TU WIEN Informatics

Construction and Visualization of Gaussian Mixture Models from Point Clouds for 3D Object Representation

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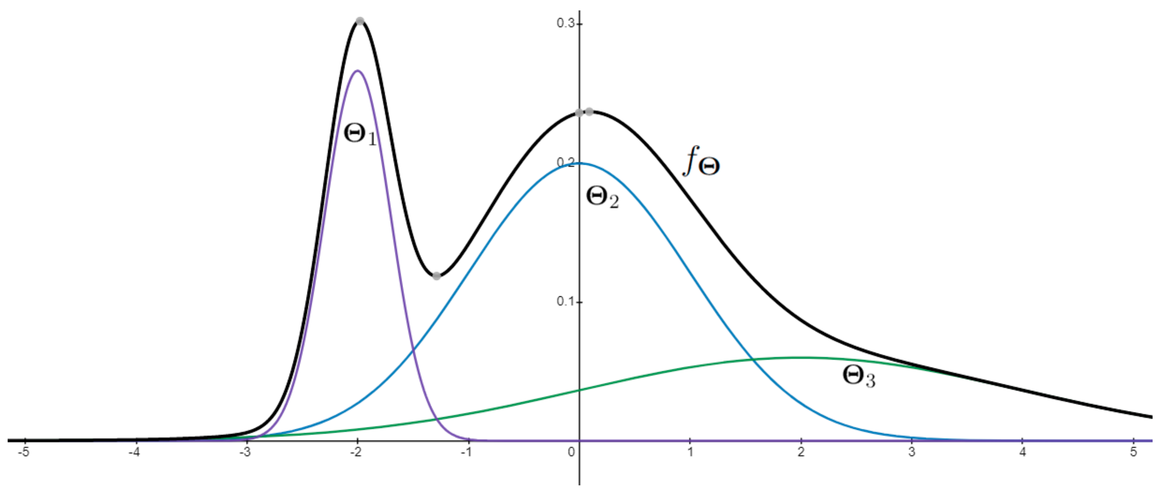
Motivation

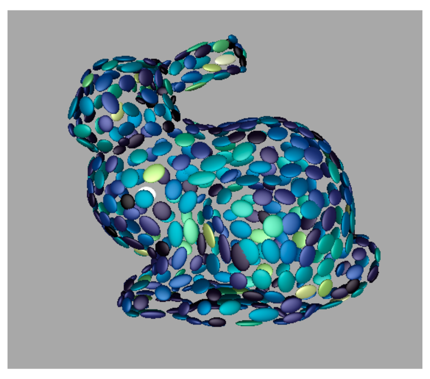


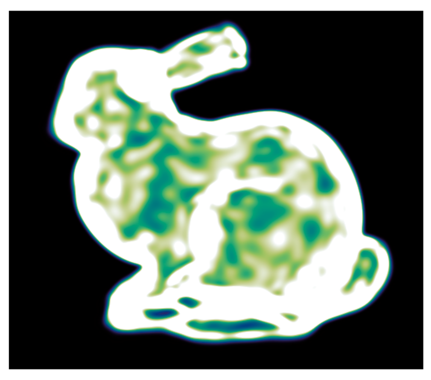
- A **Gaussian Mixture Model** (GMM) is a probabilistic model that is described by a weighted sum of normal distributions (*Gaussians*). GMMs can be fitted to 3D point clouds to describe their density.
- A novel deep learning method is being developed at TU Wien, which needs ways to **construct and visualize GMMs**.
- No **tool for GMM visualization** is available that matches our requirements.
- We want to **quantify differences** of existing GMM construction algorithms.

Contribution

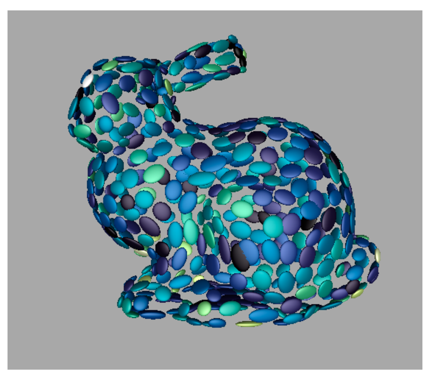
- Development of a **3D-GMM visualization tool** enabling both **isoellipsoid** and **density visualization** with different configurations.
- Description of the **closed-form solution** for the integral of a GMM along a ray, which was necessary for the visualization tool. We also correct a mistake in a previous related paper.
- Definition of **suited metrics** for evaluating a GMM's quality.
- **Implementations**, **adaptions**, and quantitative **comparison** of several **GMM-construction algorithms**: EM, Top-Down HEM, and Geometrically regularized Bottom-Up HEM.

Visualization


Colored by weights


Black to white color map, Regular


Black to white color map, Logarithmic

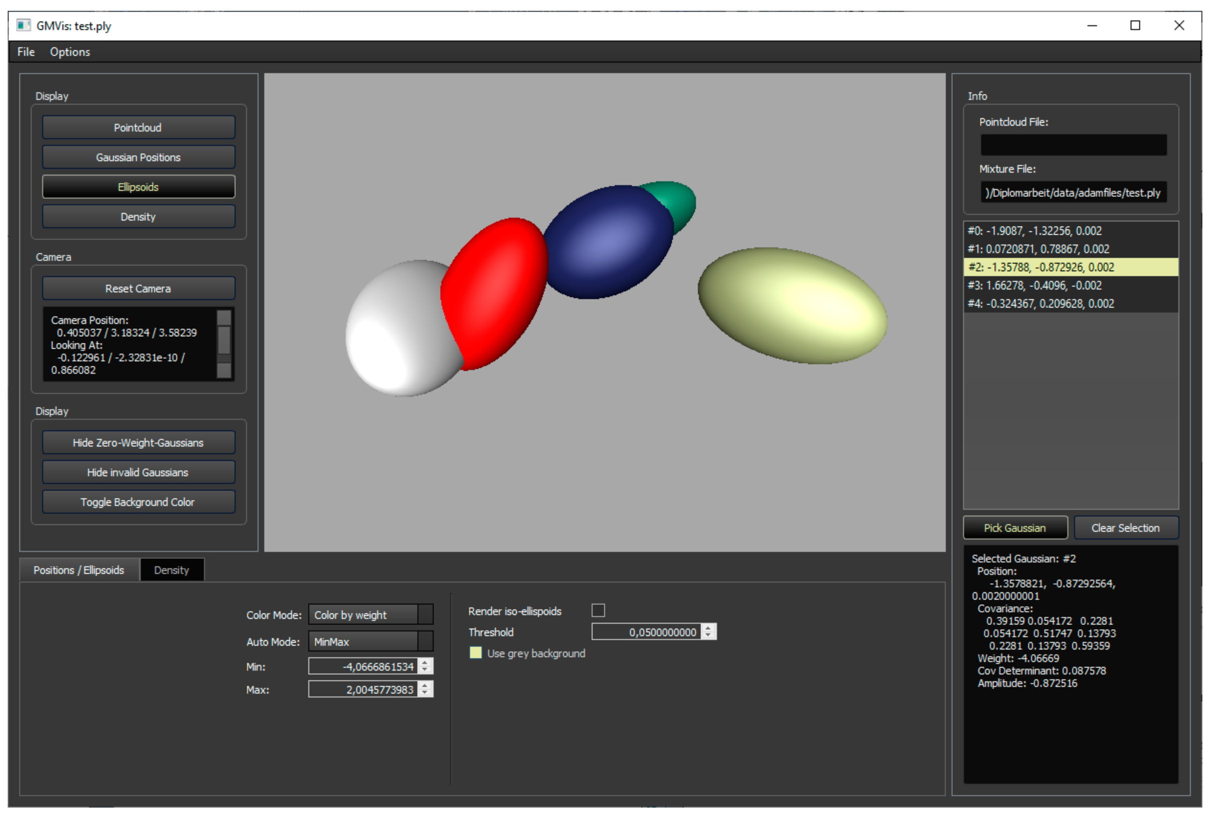

Colored by amplitudes


White to black color map, Regular


White to black color map, Logarithmic

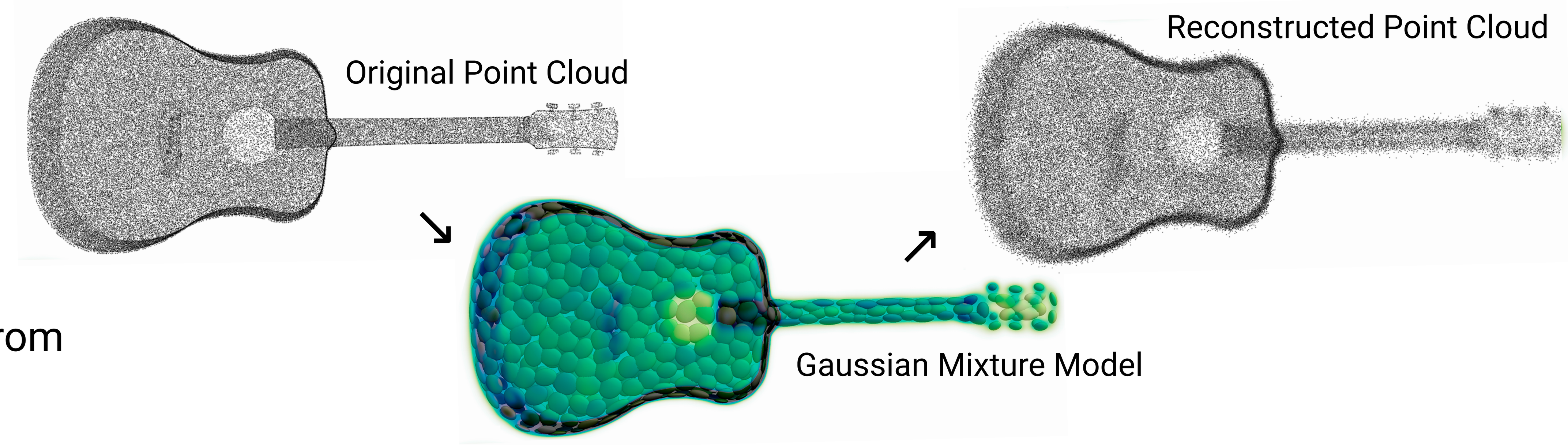
Isoellipsoids
One Ellipsoid per Gaussian

Density
Accumulated density along viewing ray through pixel


Graphical User Interface

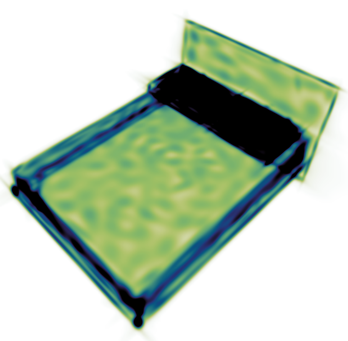
Construction

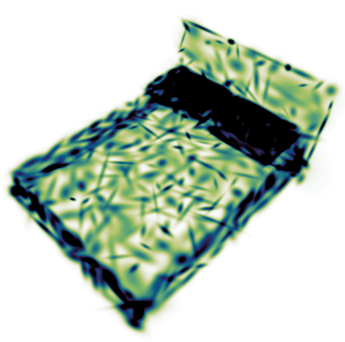
Evaluation Strategy:
- 200 Models from ModelNet40
- Each algorithm is tested in different configurations
- Metrics:
  - Reconstruction Error: Based on Chamfer Distance between point clouds from mesh and GMM
  - Irregularity: Variation of nearest-neighbor-distances from GMM point cloud to mesh point cloud



EM [1]

- E-step: Calculates point-Gaussian-responsibilities
- M-step: Updates GMM according to responsibilities
- Repeat steps until convergence
- Implementation in Python/PyTorch

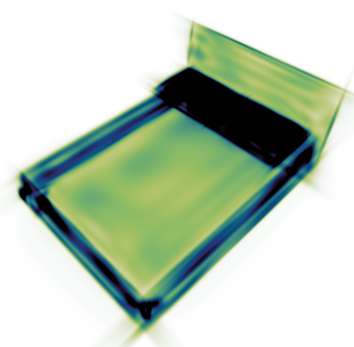

100,000 input points and 512 Gaussians

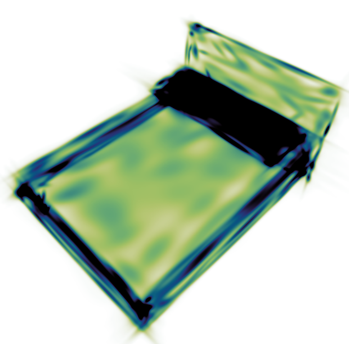

10,000 input points and 512 Gaussians

- Best results for typical setting
- Slowest algorithm
- Irregular results when using too few points

Top-Down HEM [2]

- Fits a small GMM using EM
- Repeatedly replaces Gaussians with new sub-GMMs
- Implementation in Python/PyTorch

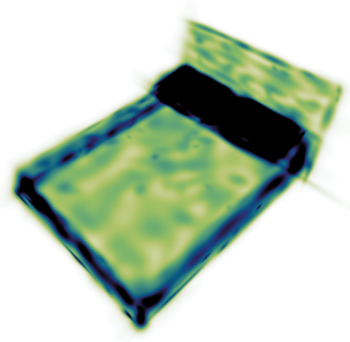

100,000 input points and 512 Gaussians

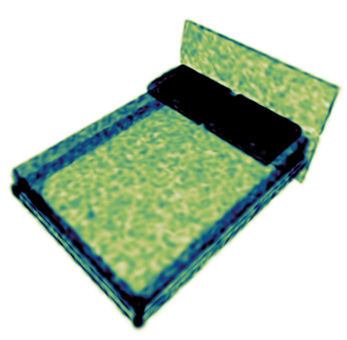

10,000 input points and 512 Gaussians

- Faster alternative to EM
- Results are slightly inferior to EM
- Less irregular results than EM for fewer points

Geometrically reg. Bottom-Up HEM [3]

- Starts with many Gaussians
- Repeatedly merges several Gaussians into one
- Adaption of open-source C++ implementation


100,000 input points and 512 Gaussians


100,000 input points and 16,000 Gaussians

- Inferior for 512 Gaussians or less
- Useful and fast algorithm for higher numbers of Gaussians

References:
[1] Arthur P Dempster, Nan M Laird, and Donald B Rubin. Maximum likelihood from incomplete data via the em algorithm. Journal of the Royal Statistical Society: Series B (Methodological), 39(1):1–22, 1977.
[2] Benjamin Eckart, Kihwan Kim, Alejandro Troccoli, Alonzo Kelly, and Jan Kautz. Accelerated generative models for 3d point cloud data. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 5497–5505, 2016.
[3] Reinhold Preiner, Oliver Mattausch, Murat Arikan, Renato Pajarola, and Michael Wimmer. Continuous projection for fast l1 reconstruction. ACM Trans. Graph.,33(4):47–1, 2014.