Analysis of Depth Restoration via Regularization in Curvelet Domain

Qirui Zhang, Takafumi Taketomi, Alexander Plopski, Christian Sandor, Hirokazu Kato

I. Introduction

RGB-D cameras have widely been used in augmented reality, computer vision, and robotics research fields. Depth maps acquired from RGB-D cameras are in low resolution with partial data loss of acquisition. Several methods attempt to obtain high resolution depth maps and enhance depth quality by associating depth maps with coupled intensity images. Depth map filtering methods based on a single depth map and a reference of intensity image are categorized as applying local filtering or using global optimization [1]. In this paper, we will discuss about applying curvelet domain regularization in the optimization scheme [2] of latter category since curvelet[3] based image restoration achieves compelling results in RGB image inpainting tasks. We evaluated the accuracy of restored depth maps compared with several standard methods.

II. Depth Upsampling Using Curvelet Transform

Given a damaged depth map aligned to its coupled RGB view $\mathbf{d}_L : \Omega_S \to \mathbb{R}$ from a calibrated RGB-D sensor, and its coupled high resolution intensity image $\mathbf{I} : \Omega \to \mathbb{R}$, we are interested in the mapped depth map with high resolution $\mathbf{d} : \Omega \to \mathbb{R}$. Given a linear operator Φ transforming image to curvelet domain $\mathbf{C}$ as $\mathbf{c} = \Phi(\mathbf{d})$, L_1 norm of coefficients c in this domain is used as regularizer to preserve certain inherent nature of transformed feature domain [2]. We are following this model to inpaint the depth map via reconstruction $\Phi^{-1}\tilde{\mathbf{c}}$.

$$\tilde{\mathbf{c}} = \arg\min_{c} \|\mathbf{c}\|_1, \quad s.t. \|\Phi^{-1}\mathbf{c} - \mathbf{d}_L\|^2 \leqslant \sigma^2_{noise} \tag{1}$$

where $\tilde{\mathbf{c}}$ represents reconstructing coefficients. For pixels Ω_S which have confident depth measurement, we allow certain noise level σ_{noise} and for pixels in $\Omega \setminus \Omega_S$ that there is no restriction from data. To solve (1), we rewrite it in Lagrange form,

$$\arg\min_{\mathbf{d}} |\Phi\mathbf{d}\|_1 + \mathbf{M}\|\mathbf{d}_S - \mathbf{d}\|_2^2 \tag{2}$$

where $\mathbf{M}$ is the mask for restoration area $\Omega \setminus \Omega_S$. Then we apply the Legendre Fenchel transform as its dual form

$$\arg\min_{\mathbf{d}} \arg\max_{\mathbf{q}} \langle \mathbf{d}, \Phi^{-1}\mathbf{q} \rangle + \lambda\|\mathbf{d} - \mathbf{d}_S\|_2^2 \tag{3}$$

where $\mathbf{q}$ is the dual variable of curvelet domain. (3) can be solved efficiently by Arrow-Hurwicz algorithm.

III. Evaluation and Conclusion

In evaluation experiment, we use depth images with 95% randomly distributed pixel data loss as input. One visual perceptual result is shown in figure 1. Curvelet based restoration achieved appearance of clear edges and smooth surfaces. We measured the RMSE on 24 images from MiddleBurry 2014 data set[4] for each method and curvelet based restoration achieved comparable result in most tests and outperformed others in certain tests. Limited by space, we omit the data detail here. In this paper we summarized a short description of global optimization techniques in depth restoration from extreme sparse measurements and verified the feasibility of utilizing curvelet regularization in such problem through simulation experiment.

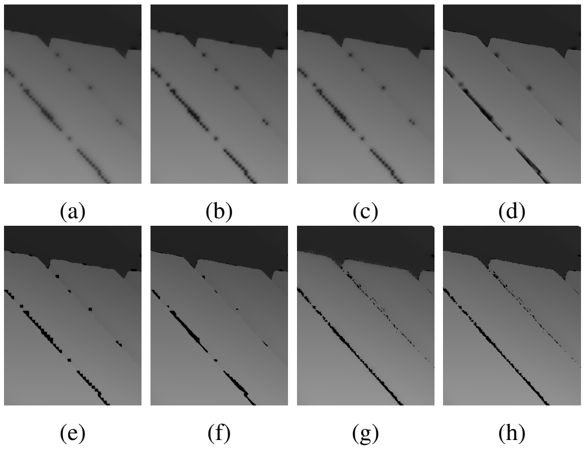

Fig. 1: Visual comparison among standard methods and curvelet domain regularization. (a) Markov Random Field (Kernel), (b) Markov Random Filed (2nd order smoothness), (c) Anisotropic Diffusion, (d) Bilateral Filter, (e) Noise Aware Filter, (f) Weight Mode Filter, (g) Curvelet Regularization, and (h) ground truth

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References

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