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Image Matching Performance Comparison using SIFT, ASIFT and Moment Invariants

[1]Zinah Mohsin Arkah, [1]Reem Ibrahim Hasan, [2]Sif. K. Ebis,
[3]Haider A. Alwzwazy and [1]Mohammed A. Fadhel
[1]University of Information Technology and Communications, Baghdad, Iraq
[2]Ministry of Education, Wassit Education Directorate, Baghdad, Iraq
[3]Missan Oil Company, Missan, Iraq

Abstract: It is important to improve the performance of images matching, so that, many algorithms have been studied to achieve this goal. However, finding best one is still a very interested field of study because the performance of matching is a wide term containing many factors like rotating invariant, scaling invariant, noise invariant and etc. In this study, we compare the performance of the algorithms by calculating the score of matching which is number of key points and number of matching. The descriptor should study with all cases such as rotation with different angels and scaling of different sizes. We have implemented the Scale Invariant Feature Transform (SIFT) as a first algorithm then we applied Affine Scale Invariant Feature Transform (ASIFT), finally we applied moment invariants. Therefore by evaluating the results of these algorithms we can know which one has good matches. ASIFT has shown a great performance in term of image matching.

Key words: Image matching, SIFT, ASIFT, moment invariants, rotating invariant, scaling invariant

INTRODUCTION

Image matching has become an interesting area to research on. Extracting features used in many applications such wide image matching (Schaffalitzky and Zisserman, 2002; Tuytelaars and van Gool, 2004) object recognition (Ferrari *et al*., 2004), object recognition (Fadhel *et al*., 2018), image retrieval (Awad *et al*., 2018), classification (Alzubaidi *et al*., 2019). The problem is to find the best matching between two images by comparing them. As a result, if we will get a high number of matches between two images with different status such as an image with its rotated image then we get a good result of matching.

It is very necessary to make sure we get matching between key points of two images. The reason behind that some applications need to be extremely accurate. For example, the security application is very sensitive to get the best matching. As a result, the matches should be accurate. These algorithms which we applied have a good number of matches between two images that made them good algorithms for image matching. There were many algorithms for extracting features but when the SIFT algorithm (SIFT descriptor) published by Lowe (2004) which made a big difference for extracting features.

The most important of this algorithm is that extract large numbers of features that densely cover the image over the full range of scales and locations. SIFT algorithm is finding key points by using the DoG and then apply SIFT descriptor to describes the image using features for effective matching. Even thought SIFT made a difference in extracting features it still has weaknesses (Yu and Morel, 2011). SIFT failed in different light conditions when the object is reflected 3D objects structure different view angles.

In order to solve these problems, we applied the second algorithm which is ASIFT. ASIFT solved the problems that SIFT failed with. If the object hasdifferent angles or not flat ASIFT can handle it and find matches. It also works with image rotation. ASIFT is more efficient and robust than SIFT algorithm. ASIFT used SIFT descriptor then it applied ORSA (Bean, 1994) (Optimized Random Sampling Algorithm) algorithm to clean up the false matches using the epipolar (Xu and Zhang, 2013) geometry constraint. However, suppose using ASIFT without ORSA, the number of ASIFT false matches is small and it is still acceptable. Finally, we compared SIFT and ASIFT with moment invariants (Keyes and Winstanley, 2001).

Moments can provide properties of an object that uniquely represent its shape. Moment invariants have used many techniques that derive invariant features for object recognition and representation. These techniques are well-known by their moment definition. It

Corresponding Author: Zinah Mohsin Arkah, University of Information Technology and Communications, Baghdad, Iraq

was which is mathematical operations for two-dimensional moment invariants and determine their applications to shape recognition. In 1977, Hu applied to aircraft shapes by (Dudani, Breeding and McGhee) and shown that Hu was quick and reliable. These moment invariant values considered whether the shape in translation, scale and rotation. The goal of this study is to evaluate the detector and descriptors then find best image matching algorithm by using three different algorithms which are (SIFT, ASIFT, moment invariants). Moreover, we need to apply different cases such as (rotation, scaling) and we need to discover which one has the higher number of matches than others even with these cases. Lastly, different hardware tools use with image matching devices and speed up the process (Farhan *et al*., 2018; Alzubaidi *et al*., 2018).

MATERIALS AND METHODS

We have used Oxford dataset to evaluate the algorithms (Philbin *et al*., 2012). Figure 1 shows some samples of the dataset. We describe the algorithms individually next.

SIFT algorithm: This algorithm has published by Lowe, (2004). SIFT extracts key points and compute its descriptors for images matching. The processing of SIFT as following:

Scale-space extrema detection: In order to detect the key points of the processed image we have applied Difference of Gaussian (DoG) which is gained as the difference of Gaussian blurring of an image with two different σ. DoG is done for different octaves of the image in the gaussian pyramid as shown.

Local extrema detection: After applying the DoG, Gaussians produces the set of scale space images. Then, it checks these images. If it is a local extremum then it is key points, as a result, the best key points shown in the next image.

Frequency of sampling in scale: In this part, each image was resampled by rotation with a random angle and scaling by a random amount between 0.2 of 0.9 times the original size. DoG function has a large number of extrema it will take time and would be expensive to detect all. Therefore, we can detect the most stable and useful.

Accurate key point localization: Using a threshold in order to filter out the extrema which are less than a threshold. On the other hand, the edges are detected and removed by calculating the condition number.

Orientation assignment: In order to find the orientation of key points, we have taken a neighborhood around the key point location depending on the scale.

The local image descriptor: First, it computes the gradient magnitude and orientation at each image sample point in a region around the key point location. It takes a subregion which is 4×4.

ASIFT algorithm: It uses SIFT descriptors and it is processing as following:

- Apply a dense set of rotations to both images A and B
- Apply in continuation a dense set of simulated tilts T×t to all rotated images
- Perform a SIFT comparison of all pairs of resulting images
- ASIFT algorithm can handle different image cases of rotation, flipping, etc

Invariant moments: Moments and functions of moments are used as invariant global features of images in pattern recognition. In our study, we programmed regular moment invariant which is a set of derived by Hu. The regular moments of a given function f(x, y) is defined in Eq. 1:

$$M_{pq} = \iint x^p y^q f(x, y)\,dxdy \tag{1}$$

M_{pq} is the two-dimensional moment of the function f(x, y). (p+ q) is the order of the moment where, p and q are both natural numbers. The digital from this for implementation is shown in Eq. 2:

$$M_{pq} = \sum_X \sum_Y x^p y^q f(x, y) \tag{2}$$

The centroids of the image should be found to normalize for translation in the image plane. The image centroids are used to define the central moments. By using Eq. 2 we can get:

$$\bar{x} = \frac{M_{10}}{M_{00}} \quad \bar{y} = \frac{M_{01}}{M_{00}} \tag{3}$$

Their discrete representation of the central moments represents in Eq. 4:

$$\mu_{pq} = \sum_X \sum_Y (x-\bar{x})^p (y-\bar{y})^q \tag{4}$$

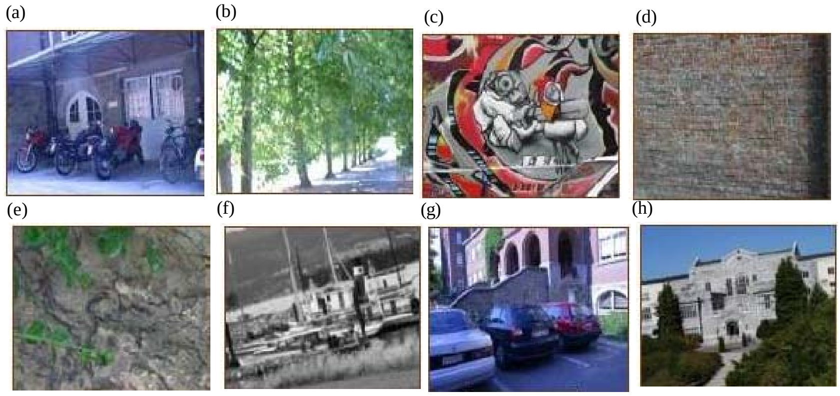

Fig. 1: Some samples of oxford dataset: a, b) Blur; c, d) Viewpoint; e, f) Zoom+rotation; g) Light and h) JPEG compressions

Further normalization has been done for the effects of change of scale using the Eq. 5 on the moments:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}} \tag{5}$$

A set of seven v alues can be calculated from the normalized central moments which are defined by Eq. 6:

$$
\begin{aligned}
& M_1 = (\eta_{20}+\eta_{02})\ M_2 = (\eta_{20}-\eta_{02})^2+4\eta_{11}^2 \\
& M_3 = (\eta_{30}-\eta_{12})^2+(3\eta_{21}-\eta_{03})^2 \\
& M_4 = (\eta_{30}+\eta_{12})^2+(\eta_{21}+\eta_{03})^2 \\
& M_5 = (\eta_{30}-3\eta_{12})(\eta_{30}+\eta_{12}) \\
& (\eta_{30}+\eta_{12})^2-3(3\eta_{21}+\eta_{03})^2+ \\
& (3\eta_{21}-\eta_{03})^2(\eta_{21}+\eta_{03}) \\
& \left[3(\eta_{30}+\eta_{12})^2-(\eta_{21}+\eta_{03})^2\right] \\
& M_6 = (\eta_{20}-\eta_{02})\left[(\eta_{30}+\eta_{12})^2-(\eta_{21}+\eta_{03})^2\right]+ \\
& 4\eta_{11}(\eta_{30}+\eta_{12})(\eta_{21}+\eta_{03}) \\
& M_7 = (3\eta_{21}-\eta_{03})(\eta_{30}+\eta_{12}) \\
& \left[(\eta_{30}+\eta_{12})^2-3(\eta_{21}+\eta_{03})^2\right]- \\
& (\eta_{30}+3\eta_{12})(\eta_{21}+\eta_{03}) \\
& \left[3(\eta_{30}+\eta_{12})^2-(\eta_{21}+\eta_{03})^2\right]
\end{aligned} \tag{6}
$$

RESULTS AND DISCUSSION

In this study, we show the result by applying two different cases which are:

Table 1: Comparison of SIFT and ASIFT of blur images

Images from Fig. 2	Match points of SIFT	Match points of ASIFT
1-2	3800	8560
1-3	2799	9124
1-4	1671	6957
1-5	1254	5902
1-6	961	4888

Table 2: Comparison of SIFT and ASIFT in case of rotation

Images from Fig. 2	Match points of SIFT	Match points of ASIFT
1-2	1380	5560
1-3	142	2626
1-4	184	1405
1-5	310	707
1-6	20	107

Blurring: In this case, we applied two images one of them is the original image and the second one is the blurred image as result we will get key points and descriptors for the original and the blurred images. After that, the matched key points between the original and the blurred images are scored, according to the distance between them. The score is calculated by Ave scores = sum (key points)/number of key points. Figure 2 shows samples of images that we have used in blurring case. Table 1 and Fig. 3 present the number of matches when the images more blur are less number of matches.

Rotation: In this case, we applied two images one of them is the original image and the second one is the rotated image with different angles as shown in Fig. 4 and the results in Table 2, Fig. 5, 6.

Moment invariants results: The equations that we explained in moment algorithm above have been done applied on the entered images after it sliced on small patches. The size of the single slice is 32×32 pixels. A rotation, translation and scaling were applied on the second entered image which is the same as the first

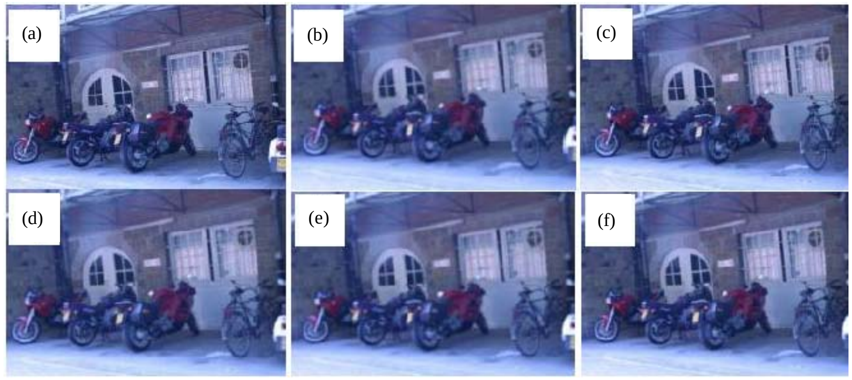

Fig. 2: a-f) The 1-6 samples of blurring images

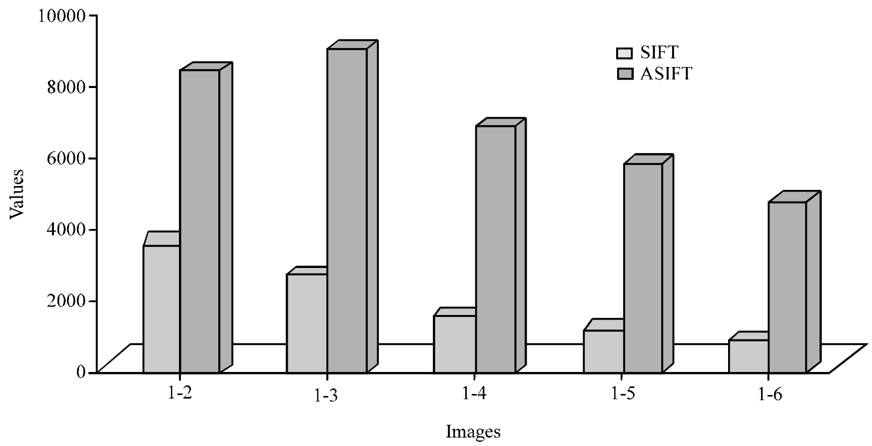

Fig. 3: Comparison of SIFT and ASIFT in case of blur images

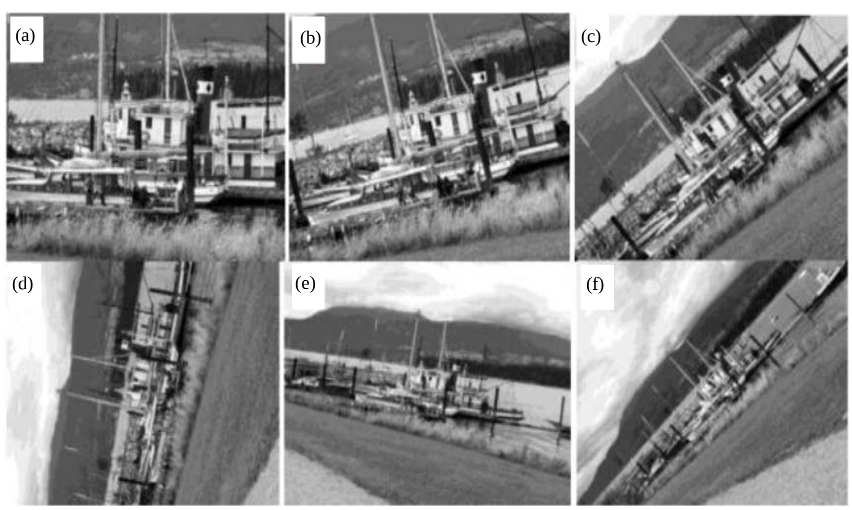

Fig. 4: a-f) The 1-6 samples of images for rotation images

one. The rotation that has been applied is 180 and the scale is by 3. After that, a comparison will be applied to measure the percentage of matching. The two images should be the same size. Figure 7 shows the example of moment invariants test sample with two images with blur case.

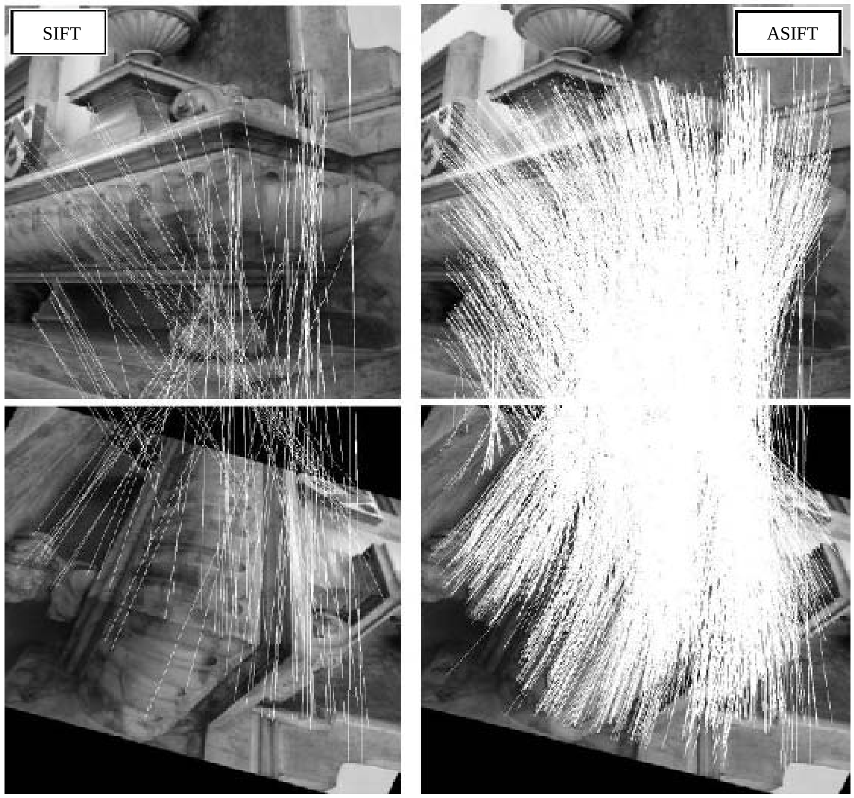

Fig. 5: Comparison of SIFT and ASIFT

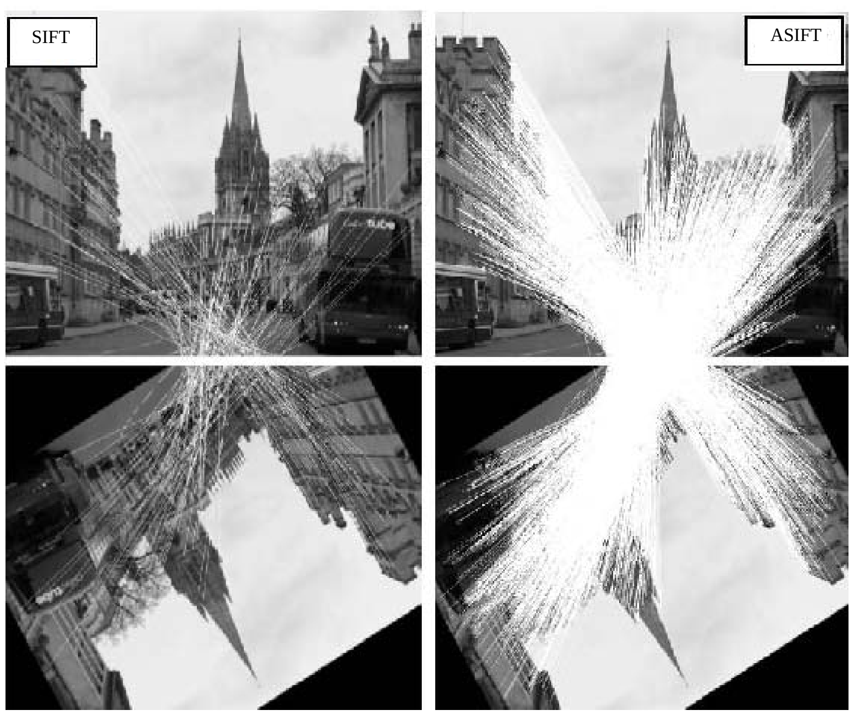

Fig. 6: Comparison of SIFT and ASIFT

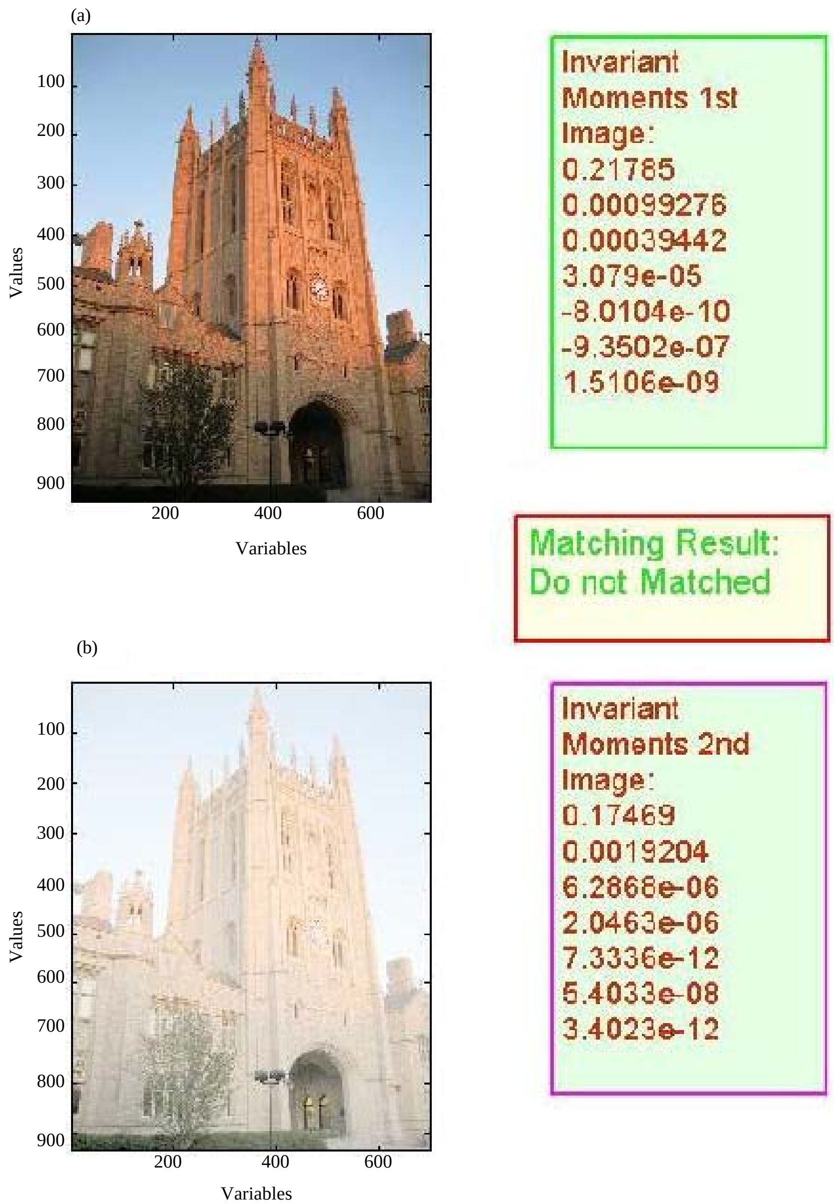

Fig. 7: Moment invariants test sample: a) Original image and b) Blur image

CONCLUSION

In this study, we have applied three different algorithms to conclude which algorithm is best image matching algorithm, we have implemented SIFT, ASIFT and moment invariants algorithms. We test these algorithms with different parameters such as rotation, blurring and scaling. As a result, ASIFT has shown great results in term of image matching. This research can be expanded to use different feature extraction algorithms such as convolutional neural networks.

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