IJERST

International Journal of Engineering Research and Science & Technology

ISSN : 2319-5991
Vol. 4, No. 4
November 2015

www.ijerst.com

Email: editorijerst@gmail.com or editor@ijerst.com

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com
Vol. 4, No. 4, November 2015

Research Paper

COMPREHENSIVE ANALYSIS OF IMAGE FILTERING TECHNIQUES

P Anil Babu[1]* and V S R Kumari[2]

*Corresponding Author: P Anil Babu ✉ anilbabu2012@gmail.com

Noise removal is one of the major concerns in computer vision and computer graphics applications. There are so many filtering algorithms are available like Sobel, Laplacian, Gaussian filters and some other edge-preserving filters to remove the noise in images. The guided filter can be used as edge-preserving smoothing filters are one of best solution for removing the noise. In this paper our proposed algorithm gives effective and efficient in a great variety of computer vision and computer graphics compare to other existing algorithms like bilateral filter.

Keywords: Image filtering, Edge-preserving filters bilateral filters

INTRODUCTION

Noise is a random variation of image Intensity and visible as grains in the image. It may arise in the image due to camera attribute parameters (internal parameterssuch as focal length, lens distortion coefficient, the uncertainty factor and the external parameters such as image rotation matrix and translation vector). The common types of noise that arises in the image are Impulse noise,Additive noise,Multiplicative noise. Different noises have their own characteristics which make them distinguishable from others. To modify this attributes we introduce image filtering algorithms.

Image filtering improves the quality of images for human viewing. It basically improves the interpretability or perception of information in images for human viewers and providing 'better' input for other automated image processing techniques. The principle objective of image filtering is to modify attributes of an image to make it more suitable for a given task and a specific observer.There are so many image filtering algorithms are available like Gaussian LPF. HPF, Mean filtering, median filtering,Homomorphic Filtering, bilateral filter, WLS filter, fuzzy filter and guided image filtering etc.

This paper will provide an overview of underlying concepts, along with algorithms commonly used for image filtering. The paper focuses on guided image filtering and its applications.

1 M.Tech Student, Department of ECE, Sri Mittapalli Engineering College, Tummalapalem Guntur 522 233, AndhraPrasesh, India.
2 Professor, Department of ECE, Sri Mittapalli Engineering College, Tummalapalem Guntur 522 233, AndhraPrasesh, India.

RELATED WORK

High Pass Filtering

A high-pass filter can be used to make an image appear sharper. These filters emphasize fine details in the image exactly the opposite of the low-pass filter. High-pass filtering works in exactly the same way as low-pass filtering; it just uses a different convolution kernel. In the example below, notice the minus signs for the adjacent pixels. If there is no change in intensity, nothing happens. But if one pixel is brighter than its immediate neighbours, it gets boosted.

0	-1/4	0
-1/4	+2	-1/4
0	-1/4	0

Unfortunately, while low-pass filtering smooth's out noise, high-pass filtering does just the opposite: it amplifies noise.

Low Pass Filtering

The most basic of filtering operations is called "low-pass". A low-pass filter, also called a "blurring" or "smoothing" filter, averages out rapid changes in intensity. The simplest low-pass filter just calculates the average of a pixel and all of its eight immediate neighbours. The result replaces the original value of the pixel. The process is repeated for every pixel in the image.

Noise always changes rapidly from pixel to pixel because each pixel generates its own independent noise. The image from the telescope isn't "uncorrelated" in this fashion because real images are spread over many pixels. So the low-pass filter affects the noise more than it does the image. By suppressing the noise, gradual changes can be seen that were invisible before. Therefore a low-pass filter can sometimes be used to bring out faint details that were smothered by noise.

Filtering can be visualized by drawing a" convolution kernel". A kernel is a small grid showing how a pixel's filtered value depends on its neighbours. To perform a low-pass filter by simply averaging adjacent pixels, the following kernel is used:

+1/9	+1/9	+1/9
+1/9	+1/9	+1/9
+1/9	+1/9	+1/9

When this kernel is applied, each pixel and its eight neighbours are multiplied by 1/9 and added together. The pixel in the middle is replaced by the sum. This is repeated for each pixel in the image.

Homomorphic Filtering

Homomorphic filtering is a generalized technique for signal and image processing, involving a nonlinear mapping to a different domain in which linear filter techniques are applied, followed by mapping back to the original domain.

The basic nature of the image F(x, y) may be characterized by two components: the amount of source light incident on the scene being viewed and the amount of light reflected by the objects in the scene. These portions of light are called the illumination and reflectance components, and are denoted i(x, y) and r(x, y) respectively. The functions i and r combine multiplicatively to give the image function F:

$$F(x, y) = i(x, y)r(x, y),$$

where $0 < i(x, y) < \infty$ and $0 < r(x, y) < 1$

Bilateral Filter

A bilateral filter is a non-linear, edge-preserving and noise-reducing smoothing filter for images. The intensity value at each pixel in an image is replaced by a weighted average of intensity values from nearby pixels. This weight can be based on a Gaussian distribution. Crucially, the weights depend not only on Euclidean distance of pixels, but also on the radiometric differences (e.g., range differences, such as colour intensity, depth distance, etc.). This preserves sharp edges by systematically looping through each pixel and adjusting weights to the adjacent pixels accordingly.

The bilateral filter is defined as:

$$I^{\text{filtered}}(x) = \frac{1}{W_p} \sum_{x_i \in \Omega} I(x_i) f_r(\|I(x_i) - I(x)\|) g_s(\|x_i - x\|),$$

where the normalization term

$$W_p = \sum_{x_i \in \Omega} f_r(\|I(x_i) - I(x)\|) g_s(\|x_i - x\|)$$

Ensures that the filter preserves image energy and

- I^{filtered} is the filtered image;
- I is the original input image to be filtered;
- x are the coordinates of the current pixel to be filtered;
- Ω is the window centred in x;
- f_r is the range kernel for smoothing differences in intensities. This function can be a Gaussian function;
- g_s is the spatial kernel for smoothing differences in coordinates. This function can be a Gaussian function;

As mentioned above, the weight W_p is assigned using the spatial closeness and the intensity difference. Consider a pixel located at (i, j) which needs to be de-noised in image using its neighbouring pixels and one of its neighbouring pixels is located at (k, l). Then, the weight assigned for pixel (k, l) to de-noise the pixel (i, j) is given by:

$$w(i,j,k,l) = e^{\left(-\frac{(i-k)^2+(j-l)^2}{2\sigma_d^2} - \frac{\|I(i,j)-I(k,l)\|^2}{2\sigma_r^2}\right)}$$

where σ_d and σ_r are smoothing parameters and I(i, j) and I(k, l) are the intensity of pixels (i, j) and (k, l) respectively. After calculating the weights, normalize them.

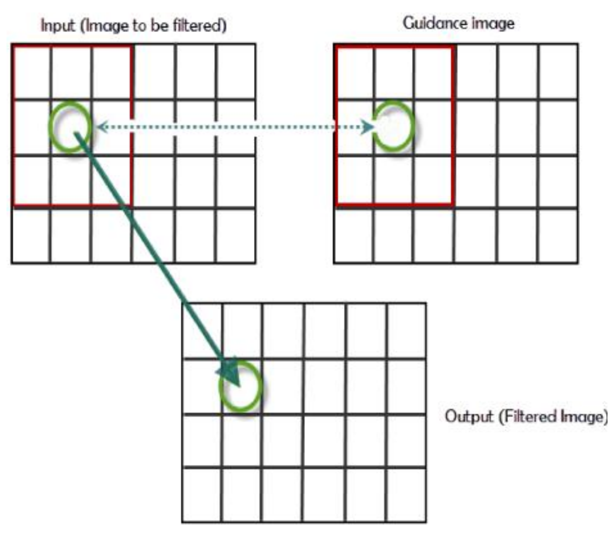
$$I_D(i,j) = \frac{\sum_{k,l} I(k,l) * w(i,j,k,l)}{\sum_{k,l} w(i,j,k,l)}$$

where I_D is the de-noised intensity of pixel (i, j).

GUIDED IMAGE FILTERING

The guided filter performs edge-preserving smoothing on an image, using the content of a second image, called a guidance image, to influence the filtering. The guidance image can be the image itself, a different version of the image, or a completely different image. Guided image filtering is a neighbourhood operation, like other filtering operations, but takes into account the statistics of a region in the corresponding spatial neighbourhood in the guidance image when calculating the value of the output pixel.

Figure 1: Guided Image Filtering



If the guidance is the same as the image to be filtered, the structures are the same an edge in original image is the same in the guidance image. If the guidance image is different, structures in the guidance image will impact the filtered image, in effect, imprinting these structures on the original image. This effect is called structure transference. Experiments show that the guided filter performs very well in terms of both quality and eûciency in a great variety of applications, such as noise reduction, detail smoothing/ enhancement, HDR compression, image matting/feathering.

Guided Filter Kernel

We first define a general linear translation- variant filtering process, which involves a guidance image I, an input image p, and output image q. Both I and p are given beforehand according to the application, and they can be identical.

The filtering output at a pixel I is expressed as a weighted average:-

$$q_i = \Sigma_j W_{ij}(I)\, p_j$$

where i and j are pixel indexes. The filter kernel Wij is a function of the guidance image I and independent of p. This filter is linear with respect to p.

The guided filtering kernel Wij is given by:

$$W_{ij}(I) = \frac{1}{|\omega|^2} \sum_{k:(i,j)\in\omega_k} \left(1 + \frac{(I_i-\mu_k)(I_j-\mu_k)}{\sigma_k^2+\epsilon}\right)$$

where I is guidance image, p is input image, q is output image, Wij is filter kernel, σ is variance, Ki is normalizing parameter, Wk is window centred at pixel k and μ_k is mean of I.

Guided Filtering Algorithm

1. Read the image says I (gray scale image), it acts as a guidance image.
2. Make p = I, where p acts as our filtering image (gray scale image).
3. Enter the values assumed for r and eps, where r is the local window radius and eps is the regularization parameter.
4. Compute the mean of I, p, I*p.
5. The compute the covariance of (I, p) using the formula:

   cov_Ip = mean_Ip - mean_I.* mean_p;
6. Then compute the mean of (I*I) and use it to compute the variance using the formula:

   var_I = mean_II - mean_I.* mean_I
7. Then compute the value of a, b. where a, b are the linear coefficents.
8. Then compute mean of both a and b.
9. Finally obtain the filtered output image q by using the mean of a and b in the formula

   q = mean_a.* I + mean_b;

APPLICATIONS

Detail Enhancement of Guided Filter

Dynamic range reduction and detail enhancement are two important issues for effectively displaying high-dynamic-range images acquired by thermal camera systems. They must be performed in such a way that the high dynamic range image signal output from sensors is compressed in a pleasing manner for display on lower dynamic range monitors without reducing the perceptibility of small details.

Flash/No Flash De-noising

Recently, several techniques [12, 3, 1, and 21] to enhance the quality of flash/no-flash image pairs have been proposed. The no-flash image tends to have a relatively low Signal-to-Noise Ratio

Figure 2: Detail Enhancement for Flower Using Bilateral and Guided Filter

Figure 3: Flash De-Noising for Guided Filter

Figure 4: No Flash De-Noising for Guided Filter

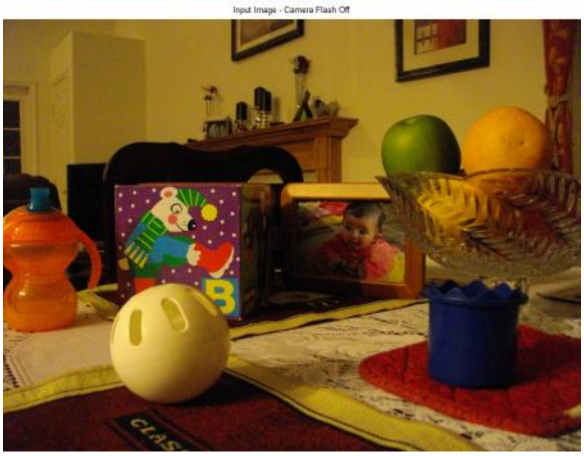


Figure 5: Einstein Figure Using the Guided Filter

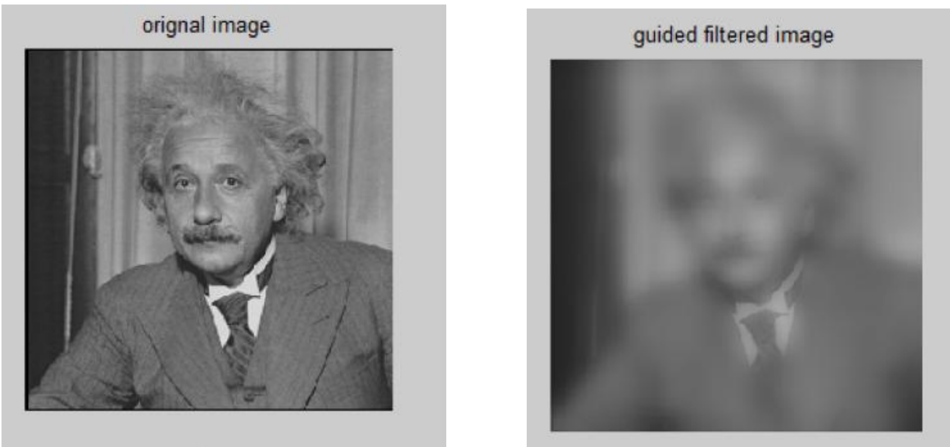


Table 1: Edge-Preserving Filtering Results of a Einstein Image Using the Guided Filter

	r = 2	r = 4	r = 8
ε = 0.1^2	31.05	29.40	28.04
ε = 0.2^2	28.04	25.99	24.28
ε = 0.3^2	26.70	24.61	22.91
ε = 0.4^2	26.01	23.92	22.26
ε = 0.5^2	25.59	23.54	21.90

Table 2: Edge-Preserving Filtering Results of a Human Image Using the Guided Filter

	r = 2	r = 4	r = 8
ε = 0.1^2	35.75	33.74	31.91
ε = 0.2^2	32.64	30.02	28.08
ε = 0.3^2	31.48	29.02	26.71
ε = 0.4^2	30.93	28.43	26.07
ε = 0.5^2	30.63	28.12	25.73

Figure 6: In Real Time Applying Human Photo Using the Guided Filter

(SNR) while containing the natural ambient lighting of the scene. The key idea of flash/no-flash photography is to create a new image that is closest to the look of the real scene by having detail from the flash image and the ambient illumination of the no-flash image.

CONCLUSION

In this paper, we have presented a novel filter which is widely applicable in computer vision and graphics. Differently from the recent trend toward accelerating the bilateral filter, we design a new filter that exhibits the nice property of edge-preserving smoothing but which can be computed efficiently and non-approximately. Our filter is more generic than "smoothing" and is applicable for structure-transferring, enabling novel applications of filtering-based feathering/ matting and dehazing. Since the local linear model is a kind of patch-wise unsupervised learning, other advanced models/features might be applied to obtain new filters.

REFERENCES

1. Adams A, Baek J and Davis M A (2010), "Fast High-Dimensional Filtering Using the Permutohedral Lattice", *Computer Graphics Forum*, Vol. 29, No. 2, pp. 753-762.

2. Adams A, Gelfand N, Dolson J and Levoy M (2009), "Gaussian KD-Trees for Fast High-Dimensional Filtering", pp. 21:1-21:12, Proc. ACM Siggraph.

3. Bae S, Paris S and Durand F (2006), "Two-Scale Tone Management for Photographic Look", Proc. ACM Siggraph.
4. Crow F (1984), "Summed-AreaTables for Texture Mapping", Proc. ACM Siggraph.
5. De-Maeztu L, Mattock S, Villanueva A and Cabeza R (2011), "Linear Stereoatching", Proc. IEEE Int'l Computer Vision Conf., pp. 1708-1715.
6. Deriche R (1993), "Recursively Implementing the Gaussian and Its Derivatives".
7. Ding Y, Xiao J and Yu J (2011), "Importance Filtering for Image Retargeting", Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 89-96.
8. Draper N and Smith H (1981), *Applied Regression Analysis*, 2nd Edition, John Wiley.
9. Fattal R, Agrawala M and Rusinkiewicz S (2007), "Multiscale Shape and Detail Enhancement from Multi-Light Image Collections", Proc. ACM Siggraph.
10. Ge Ting and Zhang Jianwei (2007), "A Minutia Preserving Smoothing Filter Based on Adaptive Threshold", in *Computer Applications and Software [J]*, No. 7, pp. 151-154.
11. GLoupas T (1989), "An Adaptive Weighted Median Filter for Speckle Suppression", in *Medical Ultrasonic Image [J].IEEE Trans on Circuits System*, Vol. CAS-36, No. 1, pp. 129-135.
12. He K, Sun J and Tang X (2010), "Fast Matting Using Large Kernel Matting Laplacian Matrices", Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 2165-2172.
13. He K, Sun J and Tang X (2010), "Guided Image Filtering", Proc. European Conf. Computer Vision, pp. 1-14.
14. Hummel R (1975), "Histogram Modification Techniques", *Computer Graphics and Image Processing*, Vol. 4, pp. 209-224.
15. Liu C, Freeman W T, Szeliski R and Kang S B (2006), "Noise Estimation from a Single Image", Proc. IEEE Conf. Computer Vision and Pattern Recognition.
16. Pablo Bauszat, Martin Eisemann and Marcus Magnor (2011), "Guided Image Filtering for Interactive High-Quality Global Illumination", Vol. 30, No. 4, The Euro Graphics Association and Blackwell Publishing Ltd.
17. Paris S and Durand F (2006), "A Fast Approximation of the Bilateral Filter Usinga Signal Processing Approach", Proc. European Conf. Computer Vision.
18. Paris S, Hasinoff S W and Kautz J (2011), "Local Laplacian Filters: Edge-Aware Image Processing with a Laplacian Pyramid", *ACM Trans. Graphics*, Vol. 30, No. 4, pp. 68:1-68:12.
19. Perreaultand S and He´bert P (2007), "Median Filtering in Constant Time", *IEEE Trans. Image Processing*, Vol. 16, No. 9, pp. 2389-2394.
20. Petschnig G, Agrawala M, Hoppe H, Szeliski R, Cohen M and Toyama K (2004), "Digital Photographywith Flashand No-Flash Image Pairs", Proc. ACM Siggraph
21. Rafael C Gonzalez and Richard E Woods (2010), "Digital Image Processing",

Chapter 4, Addison-Wesley Publishing Company.

22. Rhemann C, Hosni A, Bleyer M, Rother C and Gelautz M (2011), "Fast Cost-Volume Filtering for Visual Correspondence and Beyond", Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 3017-3024.
23. Umbaugh S E (1998), "Computer Vision & Image Processing", Prentice Hall, PTR.
24. Weickert J (1998), "Anisotropic Diffusion in Image Processing [C]", European Consortium for Mathematics in Industry, BG, Teubner Stuttgart.
25. Weickert J (1999), "Coherence-Enhancing Diffusion Filtering", in *International Journal of Computer Vision [J]*, Vol. 31, Nos. 2-3, pp. 111-127.
26. Winnemo¨ller H, Olsen S C and Gooch B (2006), "Real-Time Video Abstraction", Proc. ACM Siggraph.
27. Xing-Fang Huang and Jiang-She Zhang (2009), "Edge-Preserving Filtering for Grey and Colour Image", in Proc. of the IEEE/ Computer Science and Information Engineering, Vol. 5, pp. 139-143.
28. Xu L, Lu C, Xu Y and Jia J (2011), "Image Smoothing via l0 Gradient Minimization", Proc. ACM Siggraph Asia, pp. 174:1-174:12.
29. ZhuJuhua YangXin and Li Jun (2001), "The Improved Adaptive Minutiae Preserving Median Filter", in *Computer Engineering and Applications [J]*, No. 3, pp. 93-95.
30. Zometand A and Peleg S (2002), "Multi-SensorSuper Resolution", Proc. IEEE Workshop Applications of Computer Vision.

International Journal of Engineering Research and Science & Technology
Hyderabad, INDIA. Ph: +91-09441351700, 09059645577
E-mail: editorijlerst@gmail.com or editor@ijerst.com
Website: www.ijerst.com

ISSN 2319-5991