Signal Processing: *Image Communication* 29 (2014) 998–1014

Contents lists available at ScienceDirect

Signal Processing: *Image Communication*

journal homepage: www.elsevier.com/locate/image

# An efficient recursive edge-aware filter

Cevahir Çığla [a,*], A. Aydın Alatan [b]

[a] *ASELSAN Inc. and Electric and Electronics Department of Middle East Technical University, Turkey*
[b] *Electric and Electronics Department of Middle East Technical University, Turkey*

ARTICLE INFO

*Article history:*
Received 31 December 2013
Received in revised form
20 June 2014
Accepted 21 July 2014
Available online 30 July 2014

*Keywords:*
Content adaptive filtering
Edge-awareness
Connectivity
Permeability filter
Recursive filtering

ABSTRACT

In this study, an efficient edge-aware filtering methodology, namely permeability filter, that exploits recursive updates among horizontal and vertical axes, is extended for common image filtering applications, including denoising, segmentation and depth up-scaling. Besides, an 8-neighbor update methodology, that is applicable for all type of recursive filters, is proposed extending orthogonally generated supporting regions into multi-directional support. This extension provides fine smoothing, especially at object boundaries, and yields crisp aggregation regions for each pixel. Since it provides geometrically stable connected support regions for each pixel, the recursive filters remove the dependency on pre-defined windows that is common among the state-of-the-art edge-aware filters, and also provide complete content adaptability. Based on extensive experiments against popular edge-aware filters, it can be concluded that the permeability filter outperforms most of the state-of-the-art techniques in terms of both speed and precision, especially for geometry dependent applications, such as depth data up-scaling and stereo matching; while providing a competitive segmentation and de-nosing capability. Besides, the proposed multi-direction extension methodology significantly improves the performances of recursive filters in almost each application with up to three times increase in computation time. This remarkable performance is due to the unification of connected support regions by soft weights, while preventing over smoothing and enabling crisp models that improve performance on the specified applications. In conclusion, permeability filter and its proposed 8-neighbor recursion methodology is an efficient alternative to edge-aware filters in many application areas by the proposed multi-directional support with window size independency and providing high performance with quite low computational complexity.



## 1. Introduction

Content adaptive filtering [1–4] has been popular in computer vision for various applications with their non-linear edge preserving characteristics. The fundamental idea behind this type of filtering is to provide intensity adaptive weights within a pre-defined window by highlighting color-wise similar pixels and achieving weighted averaging. Edge preserved smoothing characteristics come up with great advantages over traditional linear time invariant (LTI) smoothing operators, such as *Gaussian*, *Laplacian* and *Sobel Filters*, which are spatially independent of image content. In that manner, anisotropic diffusion was proposed in [5,6] as a general iterative approach to provide edge-aware smoothing. Recently, the bilateral filter (BF) [1], whose relevance with anisotropic diffusion is illustrated in [7], has become the most popular of such filters with its non-iterative steps. During the last

* Corresponding author.
*E-mail address:* cevahir@eee.metu.edu.tr (C. Çığla).

http://dx.doi.org/10.1016/j.image.2014.07.005

decade, BF is adapted to various applications [8] involving image mating [9], denoising [10,11], colorization [12], multi-scale decomposition [13], stereo matching [14], tone mapping [15], video abstraction [16], motion estimation [17] and depth data up-sampling [18]. In most of these approaches, joint (cross) bilateral filter approach, where an image (data) is filtered according to the color variation of the guidance (another) image through which adaptive weights are determined, is utilized. The filtered image can be non-flashed view [15], cost data calculated in stereo matching [14] or motion estimation [17], low resolution depth map [18] or the view itself as in denoising [10].

Despite wide application areas, there are certain drawbacks of BF in terms of computational complexity and accuracy. Hence, a part of the research is focused on complexity reduction of BF, yielding various approaches that address content based filtering. Details of these techniques are further discussed in Section 2. Pointing the disadvantages of the prior art, the extension of permeability filter to common color image filtering applications is introduced in the following section, which is followed by the proposed 8-neighbor update rule for recursive filters. A detailed comparison of the state-of-the art edge-aware filters with the proposed method is presented in terms of the computational complexity and memory requirement in Section 4. The comparisons are validated by extensive experiments and the final section is devoted to the conclusion and discussions.

## 2. Related work

In this section, the state-of-the-art edge-aware filters are summarized by the help of some discussions on efficiency and precision. The edge-aware filters can be grouped into three main classes based on the computational complexity as brute-force filters which do not utilize any approximations for computational complexity, filters exploiting summed are tables (integral images) for the sake of window independence and finally recursive filters that show infinite impulse response (IIR) characteristics.

### 2.1. Brute-force filters

BF [1], one of the pioneering edge-aware filters, is the most common technique to achieve content adaptive filtering. Let $x,\ y \in Z$ be the pixel indexes among a color image, $I$, involving integer intensity levels. A bilateral filter [1] BF, outputs color adaptive average, $I_x^B$, of a pixel $x$, among a set of pixels, $N(x)$, according to

$$I_x^B = \frac{\sum_{y \in N(x)} F_S(x,y) F_R(I_x, I_y) I_y}{\sum_{y \in N(x)} F_S(x,y) F_R(I_x, I_y)} \tag{1}$$

where the range kernel, $F_R$, assigns weights depending on intensity similarities between $I_x$ and $I_y$ based on a scaling factor $\sigma$. On the other hand, spatial kernel, $F_s$, weights according to the distance between pixel locations. The range functions ($F_s$ and $F_R$) can be computed on another type data such as depth, $D_x$, and then the operation turns into joint bilateral filtering which enforces local characteristics of $D_x$. The main idea of BF is the replacement of each pixel by the weighted average of their neighbors.

The spatial kernel in BF provides weighting according to pixel locations; however, it does not consider connectedness among the support pixels, which is important for geometry related applications. Disconnected weight distribution may cause errors for geometry dependent applications, such as segmentation, depth data up-sampling, stereo matching and optic flow estimation in addition to over-smoothing of sharp edge transitions. This problem can be solved by introducing geodesic filter (GeoF) [30,31] that utilize *Geodesic Distance* [27] which is a well known reliable distance transformation. The calculation of geodesic distances is achieved by determining color-wise smooth paths from each pixel to the center pixel in a pre-defined filtering window. Direct implementations of BF and GeoF yield $O(N^2)$ complexity depending on the supporting region $(N \times N)$ where adaptive weights are calculated. Such complex computations enforce several approximations [21–23,33] to achieve faster filtering.

### 2.2. Summed area table based filters

Integral images [26,29], which are also known as summed area tables or box filters, enable very fast convolution (box filter) of an image by uniform kernels. Uniform kernels cannot provide edge-aware filters, in that manner utilization of multiple box filters is a common way to provide content adaptive filtering as in *Constant Time Bilateral Filter* (CBF) [19,20], *Guided Filter* (GF) [3], *Cosine Integral Images* (CII) [4] and *Arbitrary Shaped Cross Filter* (ASCF) [34].

The fastest approximation of BF in state-of-the-art is provided by [20], in which piecewise linear BF is applied on discretized image intensity levels. Each level is defined as Principle Bilateral Filtered Image Component (PBFIC) [20]. The actual formulation of *BF*, the relation in (1) is modified to find the filtered values ${J_x}^{B,k}$ of the specific quantization levels, $L_k$, as

$$J_x^{B,k} = \frac{\sum_{y \in N(x)} F_S(x,y) F_R(L_k, I_y) I_y}{\sum_{y \in N(x)} F_S(x,y) F_R(L_k, I_y)} \tag{2}$$

where the actual intensity level of $I_x$ in (1) is replaced by a fixed level, $L_k$ as a result of re-formulation. Filtered values for specified levels can be determined through box filter [26] utilization over the updated version of $I_y$ in constant complexity. Once, filtered values are calculated for each level (8–16 *levels*), final output of an arbitrary pixel is calculated by linear interpolation of the fixed levels ($L_k$ and $L_{k+1}$) closest to the current pixel intensity $I_x$. It has been shown by detail experiments in [20] that, utilizing 8 levels provide sufficient accuracy.

Guided filter (GF) assumes a local linear model between the guidance image and the output as

$$I_x^G = \sum_{y \in N(x)} A_x I_x + B_x \tag{3}$$

where $A_x$ and $B_x$ are the real valued linear coefficients constant within the support window, $N(x)$, of the center pixel $x$. Linear transformation among pre-defined regions preserves edge characteristics of the guided image $I$ in the filter output $I^F$. Determination of the linear coefficients for each pixel is achieved by minimizing the difference between filtered value and filter input. The solution for