

Proximity Graphs for Defining Surfaces over Point Clouds


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Surface Definition based on MLS


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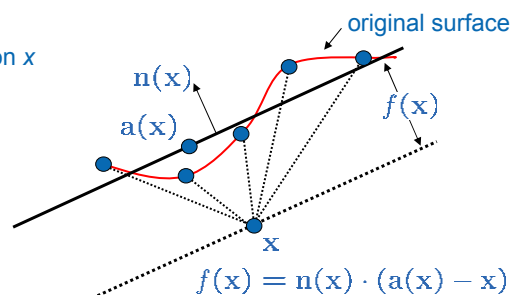
- Surface can be approximated by implicit function, i.e.,

$$S = \{x : f(x) = 0, x \in \mathbb{R}^3\}$$

$a(x)$: weighted average of points at location x

$$a(x) = \frac{\sum_{i=1}^N \theta(\|x - p_i\|) p_i}{\sum_{i=1}^N \theta(\|x - p_i\|)}$$

$$\theta(d) = e^{-d^2/h^2} \leftarrow \text{kernel bandwidth}$$



n is determined by moving least squares (MLS):

$$\text{Minimize } \sum_{i=1}^N (n(x) \cdot (a(x) - p_i))^2 \theta(\|x - p_i\|) \text{ for fixed } x \text{ and } \|n(x)\|=1.$$

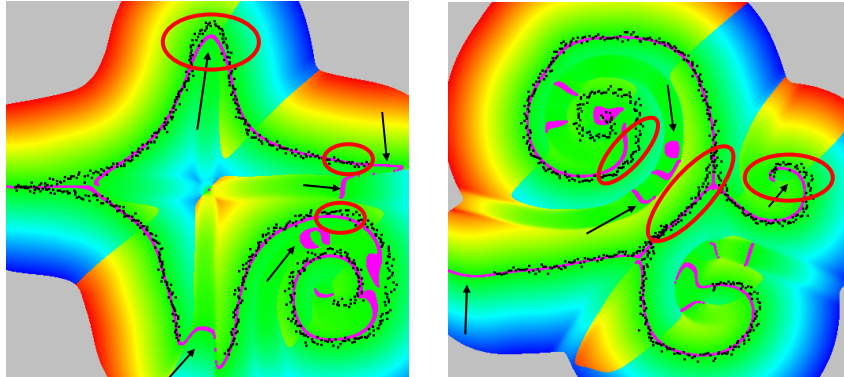
Artifacts



Surface reconstruction based on conventional MLS
can suffer from artifacts:

1. Unwanted zero sets
2. Bias

(Artifacts at borders have already been dealt with [Adamson & Alexa, 2004]).



Related Work



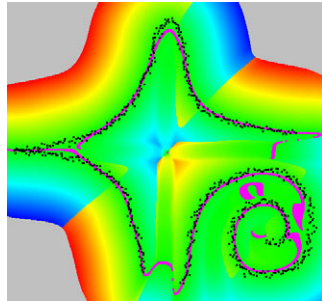
- Approximating and Intersecting Surfaces from Points [Adamson & Alexa, 2003]
- Curve Reconstruction from Unorganized Points [Lee, 2000]
- Multi-level Partition of Unity Implicits [Ohtake et al., 2003]
- Smooth Surface Reconstruction via Natural Neighbour Interpolation of Distance Functions [Boissonnat & Cazals, 2000]

Our Contribution

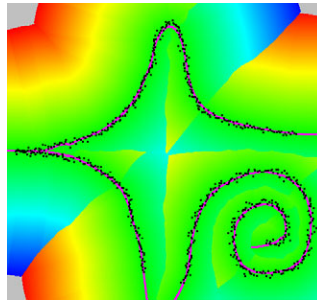


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- New definition of an implicit surface over a (noisy) point cloud.
- New kernel that approximates geodesic distances using a proximity graph.
- The performance is of the same order as that of the Euclidean kernel.
- Artifacts and root mean square error are significantly reduced.



Euclidean kernel



our new geodesic kernel

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New Point Cloud Surface Definition

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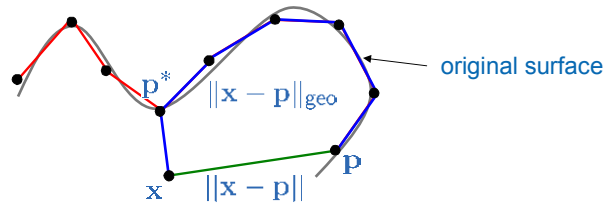
Geodesic Distance Approximation



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- Take topology of S into account \rightarrow approximate geodesic distances on S .
- Use a proximity graph where nodes are points in P :
 - compute nearest neighbor p^* of x .
 - $d(p^*, p)$ shortest path in graph from p^* to p .

$$\|x - p\|_{\text{geo}} = \|x - p^*\| + d(p^*, p)$$



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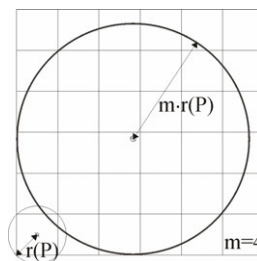
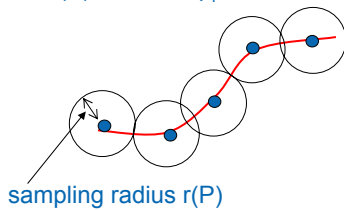
Close-Pairs Shortest-Paths (CPSP)



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- CPSP, which is a subset of APSP, can be precomputed in $O(N)$.
- $\theta(d)$ decays quickly \rightarrow compute only paths up to some length r .
- For each p_i : SSSP for all points in sphere S_i around p_i with radius r .
- If points are uniformly distributed and $r = m \cdot r(P) \rightarrow O(1)$ points in S_i .

h should be chosen so that points up to a distance $m \cdot r(P)$ around a p_i have an influence [KZ04].



sphere with radius $m \cdot r(P)$ can be covered by $O(m^3)$ spheres with radius $r(P)$ [Rog63]

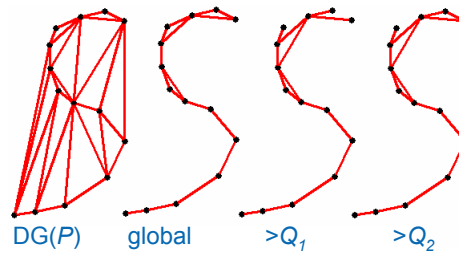
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Proximity by Delaunay Graph



- Geodesic distances can be approximated by shortest paths on edges of $DG(P)$.
- Some edges can “tunnel” through space.

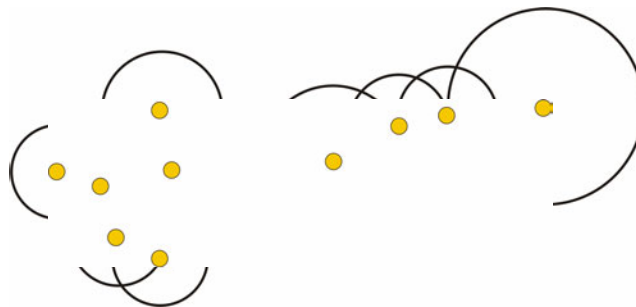


- Prune edges longer than global sampling density or use an outlier detection algorithm.
- Best results are achieved by pruning edges with length $> Q_2$ (median).

Proximity by Sphere-of-Influence Graph



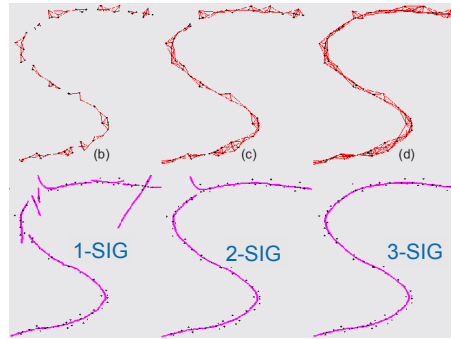
- SIG is sparse: $< 18 \cdot N$ edges ($N = \#$ nodes).
- SIG is not a subgraph of DG.
- Radius of influence: $r_i = \|p_i - \text{nearest}(p_i)\|$.
- p_i and p_j are connected, if $\|p_i - p_j\| \leq r_i + r_j \rightarrow$ connect points that are locally close.



r-SIG



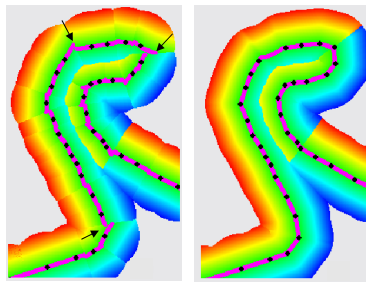
- Problems with simple SIG in noisy or irregularly sampled point clouds:
 - "mini-clusters"
 - "detours"
- Consequence: approximate geodesic distances are imprecise, because
 - close points can only indirectly be accessed
 - some points are not considered due to unconnected components.
- Our solution: r-th order SIG: use sphere determined by r-nearest neighbor.



Reducing Discontinuities



- Discontinuities in f and S can occur at borders of Voronoi regions.
- $\|x_1 - x_2\| \approx 0$, but $\|p^*(x_1) - p^*(x_2)\|$ is "large".



$$\|x - p\|_{\text{geo}(k)} = \min_{p^* \in \mathcal{P}_k(x)} \{\|x - p^*\| + d(p^*, p)\}$$

$\mathcal{P}_k(x)$ = k-nearest neighbors of x that are reachable from nearest neighbor.

Complexity for the 3D Case



- Pre-computations (under reasonable assumptions):
 - $DG(P)$ can be determined in $O(N)$ [Attali & Boissonnat, 2002]
 - $r\text{-SIG}(P)$ can be determined in $O(N)$ on average [Dwyer, 1995]
 - CPSP can be determined in $O(N)$.
 - Run-time:
 - Nearest neighbor in $O(\log N)$ by a Delaunay hierarchy [Devillers, 2002].
 - BFS allows to determine all points in a sphere around p^* of radius $m \cdot r(P)$ in $O(1)$.
- $f(x)$ can be evaluated in $O(\log N)$



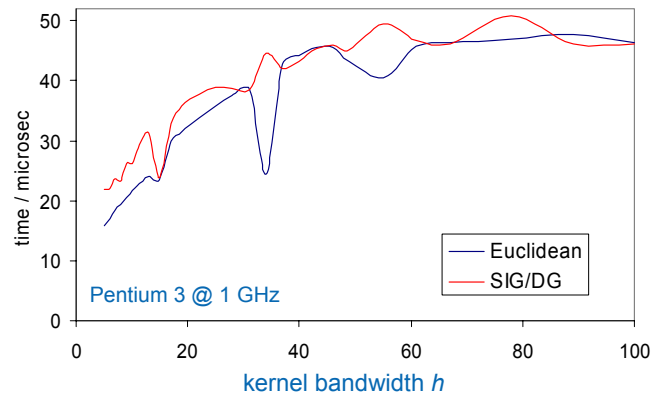
Results

Fast Evaluation



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- The performance for both kernels is of the same order.



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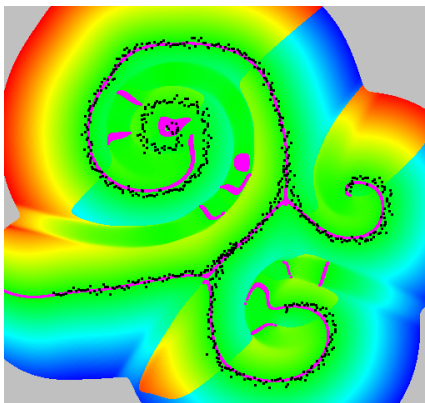
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Quality

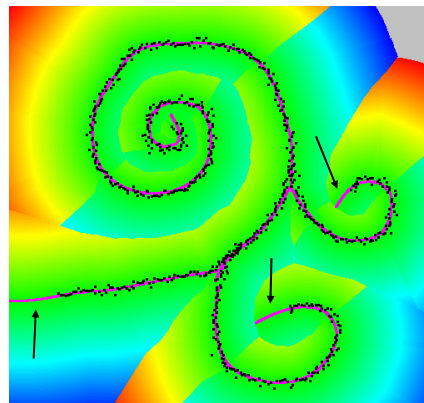


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- Artifacts can be reduced *significantly*.



Euclidean kernel



geodesic kernel

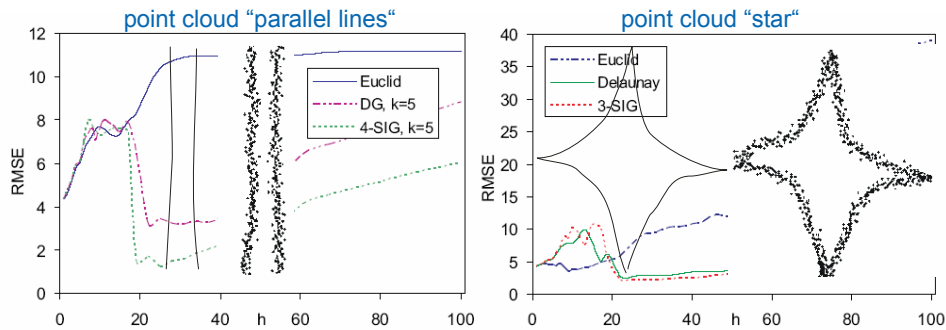
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RMSE depending on Bandwidth



- RMSE: $\sqrt{\frac{1}{|\hat{S}|} \sum_{x \in \hat{S}} f(x)^2}$ \hat{S} is sampling of the original surface.
- For nearly all h , our new kernel yields a smaller RMSE.
- New kernel is less sensitive towards h .
- SIG seems to achieve better results in several examples.



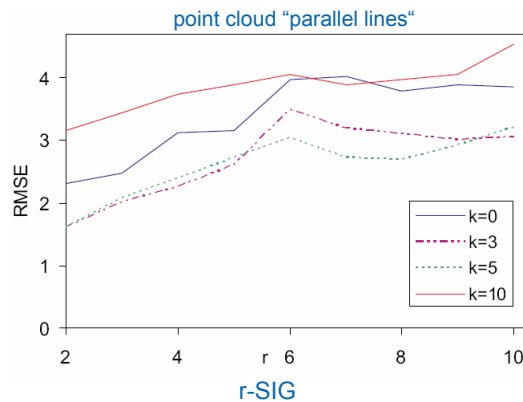
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RMSE depending on k and r



- Two parameters k and r ($\|\dots\|_{\text{geo}(k)}$ and r -SIG) are very robust.
- If k and $r \in [3 \dots 6]$, very similar results are achieved.



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Conclusions and Future Work



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- Our new definition of implicit functions over noisy point clouds yields surfaces that are much closer to the original surface.
- Less artifacts
- Auxiliary data structures can be constructed efficiently and consume only $O(N)$ space.
- $f(x)$ can be evaluated fast

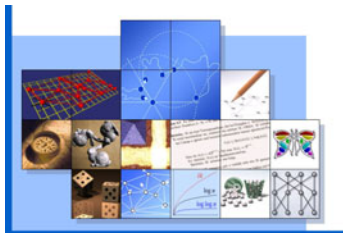
Future Work

- Models with boundaries.
- Deformable point clouds.
- Automatic detection of kernel bandwidth by proximity graph.

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Thank you!



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