SHAPE RETRIEVAL ON THE WAVELET DENSITY HYPERSHPERE

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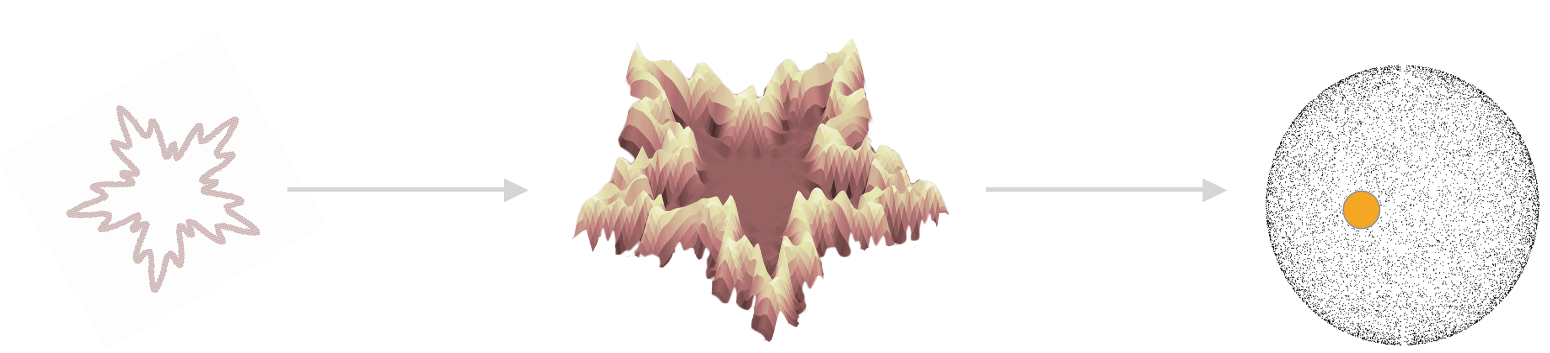
PROBLEM

INTRODUCTION

With the advancement in 3D modeling technology, understanding shape is more important than ever. Shape retrieval is the problem of searching for similar shapes in a database given a query shape, similar to search engines for text. In our novel approach, we represent shapes as probability densities and use the intrinsic geometry of this space to match similar shapes. Specifically, we expand the square-root of the density in a multiresolution wavelet basis. Under this model, each density (of a corresponding shape) is mapped to a point on unit hypersphere, where the angle between a pair of points can be used as a measure of similarity.

OUR CONTRIBUTIONS

- Faster 2D density estimation single and multiresolution
- Results from linear assignment
- Extention to multiresolution linear assignment
- Hierarchical clustering algorithm
- Proof of hierarchical runtime
- Results from hierarchical retrieval



APPROACH

WAVELET DENSITY ESTIMATION

Wavelets are crucial mathematical functions that form an orthonormal basis for probability density functions. Given a point-set representation of a shape, we use a constrained maximum likelihood approach to estimate the coefficients of the wavelet density basis expansion in eq. (1).

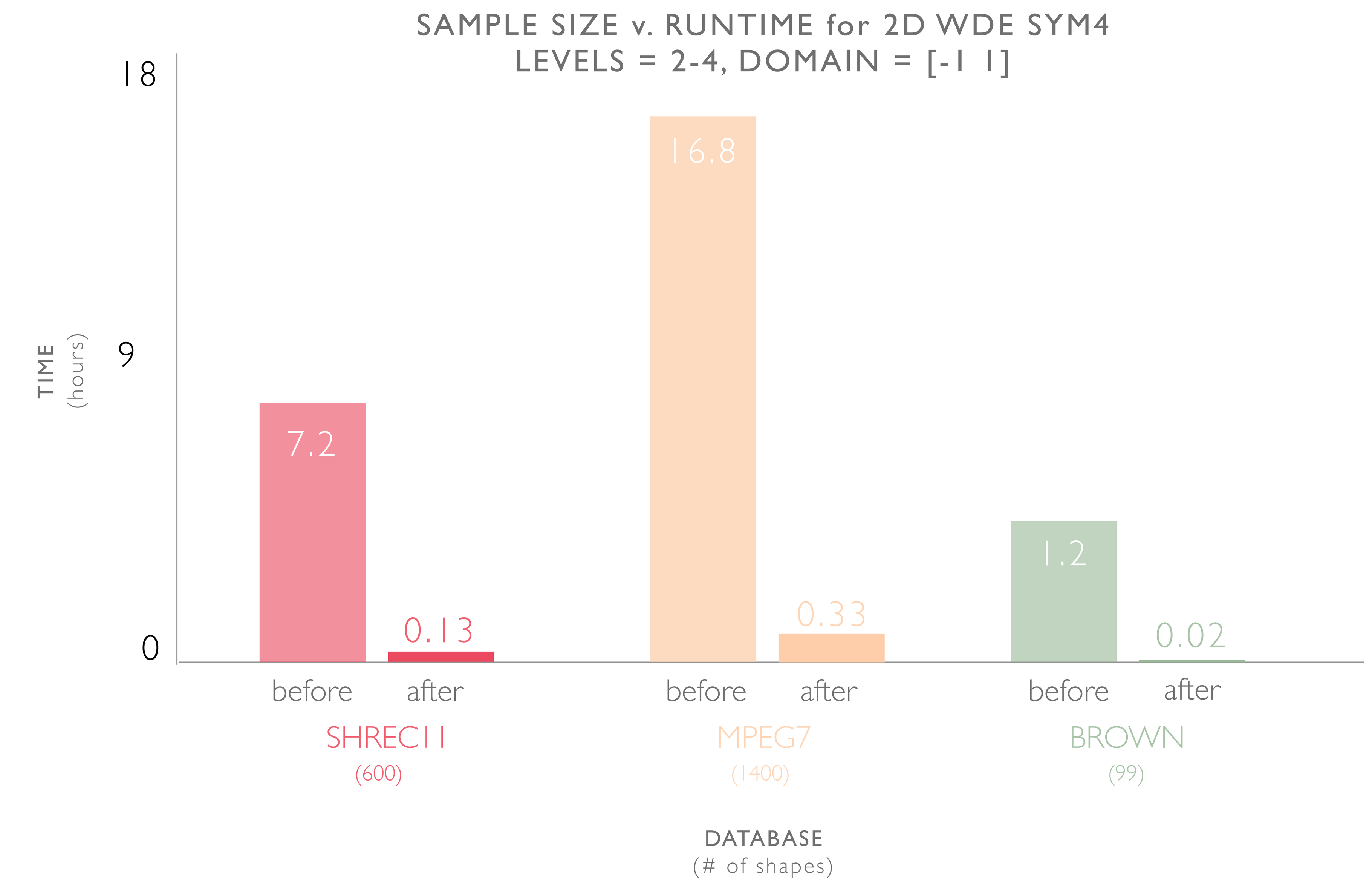
$$\sqrt{p(\mathbf{x})} = \sum_{j_0,\mathbf{k}} \alpha_{j_0,\mathbf{k}} \phi_{j_0,\mathbf{k}}(\mathbf{x}) + \sum_{j \geq j_0,\mathbf{k}}^{j_1} \sum_{w=1}^{3} \beta_{j,\mathbf{k}}^{w} \psi_{j,\mathbf{k}}^{w}(\mathbf{x}) \qquad \text{eq. (1)}$$

APPROACH & RESULTS

2D WDE OPTIMIZATION

Wavelet density estimation (WDE) is a computationally expensive task, but improved the speed by orders of magnitude through parallelization. We had significant improvements in both initializing the wavelet coefficients and in our negative log likelihood based optimization process.

100× FASTER

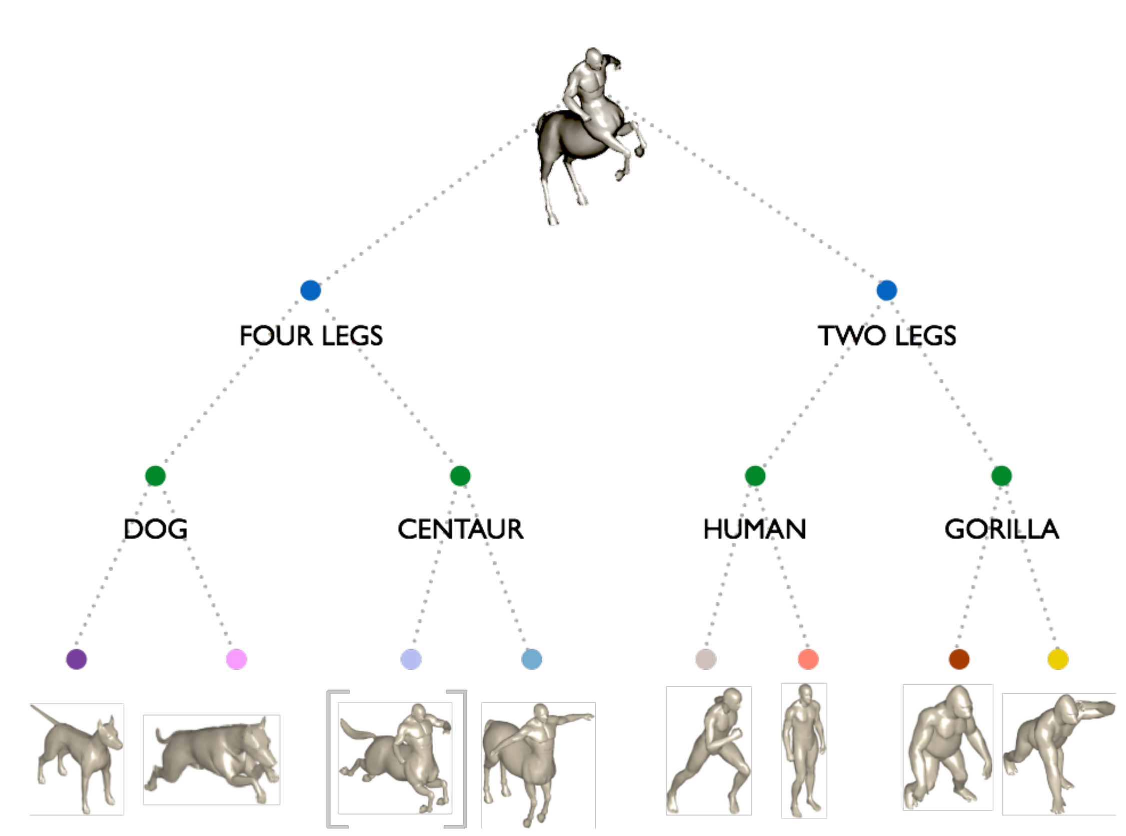


APPROACH & RESULTS

HIERARCHICAL SHAPE RETRIEVAL

Hierarchical clustering uses different levels of abstraction to group similar shapes together. Because of the hierarchical tree structure, retrieval speed and accuracy are improved.

We used spherical form of *k*-means clustering on the hypersphere for each level of clustering, and create a recursive tree structure where the means of one level form the children of the higher level.



APPROACH & RESULTS

LINEAR ASSIGNMENT

Linear assignment warps two shapes closer together to reduce non-rigid differences between them. Because shapes easily warp when they're close together, we reduce the distance between similar shapes while keeping dissimilar shapes far apart. We control the amount of warping by weighting λ at a higher value to decrease the amount of distortion.

This makes our dissimilarity metric much more robust to small deformations, which improve the accuracy of shape retrieval.

BULLSEYE SCORES LINEAR vs. NONLINEAR

	SHREC11	MPEG7	BROWN
LINEAR	99.7%	99.3%	83.0%
NONLINEAR	20.7%	75.3%	51.8%

WARPING FROM SOURCE TO TARGET

λ = [1, 0.1, 0.05, 0.03, 0.01]