Accuracy analysis of 3D object reconstruction using mesh filtering

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Abstract. In this paper, we analyze the accuracy of 3D object reconstruction using mesh filtering applied to data from a RGB-D sensor. Various methods of mesh filtering are tested and compared with respect to the reconstruction accuracy using real data. In order to improve the accuracy of 3D object reconstruction, an efficient method of mesh filtering is designed. The resented results show an improvement in the accuracy of 3D object reconstruction using the proposed mesh filtering algorithm.

1. Introduction

The availability of high-quality 3D mesh models of real objects has become an essential prerequisite in various applications, such as medicine, agriculture, architecture, engineering, industrial metrology, cultural heritage preservation and restoration [1, 2, 3]. Accurate 3D object reconstruction is an important aspect for object recognition, object retrieval, scene understanding, object tracking, virtual maintenance and visualization [4, 5, 6].

Mesh denoising is always an inevitable stage to eliminate or to reduce these negative impacts for processing, because of the limitation in the accuracy of scanning devices, the influence of surrounding environment, and the acquired raw data contains noise.

Noise and holes can greatly affect to the accurate of 3D reconstruction [7, 8, 9], therefore, noise-reduction and hole-filling enhancement algorithms are intended to serve as preprocessing step for 3D reconstruction systems with Kinect cameras [10, 11, 12]. To reduce impulsive noise and to fill small holes, filters [13, 14, 15, 16, 17] can be used.

In this paper, we are interested in the design of a filtering algorithm of a mesh to improve the quality of 3D reconstruction. The existing approaches can be classified in two core groups that treat differently noise and salient features, known as isotropic and anisotropic, respectively.

In common approach of noise reduction it is supposed that the raw mesh contains the ground truth, distorted by noise such as additive one. Although this approach could be used for quantitative comparison (with PSNR, MSE, etc), common methods reduce only artificial noise but not original noise contained in the raw mesh. In this paper, we consider denoising mesh algorithms for 3D object reconstruction. We propose a denoising method using a mesh as the input. We also evaluate the performance of denoising methods with respect to the accuracy of 3D object reconstruction. Actually, we calculate Hausdorf distance between point cloud of the accurate laser model and point cloud from mesh, and cloud to mesh distance between point cloud of accurate laser model and filtered meshes.

General denoising methods are not designed to clean coarse noise contained in the input mesh. Therefore, our main goal is to evaluate denoising methods in terms of the reconstruction accuracy which depends on the quality of the input mesh.

The performance of the proposed algorithm is compared in terms of the accuracy of 3D object reconstruction and speed with the following depth denoising algorithms: Robust and High Fidelity Mesh Denoising (RHFMD) [18], Static/Dynamic Filtering for Mesh Geometry (SDFMG) [19], Guided mesh normal filtering (GMN) [20], Bilateral mesh denoising (BMD) [21], Non-iterative, feature-preserving mesh smoothing (NIFPMS) [22], Fast and Effective Feature-Preserving Mesh Denoising (FEFPMD) [23], Bilateral Normal Filtering for Mesh Denoising (BNFMD) [24], Mesh denoising via L0 minimization (MDLM) [25].

The paper is organized as follows. Computer simulation results are provided in Section 2. Finally, Section 3 summarizes our conclusions.

2. Experimental results

In this section, we evaluate the performance of the tested mesh denoising methods in terms of reconstruction accuracy which depends on the quality of the input mesh.

Extensive experiments revealed that very good denoising results cannot be achieved using the following filters: RHFMD [18], GMN [20], BMD [21], FEFPMD [23], MDLM [25]. The main reason of this is uncorrected mesh after filtering, therefore, we do not use these filters for our next experiments and comparisons.

We compare the following mesh denoising algorithms in terms of the accuracy of 3D object reconstruction: SDFMG [19], NIFPMS [22], BNFMD [24]. The experiments are carried out on a PC with Intel(R) Core(TM) i7-4790 CPU @ 3.60 GHz and 16 GB memory.

In our experiments we use the meshes of a lion, an apollo, and an anatomy from dataset [26].

We construct couples of meshes for each model using the following steps:

(i) Registration RGB and depth data.

(ii) Making point clouds.

(iii) Making input meshes from point clouds.

(iv) Calculating Hausdorf distance (HD) between point cloud of accurate laser model and point cloud of filtered mesh, and cloud to mesh distance (CMD) between point cloud of accurate laser model and filtered meshes.

The corresponding calculated HD and CMD metrics for the model a lion, an apollo, and an anatomy without filtering (HDW and CMDW) and after denoising (HDF and CMDF) by SDFMG, NIFPMS, BNFMD filters are shown in Table 1. The NIFPMS filter yields the best result in terms HD and CMD evaluation among all mesh denoising algorithms.

3. Conclusion

In this paper, we compared various mesh denoising algorithms in terms of the accuracy of 3D object reconstruction using real data from a RGB-D sensor. The experiment has shown that the NIFPMS filter yields the best result in terms of the accuracy of 3D object reconstruction among all mesh denoising algorithms.

4. Acknowledgments

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Table 1. Calculated metrics between two point clouds of each model without filtering.

Object	Filters	HDW	HDF	CMDW	CMDF
Anatomy	SDFMG	0.041397	0.041446	0.005053	0.005055
	NIFPMS	0.041397	0.041497	0.005053	0.005147
	BNFMD	0.041397	0.041413	0.005053	0.005051
Apollo	SDFMG	0.005057	0.004935	0.000225	0.000266
	NIFPMS	0.005057	0.005091	0.000225	0.000118
	BNFMD	0.005057	0.005073	0.000225	0.000289
Lion	SDFMG	0.004753	0.004879	0.001281	0.001238
	NIFPMS	0.004753	0.004841	0.001281	0.001393
	BNFMD	0.004753	0.004838	0.001281	0.001284

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