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Guided Image Filtering for Image Enhancement

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Abstract: *Noise removing belongs to image restoration in digital image processing. It's the essential guarantee of identifying image information and the reliable guarantee of making further image processing. A satisfying result can't be found if processing method such as feature extraction, registration or image fusion is carried out on an image with noise. So removing noise is absolutely necessary for image. In this paper we compare various filtering algorithms like spatial domain filters, Frequency domain filters, Edge-Preserving filters (Bilateral filters), and guided image filtering algorithms based in terms of quality measurement parameters like PSNR.*

1. Introduction

Noise removing belongs to image restoration in digital image processing. It's the essential guarantee of identifying image information and the reliable guarantee of making further image processing. A satisfying result can't be found if processing method such as feature extraction, registration or image fusion is carried out on an image with noise. So removing noise is absolutely necessary for image. The processing method of removing noise can be divided into spatial domain and frequency domain. The algorithm theory of linear filtering in spatial domain is the most mature theory .With this theory, statistics can be analyzed simply and the random noise that not relevant to the image signal can be filtered efficiently. But there are definite weaknesses in this theory such as demand for prior's statistical knowledge, bad capacity of minutia preserving at edges of image and so on. The latter weakness even makes the linear filtering can't adapt to de noise an image. Nonlinear filtering that corresponding to linear filtering is powerful, and is used in image processing in medicine, remote sensing and so on.

The image enhancement methods can broadly be divided in to the following two categories:

1. Spatial Domain Methods

2. Frequency Domain Methods

In spatial domain techniques [1], we directly deal with the image pixels. The pixel values are manipulated to achieve desired enhancement. In frequency domain methods, the image is first transferred in to frequency domain. It means that, the Fourier Transform of the image is computed first. All the enhancement operations are performed on the Fourier transform of the image and then the Inverse Fourier transform is performed to get the resultant image. These enhancement operations are performed in order to modify the image brightness, contrast or the distribution of the grey levels. As a consequence the pixel value (intensities) of the output image will be modified according to the transformation function applied on the input values. Image enhancement is applied in every field where images are ought to be understood and analyzed. For example, medical image analysis, analysis of images from satellites etc. Image enhancement simply means, transforming an image f into image g using T. (Where T is the transformation. The values of pixels in images f and g are denoted by r and s, respectively. As said, the pixel values r and s are related by the expression, $s = T(r)$ (1) Where T is a transformation that maps a pixel value r into a pixel value s. The results of this transformation are mapped into the grey scale range as we are dealing here only with grey scale digital images. So, the results are mapped back into the range [0, L-1], where L=2k, k being the number of bits in the image being considered. So, for instance, for an 8-bit image the range of pixel values will be [0, 255]. We will consider only gray level images. The same theory can be extended for the color images too. A digital gray image can have pixel values in the range of 0 to 255.

Many different, often elementary and heuristic methods [2] are used to improve images in some sense. The problem is, of course, not well defined, as there is no objective measure for image quality. Here, we discuss a few recipes that have shown to be useful both for the human observer and/or for machine recognition [4]. These methods are very problem-oriented: a method that works fine in one case may be completely inadequate for another problem. In this paper basic image enhancement techniques have been discussed with their mathematical understanding. This paper will provide an overview of underlying concepts, along with algorithms commonly used for image enhancement. The paper focuses on spatial domain techniques for image enhancement, with particular reference to point processing methods, histogram processing.

2. GUIDED FILTER

We first define a general linear translation-variant filtering process, which involves a guidance image I, an filtering input image p, and an 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:

$$q_i = \sum_j W_{ij}(I) p_j, \qquad (1)$$

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.

2 .1 Definition

Now we define the guided filter. The key assumption of the guided filter is a local linear model between the guidance I and the filtering output q. We assume that q is a linear transform of I in a window !k centered at the pixel k:

$$q_i = a_k I_i + b_k, \forall i \in \omega_k,$$

where ak; bkÞ are some linear coefficients assumed to be constant in !k. We use a square window of a radius r. This local linear model ensures that q has an edge only if I has an edge, because rq ¼ arI. This model has been proven useful in image super-resolution [5], image matting [4], and dehazing [2].

2.2 Edge-Preserving Filtering

Given the definition of the guided filter, we first study the edge-preserving filtering property. The guided filter with various sets of parameters. Here we investigate the special case where the guide I is identical to the filtering input p. We can see that the guided filter behaves as an edge-preserving smoothing operator. The edge-preserving filtering property of the guided filter can be explained intuitively

2.3 Gradient-Preserving Filtering

Though the guided filter is an edge-preserving smoothing operator like the bilateral filter, it avoids the gradient reversal artifacts that may appear in detail enhancement and HDR compression. A brief introduction to the detail enhancement algorithm is as follows. Given the input signal p, its edge-preserving smoothed output is used as a base layer q (red). The difference between the input signal and the base layer is the detail layer (blue): d ¼ p _ q . It is magnified to boost the details. The enhanced signal (green) is the combination of the boosted detail layer and the base layer. An elaborate description of this method can be found in [5].

2.4 Extension to Color Filtering

The guided filter can be easily extended to color images. In the case when the filtering input p is multichannel, it is straightforward to apply the filter to each channel independently. A color guidance image can better preserve the edges that are not distinguishable in gray-scale. This is also the case in bilateral filtering [20]. A color guidance image is also essential in the matting/feathering and dehazing applications, as we show later, because the local linear model is more likely to be valid in the RGB color space than in gray-scale [6].

2.5 Structure-Transferring Filtering

Interestingly, the guided filter is not simply a smoothing filter. Due to the local linear model of q ¼ aI þ b, the output q is locally a scaling (plus an offset) of the guidance I. This makes it possible to transfer structure from the guidance I to the output q, even if the filtering input p is smooth .To show an example of structure-transferring filtering, we introduce an application of guided feathering: A binary mask is refined to appear an alpha matte near the object boundaries (Fig. 10). The binary mask can be obtained from graph-cut or other segmentation methods, and is used as the filter input p. The guidance I is the color image. The behaviors of three filters: guided filter, (joint) bilateral filter, and a recent domain transform filter [38]. We observe that the guided filter faithfully recovers the hair, even though the filtering input p is binary and very rough. The bilateral filter may lose some thin structures (see zoom-in). This is because the bilateral filer is guided by pixel-wise color difference, whereas the guided filter has a patch-wise model. We also observe that the domain transform filter does not have a good structure-transferring ability and simply smooths the result. This is because this filter is based on geodesic distance of pixels, and its output is a series of 1D box filters with adaptive spans [38].

3. PROPOSED ALGORITHM

3.1. 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 color 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.[1] Consider a pixel located at (i, j) which needs to be denoised 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 denoise 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 denoised intensity of pixel (i, j).

3.2. Guided Image Filter

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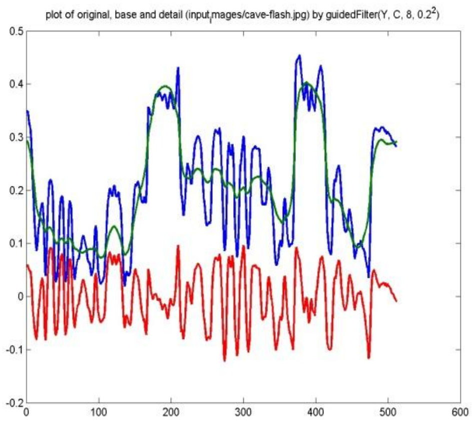
$$q_i = \sum_j W_{ij}(I) p_j,$$

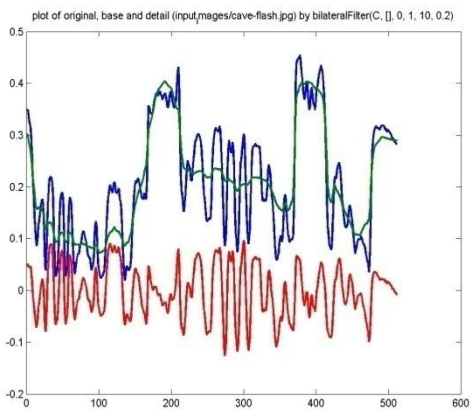
Where i and j are pixel indexes. The filter kernel W_{ij} is a function of the guidance image I and independent of p. This filter is linear with respect to p.

The bilateral filtering kernel W_{bf} is given by

$$W_{ij}^{\mathrm{bf}}(I) = \frac{1}{K_i} \exp\left(-\frac{\| \mathbf{x}_i - \mathbf{x}_j \|^2}{\sigma_s^2}\right) \exp\left(-\frac{\| I_i - I_j \|^2}{\sigma_r^2}\right)$$

4. Implementation Results





5. Conclusion and Future Scope

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.

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