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A Comparison of FAST, SURF, Eigen, Harris, and MSER Features

Engr.Farman Ali[1], Engr.Sajid Ullah Khan[2], Engr.Muhammad Zarrar Mahmudi[3], Rahmat Ullah[4]

[1, 2, 3, 4] Sarhad University Peshawar

[1]farman_puhtun@yahoo.com, [2]engr.sajid10@gmail.com, [3]engr.zarrar@gmail.com, [4]rahmat9314@gmail.com

ABSTRACT

Precise, successful in desire target, strong healthy and self loading image registration is critical task in the field of computer vision. The most require key steps of image alignment/ registration are: Feature matching, Feature detection, , derivation of transformation function based on corresponding features in images and reconstruction of images based on derived transformation function. This is also the aim of computer vision in many applications to achieve an optimal and accurate image, which depends on optimal features matching and detection. The investigation of this paper summarize the coincidence among five different methods for robust features/interest points (or landmarks) detector and indentify images which are (FAST), Speed Up Robust Features (SURF), (Eigen),(Harris) & Maximally Stable Extremal Regions (MSER). This paper also focuses on the unique extraction from the images which can be used to perform good matching on different views of the images/objects/scenes.

Keywords: *Feature detection, Feature matching, FAST, SURF, EIGEN, HARIS and MSER.*

1. INTRODUCTION AND PRIOR WORK

Several research work done in the computer vision on the basis of features detection. Which are valuable parts of computer vision. Bay and Tuytelaars (2006) speeded up robust features and used integral images for image convolutions and Fast-Hessian detector. Their experiments turned out that it was faster and it works well [2]. Lowe (2004) presented SIFT for extracting distinctive invariant features from images that can be invariant to imagebscale and rotation. Then it was widely used in image mosaic, recognition, retrieval and etc [3]. Bay and Tuytelaars (2006) speeded up robust features and used integral images for image convolutions and Fast-Hessian detector. Their experiments turned out that it was faster and it works well [4]. Image matching task to finding correspondences between two images of the same scene/object is part of manycomputer vision applications. Image registration, camera calibration and object recognize just few. This paper describes distinctive features from images is divided into two main phases. First, “key points” are extracted from distinctive locations from the images such as edges, blobs, corner etc. Key point detectors should be highly repeatable. Next, neighbourhood regions are picked around every key point and distinctive feature descriptors are computed from each region [1]. For image matching, extraction features in images which can provide reliable matching between different viewpoints of the same image. During process, Feature descriptors are extracted from sample images and stored. This descriptor has to be distinctive and, at the same time, robust to noise, detection errors. Finally, the feature descriptors are matched between different images. Feature descriptor matching can be based on distances such as Euclidean.

This paper discusses the overview of the methods in Section 2, in section 3 we can see the experimental results while Section 4 tells the conclusions of the paper.

2. OVERVIEW OF METHODS

2.1 SIFT Algorithm Overview

SIFT (Scale Invariant Feature Transform) algorithm proposed by Lowe in 2004 [6] to solve the image rotation, scaling, and affine deformation, viewpoint change, noise, illumination changes, also has strong robustness. The SIFT algorithm has four main steps: (1) Scale Space Extrema Detection, (2) Key point Localization, (3) Orientation Assignment and (4) Description Generation. The first stage is to identify location and scales of key points using scale space extrema in the DoG (Difference-ofGaussian) functions with different values of σ, the DoG function is convolved of image in scale space separated by a constant factor k as in the following equation.

$$\mathbf{D(x, y,\sigma) = (G(x, y, k\sigma) - G(x, y,\sigma) \times I(x, y)} \quad \text{…. (1)}$$

Where, G is the Gaussian function and I is the image. Now the Gaussian images are subtracted to produce a DoG, after that the Gaussian image subsample by factor 2 and produce DoG for sampled image. A pixel compared of

3×3 neighborhood to detect the local maxima and minima of D(x, y, σ).
In the key point localization step, key point candidates are localized and refined by eliminating the key points where they rejected the low contrast points. In the orientation assignment step, the orientation of key point is obtained based on local image gradient. In description generation stage is to compute the local image descriptor for each key point based on image gradient magnitude and orientation at each image sample point in a region centered at key point [2]; these samples building 3D histogram of gradient location and orientation; with 4×4 array location grid and 8 orientation bins in each sample. That is 128-element dimension of key point descriptor.

2.2 Construction Of SIFT Descriptor

Figure 1 illustrates the computation of the key point descriptor. First the image gradient magnitudes and orientations are sampled around the key point location, using the scale of the key point to select the level of Gaussian blur for the image [6]. In order to achieve orientation invariance, the coordinates of the descriptor, then the gradient orientations are rotated relative to the key point orientation. The key point descriptor is shown on the right side of Figure 1. It allows for significant shift in gradient positions by creating orientation histograms over 4x4 sample regions. The figure shows 8 directions for each orientation histogram [6], with the length of each arrow corresponding to the magnitude of that histogram entry. A gradient sample on the left can shift up to 4 sample positions while still contributing to the same histogram on the right. So, 4×4 array location grid and 8 orientation bins in each sample. That is 128-element dimension of key point descriptor.

2.3 SURF Algorithm Overview

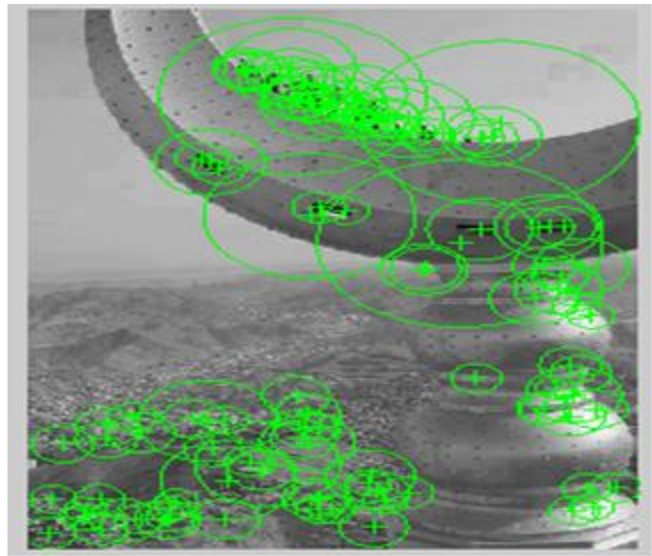
SURF (Speed Up Robust Features) algorithm, is base on multi-scale space theory and the feature detector is base on Hessian matrix. Since Hessian matrix has good performance and accuracy. In image I, x = (x, y) is the given point SURF creates a “stack” without 2:1 down sampling for higher levels in the pyramid resulting in images of the same resolution. Due to the use of integral images, SURF filters the stack using a box filter approximation of second-order Gaussian partial derivatives [3]. Since integral images allow the computation of rectangular box filters in near constant time. In Figure 2 Show the Gaussian second orders partial derivatives in y-direction and xy-direction. In descriptors, SIFT is good performance compare to other descriptors. The proposed SURF descriptor is based on similar properties. The first step consists of fixing a reproducible orientation based on information from a circular region around the interest point. And second construct a square region aligned to the selected orientation, and extract the SURF descriptor from it.

3. EXPERIMENTAL RESULTS

To verify the effectiveness of the algorithm two images are taken as the experimental data as shown in figure 1 (a) image1: 640×478, 153 KB and (b) image2: 640×478, 127 KB. The experiments are performed on Intel Core i-3 3210, 2.3 GHz processor and 4 GB RAM with windows 7 as an operating system. Features are detected in both images using SIFT and SURF algorithm. Figure 4 (c) and (d) shows the detected features using SIFT in image1 and image2 respectively. It is observed that 892 features are detected in image1 and 934 features are detected in image2. Figure 4 (f) and (g) shows the detected features using SURF algorithm from the original image1 & image2 respectively. It is observed that 281 features are detected in image1 and 245 features in image2. The features matching is shown in Figure 4(e) are 41 and Figure 4(h) shows 28 matched points. Normalised Cross Correlation technique is used here for feature matching. The experimental results are summarised in Table 1.

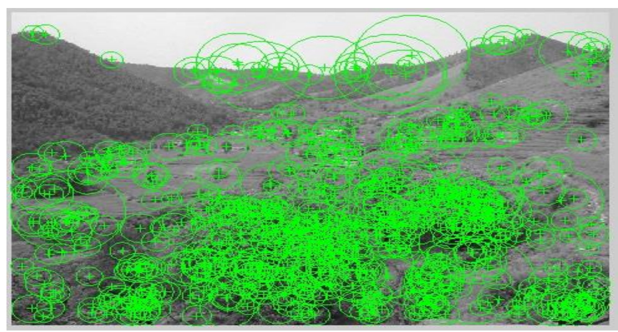
Original image (a)

Original image (b)

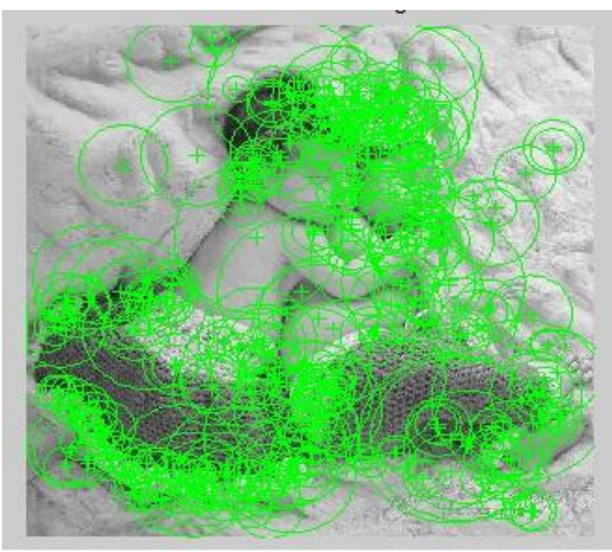


Detected features using SURF on image (b)

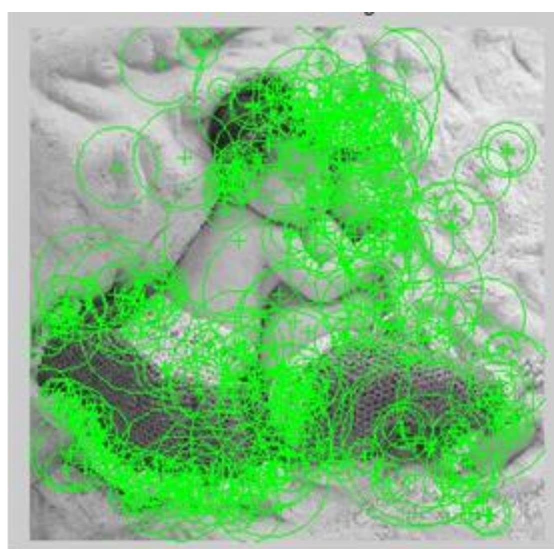
Original image (c)



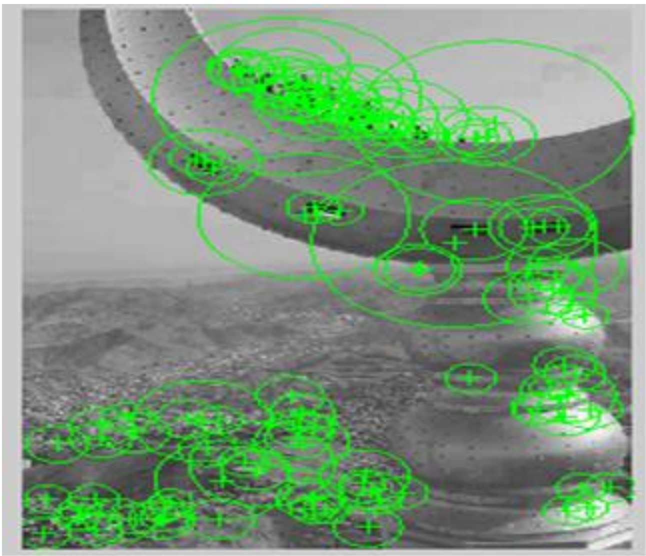
Detected features using SURF on image (c)



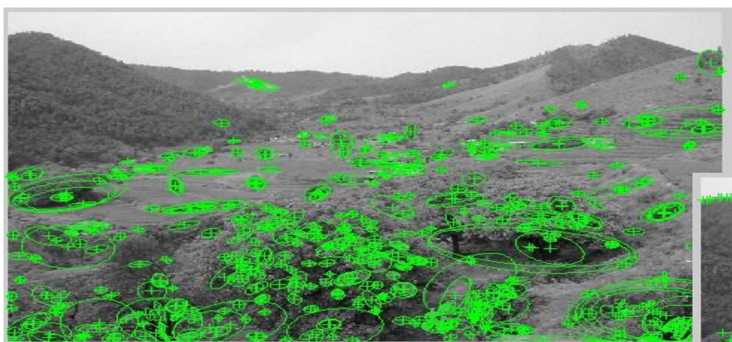
Detected features using SURF on image (a)



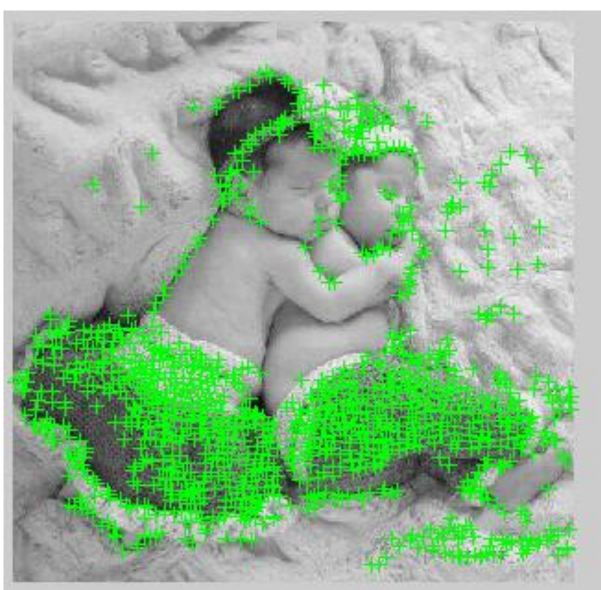
Detected features using MSER on image (a)



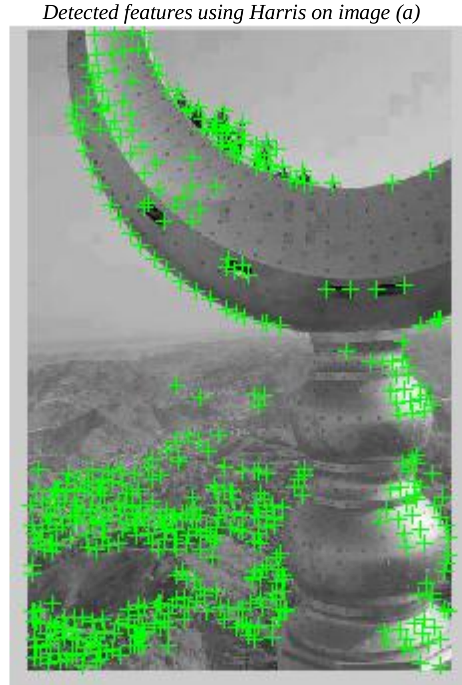
Detected features using MSER on image (b)



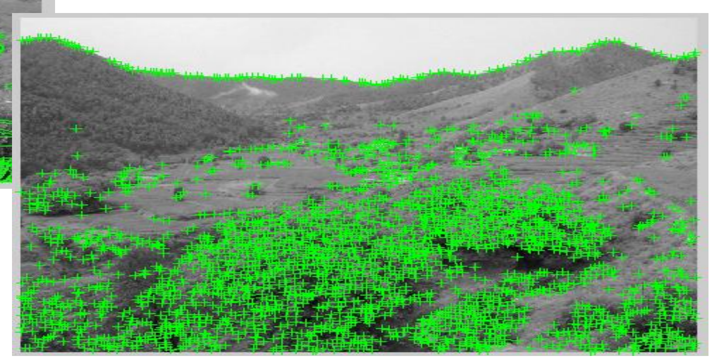
Detected features using MSER on image (c)



Detected features using Harris on image (a)

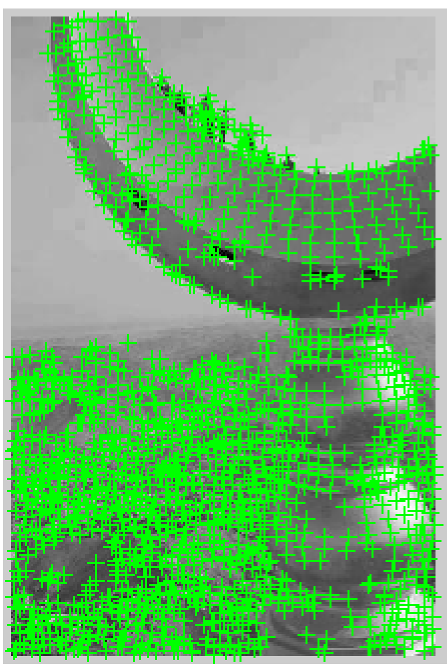


Detected features using Harris on image (b)

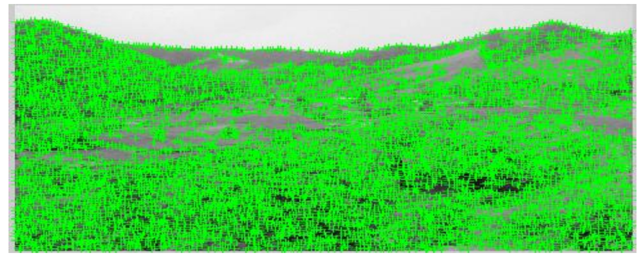


Detected features using Harris on image (c)

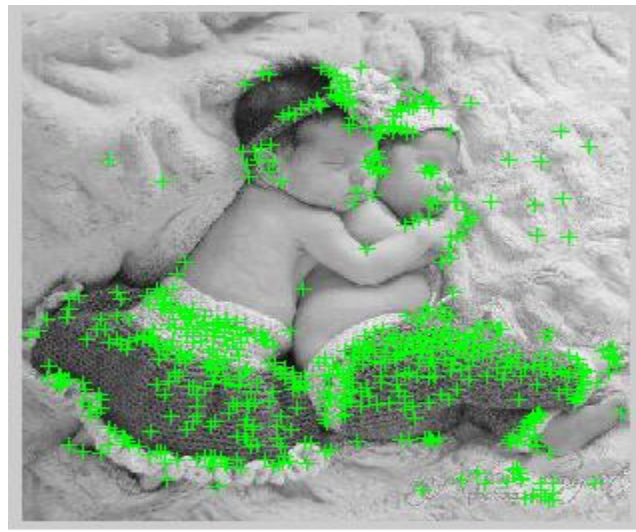
Detected features using Eigen on image (a)



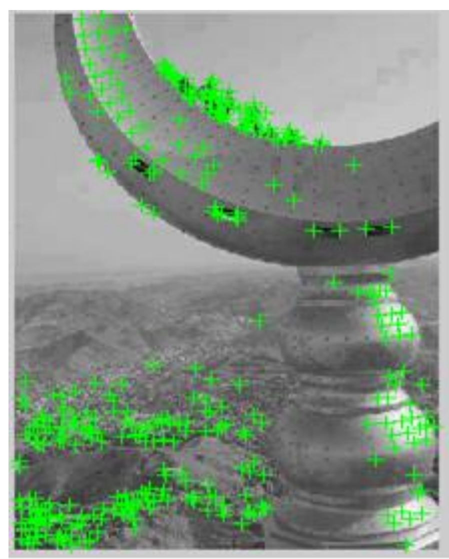
Detected features using Eigen on image (b)



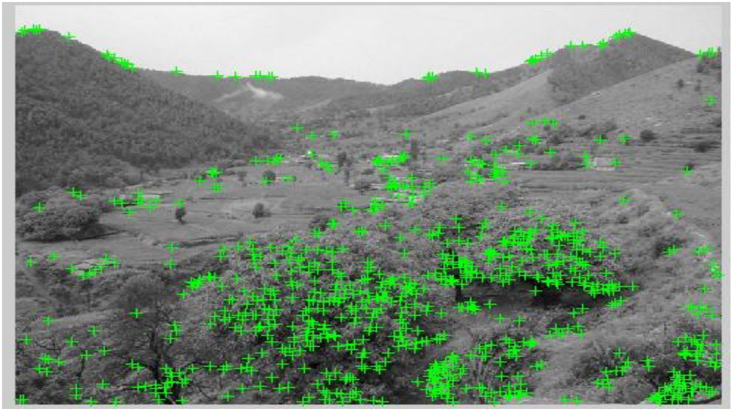
Detected features using Eigen on image (c)



Detected features using FAST on image (a)



Detected features using FAST on image (b)



Detected features using FAST on image (c)

Table 1: Algorithms Features Points Detection

Algorithm	No of features points detected			Matching features
	Image1	Image2	Image3	
FAST	631	368	809	225
SURF	334	116	680	70
Eigen	3315	1526	7272	1199
Harris	1061	503	2349	325
MSER	225	146	560	115

4. CONCLUSIONS

This paper has evaluated two feature detection methods for image registration. Based on the experimental results, it is found that the SIFT has detected more number of features compared to SURF but it is suffered with speed. The SURF is fast and has good performance as the same as SIFT. Our future scope is to make these algorithms work for the video registration.

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