Optik 125 (2014) 3283–3286

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

A weighted least squares algorithm for time-of-flight depth image denoising

Yang Li [a,b], Jianing Li [a,b], Lianghao Wang [a,b,*], Junfei Zhang [a,b], Dongxiao Li [a,b], Ming Zhang [a,b]

[a] Institute of Information and Communication Engineering, Zhejiang University, Hangzhou 310027, China
[b] Zhejiang Provincial Key Laboratory of Information Network Technology, Hangzhou 310027, China

ARTICLE INFO

Article history:
Received 29 June 2013
Accepted 17 December 2013

Keywords:
Time of flight
Denoising
Edge-preserving smoothing
Weighted least squares

ABSTRACT

In this paper, we present a new denoising method for the depth image of a time-of-flight (ToF) camera, based on weighted least squares (WLS) framework. The common method for ToF depth image denoising is to use bilateral filter. However, the ability of bilateral filter in edge preservation would be reduced while we attempt to smooth out larger spatial scale noise. In order to avoid this problem and preserve the edge information as much as possible, we introduce a new way to construct edge-preserving ToF depth image denoising based on WLS. We are to our knowledge the first to present a WLS-based method for ToF depth image denoising. Experimental results demonstrate that compared with bilateral filter, our proposed algorithm not only achieves better performance in edge preservation, but also improves the PSNR values of the denoised images by 0.5–2.6 dB.

1. Introduction

In the last few years, time-of-flight (ToF) cameras [1] have become popular to retrieve depth information from 3D scenes. The main characteristics of ToF cameras are high frame rate, good consistency of the produced depth map, good accuracy and low computational requirements. However, for the majority of practical applications, direct usage of the raw data obtained from ToF cameras is not feasible as the presence of high noise levels which would reduce the precision of distance measurement, so there is a need to denoise the ToF depth image before further processing.

A large number of methods have been proposed for noise reduction in ToF depth image. In [2] the authors present three methods which are standard median filter, uniform low-pass filter and recursive temporal filter for the denoising of depth images acquired by ToF cameras. While these methods significantly reduce the variance of the depth measurements, they also produce spatial and motion blur. In [3], temporal averaging is used to reduce the amount of noise prior to the super-resolution of the depth images. In [4] the authors present a method based on the non-local means filter to reduce noise of ToF depth data. Another recent depth images denoising methods are presented in [5–8]. These methods are mainly based on bilateral filter or wavelet techniques, combined with appropriate noise models. Despite the recent improvements to noise reduction for depth images in the image processing literature, bilateral filter is the common choice for depth data denoising [9]. However, while this filter is well suited for noise removal and edge-preserving at a fine spatial scale, it would trade off its edge preservation abilities with its smoothing abilities at the larger spatial scale, which we would explain in Section 2.

In this paper we advocate an alternative edge-preserving method based on weighted least squares (WLS) framework for the denoising of depth image acquired by ToF cameras. This framework was originally used to control ringing during de-blurring of noisy images [10]. Recently, this framework was employed for edge-preserving multi-scale image decomposition [11]. The main goal of the proposed algorithm is to achieve both finer and coarser smoothing while preserving the step edges. Experimental results demonstrate that compared with bilateral filter, our proposed algorithm provides better performance in edge-preserving while reducing the noise for both simulated data generated from Middlebury stereo database and real ToF depth data.

The rest of the paper is organized as follows: In Section 2, we examine the characteristics of the bilateral filter in edge preservation and noise reduction at different spatial scales. In Section 3, we describe the proposed weighted least squares algorithm and compare it with bilateral filter. In Section 4, we report the experimental results we have obtained by applying the proposed algorithm on both the simulated data generated from Middlebury

* Corresponding author at: Institute of Information and Communication Engineering, Zhejiang University, Hangzhou 310027, China. Tel.: +86 1396 8025 840; fax: +86 57187952017.
E-mail address: wang_sunsky@163.com (L. Wang).

0030-4026/$ – see front matter © 2014 Elsevier GmbH. All rights reserved.
http://dx.doi.org/10.1016/j.ijleo.2013.12.039

stereo database and real data taken with a ToF camera from PMDTec CamCube. Finally, In Section 5, we present our conclusions.

2. Characteristics of bilateral filter

As described above, the bilateral filter [12] has recently been used as the de facto method for depth images denoising. Bilateral filter is a non-linear filter, where each pixel in the filtered result is a weighted mean of its neighbors, with the weights decreasing both with spatial distance and with difference in value. Assume the position of a noisy image's pixel is p and the pixel value is $I(p)$. The local neighborhood set of p which may have influence on $I(p)$ is denoted as $S(p)$. Then the bilateral filter can be formulated as follows:

$$BF[I]_p = \frac{1}{W_p}\sum\nolimits_{q\in S(p)} G_{\delta_s}(||p-q||)\, G_{\delta_r}(||I(p)-I(q)||)\, I(q) \tag{1}$$

where W_p is the normalization factor.

$$W_p = \sum\nolimits_{q\in S(p)} G_{\delta_s}(||p-q||)\, G_{\delta_r}(||I(p)-I(q)||) \tag{2}$$

where G_{δ_s} is a spatial Gaussian that decreases the influence of distant pixels, and G_{δ_r} is a range Gaussian that decreases the influence of pixels q with a large intensity difference. The bilateral filter is controlled by two parameters δ_s and δ_r. δ_s determines the spatial support and δ_r controls the sensitivity to edges. In order to explain the characteristics of the bilateral filter clearly, we repeat an experiment performed in [11], on a grayscale image with several step-edges of varying magnitude that is polluted with noise at two scales (see Fig. 1(a)). For clarity, we visualize the image intensities using a color map (see Fig. 1(b)). Fig. 1(c) shows the result of applying the bilateral filter with a small δ_s which manages to smooth out most of the fine scale noise while keeping the edges mostly sharp. In Fig. 1(d), we attempt to smooth out the larger spatial scale noise by increasing only δ_s, but reintroducing some fine scale noise into the denoised image, particularly near the edges. In Fig. 1(e) and (f), we increase both δ_s and δ_r, the denoised results show that increasing δ_r could reduce the ability of the bilateral filter to preserve edges, and some of them become blurred. In summary, bilateral filter would trade off its edge-preservation abilities with its smoothing abilities.

3. Proposed method

In order to avoid the drawback of the bilateral filter, we introduce a new way to construct edge-preserving depth image denoising based on weighted least squares framework. Given an input noisy depth image g, we seek a denoised image u which is as close as possible to g and as smooth as possible everywhere except at regions where the gradient of g is large. Formally, this may be expressed as seeking the minimum of following mathematical model in [11]:

$$\sum_p \left((u_p - g_p)^2 + \lambda \left(a_{x,p}(g)\left(\frac{\partial u}{\partial x}\right)_p^2 + a_{y,p}(g)\left(\frac{\partial u}{\partial y}\right)_p^2 \right)\right) \tag{3}$$

where the subscript p denotes the spatial location of a pixel. The goal of the data term $(u_p - g_p)^2$ is to minimize the distance between u and g, while the regularization term is to achieve smoothness by minimizing the partial derivatives of u. λ is used to balance the two terms; increasing the value of λ results in progressively smoother images u. The smoothness requirement is enforced in a spatially varying manner via the smoothness weights a_x and a_y, which are defined in [13]:

$$a_{x,p}(g) = \left(\left|\frac{\partial \ell}{\partial x}(p)\right|^{\alpha} + \varepsilon\right)^{-1} \quad a_{x,p}(g) = \left(\left|\frac{\partial \ell}{\partial y}(p)\right|^{\alpha} + \varepsilon\right)^{-1} \tag{4}$$

where l is the log-luminance channel of the input noisy depth image g, the exponent a determines the sensitivity to the gradients of g. For real ToF depth images, since the edges in original depth image are always not clear enough compared with color image, the exponent a for g should be set to a large one to ensure that it can detect the edges in depth images more effectively, while λ should be decreased along with the increase of a to avoid over smoothing edges. ε is a small constant that prevents division by zero in areas where g is constant. The vector u that minimizes Eq. (3) is defined as the solution of the linear system:

$$(I + \lambda(D_x^T A_x D_x + D_y^T A_y D_y))u = g \tag{5}$$

where I is identity matrix. A_x and A_y are diagonal matrices which contain the smoothness weights $a_x(g)$ and $a_y(g)$. The matrices D_x and D_y are forward difference operators, hence D_x^T and D_y^T are backward difference operators, which means that $D_x^T A_x D_x + D_y^T A_y D_y$ is a five-point spatially inhomogeneous Laplacian matrix and there is a fast solution method presented in [14]. Eq. (6) shows that u is obtained from g by applying a non-linear operator which depends on g:

$$u = (I + \lambda(D_x^T A_x D_x + D_y^T A_y D_y))^{-1} g \tag{6}$$

In order to compare the characteristics between bilateral filter and the proposed method, we apply the proposed method to the same image in Fig. 1(a). Fig. 1(g) and (h) is the denoised results by using the proposed method with different a and λ. These results show that the proposed method can achieve both finer and coarser smoothing while preserving the step edge compared with bilateral filter. In next section we will demonstrate these characteristics by using simulated data and real ToF depth images.

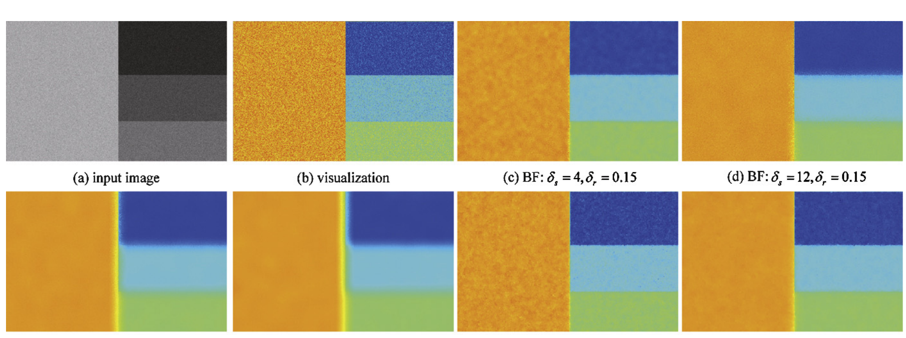

Fig. 1. Results of applying bilateral filter and proposed method on a noisy image.