

Variational Shape Approximation

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SIGGRAPH - 2004









Other approaches:

Partitioning

- Mesh decimation: Garland, ...

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Other approaches: Partitioning Mesh decimation: Garland, ... Greedy => Suboptimal meshes Global Optimization Energy Functional: Hoppe et al. Irregular mesh, geometric efficiency Anisotropy Remeshing: Turk, Lee, Kobelt, ... Quality of the mesh?



Approximation Theory:
 ■ Functional Setting
 ▶ Strong Results in L_p: Splines, ...

Relies on Parameterization :-(

Approximation Theory:

- Height Field Approximation
 - Obvious Parameterization.
 - Few results about optimality in \mathcal{L}_p .
 - Few results on approximation of error.
 - Results are fairly narrow in scope
 - restricted to height fields,
 - triangulations are assumed to be interpolating the height field at vertices,
 - asymptotical case does not help for a small number of triangles.

Approximation Theory:

- Arbitrary Geometry
 - Lack of knowledge on optimally efficient piecewise linear approximation.
 - Greedy Algorithms: (- triangles, ? error) or (- error, ? triangles)

• Metric commonly used: \mathcal{L}_p

$$\mathbf{d}_p(X,Y) = \left(\frac{1}{|X|} \int_{x \in X} \mathbf{d}_p(x,Y)^p \mathbf{d}x\right)^{\frac{1}{p}}$$

 $\mathbf{d}_p(x,Y) = \inf_{y \in Y} ||x - y||_p$



Variational Partitioning and Proxies

- Remove topology from the search
- Partitioning
 - iteratively seek a partition that minimizes a given error metric.
- Partition and proxies
 - Given a mesh partition $R = \{R_i\}$
 - A shape proxy is a pair $P_i = (\mathbf{x}_i, \mathbf{n}_i)$, where $\mathbf{x}_i \leftarrow \text{"average" Point}$ $\mathbf{n}_i \leftarrow \text{"average" Normal}$



Metrics on Proxies

$$\mathbf{d}_{2}(R_{i}, P_{i}) = \int_{x \in R_{i}} \|x - \Pi_{i}(x)\|^{2} \mathrm{d}x$$





Metrics on Proxies

$$\mathbf{d}_{2,1}(R_i, P_i) = \int_{x \in R_i} \|\mathbf{n}(x) - \mathbf{n}_i\|^2 \mathbf{d}x$$





Optimal shape proxies

$$E(R,P) = \sum_{i=1}^{k} \mathbf{d}(R_i, P_i)$$





The algorithm

It is inspired in Lloyd's Clustering Algorithm

Geometry Partitioning. It is used an error-minimizing region-growing algorithm. The object is segmented in non-overlapping regions.

Proxy Fitting.

For each partition it is computed an optimal local representative.



Geometry Partitioning: Initial seed

Given a partition \mathcal{R} , a set of proxies \mathcal{P} , and an error metric E:

For each region \mathcal{R}_i , select the triangle T_i of \mathcal{R}_i that is most similar to P_i .

In the first step, select k arbitrary triangles. For each one, assign as proxy its barycenter and normal.



Geometry Partitioning: Region growing

Use a priority queue to "propagate" the regions:

For each seed triangle T_i , insert its 3 neighbors in the queue

• Priority = $E(T_j, P_i)$

 \blacktriangleright Tag them with the same label of T_i

- For each popped triangle:
 - ► IF it has been assigned to a proxy, END
 - ELSE Assign it to the region with its tag and push its (untagged) neighbors in the queue

Proxy Fitting

- $\blacksquare \mathcal{L}_2$ Metric:
 - ▶ \mathbf{x}_i = Barycenter of the region \mathcal{R}_i .
 - ▶ \mathbf{n}_i = Eigenvector of the smallest eigenvalue of the covariance matrix of \mathcal{R}_i .

$\blacksquare \mathcal{L}_{2,1}$ Metric:

- ▶ \mathbf{x}_i = Barycenter of the region \mathcal{R}_i .
- ▶ n_i = area-weighted average of normals of triangles in \mathcal{R}_i .

Improvements

Choosing the number of proxies
Region Teleportation
Farthest-point initialization
Tailoring Refinements
Smoothing the normal field







Application to meshing

Anchor Vertices
Edge Extraction
Triangulation
Polygons

Limitations

- Cannot compete (in time) with greedy methods
- Not Real-Time. I mean, just for offline computations
- Meshing does not handle non-manifold meshes.



















