State of the Art in Surface Reconstruction from Point Clouds

Matthew Berger  Andrea Tagliasacchi
Lee M. Seversky  Pierre Alliez
Joshua A. Levine  Andrei Sharf  Claudio T. Silva
State of the Art in Surface Reconstruction from Point Clouds

Matthew Berger

Andrea Tagliasacchi

Lee M. Seversky

Pierre Alliez

Joshua A. Levine

Andrei Sharf

Claudio T. Silva
Longstanding Goal in Computer Graphics

Model The World Around Us

Need to first acquire the world
Acquisition

Desktop Scanners

- Single object
- Fine-grained control
- Controlled setting

[LaBman & Taubin 09]
Acquisition

Terrestrial LiDAR

- Large scenes
- Low control
- Occlusion
Acquisition

- Large environments
- Top-down perspective
- Lower resolution

Aerial LiDAR
Acquisition

Compact Real-time Scanning

- Fine-grained detail
- Small scenes
- Easy and cheap to use

[Kim et al. SIGA’12]
General Pipeline
General Pipeline
General Pipeline

Surface Reconstruction from Point Clouds!
General Pipeline

Surface Reconstruction from Point Clouds!
Why Reconstruction?

- Captured point cloud unsuitable for many geometry processing tasks
- Noisy, incomplete
- Topology not well-defined
- Does not define continuous representation
Why Reconstruction?

Raw Point Cloud Not Enough!
Finding correspondences between a discrete set of points on two objects in different poses, and thus alignment of extrinsic shapes is insufficient. However, the intrinsic shapes for objects of the same class are often approximately isometric, and sometimes they are composed of large parts that are nearly isometric. For example, as for cloth deformations (perfect isometries), faces, and surfaces this is the case for the dog and the wolf shown in Figure 1, as well as for predicted correspondences between the mutually closest points.

The key observation is that the space of isometries between simply-connected objects is one-dimensional, and thus strategies for searching this space with the hope of finding corresponding points in that plane.

The goal of our work is to develop an efficient, automatic algorithm for discovering point correspondences between surfaces that is robust to deformation errors, and/or take long computation times. Second, even if it were possible to consider all potential correspondence sets, it would be difficult to compute an appropriate deformation error (deviation from isometry) for each one. Our approach is based on three observations. First, isometries are composed of large parts that are nearly isometric. Second, computing the M"obius transformation that interpolates any three points can be computed in closed-form after a simple rational function that is fast to compute, and 4) deviations from an isometric mapping can be modeled with a simple function.

Third, the M"obius transformation defined by three points, where: 1) the discrete conformal error of the edge representation of the mesh onto a 2D canonical domain deforming (Uniformization) operator (based on Pinkall and Polthier's non-conforming conjugate harmonic maps [1993]) that takes a mid-surface representation of the mesh onto a 2D canonical domain (Isometrically correct parameterization [2005]). Our algorithm is a Hough-style voting scheme where three random points are repeatedly sampled from each of two meshes and used to define M"obius transformations that map them to a shared canonical domain on the complex plane, and 3) produces "votes" for predicted correspondences between the mutually closest points.

For many of these applications, the input meshes represent different poses fully automatically. We have developed a M"obius Voting algorithm for discovering point correspondences between surfaces that is robust to deformation errors, and outputs as a discrete set of point correspondences with magnitude representing their estimated deviation from isometry. The result of this process is a fuzzy correspondence matrix, which is converted to a permutation matrix with simple matrix operations. The main advantage of this algorithm is that it can find intrinsic confidence values.
Why Reconstruction?

Raw Point Cloud Not Enough!

[Lipman & Funkhouser SIG’09]  [Yu et al. EG’12]
Traditional Reconstruction

- Take point cloud as input
- Output: continuous representation
- Assumption: output should be smooth
Traditional Reconstruction

- Take point cloud as input
- Output: continuous representation
- Assumption: output should be smooth
Traditional Reconstruction

- Take point cloud as input
- Output: continuous representation
- Assumption: output should be smooth

[Kazhdan SGP’05]
How do we handle substantial artifacts in the point cloud?

**Priors!**

• Priors on the scanned shape
• Priors on the acquisition
• Priors on the interaction
Volume Smoothness

[Tagliasacchi et al. SIG’09]
Global Regularity

[Zheng et al. SIG’10]
Data-Driven

[Shen et al. SIGA’12]
Present survey of surface reconstruction from the perspective of priors

- Characterization of surface reconstruction
- Surface smoothness methods
- Specialized priors
  - visibility, volume smoothness, primitives, global regularity, data-driven, interactive
- Where surface reconstruction is headed
Characterization

● Point Cloud Artifacts
● Point Cloud Input
● Shape Class
Characterization

- Point Cloud Artifacts
  - Point Cloud Input
  - Shape Class
Characterization

- Point Cloud Artifacts
- Point Cloud Input
- Shape Class
Characterization

- Point Cloud Artifacts
- Point Cloud Input
- Shape Class
Artifacts

- Distribution of sampled points
- Useful in computing many surface quantities
- Challenge: *nonuniform*
**Abstract**

In this paper we present a new Point Set Surface (PSS) definition based on moving least squares (MLS) fitting of algebraic spheres. Our surface representation can be expressed by either a projection procedure or in implicit form. The central advantages of our approach compared to existing planar MLS include significantly improved stability of the projection under low sampling rates and in regions of high curvature. The method can approximate or interpolate the input point set and naturally handles planar point sets, fast mean curvature evaluation and shading, significantly increased stability in regions of high curvature, sharp features with controlled smoothness. Sample positions are partly highlighted.

**I. Introduction**

A key ingredient of most methods in point based graphics is the unification of surface representations and evaluation procedures to efficiently perform the sphere fit. For point sets with normals we designed procedures to efficiently perform the sphere fit. For point sets with normals we designed procedures to efficiently perform the sphere fit. In addition, our approach provides a reliable estimate of the mean curvature of the surface at no additional cost and allows for a simple point set as input, but can also take significant advantage of surface normals to improve robustness, quality and performance. Furthermore, the spherical fitting enables us to design interpolatory weighting schemes by using weight functions with singularities at multiples of sheet separation (figure 3) and exhibit a high degree of stability where planar MLS fails. For instance, tight data approximation is achieved, spheres perform much better in the correct handling of very complex point clouds. In addition, our approach provides a reliable estimate of the mean curvature of the surface. This enables us, for instance, to compute real-time accessibility shading on large input sets, fast mean curvature evaluation and shading, significantly increased stability in regions of high curvature, sharp features with controlled smoothness. Sample positions are partly highlighted.

**Artifacts**

**Sampling Density**

- Distribution of sampled points
- Useful in computing many surface quantities
- Challenge: *nonuniform*

[Guennebaud et al. SIG’07]
• Distribution of sampled points
• Useful in computing many surface quantities
• Challenge: nonuniform

[Guennebaud et al. SIG’07]
• Distribution of sampled points
• Useful in computing many surface quantities
• Challenge: nonuniform

Sampling Density

[Guennebaud et al. SIG’07]
Artifacts

- Points randomly distributed near the surface
  - Basic assumption: noise distribution is zero mean
- Due to numerous factors
  - Sensor noise, depth quantization, surface material properties
- May also be spatially-varying
Artifacts

- Points randomly distributed near the surface
  - Basic assumption: noise distribution is zero mean
- Due to numerous factors
  - Sensor noise, depth quantization, surface material properties
- May also be spatially-varying

[Avron et al. TOG'10]
Due to numerous factors, points randomly distributed near the surface:
- Basic assumption: noise distribution is zero mean.

- Due to numerous factors:
  - Sensor noise, depth quantization, surface material properties.

- May also be spatially-varying.
Outliers

- Points far from the surface
- Structural artifacts in acquisition
- Can be randomly distributed in the volume
- But can also be highly structured
Artifacts

- Points far from the surface
- Structural artifacts in acquisition
- Can be randomly distributed in the volume
- But can also be highly structured
Artifacts

- Points far from the surface
- Structural artifacts in acquisition
- Can be randomly distributed in the volume
- But can also be highly structured

[Figure 16: Two levels of noise.](#)

[Figure 17: Two levels of noise.](#)

[Figure 18: Noise and structured outliers.](#)

[Figure 19: Noise almost beyond dimension assumption.](#)

[Figure 20: Noise beyond dimension assumption.](#)

[Figure 21: Variable density.](#)

4.1. Limitations

Using a uniform grid for the nodes of the graph requires a large number of nodes to capture the correct topology of shapes with small feature size due to small separation or thickness. This obviously leads to scalability issues. We experimented with a non-uniform graph where the nodes are reusing the vertices of the adaptive triangulation used in step 1, and where appropriate weights per edge are devised to compensate for the non-uniformity. None of these experiments led to satisfactory results.

For computing the sign attribute of an edge of the graph, we use an exhaustive combinatorial search in the number of (retained) local minima. In our experiments the number of retained minima is on average below 6, but for complex shapes with many sheets this can also lead to scalability issues.

Finally, we are using a two-step approach for guessing the sign, then solving for the signed implicit function. Our approach is scalable as involves only linear solves, but it would be more consistent to do everything in one step without hampering the scalability.

[Meier et al. SGP’14]
Artifacts

- Imperfect registration of range scans
- Introduces highly structured noise
Artifacts

- Imperfect registration of range scans
- Introduces highly structured noise

[Li et al. SIG’11]
Artifacts

Missing Data

- Regions of zero sampling density
- Different ways to handle missing data
  - Watertightness
  - Reconstruct higher-level information in lieu of the original shape
Artifacts

• Regions of zero sampling density
• Different ways to handle missing data
  • Watertightness
  • Reconstruct higher-level information in lieu of the original shape

[Sharf et al. SIG’07]
• Regions of zero sampling density
• Different ways to handle missing data
  • Watertightness
  • Reconstruct higher-level information in lieu of the original shape
Characterization

- Point Cloud Artifacts
- Point Cloud Input
- Shape Class
**Inputs**

- The direction perpendicular to the tangent space at each point
- Represents a localized approximation to the surface
- Orientation: all normals are consistently pointing inside/outside of the surface
Normal Orientation

- Provides useful cues about the surface
- Distinguish thin sheets from a single sheet
- Challenging research problem in its own right: [Hoppe et al. SIG’92, Huang et al. SIGA’09, Liu & Wang SMI’10]
Normal Orientation

- Provides useful cues about the surface
- Distinguish thin sheets from a single sheet
- Challenging research problem in its own right: [Hoppe et al. SIG’92, Huang et al. SIGA’09, Liu & Wang SMI’10]
Normal Orientation

- Provides useful cues about the surface
- Distinguish thin sheets from a single sheet
- Challenging research problem in its own right: [Hoppe et al. SIG’92, Huang et al. SIGA’09, Liu & Wang SMI’10]
Normal Orientation

- Provides useful cues about the surface
- Distinguish thin sheets from a single sheet
- Challenging research problem in its own right: [Hoppe et al. SIG’92, Huang et al. SIGA’09, Liu & Wang SMI’10]
Normal Orientation

- Provides useful cues about the surface
- Distinguish thin sheets from a single sheet
- Challenging research problem in its own right: [Hoppe et al. SIG’92, Huang et al. SIGA’09, Liu & Wang SMI’10]
Sensitivity to Normal Orientation

[Hoppe et al. SIG’92]  [Kazhdan et al. SGP’06]  [Liu & Wang SMI’10]  [Kazhdan et al. SGP’06]
Inputs

Scanner Information

- Provides a variety of useful information
- 2D lattice structure
- Estimate sampling density
- Outliers
- Confidence of a point
- Line of sight
Inputs

Scanner Information

- Provides a variety of useful information
- 2D lattice structure
- Estimate sampling density
- Outliers
- Confidence of a point
- Line of sight
Scanner Information

- Provides a variety of useful information
- 2D lattice structure
- Estimate sampling density
- Outliers
- Confidence of a point
- Line of sight
Scanner Information

- Provides a variety of useful information
- 2D lattice structure
- Estimate sampling density
- Outliers
- Confidence of a point
- Line of sight
Inputs

Scanner Information

- Provides a variety of useful information
- 2D lattice structure
- Estimate sampling density
- Outliers
- Confidence of a point
- Line of sight
Inputs

Scanner Information

- Provides a variety of useful information
- 2D lattice structure
- Estimate sampling density
- Outliers
- Confidence of a point
- *Line of sight*
Inputs

Scanner Information

- Provides a variety of useful information
- 2D lattice structure
- Estimate sampling density
- Outliers
- Confidence of a point
- Line of sight
Scanner Information

- Provides a variety of useful information
- 2D lattice structure
- Estimate sampling density
- Outliers
- Confidence of a point
- Line of sight
Inputs

- RGB Imagery

  - Complements depth capture, particularly when data is missing
  - Fuse features between the depth and RGB image
Inputs

RGB Imagery

- Complements depth capture, particularly when data is missing
- Fuse features between the depth and RGB image
RGB Imagery

- Complements depth capture, particularly when data is missing
- Fuse features between the depth and RGB image

[Shen et al. SIGA'12]
Characterization

- Point Cloud Artifacts
- Point Cloud Input
- Shape Class
Shape Class

CAD Models
Shape Class

CAD Models
Shape Class

CAD Models
Shape Class

CAD Models

State of the Art in Surface Reconstruction from Point Clouds
Shape Class

Man-made shapes
Shape Class

Man-made shapes
Shape Class

Man-made shapes
Shape Class

Man-made shapes
Organic shapes
Shape Class

Architectural shapes
Indoor environments
Indoor environments
Indoor environments
Point Cloud Artifacts

- Nonuniform Sampling
- Noise
- Outliers
- Misalignment
- Missing Data
Questions?

Point Cloud Artifacts
- Nonuniform Sampling
- Noise
- Outliers
- Misalignment
- Missing Data

Point Cloud Input
- Normals
- Oriented Normals
- Scanner Information
- RGB Imagery
Point Cloud Artifacts
- Nonuniform Sampling
- Noise
- Outliers
- Misalignment
- Missing Data

Point Cloud Input
- Normals
- Oriented Normals
- Scanner Information
- RGB Imagery

Shape Class
- CAD Models
- Man-made Shapes
- Organic Shapes
- Architectural Shapes
- Indoor Environments

Questions?
These factors inform prior development in surface reconstruction.