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Analysis of Various Image Feature Extraction Methods against Noisy Image: SIFT, SURF and HOG

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***Abstract*— We present the performance of three popular image feature extraction methods such as Scale Invariant Feature Transformation (SIFT), Speeded-Up Robust Features (SURF) and Histogram of Oriented Gradient (HOG). Specifically, we compare the performance of feature detection methods for images corrupted with different types of noise. The efficiency of three methods are measured by considering number of correct matches between original and noisy image found by the algorithm. In this study, we use images corrupted by three types of noise such as gaussian, salt & pepper and speckle. It is observed from the experimental results that for most of the noisy images, SIFT presents its stability but it is slow. SURF is the fastest one and its performance is close to SIFT. However, HOG show its advantages in detecting edge and texture information of image.**

Keywords*— *Feature extraction, Image Matching, SIFT, SURF, HOG

I. INTRODUCTION

Digital images find its use in various applications in everyday life such as medical imaging, geographical information systems, satellite television and astronomy. Generally, noise is introduced in an image during image acquisition process [1]. The noise arises in an image is due to imperfect instruments, transmission errors, compression and problems with the data acquisition process. Zero mean white Gaussian noise is common in most natural images where as Speckle and Rician noise affect ultrasound images and MRI images respectively [2][3].

Thus, the similarity measurement between original and noisy images has become a demanding problem in image processing applications [4]. The focus of this paper is to extract feature descriptors from images and to find reliable matching points between original and noisy images [5]. Feature descriptors provide the unique information of an image and this information is suitable for image matching. Generally, the features are highly distinctive and invariant to location and scale. The features are matched one by one between two images and this feature matching is based on Euclidean distance [6]. In the literature, several feature detection methods were reported to compute keypoint descriptors for image matching [7-8]. But, current research on image matching is typically based on SIFT [9], SURF [10] and HOG [11] descriptors due to good performance and wide range of applications.

In this paper, we evaluate the performance of SIFT, SURF and HOG on images corrupted with several types of noise such as Gaussian, Speckle and salt and pepper. Also, we compute matching points between original and noisy image using SIFT, SURF and HOG descriptors.

II. FEATURE DETECTION METHODS

SIFT

SIFT provides a robust mechanism for detecting distinctive invariant image features which provide robust matching between different views of an image. SIFT consist of four computational stages such as scale-space extrema detection, keypoint localization, orientation computation and keypoint descriptor [9]. Each stage is implemented in a descending order and on every stage a filtering process is made so that only the keypoints that are robust enough are allow to jump to the next stage [12]. In first stage of computation, it uses Difference of Gaussians (DoG) function to identify keypoints, which are invariant to locations and scales [13]. The scale space of an image $L(x, y, \sigma)$ is computed by performing convolution between Gaussian function $G(x, y, \sigma)$ and the input image $I(x, y)$.

The scale space function is

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (1)$$

Where $G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}$

To improve the computation speed, DOG was used

instead of Gaussian and is computed as

$$D(x,y,\sigma) = (G(x,y,k\sigma) - G(x,y,k\sigma)) * I(x,y)$$
$$= L(x,y,k\sigma) - L(x,y,\sigma) \quad (2)$$

In the second stage, Keypoints are localized by eliminating low contrast keypoints. In the third stage, orientations are assigned based on the image gradient at each keypoint location. The final phase measures local image gradients around each keypoint and according to keypoint orientation, descriptor orientations are rotated [14].

SURF

SURF, which is motivated by SIFT, uses integral images and is based on multi-scale space theory to generate keypoints and descriptors. Because of integral images, SURF requires less number of operations for single box convolution and the speed has improved [10]. Normally, SURF consists of two stages such as keypoint detection stage and keypoint description stage. Keypoint detection stage uses integral images, instead of using Difference of Gaussians (DoG) which is used in SIFT [14]. The integral image $I(X)$ corresponds to the sum of all pixels in the input image I within a rectangular region.

$$I(X) = \sum_{i=0}^{x}\sum_{j=0}^{y} I(i,j) \quad (3)$$

The computation time is independent of filter size due to the integral image representation. Then keypoint is detected by using determinants of the Hessian matrix. The locations having maximum determinant, blob-like structures are detected [15]. For a given location X, the Hessian matrix is given by

$$H(X,\sigma) = \begin{bmatrix} L_{xx}(X,\sigma) & L_{xx}(X,\sigma) \\ L_{xx}(X,\sigma) & L_{yy}(X,\sigma) \end{bmatrix} \quad (4)$$

Usually, SURF keeps the same image size and only varies the filter size. Finally, SURF descriptor is extracted by creating a square region associated to the selected orientation. In order to assign orientation, Haar wavelet responses are computed both in x and y directions which reduce both feature extraction and matching time.

HOG

HOG descriptors are widely used in Computer Vision for the purpose of object detection. The fundamental of HOG is to characterize local object appearance and shape by the distribution of local intensity gradients or edge directions without the prior knowledge about edge location [11] [16].

The implementation of HOG descriptor at a specified image location is achieved by dividing image into small sub-images, known as cell. Accumulate histogram of edge orientations within each cell by quantizing the gradient directions and, for each such orientation bin, add gradient magnitudes for each pixels within that cell [17]. The histograms are stacked into one vector and the resulting vector represents the descriptor.

The gradient is calculated by filtering the standard grayscale image I with the subsequent filter kernels [18].

$$D_x = [-1\ 0\ 1] \quad \text{and} \quad D_y = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}$$

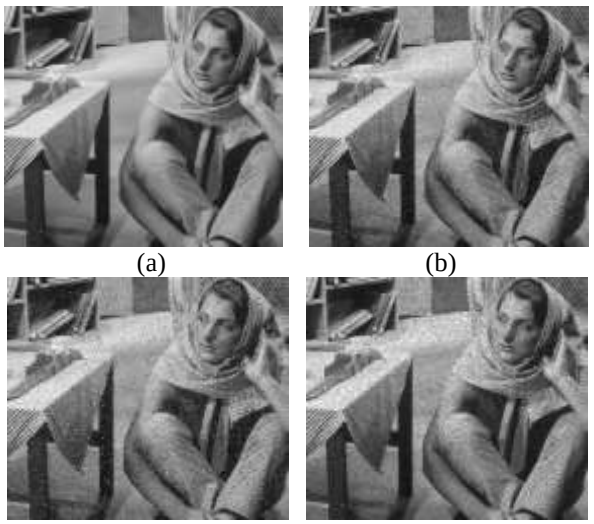
The x and y derivatives of the image I is derived by performing convolution with filter kernels as

$I_x = I * D_x$ and $I_y = I * D_y$

The magnitude and orientation of x and y derivatives of image I are calculated as $|G| = \sqrt{I_x^2 + I_y^2}$ and $\theta = \arctan \frac{I_x}{I_y}$ respectively.

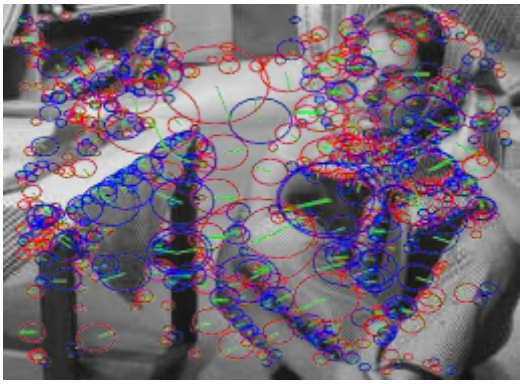
III. EXPERIMENTAL RESULTS AND DISCUSSION

In this work, we measure efficiency of various feature detection methods such as SIFT, SURF and HOG on the noisy images.

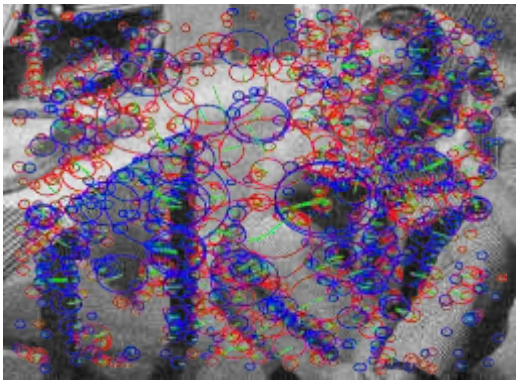


(a) (b) (c) (d)

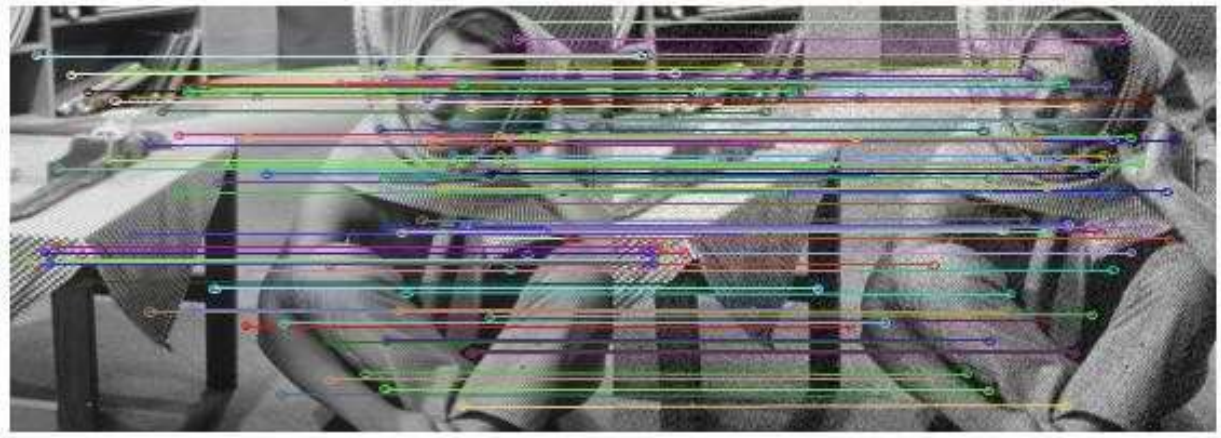
Fig.1. Test images (a) Original Barbara Image (b) in presence of Gaussian Noise (c) in presence of Salt and Pepper Noise (d) in presence of Speckle Noise



(a)



(b)



(c)

Fig.2. (a) Detected features in original Barbara Image using SURF (b) Detected features in Noisy Image corrupted with Gaussian using SURF (c) Matching Points between Original and Noisy Image using SURF.

Fig.3. Matching Points between Original and Noisy Image using SIFT.

To test the noise invariance, we apply three types of noise namely Gaussian, salt & pepper and speckle noise to the test image Barbara. In this experiment, we add Gaussian noise with variance range from 0.01 to 0.03, salt and pepper noise with variance range from 0.05 to 0.07, and speckle noise with variance range from 0.04 to 0.06. We detect features both in original and noisy images using SIFT, SURF and HOG algorithms. To find the matching between original and noisy image, all feature correspondence is recorded. If more feature correspondence found between original and noisy image, then the matching accuracy increases. All detected features of original image are tested one by one against the noisy image and when same information is found then a new match is originated.

Table.1 Comparative Results Of Sift And Surf Algorithms

Types of Noise	Noise Variance	SURF			SIFT		
		Detected Feature Points	Detected Matching Points	% Effectiveness	Detected Feature Points	Detected Matching Points	% Effectiveness
Gaussian	0.01	1214	205	17	1536	236	15
	0.02	1351	167	13	1432	176	12
	0.03	1371	124	9	1402	138	10
Salt & Pepper	0.05	1363	213	15	1833	267	14
	0.06	1507	185	12	1840	215	14
	0.07	1413	155	11	1936	176	9
Speckle	0.04	1222	231	19	1562	263	17
	0.05	1258	198	16	1621	223	14
	0.06	1262	189	15	1532	199	13

Fig.1. shows the sample image Barbara and various noisy versions of it. Fig. 1(a) shows the original grayscale Barbara image and Fig. 1(b), (c) and (d) show image corrupted with Gaussian, Salt & Pepper and Speckle noise respectively. Fig. 2 (a) and (b) demonstrate the detected features in original Barbara image and noisy image corrupted with Gaussian noise with variance 0.01 respectively using SIFT. Fig.2 (c) shows the matching points between original and noisy image. Fig. 3 shows the matching points between original and noisy image degraded with Gaussian noise with variance 0.01. Similarly, Table.1 shows the comparative result of SIFT and SURF for different types of noisy image corrupted by varying amount of noise. It is observed from Table.1 that SIFT detects more features and matches than SURF for all types of noisy images.

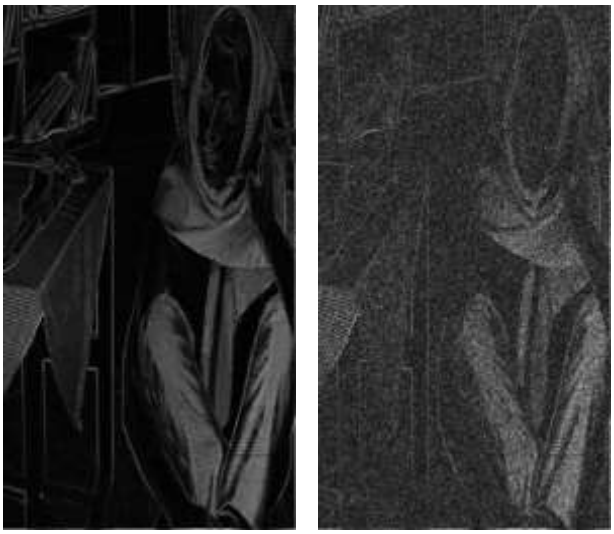


Fig.3. (a) Appearance of Gradient orientation of original Image using HOG (b) Detected Appearance of Gradient orientation of Noisy Image corrupted with Gaussian with variance 0.01 using HOG

But, SURF detects more robust features having enough information for image matching. Also, it is observed from Table. 1 that SIFT has less effectiveness as compared to SURF. The effectiveness is the measure of matching features with respect to detected features.

Also, we detect the features points using HOG descriptor. Similarly, Fig. 4 (a) and (b) shows appearance of Gradient orientation of original Image and noisy image using HOG respectively. Here, HOG computes both magnitude and directions of image gradient by thresholding small gradient magnitudes to zero.

IV. CONCLUSION

In this paper we have analyzed different feature extraction approaches on various types of noisy images. Also we determined the matching points between the original and noisy images. Based on the results, SIFT descriptor detects maximum feature points and matching points in an image as compared to SURF and HOG. However, SIFT randomly find the keypoints in an image and also, it is slow. But, SURF is fastest among all and has good performance at par with other, but it is not stable. Although, SIFT detects more features points and matching points but the effectiveness of SURF is better than SIFT. However, HOG descriptor focuses more on the textural information of the image. The future work is to get better performance of feature detection algorithms and to apply them for Image denoising.

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