Poisson Surface Reconstruction

1. Briefly summarize the paper's contributions. Does it address a new problem? Does it present a new approach? Does it show new types of results?

- **[AS]**
  This paper presents a new global approach to tackle the surface reconstruction problem by showing that surface reconstruction from an oriented set of points can be cast as a spatial Poisson problem. The results in this paper show surface reconstruction with greater detail than previously achievable.
- **[DS]**
  Given a set of oriented points, the method presents a surface reconstruction algorithm by formulating the problem as a spatial Poisson problem. The method considers all the points at once, which makes it resilient to noise. The result is a smooth surface that robustly approximates noisy data. The algorithm allows a hierarchy of locally supported basis functions, so that the problem is reduced to a well-conditioned sparse linear system. The method takes into account non-uniformly sampled data, so it can preserve sharp details or smooth out regions, accordingly.
  This algorithm allows for reconstructions with greater detail than was possible before.
- **[FP]**
  Previous implicit approaches to surface reconstruction were based in approximate signed distance functions. In this paper the authors propose using a smooth indicator function instead. The gradient field of the smoothed indicator function is quickly computed (following the Divergence Theorem) by taking a weighted average of the normal at sample positions. The solution to the smoothed indicator function that best approximates this gradient field is found solving the Poisson equation. Despite the apparent data smoothing induced by this approach, the paper present results with high detail in large data sets.
- **[JD]**
- **[LF]**
  This paper presents a new approach to the surface reconstruction problem, recasting it as a Poisson problem.
- **[MK]**

2. What is the key insight of the paper? (in 1-2 sentences)

- **[AS]**
  The key insight of this paper is that oriented points sampled from the surface of a model can be viewed as samples of the gradient of the indicator function (1 at points inside the model, 0 outside) of the model, which is zero everywhere, except at points near the surface, where it is equal to the inward surface normal. Therefore, the problem of surface reconstruction simply becomes a problem of finding the indicator function whose gradient best approximates a vector field defined by the samples, which can be expressed as a standard Poisson problem.
- **[DS]**
  The key insight is the formulation of a surface reconstruction problem as a Poisson problem. The proposed solution to the non-uniform sampling problem provides an adaptive resolution to different parts of the surface depending on the sampling density.
- **[FP]**
  Solving the Poisson equation for the gradient field of a smoothed indicator function can be efficiently using hierarchical octree.

- **[JD]**
  The key insight of this paper was to demonstrate that a global solution to implicit surface reconstruction could be obtained as the solution to a well-conditioned, sparse linear system through use of a hierarchy of locally supported functions. (Rather than an ill-conditioned, dense solution from use of a set of non-decaying functions in the case of RBFs)
- **[LF]**
- **[MK]**

3. What are the limitations of the method? Assumptions on the input? Lack of robustness? Demonstrated on practical data?

- **[AS]**
  One limitation of this method is that the input is assumed to be oriented, which is not always the case. Another limitation is that this method does not incorporate information from the acquisition modality, and hence is not able to make use of secondary information such as line of sight to perform space carving and disconnecting two connected components in the absence of sampling in that region.
- **[DS]**
  The method does not incorporate information associated with the acquisition modality. For example, in the Buddha reconstruction the two feet are connected, since there are no sample points on the inside of them.
- **[FP]**
  The main assumption of the method is the availability of reliable normal information. This is crucial to accurately define the gradient field of the smoothed indicator function.
  Since the method is based on solving the Poisson equation (which is a Least Square approach), the method is may be not robust enough to noise and outliers (in either sample positions or normal).
  At undersampled regions the method can lose the topology of the surface, by doing an undesired hole filling. As the authors claim, this could be solved using acquisition information of the sampled set.
- **[JD]**
- **[LF]**
  The method requires normal information and as noted by the author, does not take any information about how the data would acquired into account. Among other results, the method was directly compared against seven other reconstruction algorithms on the Stanford bunny.
- **[MK]**

4. Are there any guarantees on the output? (Is it manifold? does it have boundaries?)

- **[AS]**
  The output is guaranteed to be a smooth, watertight, and manifold triangulated approximation to the surface defined by the input points.
- **[DS]**
  The output is an implicit function, from which a manifold surface can be obtained.
- **[FP]**
  The generated mesh is watertight due to the implicit approach and, it is expected to be manifold from the isosurface extraction procedure.
- **[JD]**
- **[LF]**
  The output its guarenteed to be water tight.

- **[MK]**

5. What is the space/time complexity of the approach?

- **[AS]**
  The space and time complexity of this method are roughly quadratic in the resolution of the reconstruction.
- **[DS]**
  The space and time complexity are both O(N^2) [linear in the size of the reconstructed model].
- **[FP]**
  In order to attain a good approximation of the smooth indicator function near the sample points, without paying the high costs of a fine grid, the authors propose use a hierarchical octree to solve the Poisson equation. The authors use a conjugate gradient solver to find a solution of the linear system restricted to certain depth of the octree and then update the residual. In order to solve the system at finest levels, they use a block Gauss-Seidel solver to deal with limited space.
  In their experiments, the authors show the time and space complexity of their approach is roughly linear with the output number of triangles.
- **[JD]**
- **[LF]**
  The author say the method is quadratic in both time and space complexity.
- **[MK]**

6. How could the approach be generalized?

- **[AS]**
  This approach could be generalized by adding sample confidence values into the solution process, and including line-of-sight information to achieve more accurate reconstructions.
- **[DS]**
  Could be extended to take into account confidence values for each sample point.
  Could incorporate line-of-sight information to avoid incorrectly joining two surfaces where the sampling is low.
- **[FP]**
  As the authors suggest, one initial extension to make the method more robust is to include acquisition information (such as line of sight) in the reconstruction process.
  Another strategy is to define confidence weights on the samples, so noise and outliers are easily discarded.
  The approach described by the authors use the same basis of functions to **fit** the implicit function χ function, and to **filter** the gradient field V. This condition effectively simplifies the computations but does not seem to be a strong condition. Therefore, the method could be extended by considering distinct type of functions at each octree leaf either to fit the implicit function or to filtering the gradient field.
- **[JD]**
- **[LF]**
  "Extend the approach to exploit sample confidence values."; "Incorporate line-of-sight information from the scanning process into the solution process."; "Extend the system to allow out-of-core processing for huge datasets."
- **[MK]**

7. If you could ask the authors a question (e.g. “can you clarify” or “have you considered”) about the work, what would it be?

- **[AS]**
  Have you considered using an edge aware smoothing filter to convolve the indicator function with, in order to avoid over-smoothing in areas where there is a large variance in normal direction and therefore preserving more detail near edges?
- **[DS]**
  Is there a way to make this interpolatory instead of approximating?
  How was the base function F chosen and are there other choices? How will these affect the results?
- **[FP]**
  As the authors claim, choosing the filter used on smoothing the indicator function is a fundamental step. In their approach they suggest using a bspline2, which is fast to compute and small supported, however no comparisons are made with other kind of filters. What kind of results are obtained by using other filters? Simpler filters (hat)? Smoother filters (bspline higher orders)?, Near ideal low pass filters (cardinal bsplines, OMOMS)?
  The Poisson equation solved for the smoothed indicator function. Is the smoothed indicator function the used in the isosurface extraction phase?, Is there no way to get an approximation to the nonsmoothed indicator function given that we actually know the smoothing filter F?.
- **[JD]**
- **[LF]**
  How did you choose that node function?
- **[MK]**