

A Comprehensive Review of Image Smoothing Techniques

Aditya Goyal, Akhilesh Bijalwan, Mr. Kuntal Chowdhury

Abstract— Smoothing is often used to reduce noise within an image or to produce a less pixelated image. Image smoothing is a key technology of image enhancement, which can remove noise in images. So, it is a necessary functional module in various image-processing software. Excellent smoothing algorithm can both remove various noises and preserve details. This paper analyzed some image smoothing algorithms. These algorithms have the ability of preserving details, such as gradient weighting filtering, self-adaptive median filtering, robust smoothing and edge preserving filtering. Appropriate choice of such techniques is greatly influenced by the imaging modality, task at hand and viewing conditions. This paper will provide an overview of underlying concepts, along with algorithms commonly used for image smoothing.

Index Terms— Bilateral Filtering, Guided Filtering, Image smoothing, Salt and Pepper Noise, Robust.

I. INTRODUCTION

The main aim of image smoothing is to remove noise in digital images. It is a classical matter in digital image processing to smooth image. And it has been widely used in many fields, such as image display, image transmission and image analysis, etc. Image smoothing [5] has been a basic module in almost all the image processing software. So, it is worth studying more deeply.

Image smoothing is a method of improving the quality of images. The image quality is an important factor for the human vision point of view. The image usually has noise which is not easily eliminated in image processing. The quality of the image is affected by the presence of noise. Many methods are there for removing noise from images. Many image processing algorithms can't work well in noisy environment, so image filter is adopted as a preprocessing module. However; the capability of conventional filters based on pure numerical computation

is broken down rapidly when they are put in heavily noisy environment. Median filter is the most used method [1], but it

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Aditya Goyal, Computer Science and Engineering, Uttarakhand Technical University/Dehradun Institute of Technology/Dehradun, India, /9997030797, (e-mail: goyaladit@gamil.com).

Akhilesh Bijalwan, Computer Science and Engineering, Uttarakhand Technical University/Dehradun Institute of Technology/Dehradun, India, /8899806686, (e-mail: bijalwanakhilesh@gmail.com).

Mr. Kuntal Chowdhury, Computer Science and Engineering, Uttarakhand Technical University/Dehradun Institute of Technology/Dehradun, India, /8650198209 (e-mail: ikuntal09@gmail.com).

will not work efficiently when the noise rate is above 0.5. Yang and Toh [2] used heuristic rules for improving the performance of traditional multilevel median filter. Russo and Ramponi [3] applied heuristic knowledge to build fuzzy rule based operators for smoothing, sharpening and edge detection. They can perform smoothing efficiently but not in brightness. Choi and Krishnapuram [4] used a powerful robust approach to image enhancement based on fuzzy logic approach, which can remove impulse noise, smoothing out non-impulse noise, and preserve edge well.

Different factors can cause different kinds of noise. In practice, an image usually contains some different types of noise. So good image smoothing algorithm should be able to deal with different types of noise. However, image smoothing [6] often causes blur and offsets of the edges. While the edge information is much important for image analysis and interpretation. So, it should be considered to keep the precision of edge's position in image smoothing.

II. THE ANALYSIS OF SOME SMOOTHING ALGORITHMS

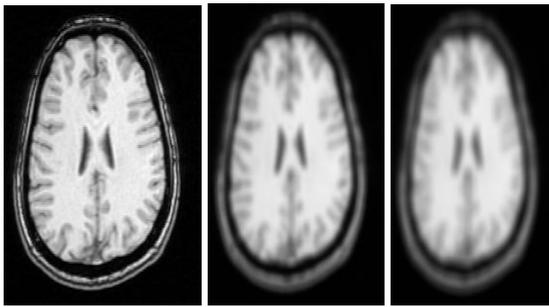
A. Gaussian Smoothing

The Gaussian smoothing operator is a 2-D convolution operator that is used to 'blur' images and remove detail and noise. The idea of Gaussian smoothing is to use this 2-D distribution as a 'point-spread' function, and this is achieved by convolution. Since the image is stored as a collection of discrete pixels we need to produce a discrete approximation to the Gaussian function before we can perform the convolution. In theory, the Gaussian distribution is non-zero everywhere, which would require an infinitely large convolution kernel, but in practice it is effectively zero more than about three standard deviations from the mean, and so we can truncate the kernel at this point. Figure 3 shows a suitable integer-valued convolution kernel that approximates a Gaussian with a σ of 1.0.

Once a suitable kernel has been calculated, then the Gaussian smoothing can be performed using standard convolution methods. The convolution can in fact be performed fairly quickly since the equation for the 2-D isotropic Gaussian shown above is separable into x and y components. Thus the 2-D convolution can be performed by first convolving with a 1-D Gaussian in the x direction, and then convolving with another 1-D Gaussian in the y direction. The Gaussian is in fact the only completely circularly symmetric operator which can be decomposed in such a way. The y component is exactly the same but is oriented vertically.

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

Where x, y are the spatial dimensions.



Original Image sigma = 20 sigma = 40
 Figure 1. Example of Gaussian smoothing

B. Edge Preserved Filtering

Typical edge preserved filtering includes two types: Kuwahara filtering and selective mask filtering. The basic process of them is described as follows: Firstly, some different templates are made based on the center pixel. Secondly, the mean value and the standard deviation of the pixels in different templates are calculated. Finally, the gray value of the center pixel is defined as the mean value in the template where the standard deviation is the least. The Kuwahara filtering selects one template from 4 square windows. While the selective mask filtering chooses one template region from 9 windows, which include 4 pentagon, 4 hexagon and 1 square. The effect of preserving details of the selective mask filtering is better than that of the Kuwahara filtering, because the former has more fine window choice. Through the analysis of these algorithms, we find that the image details can be preserved from selecting a suitable template according to the rule of minimizing the standard deviation. When the template is selected, we can use other smoothing algorithms with better smoothing effects. For example, considering that the medium filtering can preserve details more effectively than mean filter does and that it is more effective for salt and pepper noise, we can take the medium grey value in the template window where the standard deviation is the least as the grey value on the centre pixel. And so we can remove salt and pepper noise more effectively.

C. Bilateral Filter

The bilateral filter [7] computes the filter output at a pixel as a weighted average of neighboring pixels. It smooths the image while preserving edges. Due to this nice property, it has been widely used in noise reduction, HDR compression, multi-scale detail decomposition, and image abstraction. It is generalized to the joint bilateral filter in [8], in which the weights are computed from another guidance image rather than the filter input. The joint bilateral filter is particularly favored when the filter input is not reliable to provide edge information, e.g., when it is very noisy or is an intermediate result. The joint bilateral filter is applicable in flash/no-flash denoising, image upsampling, and image deconvolution. However, it has been noticed [11, 13, 14] that the bilateral filter may have the gradient reversal artifacts in detail decomposition and HDR compression. The reason is that

when a pixel (often on an edge) has few similar pixels around it, the Gaussian weighted average is unstable. Another issue concerning the bilateral filter is its efficiency. The brute-force implementation is in $O(Nr^2)$ time, which is prohibitively high when the kernel radius r is large. In [14] an approximated solution is obtained in a discretized space-color grid. Recently, $O(N)$ time algorithms [8, 9] have been developed based on histograms. Adams et al. [10] propose a fast algorithm for color images. All the above methods require a high quantization degree to achieve satisfactory speed, but at the expense of quality degradation.

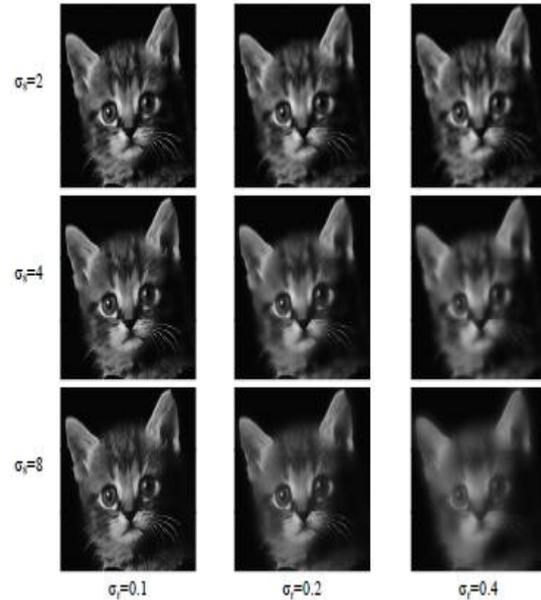


Figure 2. Example of Bilateral Filtering

D. Optimization-Based Image Filtering

A series of approaches optimize a quadratic cost function and solve a linear system, which is equivalent to implicitly filtering an image by an inverse matrix. In image segmentation and colorization, the affinities of this matrix are Gaussian functions of the color similarities. In image matting, a matting Laplacian matrix is designed to enforce the alpha matte as a local linear transform of the image colors. This matrix is also applicable in haze removal [12]. The weighted least squares (WLS) filter in [11] adjusts the matrix affinities according to the image gradients and produces a halo-free decomposition of the input image. Although these optimization-based approaches often generate high quality results, solving the corresponding linear system is time-consuming.

It has been found that the optimization-based filters are closely related to the explicit filters. In [15] Elad shows that the bilateral filter is one Jacobi iteration in solving the Gaussian affinity matrix. In [16] Fattal defines the edge-avoiding wavelets to approximate the WLS filter. These explicit filters are often simpler and faster than the optimization-based filters.

E. Nonlinear Diffusion Filtering

NLDF was originally formulated by Perona and Malik (1987). Noise is smoothed locally, 'within' regions defined by object boundaries whereas little or no smoothing occurs between image objects. Local edges are enhanced since discontinuities, such as boundaries, are amplified.

Mathematically one treats the problem like a diffusion process, where the diffusion coefficient is adapted locally to the effect that diffusion stops as soon as an object boundary is reached

Diffusion can be thought of as the physical process that equilibrates concentration differences without creating or destroying mass. Mathematically, this is described by Fick's law:

$$j = -D \cdot \nabla u$$

where the flux j is generated to compensate for the concentration gradient ∇u . D is a tensor that describes the relation between them. Now, using the Continuity Equation (Conservation of mass):

$$\partial_t(u) = -div(j)$$

We get:

$$\partial_t(u) = div(D \cdot \nabla u)$$

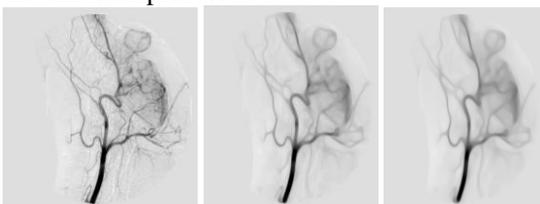
The solution of the linear diffusion equation with a scalar diffusivity d is exactly the same operation as convolving the image u with a Gaussian kernel of width $\sqrt{2t}$.

$$\partial_t u = div(d \nabla u)$$

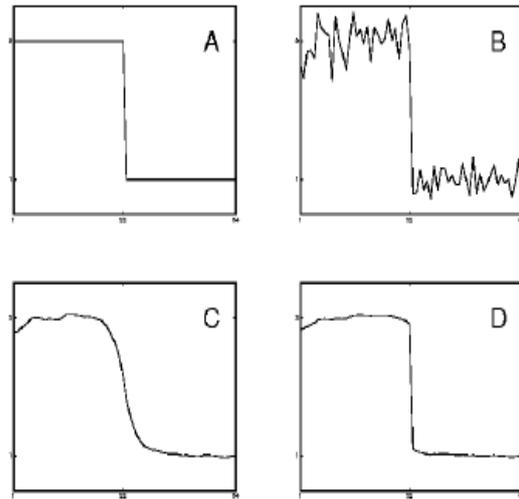
Perona and Malik proposed to exchange the scalar diffusion constant d with a scalar-valued function g of the gradient ∇u of the grey levels in the image. The diffusion equation then reads:

$$\partial_t u = div(g(|\nabla u|) \nabla u)$$

The length of the gradient $|\nabla u|$ is a good measure of the edge strength of the current location which is dependent on the differential structure of the image. This dependence makes the diffusion process nonlinear.



Original image smoothed image
Figure 3. Example of non-diffusion Filtering



Comparison of low pass filtering to NLDF. a) Original step. b) Original step with white noise superimposed. c) Result of simple low pass spatial frequency filtering. d) Result of NLDF (edge-preserving noise reduction).

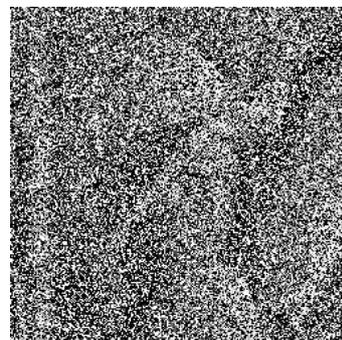
Figure 4. Comparison of low pass filtering to non-diffusion filtering.

F. Robust Smoothing Filter

Robust smoothing filter is a simple and fast nonlinear filter. It can remove salt and pepper noise with lower density effectively. Because it adopts the strategy of losing the ability of smoothing to preserve edges, it can preserve more edge details than the medium filtering can do. The process can be described as follows:

- (1) Calculate the maximum and the minimum of the gray values in the template window except the centre pixel.
- (2) Compare the gray value on the centre pixel with the maximum and the minimum.
- (3) If the gray value is larger than the maximum, the maximum is output; If the gray value is smaller than the minimum, the minimum is output; If the gray value is between them, the gray value is output.

In order to preserve more details, we adopt the same idea in robust smoothing filtering as in the adaptive medium filtering. It can reduce the image distortion by unchanging the gray on 'middle level' pixels.



(a) the image corrupted with salt and pepper noise



(b) The result smoothed by robust smoothing method
 Figure 5. Example of Robust Smoothing method

G. Gradient Weighting Filter

The gradient-dependent weighting filters are mainly based on the following principle: in a discrete image, the difference of the gray values on pixels in outer area is larger than that in inner area. In same area, the change on centre pixels is smaller than that on edge pixels. The gray gradient is direct ratio to the gray difference in vicinity. That is, where the gray change is slower, the gradient is smaller. A function whose value reduces with the increase of the gradient is adopted, and it is chosen as the weight of the window. So, the smoothing contribution is mainly coming from the same area. Accordingly the edge and the detail cannot be lost apparently after image smoothing.

In designing gradient-selected filters, power and exponential function are often chosen as weighting function. Especially when the power is equal to -1, the filtering is called gradient reciprocal weighting filtering. When the function is the exponential one, the filtering is called adaptive filtering. When we extract lines from remote sensing images, the adaptive filtering is often adopted in preprocessing to realize the aim of noise removal and edge enhancement. It can be described as:

$$f(x) = e^{-x^2/2k^2}$$

Where, x is the gradient, k is the parameter that determines the smoothing degree.

By analysis, we find that k can be used to adjust the degree of sharp of the exponential function. If k is bigger, the exponential function will be slower in change. So, if the gradient is bigger than k , the gradient will increase with the adding of the iterative times, so as to realize the aim of sharpening edge. Oppositely, if the gradient is smaller than k , the details will be smoothed. Thus, the value of k is critical to the smoothing effect.

H. Guided Image Filter

Guided image filter [7] is an explicit image filter, derived from a local linear model; it generates the filtering output by considering the content of a guidance image, which can be the input image itself or another different image. Moreover, the guided filter has a fast and non-approximate linear-time algorithm, whose computational complexity is independent of the filtering kernel size. The guided filter output is locally a linear transform of the guidance image. This filter has the edge-preserving smoothing property like the bilateral filter, but does not suffer from the gradient reversal artifacts. It is also related to the matting Laplacian matrix, so is a more

generic concept and is applicable in other applications beyond the scope of "smoothing". Moreover, the guided filter has an $O(N)$ time (in the number of pixels N) exact algorithm for both gray-scale and color images. Experiments show that the guided filter performs very well in terms of both quality and efficiency in a great variety of applications, such as noise reduction, detail smoothing/enhancement, HDR compression, image matting/feathering, haze removal, and joint up sampling.

1. 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:-

$$q_i = \sum_j W_{ij}(I) p_j \quad (4)$$

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

The guided filtering kernel W_{ij} is given by:-

$$W_{ij}(I) = \frac{1}{|\omega|} \sum_{k: (i,j) \in \omega_k} \left(1 + \frac{(I_i - \mu_k)(I_j - \mu_k)}{\sigma_k^2 + \epsilon} \right) \quad (5)$$

Where I is guidance image, p is input image, q is output image, W_{ij} is filter kernel, σ is variance, K_i is normalizing parameter, ω_k is window centered at pixel k and μ_k is mean of I .



Figure 6. Guided image filter against other filters.

III. CONCLUDING REMARKS

Image smoothing algorithms offer a wide variety of approaches for modifying images to achieve visually acceptable images. The choice of such techniques is a function of the specific task, image content, observer characteristics, and viewing conditions. There are two major shortcomings of Gaussian smoothing, it shrinks shapes and dislocates boundaries when moving from finer to coarser scales, blurs important image features. Bilateral filter produces staircase effect, bilateral filter tends to remove texture, create flat intensity regions and new contours. The robust smoothing filtering only can remove salt and pepper noise with lower density. Nonlinear diffusion filtering approach smooth's regions of low brightness gradient while regions of high gradients are not smoothed. These anisotropic diffusion approaches are contrast-driven and smooth globally salient but low contrast image features. The guided filter has a fast and non-approximate linear-time algorithm, whose computational complexity is independent of the filtering kernel size. As a locally based operator, the guided filter is not directly applicable for sparse inputs like strokes. It also shares a common limitation of other explicit filter - it may have halos near some edges.

Although we did not discuss the computational cost of image smoothing algorithms in this article it may play a critical role in choosing an algorithm for real-time applications. Despite the effectiveness of each of these methods when applied separately, in practice one has to devise a combination of such methods to achieve more effective image smoothing. We believe that the simplicity and efficiency of the guided filter still make it beneficial for image smoothing.

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Aditya Goyal, B.Tech (IT), MBA (Marketing) and pursuing M.Tech (CSE) from Dehradun Institute of Technology Dehradun.

Akhilesh Bijalwan, M.Sc (IT) and pursuing M.Tech (CSE) from Dehradun Institute of Technology Dehradun.

Mr. Kuntal Chowdhury, Assistant Professor, Dehradun Institute of Technology, Dehradun.