Performance Evaluation of BRISK Algorithm on Mobile Devices

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Abstract: The great number of researches about local features extraction algorithms in the last years, allied to the popularization of mobile devices, makes desirable efficient and accurate algorithms suitable to run on such devices. Despite this, there are few approaches adequate to run efficiently on the complexity-, cost- and power-constrained mobile environments. The main objective of this work is to evaluate the performance of the recently proposed BRISK algorithm on mobile devices. In this way, a mobile implementation, named M-BRISK, is proposed. Some implementation strategies are considered and successful applied to execute the algorithm in a real-world mobile device. As evaluation criterion repeatability, recall, precision and running time metrics are used, as well as the comparison with the classical well established algorithm SURF and also with the more recently proposed ORB. The results confirm that proposed mobile implementation of BRISK (M-BRISK) performs well and it is adequate to mobile devices.

1 INTRODUCTION

The widespread use of digital cameras is responsible for the generation of millions of images daily. Mobile digital devices, such as mobile phones and tablet PCs, extend the digital still cameras functionalities, allowing real-time exchange of images through their communication modems. These kind of devices, usually capable of capturing images and videos, are nowadays available to millions of people over the world. This fact makes them important tools for image acquisition, allowing anyone to easily capture images of products, advertisements, people's faces and bodies, pieces of art or any other visual data from the environment where he or she is inserted. Extracting useful information from all these data, through efficient computational algorithms, is an important goal of the Computer Vison research community.

The use of distinctive visual features to accomplish this goal has been highly explored in the last decade and applied to many problems such as content-based image retrieval (CBIR) (Smeulders et al., 2000), markerless augmented reality (MAR) (Skrypnyk and Lowe, 2004) and 3D scene reconstruction (Brown and Lowe, 2005). When a feature extraction algorithm employs an unique descriptor to an entire image it is called global. Otherwise, if it uses descriptors to many image points, it is called local. The local feature extraction algorithms are widely used because their invariance to many visual transformations. These extractors are able to detect salient regions into an image, which are called keypoints. Each keypoint is described by a feature vector, that represents numerically the image properties on the neighborhood of such point. These sets of keypoints descriptors can be used to perform matching between images, through the calculation of similarity metrics among them.

Despite the great profusion of researches about features extraction algorithms in the last years, there are few approaches suitable to run efficiently into mobile devices. Some algorithms, developed to have the best performance into unconstrained environments, do not perform well in the complexity-, cost- and power-constrained environment of such devices (Budagavi, 2006).

In this context, the main contribution of this work is to evaluate the performance of the recently proposed BRISK algorithm (Leutenegger et al., 2011), a local feature extractor, on a mobile device. To achieve it, we did a consistent analysis of the BRISK method, as well as the identification of its critical points concerning the computational cost. Some implementation strategies were considered and successful applied to execute the algorithm in a real-world mobile device. As evaluation criterion repeatability, recall, precision and running time metrics (Mikolajczyk and Schmid, 2005) were used, as well as the comparison

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with the classical well established algorithm SURF (Bay et al., 2006) and also with the more recently proposed ORB (Rublee et al., 2011). The results confirm the hypothesis that proposed mobile implementation of BRISK (M-BRISK) performs well and it is adequated to mobile devices.

This paper is organized as follows. In Section 2 we present the main considered algorithms for local features extraction. In Section 3 the BRISK method is reviewed, while their mobile implementation is presented in Section 4. The experiments and results are shown in Section 5. And finally, Section 6 presents the conclusions and future work.

2 LOCAL FEATURES DETECTION AND DESCRIPTION

Lowe (Lowe, 2004) proposed the Scale Invariant Feature Transform (SIFT) detector and descriptor algorithm, for extracting high distinctive features from images. The SIFT method, one of the most reliable features extractors, is invariant to scale and rotation transformations, and partially invariant to brightness and viewpoint changes. This algorithm is composed by four main stages: scale-space extrema detection, keypoints localization, keypoints orientation and keypoints description.

Due to the high dimensionality of the SIFT descriptor and its poor computing performance, other less time-consuming alternatives began to be proposed in the literature, with the purpose of enabling their use in real-time applications. In PCA-SIFT (Ke and Sukthankar, 2004) algorithm, the Principal Components Analysis (PCA) was applied to decrease the dimension of SIFT descriptors and to improve the matching time.

Bay et al. (Bay et al., 2006) presented a novel approach, partly based on SIFT, called Speed Up Robust Features (SURF). For some cases, the SURF algorithm is more robust than SIFT, taking less computing time. SURF employs integral images to build a fast detection method called Fast-Hessian. The description is based in a first order Haar Wavelet distribution. The SURF proves to be a very efficient method, however it has limited performance when compared to recent binary description approaches.

Calonder et al. (Calonder et al., 2010) built a binary descriptor, called Binary Robust Independent Elementary Features (BRIEF), with low dimensionality and more suitable for real-time applications. In this approach, the descriptors are formed by binary strings which makes comparisons more efficient. However, despite the high performance, the algorithm suffers in terms of robustness and reliability, because it has low tolerance in terms of distortion and image transformations, such as scale and rotation.

In order to overcome the BRIEF limitations, in terms of rotation invariance, the Oriented FAST and Rotated BRIEF (ORB) (Rublee et al., 2011) algorithm was proposed. This method uses Features from Accelerated Segment Test (FAST) (Rosten and Drummond, 2006) detector to provide a complete detection and description algorithm. It has a good robustness and a good performance, even concerning mobile devices.

Leutenegger et al. (Leutenegger et al., 2011) proposed the Binary Robust Invariant Scalable Keypoints (BRISK), a new approach that joins the fast and efficient Adaptative and Generic Accelerated Segment Test (AGAST) (Mair et al., 2010) detector to a binary descriptor inspired by BRIEF. This algorithm, that uses a sampling pattern resembling the one used in DAISY dense descriptor (Tola et al., 2010), is invariant to many transformations, such as scale and rotation. BRISK allies high-quality descriptor to low computational requirements, what makes it proper to real-time applications.

3 BRISK REVISITED

The BRISK method can be divided in three steps: **keypoints detection**, **keypoints description** and **descriptors matching**[1]. These stages are executed sequentially.

3.1 Keypoints Detection

It is performed at the first moment. The goal at this step is to identify salient points in the image that, ideally, could be uniquely differentiated from any other point. To do so, these points must be searched across the image and scale dimensions using a saliency criterion (Leutenegger et al., 2011). The search through scale space is fundamental to achieve scale invariance and it is realized in BRISK by the use of a pyramid of images. This pyramid is formed by many layers which correspond to resamples of the original image. In BRISK method, these layers are divided in n octaves c_i and n intra-octaves d_i, with $i = \{0, 1, ..., n\}$ and usually $n = 4$. The intra-octaves d_i are located between octaves c_i and c_{i+1}. These intra-octaves

[1]The matching step can also be seen as an independent stage.

and octaves are formed by the original image sub-sampled by factors $\frac{1}{2}$ (half-sampling) and $\frac{2}{3}$ (two-third-sampling). The original image is progressively half-sampled to form the octaves, while the intra-octaves are formed by progressives half-sampling of the first intra-octave d_0, which in turn is composed by a two-third-sampling of the original image.

After the octaves and intra-octaves calculation, the AGAST corner detector (Mair et al., 2010) is applied to each one of them. All the points of each layer will be evaluated as a keypoint candidate, and to be elected a point must be salient among their intra-layer and inter-layers neighbors. It means that each point is compared with its neighbors in the same layer and also with those in the above and bellow layers. After the analysis of all octaves and intra-octaves, the detection stages finally ends, producing a set of keypoints with space and scale coordinates, what means that each one of them can be exactly located.

3.2 Keypoints Description

In this stage, around each keypoint, which has its coordinates found in the previous step, a sampling pattern is positioned. The BRISK algorithm uses a sampling pattern similar to the one in DAISY descriptor (Tola et al., 2010). However, it is important to note that the use of this pattern is quite different. The pattern relies on 60 equally spaced points located in four concentric rings. In order to produce a scale and rotation invariant description, the sampling pattern is exactly scaled and rotated according to each keypoint. The BRISK descriptor is composed as a binary string of length 512. This string concatenates the results of simple brightness comparisons tests between each keypoint and its 60 neighbors in the pattern (Leutenegger et al., 2011). This approach was inspired by the BRIEF method (Calonder et al., 2010).

3.3 Matching

Finally, to perform the comparison between two or more keypoint descriptors, the Hamming distance is used. This distance measures the number of different bits between two binary strings and it represents the degree of inequality of the descriptors being compared.

4 M-BRISK

This section presents the mobile implementation of BRISK algorithm and the main aspects concerning to the environment where it was developed and tested. This mobile implementation is called M-BRISK (Mobile-BRISK).

4.1 Implementation

In order to implement the algorithm to be executed into a mobile device, some issues had to be overcame. The first of them was the fact that SSE2 and SSE3 instructions (Intel, 2006), the Intel's SIMD instructions set (Flynn, 1972), were employed by Leutenegger et al. (Leutenegger et al., 2011) in their original implementation of BRISK[2]. It was used as a crucial resource to improve the BRISK performance at critical time-consuming routines.

SIMD instructions are available in ARM architecture (ARM, 2012b), the most popular architecture of mobile devices processors, just since the ARMv7 version, through the NEON instructions (ARM, 2012a). As these instructions are not available into all devices, specially into the low-end ones, it was decided not to use them in the present implementation. This choice allows M-BRISK to be a more generic implementation, avoiding the dependence of specific mobile processors and instructions sets. This approach also constitutes a baseline assessment of the algorithm once it is being evaluated in a most ordinary condition.

The sub-sampling routines, originally implemented trough the SSE instructions, was replaced by a bilinear interpolation function implemented using the OpenCV library (OpenCV, 2011). This approach showed to be efficient and applicable to a mobile environment while it kept robustness.

Another critical point is the sampling pattern routine. In the original BRISK implementation, as a manner to obtain this pattern efficiently, 65536 samples are generated to each one of the 60 pattern points during the algorithm initilization and stored in a look-up table. These samples corresponds to all possible discretized values of scale and rotation. There are 64 and 1024 possible values to each dimension, respectively. The goal of this approach is to save running time in the description construction of each keypoint. However, such process is so time-consuming that its use is prohibitive on mobile devices. Thus, to avoid this problem, we chose to previously save a binary representation of the look-up table in mobile device memory card. Doing so, at the time of descriptors construction the table is already completely loaded into device memory.

Finally, during the matching routine, the SSE instructions were also used to improve the performance

[2]The original BRISK implementation is available in: http://www.asl.ethz.ch/people/lestefan/personal/BRISK

of original BRISK implementation. These instructions were used in this stage to optimize the calculation of the Hamming distance, employed to compare two keypoint descriptors. In M-BRISK the Hamming distance was also implemented through the OpenCV library. Unfortunately this change represented considerable addition in the running time of matching.

4.2 Mobile Execution Environment

The mobile platform chosen to support the implementation of M-BRISK algorithm was the Android (Google, 2012). This decision was motivated mainly because it is a well documented open development platform. Another distinguishing feature of Android is its ability to run very efficiently C and C++ libraries, allowing the reuse of previously implemented code. In order to execute these libraries into Android, the Native Development Kit (NDK) (Google, 2011) was used. Since Android applications are written in Java, to enable interfacing between the different languages, the NDK relies on the Java Native Interface (JNI) (Liang, 2003). The Android 2.2 version was used.

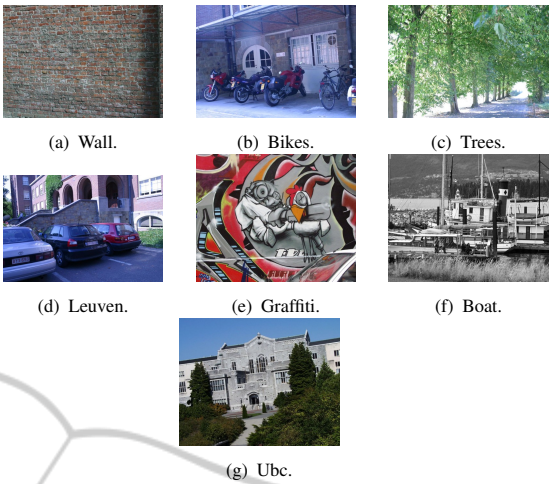
The employed device was a low-end mobile phone with Mediatek MTK6516 416MHz ARMv5 processor, with 256MB of RAM memory. As mentioned earlier, the NEON instructions are not available on this processor architecture version.

5 EXPERIMENTS AND RESULTS

Leutenegger et al. (Leutenegger et al., 2011) compared BRISK with SIFT and SURF algorithms, showing the high performance of the former. The purpose of the present experiments was to evaluate the performance of M-BRISK. To accomplish this, the mobile implementation is compared with the original BRISK implementation. Tests were performed to compare the repeatability rate and to measure the relation between execution time in the steps of detection, description and matching of the both approaches. Moreover, M-BRISK it is compared with SURF and ORB using the recall and precision metrics and also on a real mobile device, used to compare the running time of such algorithms.

5.1 Image Dataset

The image dataset[3] used to perform the experiments is a well established benchmark, largely employed to evaluate many methods in this field (Calonder et al., 2010), (Mikolajczyk and Schmid, 2005), including the BRISK algorithm (Leutenegger et al., 2011). The transformations covered by the dataset, shown in the Figure 1, are: viewpoint change (Graffiti and Wall), blur (Bikes and Trees), brightness change (Leuven), zoom and rotation (Boat) and JPEG compression (Ubc).



(a) Wall. (b) Bikes. (c) Trees.

(d) Leuven. (e) Graffiti. (f) Boat.

(g) Ubc.

Figure 1: Image dataset used for the tests.

5.2 Repeatability Test

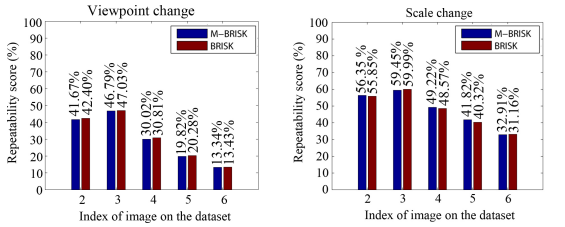
The repeatability test was used to identify the ability of the detector to find the same keypoint into distinct images modified by some kind of transformation. The goal of this test is to evaluate if the modifications in the sub-sampling methods (half-sampling and two-third-sampling) affected the quality of the detection in the M-BRISK implementation.

The results in Figure 2 show the repeatability for viewpoint change (Boat images) and zoom and rotation transformations (Wall images). The percentual of repeatability measured for each algorithm is shown on top of each bar. Based in the values, we can conclude that M-BRISK has repeatability similar to the BRISK, proving that the mobile implementation of the detection step did not degrade the quality of the algorithm. In some cases, M-BRISK has even slightly better results than BRISK.

5.3 Recall × 1-Precision Evaluation

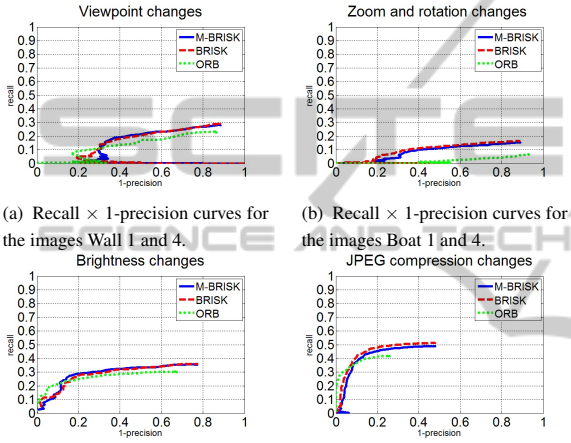
Recall and 1-precision are two relevant metrics used to show the effectiveness of a descriptor method. Recall measures the proportion of correct positives matches, considering all the possible correct positive matches between two images. While 1-precision

[3]The image dataset is available in: http://www.robots.ox.ac.uk/∼vgg/research/affine/.



(a) Wall (b) Boat

Figure 2: Repeatability test for images of Wall and Boat sets, with different transformations. The degree of changes of viewpoint, zoom and rotation gradually increases from the image 2 to image 6 in each image set. The image 1 is considered as the original image in both sets.



(a) Recall × 1-precision curves for the images Wall 1 and 4.

(b) Recall × 1-precision curves for the images Boat 1 and 4.

(c) Recall × 1-precision curves for the images Leuven 1 and 4.

(d) Recall × 1-precision curves for the images Ubc 1 and 4.

Figure 3: Results shown recall × 1-precision curves for M-BRISK, BRISK and ORB. Values of recall and 1-precision were calculated for different matching thresholds (Hamming distance limit bellow which two keypoints descriptors are considered equal).

measures the proportion of false positives matches, considering all the performed matches between those images.

These curves represent the algorithm capacity to keep a small number of false positives (1-precision) while it associates the maximum number of keypoints between two images (recall).

The resulting to recall × 1-precision curves, shown in Figure 3, allow to compare the effectiveness of M-BRISK, BRISK and ORB. It enables to evaluate the quality of the algorithms in all steps. The curves allow us to observe that M-BRISK and BRISK have similar robustness to viewpoint and brightness changes. However, BRISK has slightly better results to JPG compression, zoom and rotation transformations. Besides this, it is clear that ORB presents worst results for almost all threshold values.

5.4 Running Time Test

These tests compare the time variations in the different stages of BRISK and M-BRISK implementations. Moreover, the comparison between the mobile device running time of M-BRISK, SURF and ORB are shown.

5.4.1 Distribution of Running Time between BRISK and M-BRISK Stages

In Figure 4, the mean time per point spent in each step of BRISK and M-BRISK is presented. The purpose is to analyse the relation between the running time of each algorithm step aiming to evaluate the effects of the modifications over BRISK. The tests were performed using 100 samples of images for the sets Graffiti, Boat and Leuven. The execution was host in a computer with a Core2Duo T8100 2.10Ghz processor, 3GB of RAM memory and Windows 7 (64-bits) operating system.

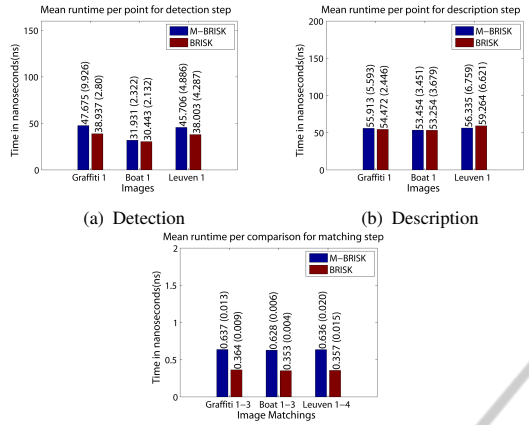
The mean times and the standard deviations are showed at the top of the bars. As can be observed, in the average, M-BRISK had performances in the detection and matching stages, respectively, around 15% and 75% worst than BRISK. Even without the use of SSE instructions, what was the reason of the M-BRISK worst results, the time consumed in the detection stage was not affected so significantly. In the description stage the performance of both implementations was similar.

Another important difference between the two approaches is concerning the look-up table usage. While it is calculated during the execution in BRISK, in M-BRISK the look-up table is calculated previously. The mean time consumed in the BRISK look-up table calcutation is 1.269s, while the mean time spent to load it from memory in M-BRISK is 0.088s. The latter amount of time corresponds to less than 10% of the former.

5.4.2 Running Time Test on a Mobile Device

The purpose of this test is to provide a reference for running times of M-BRISK, SURF and ORB in a real mobile device. These tests are performed using the images Graffiti 1-3 with 50 samples.

Tables 1 and 2 show the execution running times in the mobile device. The times in the tables represent an average of all running time samples with their respective standard deviation between parenthesis. As we can observe, the M-BRISK is about twice faster than ORB and more than 20 times faster than SURF in detection and description steps. In the matching



(a) Detection (b) Description

(c) Matching

Figure 4: Comparison between the running time of BRISK and M-BRISK steps. The mean amount of time spent per point in each step is shown at the top of the bars, as well as the standard deviations in parenthesis.

step, the time difference is not so significant comparing ORB and M-BRISK. However, SURF had worst results than M-BRISK in all execution steps.

The Table 1 shows the detection and description times. The time per point represents the average time for detection and description for each keypoint. This value represents a fairness comparison between the algorithms. The Table 2 shows the matching times, including the average time spent during each descriptor comparison. The serial implementation of Hamming distance decreased the matching performance, however remained very fast when compared with SURF descriptors matching. Even compared with ORB, M-BRISK implementation still demonstrates pretty competitive timings.

Table 1: Detection and description timings for the Graffiti image 1.

	SURF	ORB	M-BRISK
Number of points	3201	1000	1957
Detection time (s)	65.87 (1.56)	3.17 (1.13)	1.83 (1.81)
Description time (s)	140.66 (0.50)	2.85 (1.25)	3.59 (3.53)
Total time (s)	206.54 (1.71)	6.02 (1.89)	5.42 (5.35)
Time per point (ms)	**64.52 (0.53)**	**6.02 (1.89)**	**2.77 (2.78)**

Table 2: Matching timings for the Graffiti images 1 and 3.

	SURF	ORB	M-BRISK
Points in first image	3201	1000	1957
Points in second image	3820	1000	2529
Total time (s)	370.66 (17.90)	5.99 (2.44)	26.59 (9.66)
Time per comparison (ns)	**30.31 (1.46)**	**5.99 (2.44)**	**5.37 (1.95)**

6 CONCLUSIONS

The wide use of local features extractors applied to many computer vision problems, allied to the popularization of mobile devices, makes desirable efficient and accurate algorithms suitable to run on such devices. These algorithms must join robustness and low computational cost, and still there are few methods efficiently adequate to the constrained mobile environments. Thus, the main objective of this work was to evaluate the performance of the recently proposed BRISK algorithm on a mobile device. To do so, a mobile implementation, named M-BRISK, was proposed.

M-BRISK is focused to run in the most common ARM processors architecture. The implementation successfully overcame some mobile environment constraints, as processing power and limited instructions set, confirmed through the analysis of the obtained results. These showed that M-BRISK is so efficient and accurate as the original BRISK implementation, which presents excellent results even when compared with the well established SIFT and SURF. Moreover, M-BRISK presented a overall running time approximately twice smaller than ORB and 20 times smaller than SURF, the other mobile approaches evaluated. Thus, it is possible to point M-BRISK as a very suitable approach for detection and description on mobile applications.

In future works, a version of M-BRISK with NEON instructions will be tested against the serial version. Also other parallel development paradigms, such as GPGPU processing, supported by the most advance mobile devices, must be considered. Moreover, a detailed analysis of M-BRISK computational complexity is desirable.

REFERENCES

ARM (2012a). Arm neon instructions. Available in: http://www.arm.com/products/processors/technologies/neon.php, accessed on June 05, 2012.

ARM (2012b). Arm processor architecture. Available in: http://www.arm.com/products/processors/technologies/instruction-set-architectures.php, accessed on June 05, 2012.

Bay, H., Tuytelaars, T., and Gool, L. V. (2006). Surf: Speeded up robust features. In *Proceedings of the Ninth European Conference on Computer Vision (ECCV 2006)*, pages 404–417.

Brown, M. and Lowe, D. G. (2005). Unsupervised 3d object recognition and reconstruction in unordered datasets. In *Proceedings of the Fifth International Conference on 3-D Digital Imaging and Modeling (3DIM 2005)*, pages 56–63.

Budagavi, M. (2006). Real-time image and video processing in portable and mobile devices. *Journal of Real-Time Image Processing*, 1(1):3–7.

Calonder, M., Lepetit, V., Strecha, C., and Fua, P. (2010). Brief: Binary robust independent elementary features.

In *Proceedings of the 11ht European Conference on Computer Vision (ECCV 2010)*, pages 778–792.

Flynn, M. J. (1972). Some computer organizations and their effectiveness. *IEEE Transactions on Computers*, C-21(9):948–960.

Google (2011). Android ndk. Available in: http://developer.android.com/sdk/ndk/overview.html, accessed on November 15, 2011.

Google (2012). Android. Available in: http://www.android.com/, accessed on February 29, 2012.

Intel (2006). Intel c++ compiler for linux intrinsics reference. Available in: http://software.intel.com/file/6337/, Accessed November 15, 2011.

Ke, Y. and Sukthankar, R. (2004). Pca-sift: a more distinctive representation for local image descriptors. In *Proceedings of the 2004 IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2004)*, volume 2, pages II–506 – II–513.

Leutenegger, S., Chli, M., and Siegwart, R. (2011). BRISK: Binary Robust Invariant Scalable Keypoints. In *Proceedings of the 13ht International Conference on Computer Vision (ICCV 2011)*.

Liang, S. (2003). *Java Native Interface: Programmer's Guide and Specification*. Addison-Wesley.

Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. 60(2):91–110.

Mair, E., Hager, G. D., Burschka, D., Suppa, M., and Hirzinger, G. (2010). Adaptive and generic corner detection based on the accelerated segment test. In *Proceedings of 11th European Conference on Computer Vision (ECCV 2010)*, pages 183–196.

Mikolajczyk, K. and Schmid, C. (2005). A performance evaluation of local descriptors. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 27(10):1615 –1630.

OpenCV (2011). Opencv v2.1 documentation. Available in http://opencv.willowgarage.com/wiki/, Accessed November 15, 2011.

Rosten, E. and Drummond, T. (2006). Machine learning for high-speed corner detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 3951:430–443.

Rublee, E., Rabaud, V., Konolige, K., and Bradski, G. (2011). Orb: An efficient alternative to sift or surf. In *Proceedings of 13th IEEE International Conference on Computer Vision (ICCV 2011)*, pages 2564 –2571.

Skrypnyk, I. and Lowe, D. G. (2004). Scene modelling, recognition and tracking with invariant image features. In *Proceedings of the Third IEEE and ACM International Symposium on Mixed and Augmented Reality (ISMAR 2004)*, pages 110–119.

Smeulders, A., Worring, M., Santini, S., Gupta, A., and Jain, R. (2000). Content-based image retrieval at the end of the early years. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(12):1349 –1380.

Tola, E., Lepetit, V., and Fua, P. (2010). Daisy: An efficient dense descriptor applied to wide-baseline stereo. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 32(5):815 –830.