Analysis of Image Tranforms for Sketch-based Retrieval

Diploma Thesis

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Outline

Motivation

foo

Challenges of CBIR

The Semantic Gap

"The semantic gap is the ***lack of coincidence*** *between the information that one can extract from the* ***visual data*** *and the* ***interpretation*** *that the same data have for a user in a given situation." – Smeulders et al.*

The Sensory Gap

"The sensory gap is the gap between the ***object in the world*** *and the information in a (computational) description derived from a* ***recording of that scene****." – Smeulders et al.*

Prior Work on Human Recognition

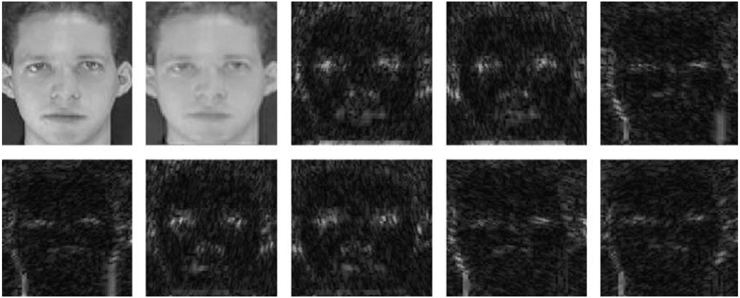


Figure: "Face recognition using curvelet based PCA.", T. Mandal and Q. M.J Wu, ICPR 2008

Prior Work on Human Recognition

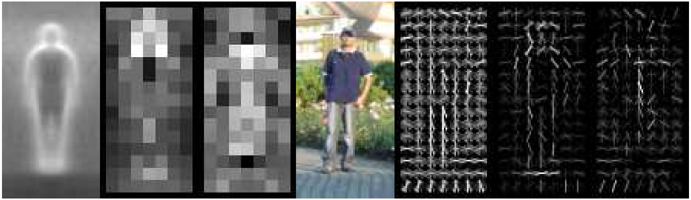
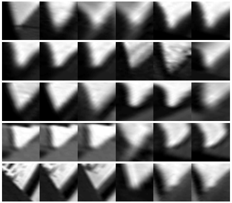


Figure: “Histograms of oriented gradients for human detection”, Dalal and Triggs, CVPR 2005

Prior Work on Visual Codebooks



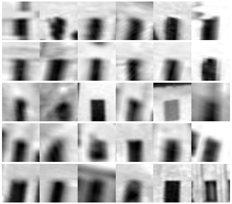


Figure: "Video Google: A text retrieval approach to object matching in videos", Sivic and Zisserman, ICCV 2003

Prior Work on Scene Classification

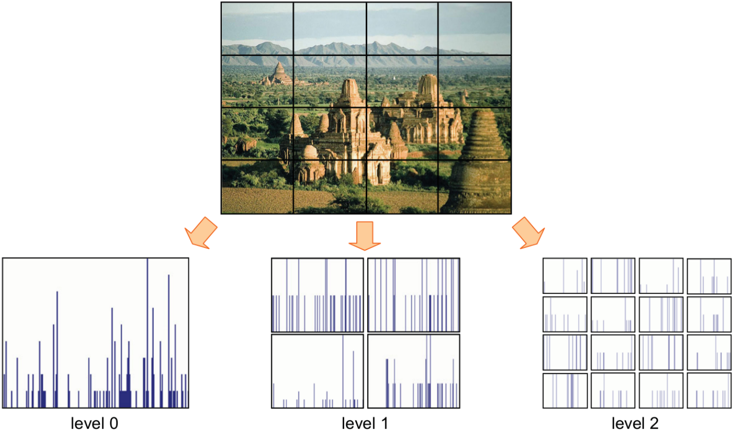


Figure: "Spatial pyramid matching", Lazebnik et al., 2009

Anatomy of a CBIR System

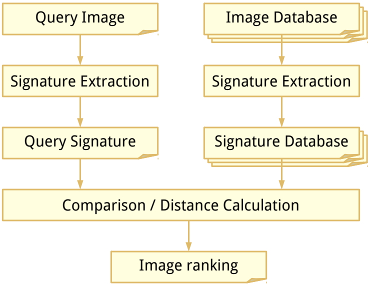


Figure: Global Descriptors

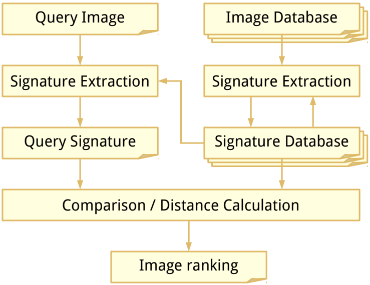
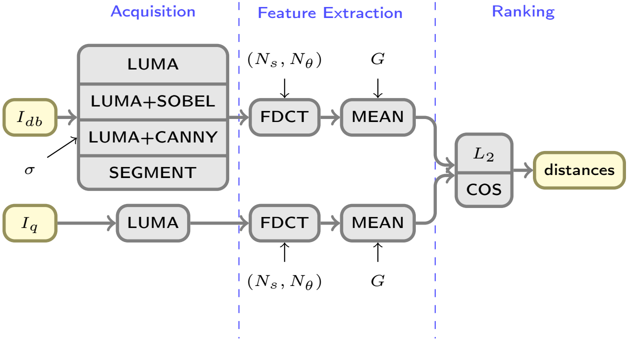


Figure: Local Descriptors

Proposed Retrieval Pipelines (Global)



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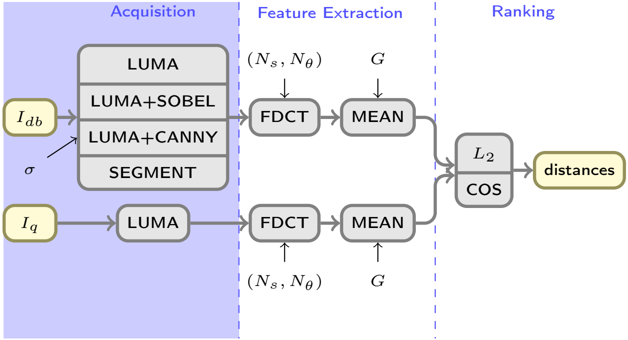

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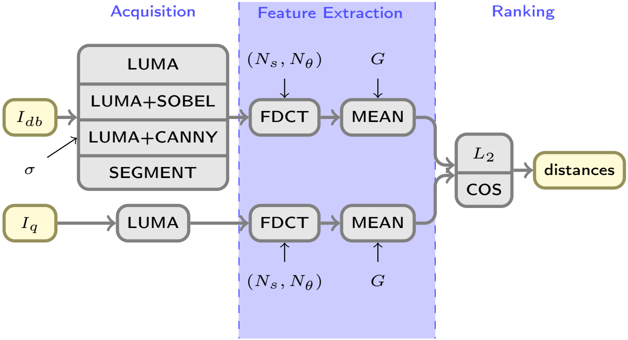

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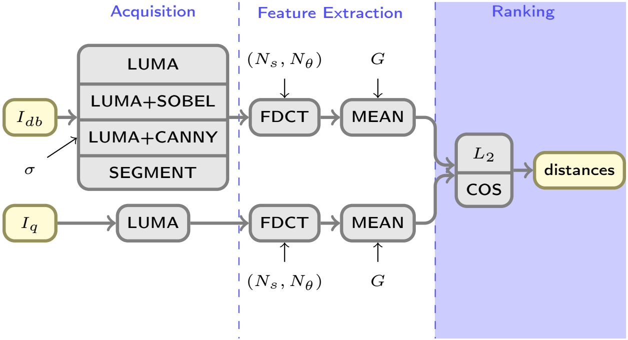
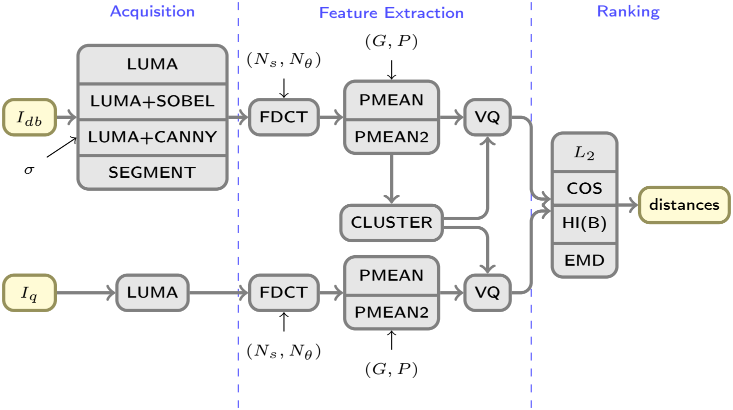
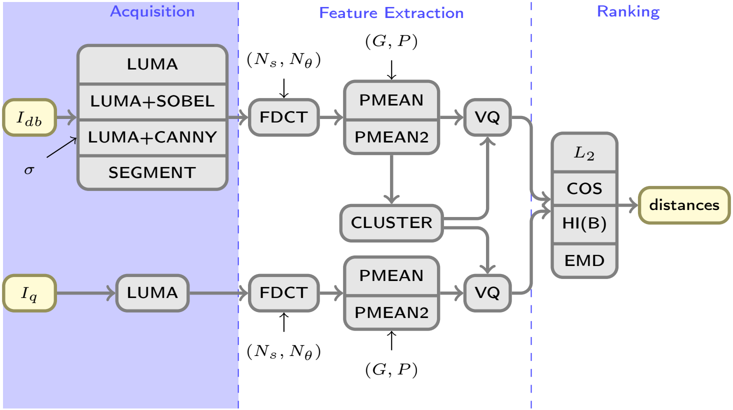


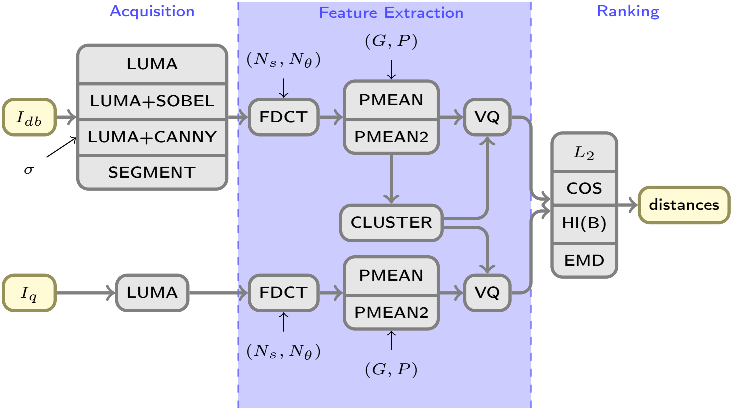
Proposed Retrieval Pipelines (Local)



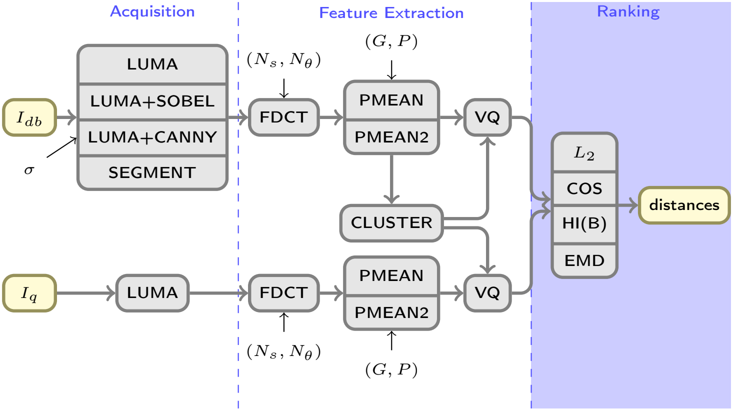
Proposed Retrieval Pipelines (Local)



Proposed Retrieval Pipelines (Local)



Proposed Retrieval Pipelines (Local)



Acquisition

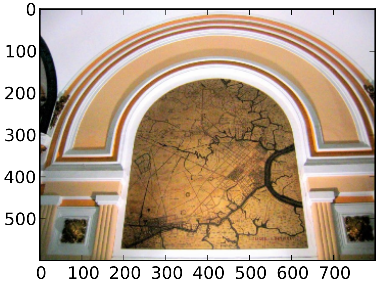


Figure: Original Image

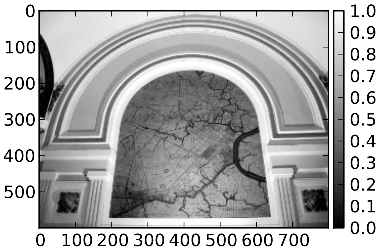
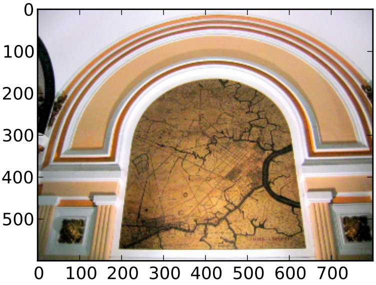


Figure: Luma Conversion

Acquisition



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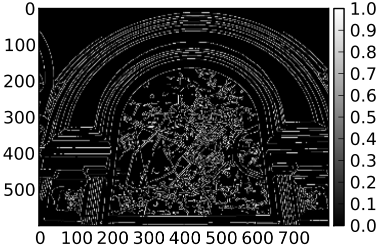
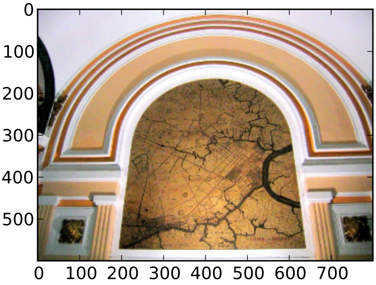


Figure: Canny Operator

Acquisition



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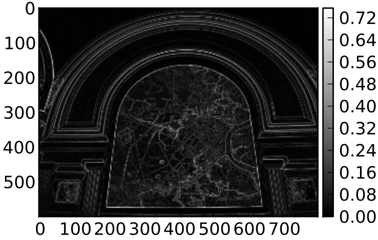
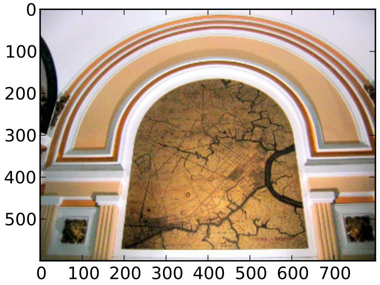


Figure: Sobel Operator

Acquisition



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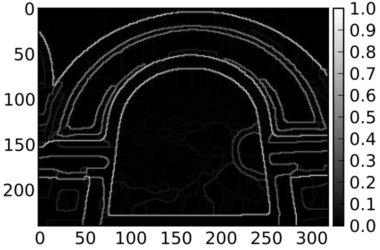


Figure: gPb-owt-ucm Transform

Properties of the Curvelet Transform

- An extension of the wavelet transform
- Localized in *position*, *scale* and *orientation*
- Curvelets obey parabolic scaling: $width \approx length^2$
- Approximation error along edges using m largest coefficients decays with $\frac{log(m)^3}{m^2}$ (compare $\frac{1}{m}$ for wavelets)
- Defined and applied in frequency domain as $\hat{\varphi}_{j,l,k}$ using the forward and inverse Fourier Transforms:

$$c(j,l,k) := \langle f, \varphi_{j,l,k} \rangle = \int_{\mathbb{R}^2} f(x) \overline{\varphi_{j,l,k}(x)} dx$$

Constructing the Curvelets

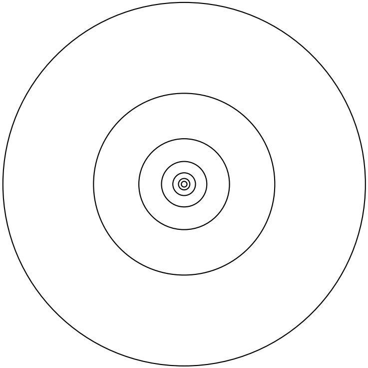


Figure: Frequency Domain

Figure: Spatial Domain

Constructing the Curvelets

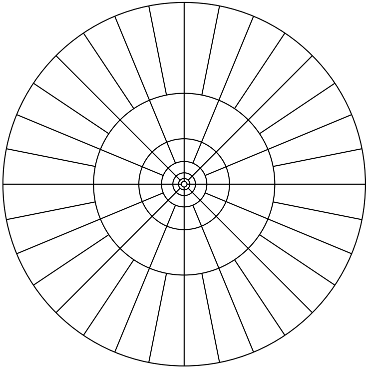


Figure: Frequency Domain

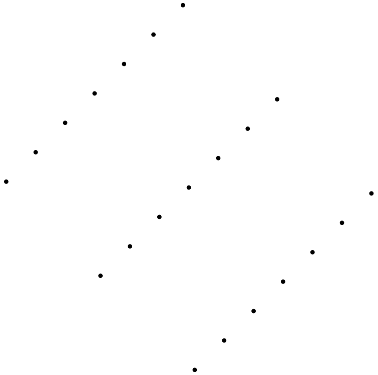


Figure: Spatial Domain

Constructing the Curvelets

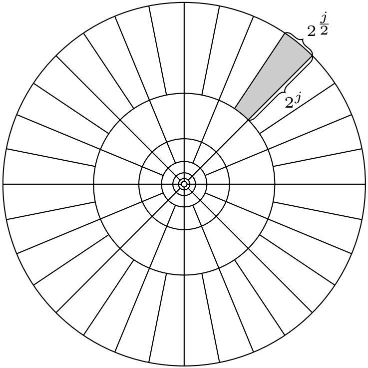


Figure: Frequency Domain

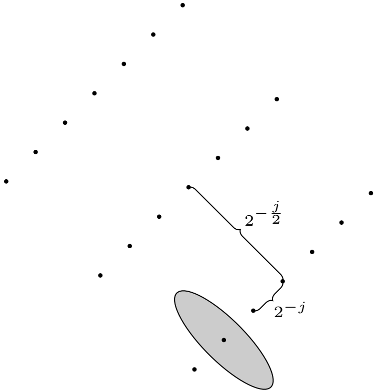


Figure: Spatial Domain

Constructing the Curvelets

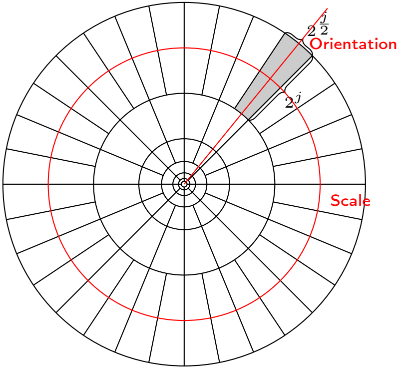


Figure: Frequency Domain

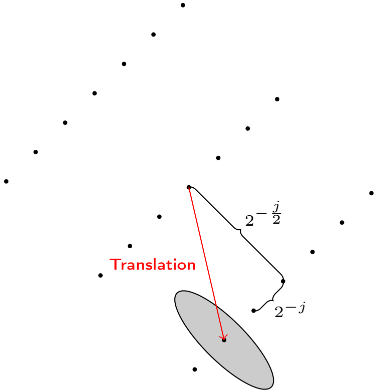


Figure: Spatial Domain

Example Curvelets

Figure: Frequency Domain

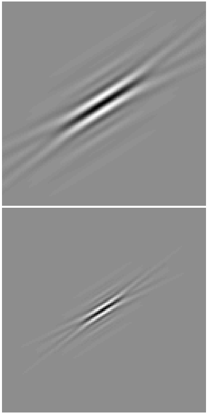


Figure: Spatial Domain

The Fast Discrete Curvelet Transform

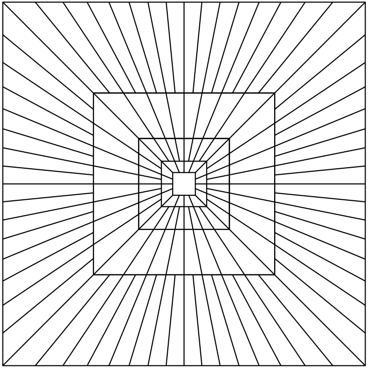


Figure: Frequency Domain

Figure: Parallelogram Support

The Fast Discrete Curvelet Transform

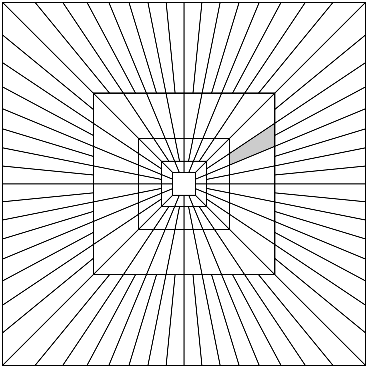


Figure: Frequency Domain

Figure: Parallelogram Support

The Fast Discrete Curvelet Transform

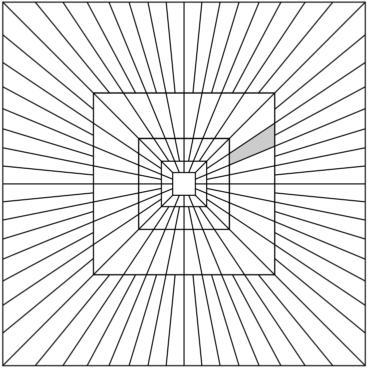
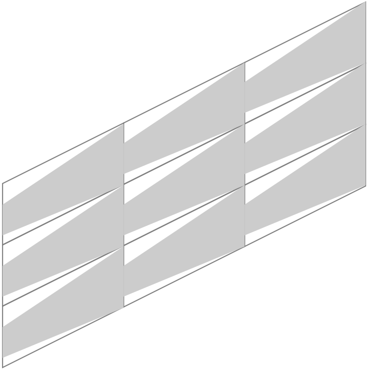


Figure: Frequency Domain



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The Fast Discrete Curvelet Transform

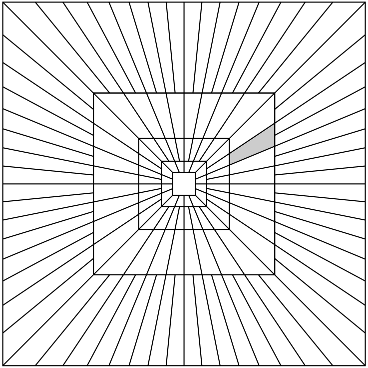


Figure: Frequency Domain

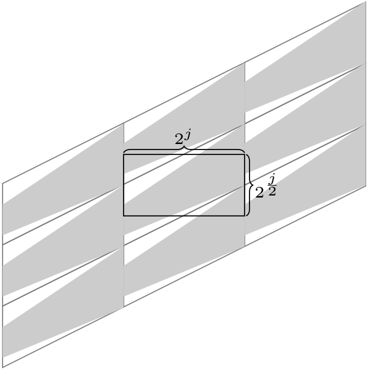


Figure: Parallelogram Support

Global Feature Extraction

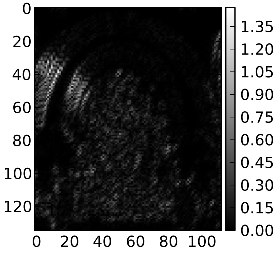


Figure: Curvelet coefficients at a specific scale and angle

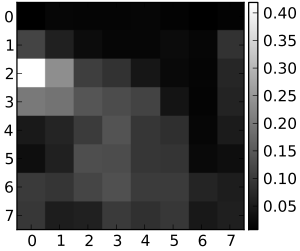


Figure: Mean values on an 8×8 grid

Local Feature Extraction (Sampling)

PMEAN Collect $(n-m+1)^2$ sample vectors of length $N_s \cdot N_{\theta_s} \cdot m^2$ by concatenating across scales and angles

PMEAN2 Collect $N_s \cdot (n-m+1)^2$ sample vectors of length $N_{\theta_s} \cdot m^2$ by concatenating across angles

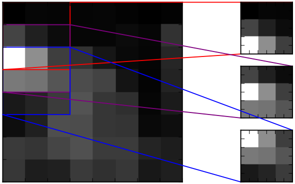


Figure: 8×8 mean coefficient grid sampled using 3×3 window

- n image width and height
- m window width and height
- N_s Number of scales
- N_{θ_s} Number of angles at scale s

Local Feature Extraction (Clustering)

- k-means clustering
- Codebook size $k = 1000$
- Each sample vector is assigned to the cluster S_i, $i = 1, \ldots, k$ the center of which it is closest to
- Image signature is the number of occurences of each "visual word" in the image:

$$\tilde{I} = [|S_1|, |S_2|, \ldots, |S_k|]$$

Distance Metrics

L_2 $d_{EUCL}(p,q) = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2}$

Cosine $d_{COS}(p,q) = 1 - \frac{p \cdot q}{\|p\|\|q\|}$

Histogram Intersection (HI) $d_{HI}(P,Q) = 1 - \frac{\sum_{i=1}^{n}\min(p_i,q_i)}{\sum_{i=1}^{n} q_i}$

Earth Mover's Distance (EMD) $d_{EMD}(P,Q) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} d_{i,j} f_{i,j}}{\sum_{i=1}^{n}\sum_{j=1}^{m} f_{i,j}}$

TF-IDF Weighting

Term t_i occurs $tc_{i,j}$ times in document $d_j \in D$ with length n_j and is present in m_i documents overall.

Term Frequency $tf_{i,j} = \frac{tc_{i,j}}{n_j}$

Inverse Document Frequency $idf_i = \log \frac{|D|}{m_i}$

Total Term Weight $w_{i,j} = tf_{i,j} \cdot idf_i = \frac{tc_{i,j}}{n_j} \cdot \log \frac{|D|}{m_i}$

Cross-Domain Dataset

Figure: Example images from "Sketch-based image retrieval: benchmark and bag-of-features descriptors", Eitz et al., 2011

Cross-Domain Benchmark

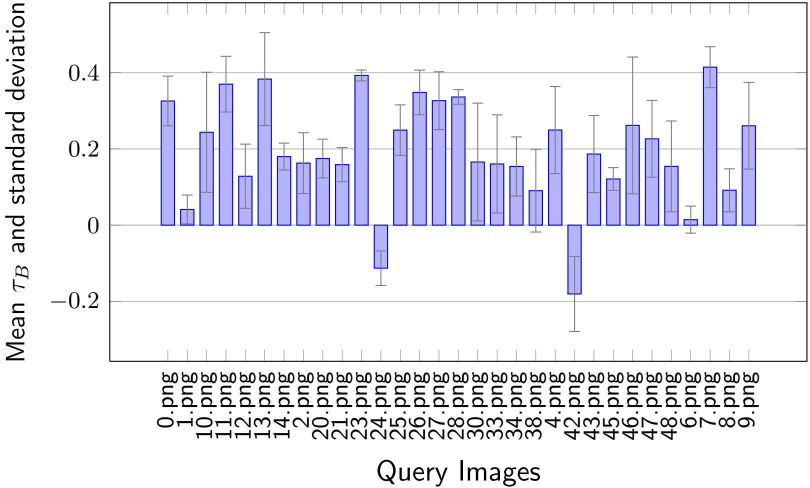
- 31 user study-based ground-truth rankings of 40 images with corresponding query sketches (Eitz et al., 2011)
- Kendall rank correlation coefficient $-1 \leq \tau_B \leq 1$
- τ_B is based on the number of similarly ordered pairs of measurements between two distributions
- $\tau_B = 1$ means same ordering, $\tau_B = -1$ means inverted ordering
- independent of the scaling differences between the two distributions

Cross-Domain Results

Preproc.	Sampling	G	P	σ	Metric	Mean τ_B correlation coefficient
CANNY	MEAN	8		1.5	COS	0.188
CANNY	PMEAN	8	3	1.5	HI	0.22
CANNY	PMEAN2	8	3	1.5	COS	0.19
LUMA	MEAN	12			COS	0.191
SOBEL	MEAN	12			COS	0.2
SOBEL	PMEAN	8	3		HIB	0.187

Table: Best performing pipeline configurations

Cross-Domain Distribution



Intra-Domain Dataset

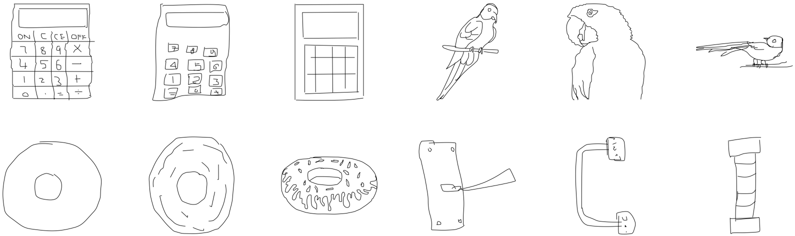


Figure: Example sketches from four categories from "How do humans sketch objects?", Eitz et al., 2012

Intra-Domain Benchmark

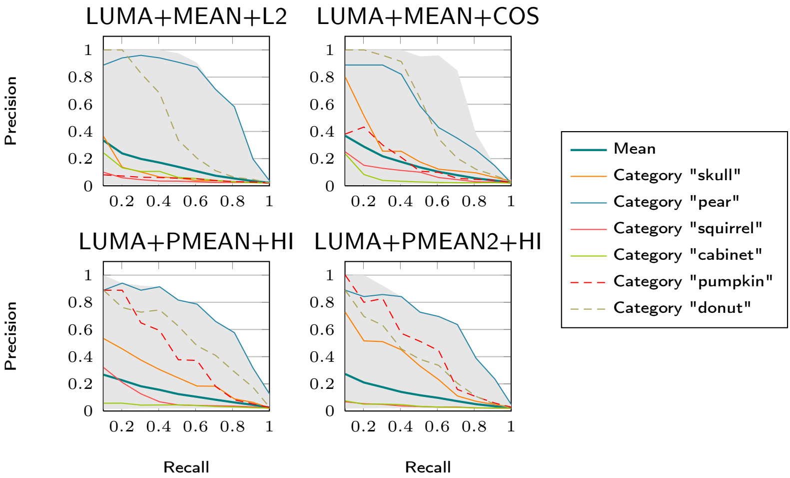
- 50 categories with 80 hand-drawn sketches each (Eitz et al., 2012)
- Precision-recall statistics

$$recall = \frac{\text{number of correct positive results}}{\text{total number of positives}}$$

$$precision = \frac{\text{number of correct positive results}}{\text{total number of results}}$$

- no edge-detecting preprocessing

Intra-Domain Results



Discussion and Conclusions

- Retrieval performance comparable to other descriptors
- For cross-domain retrieval, local LUMA+CANNY+HI performs best
- For intra-domain retrieval, global descriptors work better
- Large performance differences between queries

$\Rightarrow$ Possibly much better results for narrower problem statements and specialized applications