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Implementation and Application of Orientation Correction on SIFT and SURF Matching

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Abstract

Post-processing after matching technique such as RANSAC is useful for reducing outliners. However, such methods may not be able to increase the number of correctly matched pairs that is important in some application such as image stitching. In this work, a post-processing technique for increasing the number of correct matched points between two images with on-plane rotation is proposed. The proposed method makes use of the dominant rotational degree between two corresponding images to increase the number of matched points after feature extraction process using state-of-the-art methods such as Scale Invariant Feature Transform (SIFT) or Speeded-Up Robust Feature (SURF). The proposed method can generally increase the number of matched points around 10% to 20%. Furthermore, it can also correct the false matching which is caused by similar appearance of features.

Keywords: *Descriptor, Feature Matching, Orientation Correction, Rotation, SURF.*

1 Introduction

Feature matching is an important stage for finding correspondence between images and it is useful in many applications such as visual surveillance system and depth estimation. Prior to the matching process, normally an image has to undergo features extraction process which will generate a descriptor that is invariant to rotation, illumination, noise, small viewpoints changes and scale changes. Two widely used techniques for this purpose are Scale Invariant Feature Transform (SIFT) and Speeded-Up Robust Feature (SURF). Both of them achieve the robustness by adapting scale-space construction, feature localization through scale-space, orientation assignment and descriptor generation. The robustness of SIFT and SURF towards rotation is strong, since features descriptors are computed relative to the orientation assigned using the gradient information of the feature. However, the matching leads to imperfect if there are more features with high correlation for one descriptor value during matching. Several post-processing methods such as Random Sample Consensus (RANSAC) [1] and graph matching [2] are introduced, but such post-processing methods are normally used to remove false matching or outliers only and are not able to increase the number of correctly matched points. Since applications like 3D depth computation [3], fundamental matrix computation [4], rectification [5] or image stitching [6] are highly dependent on the feature matching, more good candidates of correct matched pairs and less false matching are necessary. A method which can produce more correct matched pairs is essentially important. Therefore, in this paper we propose a post-processing method which can increase the number of matched points and correctly matched points on the state-of-art methods such as SIFT and SURF. Unlike other post-processing methods such as RANSAC, our objective is not only removing outliers, but at the same time also increasing the number of matched points.

In this paper, related works are introduced in Section 2. The concept of proposed technique will then be explained in Section 3 while the experimental results are discussed in Section 4. Lastly, Section 5 will be the conclusion of this paper.

2 Related Works on Feature Matching

SIFT [7] and SURF [8] is commonly used in many applications like face recognition [9] or classification [10]. Features which are rotational and scale invariant will be computed after the input image and the reference image undergo scale-space construction, orientation assignment and descriptor generation. However, SIFT is not suitable for real time application because of the heavy computation [11][12]. This disadvantage is alleviated in SURF by adapting integral image in its process [13][14]. Both methods only focus majorly on the four operations mentioned above but not the feature matching process. Matching performance is strongly dependent on descriptors generated relative to the orientation. If the orientation is incorrect, the matching could result in a failure because the two descriptors on a similar point will have low correlation to each other. This is because the possible candidate feature will be rotated in a different way after normalization and the descriptor value relative to the orientation for matching will not be similar to the descriptor of the reference feature. Therefore, the pair of feature cannot be considered as matched pairs. In SIFT and SURF, the orientation assignment is done based on the gradient magnitude. In [15][16], Taylor’s method is proposed by computing the orientation using intensity differences of eight pixels pairs around the feature point. This method is computationally efficient but applicable only for features with strong intensity differences. In [17], the local gradient is smoothed with Gaussian window for computing orientation. In [18], “centre of mass” and histogram of intensity is introduced. In [19][20], Gabor filter is used to compute the orientation. Most of the existing methods get the orientation based on the intensities or local gradients of pixels.

For matching case, some techniques for the matching process such as the Euclidean Distance [21], normalized cross correlation [22], and nearest neighbourhood [23][24] search have been introduced by different researchers. In [21], one feature point was matched with more than one point for correspondence. One-to-many matching is not robust because the correct correspondence cannot be identified, This is because there may have more than one feature with similar descriptor value which is very close to the reference feature. As a result, there will be several possible candidates for one feature and this will confuse the system to make the decision to choose the best corresponding point .This problem is solved in [25] and [26] by introducing a decision making matrix which allows one-to-one point matching only. This is done by selecting matched points only if the current decision matrix element is maximum on both column and row of the matrix. Note that, maximum value was used because work in [25] applied cross correlation between features. For post-processing stage, in [1] and [2], RANSAC and graph matching is introduced in each work respectively. RANSAC is used to remove those outliers based on model fitting paradigm, while graph matching is based on graph representative similarity measure. Both methods are strongly depended on the correct correspondences to discard false matching. However, both post-processing methods are not able to increase the number of correctly matched points.

Based on the previous methods, we concluded three major concerns. First, the matching will be incorrect if the orientation extracted is inaccurate or imperfect. Second, the matching will be confused if there are more possible candidates for one feature. Third, available post-processing approaches are not able to increase the number of matched points. Based on these three concerns, we proposed a method by introducing an orientation correction in the post-processing stage after computing the relative rotational angle between two images. Our method differs from existing approaches, in which we do not improve the accuracy of orientation assignment stage, but we just focus on the post-processing stage based on a simple assumption. We also show that our post processing method is able to increase the number of correct correspondences while at the same time remove outliers.

3 The Proposed Method

This paper proposes a method to update the descriptor generated by correcting the orientation in the post-processing stage using the feedback from the matched points in the first round matching. Our method can be applied on any feature matching technique, as long as the matching is done based on the comparison of the Euclidean distance of the descriptors relative to the orientation. Fig. 1 shows the diagram of our approaches.

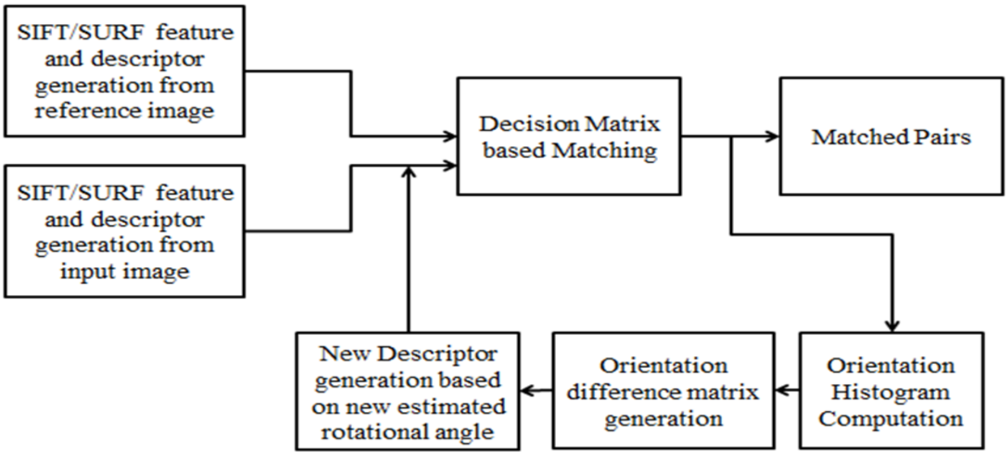


Fig. 1 General process of feature matching with proposed technique

We used SURF feature in our proposed method because SURF feature is invariant to scale, rotation, and noise. The scale-space construction will help to extract features from different scale level so that the feature is invariant to scale, while the orientation will be assigned to every feature to make the feature rotational invariant. In scale-space construction and orientation assignment, Gaussian filter is applied to avoid noise disturbance. Further explanation of the preservation of invarianceness can refer to the original paper of SIFT and SURF. Our method is relatively simple but effective. First, we start by extracting SIFT and SURF features from the reference image and input image, which are denoted as I_1 and I_2 respectively. Feature points extracted from reference image and input image are denoted as $\mathbf{p}_{1,m}$ and $\mathbf{p}_{2,n}$ where each vector contains $m=\{1,2, \ldots ,M\}$ and $n=\{1,2,\ldots,N\}$ number of points respectively. Each vector equation is shown in (1) and (2).

$$\mathbf{p}_{1,m} = \{(x_1,y_1),(x_2,y_2),\ldots,(x_M,y_M)\} \tag{1}$$

$$\mathbf{p}_{2,n} = \{(x_1,y_1),(x_2,y_2),\ldots,(x_N,y_N)\} \tag{2}$$

Then, the orientation of each features extracted is generated and assigned. $\theta_{1,m}$ and $\theta_{2,n}$ indicates the orientation of features from both image respectively. The descriptor is generated relative to the orientation assigned on all features from both images. In this paper, the matching is done by computing the Euclidean distance between descriptors of features, $\mathbf{d}_{1,m}$ and $\mathbf{d}_{2,n}$ by using (3).

$$\mathbf{G}(m,n) = \sqrt{\sum_{1}^{k=64} \mathbf{d}_{1,m}(k)^2 - \mathbf{d}_{2,n}(k)^2} \tag{3}$$

If the Euclidean distance is below a threshold value (determined experimentally), the pair of descriptors is considered as matched points. Original SIFT and SURF allows more than one possible matched candidates if there are more than one possible points that can produce high correlation value which are also under threshold value. To find one-to-one matched pairs, we apply the method in [26] to find the initial matches by using the decision matrix with size $M \times N$ computed using (3). The number of row of the matrix represents the number of the reference image features while the number of the column represents number of input image features. Every element inside the matrix is the Euclidean distance of respected feature (i.e: $\mathbf{G}(2,3)$ is the Euclidean distance of the second feature from reference image and third feature from input image). To find one-to-one corresponding point, a scanning procedure on the **G** matrix is necessary. The reference image feature will consider the other feature from the input image as correspondence if the Euclidean distance of the pair is the minimum value among all values in current row and column (i.e: $\mathbf{G}(2,3)$ is matched pairs if the value is minimum among all values in second row and third column).

Our proposed method further extends by introducing orientation correction as shown in Fig. 1. Instead of introducing another method which can increase the accuracy of rotational matching, we use the matching information from SIFT and SURF to further increase the rotational matching accuracy. The orientation correction is based on all corresponding points. If the image is rotated, all the feature points must be rotated at a similar angle. Note that the orientation correction within the feedback loop is iterated only once. In this paper, the orientations used to generate descriptors were extracted using SIFT and SURF orientation assignment methods so that the comparison can be made between these two established methods in terms of the rotational robustness. For further improvement, once a set of matched points coordinates, **m** is obtained; a histogram of the orientation difference of **m** is established. The highest bin of the histogram is used to compute an approximated rotational angle between I_1 and I_2 image. The bins of the histogram are weighted by the number of angles in certain range with interval of 10 degree. This average angle, θ_{avg} of the highest bin will be assumed as the estimated rotational angle between two images. Then, orientation difference matrix $\mathbf{T}(m,n)$ is generated, whose elements are formed based on the orientation difference between feature points of the two images by using $\theta_{2,n}$, $\theta_{1,m}$. We check each elements of the **T** matrix and replace the value with θ_{avg} if the element value is out of the range of $\theta_{avg} \pm 10^\circ$. We calculate the new orientation of the input image features again using (4) in the condition that the I_2 feature's descriptors are rotated again based on the new generated orientation while the orientations of all features in I_1 remain unchanged.

$$\theta'_{2,\boldsymbol{n}} = \theta_{1,\boldsymbol{m}} + \theta_{\boldsymbol{avg}} \tag{4}$$

After the new orientation computation, we generate the features descriptors again based on SURF theory. A region of the feature is rotated relative to the new orientation. Then, the region is divided by 4 × 4 subregions, where each subregion contains 5*s* × 5*s* pixels, where s represents scale of the feature. All information of vertical response ,*dy*, horizontal response, *dx*, absolute value of horizontal and vertical responses, |*dx*| and |*dy*| are summed up together to obtain 4 vectors respectively in each subregion. Hence, a 4× 4 ×4 vector over the square region is obtained with a length of 64. Lastly, the **G** is regenerated again based on on the comparison of the new descriptors and the reference image feature descriptor. The final improved matching process will be made based on updated ***G*** matrix by applying the same scanning procedure which mentioned earlier.

Besides extending the approaches, we also apply RANSAC on our application to remove the outliers of the final matched pairs because we need to check that how many final matches will be considered as outliers after we perform the orientation correction on SIFT and SURF.

4 Experimental Results

To test the proposed method, three outdoor real scene images were used. 5 samples with different rotational angles were taken to test the robustness of the proposed method. A total of 15 images were used for testing the algorithm. All samples were tested using both SIFT and SURF so that comparison between with and without the orientation correction can be made. The performance was evaluated in terms of number of matched pairs (include false matched pairs), and the number of correct matched pairs. We compare our result with SIFT, SIFT + RANSAC, SIFT + proposed method, and SIFT+ proposed method+ RANSAC, as well as SURF method. We will see that whether our proposed method can achieve more correct matched pairs compare with RANSAC. Besides, we also calculate the increment percentage of the correct matched pairs before and after applying orientation correction for both approaches without RANSAC. Since there are four type of data used to compare, we define each data with another name in Table 1 so that the figure will not seems fuzzy.

Table 1: Data Description

Data Name	Description
1st data	SIFT
2nd data	SIFT+ RANSAC
3rd data	SIFT+ Proposed method
4th data	SIFT+ Proposed method + RANSAC
1st data S	SURF
2nd data S	SURF+ RANSAC
3rd data S	SURF+ Proposed method
4th data S	SURF+ Proposed method + RANSAC

4.1 Simple Building Scene Image

The first sample was an image containing a simple building which is rotated in 5 different angles. The 90 degrees rotation was done using image editing software whereas other 4 images were obtained by rotating the camera manually. Since this is a simple building image, the points extracted were relatively less. There were total 194 points detected in the reference image. Fig. 2 shows the reference image and the rotated image in this dataset.

(a) (b) (c)

Fig.2 Simple Building Scene Image (a) reference image (b) 30 rotated image (c) 180 rotated image

The results are summarized and presented in Fig. 3 for SIFT before and after orientation correction implementation.

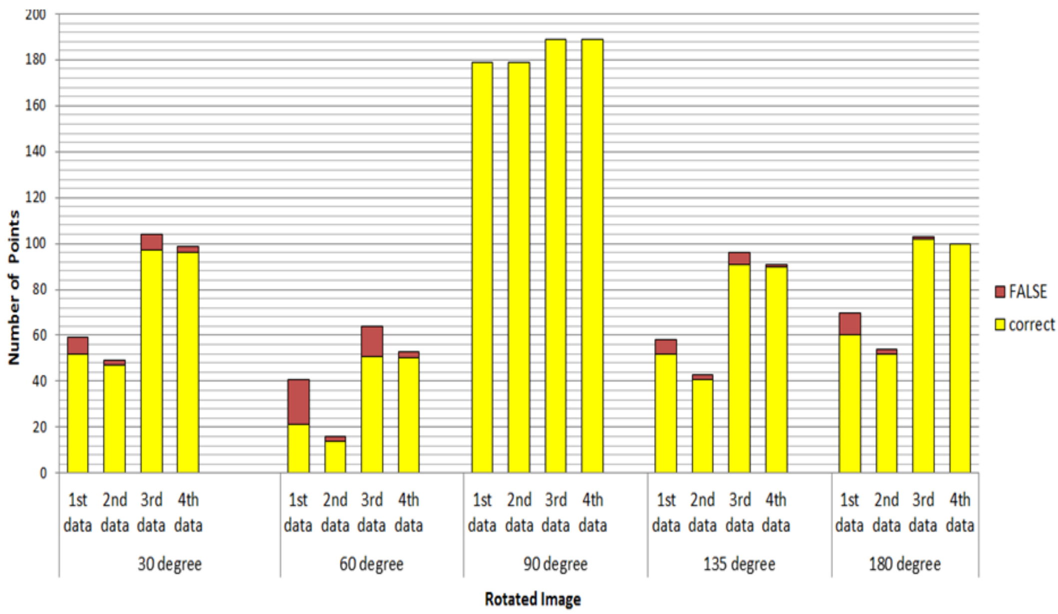


Fig. 3 Number of Correct Matched Pairs in Simple Building Image Using SIFT before and after Orientation Correction

From Fig.3, the orientation correction can significantly increase the number of matched points in every sample except for 90 degree sample. Since 90 degree sample is rotated using image editing software, there will be lack of the sensor noise and resampling in the input image. Therefore, original SIFT can provide almost perfect matched pairs without false matching. Since there is no false matching, RANSAC is useless for removing outliers. Unlike RANSAC, our proposed method is still able to increase the number of matched pairs around 10 points under this condition. From Fig.3, RANSAC does not successfully increase the number of correctly matched points. In the other samples, RANSAC is not only removing outliers, but at the same times also accidentally remove some correct matched pairs. Our proposed method may not remove outliers as much as RANSAC could, but we successfully increase the number of correct matched pairs in every sample. We also use RANSAC to apply on our proposed method to remove those outliers. For first sample, the number of correct matched pairs has been increased around 25% of the total detected points in the reference image while for second sample; around 5% number of correct pairs is increased. The increasing percentage of the third sample, fourth and fifth sample are around 5%, 20% and 22%. Take note that the percentage is calculated by correctly matched points over total detected points. We also apply orientation correction on the SURF technique and the result is shown in Fig. 4.

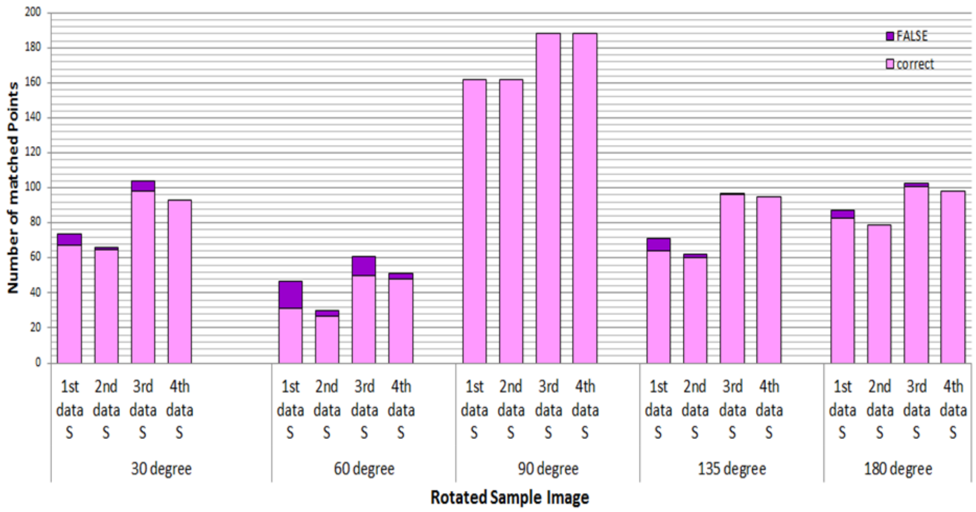
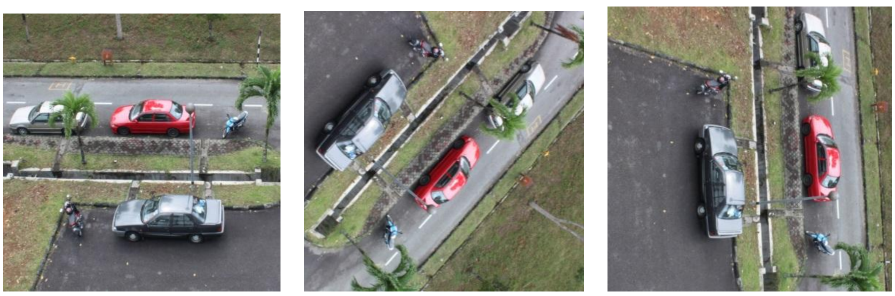


Fig. 4 Number of Correct Matched Pairs in Simple Building Image Using SURF before and after Orientation Correction

The original SURF basically can get more matched pairs if compared to original SIFT except for 90 degree sample. The increment of the percentage for each sample is around 16%, 10%, 13%, 17%, and 10%. Our proposed method once again proved that we can increase the number of correct matched pairs in the rotational matching. To test the robustness of our proposed method, we also test our algorithm with image with more complex scene.

4.2 Complex Real Scene Short Image

More complex scene can provide more feature point to be matched. In this sample, 384 points were detected in the reference image. Unlike previous sample, all samples in this set of data were taken manually by rotating the camera. Fig. 5 shows some of the samples of the short distance image.



(a) (b) (c)

Fig.5 Complex Short Distance Image (a) reference image (b) 135 rotated image (c) 90 rotated image

Compare to the simple building image, more objects were in this set of sample, such as trees and vehicles. Fig. 6 shows the result of the computation of the algorithm for SIFT.

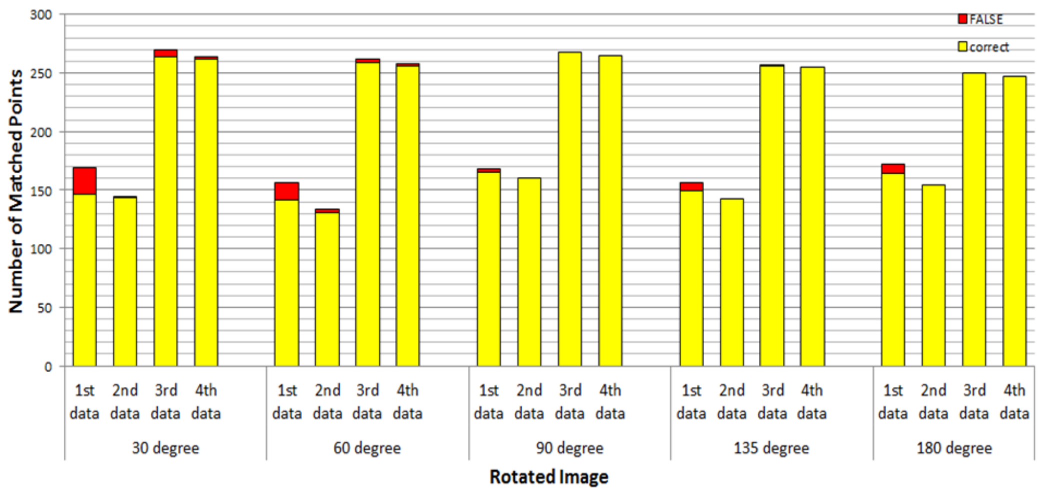


Fig. 6 Number of Correct Matched Pairs in Complex Short Distance Image Using SIFT before and after Orientation Correction.

In this set of samples, orientation correction can generally increase all correct matches in all samples. All numbers of correct matches are increased from 150-160 pairs to 250-270 pairs. The number of outliers in 3rd data, which is our approach, is reduced in every sample after applying orientation correction. Our approach is also able to remove the same numbers of outliers as RANSAC did, such as in 60 degree sample and 180 degree sample. RANSAC is useful for removing outliers, but it has a risk of removing some useful points since RANSAC work randomly. Compared to RANSAC, our method is more reliable. The increment of the percentage for every sample is 30%, 31%, 27%, 28%, and 23%. Similar to section 4.1, we did the same experiment using SURF approaches.

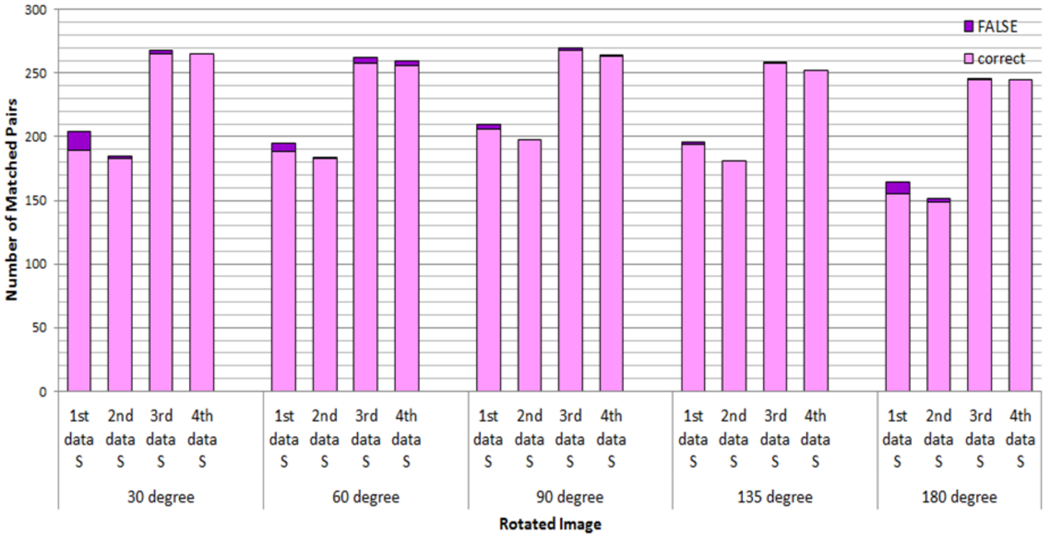


Fig. 7 Number of Correct Matched Pairs in complex short distance Using SURF before and after Orientation Correction

Fig.7 shows that original SURF can provide more correct matched points compared to SIFT shown in Fig 5. Therefore, orientation correction will increase less correct matched points. Overall, the number of correct matches is increased around 60 to 100 points according to Fig. 7. The increment percentage is around 16% to 23% of the total detected points. Our approach is robust towards short distance image. Next, we will implement our algorithm to real far field image scene.

4.3 Real Far Field Image Scene

This experiment was done on real scenes with a far field view with complex background. 273 feature points were extracted from the reference image. Some samples from these set of images are shown in Fig. 8. Similarly, the camera has been set in different angles of rotation and results are shown in Fig. 9 and Fig. 10

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(a) (b) (c)

Fig.8 Real far field image scene (a) reference image (b) 30∘ rotated image (c) 60∘rotated image

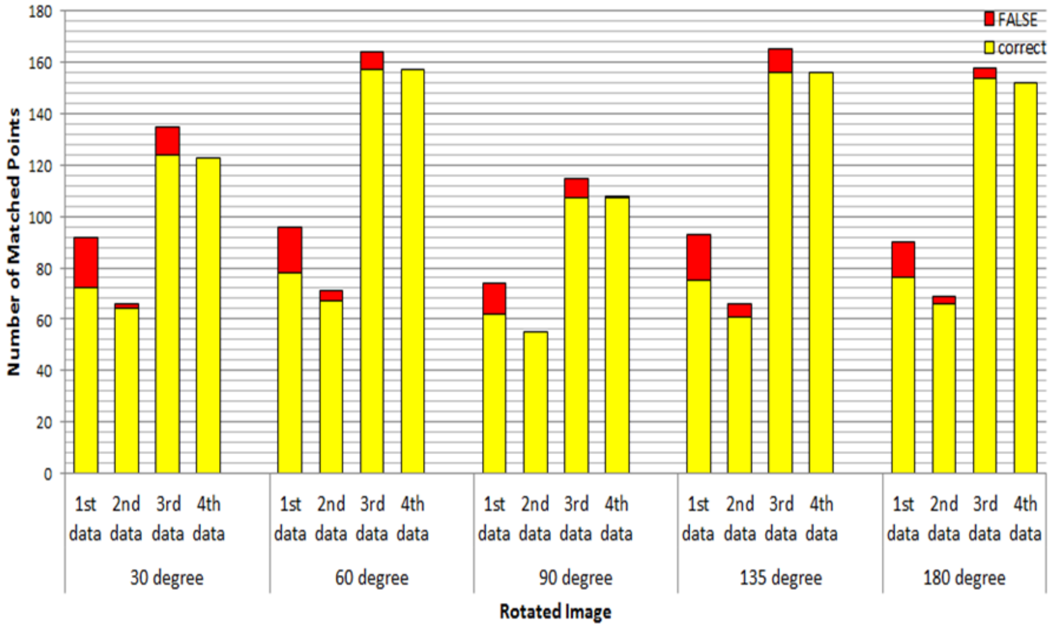


Fig. 9 Number of Correct Matched Pairs in real far field image scene Using SIFT before and after Orientation Correction

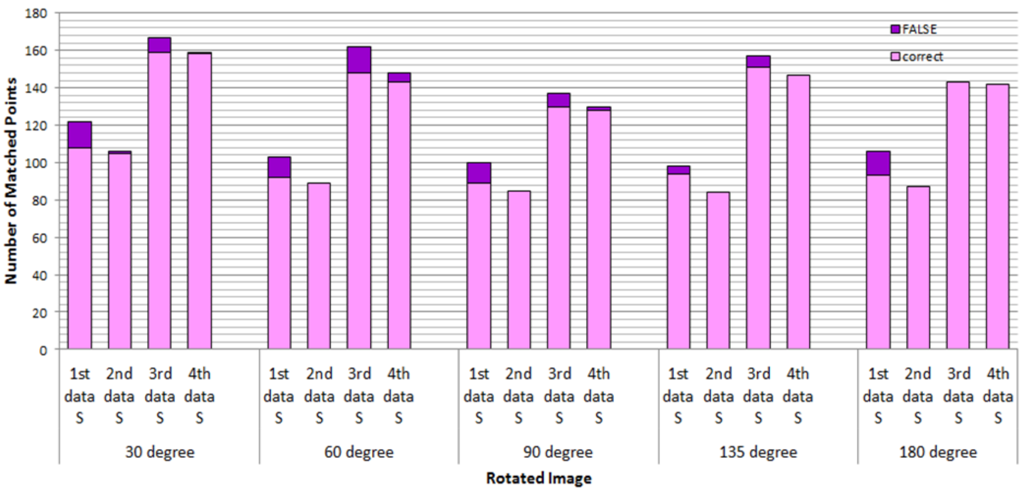
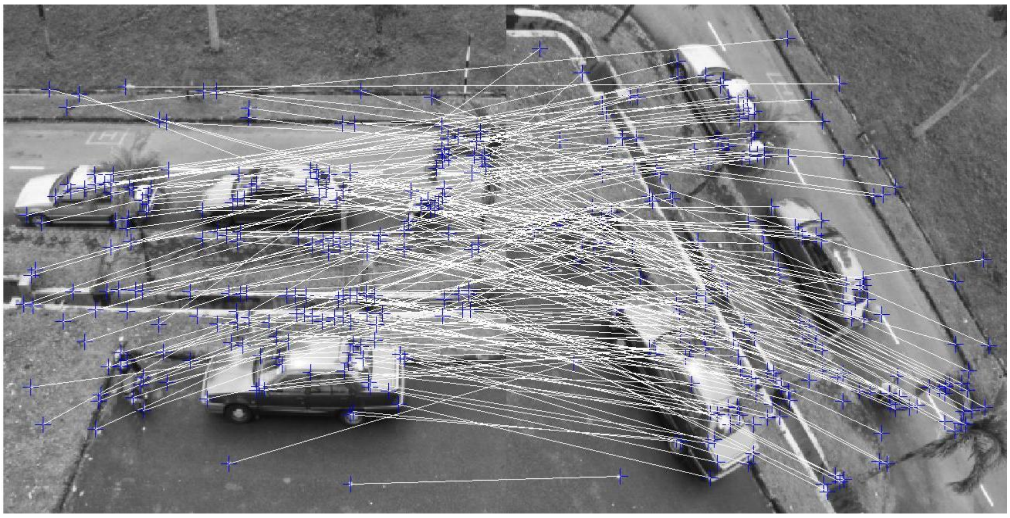


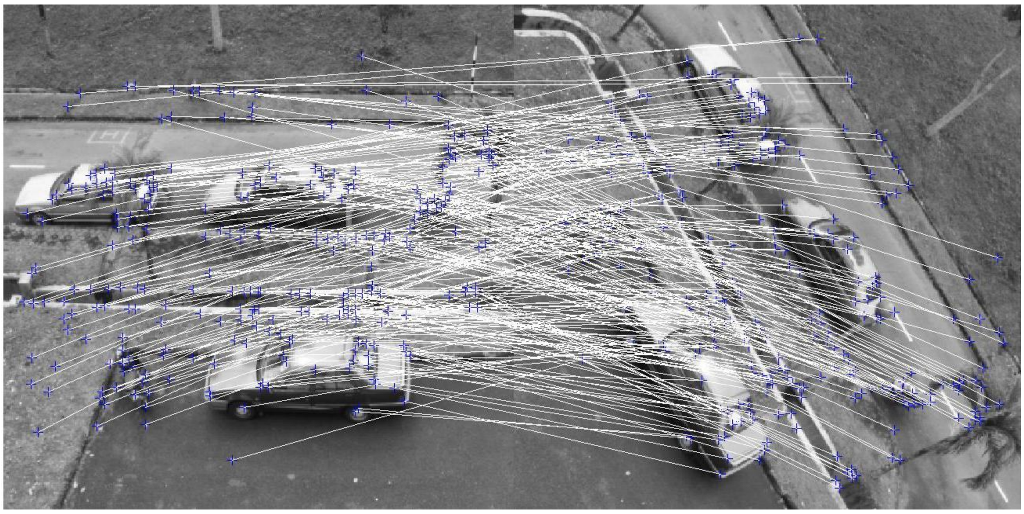
Fig. 10 Number of Correct Matched Pairs in real far field image scene Using SURF before and after Orientation Correction

In Fig. 9, the proposed methods shows that there are still a number of outliers after applying orientation correction on the SIFT approach. However, the numbers of matched points were increased around the range of 19% to 30%. For SURF approach as shown in Fig 10, the increment percentages were in the range of 15%

to 21%. Based on all the experiment done, we conclude that our approach is able to provide more accurate and correct points but not only remove outliers compared to other post-processing approach like RANSAC which is just removing outliers but not increasing the inliers. For other application such as depth estimation, or rectification, our approach is able to provide sufficient and good possible candidates. Fig. 11 shows the results before and after orientation correction is applied. The number of matched points in Fig. 11(b) is more than the number of matched points in Fig. 11(a).



(a)



(b)

Fig.11 (a) before orientation correction (b) after orientation correction is applied. The number of matched points in (b) is obviously more than matched points in (a)

5 Conclusion

This paper presented a method which increases the number of correct matches of SIFT and SURF by introducing orientation correction and update the descriptor for matching, and at the same time removes outliers. Our proposed method is beneficial to those applications such as image stitching. However, the complexity of the proposed method is still an issue yet to be solved. The algorithm with more complexity will lead to higher computation cost and time. In the future, the complexity of the algorithm will be focused.

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