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SPEEDING UP SIFT, PCA-SIFT AND SURF USING IMAGE PYRAMID

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ABSTRACT

Scale Invariant Feature Transform (SIFT), Principal Component Analysis (PCA)–SIFT and Speeded Up Robust Features (SURF) are common robust feature detection methods used in photogrammetry and computer vision applications. The performance of these methods have been widely investigated and compared. In terms of processing time, results show that SURF is relatively the fastest due to utilizing integral image. However, these techniques are still slow and need to be improved for nearly real time applications, such as those based on vision navigation.

This paper works on speeding up SIFT, PCA-SIFT and SURF using image pyramid. The images are firstly resampled and matched to detect the interest points. Then, the approximate locations of the matched points are determined on the original images from similar triangles. These points are surrounded by small searching windows and matched again with the corresponding searching windows in the other image. As a result, instead of matching the whole two images, a number of tiny images are matched together. The results show that the idea is powerful for reducing the processing time of such techniques significantly. The performance of this idea is affected by the resampling level and method, the image size, and the selected number of matching points.

KEYWORDS: SIFT, PCA-SIFT, SURF, Image Pyramid,Automatic Image Matching,Speeding Up Processing Time.

1. INTRODUCTION

Scale Invariant Feature Transform (SIFT), Principal Component Analysis (PCA)–SIFT and Speeded Up Robust Features (SURF) are considered to be from the most common automatic image matching methods used in photogrammetry and computer vision applications, such as image registration, camera calibration, vision based navigation [1], Simultaneous Localization And Mapping (SLAM), automatic image mosaic [2], indexing [3], recognizing panoramas [4], and traffic sign recognition [5]. These automatic image matching algorithms consist generally of two processes: feature point detection and description. The first aims to find the interest points and should be robust to rotation, scaling and image noise, whereas the second is to construct unique distinctive descriptors for the feature points on the first image to be reliably identified from those on the other image.

SIFT were introduced by David Lowe in 2004 as a scale space based feature matching technique [6]. The algorithm is regarded as a powerful tool in the area of automatic images matching, with high ability to extract stable features. SIFT is one of the most robust local invariant detector and descriptor with respect to geometrical changes [7][8]. SIFT were designed to be invariance to image scale, rotation and affine transformation which might attribute the wide spared of this technique in photogrammetry and computer vision applications, such as image mapping, recognition, 3D modeling, GIS, and vision navigation. Four main steps are considered in SIFT, namely: the extreme point detection in scale space, precise positioning of interest points, assigning the main orientation of these points, and constructing a unique distinctive descriptor for each interest

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point. For faster processing time, Difference-of-Gaussian (DOG) is used in SIFT instead of Gaussian in the first step to find out possible interest scale and orientation invariant points [6].

For faster matching and considerable space advantages, PCA has been used in PCA-SIFT to normalize gradient patch as an alternative for histograms [9]. PCA is a dimensionality reduction method exploited in PCA-FIFT to make the feature vector considerably smaller than that of SIFT. This helps to reduce computations and as a consequence decrease the processing time and save significant storage space [9]. SURF has been developed to overcome the limitations of image matching algorithms, such as SIFT and PCA-SIFT, in terms of processing time using an intermediate image representation known as integral image and Fast-Hessian detector [10]. This intermediate image can be computed rapidly from an input image as the summation of the intensity values between the point and the origin. This can help to speed up the time of any upright rectangular calculation considerably [11]. Detection procedures in SIFT and SURF are different to some extends. SIFT creates an image layers which are filtered individually with Gaussians and uses the difference of sigma values. This is not the case with SURF where a “stack” is generated providing images of the same size [7]. Using the integral images in SURF helps to filter the stack using a box filter approximation of second-order Gaussian partial derivatives as the computation of rectangular box filters can be applied in near constant time [7].

Different researches, such as [7] [12] [13] have investigated and compared the performance of such matching methods for image deformation, such as scale changes, rotation, blur, compression, illumination changes, and affine transformations. In [7], the performance of the three robust feature detection methods adopted in this paper, namely SIFT, PCA-SIFT, and SURF has been investigated and compared. K-Nearest Neighbour and Random Sample Consensus (RANSAC) have been adopted for evaluating and analysing the results. K-Nearest Neighbour has been utilized for getting the common points, which are filtered using RANSAC to determine the number of correct matched points. The performance of these has been assessed using the repeatability where higher repeatability means more stability. For evaluating the accuracy, the number of correct matched points achieved from RANSAC has been used. For reliable investigation, the same image dataset as well as PC and operating system have been used. Processing time including feature detection, description and matching has been determined for evaluating the fastness of each method. Results show that SURF is relatively the fastest comparing to SIFT and PCA-SIFT, which is attributed to utilizing integral image. Also, SURF detector known as ‘Fast-Hessian’ is more than three times faster that SIFT detector and five times faster than Hessian-Laplace [10]. SIFT shows high stability with most image deformation cases although it’s slow. PCA-SIFT is faster than SIFT to some extends with good stability in rotation and illumination changes.

Overall, although each method of these three matching techniques has its own advantages, they are still limited in terms of processing time and considered to be slow, especially for real and nearly real time applications, such as vision navigation based robots. This paper works on speeding up SIFT, PCA-SIFT and SURF using image pyramid. Different tests will be carried out for evaluating this idea with different image resolutions, different image resampling levels and techniques, and different numbers of matched points. Open source image processing matlab toolbox, including these three algorithms and available at Benghazi University has been used in this paper. For reliable investigations, the same images as well as PC and operating system will be used with all techniques and the results are discussed in details showing the advantages and limitations of this speeding up processing time method.

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2. METHODOLOGY

In this paper, the image pyramid is used with SIFT, PCA-SIFT and SURF to limit the computation time due to the large amount of image data. The image pyramid is a data structure showing the same image with different resolution rates. Figure 1 shows image pyramid with different resolutions. There are different resampling methods available for generating an image pyramid, such as nearest neighbour, bilinear interpolation and bicubic interpolation. In nearest neighbour method, pixels on the resampled image take the intensity value of the pixels on the original image within which the points fall. In bilinear interpolation and bicubic interpolation methods, the intensity value of the resampled pixel equals to the weighted average of the intensity value of the original pixels in the nearest 2 by 2 and 4 by 4 area, respectively [11].

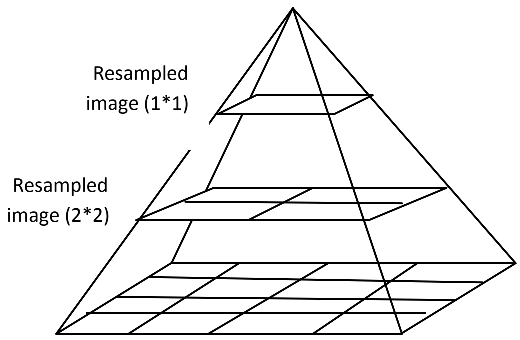

Fig. (1): Image pyramid

The idea of speeding up SIFT, PCA-SIFT and SURF is based on the truth that there is a high probability for each interest point in the original image to stay as an interest point in the different image pyramid levels [13]. Based on that, automatic matching between any two images can be firstly performed at the resampled images to find the interest common points between these images. This can be carried out quickly with the low resolution levels where the lower the image size, the faster the processing time. Then, the approximate locations of these matched points are determined on the original images based on basic similar triangles. The approximate locations of these points on the original image are then surrounded by small searching windows and matched again with the corresponding searching windows in the second image. This means that instead of matching the whole two high resolution images with large amount of image data, a number of tiny images are matched together for the common points between the original images. This leads to reducing the amount of computations to great extends and as a consequence, reducing the processing time significantly. Figure (2) shows the workflow diagram of the suggested idea. This idea is theoretically affected by the original image size, the resampling level and method, and the number of matched points, which will be reliably investigated during this paper for these three matching technique using the same images as well as PC and operating system.

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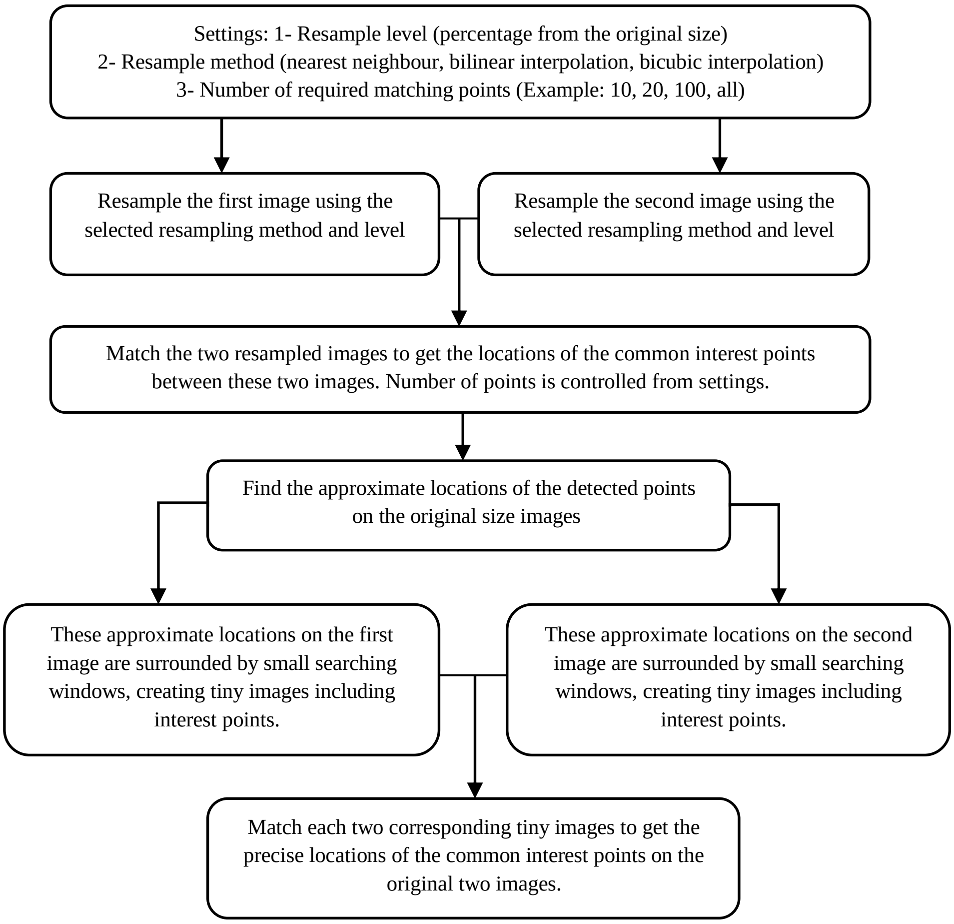

Fig.(2): Workflow diagram of the suggested idea

3. RESULTS AND DISCUSSION

The first test has been performed to evaluate the processing time of SIFT, PCA-SIFT and SURF with and without applying the suggested idea of speeding up these automatic matching algorithms. Two images with the same resolution have been used in this test with the settings of 25% resampling rate, 10 matching points, and bicubic interpolation method. Figure 3 shows an example of the automatic matching using SURF. Table 1 illustrates the processing time of SIFT, PCA-SIFT and SURF in milliseconds before and after applying the suggested idea and the improvement rate. From the results, it is clear that with the suggested technique, the processing time of SIFT, PCA-SIFT and SURF is improved considerably comparing to the original time. The order of the three algorithms in terms of processing time is the same before and after applying the speeding up method where SURF and SIFT are the fastest and slowest, respectively. The results show also that SURF has the highest improvement rate which can be attributed to the truth that the suggested speeding up idea depends on repeating utilizing the algorithm by a number of times equals to the selected matching points + 1. This means that with 10 selected matching points, SURF, for example, will be used 11 times to get the final matched common points (one for the resampled pair of images and one for each tiny corresponding two images). As a result, the faster the algorithm without the suggested idea, the higher processing time improvement rate can be achieved with this suggested idea. However, it is difficult to use the processing time and the improvement rates shown in the table as fixed values where they depend on the number of matching points, resample level, resample method, and original image size.

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Table(1): The processing time of SIFT, PCA-SIFT, and SURF with and without using the suggested speeding up idea (milliseconds)

SIFT (10 points)			PCA-SIFT (10 points)			SURF (10 points)		
Time with	Time without	Rate	Time with	Time	Rate	Time with	Time without	Rate
118019	581479	4.927	91111	489634	5.374	22198	153021	6.893

Fig. (3): Examples of automatic image matching using SIFT (Up) and SURF (Down)

The second test has been performed to investigate the effect of resampling rate on the speeded up processing time of SIFT, PCA-SIFT and SURF. Three different resampling levels (25, 50, 75) have been used with the settings of bicubic interpolation method and 10 matching points. Table 2 illustrates the processing time of each resampling level for each algorithm comparing to the original time. It is clear from the results that the higher the resampling rate, the faster the processing time. This is theoretically expected as high resample level decrease the large amount of image data and as a consequence, the computation time is reduced significantly. As the suggested technique is based on applying the matching algorithm on the resampled images firstly before reapplying the algorithm on the resulted tiny images, the resampling level will play a significant role in reducing the processing time as clear from the table. As in the first test, the performance of the algorithms with the suggested speeding technique is considerably better in terms of processing time. SURF has the fastest processing time for all resample levels, PCA-SIFT comes second and SIFT is last.

Table (2): The speeded up processing time of SIFT, PCA-SIFT, and SURF with different resampling rates (milliseconds)

SIFT (10 points)			PCA-SIFT (10 points)			SURF (10 points)		
25%	50%	75%	25%	50%	75%	25%	50%	75%
118019	263665	394558	91111	215324	325642	22198	61300	104876

The effect of image resolution on the speeded up processing time of SIFT, PCA-SIFT and SURF has also be investigated in the third test. The number of matching points, resampling rate, and resampling method have been fixed as 10 points, 25%, and bicubic interpolation, respectively for all algorithms and images with different resolutions, namely: 10, 12, and 20 megapixel have been used. Theoretically, this effect is similar to changing the resampling rate but in different way where the higher the image resolution, the slower the processing time. However, as seen from table 3, the difference between the speeded up processing time and the original time becomes more and more significant with increasing the image resolution where great amount of image data calculations are reduced significantly with the suggested idea making the procedure considerably faster.

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Table (3): The speeded up processing time of SIFT, PCA-SIFT, and SURF with different image resolutions (milliseconds)

Speeded up SIFT			Speeded up PCA-SIFT			Speeded up SURF		
10 meg.	12 meg.	20 meg.	10 meg.	12 meg.	20 meg.	10 meg.	12 meg.	20 meg.
118019	135042	155942	91111	108431	131769	20198	23381	28054
Original SIFT			Original PCA-SIFT			Original SURF		
581479	842117	1.39 *	489634	709318	1.02 *	153021	220360	371985

In the fourth test, the effect of the number of matching points on the speeded up processing time of SIFT, PCA-SIFT and SURF has been investigated. The test has been applied with 25% resampling level and bicubic interpolation method. Different numbers of matching points have been applied in this test (10, 100 and all detected points) and the results are illustrated in table 4. The differences in the total number of detected points between the three algorithms can be attributed to utilizing descriptor vectors with different lengths [11]. It is clear from the table that the number of matching points has also an effect on the processing time where matching procedure in the applied technique is repeatable depending on the number of selected points. As a result, the more matching points, the more calculations and the longer processing time. However, even when using all points detected by the algorithms, the differences between the speeded up processing time and the original one is still considerable.

Table(4): The speeded up processing time of SIFT, PCA-SIFT, and SURF with different numbers of matching points (milliseconds)

Speeded up SIFT			Speeded up PCA-SIFT			Speeded up SURF		
10	100 points	All. 243	10 points	100 points	All. 211	10	100 points	All. 182
118019	169004	232547	91111	132864	176209	20198	28891	38824

The last test has been applied to study the effect of three resampling methods, namely: nearest neighbour, bilinear interpolation and bicubic interpolation on the speeded up processing time of SIFT, PCA-SIFT and SURF. The resampling rate has been fixed at 25% and the required matching points have been chosen to be 10. Table 5 shows the processing time of each algorithm for each resampling method.

Table (5): The speeded up processing time of SIFT, PCA-SIFT, and SURF with different numbers of matching points (milliseconds)

Speeded up SIFT			Speeded up PCA-SIFT			Speeded up SURF		
Nearest	Bilinear	Bicubic	Nearest	Bilinear	Bicubic	Nearest	Bilinear	Bicubic
118019	121912	123201	91111	94626	95743	20198	23763	25175

The results shows that the differences in processing time between the three resample methods are small to be neglected. This can be attributed to the fact that in the suggested idea of speeding up SIFT, PCA-SIFT and SURF, the resampling procedure is not repeatable and it is used once at the beginning when resampling the image. Nearest neighbor provides relatively the fastest processing time and bicubic interpolation is the slowest which is attributable to the differences in the amount of calculations between the methods. The difference in processing time can become more significant with higher resolution images where more and more calculations are required by the interpolation resampling techniques. The interpolation methods are theoretically better than the nearest neighbour method where the intensity values of all pixels are utilized allowing all interest points in the original image to be considered in the resampled image. This is not the case with the nearest neighbour method where the resulted pixel takes just the intensity value of the corresponding pixel in the original image and consequently, some interest points might be neglected. With high resample rates, the differences in the performances between

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nearest neighbour and the other interpolation based methods become significant in terms of detecting high number of interest points where lots of these points may not be considered using nearest neighbor. Reducing the number of detected interest points may not be suitable for some engineering applications that require dense matched point cloud, such as digital elevation models and ortho-images. On the other hand, there are many subjects that need fast processing time for real or nearly real time applications with limited number of matching points, such as vision navigation, robots, and SLAM.

4. CONCLUSION

This paper introduces a new idea for enhancing the performance of common automatic matching methods, namely SIFT, PCA-SIFT and SURF in terms of processing time. Different tests have been carried out for evaluating the processing time of each algorithm with and without applying the suggested idea with different image resolutions, different image resampling levels and techniques, and different numbers of matched points. The results show that the applied idea is powerful in terms of reducing the processing time. The performance of the suggested method is affected by the resampling level where the higher the rate, the faster the processing time. However, higher resampling levels might have an effect on the number of detected points, especially with non-interpolation methods, such as nearest neighbor. The resampling method has also an effect on the processing time of the introduced idea and this effect increases with increasing the image resolutions. The idea works well with high image resolutions where the differences between the obtained processing time and the original time are significant. The results show also that the processing time is affected by the number of required matching points where the smaller the number, the faster the technique. However, even the whole number of detected points, the enhancement in processing time is still significant. In general, the suggested idea for speeding up SIFT, PCA-SIFT and SURF is effective in reducing the processing time significantly which might be extremely useful for nearly real time applications based on automatic image matching, such as vision navigation based robots and real time indoor navigation.

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