SHAPE RETRIEVAL ON THE WAVELET DENSITY HYPERSHPERE

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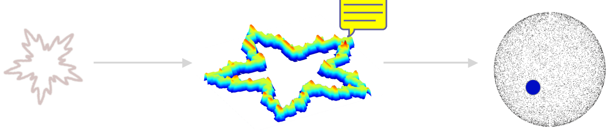
ABSTRACT

Fig 1.

(a) original 2D pointset (b) wavelet density representation (c) shape becomes point on hypersphere



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.

CONTRIBUTIONS

- Optimized performance of 2D multiresolution wavelet density estimator
- Improved shape similarity metric using linear assignment and multiresolution wavelets
- Implemented hierarchical clustering algorithm on high-dimensional unit hypersphere and analyzed algorithmic complexity
- Time complexity proof of hierarchical retrieval scheme
- Experimental validations across multiple datasets, with empirical results competitive with state of the art

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).

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

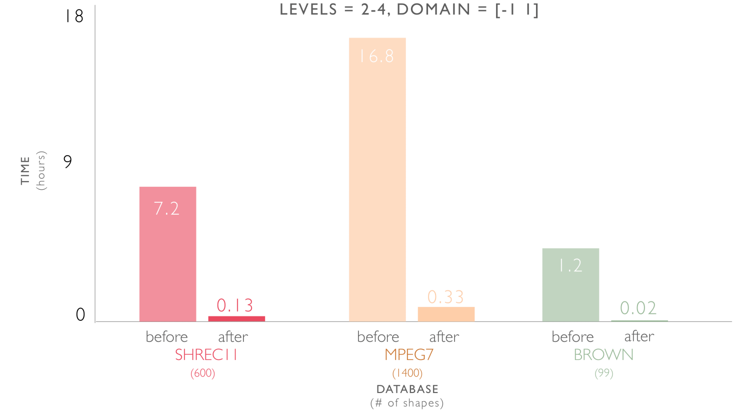
APPROACH & RESULTS

WDE OPTIMIZATION

Wavelet density estimation (WDE) is a computationally expensive task, but we improved the speed by orders of magnitude through parallelization. We had significant improvements in both initializing the wavelet coefficients (α and β in eq. 1) and in our negative log likelihood based optimization process.

100× FASTER

Fig 2. SAMPLE SIZE v. RUNTIME for WDE SYM4 LEVELS = 2-4, DOMAIN = [-1 1]



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.

Fig 3. HIERARCHICAL STRUCTURE

(captions for illustration only)

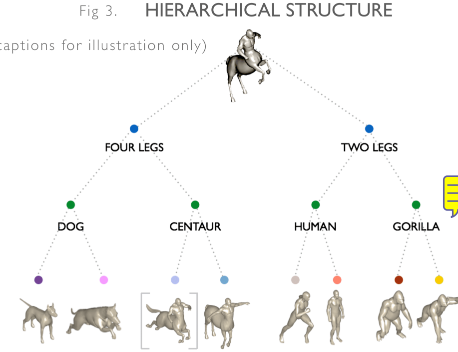


Table 1. ACCURACY

	SHREC11	MPEG7	BROWN
w/o HIERARCHY	20.7%	75.3%	51.8%
w/ HIERARCHY.	99.7%	99.3%	83.0%

REFERENCES

- Adrian M Peter and Anand Rangarajan. Maximum likelihood wavelet density estimation with applications to image and shape matching. IEEE Transactions on Image Processing, 17(4):458–468, 2008.
- Adrian M. Peter, Anand Rangarajan, and Jeffrey Ho. Shape lane rouge: Sliding wavelets for indexing and retrieval. IEEE Conference on Computer Vision and Pattern Recognitio[illegible]008.
- Vinh Nguyen. Gene clustering on the unit hypersphere with the spherical k[illegible] algorithm: coping with extremely large number of local optima. In World Congress in Computer Science, Computer Engineering, and Applied Computing, 226–233. CSREA Press, 2008.

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

We have an objective function that balances warping the shapes together with regularizing the amount of warping allowed. We decrease the amount of warping by increasing the parameter λ.

Fig 4. WARPING FROM SOURCE TO TARGET λ = [1, 0.1, 0.05, 0.01, 0.001]

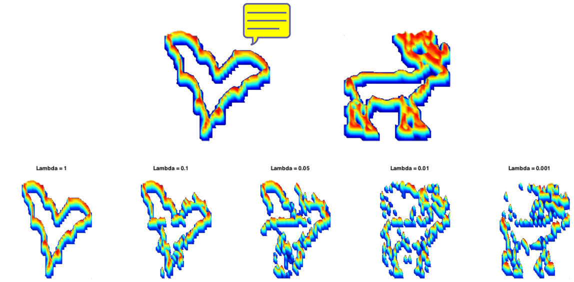


Table 2. ACCURACY FOR MPEG7 MULTIRES HAAR LEVELS 2-3, DOMAIN = [-1 1]

no lin. assgn.	λ = 0.036	λ = 1e-6	λ = 1e-8
80.2%	80.0%	70.9%	73.2%