A New Method to Improve the Difference of Gaussian Feature Detector

Hassan Amerehie, Rouhollah Dianat, Farshid Keynia

***Abstract*— One of the basic requirements in images representation was the feature extraction and its proper description and has many applications in the image processing and the machine vision. Many of the local feature descriptors of image use the difference of Gaussian feature detector. This detector is too much invariant against the scale changes. In this paper, a procedure is presented to select a proper threshold for the standard deviation in Gaussian filter to improve the performance of difference of Gaussian detector. In this paper's method, based on the properties of co-occurrence matrixes, the spatial dependences between available points in the image are divided into three general classes: sharp points, middle points and unsharp points, and then, on the basis of this division, the appropriate position is determined for stopping the development of standard deviation in Gaussian filter in some way that it is prevented to destroy the sharp points in the image and also to select the noise points as the key points of image.**

***Index Terms*— Difference of Gaussian (DOG), Feature Detector, Interest Point, Key Point**

I. INTRODUCTION

Many algorithms are presented to detect and extract the key features in the images that in spite of the apparent differences in the way of the performance, the natures follow the same purpose that is the reduction of the available data sets in the image than the set of clear and important features in the image; if this operation is completed well, the extracted features can act as an appropriate and perfect descriptor for the input image[2]. Geometric transformations are the important difficulties in extracting the features of the images that must be considered in this process. In several recent decades, the difference of Gaussian feature detector is considered as the most successful feature detectors. This method is invariant against some geometric transformations specially scaling transformation and has a good performance. It is also used in many of feature description methods, such as SIFT [3]–[5].

In this paper, a method is presented to improve the Difference of Gaussian Feature Detector. This method is based on the spatial dependences in the co-occurrence matrix and three mentioned classes in this paper. In this method, a procedure is presented for selecting an appropriate threshold for the standard deviation in the Gaussian filter to improve the difference of Gaussian detector performance.

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The second section is devoted to introduce the previous brief works by two topics of the difference of Gaussian feature detector and the co-occurrence matrixes. In the third section, the mentioned method is explained. In the fourth section, the results of this method are presented. And finally in the fifth section, the suggestions and the future works are discussed.

II. THE PREVIOUS WORKS

A. The Difference of Gaussian Feature Detector

The scaling transformation can be called as one of the considered geometric transformation on the image[1]. The points which are extracted as the image feature must be invariant than the scale changes, so that if there are the scale changes in the same images, there are not any problem in matching these images by considering the extracted features[4]. The methods which are based on the scale space can be considered as the most successful methods for overcoming the problem of the scale changes. It is showed that the best kernel is Gaussian kernel to create the scale space[9]. The Gaussian kernel is known as an optimum operator for images smoothing. The pattern of the Gaussian operator has the values that is determined by the Gaussian function. The G The Gaussian function in the coordinate (x,y) is controlled by variance (σ^2), defined by:

$$g(x,y,\sigma) = \frac{1}{2\pi\sigma^2} e^{-(\frac{x^2+y^2}{2\sigma^2})} \quad (1)$$

The (1) presents a method for calculating the coefficients of a Gaussian pattern that, in final, it is convolved by an image. Because of convolving this operator by any image, that image smooth. The amount of the image smoothing depends on two parameters in the Gaussian filter; the first one is the size of the Gaussian window and the second is the optional amount for σ(standard deviation). The size of Gaussian window determines the amount of the surrounding points that involve in convolving the image with the Gaussian filter. Whatever the size of window become bigger, the process of smoothing the image will certainly be faster. The σ measure indicate the standard deviation in Gaussian filter, in consequence, the image smoothes faster according to the measure of the optional σ, as the previous parameter. Thus, the scale space is described as the function L(X,Y,σ) for an image which is obtained by Convolving the image L(X,Y) with a function of the Gaussian variance scale G(X,Y,σ)[7], [8] , [13]. Pay attention to figure (1).

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

Figure 1. The Produced Scale Space by Gaussian Filter

After producing the scale space, we must present a method on the basis of this space for extracting the proper features. This method applies the difference of Gaussian feature (DOG) detector. This method uses the DOG function defined as (3).

$$D(x,y,\sigma)=(G(x,y,k\sigma)-G(x,y,\sigma))*I(x,y) = L(x,y,k\sigma)-L(x,y,\sigma) \qquad (3)$$

Equation(3) can be explained in the simpler way; that is the scale space is produced on the main image by implementing the increasing paces of Gaussian kernel standard deviation(σ). The difference of each new image is obtained by using Gaussian filter from its prior image, is called the Gaussian difference. Now, if the Gaussian difference covers all images of the scale space, we can obtain the differences of Gaussian images on the scale space. Figure(2) displays the way of producing the differences of the Gaussian images.

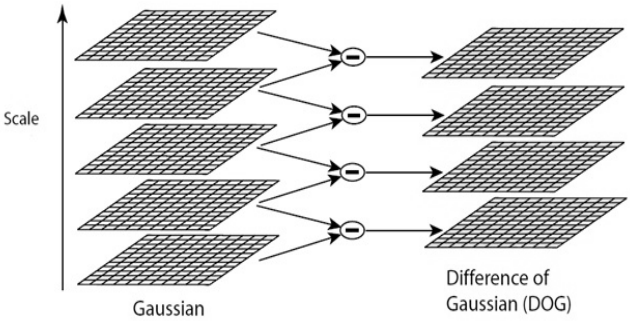

Figure 2. The Produced Scale Space by Gaussian Filter and Gaussian Differences

The differences of Gaussian feature detector introduces the points as interest points which is known as local extremum in differences of Gaussian images[6], [10]. By considering figure(3), to find the local extremum points, each pixel of the image obtained by Gaussian difference is compared by its 8 adjacent pixels and 9 equivalent pixels in a higher scale and 9 equivalent pixels in a lower scale than itself. If it is bigger or smaller than all of them, it can be introduced as an interest point.

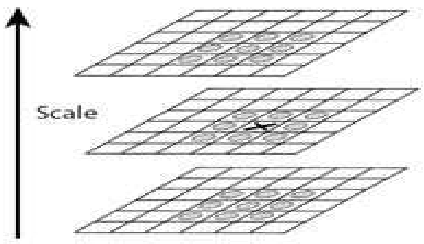

Figure 3. The Way of Comparing the Points to Get Extremum Points

These comparisons and the extremum finding are done for all pixels in the difference of Gaussian images, and at the end, all points that are extermum and their contrast is more than a threshold, are extracted and considered as the key points. These points are the introduction candidate as the local features of the image[12], [14], [15].

B. The Co-Occurrence Matrixes

The co-occurrence matrixes are simple accounting approaches based on the available spatial dependences among the image pixels. The idea of expressing the spatial dependences among the image pixels in the form of the co-occurrence matrixes in[11], is suggested in order to extract the texture features from the image data blocks. This idea is based on the assumption that the information of texture content in image is covered in the spatial dependences that the gray level have with each other. More specially, the information of the texture content is presented by the co-occurrence matrixes. The co-occurrence matrix is a function of angular dependences between the neighbor cells in a predetermined space. This matrix is also called the gray tone spatial dependence or the gray tone co-occurrence matrix. According to the Figure(4), there are eight neighbor cells for each image cell, except those put in the margin of image.

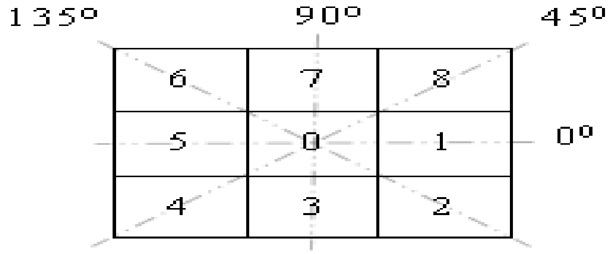

Figure 4. 8 Neighbor Cells for Each Image Cell

Now for instance, the available value in cell [1, 2] from the co-occurrence matrix is the number of times that the gray levels with the values of 1 and 2 occurs in the certain direction and space in the adjacent of each other. To determine this number, we account the numbers of the couple cells in the gray levels matrix of the first image that is the first cell of the couple cells contain the gray level 1 and the second cell of couple cells contain the gray level 2, of course provided that the determined direction and space are also considered.

III. THE PROPOSED METHOD

In the mentioned method of this paper, the spatial dependences among the available points in image are divided into three general classes: sharp points(S), middle points(M) and Unsharp points(U) on the basis of the co-occurrence matrix properties. The sharp ones are points that from the aspect of co-occurrence matrix dependences in the dependence with their neighbors have considerable difference from the aspect of intensity. Unsharp points, by considering the presented dependences by co-occurrence matrix do not have very different intensity than its neighbors and have a lot of similarity to their neighbors and the third class is the middle points which are put between the first and the second classes and contains the soft middle dependences. The intensity of pixels in every image of the gray level can be in range [0...255], so co-occurrence matrix can say their dependences in level 256. To understand better the

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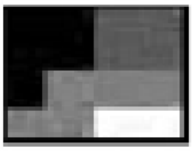
classifications, for example, suppose the values of the gray level of image normalized from 256 levels to eight levels, and based on these eight levels, the pixels dependences were described in co-occurrence matrixes; then the points are divided into the mentioned classes according to figure(5). For the image in part(a) of figure(6) that contains the values of the intensity in 265 levels(part(b)), co-occurrence matrix, for the dependences with the zero degree and by primary assumption of normalizing the image gray levels in 8 levels, is showed in the part(c) of figure(6). The dependence of every point in the image with its near neighbor in the zero degree direction can put in these 8 levels. By paying attention to position of this dependence in co-occurrence matrix, the class of this dependence can be determined.

	1	2	3	4	5	6	7	8
1	U	M	M	M	S	S	S	S
2	M	U	M	M	M	S	S	S
3	M	M	U	M	M	M	S	S
4	M	M	M	U	M	M	M	S
5	S	M	M	M	U	M	M	M
6	S	S	M	M	M	U	M	M
7	S	S	S	M	M	M	U	M
8	S	S	S	S	M	M	M	U

Figure 5. Classifying the Points in Image into Three Classes by Considering Co-Occurrence Matrix Dependences

As it is observed in the co-occurrence matrix of figure (6), if we want to assign the values of the intensity in range [0...255] to 8 dependence levels in the co-occurrence matrix, each 32 gray levels of input image are assigned to a level of the co-occurrence matrix. In this example, the values of zero intensity in level 1, the values of 90 intensity in level 3, the values of 127 intensity in level 4, and the values of 255 intensity in level 8 of the co-occurrence matrix are put. By considering these levels, the dependences among image points are described in the co-occurrence matrix.



(a)

0	0	90	90
0	0	90	90
0	127	127	127
127	127	225	225

(b)

	1	2	3	4	5	6	7	8
1	4	0	2	1	0	0	0	0
2	0	0	0	0	0	0	0	0
3	2	0	4	0	0	0	0	0
4	1	0	0	6	0	0	0	1
5	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0
8	0	0	0	1	0	0	0	2

(c)

Figure 6. The Original Image (A) and the Values of its Gray Level Matrix (B) Co-Occurrence Matrix of the Original Image with 8 Level (C)

Of course, in this paper, the levels of co-occurrence matrix dependences are explained in 256 levels and the above example is exclusively presented to understand better. By paying attention to figure(6) and by threshold between S, M and U classes, in the way of figure(5), for the above example, the numbers of points of each class are obtained in the following way.

S= 2, M= 6, U= 16

Paying attention to the recorded values in the co-occurrence matrix in this example are calculated symmetrical. In the rest of this paper, we will apply the mentioned classifications for presenting a new method to improve the difference of Gaussian feature detector. Selecting the threshold of the standard deviation in Gaussian filter is one of the vague points in the past researches that this important point, are not seriously and exactly considered in the previous studies, whereas the act of selecting the pause position of using the Gaussian filter is very important. We exactly consider this matter in this section of the paper and will completely explain our mentioned method for this subject. The pause position of using the Gaussian filter in scale space is important in the variable aspects that we refer to two points before explaining the proposed methods. The first one is to consider this point that using the Gaussian filter causes to smooth the image and the feature detector get the ability of detecting the scale invariant points in the process of smoothing; but smoothing the image has the other effects that the reduction of the sharp points of image is the most important effect. The sharp points of image that is included the details in the image and has important information about the image, are one of the main candidates to introduce as the interest points. Using the Gaussian filter a lot and developing steadily the standard deviation in this filter can have the destructive effects, such as changing extremely the sharp points to the middle points. So, by considering whatever is observed in figure(7), if the procedure of using the Gaussian filter continue, it causes to destroy completely the sharp points into the image.

(a) (b)

Figure7. The Original Image (A) and the Extreme Smoothed Image by Gaussian Filter (B)

The second point, can be about noise images. Noise appears in an image in different forms, but the available common point in all noises is that, the noise defects the details of the image. Since the local features are extracted from the details in the image, noise can defect and make a mistake in extracting the image features and it is possible that there are the points in the sets of points which are introduced as the local features of image that in fact are not a part of image and the result of this defect and mistake in determining the feature can make the lack of proper correspondence of two same images. Using the Gaussian filter on the noise image must also stop in an appropriate position, because the experiments which are performed by us on the different images demonstrate that if Gaussian filter are extremely used on noise image, the process of smoothing the original

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information of image will have a faster procedure than the process of smoothing the noise. And finally, it is possible that the points related to noise appear and remain sharper than the point related to the main information of image. Thus, producing the pause point in using Gaussian filter can prevent this unsatisfied effect in creating the scale space. Observing the images in figure(8), that is one of the experiments that are performed by us, can help to perceive better this subject. These images are the production of using Gaussian filter on a sample image and the noise image of the same image. These images are created in two paces of using Gaussian filter. As you observed, after developing extremely the standard deviation(σ) in Gaussian filter and using it on noisy image, the noises of image show the more permanence than the original information of image.

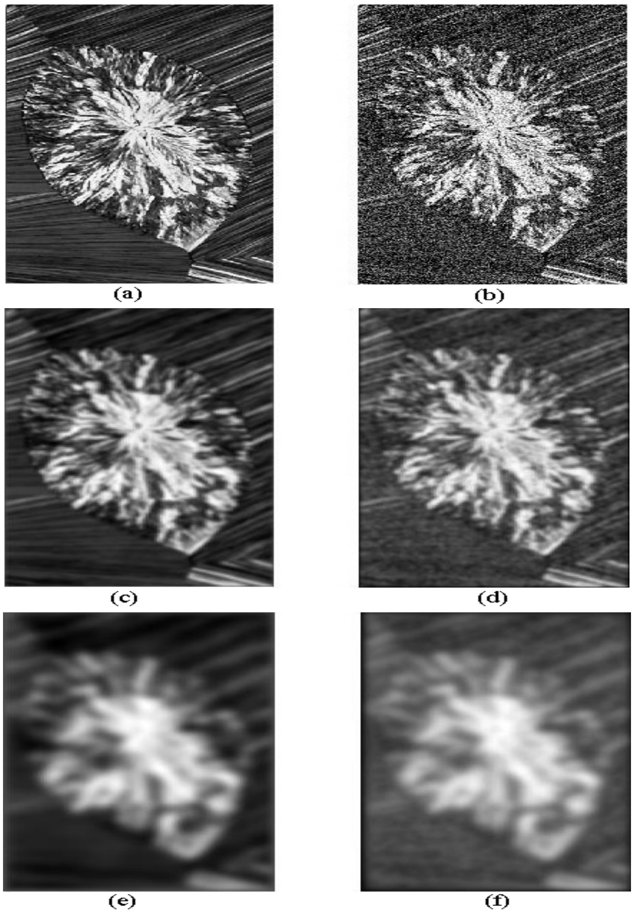

Figure 8. The Original Image Without Noise (A) and Two Phases of Using Gaussian Filter Accompanied by the Above Standard Deviation (C),(E), Noised Image (B) and Two Phases of Using Gaussian Filter Accompanied by the Above Standard Deviation (D),(F)

By considering two above mentioned cases, we propose a method to prevent the extreme development of using this filter and finally its destructive effects by presenting threshold of using Gaussian filter in producing the scale space. Our method is based on using the co-occurrence matrix and the mentioned classifications too.

By paying attention to the materials which were already explained, suppose we want to produce a scale space for an input image. First, we do a normalized operation on input image so that the space of the intensity of each point from the image to intensities sum mean of image, becomes approximately 0, and the sum points of the image standard deviation become 1. Then, the co-occurrence matrix of the normalized image are calculated symmetrical and in four directions, i.e. 0, 45, 90 and 135 degrees and saved separately in four co-occurrence matrix. After passing this stage, we calculate and save the numbers of points related to each kind of the classes, sharp(S), middle(M) and unsharp(U) that are obtained from four co-occurrence matrixes. This act leads us to be able to account all spatial dependences between the image points and each of them put in one of the specific classes or categories. In the next stage, the normalized image in a N pace range is produced by the convolved Gaussian function and N Gaussian image in the scale space. That is important to say that we consider the range of Gaussian standard deviation [0.01…3] in our experiments (N=300). Then, we reach to the stage of producing the scale space of 300 Gaussian image. After the new Gaussian image is produced each time, the first stage will repeat on it. It means, for each Gaussian image, the co-occurrence matrixes are calculated in four directions and accounted the point related to each three classes. After the N paces we will have a N*4 matrix that are put in each row of the numbers of Gaussian filter pace, the sum points of S class, the sum points of M class and the sum points of U class related to that pace. By increasing the Gaussian filter paces, gradually, the standard deviation measure in this kernel is increasing and it causes to change gradually the sharp points(S) to middle points(M) and unsharp points(U), and middle points(M) to unsharp points(U) too and if this procedure does not stop in a proper position, almost all sharp and middle points will change to unsharp points. Thus, in the images without noise, the diagram of sharp points and middle points with related slopes to itself is descending in a downward direction and the diagram of the unsharp points is ascending with its related slope in an upward direction. The destructive effect of ascending the Gaussian filter paces is completely obvious in noise images. If the ascending of standard deviation in Gaussian filter does not stop on time, the noise points will introduce as the key point of image. In the next stage, we make noise the same proper image and produce the scale space for noise image in 300 paces and by the ascending pace 0.01. The numbers of spatial dependences of points that are put in S, M and U classes are saved in an elemental 300*4 array in each kind of these paces. The Standard deviation pace(σ), S points numbers, M points numbers and U points numbers related to this pace are put in each row of this array. Then, we draw the diagram of 300 paces for each kind of S, M, and U classes. These results are indicated in figure(9) to (14). In (9), (11) and (13) figures, the (a) one shows the values of co-occurrence matrix in four determined directions for 300 paces, the (10), (12) and (14) figures shows the sum values of the co-occurrence matrix for four directions and the (b) demonstrates the (a) corresponding derivations. Paying attention to U and M diagrams that shows the unsatisfied events are occurring around the 0.40 pace, toward. These events are very important, so we consider them. As it was explained before, the ascending procedure of the standard deviation paces, gradually change the sharp and middle points to unsharp points, but it is observed, in the drawn diagram that this procedure is reversed around 0.40 pace in U and M diagrams and the middle points are increasing and the unsharp points are decreasing by ascending the standard deviation paces. Our experiments indicate that around this

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standard deviation, the related noise points are being introduced as the key points of image. To prevent from this event, using Gaussian filter must be stopped around this point. In the rest, we present the results of supplementary experiments to prove the mentioned discussion.

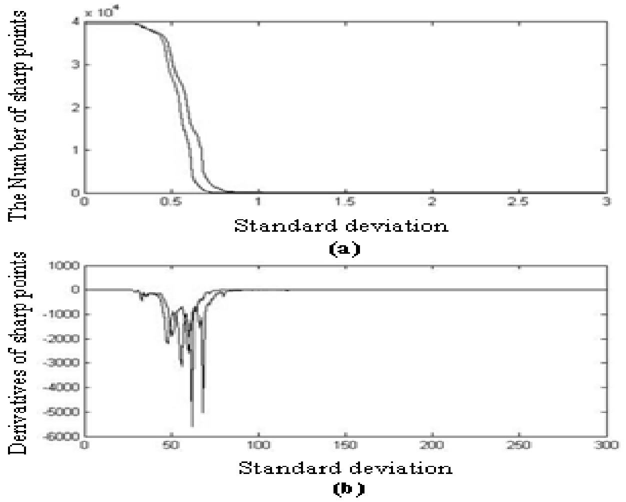

Figure 9. The Number of Sharp Values of Co-Occurrence Matrix in Four Directions

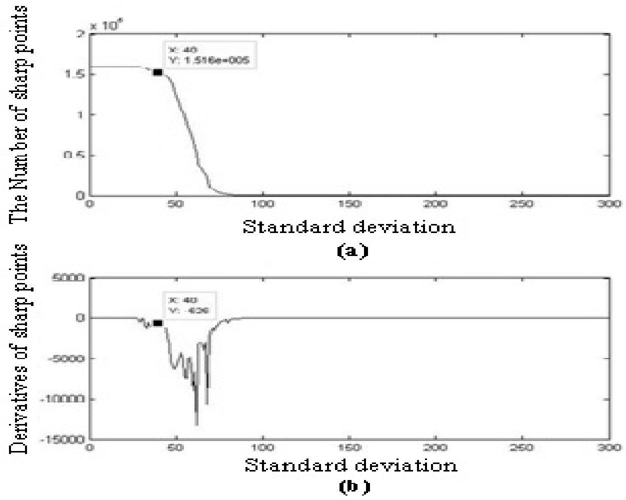

Figure 10. The Sum Sharp Values of the Co-Occurrence Matrix for Four Directions

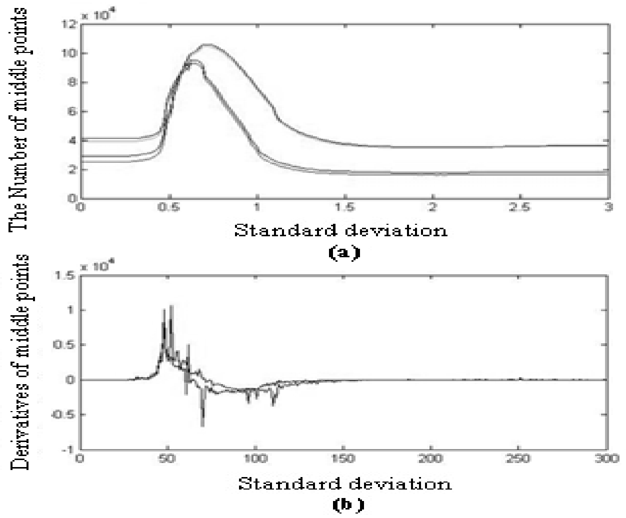

Figure 11. The Number of Middle Values of Co-Occurrence Matrix in Four Directions

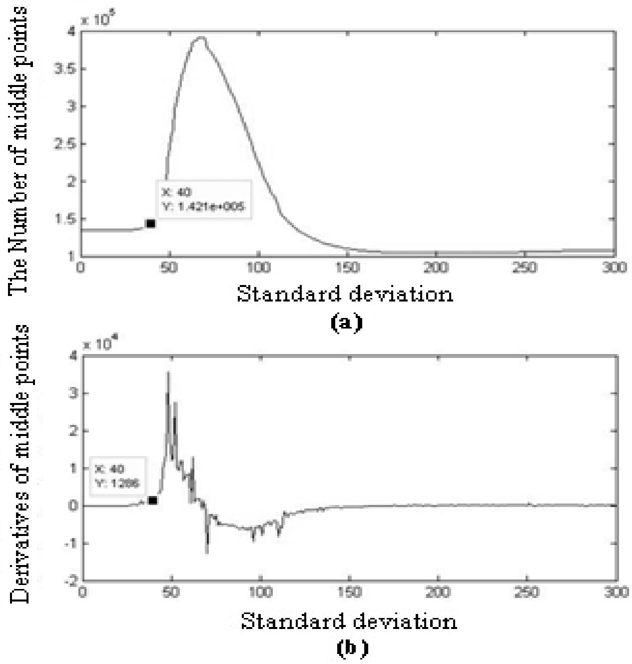

Figure 12. The Sum Middle Values of the Co-Occurrence Matrix for Four Directions

By considering the produced noise image in the previous stage, the points related to noise are gained by the difference of noise image and the original image and we transform an image which contains just noise to a binary image by selecting a proper threshold, that number 1 is an indicator of the noise point and zero is an indicator of the lack of noise. Observe figure(15). Then, we produce the scale space for noise image in 300 paces and by increasing pace 0.01. In each kind of these paces, we save the numbers of points that are extracted as interest point in an elemental 300 array. On the other side, by considering this fact that we already save just the noise image; therefore we possess coordinate of the noise point. In the other elemental 300 array, we save the numbers of interest point that in each pace, are exactly put on noise.

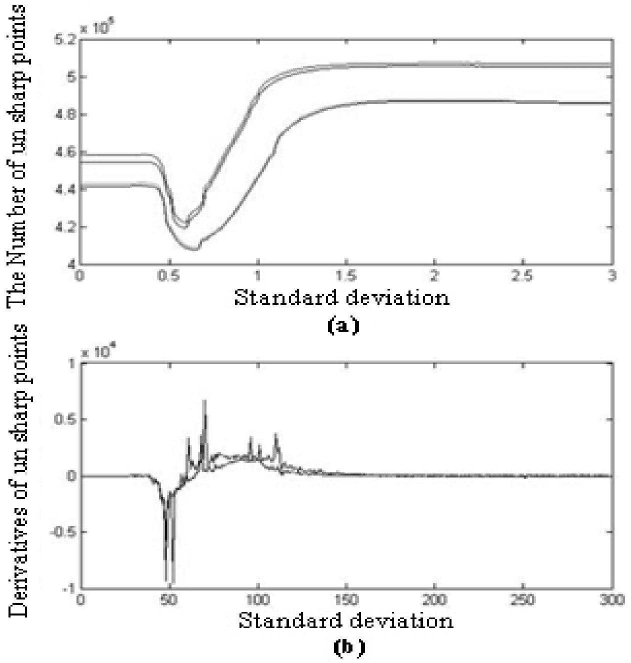

Figure 13. The Number of Unsharp Values of Co-Occurrence Matrix in Four Directions

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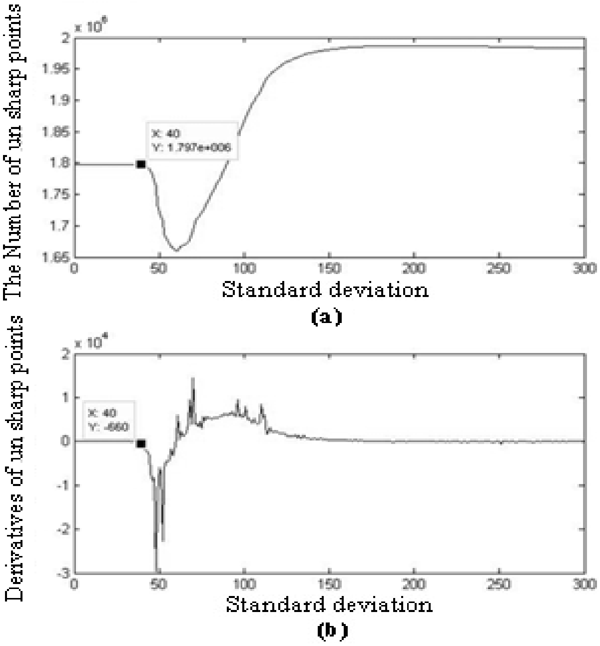

Figure 14. The Sum Unsharp Values of the Co-Occurrence Matrix for Four Directions

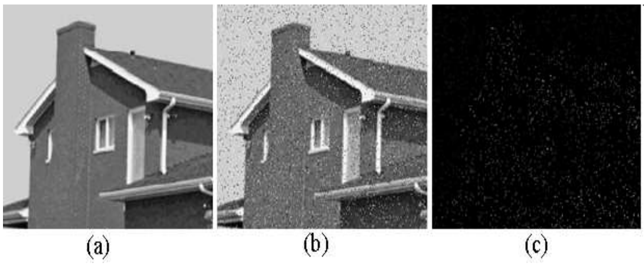

Figure 15. The Original Image (A), the Noise Image (B), the Noise Point Image (C)

In the rest, we draw two diagrams, figure(16) is the diagram related to the numbers of extracted interest points in each pace of increasing the standard deviation of Gaussian filter and figure(17), is the diagram of the numbers of extracted interest points in each pace of using Gaussian filter that are exactly put on noise. By paying attention to the first diagram we understand that nearly in the standard deviation after 0.40, a considerable jump occurs in the number of points that is known as interest point that exactly, and in this example, this raise ascends in 0.43 to 0.44. If you observe figure(17) you will see that around this point, i.e. approximately 0.40, interest points that are put on noise are considerably increasing and in this example, this raise ascends exactly in passing of 0.43 pace to 0.44. The gained results in supplementary experiment prove the obtained results of the co-occurrence matrix and the proposed classes. Our experiments demonstrate if the image becomes normal in the way that the space of the point from the points mean approximately zero and the standard deviation of the whole image become 1, interest point for the standard deviation of Gaussian filter in normalized images is approximately 0.4, by a little increase or decrease. This result is obtained by helping and using the co-occurrence matrix variance and is proved by the supplementary experiments.

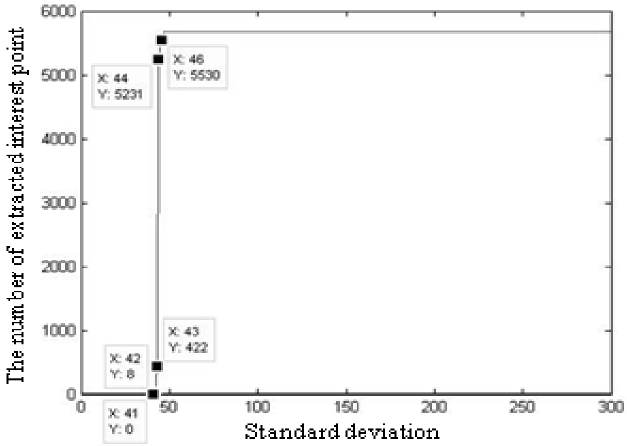

Figure 16. The Extracted Interest Point of Noise Image

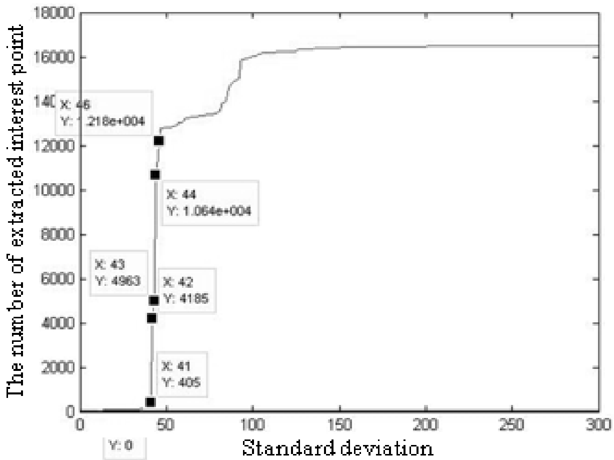

Figure 17. The Extracted Interest Point of Noise Image Which are Exactly Put on Noise

IV. THE RESULTS OF PROPOSED METHOD

In this section, we consider presenting the obtained results from applying the proposed method. To evaluate accurately, we apply this method on the numbers of image with a different amount of information that are selected from the set of the known standard images and it is determined that the threshold of standard deviation in them is almost 0.41 to 0.43, based on the primary normalized image which are already explained. And at the end, in table(1) we show the results or the reduction of the key points on noise accompanied by the obtained threshold, on the numbers of examined images; the same images of figure(18).

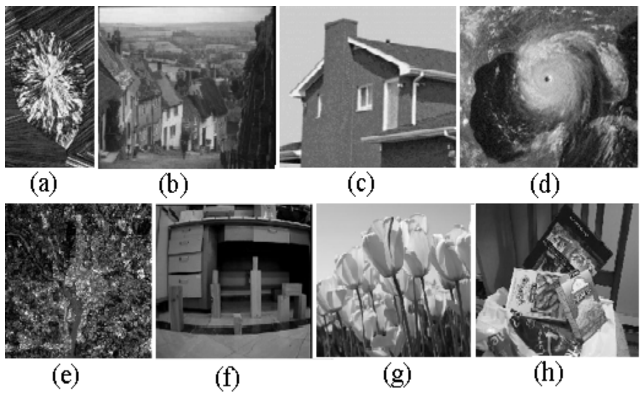

Figure 18. The Optional Images to Evaluate the Proposed Method

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Table 1. The Results of Proposed Method on the Numbers of the Sample Image

Image number	The obtained standard deviation limit of proposed method	The numbers of decreased key points which are exactly put on noise
a	0.41 to 0.43	2623
b	0.41 to 0.43	7358
c	0.41 to 0.43	5313
d	0.41 to 0.43	31108
e	0.41 to 0.43	21923
f	0.41 to 0.43	6614
g	0.41 to 0.43	3647
h	0.41 to 0.43	3858

V. CONCLUDING AND SUGGESTIONS

A. *Concluding*

In this paper, a method is presented to improve the difference of Gaussian feature detector. This method uses the spatial dependences which are considered in the co-occurrence matrixes and the dependences classes, sharp, middle and unsharp which are proposed in this paper on the basis of co-occurrence matrixes. Difference of Gaussian feature detector is one of the most important detectors in determining the local features that in many known descriptors is also used. The main mentioned idea in this detector is to use the Gaussian function for extracting the invariant key points against the scale transformations. The vague point in this detector is the threshold of developing the standard deviation in used Gaussian filter that in the past researches are not seriously considered. Therefore, in the proposed method, a method is presented to find the proper threshold for the standard deviation in Gaussian filter. The presented method follow two purposes, that the first is to control the sharp points destruction in image because of using the Gaussian filter, and the other is to prevent from introducing related noise points in noise images as the key points. The results of the proposed method indicate that by using this idea, it is avoided to select many noise points as key points.

B. *The Suggestions and the Future Work*

It is possible to increase the accuracy in the key points extracting by making the standard of selecting the threshold more exact, in separating the sharp, middle and unsharp dependences classes. Thus, the methods select the threshold automatically can help to increase the accuracy of detector. To improve the performance of proposed method, we can use the neural network to select the proper threshold in the standard deviation for Gaussian filter. The variable researches about the neural network explain that if these networks have the accurate training procedure, they can increase the accuracy of mentioned method.

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