Edge-preserving Smoothing Methods: Overview and Comparison

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Abstract

Filtering is one of most fundamental operations in image processing. Image noise can be reduced through smoothing methods that rely on filtering. Using conventional smoothing methods like [13] leads to noise reduction. However, the objects in the image might become indistinguishable due to the smoothing of the object edges. Edge-preserving smoothing (EPS) methods are a solution to this problem.

This paper gives an overview of edge-preserving image smoothing methods and compares them based on their performance and visual quality of results. Main focus of this paper is the bilateral filter [24] and the guided image filter [4]. Despite being one of the oldest EPS filters [24], there are several recent works aimed at improving or enhancing bilateral filters [2] [3] [28]. On the other hand, one of the most recent and efficient methods, at the time of the writing of this paper, is the guided image filtering. In addition to the two focus methods, Kuwahara filters and anisotropic diffusion are presented in order to compare the bilateral and guided filters with other different approaches.
1 Introduction

Image smoothing is a technique utilized by image noise reduction methods. It is based on filtering, which is one of the most fundamental image processing operations. In filtering, the pixel value at a specific location of an output image is given by a function of the pixel values of an input image in a neighborhood of the same location [24]. For example, if $p_k$ is a pixel of an input image at position $k$, a weight-average filter would compute the pixel $q_k$ of an output image as an average of neighboring pixels of $p_k$. The size of the window, or the number of neighboring pixels, is referred to as filter window size.

Applying the conventional smoothing method like a mean filter [30], where a pixel is calculated simply by an averaging function in order to reduce noise, can lead to indistinguishable objects in an image. Even by using more recent methods like mean-shift smoothing [13] can lead to similar results. Texture smoothing presents a solution to this problem. This is a technique based on image smoothing and filtering, where fundamental image constituents are characterized and enhanced, while details less significant for object distinguishability are diminished. These fundamental image constituents are referred to as base layer, and less significant details as detail layer of an image [10]. The process of this separation of base layer from detail layer is referred to as image abstraction.

Texture smoothing methods preserve objects in an image while more or less effectively, depending on the method, reducing noise. Smoothing methods must preserve edges in an image, in order to keep objects distinguishable one from another. Therefore, the methods from this category are classified as edge-preserving smoothing (EPS) methods. Filters like bilateral filter [24] and guided image filter [4] are present a solution for such effective texture smoothing algorithms. Advantages of bilateral filters [2][3][7][14][17][19][28][29], guided filters [4][18][21] and their modifications, are better visual quality of results as well as faster processing times. These advantages over other methods are the reasons why this paper focuses on these two methods and their variations. However, two additional methods, Kuwahara filters [8] and anisotropic diffusion [16], are discussed. The two additional methods were chosen based on
the attention they received at the time of writing of this paper [8][10][11][16][22][27]. The main purpose of presenting two additional methods is to give a better insight in comparison of bilateral and guided filter not only between themselves and between their modifications, but also with other filtering techniques. The mentioned methods are described in detail in the second chapter.

While the primary goal of texture smoothing is the noise reduction, there are also additional applications of this technique in image processing. As described in [9], an EPS method can be used as a tool for artistic stylization of images. The paper presents a solution how smoothing algorithms can be used to achieve an artistic simplified abstract image. Another application is automatic skin smoothing in images proposed in [12]. Lee et al. present an automatic method for retouching digital portraits by smoothing the skin texture and removing any scars or skin irregularities. These retouching techniques are an integral part of fashion and advertisement industries [12]. Another example of texture smoothing applications is the single image fog removal, proposed in [25]. The filter is used for the estimation of air-light and recovering scene contrast. Figure 1 shows the results of the solution proposed in [25].

In the third chapter of this paper a comparison of performance and resulting visual quality based on objective evaluation methods is given.

![Figure 1: Results of fog removal in a single image using Bilateral Filter proposed by Tripathi et al [24]. Original foggy image (left), restored image (right).](image-url)
2 Methods

Texture smoothing methods have a goal to smooth homogenous areas while preserving edges, thus making objects of an image distinguishable even after extensive smoothing. The smoothing is thereby performed by a filtering technique on an input image. Applying a simple blur effect on an image ensures that the image noise is reduced greatly, however because of the blurred edges, the objects in the image may become less distinguishable for a human eye. EPS methods present an effective solution to this problem.

This paper focuses on two methods: bilateral filtering [24] and guided image filtering [4]. Modifications of bilateral filter have been presented in [14], [2], [3] and [7]. Guided image filtering [4] technique has also an adaptation which attempts to modify the filter so that it produces better visual quality of results [18]. These are the reasons why bilateral and guided image filtering are two focus methods of this paper. However, to further explain possible solutions, and to be able to compare the results with other methods, two additional methods: Kuwahara filters [8] and anisotropic diffusion [16] are presented.

2.1 Bilateral filtering

The bilateral filter can be classified as a weight-average filter. This means that for each pixel a, filter output is computed as the average of neighboring pixels of filter input. It can further be classified as an edge preserving, non-iterative, non-linear filter that smooths low gradient regions [18]. The term bilateral filter and the first version of the method were presented in the [24]. The bilateral filter has two filter kernels, a spatial and a range kernel, for calculating the spatial and intensity range distance between the center pixel and its neighbors.

As presented in [18], if \( I_p \) is the intensity value of a specific pixel \( p \), and \( w_k \) is the kernel window which is centered at pixel \( k \), then we can define bilateral filter as:

\[
BLF(I)_p = \frac{1}{\sum_{q \in w_k} W_{BLFpq}(I)} \sum_{q \in w_k} W_{BLFpq}(I)I_q
\]  
(1)
The kernel weights function $W_{BLF_{pq}}(I)$ can be expressed by:

$$W_{BLF_{pq}}(I) = \exp\left(-\frac{||p-q||^2}{2\sigma_r^2}\right)\exp\left(-\frac{|I_p-I_q|^2}{2\sigma_I^2}\right)$$  \hspace{1cm} (2)$$

The standard deviation parameter is responsible for control of decrement of weight in spatial domain, whereas the parameter $\sigma_r$ controls the decrement of weight in intensity range domain. These parameters are referred to as “tuning” parameters because of their effect on the two domains [14]. $||.||$ denotes the *Euclidean distance* between pixels $p$ and $q$. The spatial weighting function decreases with the Euclidean distance, which makes the distant pixels less influential on the result. The intensity weighting function ensures that the pixels whose intensity values significantly differ from the central pixel have less influence on the result. This ensures the preservation of edges in an image. To summarize, defining an exemplary filtering window is the first step in construction of a bilateral filter. In addition to that, an array of Euclidean distances between the observed pixel and all other pixels within the defined window is defined. Furthermore an array of the absolute differences of intensities is needed.

### 2.1.1 Modified bilateral filter

*Impulsive noise* is characterized by appearance of light pixels on dark background and dark pixels on light background. One problem of bilateral filters is that pixels that appear due to this impulsive noise process are often not removed. It is possible that the pixels in the neighborhood of the center pixel are corrupted by noise. Furthermore, the center pixel might be a noisy pixel itself. Then, after calculating the new pixel value on this position, the impulses are preserved. The reason is that the noisy pixel is included with large weights during the range weighting function. This causes a preservation of impulses. In [14] Malik et al. propose a *modified bilateral filter* that solves such problems.

Each pixel from the filtering window $W_x$ is assigned a minimum connection cost of a path that joins them with the central pixel $x$. The cost of a path is the sum of connection costs of adjacent
pixels forming a path. The connection cost in this case is a function of absolute differences of pixel intensities. The minimum cost paths of each pixel are calculated by applying Dijkstra algorithm [14]. This means that every pixel from the filtering window is connected to center pixel $x$ through a minimum cost path. The connection costs are then used to calculate the weight of each pixel within the filtering window, and the filter output is calculated as a weight average of surrounding pixels of $x$. An example of minimum path in an image is shown in Figure 2.

![Figure 2: Connection costs with an exemplary minimum path [14].](image)

### 2.1.2 Recursive bilateral filter

A recursive implementation of the filter has been proposed in [26]. In this research the range filter kernel is constrained to achieve faster performance. In standard implementation of the bilateral filter the range kernel measures the range distance between two pixels based on their color differences. In recursive bilateral filter the range distance between two pixels $p$ and $q$ is measured by accumulating the color difference between every two neighboring pixels on the path between $p$ and $q$. If proposed range filter kernel is combined with any other spatial filter kernel that can be recursively implemented, a recursive implementation is possible by altering the coefficients of the system.
2.1.3 Joint bilateral filter

The joint bilateral filter [17] is an extension of bilateral filter. Two correlated images are used for filtering process. The method filters an image by weight-average under guidance by another image. The filter has been used for producing high quality pictures by combining two images, one taken with flash to capture details and one without to capture ambient illumination. Thereby the flash image is used as an estimator. This guidance image is explicitly built into filter kernels. Computational cost of brute force implementation of joint bilateral filter is in the same range as brute force implementations of standard bilateral filter. A less complex implementation method is proposed in [29]. Zhang et al. based their solution on data structure called joint integral histograms (JIH). In JIH, the value at each bin represents an integral that is determined by both the input and the guiding image. It contains the global information about the two images. The proposed joint bilateral filter based on JIH performs in constant time regardless of the filter radius.

2.1.4 Adaptive bilateral filter

Adaptive bilateral filter was proposed in [28] and it was implemented by more techniques. The technique that is the most relevant for this paper is the shift-variant technique. The later discussed adaptive guided filter relies on the basics of this technique. The main difference to the standard implementation of bilateral filter is the introduction of this shifting technique. Another improvement is that the parameters are locally adaptive. The proposed method is aimed at achieving better image sharpening and de-noising and less at reducing computational cost, as can be seen in the comparison chapter of this paper.

2.2 Guided Image Filtering

Guided image filtering [4] is a filtering technique that includes the usage of a guidance image. In the bilateral filtering the guidance was either the input image, as presented in the standard implementation
[24], or an additional guidance image, as proposed in joint bilateral filtering [17]. Guided image filter is therefore a filtering technique that is technically comparable to bilateral filters, or more specifically, joint bilateral filters.

To define the guided image filter one first has to define an input image \( I \) and guidance image \( G \). If \( I_p \) and \( G_p \) are the corresponding intensity values at a pixel \( p \) and \( w_k \) is the kernel window centered at pixel \( k \), then guided image filter is given by:

\[
GIF(I)_p = \frac{1}{\sum_{q \in w_k} W_{GIF_pq}(G)} \sum_{q \in w_k} W_{GIF_pq}(G) I_q
\]

The kernel weights function can be expressed as:

\[
W_{GIF_pq}(G) = \frac{1}{|w_k|} \sum_{k:(p,q) \in w_k} \left( 1 + \frac{(G_p - \mu_k)(G_q - \mu_k)}{\sigma_k^2 + \varepsilon} \right)
\]

Where \( \mu_k \) and \( \sigma_k \) represent the mean and the variance of guidance image in window \( w_k \), whereas \(|w|\) is the number of pixels in the window. Parameter \( \varepsilon \) determines the degree of smoothing. The larger the value of \( \varepsilon \) is, the smoother the output image.

The filter can be extended to be used on color images. If the input is multichannel, the filter can be applied to all the channels separately. In case that the guidance image has more than one channel, the local linear model has to be slightly modified so that the guidance image becomes a 3×1 color vector that contains color information.

### 2.2.1 Adaptive guided image filter

In [28] authors presented an adaptive bilateral filter (ABF) that is based on shifting technique. With this method as a reference an adaptive guided image filter (AGF) has been proposed [18]. The main differences between the bilateral filter and the guided filter are their weighting functions, however the range domain of bilateral filter and kernel of guided filter are similar. Both filters use intensity
values of center pixel, its local neighbors and a smoothing parameter. Based on this similarity the AGF filter is realized by same approach of adding an offset to the intensity value of the center pixel. While this offset in ABF is added in the intensity range domain, in AGF it is added in the kernel weighting function. Result produced by AGF with standard offset contains, similar to ABF, anomalies like aliasing. In order to achieve satisfying results the AGF smoothing parameter $\varepsilon$ has to be calculated based on smoothing parameter of ABF $\sigma$. The method was developed in order to achieve better visual quality of images where sharpness enhancement is simultaneously performed with noise reduction.

### 2.3 Anisotropic diffusion

Anisotropic diffusion is another EPS method that was proposed by Perona and Malik [16]. Diffusion algorithms are modeled as solutions of partial differential equation (PDE). They modify the image by PDE and throughout the process remove the image noise. The technique includes a creation of a set of parameterized images, where each resulting image is the combination of the original image and a filter that is dependent on the local content of the image. Each next image is computed by applying a generalized diffusion equation to the previous image in the set. Diffusion coefficient thereby regulates the degree of smoothing and defines how the function handles edges in an image. The process itself is non-linear and iterative. In the anisotropic diffusion proposed by Perona and Malik [16], the smoothing effect is effectively controlled. The smoothing can be stopped at certain points and the edges are preserved. The problem is that because of the parameters that cannot be altered during the process, the stopping times can be uncertain. This leads to blurred edges and excessively smoothed images. Possible solutions for such problems are presented in [27] and [22].

### 2.4 Kuwahara filter

The Kuwahara filter [8] is a noise reduction approach that was first used in the context of biological image processing. The general
The idea is to divide the filter kernel in four rectangular regions that have an overlapping pixel. The output is then defined by the mean of region with smallest variance. Due to use of rectangular shapes several unwanted artifacts like different image errors and irregularities can appear. Several solutions were proposed throughout the years, one of them being the generalized Kuwahara filter [15].

2.4.1 Single-scale anisotropic Kuwahara filter

Based on generalized Kuwahara filter and combined with anisotropic diffusion, an anisotropic Kuwahara filter [11] has been proposed. The key improvement is that the weighting functions are defined over ellipses and not rectangular shape like in previous implementations. By adapting shape, scale and orientation of these ellipses to the local structure of the input image, artifacts can effectively be avoided. The implementation preserves directional image features effectively, resulting in clearer edges and high visual quality of results.

2.4.2 Multi-scale anisotropic Kuwahara filter

A limitation of anisotropic Kuwahara filter is the filter radius. However, increasing the radius would not be a suitable solution since the computational time would increase significantly. The multi-scale anisotropic Kuwahara [10] filter presents a solution to this problem by applying the anisotropic Kuwahara filter at multiple scales. The Kuwahara filter is used for strong abstraction of images in order to achieve an artistic effect. Figure 3 shows results of single and multi-scale anisotropic Kuwahara filter applied on an example image.

![Figure 2: Visual quality of an image (left), filtered with single-scale (middle) and multi-scale (right) Kuwahara filter [10].](image-url)


3 Comparison

The comparison of different methods presented in this paper is based on performance and visual quality of result. Performance based comparison of ESP methods can be conducted by comparing the computational complexity, whereas the quality of results can best be evaluated using objective visual evaluation methods as peak signal to noise ratio (PSNR) [6] and mean absolute error (MAE).

3.1 Performance

This section presents the results of performance tests of previously mentioned methods from respective papers. Computational complexities of methods as well as processing time are crucial aspects in this comparison. The input images used in respective papers differ in number of channels in some cases. Since this difference can cause differences in performance, whenever a grayscale image is used the reader is notified. The testing environment is not consistent due to the fact that the performance numbers come from several respective papers. However, information about the environment is provided when available.

Due to the fact that bilateral filters use joint spatial and range filtering their implementations are computationally very expensive. The brute force implementations of the bilateral filter performs in $O(r^2)$ time where $r$ is the spatial filter size [19]. The modified bilateral filter proposed in [14] was developed purely for purposes of better quality of results while the computational and memory complexity, therefore the performance in general of the method is ignored. However, the proposed recursive bilateral filter [26] is an improvement that significantly reduces processing time. If $N$ represented the number of pixels of an image, and $D$ the number of channels, the computational and memory complexity of this recursive solution are both $O(ND)$. The proposed solution takes about 43 ms to process a one megapixel color image. The machine used for testing purposes was a computer with 1.8 GHz Intel Core i7 CPU and 4 GB memory. Compared to the implementation presented in [1], it performs about 18 times faster.
The computational cost of the adaptive bilateral filter (ABF) is high in case of brute force implementation, namely $O(|w|^2)$, where $w$ is the window radius. The ABF method needs 12.7 ms to process a one-megapixel gray-scale image on a Dual Core 2.0 GHz CPU. The authors discuss that the usage of the calculated optimal parameters obtained in ABF should be used in adaptive guided image filtering, thus making the ABF inferior to the AGF method.

The brute force implementation of joint bilateral filter has a high computational complexity, due to the pixel-wise adaptive weights. The brute force implementations are in the range of $O(r^2)$, with $r$ being the filter radius. The computational cost of the filter is therefore similar to computational cost of brute force implementation of standard unmodified bilateral filter. However as proposed in [29], it is possible to implement the filter in constant time by using the proposed joint integral histograms. The complexity is then reduced to constant time and it is independent of the filter radius.

The basic implementation of guided image filter has an $O(N)$ time algorithm in its core. The computational complexity is, contrary to bilateral filters, independent of the window radius and the intensity range. Only computationally expensive part of the guided filter is the mean filter, that can however also be computed in $O(N)$ time. The performance tests were conducted on a 3.0 GHz Intel Core i7 CPU and 8 GB machine. Gray-scale image edge-preserving smoothing takes about 40 ms per megapixel, if the input and guidance image have the same number of channels. For color images the filter takes 300 ms to process a one megapixel image, or 150 ms if the number of channels in guidance and input image are the same. Previously mentioned adaptive guided image filter has a computational complexity of $O(N)$, and it takes about 1.4 s to process a one-megapixel gray-scale image. The AGF method outperforms ABF in computational complexity by more than 10 seconds.

The presented multi-scale Kuwahara filter [11] that uses the advantages of CUDA was tested on a one megapixel image while the testing environment and the machine used are not specified. Only information about the computer used in performance experiments is that an NVIDIA GTX 580 graphics card was integrated. The processing of a one-megapixel gray-scale image takes approximately
<table>
<thead>
<tr>
<th>Method</th>
<th>Computational complexity</th>
<th>Processing time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard bilateral filter (brute force implementation)</td>
<td>$O(r^2)$</td>
<td>N/A</td>
</tr>
<tr>
<td>Recursive bilateral filter [26]</td>
<td>$O(ND)$</td>
<td>0.043 s</td>
</tr>
<tr>
<td>Adaptive bilateral filter [28]</td>
<td>$O(</td>
<td>w</td>
</tr>
<tr>
<td>Constant time bilateral filter [19]</td>
<td>$O(1)$</td>
<td>0.155 s *</td>
</tr>
<tr>
<td>Constant time joint bilateral filter [29]</td>
<td>$O(1)$</td>
<td>2 to 3 times faster than brute force [17]</td>
</tr>
<tr>
<td>Guided image filter [4]</td>
<td>$O(N)$</td>
<td>0.150 s</td>
</tr>
<tr>
<td>Adaptive guided filter (AGF) [28]</td>
<td>$O(N)$</td>
<td>1.400 s *</td>
</tr>
<tr>
<td>Multi-scale anisotropic Kuwahara filter [11]</td>
<td>N/A</td>
<td>0.150 s *</td>
</tr>
<tr>
<td>Anisotropic Diffusion [31]</td>
<td>$O(N^2)$</td>
<td>N/A</td>
</tr>
</tbody>
</table>

*Table 1: Comparison of different ESP methods implementations by computational complexity and processing time of one-megapixel image, if $r$ is the kernel radius, $N$ the number of pixels in an image, $D$ number of channels, $W$ filter window.*

150 ms to finish. Therefore, efficiency-wise is the solution less capable than most recent implementations of recursive bilateral filter and guided filter that can process a one-megapixel color image in 43 ms.

* a grayscale image was used as the input image
and a gray-scale image 40 ms respectively. However, guided filter was tested on a machine with twice as much memory and nearly twice as better CPU than the machine that the recursive bilateral filter was tested on. Based on this difference in testing environment, one can conclude that the recursive bilateral filter significantly outperforms the guided filter.

Table 1 gives an overview of the ESP methods presented in this paper as measured in respective papers. As can be seen, the recursive bilateral filter is the fastest method of the methods presented. It is capable of processing a one-megapixel color image in 43 ms. The processing time of constant joint bilateral filter is unavailable and therefore the implementation cannot be taken in consideration. However, the constant time bilateral filter [19] is a very effective solution that can process a one-megapixel grayscale image in 155 ms on a 3.2 GHz Pentium 4 CPU. This implementation has not been tested recently on a more advanced machine, therefore it cannot be classified as the second best presented method. Based on recent experiments [4], the second fastest method is the guided image filtering, which processes an color image in 150 ms if the input and guidance image have the same number of channels.

3.2 Visual quality of results

Methods that can be used for quantitative evaluation of filters are peak signal to noise ratio (PSNR) [6] and mean absolute error (MAE). PSNR is a term for ratio between the maximum power of a signal and the power of the corrupting noise. The method is very often used as a measure of quality of reconstruction of image compression. It is evaluated in decibels, simple to calculate, has clear physical meanings, and it is mathematically convenient in the context of optimization [20]. A disadvantage is that this measurement is only effective if the two compared images differ by increased distortion of a certain type. When analyzing the obtained PSNR values, the greater values indicate greater similarity between the images, whereas the two completely similar images are given the value of infinity. MAE is used for measurement of how close a forecast is to an eventual outcome. It can also be a measurement tool for filter's capability to
preserve details in an image. The smaller the MAE value the better edge-preserving results are produced.

The error measurement results presented in this paper are from respective papers. As can be observed, not all the methods mentioned in the text are also compared based on error measurement results because of the unavailability of such results. The results of PSNR and MAE of the two focus methods, bilateral and guided filter, are however presented and explained in detail.

The modified bilateral filter was compared with anisotropic diffusion [16] and standard bilateral filter in [14]. First, the images were corrupted with Gaussian and mixed Gaussian and impulse noise, and then the noise removal method was tested by applying it on the images. The PSNR was used to evaluate the efficiency of a filtering technique in images with impulsive noise, while MAE was used for evaluation of filter's capability to preserve edges. The test image is presented in Figure 4. The filter kernel size in standard and modified bilateral filter was set at 5×5. As can be observed in Table 2, the comparison gave two important results. First, in case of only Gaussian noise the modified bilateral filter produces slightly lower PSNR value than standard bilateral filter, whereas the anisotropic diffusion produced the highest value. However, the modified

<table>
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<th>Anisotropic diffusion</th>
<th>Bilateral filter</th>
<th>Modified bilateral filter</th>
</tr>
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<tbody>
<tr>
<td><strong>Gaussian noise</strong></td>
<td>33.03</td>
<td>32.15</td>
<td>31.74</td>
</tr>
<tr>
<td><strong>Mixed noise</strong></td>
<td>24.33</td>
<td>26.37</td>
<td>26.95</td>
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<table>
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<th></th>
<th>Anisotropic diffusion</th>
<th>Bilateral filter</th>
<th>Modified bilateral filter</th>
</tr>
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<tbody>
<tr>
<td><strong>Gaussian noise</strong></td>
<td>4.41</td>
<td>4.90</td>
<td>4.91</td>
</tr>
<tr>
<td><strong>Mixed noise</strong></td>
<td>10.69</td>
<td>8.24</td>
<td>7.20</td>
</tr>
</tbody>
</table>

*Table 2: Comparison of PSNR (top) and MAE (bottom) values obtained when restoring the color test images with anisotropic diffusion, standard bilateral filter and modified bilateral filter.*
implementation gives better results in noise reduction of the images contaminated by mixed Gaussian and impulsive noise. MAE results show that there is an insignificant difference between modified and standard bilateral filter in edge-preserving capabilities. However, the value of MAE in case of mixed Gaussian and impulse noise shows that the modified filter produces significantly higher results than anisotropic diffusion and standard bilateral filter.

Figure 4 shows visual results of the standard and modified filter applied on an image contaminated with mixed noise. The resulting images confirm that the results from PSNR and MAE test. However, small regions consisting of two or more pixels are sometimes preserved in the images corrupted with mixed Gaussian and impulsive. Restoration results of a noisy image acquired using a high speed camera under poor lighting conditions, presented in Figure 5, shows that the high efficiency of the proposed modified approach is confirmed. As can be observed, the noise is better suppressed and the edges are well preserved [14].

![Figure 4: Overall visual quality of standard bilateral filter (middle) and modified bilateral filter (right) on an noisy image (left) [14].](image1)

![Figure 5: Overall visual quality of standard bilateral filter (middle) and modified bilateral filter (right) on an noisy image (left) [14].](image2)
Recursive bilateral filter [26] produces similar results to standard bilateral filter at very low processing times. The visual results of the filter can be seen in Figure 6. In [26], Yang describes the filter as equally as effective as other EPS methods with significantly lower computational cost.

![Figure 6: Input image (left), standard implementation (middle) and recursive implementation (right) of the bilateral filter [25].](Image)

As presented in [14] there is a correlation of parameters used in guided image filter (GIF) and bilateral filter (BF). In bilateral filtering techniques the range variance $\sigma_r^2$ determines what high variance patch should be preserved. In other words, this parameter determines what region is an edge. The $\varepsilon$ parameter in guided image filtering techniques has a similar effect. Another correlation that authors set up empirically is the similarity between the decrement of weight in spatial domain $\sigma_s$ in BF and the radius $r$ of the filter in GIF. These correlations of parameters enable a quantitative comparison of BF and GIF. Since GIF is a more recent method compared to BF, the comparison is conducted so that the resulting filtered images of GIF are compared to images filtered with BF. Figure 7 presents the results of this comparison. Visually the differences are almost not recognizable, since the difference is often considered as visually insensitive when PSNR is greater than 40db.

<table>
<thead>
<tr>
<th></th>
<th>$r = 2$</th>
<th>$r = 4$</th>
<th>$r = 8$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\varepsilon = 0.1^2$</td>
<td>39.38</td>
<td>38.25</td>
<td>37.23</td>
</tr>
<tr>
<td>$\varepsilon = 0.2^2$</td>
<td>38.11</td>
<td>37.78</td>
<td>37.09</td>
</tr>
<tr>
<td>$\varepsilon = 0.4^2$</td>
<td>38.09</td>
<td>39.04</td>
<td>37.72</td>
</tr>
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</table>

*Table 3: PSNR results of comparison from Figure 7 [14].*
[19]. As can be seen in Table 3, the values are very close to 40db which proves that the GIF gives similar filtering results.

Figure 7: PSNR values comparison of grayscale images filtered with bilateral and guided filter. [14]
The mentioned adaptive guided filter, as well as adaptive bilateral filter, produces significantly better visual results than standard implementations of these methods respectively when a simultaneous noise reduction and sharpness enhancement are needed [28]. Figure 8 shows a comparison of visual results of guided filter and its adaptive version. The result of AGF when using the naive offset might contain the aliasing effect and pixels that differ significantly. This however can be solved by using the optimal parameters of ABF. [28]

Comparison of visual quality of images filtered with mentioned anisotropic single-scale and multi-scale Kuwahara filters and bilateral filter is shown in Figure 9. As can be observed the single-scale and multi-scale anisotropic Kuwahara filters are used for artistic stylization.

Figure 8: Normal (upper left) and detailed view (upper right) of an image filtered with standard GIF, and with AGF (lower two images). [28]
3.3 Summarized comparison of bilateral and guided filter

As presented in Figure 7 and Table 3, the quality of results proves that there is not a significant difference between the bilateral filter and guided filter. However, there is a great difference in the computational complexity and efficiency. The main advantage of guided filter presented in [14] over standard bilateral filter is that it uses an $O(N)$ time algorithm, that is independent of the window radius $r$ and the intensity range. Only computationally expensive part is the mean filter, that can however also be computed in $O(N)$ time. Another advantage is that the guided filter is applicable for intensity of any range, while the $O(N)$ bilateral filter may produce quantization artifacts. The processing time of a one-megapixel color image by using a guided filter is 150 ms. Its performance is significantly better than standard or modified bilateral filter.
implementations, but it is still slower than the processing time of recursive bilateral filter, which clocks at 43 ms. Joint bilateral filter requires significantly more time to process a single-channel image while producing similar results, therefore it cannot compete with guided and recursive bilateral filters. Processing time of constant time bilateral filter presented in [19] is 155 ms for a one-megapixel grayscale image. However, the testing environment and machine used in the research are obsolete, which means that this filter might be close to recursive bilateral filter in computational time if it was tested on a faster computer. The adaptive bilateral and guided filter are both more time consuming then their standard implementations. However, as mentioned before, the focus of these adaptive filters is achieving better results in simultaneous noise reduction and edge sharpening, even at cost of processing time.

4 Conclusion

In this paper, several techniques of smoothing a texture while preserving the edges in an image were presented. The main focus of this paper were bilateral filtering and guided image filtering. While the bilateral filter has been proposed much earlier than guided filter, number of improvements and modifications of this filter were published in recent years. The modifications presented in this paper are recursive implementation, modified and adaptive bilateral filter. Also joint bilateral filter is a significant enhancement, that later proved to be a foundation for guided image filtering, since this method also relies on guidance images while performing edge-preserving smoothing. The guided image filtering method has also seen a recent improvement that was also presented in this paper, namely adaptive guided filtering. While not being the fastest solution in sense of processing time, the modification is measured to give higher visual quality of results than its predecessor. Furthermore, modifications to Kuwahara filters were also presented. Single-scale and multi-scale anisotropic Kuwahara filters have been proposed, and these adaptations improve the visual quality of results, as well as decrease the computational complexity. Kuwahara filters and anisotropic diffusion are used for better comparison of performance
and visual quality, but these methods are not the main focus of this paper, because the bilateral and guided filter have been more documented and saw more modifications at the time of the writing.

The section of this paper that gives a better overview of the mentioned methods is the comparison of different proposed implementations and methods. When it comes to visual quality of results the differences are dependent on various variables, noise types and requested effects. In artistic stylization and image abstraction, multiple iterations might be needed while in application as image noise reduction this might not be the case. Similarity of visual results of different techniques presented in this paper is another reason why it is difficult to decide what solution produces the best results. Results are in general very hard to differentiate one from another, and the differences are often visually insensitive, which makes it impossible for human eye to differentiate them. That is where criteria of processing time helps in comparison. Through experiments conducted in different papers it is obvious that the recursive implementation of bilateral filter is one the fastest smoothing techniques, whereas the guided image filtering produces very similar results in slightly more time. Modifications of Kuwahara filter give it also a performance boost, but it is still one of more time consuming methods comparing to recursive bilateral filter and guided filter.
References


