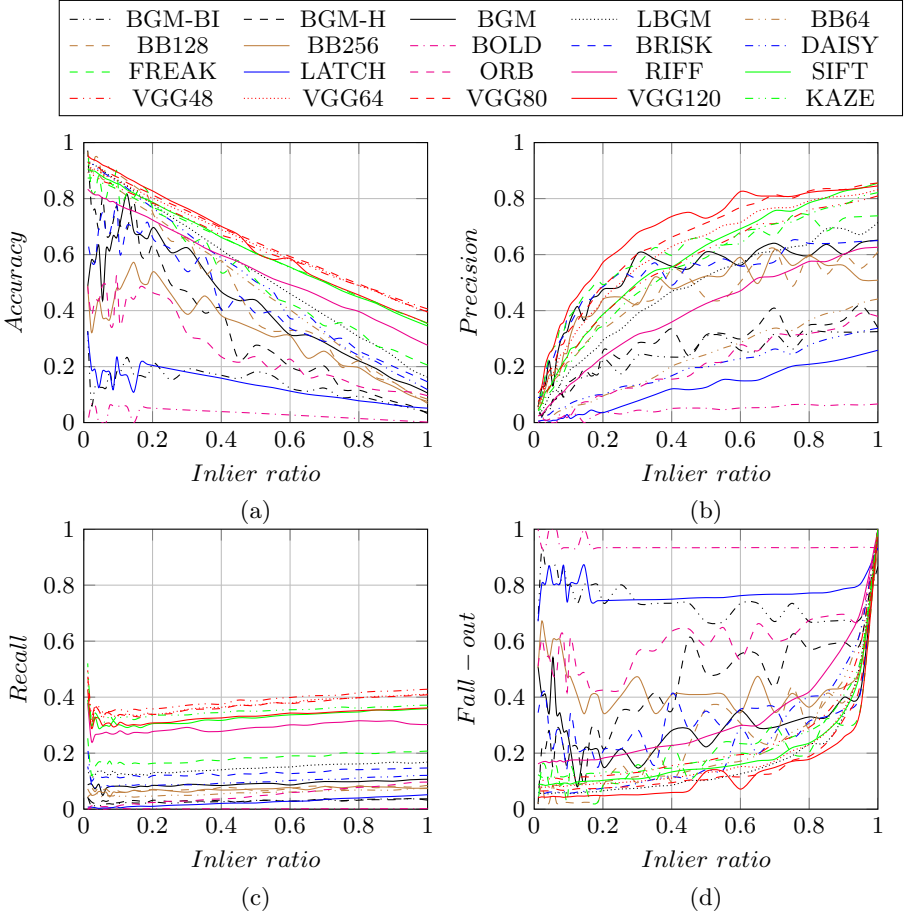
**Fig. 2.** Varying inlier ratio compared to mean (a) accuracy, (b) precision, (c) recall, and (d) fall-out using KAZE keypoints for the entire **KITTI flow dataset** from Menze and Geiger [2]. For comparison, the following descriptors were used: KAZE [1], BOLD [3], BRISK [4], DAISY [5], FREAK [6], LATCH [7], ORB [8], RIFF [9], SIFT [10], BGM-Bilinear (BGM-BI) [11], BGM-Hard (BGM-H) [11], BGM [11], LBGM [11], Bin-Boost [12, 13] with a descriptor size of 64 bits (BB64), 128 bits (BB128), and 256 bits (BB256), in addition to the VGG descriptor [14] with a descriptor size of 48 bits (VGG48), 64 bits (VGG64), 80 bits (VGG80), and 120 bits (VGG120). On the results of all algorithms, a ratio test was performed.



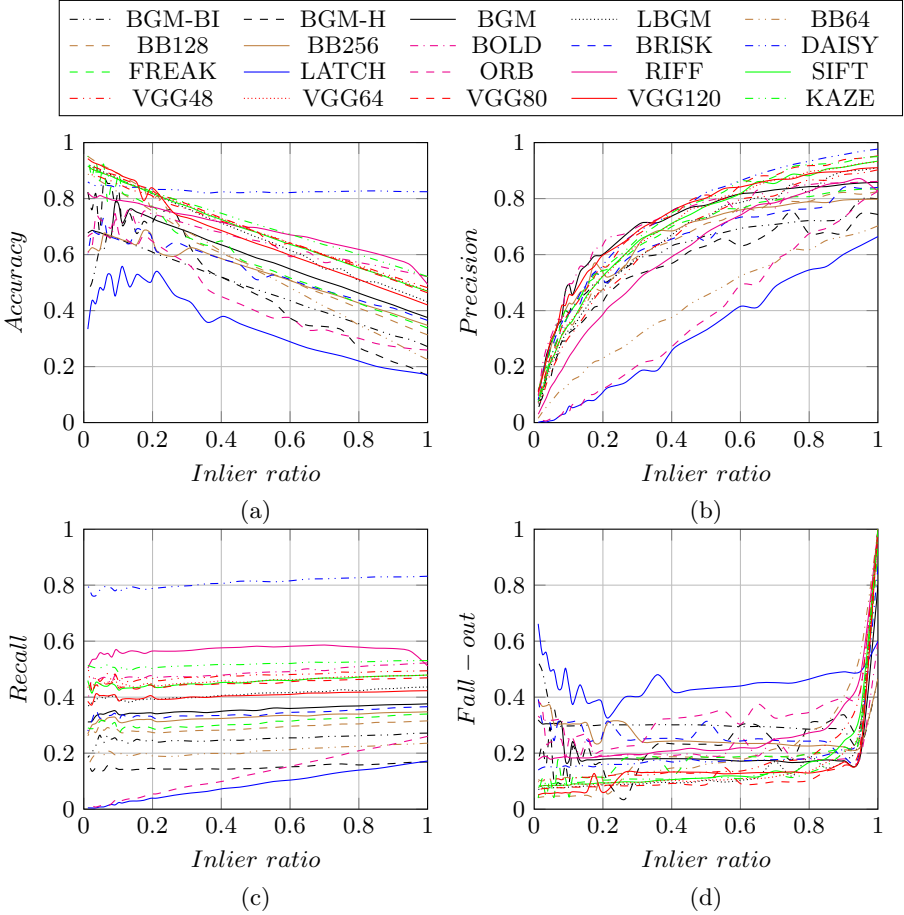
**Fig. 3.** Varying inlier ratio compared to mean (a) accuracy, (b) precision, (c) recall, and (d) fall-out using KAZE keypoints for the entire “**graffiti**” dataset from Mikolajczyk *et al.* [15, 16]. For comparison, the following descriptors were used: KAZE [1], BOLD [3], BRISK [4], DAISY [5], FREAK [6], LATCH [7], ORB [8], RIFF [9], SIFT [10], BGM-Bilinear (BGM-BI) [11], BGM-Hard (BGM-H) [11], BGM [11], LBGM [11], Bin-Boost [12, 13] with a descriptor size of 64 bits (BB64), 128 bits (BB128), and 256 bits (BB256), in addition to the VGG descriptor [14] with a descriptor size of 48 bits (VGG48), 64 bits (VGG64), 80 bits (VGG80), and 120 bits (VGG120). On the results of all algorithms, a ratio test was performed.



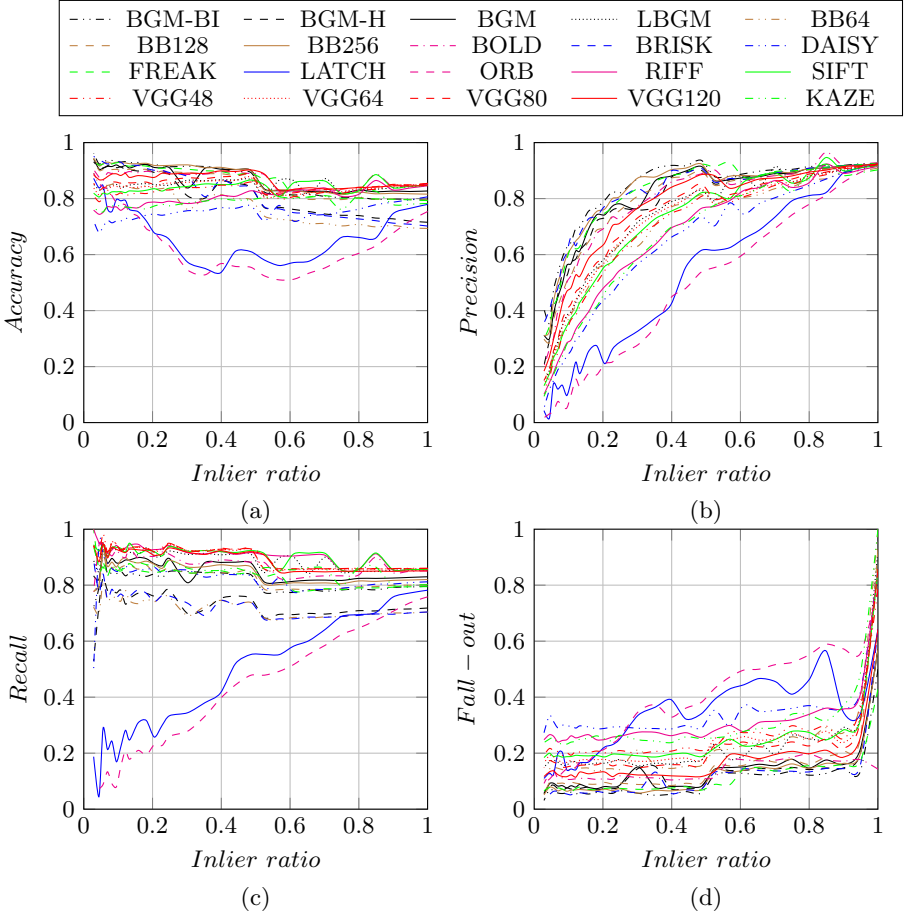
**Fig. 4.** Varying inlier ratio compared to mean (a) accuracy, (b) precision, (c) recall, and (d) fall-out using KAZE keypoints for the entire “**bark**” dataset from Mikolajczyk *et al.* [15, 16]. For comparison, the following descriptors were used: KAZE [1], BOLD [3], BRISK [4], DAISY [5], FREAK [6], LATCH [7], ORB [8], RIFF [9], SIFT [10], BGM-Bilinear (BGM-BI) [11], BGM-Hard (BGM-H) [11], BGM [11], LBGM [11], Bin-Boost [12, 13] with a descriptor size of 64 bits (BB64), 128 bits (BB128), and 256 bits (BB256), in addition to the VGG descriptor [14] with a descriptor size of 48 bits (VGG48), 64 bits (VGG64), 80 bits (VGG80), and 120 bits (VGG120). On the results of all algorithms, a ratio test was performed.



**Fig. 5.** Varying inlier ratio compared to mean (a) accuracy, (b) precision, (c) recall, and (d) fall-out using KAZE keypoints for the entire “**boat**” dataset from Mikolajczyk *et al.* [15, 16]. For comparison, the following descriptors were used: KAZE [1], BOLD [3], BRISK [4], DAISY [5], FREAK [6], LATCH [7], ORB [8], RIFF [9], SIFT [10], BGM-Bilinear (BGM-BI) [11], BGM-Hard (BGM-H) [11], BGM [11], LBGM [11], Bin-Boost [12, 13] with a descriptor size of 64 bits (BB64), 128 bits (BB128), and 256 bits (BB256), in addition to the VGG descriptor [14] with a descriptor size of 48 bits (VGG48), 64 bits (VGG64), 80 bits (VGG80), and 120 bits (VGG120). On the results of all algorithms, a ratio test was performed.

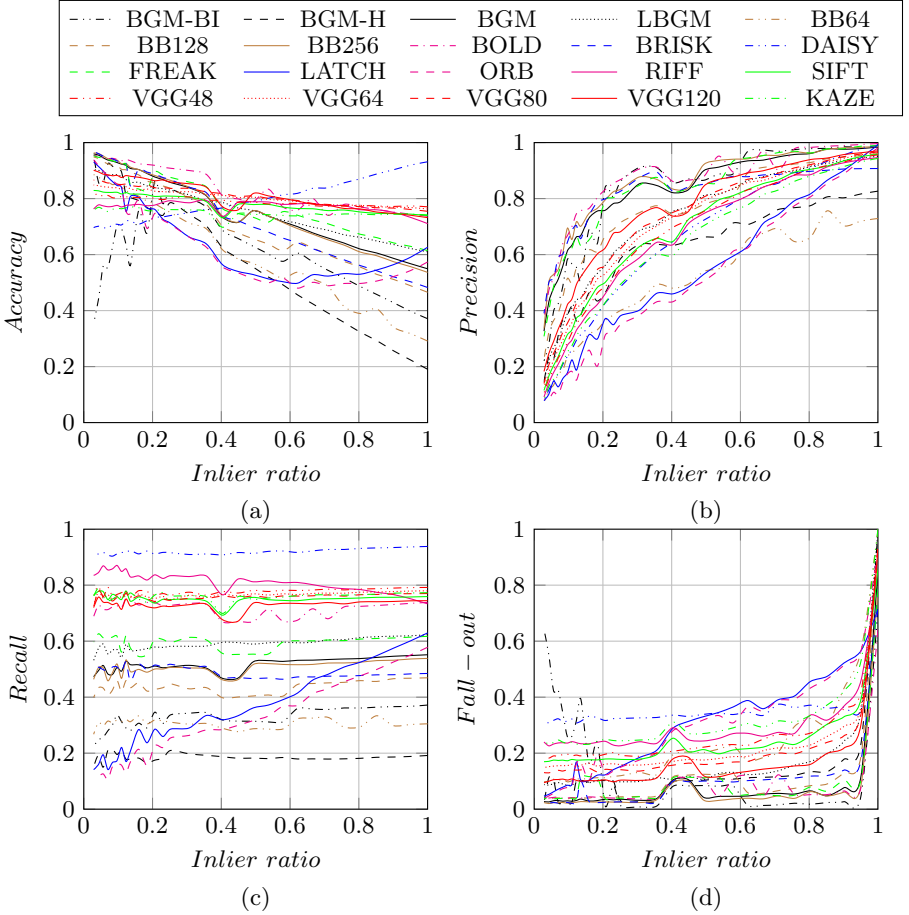


**Fig. 6.** Varying inlier ratio compared to mean (a) accuracy, (b) precision, (c) recall, and (d) fall-out using KAZE keypoints for the entire “wall” dataset from Mikolajczyk *et al.* [15, 16]. For comparison, the following descriptors were used: KAZE [1], BOLD [3], BRISK [4], DAISY [5], FREAK [6], LATCH [7], ORB [8], RIFF [9], SIFT [10], BGM-Bilinear (BGM-BI) [11], BGM-Hard (BGM-H) [11], BGM [11], LBGM [11], Bin-Boost [12, 13] with a descriptor size of 64 bits (BB64), 128 bits (BB128), and 256 bits (BB256), in addition to the VGG descriptor [14] with a descriptor size of 48 bits (VGG48), 64 bits (VGG64), 80 bits (VGG80), and 120 bits (VGG120). On the results of all algorithms, a ratio test was performed.

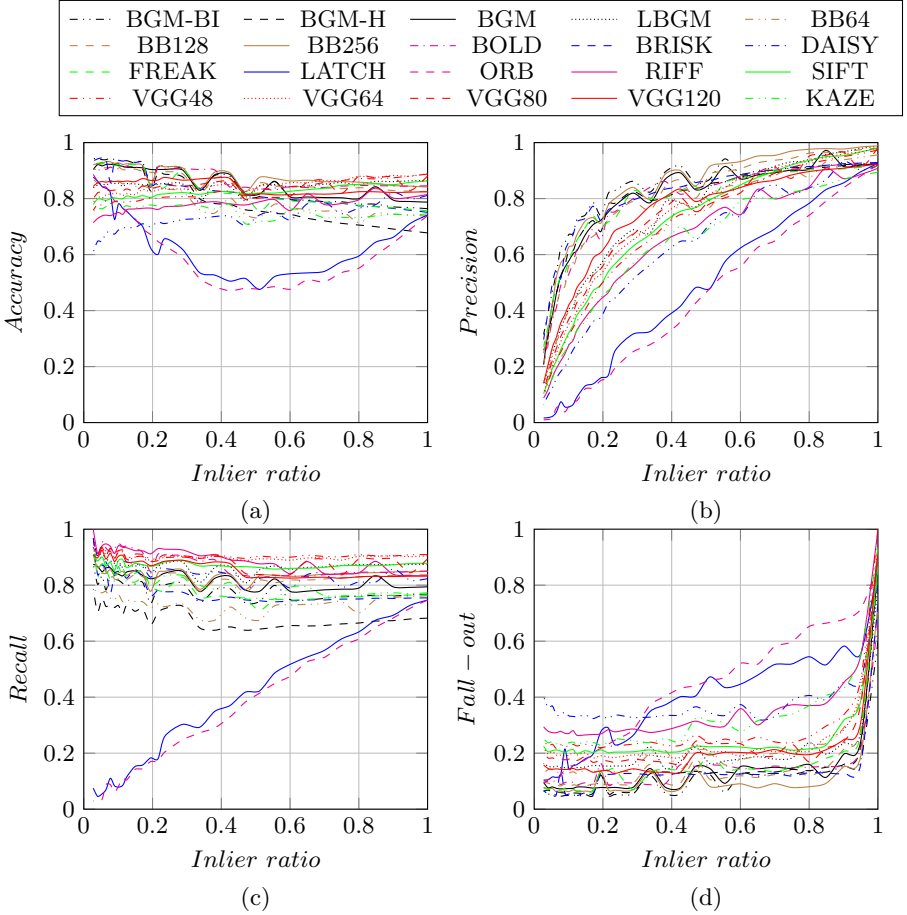


**Fig. 7.** Varying inlier ratio compared to mean (a) accuracy, (b) precision, (c) recall, and (d) fall-out using KAZE keypoints for the entire “**bikes**” dataset from Mikolajczyk *et al.* [15, 16]. For comparison, the following descriptors were used: KAZE [1], BOLD [3], BRISK [4], DAISY [5], FREAK [6], LATCH [7], ORB [8], RIFF [9], SIFT [10], BGM-Bilinear (BGM-BI) [11], BGM-Hard (BGM-H) [11], BGM [11], LBGM [11], BinBoost [12, 13] with a descriptor size of 64 bits (BB64), 128 bits (BB128), and 256 bits (BB256), in addition to the VGG descriptor [14] with a descriptor size of 48 bits (VGG48), 64 bits (VGG64), 80 bits (VGG80), and 120 bits (VGG120). On the results of all algorithms, a ratio test was performed.





**Fig. 8.** Varying inlier ratio compared to mean (a) accuracy, (b) precision, (c) recall, and (d) fall-out using KAZE keypoints for the entire “**JPEG**” dataset from Mikolajczyk *et al.* [15, 16]. For comparison, the following descriptors were used: KAZE [1], BOLD [3], BRISK [4], DAISY [5], FREAK [6], LATCH [7], ORB [8], RIFF [9], SIFT [10], BGM-Bilinear (BGM-BI) [11], BGM-Hard (BGM-H) [11], BGM [11], LBGM [11], Bin-Boost [12, 13] with a descriptor size of 64 bits (BB64), 128 bits (BB128), and 256 bits (BB256), in addition to the VGG descriptor [14] with a descriptor size of 48 bits (VGG48), 64 bits (VGG64), 80 bits (VGG80), and 120 bits (VGG120). On the results of all algorithms, a ratio test was performed.



**Fig. 9.** Varying inlier ratio compared to mean (a) accuracy, (b) precision, (c) recall, and (d) fall-out using KAZE keypoints for the entire “**light**” dataset from Mikolajczyk *et al.* [15, 16]. For comparison, the following descriptors were used: KAZE [1], BOLD [3], BRISK [4], DAISY [5], FREAK [6], LATCH [7], ORB [8], RIFF [9], SIFT [10], BGM-Bilinear (BGM-BI) [11], BGM-Hard (BGM-H) [11], BGM [11], LBGM [11], Bin-Boost [12, 13] with a descriptor size of 64 bits (BB64), 128 bits (BB128), and 256 bits (BB256), in addition to the VGG descriptor [14] with a descriptor size of 48 bits (VGG48), 64 bits (VGG64), 80 bits (VGG80), and 120 bits (VGG120). On the results of all algorithms, a ratio test was performed.

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