International Journal of Soft Computing and Engineering (IJSCE)
ISSN: 2231-2307, Volume-4 Issue-4, September 2014

A New Method to Improve Feature Detection Methods Based on Scale Space

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Abstract— ***Scale-space theory provides a well-founded framework for modelling image structures at multiple scales, and the output from the scale-space representation can be used as input to a large variety of visual modules. Visual operations such as feature detection, feature classification, stereo matching, motion estimation, shape cues and image-based recognition can be expressed directly in terms of (possibly non-linear) combinations of Gaussian derivatives at multiple scales. In this sense, scale-space representation can serve as a basis for early vision. The Gaussian scale-space is widely used to model the human visual system. The main reason why Gaussian scale-space solely being used is that the Gaussian function is the unique kernels which satisfies the causality property i.e., it states that no new feature points are created as the scale increasing. The Gaussian filter are highly suitable for smoothing image. The amount of smoothing depends on the value of the standard deviation parameter of the Gaussian function. The problem of creating Gaussian scale- space is that if image smoothing does not stop in a proper point; it may lead to extreme destruction of local features of the image. In this paper, an approach has been presented to enhance a scale-space based on Gaussian function in order that a threshold is chosen for standard deviation in Gaussian filter with aim of preventing extreme destruction of image local features. Results of the proposed method indicate that this method affects considerably prevention of extreme destruction of image features and it can be very effective on creation of scale-space with high accuracy.***

Index Terms— ***Destruction Rate, Feature Detection, Gaussian Scale Space, Scale-space representation***

I. INTRODUCTION

The concept of scale-space was coined to the image analysis community by Witkin in 1983[9]. The idea is to handle the multiscale nature of real-world objects, which implies that objects may be perceived in different ways depending on the scale of observation. If one aims to develop automatic algorithms for interpreting images of unknown scenes, there is no way to know a priori what scales are relevant. Hence, the only reasonable approach is to consider representations at all scales simultaneously. From axiomatic derivations is has been shown that given the requirement that coarse-scale representations should correspond to true simplifications of fine scale structures, convolution with Gaussian kernels and Gaussian derivatives is singled out as a canonical class of image operators for the earliest stages of visual processing[7]. These image operators can be used as basis to solve a large variety of visual tasks.

Manuscript Received on September 2014.

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By complementing scale-space representation with a module for automatic scale selection based on the maximization of normalized derivatives over scales, early visual modules can be made scale invariant[6][19]. In this way, visual modules can adapt automatically to the unknown scale variations that may occur because of objects and substructures of varying physical size as well as objects with varying distances to the camera[12][20]. DOG scale space had been successfully applied by Lowe in designing scale-invariant feature transform (SIFT), which is one of the most popular keypoint detection techniques used to detect and describe local features in images [10]. In this method, DoG scale-space is applied to find key points that are invariant to scales [1]. In this paper, a method has been represented in order to enhance accuracy of creation of scale-space based on Gaussian function. This method presents a stop point for growth of standard deviation in Gaussian filter concerning a new measure so called features' destruction rate that is individual for each image based on amount of information inside the image. In the second section, scale-space representation is described. The proposed method and the results will be presented in sections three and four respectively. Finally, conclusion and suggestions are expressed.

II. SCALE-SPACE REPRESENT

An inherent property of real-world objects is that they exist as meaningful entities over a limited range of scales. The classical example is a tree branch. A tree branch is meaningful at the centimeter or meter levels, but loses its meaning at very small scales where cells, molecules or atoms make sense, or at very large scales where forests and trees make sense[8][20]. A technique for dealing with features at multiple scales is to derive representations of the data through multiple scales. The scale-space representation framework introduced by Witkin (Witkin 1983) allows us to derive such multi-scale representations in a mathematically way [9]. The virtues of the scale-space approach are twofold. First, scale-space representation allows multiple interpretations of the data from fine details to high level descriptions of the overall structure of the image content. Second, the scale-space approach provides the flexibility for selecting a scale or a set of scales by looking at how the interpretation of the structure / object captured in the scale-space changes with the scale [1]. The basic idea behind the scale-space representation is to generate successively higher level descriptions of a signal by convolving it with a filter. As our filter, we use the Gaussian defined as[4][5][15][16][17]:

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

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where σ is the smoothing parameter that controls the scale. According to the Figure(1), A higher σ means a coarser scale, describing the overall features of the data, while a smaller σ corresponds to finer scales containing the details.

Figure 1. The Effect of Increasing σ of the Gaussian Function on the Image

The Gaussian filter does not introduce new feature points as the scale increases. This means that as scales get coarser, the number of features (obtained by extrema of the data in question) either remains the same or decreases. The Gaussian kernel is unique in this respect for use in scale space filtering as discussed in (Yuille & Poggio 1986) and (Babaud et al. 1986)[2][13].

III. THE PROPOSED METHOD

In this section, a summary of performance and effects of Gaussian filter is explained. Then, destruction rate and suitable sigma are calculated and five stages of the proposed method are explained.

A. Gaussian Filter

Gaussian averaging operator is known as an ideal operator for image smoothing. Gaussian operator pattern has values determined by Gaussian relation. Gaussian function expressed in (1) presents a method for calculation of coefficients of a Gaussian pattern which convolves with the image. The image is smoothed in order to convolve this operator with each image. Image smoothing depends on two parameters in Gaussian filter: the first, size of Gaussian window and the second, value chosen for σ (standard deviation). Size of Gaussian window determines extent of neighboring points by which the image is convolved with Gaussian filter. If the size of the window is increased, the process of image smoothing will be fast. Size of σ shows standard deviation in Gaussian filter. Therefore, if σ is chosen as large as possible, the image will be smoothed rapidly[11]. Generally, image smoothing is equivalent to decreased image details. Due to decreased details, many things are happened including conversion of salient points of the image into smooth points with little or without information. Also, details lost due to smoothing can be features present in the image which are unpleasant. Noise is taken into account as one of image details and it is deleted by Gaussian filter. Noise deletion is ideal. Generally, image smoothing with Gaussian filter, despite providing an appropriate context for extracting features and other applications such as noise deletion and image enhancement, can have destructive effects on the image. These effects are appeared when σ size has maximized extremely in Gaussian filter. In other words, a big σ has been chosen. In this paper, we attempt to present a method in order to choose a suitable size for σ in different images and thus to prevent unreasonable growth or false selection of σ followed by destructive effects of incorrect selection. The proposed method is known as features destruction rate in operations of Gaussian filter. The aim of obtaining features destruction rate after operation of Gaussian filter is to calculate a suitable σ for each image in a way that advantageous image information dose not destroy due to Gaussian filter. The proposed method introduces and calculates a threshold for σ per input image.

B. Calculation of Destruction Rate and Suitable σ

We have chosen edge local feature to describe our method but the method presented for other features such as corner is used as well. The edge is one of the most important local features of the image. Methods for extracting it accurately have been studied in several researches [3][18]. As mentioned, in addition to suitable and positive effects, operation of Gaussian filter on images can destroy image features. The edge destruction is considered as one of negative effects of improper operation of Gaussian filter. Edge destruction should not damage structure of features in a way that those features are not recoverable. This destruction will be managed correctly if incorrect growth of σ is prevented in Gaussian filter. In this section, the proposed method is introduced. In this method, rate of features destruction on set of standard images is calculated then a threshold is proposed for σ in Gaussian filter. The threshold can be variable considering nature of the image and amount of advantageous information inside it. The proposed method can determine an individual threshold for each input image. For better understanding, stages of the proposed method are explained for edge local features but as mentioned at the beginning of this section, this method can be generalized to other local and global features.

Stages of the proposed method are as follows:

Stage 1: at first, input image is normalized in order that distance of intensity from each point of the image to total mean image intensity is close to zero and standard deviation of total image points becomes one.

Stage 2: edges of input images are extracted using one of edge detectors. The new image is called the edge image, pay attention to figure (2).

Figure 2. Original Image (a) and Edge Image (b)

All points of edge image contain binary values of zero or one where one shows edge points in edge image. Then, edge percentage is calculated in edge image. Output of the first stage is edge image and percentage of edges present in the image. Stage 3: Gaussian filter is performed on the image with an interval of standard deviation (for example in this paper, 80 values for standard deviation in 0-4 interval with incremental step of 0.05). In each step of Gaussian filter, images are obtained known as Gaussian images. Then, like the first stage, by operation of edge detector on the Gaussian image in that step, the edge image of Gaussian images related to that step is obtained. After operating Gaussian filter and obtaining edge

image of that step, the difference of total edge points between edge image of input image and edge image of current Gaussian image will be calculated. In fact, this difference indicates rate of edge destruction due to operation of Gaussian filter with σ determined in that step (see figure 3).

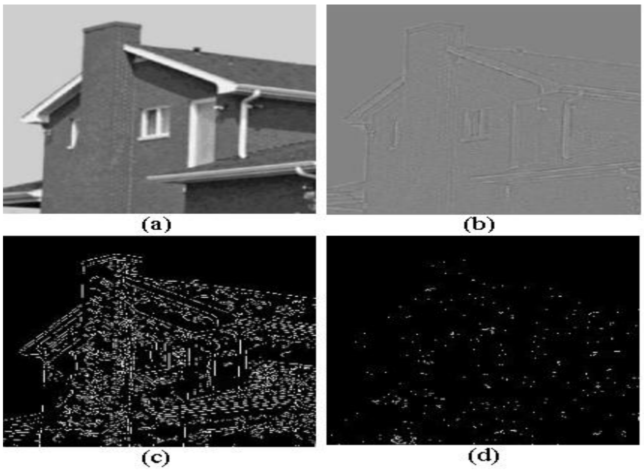

Figure 3. Original Image (a), Edge Difference of Original Image (b), Edge Image of One of σ Steps(c) and Edge Difference of Edge Image (d)

There are 80 values in 0-4 interval with step of 0.05. Therefore, 80 Gaussian images and 80 edge images will be obtained from input image. 80 rates of destruction per σ step are obtained by calculation of difference of edge points in each edge images resulted from input image. Incremental steps of Gaussian filter and rate of destruction of each step are saved in a two-dimensional array. This array shown in figure(4) for sample image in part(a) of figure(2) is submitted to next stage as an input. Stage 4: input of this stage is a two-dimensional array in which σs used in Gaussian filter are placed in the first column and rate of edge destruction resulted from σ is placed in the second column. In this stage, first order derivative of values of edge destruction is calculated and saved (see figure 5). Our experiments on different images show that destruction rate has a considerable jump when calculated derivative has a maximum value. Number of σ step equivalent to the found jump is sent to next stage.

σ	d_{ratio}	σ	d_{ratio}	σ	d_{ratio}	σ	d_{ratio}
0.0500	0	1.0500	0.0373	2.0500	0.0401	3.0500	0.0408
0.1000	0	1.1000	0.0374	2.1000	0.0401	3.1000	0.0408
0.1500	0	1.1500	0.0380	2.1500	0.0401	3.1500	0.0408
0.2000	0	1.2000	0.0381	2.2000	0.0403	3.2000	0.0408
0.2500	0.0000	1.2500	0.0383	2.2500	0.0405	3.2500	0.0409
0.3000	0.0002	1.3000	0.0383	2.3000	0.0405	3.3000	0.0409
0.3500	0.0011	1.3500	0.0384	2.3500	0.0405	3.3500	0.0409
0.4000	0.0031	1.4000	0.0384	2.4000	0.0405	3.4000	0.0409
0.4500	0.0059	1.4500	0.0386	2.4500	0.0407	3.4500	0.0409
0.5000	0.0075	1.5000	0.0387	2.5000	0.0408	3.5000	0.0409
0.5500	0.0098	1.5500	0.0391	2.5500	0.0408	3.5500	0.0409
0.6000	0.0114	1.6000	0.0395	2.6000	0.0408	3.6000	0.0409
0.6500	0.0136	1.6500	0.0395	2.6500	0.0408	3.6500	0.0409
0.7000	0.0149	1.7000	0.0396	2.7000	0.0408	3.7000	0.0409
0.7500	0.0157	1.7500	0.0397	2.7500	0.0408	3.7500	0.0409
0.8000	0.0167	1.8000	0.0398	2.8000	0.0408	3.8000	0.0409
0.8500	0.0179	1.8500	0.0398	2.8500	0.0408	3.8500	0.0409
0.9000	0.0365	1.9000	0.0399	2.9000	0.0408	3.9000	0.0409
0.9500	0.0368	1.9500	0.0399	2.9500	0.0408	3.9500	0.0409
1.0000	0.0371	2.0000	0.0400	3.0000	0.0408	4.0000	0.0409

Figure 4. Destruction Rates Calculated per Different σ Steps

diff	diff	diff	diff
0	0.0001	0.0000	0.0000
0	0.0006	0.0000	0.0000
0	0.0001	0.0002	0.0000
0.0000	0.0001	0.0002	0.0000
0.0001	0.0001	0.0000	0
0.0009	0.0000	0.0000	0.0000
0.0021	0.0001	0.0000	0
0.0027	0.0002	0.0002	0.0000
0.0016	0.0000	0.0001	0.0000
0.0023	0.0004	0.0000	0
0.0016	0.0004	0.0000	0
0.0022	0.0000	0.0000	0.0000
0.0013	0.0000	0	0.0000
0.0009	0.0001	0.0000	0.0000
0.0010	0.0001	0	0.0000
0.0011	0.0001	0.0000	0
0.0187	0.0000	0.0000	0
0.0002	0.0000	0	0.0000
0.0003	0.0001	0.0000	0
0.0002	0.0000	0.0000	

Figure 5. Derivative Values Calculated from Destruction Rates of the Third Stage

Stage 5: threshold of destruction is calculated by placing the number obtained from previous stage in following formula: Destruction threshold = starting σ + ((number of σ step obtained from maximum derivative of destruction rate-1)* σ incremental step).

IV. THE RESULTS OF PROPOSED METHOD

In this section, results obtained from the proposed method are presented. In our experiments, we implement this method on many images in figure(6) with different information that are chosen from famous standard images[14]. Both original and noised images have been used to prove positive effect of the presented method. Table(1) shows total number of points, number of points placed on the edge, ratio of edge points to total points and stop point of sigma obtained by the proposed method for each image. Table(2) and figure(7) show status of destructed edges and percentage of destruction in two states, default sigma and proposed sigma for images without noise. Table(3) and figure(8) shows status of destructed edges and percentage of destruction in two states, default sigma and proposed sigma for noised images. Result comparisons show that the proposed method had a good effect on prevention of extreme destruction of edge feature in chosen images.

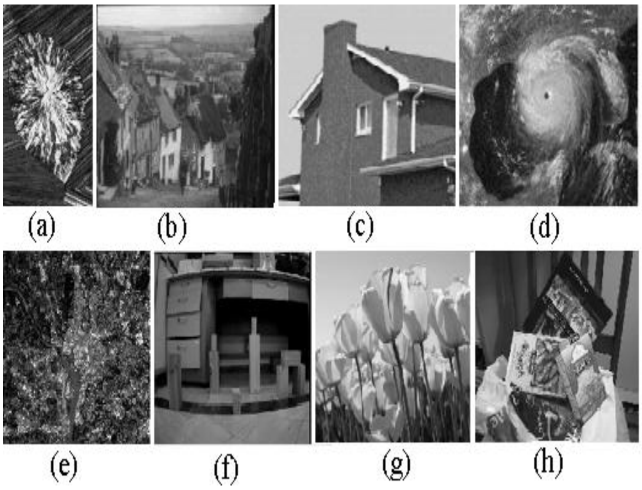

Figure 6. The Optional Images to Evaluate the Proposed Method

Table 1. Stop Point of σ Obtained by the Proposed Method

Image Number	total number of points	number of points placed on the edge	ratio of edge points to total points	stop point of sigma
Image 1	136321	20627	0.1515	0.400
Image 2	367200	44061	0.1200	0.400
Image 3	262144	25838	0.0986	0.850
Image 4	1476993	177793	0.1204	0.400
Image 5	1050624	185312	0.1764	0.450
Image 6	307200	21938	0.0714	0.600
Image 7	187500	18790	0.1002	0.500
Image 8	196608	18721	0.0952	0.600

Table 2. Number and Percentage of Destructed Edges for Images without Noise

Image Number	Default sigma		Proposed sigma	
	Number of destructed edges	percentage of destruction	Number of destructed edges	percentage of destruction
Image 1	4491	21.7724	601	2.9137
Image 2	9752	22.1330	1004	2.2787
Image 3	10719	41.4854	4682	18.1206
Image 4	44096	24.8019	6218	3.4973
Image 5	43379	23.4086	8416	4.5415
Image 6	4722	21.5243	1925	8.7747
Image 7	3268	17.3922	937	4.9867
Image 8	3445	18.4018	1512	8.0765

Table 3. Number and Percentage of Destructed Edges for Noised Images

Image Number	Default sigma		Proposed sigma	
	Number of destructed edges	percentage of destruction	Number of destructed edges	percentage of destruction
Image 1	3037	19.8640	328	2.1244
Image 2	6779	20.5449	789	2.3958
Image 3	25867	43.4761	20815	35.2904
Image 4	31747	25.5762	3443	2.7949
Image 5	32909	21.5011	5566	3.6539
Image 6	9415	32.7501	6166	21.4993
Image 7	6948	39.4930	3935	22.0770
Image 8	7363	33.8016	5385	24.7689

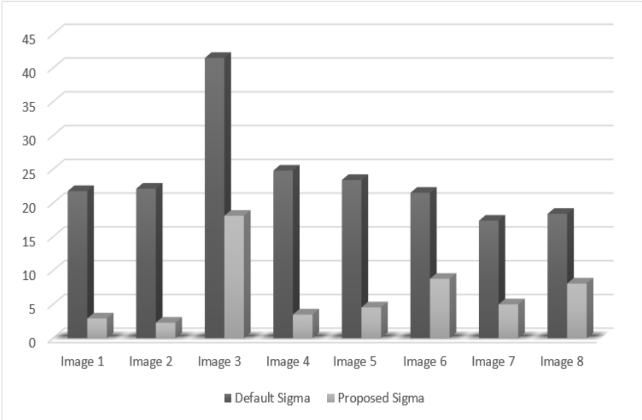

Figure 7. Comparison of the Percentage of Edge Destruction in Default and Proposed σ for Images without Noise

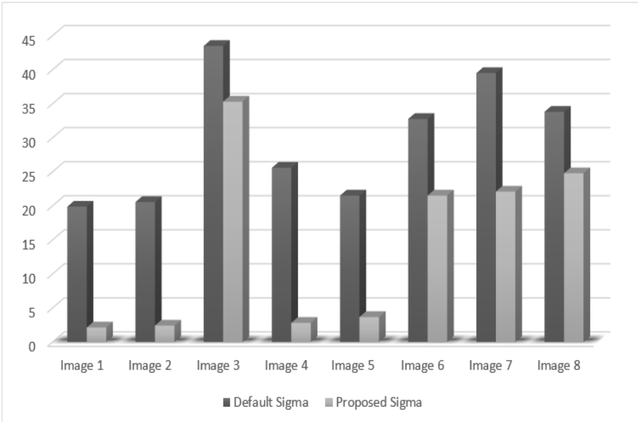

Figure 8. Comparison of the Percentage of Edge Destruction in Default and Proposed σ for Noised Images

V. CONCLUDING

In this paper, a method has been presented to enhance scale space in methods of feature detection based on scale space. The most important approach of scale space is to use Gaussian smoothing function. The point that has been less paid attention in use of Gaussian function is destruction of features due to extreme smoothing of the image. The proposed method presented in this paper calculates rate of image feature destruction and finds stop point of growth of standard deviation in Gaussian function. The stop point is chosen in a way that both positive effect of using Gaussian functions in creating scale space is maintained and extreme destruction of proper image features is prevented. Results of the presented method for each image (concerning its information) can be unique. In present paper, experiments have been done on images with and without noise in order to prove accuracy of the proposed method. The images chosen for experiments were from standard images. Results show that this method affect prevention of extreme destruction of image features.

REFERENCES

1. S.Nilufar, N.Ray, H.Zhang, "Object Detection With DoG Scale-Space:A Multiple Kernel Learning Approach", IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL.21, NO.8, 2012, pp.3744-3756.
2. j.Babaud, A.P.Witkin, M.Baudin, R.O.Duda, "Uniqueness of the gaussian kernel for scale-space filtering", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.8, 1986, pp.26-33.
3. T.Tuytelaars, K.Mikolajczyk, "Local Invariant Feature Detectors: A Survey", Computer Graphics and Vision, Vol.3, No.3, 2007, pp.177-280.
4. T.Lindeberg, "Generalized Gaussian scale-space axiomatics comprising linear scale-space,affine scale-space and spatio-temporal scale-space", School of Computer Science and Communication, 2010.
5. S.A.Karim, K.V. Pang, "Data Smoothing Using Gaussian Scale-space and Discrete Wavelet Transform", International Conference on Electrical, Control and Computer Engineering (INECCE), 2011, pp. 334-338.
6. J.A.Kalomiros, "Optimization of a Scale-Invariant Feature detector using scale-space scans", IEEE 7th International Conference on Intelligent Data Acquisition and Advanced Computing Systems (IDAACS), Vol.1, 2013, pp.388-393.
7. A.Kuijper, "On Manifolds in Gaussian Scale Space", Scale Space Methods in Computer Vision Lecture Notes in Computer Science, Vol. 2695, 2003, pp.1-16.
8. L.Florack, A.Kuijper, "The Topological Structure of Scale-Space Images", Journal of Mathematical Imaging and Vision, Vol.12, Issue.1, 2000, pp.65-79.
9. A. Witkin, "Scale-space filtering: A new approach to multi-scale description", Acoustics, Speech, and Signal Processing, IEEE International Conference on ICASSP, Vol.9, 1984, pp.150-153.
10. D.G.Lowe, "Object Recognition from local Scale-Invariant Features", in Proceedings of the International Conference on Computer Vision(ICCV), Vol.2, 1999, pp.1150-1157.
11. D. G. Lowe, "Distinctive image features from scale-invariant keypoints,"International Journal of Computer Vision, Vol. 60, No.2, 2004, pp.91-110.
12. T.Lindeberg, "Scale-space theory: A basic tool for analysing structures at different scales". Journal of Applied Statistics, Vol.21, No.2, 1994, pp.224-270.
13. T.M.Sezgin, R.Davis, "Scale-space Based Feature Point Detection for Digital Ink", American Association for Artificial Intelligence (AAAI), 2004, pp.145-151.
14. H.Amerehie, R.Dianat, F.Keynia, "A New Method to Improve the Difference of Gaussian Feature Detector", International Journal of Soft Computing and Engineering (IJSCE),Vol.4, Issue.4, 2014, to be published.
15. T.Lindeberg, "Scale-Space Theory in Computer Vision", The Kluwer International Series in Engineering and Computer Science, Kluwer Academic Publishers, 1994.
16. J. Sporring, M. Nielsen, L. Florack, P. Johansen, "Gaussian Scale-Space Theory", Springer- Computational Imaging and Vision, Vol. 8, 1997.
17. A.Zhihui, C.Wenjuan, Z.Mengmeng, "Deep Structure of Gaussian Scale Space", International Conference on Computer Science and Software Engineering, Vol.6, 2008, pp.381-384.
18. C.Harris, M.Stevens, "A combined corner and edge detector", In Proc. of Fourth Alvey Vision Conference, 1988, pp.156-162.
19. T.Lindeberg, "Feature detection with automatic scale selection", International Journal of Computer Vision, Vol.30, No.2, 1998, pp.77-116.
20. T.Lindeberg, "Scale-space". Encyclopedia of Computer Science and Engineering, Vol.4, 2009, pp.2495-2504.