

zentrum für virtual reality und visualisierung forschungs-gmbh



- Abstract

Consolidation of point clouds, including denoising, outlier removal and normal estimation, is an important pre-processing step for surface reconstruction techniques. We present a consolidation framework specialized on point clouds created by multiple frames of a depth camera. An adaptive view-dependent locally optimal projection operator denoises multiple depth maps while keeping their structure in two-dimensional grids. Depth cameras produce a systematic variation of noise scales along the depth axis. Adapting to different noise scales allows to remove noise in the point cloud and preserve well-defined details at the same time. Our framework provides additional consolidation steps for depth maps like normal estimation and outlier removal. We show how knowledge about the distribution of noise in the input data can be effectively used for improving point clouds.

Introduction

Input

- Depth precision of stereo cameras depends on camera distance
- Actual error is random noise
- Noise scale can be analyzed systematically
- Combining multiple frames
- Areas with reliable 3D points captured from near viewpoints
- Noisy areas captured only from distant camera locations
- Overlapping areas with different confidences
- Motivation
- Improve surface reconstruction by including information on varying point precision
- Points with high precision have more impact
- Keep details in confident areas
- Remove outliers and noise in areas without any confident points by smoothing

- State of the Art

Locally Optimal Projection (LOP) operator [0,1]

- Project points onto surface without a local 2D parameterization
- Iterative algorithm

$$\sum_{j} p_j \frac{\alpha_j^i}{\sum_{i} \alpha_j^i} + \mu \sum_{i'} (x_i - x_{i'}) \frac{\beta_{i'}^i}{\sum_{j'} \beta_{i'}^i}$$

- First term attracts points to object surface
- Second term is a repulsive force to keep points well distributed
- α depends on distances between input and projected points
- β depends on distances between projected points
- θ and η are fast decaying weight functions

Consolidation of Multiple Depth Maps

 $\beta_{i'}^{i} = \frac{\theta(\left\|\delta_{ii'}^{\kappa}\right\|) \left|\eta'(\left\|\delta_{ii'}^{k}\right\|)\right|}{\left|\eta'(\left\|\delta_{ii'}^{k}\right\|)\right|}$

- Adaptive view-dependent LOP

Adapting to different noise scales

- Global neighborhood size controls the amount of smoothing • Adjust neighborhood size for each point depending on its noise scale \rightarrow more smoothing in areas with low confidence
- Noise scale increases quadratically with increasing depth values
- Neighborhood size is computed in each iteration based on average depth values (z_i) of nearby input points
- Higher attraction to confident input points than to noisy points • Weight attraction term (α) with reciprocal of the input point's
- depth

View-dependent projection

- Keep point cloud organized in depth maps
- Translations along viewing directions are the only possible adjustment
- Project all points onto viewing ray of current point
- Sum over displacements along ray rather than over 3D input points

Results





$$h_i = h \left(\frac{\sum_{j} z_j \ \theta(\|\xi_{ij}\|, h_i)}{\sum_{j} \theta(\|\xi_{ij}\|, h_i)} \right)^2$$



Repulsion term

- nearby points
- Only important for points within the same frame
- Points on slanted surfaces might
- be attracted to local clusters
- and slanted surfaces $\mu(1 |v_i \cdot n_i|)$
- viewing direction $|(x_i x_{i'}) \cdot v_i|$



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[0] H. Huang, D. Li, H. Zhang, U. Ascher, and D. Cohen-Or. Consolidation of unorganized point clouds for surface reconstruction. In Proc. of ACM SIGGRAPH Asia, 2009. [1] Y. Lipman, D. Cohen-Or, D. Levin, and H. Tal-Ezer. Parameterization-free projection for geometry reconstruction. In Proc. of ACM SIGGRAPH, 2007.