3D Object Decomposition and Super Resolution

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Abstract

In this paper we propose to address the problem of 3D object decomposition and super resolution. We model the 3D object as a set of Riemannian manifolds and propose metric tensor and Christoffel symbols as a novel set of features for 3D object decomposition using polynomial kernel SVM classifier. The super resolution of the 3D point clouds is carried out using the decomposed object by using selective interpolation techniques. The effectiveness of the proposed framework is demonstrated on 3D objects obtained from different datasets and achieve comparable results.

1 Introduction

The 3D objects under consideration are modeled as a set of Riemannian manifolds [Weinberg 1972]. The inherent geometrical properties of a 3D object show similarities to the basic 3D shapes like cone, sphere and cylinder on a local basis. 3D point cloud super resolution is an important processing step for 3D point cloud data obtained from inexpensive sensors like Kinect and time-of-flight (ToF) cameras. Super resolution of a 3D point cloud involves interpolation of the point cloud using geometrical features and are addressed using Bezier curves in [Guennebaud et al. 2004] and decision framework of interpolation in [Ganihar et al. 2014]. The identification of the geometrical properties of a 3D object are essential which requires the selection of an appropriate interpolation technique for super resolution. In this paper we propose to decompose the given 3D object into basic 3D objects like cone, sphere and cylinder and the corresponding interpolation technique is employed for the super resolution of the 3D point cloud.

2 Approach

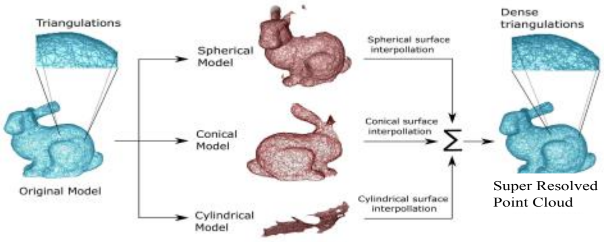

Figure 1: *Overview of the proposed 3D object super resolution framework*

The global geometrical properties for a 3D object is the union of the local geometrical properties which are non-uniformly distributed over the surface of the 3D object. The local geometrical properties of the 3D object are modeled as a set of Riemannian manifolds. The local geometrical properties for a 3D object show similarities towards basic geometrical objects like cone, sphere and cylinder. The 3D object is decomposed into basic geometrical objects using a kernel based SVM learning framework with Riemannian metric tensor and Christoffel symbols as features. Riemannian metric tensor is a 2^{nd} order tensor which computes the numerical deviation of the local Riemannian manifold on the 3D object from the Euclidean manifold. The deviations in the manifold are determined by computing the inner product on the local Riemannian manifold using numerical geodesic distance computation on the manifold. The Christoffel symbols is a 3^{rd} order pseudo tensor which gives a numerical measure for the deviations in the metric tensor over the surface of the 3D object. The Christoffel symbols for the 3D point cloud are computed by taking the numerical derivatives of the metric tensor computed over the local manifolds. The decomposed objects portray specific geometrical properties which are harnessed to super resolve the decomposed objects. The decomposed objects are independently super resolved using the appropriate interpolation technique for example, the spherically decomposed object is super resolved using spherical surface interpolation technique. The independently super resolved objects are then merged together to obtain the super resolved object. The overview of the super resolution framework is shown in Figure 1.

3 Implementation

The results for the decomposition and super resolution of the 3D point cloud is carried out using the 3D objects obtained from Aim@shape project and Standford 3D scanning repository. The input point cloud is generated by downsampling the ground truth point cloud by 2,4 & 8 factors. Super resolution of the input point cloud is carried out using the proposed method with the same factors of 2,4 & 8 and achieve absolute error of 4.49%, 7.20% & 10.27% respectively with ground truth which is better than the % absolute error reported in the literature using MLS random density (67.18%, 149.50% & 225.36%), [Ganihar et al. 2014] (15.59%, 18.11%, & 28.43), cubic spline interpolation (15.51%, 17.84% & 27.33%) and quadratic spline interpolation (15.99%, 19.03% & 28.69%).

References

GANIHAR, S. A., JOSHI, S., PATIL, N., MUDENAGUDI, U., AND OKADE, M. 2014. Voting-based decision framework for optimum selection of interpolation technique for 3d rendering applications. In *Students' Technology Symposium (TechSym), 2014 IEEE*, 270–275.

GUENNEBAUD, G., BARTHE, L., AND PAULIN, M. 2004. Dynamic surfel set refinement for high-quality rendering. *Comput. Graph. 28*, 6 (Dec.), 827–838.

WEINBERG, S. 1972. *Gravitation and Cosmology: Principles and Applications of the General Theory of Relativity*. Wiley, New York, NY.

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