A Survey of Surface Reconstruction from Point Clouds

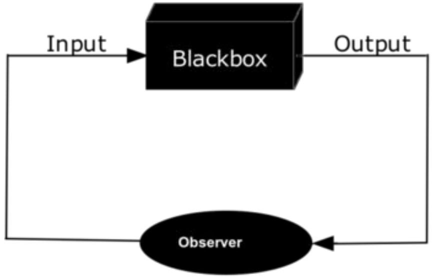
Matthew Berger, Andrea Tagliasacchi, Lee M. Seversky, Pierre Alliez, Joshua A. Levine, Andrei Sharf, Claudio T. Silva

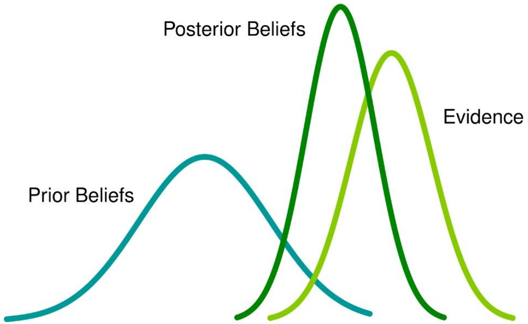
“State of the Art in Surface Reconstruction from Point Clouds”

Presented by William Ashbee

Why a survey from 2014 is interesting

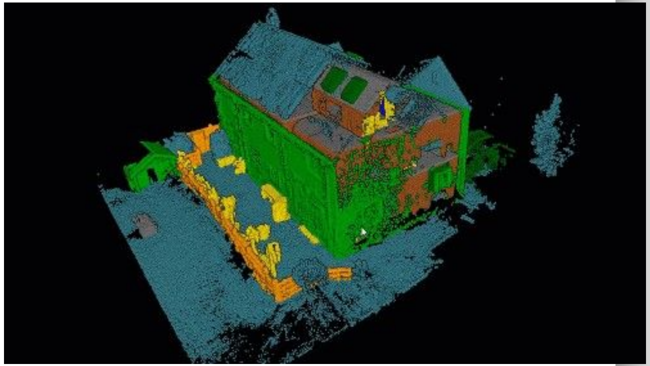
- Deep learning methods which have evolved since 2014 are **black boxes** that often fail for reasons that are poorly understood by me especially, but probably also the community at large.
- It is worth knowing the **prior assumptions** made of **algorithms that are more transparent** in order to gain insights into the difficulty deep learning algorithms may be facing.
- Many of the deep learning algorithms that are successful are **simply evolutions of approaches described in the paper**, so it is possible to look for ways to **incorporate old methods into the new deep learning paradigm.**





Introduction

- Surface reconstruction from point cloints has many acquisition and domain specific quirks
  - Urban environments, single objects, small 2d scanner, lidar, etc.
- These quirks allow algorithms to shrink the problem scope with the use of priors (prior assumptions).
- This paper covers the various **priors across several domains** of surface reconstruction that are important.



Point cloud artifacts -- Sampling density

- The distribution of the points sampling the surface is referred to as sampling density.
- 3D scans typically produce a nonuniform sampling on the surface
- The level of nonuniformity in the sampling can have a great impact on estimation accuracy.

(b) Nonuniform sampling

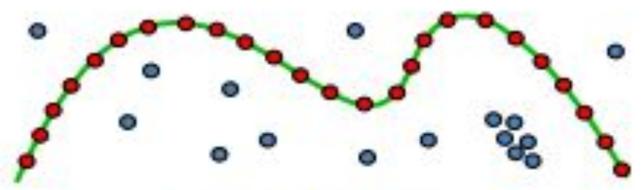
Point cloud artifacts -- Noise

- Points that are randomly distributed near the surface are traditionally considered to be noise
- In the presence of such noise, the typical goal of surface reconstruction algorithms is to produce a surface that passes near the points without overfitting to the noise

(c) Noisy data

Point cloud artifacts -- Outliers

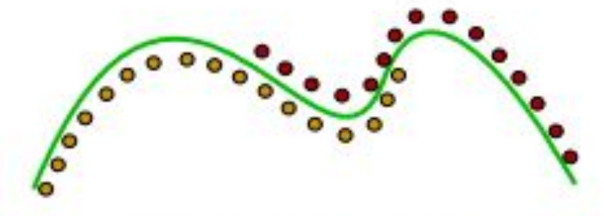
- Points that are far from the true surface are classified as outliers
- Outliers are commonly due to structural artifacts in the acquisition process.
- Unlike noise, outliers are points that should not be used to infer the surface



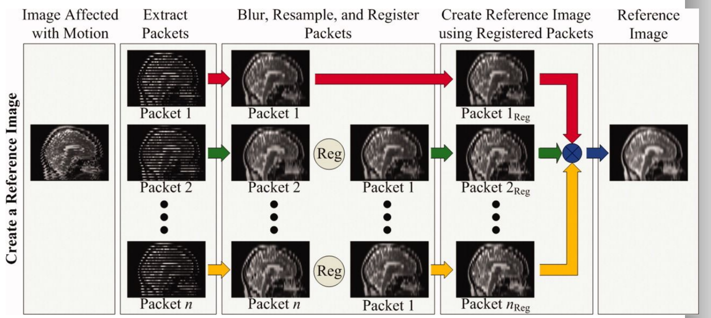
(d) Outliers

Point cloud artifacts -- Misalignment.

- The imperfect registration of range scans results in misalignment.
- Misalignment tends to occur for a registration algorithm when the initial configuration of a set of range scans is far from the optimal alignment
- Misalignment is a significant challenge for surface reconstruction, as it introduces structured noise via scans that are slightly offset from the surface
- Some parallels in mri -- motion artifacts



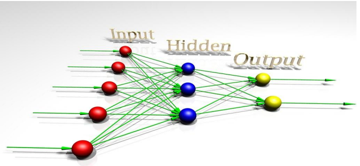
(e) Misaligned scans



Point cloud artifacts -- Missing data

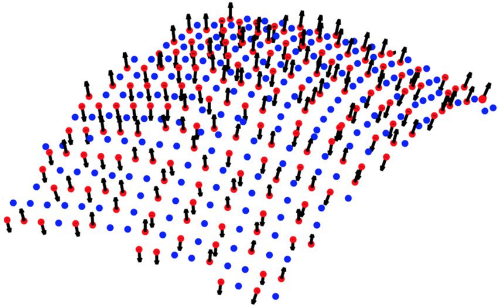
- A motivating factor behind many reconstruction methods is dealing with missing data.
- Parallels in neural networks -- not enough variance in dataset to extrapolate to test set **with a given architecture and priors**.
  - Data augmentation, equivariance, symmetry have made efforts to improve this, but still MUCH to be done here.

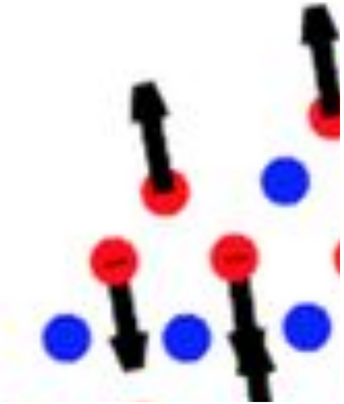
(f) Missing data



Point Cloud Input -- Surface Normals -- Unoriented normals

- A manifold is locally euclidean. Essentially, if you are trying to extract a manifold from a point cloud, it helps if the points have normals specifying the direction of the surface to the point.
- When points clouds do not tell you their orientation in relation to a surface, you can compute it using PCA, which computes a Least squares tangent plane to a collection of points.
- Several other methods exist to compute normals and how best to sample them given various data distributions, which is cited in the survey.
    - These methods must define a notion of neighborhood of a point where the point's normal is to be calculated.





Point Cloud Input -- Surface Normals -- Oriented normals

- Normals that have consistent directions, either pointing in the inside or the outside of the surface are referred to as being **oriented**.
- It can be used to construct a signed distance field over the ambient space, where up to a sign, the field takes on positive values in the exterior and negative values in the interior

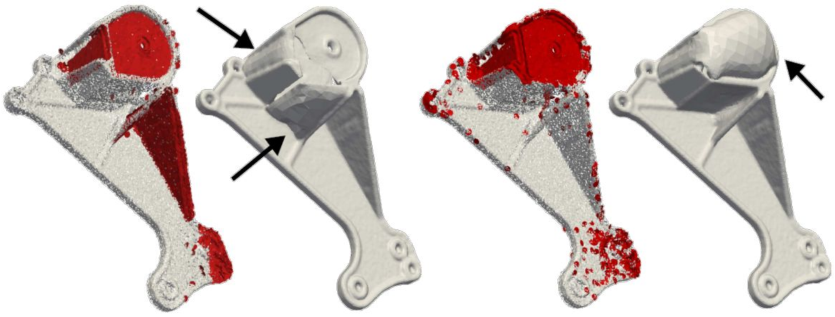


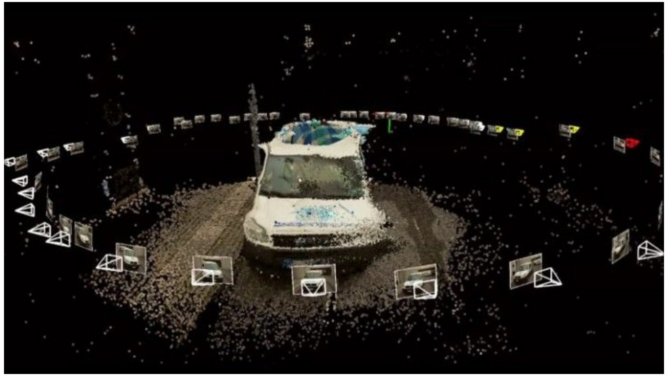
Figure 3: *The impact of incorrect normal orientation. On the left we show the result of normal orientation via [HDD*92], where red splats indicate incorrect orientation. The results of running Poisson surface reconstruction [KBH06] on this point cloud are shown in mid-left, where we indicate unwanted surface components due to the clustered normal flips. Similarly, on the right we show the orientation results of [LW10], and the corresponding results of [KBH06].*

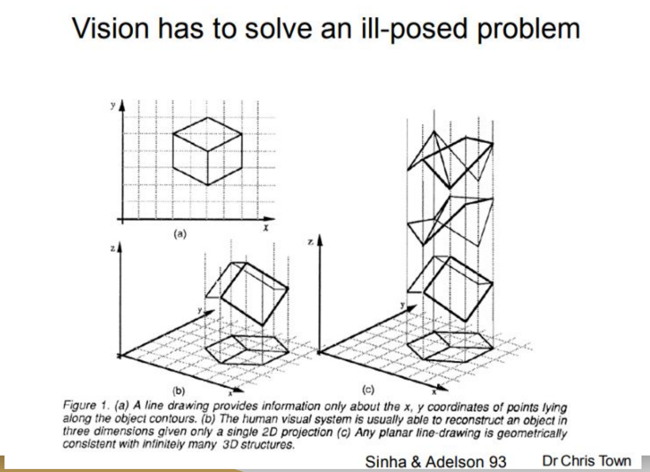
Point Cloud Input -- Scanner information

- The scanner from which the point cloud was acquired can provide useful information for surface reconstruction.
- Scanner information may also be used to define the confidence of a point, which is useful in handling noise

Point Cloud Input -- RGB Imagery

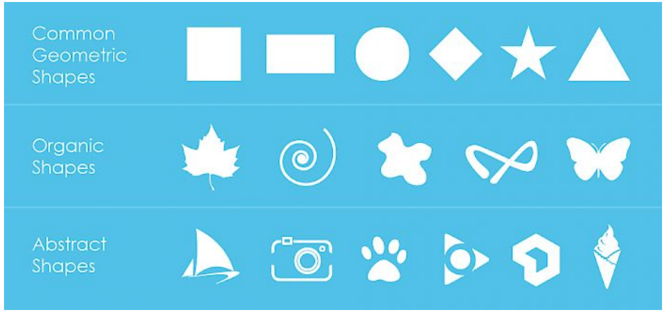
- RGB image acquisition is best when **accompanied with depth information**
- Depth information can be obtained with numerous accompanying sensors
- Vision solves an ill posed problem--many shapes collapse onto one plane





Shape Class

- Surface reconstruction algorithms can be further distinguished by the class of shapes they support.
- Quite often, a reconstruction prior is in part driven by a shape class, so understanding the characteristics of a shape class is an essential component to gaining insight into surface reconstruction.



Shape Class (Cont.)

CAD models

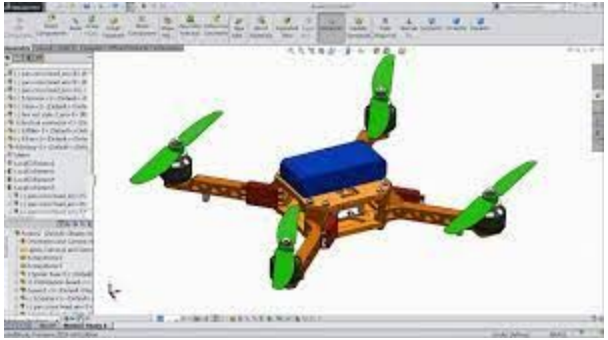
- These models are typically composed of a collection of simpler geometric primitives such as planes, cylinders, and spheres

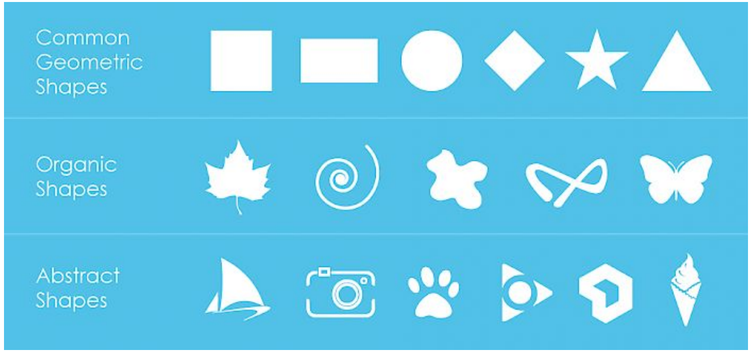
Man-made (synthetic) shapes

- Driven by aesthetic considerations, cost, functional requirements, and fabrication constraints.

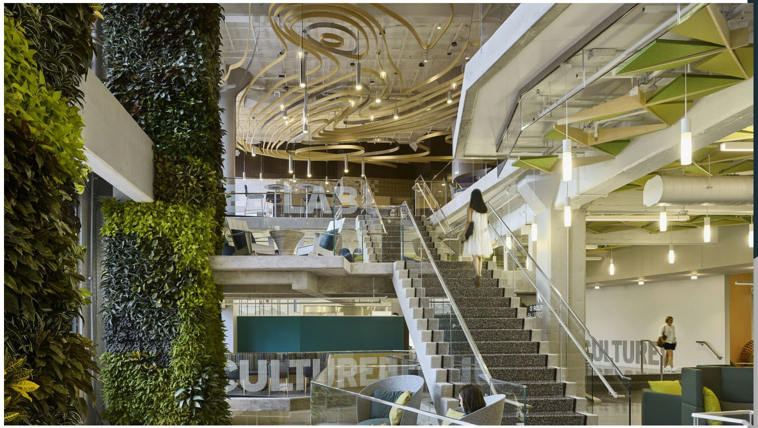
Organic shapes

- E.g plants, trees.





Shape Class



Architectural models

- The problem can be greatly regularized by making assumptions on facade structures and structural regularity

Urban environments

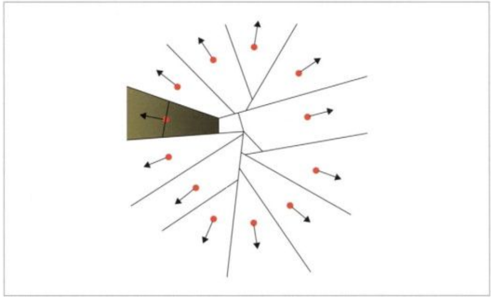
- For instance one can make assumptions on the presence of ground, buildings, vegetation, and other urban objects to aid in reconstruction

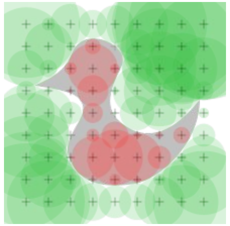
Indoor environments

- Types of shapes within this environment tend to be a **mixture of man-made and organic**
- Each type of object can often be defined through a **low-dimensional shape space**

Reconstruction Output

- **Implicit function**
  - Implicit functions can be combined to create complex objects using the Boolean operators union, intersection, and difference. They can be used to describe a geometric object.
- **Signed distance field**
  - The orthogonal distance of a given point *x* to the boundary of a set Ω in a metric space, with the sign determined by whether or not *x* is in the interior of Ω.
- **Indicator function**
  - **Indicator function** or a **characteristic function** of a subset of a set is a function that maps elements of the subset to one, and all other elements to zero

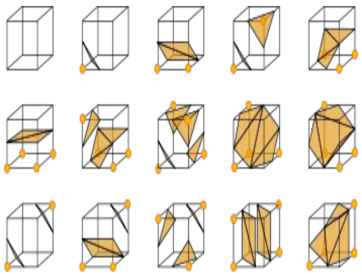


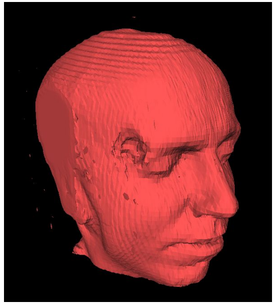


$$1_{A'}(x) = 1 - 1_A(x)$$
$$1_{A\cap B}(x) = 1_A(x) \cdot 1_B(x)$$
$$1_{A_1\cap A_2\cap\ldots\cap A_n}(x) = 1_{A_1}(x) \cdot 1_{A_2}(x) \cdot \ldots \cdot 1_{A_n}(x)$$

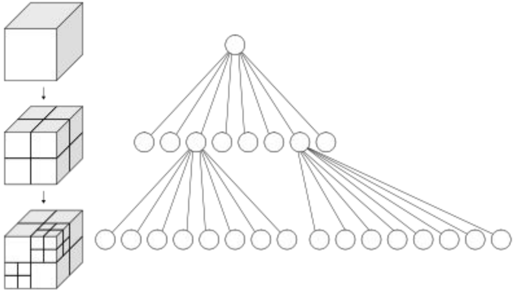
$$1_{A\cup B}(x) = 1_A(x) + 1_B(x) - 1_{A\cap B}(x)$$
$$(1_A(x))^2 = 1_A(x)$$

Reconstruction Output

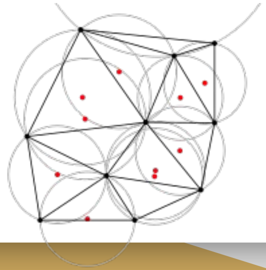


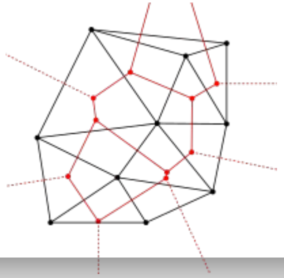


- Marching Cubes - Fit points locally with a small set of planes
- Octrees
  - An **octree** is a tree data structure in which each internal node has exactly eight children.
  - Octrees are most often used to partition a three-dimensional space by recursively subdividing it into eight octants

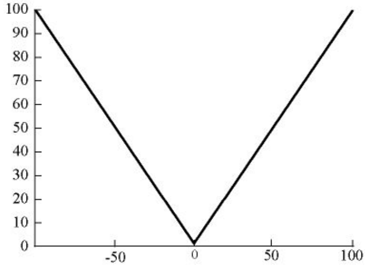


- Delaunay refinement techniques
  - **Delaunay triangulation** for a given set **P** of discrete points in a general position is a triangulation DT(**P**) such that no point in **P** is inside the circumcircle of any triangle in DT(**P**).
  - Delaunay triangulations maximize the minimum of all the angles of the triangles in the triangulation

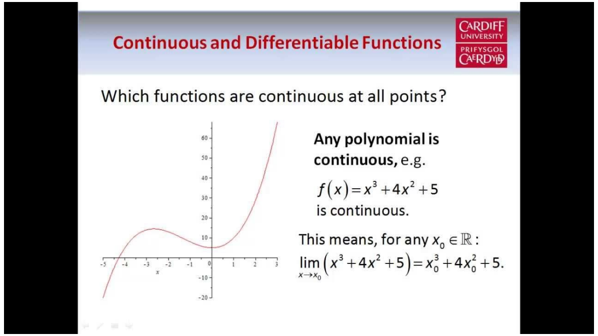


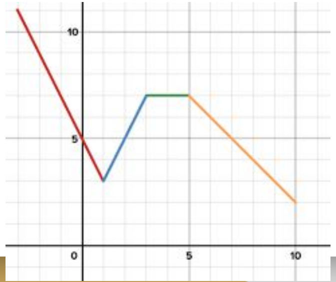


Surface Smoothness Priors



- local smoothness -- creates surfaces that are smooth near the point cloud
- global smoothness -- creates surfaces that are smooth everywhere
- piecewise smoothness -- Interested in smoothness near specific features

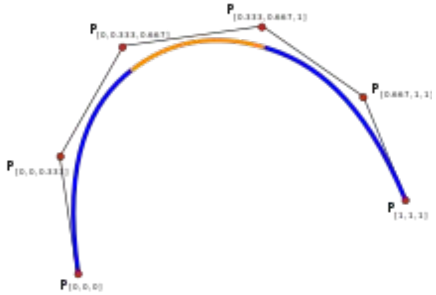




Local Surface Smoothness Priors

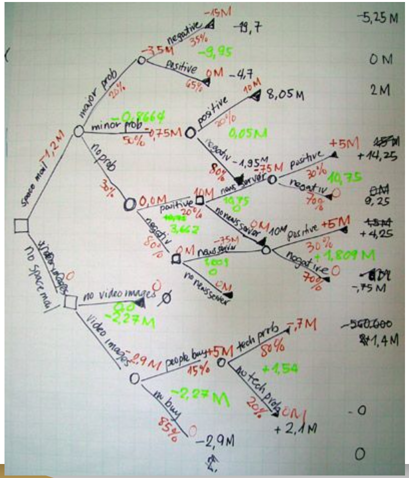
Moving least squares (MLS)

- These methods approach reconstruction by approximating the surface as a spatially-varying low-degree polynomial
- We note that this projection process only requires unoriented normals and can also be used to define an unsigned distance function



Multi-level partition of unity (MPU)

- Approached as a **hierarchical fitting problem**
- At a certain scale, a local shape fit is determined adequate if its error residual is sufficiently small, otherwise the occupied space is refined and the overall procedure is repeated



Global Surface Smoothness Priors

Radial basis functions (RBFs)

- Given a set of points with prescribed function values, RBFs reproduce functions containing a high degree of smoothness through a linear combination of radially symmetric basis functions
- An advantage of RBF for surface reconstruction is that the resulting implicit function is globally smooth and seamless

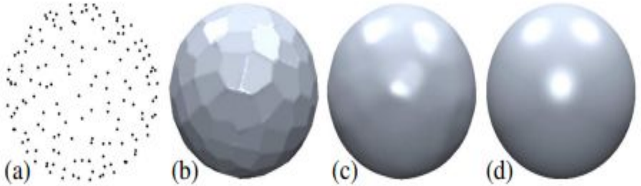


Figure 6: *A point cloud sampling a sphere consisting of 150 points (a) is reconstructed by [HDD*92] resulting in a C^0 surface (b). A locally supported RBF [Wen95] reconstruct a C^1 surface, while the global triharmonic RBF ($\Delta^3 f = 0$, $\phi(x) = x^3$) outperforms the previous methods, although incurring a high computational cost.*

- Gaussian:

$$\varphi(r) = e^{-(\varepsilon r)^2},$$

- Multiquadric:

$$\varphi(r) = \sqrt{1 + (\varepsilon r)^2},$$

- Inverse quadratic:

$$\varphi(r) = \frac{1}{1 + (\varepsilon r)^2},$$

- Inverse multiquadric:

$$\varphi(r) = \frac{1}{\sqrt{1 + (\varepsilon r)^2}},$$

Global Surface Smoothness Priors -- Indicator function

- These methods approach surface reconstruction by estimating a soft labeling that discriminates the interior from the exterior of a solid shape.
- This is accomplished by finding an implicit function χ that best represents the indicator function, taking on the value of 0 in the interior of the shape and 1 otherwise.
- The key observation in this class of methods is that, assuming a point cloud with oriented normals, χ can be found by ensuring its gradient is as-close-as-possible to the normal field N, in a least-squares sense.

Global Surface Smoothness Priors -- Indicator function

- If we apply the divergence operator to this problem, then this amounts to solving the following Poisson equation (see right)
- Once solved, the surface is found via χ with a suitable isovalue, typically the average or median value of χ evaluated at all of the input points.
- X : implicit function
- N: Normal field of points

$$\nabla \cdot \nabla \chi = \Delta \chi = \nabla \cdot N.$$

Visibility Priors

1. The first class of methods considers how to use the **visibility provided by the scanner** that produced the point cloud – this is used primarily to obtain the line of sight associated with each sample
2. The second class of methods uses line of sight that is **not provided from the scanner, but rather approximated from the exterior space**
3. The third class of methods uses visibility to approximate **parity – the number of times a ray intersects a surface –** in order to approximate the interior and exterior

Visibility Priors -- Scanner Visibility

- The most common method for using the visibility information provided by a scanner is the **merging of individual range scans**
- A **confidence** can be assigned to each point in the range scan via line of sight information where associates low confidence weights with high grazing angles
- This is particularly useful in **combating noise in the point cloud**, since one can easily over smooth or under smooth if no confidence values are associated with points

Exterior Visibility

- It is possible to exploit visibility even in the absence of explicit information from the scanner
- **Occlusion culling** -- remove points that are not visible from the reconstruction
- **Cone carving** -- It computes high-likelihood visibility cones originating at each sample and takes the boundary of the union of all cones as an approximation to the surface.

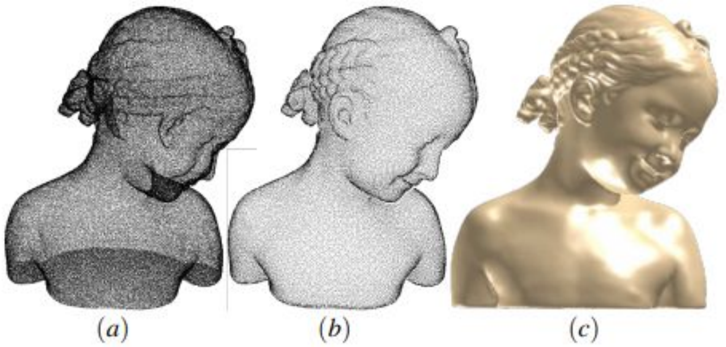


Figure 8: *The point cloud "hidden point removal" operator from [KTB07] applied to an input (a) determines the subset of visible points as viewed from a given viewpoint (b). Given this labeling, a view-dependent on-the-fly reconstruction (c) can be obtained by retaining the topology of well shaped triangles from the convex hull of the spherical inversion.*

Parity

- Assuming a closed surface, the parity for a given ray (point and direction) is defined as the number of times the ray intersects the surface –
    - **if an odd number of times, this indicates the point lies in the interior,**
    - **otherwise the point is in the exterior**

Figure 9: *The approach of [MDGD* 10] first computes a robust unsigned distance function (left), and constructs an interior/exterior labeling (middle), and associated confidence (right) of the labeling. Note that low confidence is associated with regions of missing data, such as the bottom of the scan.*

Geometric Primitives

Knowledge of a surface that can be described as the composition of geometric primitives can be extremely helpful for denoising and filling in missing data.

- **Detecting primitives**
  - RANSAC to robustly find **planes, spheres, cylinders, cones, and torii**, through an efficient means of sampling points for fitting and evaluating scores, both based on locality sensitive methods.
- **Primitive consolidation**
  - After primitives are detected, they must be **merged/stitched** together
- **Volumetric primitives**
  - E.g. search the space for **cuboids**
- **Limitations**
  - primitive methods **don't degrade gracefully** when the dictionary of primitives poorly represents the shape.

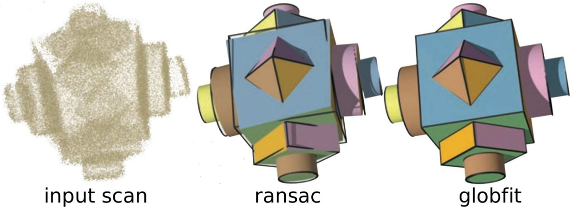


Figure 14: *From a set of misaligned scans shown on the left, the primitives extracted via [SWK07] (middle) retain the misalignment. Globfit [LWC*11] (right) is able to correct misalignment by enforcing consistent canonical relationships across primitives.*

Global Regularities

Symmetry

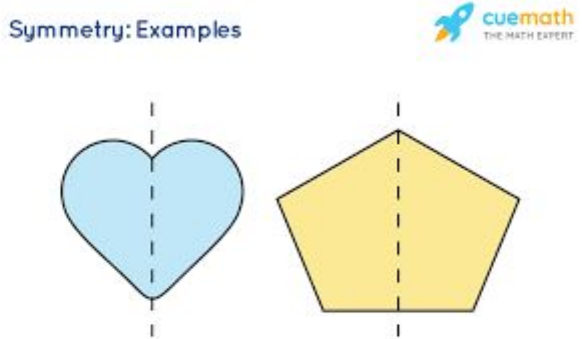
- Symmetry detection is focused on finding either global or local transformations on the shape that **maps the shape onto itself**

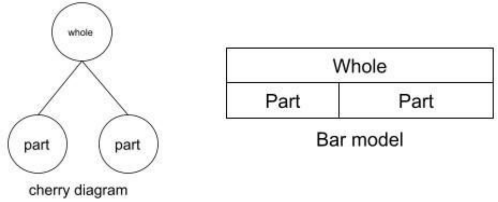
Repetition

- Repetition of similar patterns is an assumption that can be exploited to reconstruct a surface

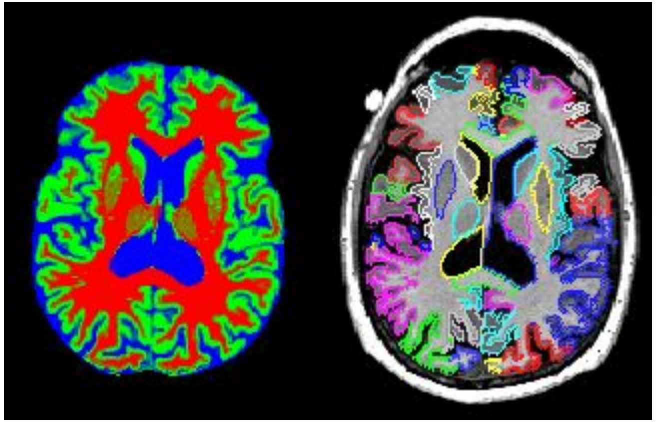
Canonical relations

- Part / hole relationships are often useful in determining a set of primitives to use (**hinton exploits this for capsule networks**)





Data-driven priors



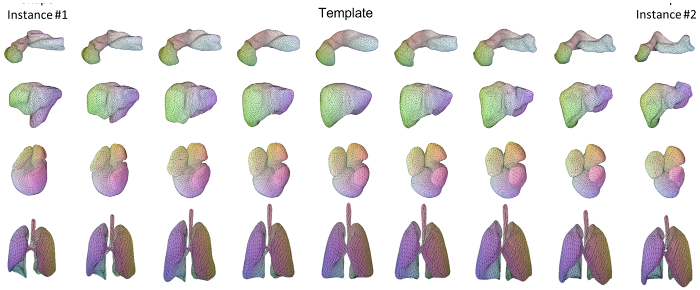
A more flexible method of specifying a prior is through a data-driven means: **using a collection of known shapes to help perform reconstruction**.

Reconstruction by rigid retrieval

- **First semantically segment, the replace each segment** (narrowing the scope of potential replacements within a segment) *****

Reconstruction by non-rigid retrieval

- consider **non-rigid transformations of the template geometry** to the input data (cortical flow essentially does this)



Evaluation of Surface Reconstruction

$$d_{CD}(S_1, S_2) = \sum_{x \in S_1} \min_{y \in S_2} \|x - y\|_2^2 + \sum_{y \in S_2} \min_{x \in S_1} \|x - y\|_2^2$$

- **Geometric Accuracy**
  - Distance measures -- Chamfer, hausdorf, MSE.
- **Topological Accuracy**
  - Is topology preserved in your results, are there any guarantees?
- **Structure Recovery**
  - Are primitives, repetitions, and symmetries preserved?
- **Ease of Use/ Reproducibility**
  - Would anyone reasonably want to use this approach?

Discussion

Floor is open