SIFT-EST
A SIFT-based Feature Matching Algorithm using Homography Estimation

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Keywords: Image Correspondences, Feature Matching, Local Features, SIFT, Homography Estimation.

Abstract: In this paper, a new feature matching algorithm is proposed and evaluated. This method makes use of features that are extracted by SIFT and aims at reducing the processing time of the matching phase of SIFT. The idea behind this method is to use the information obtained from already detected matches to restrict the range of possible correspondences in the subsequent matching attempts. For this purpose, a few initial matches are used to estimate the homography that relates the two images. Based on this homography, the estimated location of the features of the reference image after transformation to the test image can be specified. This information is used to specify a small set of possible matches for each reference feature based on their distance to the estimated location. The restriction of possible matches leads to a reduction of processing time since the quadratic complexity of the one-to-one matching is undermined. Due to the restrictions of 2D homographies, this method can only be applied to images that are related by pure-rotational transformations or images of planar object.

1 INTRODUCTION

Finding correspondences between multiple views of the same scene or object is a key component of various computer vision and robotics applications, such as camera calibration, image stitching, automated 3D modeling, motion tracking, and many more. A correspondence is given by image points that depict the same physical point in different images. Such correspondences can be found by the help of local image *features*. Local features hold some distinctive information on the visual content of a relatively sparse set of distinguished image regions.

The process of finding image correspondences can be divided into three steps: *feature extraction*, *feature description* and *feature matching*. The feature extraction step explores an image to detect distinctive features. The distinctiveness of features allows for locating them in different views. The feature description step captures some information on the local appearance of the detected features. This information is stored in a feature *descriptor*, which is a vector of fixed size. In order to find correspondences, the feature descriptors of a reference image are compared to those of a test image. This comparison is done in the feature matching step.

The matches between image features are determined by a similarity measure. Therefore, the changes in the appearance of the images disturb the matching process. Images that are involved in feature matching are related by different photometric and geometric transformations, such as illumination change, blur, zooming, camera translation, and rotation. These transformations modify, among others, the shape, scale, position, and orientation of the depicted scene objects in the image. Moreover, due to these transformations, some objects may get occluded by others or may be moved out of the visible frame. The challenge is to design extraction, description, and matching algorithms that are invariant or, at least to some extent, robust against such distortions.

This paper proposes a feature matching method based on the well-known SIFT-Method. With this approach, the computational cost of the matching step of SIFT can be reduced significantly. The proposed method utilizes a small set of initial matches in order to estimate the transformed position of the reference features and restrict the set of possible test features for the following matching attempts. The estimation is based on the homography that defines the transformation between the two images. The homography do not cover the general transformation. Therefore, the application of the proposed method is limited to two specific scenarios. First scenario is when the images

Shahbaz Badr A., Prapitasari L. and Grigat R..
SIFT-EST - A SIFT-based Feature Matching Algorithm using Homography Estimation.
DOI: 10.5220/0005296105040511
In *Proceedings of the 10th International Conference on Computer Vision Theory and Applications* (VISAPP-2015), pages 504-511
ISBN: 978-989-758-091-8

are captured by cameras that have a common center of projection. This means that the cameras are related by pure rotation around the optical center (no translation). The second scenario is when all image points lie on the same plane in the scene. Possible applications are, for instance, generating panorama images and optical text recognition.

The remainder of this paper is organized as follows. Section 2 gives an overview of some of the popular existing methods. Section 3 briefly reviews the SIFT method. Section 4 describes the proposed method. Section 5 evaluates the proposed method by representing the experimental results. And finally, Section 6 concludes this paper.

2 RELATED WORK

There exists a wide variety of approaches for finding correspondences between digital images. Some approaches provide a framework for the whole process (extraction, description, and matching), while others introduce novel methods for specific steps and use existing methods for the others. In this section, some of the most popular methods are introduced.

Harris corner detector (Harris and Stephens, 1988) is a relatively simple, though widely-used feature detector. This method searches for points with significant signal changes in two orthogonal directions. Such points correspond mostly to physical corners in the scene. The detection is done by observing a self-similarity measure while shifting a small window around a point. The biggest weakness of the Harris method is the lack of scale invariance.

SIFT (Lowe, 2004) is one of the most prominent approaches. SIFT features provide scale and rotation invariance in addition to partial illumination and affine invariance. These strengths come at the price of high computational complexity, mainly caused by scale-space processing and high dimensionality of description vectors. Furthermore, the matching accuracy drops drastically in case of changes higher than about 30 degrees in viewpoint angle (affine transformation). Nevertheless, due to its solid performance, SIFT has become a supposed standard for finding image correspondences.

Due to the strengths of SIFT, numerous variations have been proposed in the recent decade to overcome its shortcomings. ASIFT (Yu and Morel, 2011), for instance, extends SIFT with full affine-invariance by applying various tilts and rotations to the image to simulate different camera orientations. After the viewpoint simulation, ASIFT follows the standard SIFT method. Although ASIFT outperforms SIFT in scenarios with high viewpoint changes, the complexity caused by the preprocessing increases the computation time considerably (Wu et al., 2013). PCA-SIFT (Ke and Sukthankar, 2004) is another SIFT-variant, which aims at reducing the computational complexity. This method utilizes the Principle Component Analysis (PCA) to reduce the descriptor dimension. The compact descriptor declines the matching time, but the PCA-processing introduces further costs in the description step. The overall processing time is reduced slightly, but the performance is compromised in some cases (Mikolajczyk and Schmid, 2005), (Wu et al., 2013). SURF (Bay et al., 2008) is a further approach that reduces the complexity of SIFT. The lower complexity is due to rough approximations and reduced descriptor size. SURF has shown to improve the computation efficiency of SIFT significantly while achieving comparable accuracy (Bay et al., 2008), (Grauman and Leibe, 2011), (Wu et al., 2013).

Affine invariant region detectors (Mikolajczyk and Schmid, 2002), (Mikolajczyk and Schmid, 2004) achieve limited affine-invariance by iteratively estimating and normalizing the local affine shape of the features. However, due to the fact that the features are extracted in a non-affine manner, full affine invariance cannot be achieved (Lowe, 2004).

Lepetit and Fua (Lepetit and Fua, 2006) redefine the feature matching problem as a classification problem, where the features of the reference image are considers as classes and the features of the test image are classified based on their appearance. The classifier is trained by applying random affine transformations to the reference image to simulate different views of each feature. The features are matched (classified) in real-time using randomized trees. With this scheme, the computational complexity is moved to the extraction (training) step to enable fast matching phase.

3 REVIEW OF SIFT

As mentioned before, the proposed method is based on the SIFT approach. Therefore, this section presents a short review of the different steps of this method based on (Lowe, 2004).

3.1 Feature Extraction

In order to achieve scale invariance, SIFT exploits the concept of the scale space, which builds a 3-dimensional space by enhancing the image space with scale. For this purpose, the image is smoothed successively with the scale-normalized Gaussian kernel. Each blurred image represents one instance of the scale space. The complete scale space is constructed by successive application of Gaussian filters of varying scales.

For detecting the features, the Difference-of-Gaussian function (DoG) is convolved with the image. The DoG is the subtraction of two Gaussian functions that are separated by a constant scale factor. Therefore, the convolution is equivalent to subtraction of two adjacent scale-space levels. The potential features are localized at the local extrema of the computed subtractions in scale and space.

The detected feature candidates are discrete with respect to scale and space. Hence, they may not be located at the actual extrema of the DoG function. In order to achieve a sub-pixel and sub-scale precision, a 3D fitting is performed. In the last step, low-contrast points and points along edges are discarded due to their instability.

3.2 Feature Description

An important property of SIFT-features is their rotation invariance. This property is achieved by generating the descriptors relative to the local orientations of the features. For this purpose, the gradient magnitudes and orientations of the pixels around each feature are computed. The gradient orientations are then weighted with the respective gradient magnitudes and a Gaussian window. Subsequently, for each feature a 36-bin histogram of the weighted orientations is generated corresponding to 360 degrees. The peaks of the histograms determine the orientations of the features.

For a distinctive description, a 16×16 pixels patch around each feature is divided into sixteen 4×4 subregions. For each subregion, a histogram of weighted orientations is built. Each histogram consists of 8 bins, which gives rise to $16 \times 8 = 128$ elements in the descriptor vector. To reduce the sensitivity to illumination changes, the descriptor is lastly normalized.

3.3 Feature Matching

For finding matching features in different images, SIFT utilizes a ratio threshold that checks the gap between the best match and the second best match. The best and second best matches are given by the two nearest neighbors of the feature considering the Euclidean distances of the descriptor vectors. Suppose that the descriptor of a reference feature has the Euclidean distances d_1 and d_2 to its first and second nearest neighbors in the test image. If the ratio $\frac{d_1}{d_2}$ is lower than a predefined threshold, the nearest neighbor is chosen as the matching feature, otherwise no match is assigned to the feature. This approach outperforms a simple distance thresholding approach since it can discard indistinctive matches independent of the actual distance d_1.

The one-to-one matching of features has a quadratic complexity in the number of detected features. Moreover, it has been shown that no search algorithm exists that performs better than the exhaustive search in spaces with dimensions higher than about ten (Lowe, 2004), (Mount, 1998). To ensure a practicable implementation, SIFT exploits a priority search, called Best-Bin-First (BBF), which provides an indexing scheme based on the distance of the nodes to the query. The search is stopped after 200 nodes have been checked. BBF is an *approximating* algorithm that returns the exact nearest neighbor with high probability or a close neighbor in other cases. This approach gives rise to considerable reduction of processing time for images with high number of features.

4 PROPOSED METHOD

The proposed method is dubbed SIFT-EST, which stands for pre-estimated matching of SIFT features. Figure 1 shows the block diagram of the method. As implied by the diagram, SIFT-EST makes use of features that are extracted and described by the SIFT method, and differs from SIFT in the matching phase. The matching step is divided into an *initial matching* step, followed by *homography estimation* and *final matching*. The initial matching finds a small subset of correspondences. These correspondences are utilized to estimate the homography that defines the transformation between the two images. The estimated homography is then used to roughly estimate the position of the reference features in the test image. In the final matching step, for each reference feature a set of relevant test features are specified. A test feature is relevant for a reference feature if it is located within a predefined radius from the estimated location of the transformed reference feature. Subsequently, the reference features are matched only against the relevant test features. With this scheme, the quadratic complexity of the exhaustive search is undermined since the reference features are only matched against a small fraction of test features. The three steps of the proposed matching scheme are elaborated in the following subsections.

4.1 Initial Matching

After feature extraction and description, the initial matching step finds a predefined number of matches.

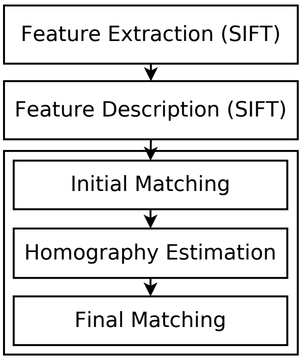

Figure 1: The block diagram of the proposed method.

The matching is iterated until enough matches are found, or all reference features have been checked. The matching procedure is similar to SIFT, however the order of selecting features differs. In SIFT, the reference features are matched according to the order in which they are extracted. This order is based on the location of features in the image. The initial matching step finds only a small subset of correspondences. Following this order would result in matches that are, with high probability, very close to each other or even overlapping. In this case, the homography estimation would possibly fail to find a proper transformation. For this reason, SIFT-EST chooses the reference features randomly. The drawback of this scheme is that the deterministic behavior of SIFT is lost since different sets of initial matches can result in different results.

Since the initial matches specify the homography and, consequently, affect the performance, their accuracy is of utmost importance. Therefore, the ratio threshold used in the initial matching step has to be set relatively low to suppress the chance of mismatches. Considering the empirical observations in (Lowe, 2004), a ratio threshold of 0.25 has been chosen, which provides a nearly-zero probability of incorrect matches.

4.2 Homography Estimation

The initial matches found previously are utilized to estimate the transformation between the two images. The proposed method makes use of the 2D homography, H, to relate the images. The respective transformation of image points is defined as:

$$x_2 = Hx_1 \,, \tag{1}$$

where H is a 3×3 transformation and x_1, x_2 denote the homogeneous coordinates of two corresponding points in the first and second image.

To ensure fast processing, the estimation is carried out by a simple, linear method called normalized DLT (Direct Line Transformation) as described in (Hartley and Zisserman, 2004). The homography has eight degrees of freedom (one less than the number of elements due to scale ambiguity of homogeneous coordinates). Each point correspondence generates two linear equations constraining the x and y coordinates. Hence, only four correspondences are sufficient for the estimation. However, using the minimum number of initial matches often results in inaccurate estimations. For the experiments of this paper, the number of initial matches is set to six, which showed reasonable results at low cost.

4.3 Final Matching

Once the homography is estimated, it is used to estimate the position of the reference features in the test image. For this purpose, all reference features that have not been involved in the initial matching step are mapped to the second image based on the homography. For each reference feature, the relevant test features are determined by checking the distance of all test features form the respective mapped location. Test features that are within a predefined radius from the mapped location are considered for the matching. Figure 2 illustrates this scheme.

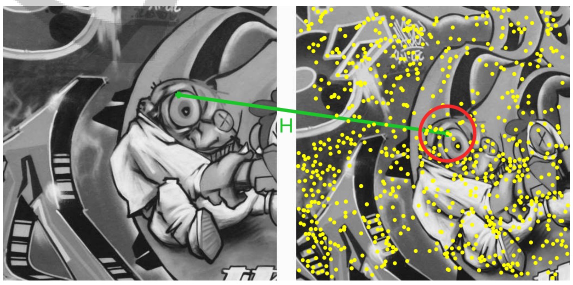

Figure 2: Specifying relevant features. The line visualizes the mapping of a feature of the reference image to the test image using the estimated homography. The circle determines the relevant test features based on their distance to the mapped location. The points indicate the location of all test features.

The radius should be large enough to count for the estimation error. The experiments use a radius of 50 pixels. This value may seem large, but the area that is covered by this circle is much smaller than the complete image area. For instance, in an image with the resolution of 765×512 pixels (smallest image used in the experiments) this circle covers only 2% of the area of the image. Respectively, the number of features within this circle is relatively small.

After finding the relevant test features, the matching process is similar to the standard matching method of SIFT. The difference is that the ratio thresholding is followed by a distance thresholding.

The strength of the ratio threshold in SIFT is due to the dense set of test features. However, here exists only a small number of relevant test features or even a single one. Thus, the ratio threshold alone cannot determine the distinctiveness of the matches. Therefore, a distance threshold is required to check if the respective features are indeed similar. Furthermore, the experiments showed that applying a sole distance threshold declines the performance slightly. Hence, the combination of both thresholds is implemented. The additional cost introduced by applying the second threshold is minimal since the descriptor distances are already computed for the first thresholding procedure.

5 EVALUATION

In this section, the proposed method is evaluated. For this purpose, the accuracy and processing time of SIFT-EST is compared to SIFT to see if the expected improvements are achieved. Before presenting the results, the procedure of the experiments and the evaluation measures are described to make the respective results reproducible.

5.1 Experimental Setup

All the experiments are run on a PC with Intel Core i5-4670@3.40 GHz processor and 16 GB memory running 64-bit Windows 7. The experiments are implemented and executed with Matlab 2013b. Beside the scripts that are implemented to execute and evaluate the experiments, additional toolboxes or functions have been utilized, which are discussed here.

For extraction, description and matching of SIFT features, the VLFeat[1] library version 0.9.17 is used. The features are extracted and described using the default parameters given by the author of SIFT. For the matching step a ratio threshold of 0.5 is used. Please note that the VLFeat library uses the inverse of the threshold proposed by Lowe. Therefore, the actual input of the respective SIFT-function is set to 2.

The SIFT-EST method differs from SIFT in the matching step. Hence, the Feature extraction and description are performed with the respective functions from the VLFeat library. In the initial matching phase, the call to the matching function has been modified to change the order of matching attempts as discussed in 4.1. The ratio threshold used in this phase is 0.25. The homography estimation is performed by the help of the Homography Estimation Toolbox[2] with six putative correspondences. In the final matching phase, a ratio threshold of 0.5 is used. The ratio thresholding is followed by an additional distance thresholding as discussed in 4.3.

For the experiments, four sets of images have been used, which are distributed by the Visual Geometry Group (VGG) of the Oxford University [3] and are frequently used in literature for the evaluation of feature extraction, description and matching algorithms. These sets are chosen since all images either depict planar scenes or are captured without camera translation. Therefore, they comply with the proposed method. Two sets (*Graf* and *Wall*) contain viewpoint changes ranged from a fronto-parallel view to one at approximately 60 degrees relative to the camera. The other two sets (*Bark* and *Boat*) represent combinations of rotation and scale changes. The scaling is obtained by varying the camera zoom. The rotation changes are produced by rotating the camera around its optical axis (Z-direction) between 30 and 45 degrees. Figure 3 shows one image of each set.

Figure 3: Four sets from the VGG database are used for the experiments. Set names from left to right: Bark, Boat (top), Graf, and Wall (bottom).

Each set contains six images, where the first input image is used as the reference for the other five. For each set, five homographies are provided as ground truth that define the geometric transformations relative to the reference image. Using these homographies, the accuracy of the methods can be determined with the following procedure. After applying a feature matching algorithm, the matched reference features are transformed to the respective test image based on the provided homography. Subsequently, the spatial distances between the transformed locations and the corresponding test features are determined. If the distance is below a threshold of three pixels, the

[1] www.vlfeat.org

[2] www.it.lut.fi/project/homogr

[3] www.robots.ox.ac.uk/∼vgg/research/affine

match is a correct one. Otherwise, it is considered as a mismatch.

5.2 Evaluation Measures

Since SIFT and SIFT-EST have the same extraction and description methods, this work focuses on measures that evaluate the matching step. The first measure is the precision of a matching algorithm, which specifies the fraction of inliers (i.e. correct matches) in the set of detected matches. This measure is given by the number of correct matches divided by the number of all matches:

$$precision = \frac{\#\text{ correct matches}}{\#\text{ all matches}} \,. \tag{2}$$

As can be seen, the precision is defined relative to the number of detected matches. Consequently, for a meaningful comparison, the precision should be observed along with the number of matches. In this way, the actual number of correct matches can be determined, which allows for better decision making if an application requires a certain number of correspondences.

The processing time of each method is also observed. For an adequate comparison, the processing time of the matching step is tracked solely since the other steps are identical with SIFT.

5.3 Results

The experiments are designed to compare the performance of SIFT-EST to SIFT. Considering the experimental results as shown in Figure 4, the following trends can be observed. The precision of SIFT-EST is almost always nearly equal to SIFT or slightly better. This shows that the accuracy of the correspondences is not compromised by the new matching scheme. In case of high viewpoint changes (last samples of Graf and Wall sets), due to the strict threshold of the initial matching phase, no matches are found by SIFT-EST. The respective undefined precision values ($\frac{0}{0}$) are replaced by zeros for better visualization.

Considering the number of detected matches, SIFT-EST performs comparable to SIFT. Although SIFT finds generally more matches than SIFT-EST, the difference is in most cases insignificant. One reason for the reduction of detected matches is the low ratio threshold of the initial matching step, which rejects many correspondences that would be accepted by SIFT. Furthermore, in cases where SIFT-EST achieves higher precision values than SIFT, a part of the decrease in the number of matches can be explained by the removal of some mismatches, which is implied by the higher precision.

Regarding the processing time of the matching phase, it can be seen that the expected improvement is attained. There exists a noticeable separation between SIFT and SIFT-EST in general. A reduction of order two to three can be observed at most samples. In a few cases, the matching time of SIFT-EST is slightly higher than SIFT. The reason is the indistinctness of the features, which is indicated by the low number of matches. If the detected features are highly indistinctive, a high fraction of features, or even all of them, are checked in the initial matching step. This step has the same computational complexity as the matching step of SIFT. The additional costs of the SIFT-EST method (changing the order of matching, homography estimation, determination of relevant features) result in a matching time higher than SIFT. However, considering the results in Figure 4 one can see that in all these extreme cases also SIFT does not perform well. The low number of matches found by SIFT and their low precision makes the correspondences unusable for most common applications.

In these experiments, the matching step allocated only around 7% to 13% of the overall processing time. Therefore the achieved improvement may not seem critical. However, it should be noticed that the utilized images have relatively low resolutions (between 765×512 and 1000×700 pixels). In high-resolution images, the number of detected features increases drastically. Since the complexity of matching is quadratic in number of features, the matching phase seizes a higher portion of the overall computation time by increasing the resolution. Accordingly the effect of the improvement gets more significant.

Some examples of the results of SIFT and SIFT-EST are presented in the appendix.

6 CONCLUSION

In this paper, a SIFT-based matching algorithm was proposed and evaluated. The aim of the method was reducing the processing time of SIFT without compromising its performance. Considering the experimental results, we can conclude that SIFT-EST could fulfill these requirements. In most cases, a reduction of order two to three could be observed in the processing time of the matching step. The precision values of SIFT-EST are nearly equal to SIFT and in some cases even outreached it. The number of detected matches of SIFT-EST was often lower than SIFT, but in most cases this number would still be sufficient for the common applications.

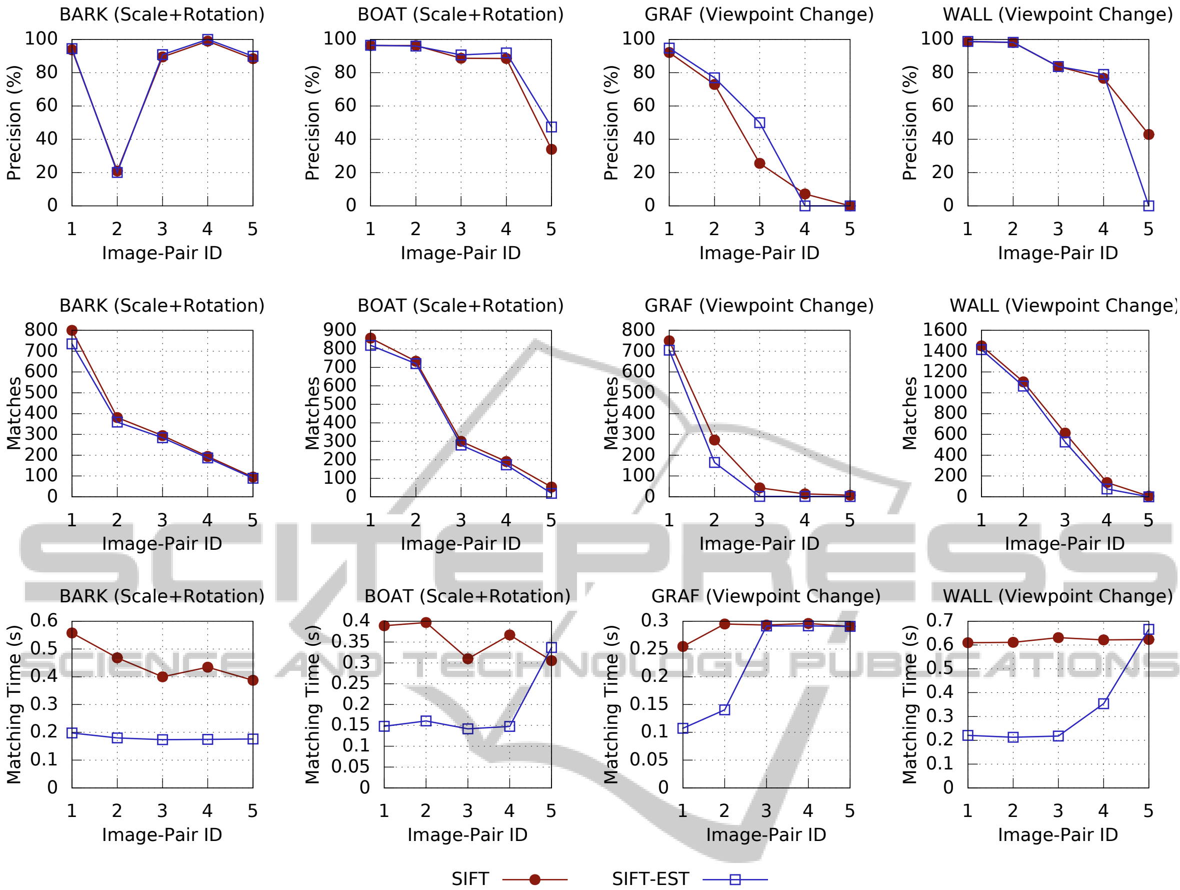

Figure 4: The experimental results of all four sets.

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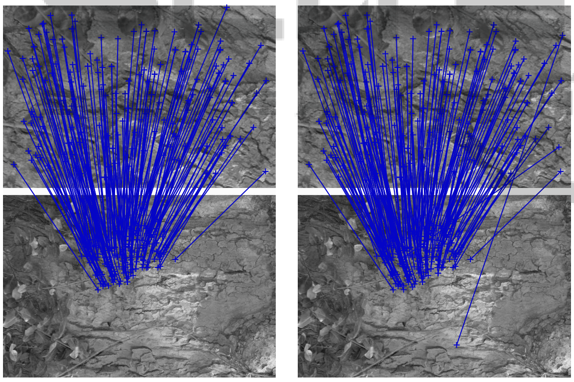
APPENDIX

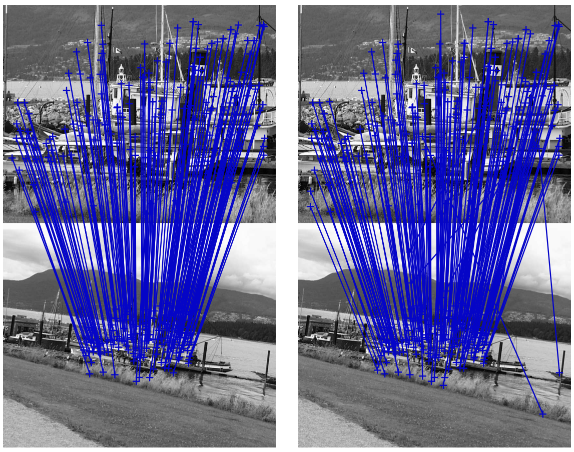
For better comparison between SIFT-EST and SIFT, some examples of the outputs of the methods are presented in this appendix. From each set, one sample (the fourth image-pair) is chosen for the demonstration. This specific sample has been chosen due to the moderate number of matches for almost all sets, which allows for better illustration. The respective matches are visualized in Figures 5 to 8.

It can clearly be seen in Figures 5, 6 and 8 that SIFT-EST can improve the accuracy of SIFT by discarding some of its mismatches. The Graf set, as demonstrated in Figure 7, can be seen as the worst case. Due to the strong distortion, both methods failed in finding enough correspondences. From 14 matches found by SIFT, only one was correct, and SIFT-EST found a single match, which was incorrect.



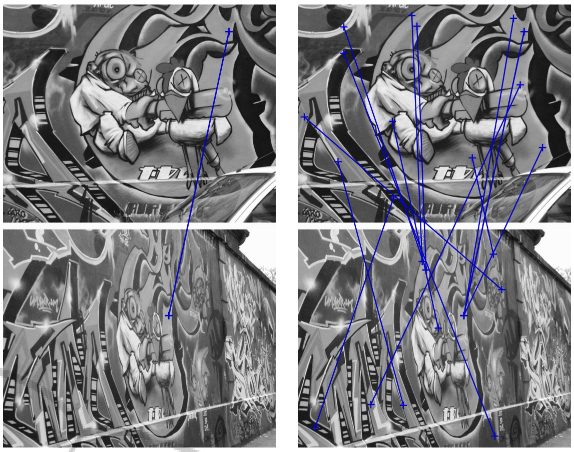
(a) SIFT-EST (b) SIFT

Figure 5: Example of the results of the Bark set.



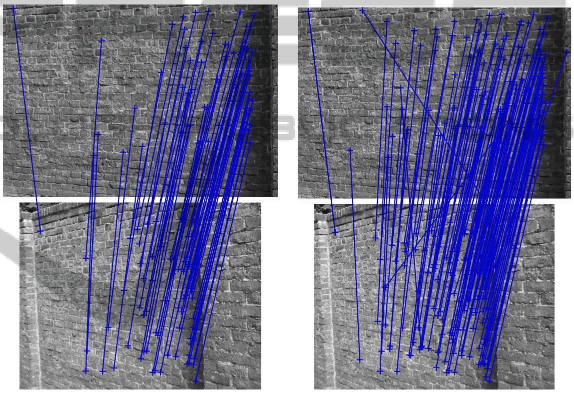
(a) SIFT-EST (b) SIFT

Figure 6: Example of the results of the Boat set.



(a) SIFT-EST (b) SIFT

Figure 7: Example of the results of the Graf set.



(a) SIFT-EST (b) SIFT

Figure 8: Example of the results of the Wall set.