Analysis of Image Tranforms for Sketch-based Retrieval

Diploma Thesis

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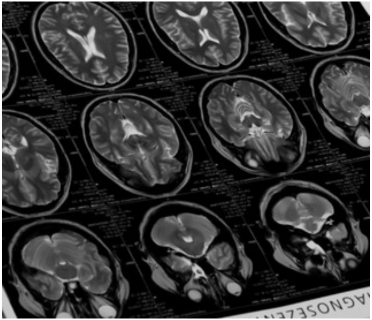
02.11.2012

Outline

Motivation

- Increasing amount of visual information in
  - the internet
  - medicine
  - astronomy
- Manual search largely infeasible
- Textual queries require cognitive effort by human and machine
- Sketches allow for easy *expression of query intent*



Prior Work on Face Recognition

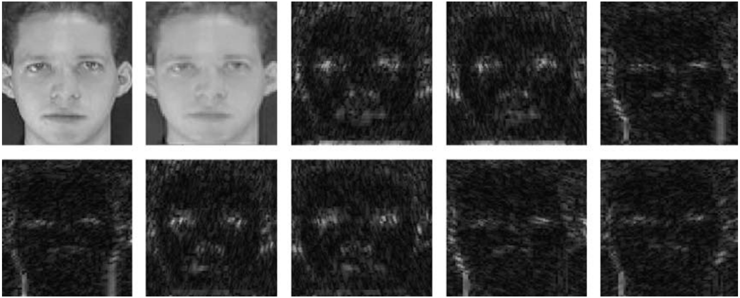


Figure: "Face recognition using curvelet based PCA.", T. Mandal and Q. M.J Wu, ICPR 2008

Prior Work on Human Recognition

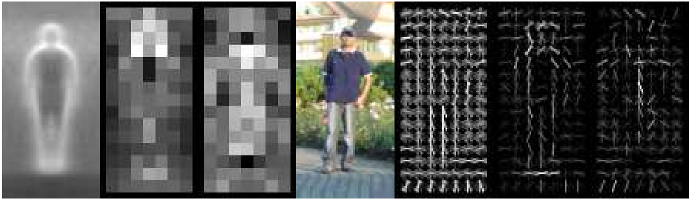
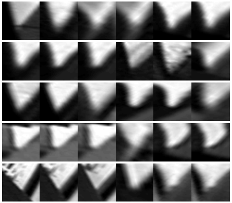


Figure: "Histograms of oriented gradients for human detection", Dalal and Triggs, CVPR 2005

Prior Work on Visual Codebooks



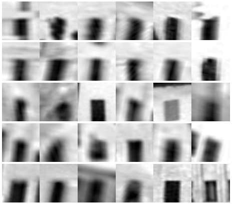
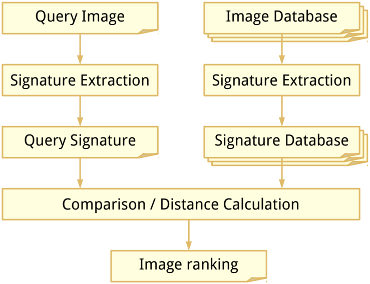


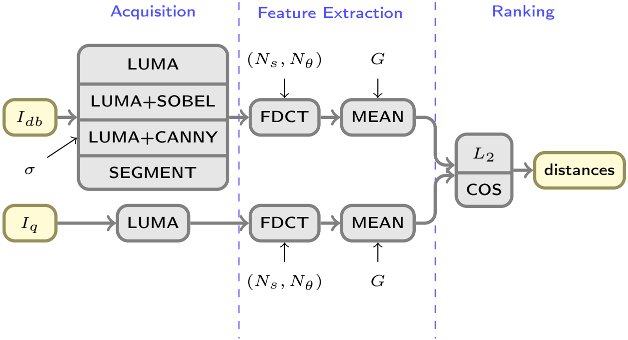
Figure: "Video Google: A text retrieval approach to object matching in videos", Sivic and Zisserman, ICCV 2003

Anatomy of a CBIR System

1. Image Acquisition
2. Signature Extraction
3. Ranking



Proposed Retrieval Pipelines (Global)



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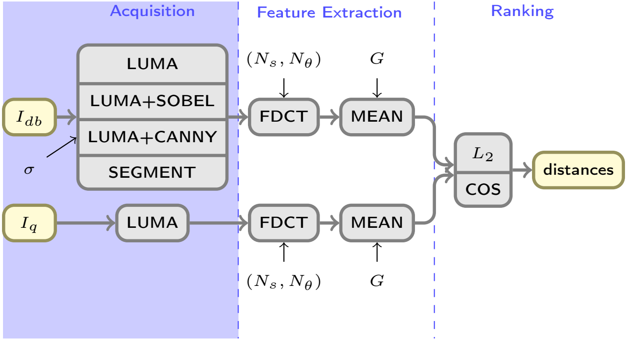

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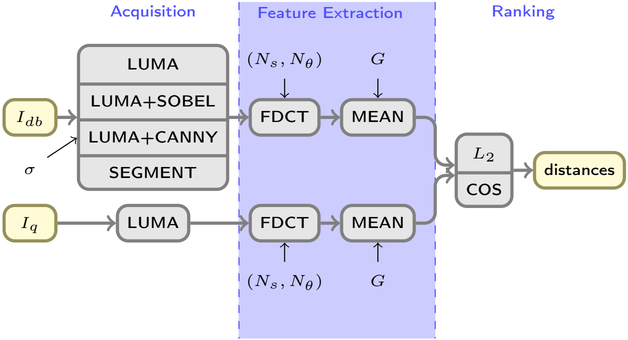

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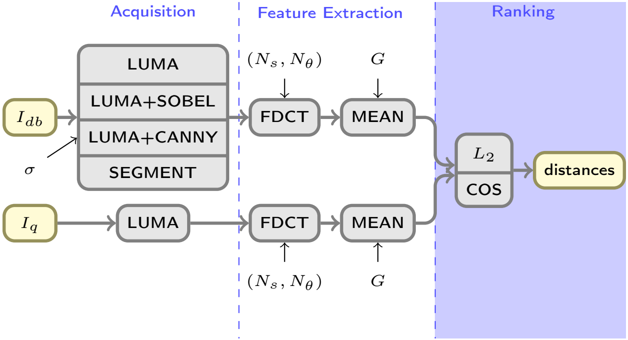
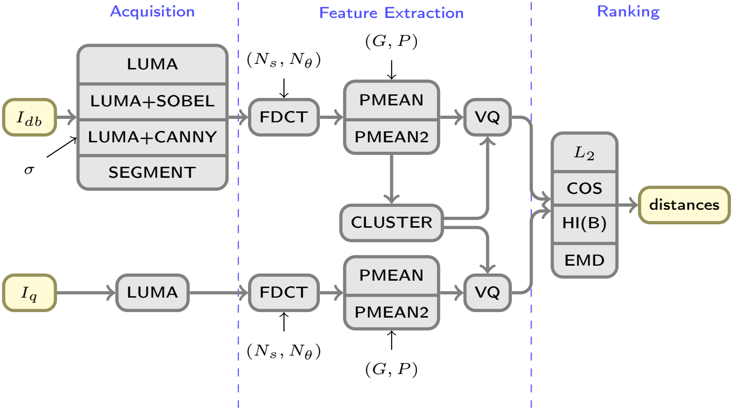


Proposed Retrieval Pipelines (Local)



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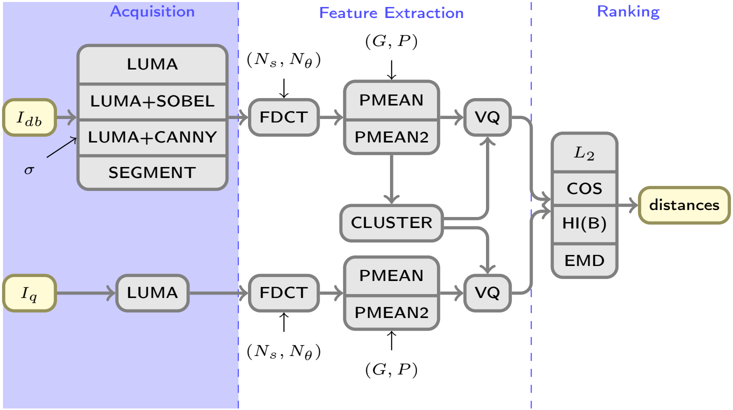
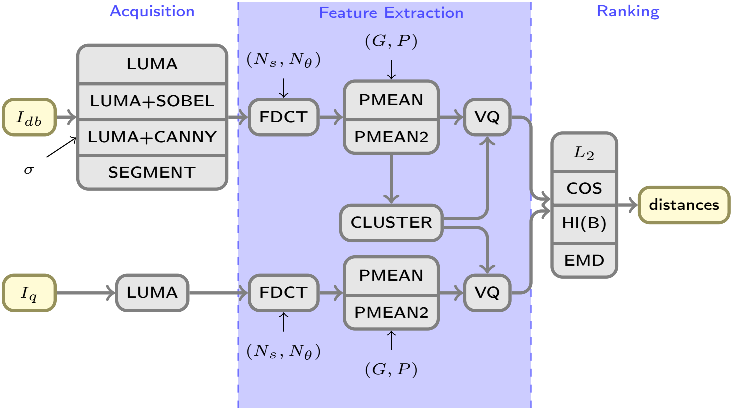
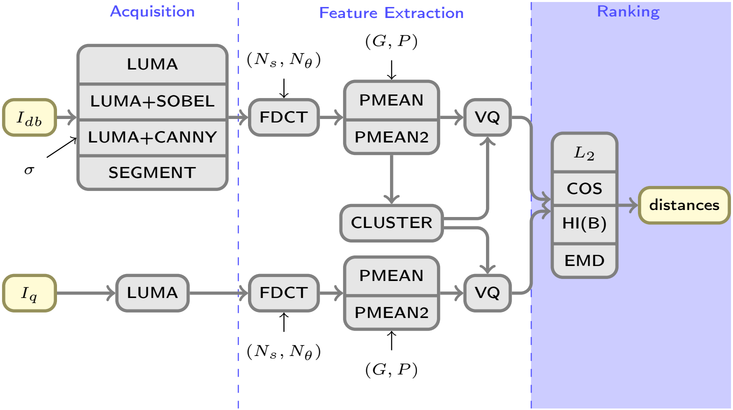


Proposed Retrieval Pipelines (Local)



Proposed Retrieval Pipelines (Local)



Acquisition

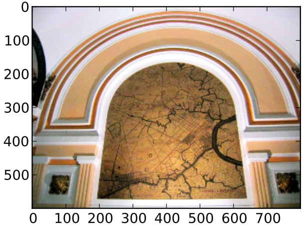


Figure: Original Image

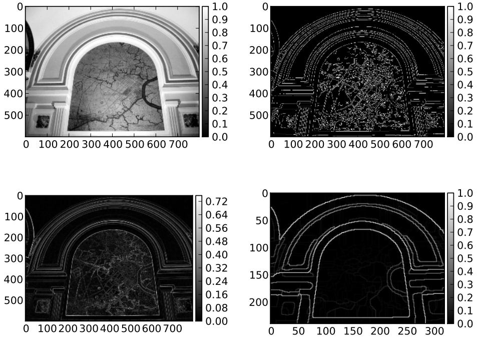


Figure: Luma, Canny, Sobel and gPb contour transformations

Properties of the Curvelet Transform

- Published by Candes and Donoho, 2004
- An extension of the wavelet transform
- Especially suited for representing curve-like discontinuities, because
- Curvelets obey parabolic scaling: $width \approx length^2$
- Parameterized by *location*, *scale* and *orientation*
- Approximation error along edges using m largest coefficients decays with $\frac{1}{m^2}$ (compare $\frac{1}{m}$ for wavelets)
- Defined and applied in frequency domain as $\hat{\varphi}_{j,l,k}$ using the inverse Fourier Transform:

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

Constructing the Curvelets

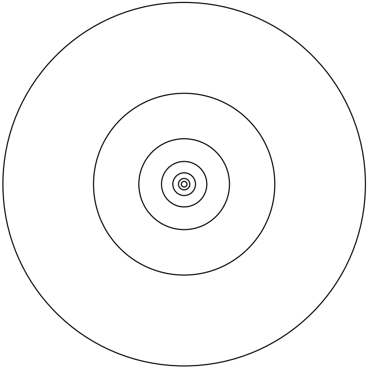


Figure: Frequency Domain

Figure: Spatial Domain

Constructing the Curvelets

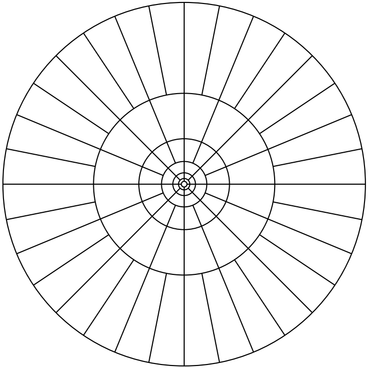
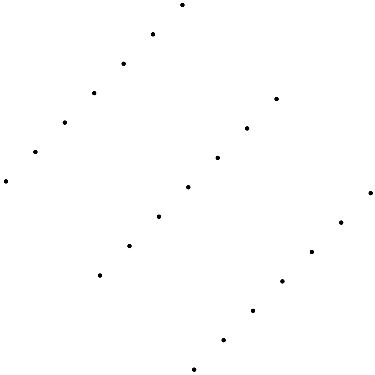


Figure: Frequency Domain



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Constructing the Curvelets

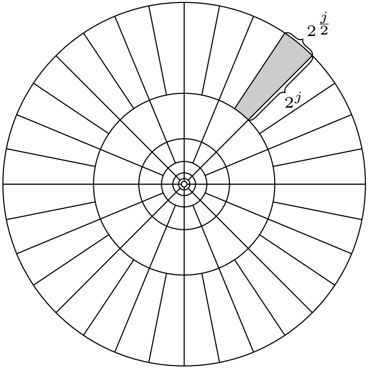
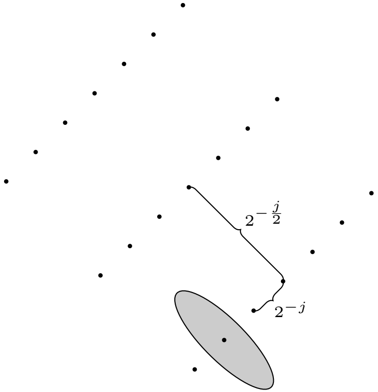


Figure: Frequency Domain



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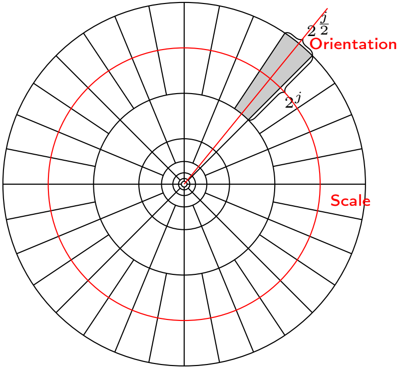

Figure: Frequency Domain

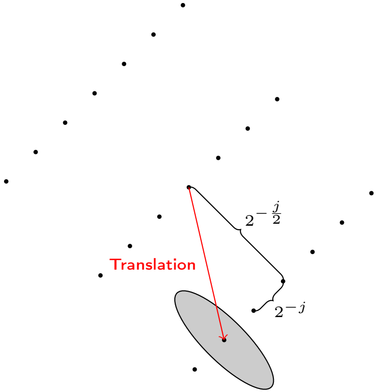

Figure: Spatial Domain

The Fast Discrete Curvelet Transform (via Wrapping)

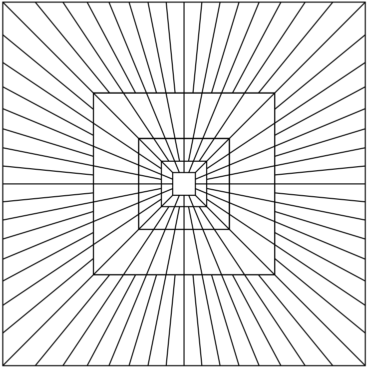

Figure: Frequency Domain

Figure: Parallelogram Support

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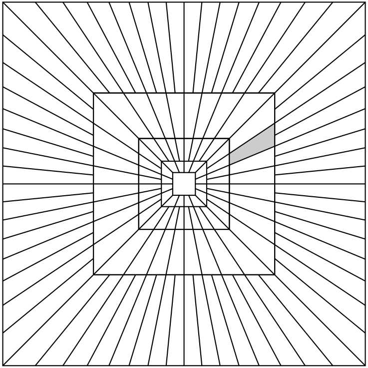


Figure: Frequency Domain

Figure: Parallelogram Support

The Fast Discrete Curvelet Transform (via Wrapping)

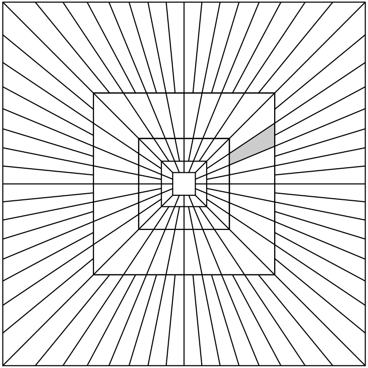
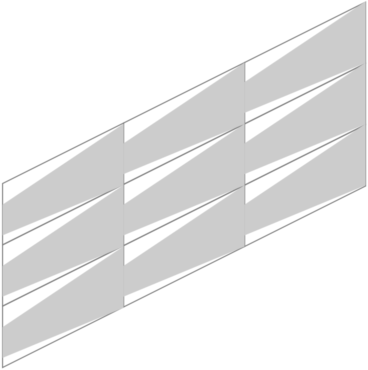


Figure: Frequency Domain



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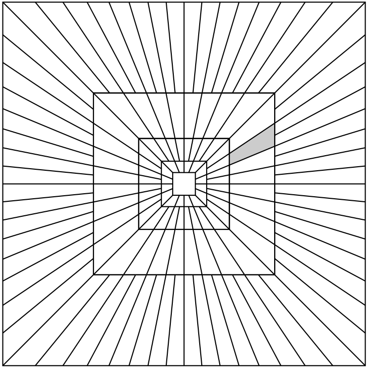


Figure: Frequency Domain

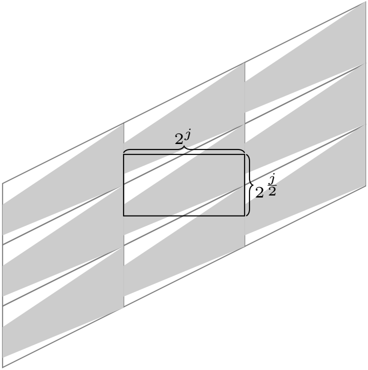


Figure: Parallelogram Support

The Fast Discrete Curvelet Transform (via Wrapping)

1. Transform image f to $\hat{f}$ using 2D FFT
2. For each scale and angle, multiply $\hat{f}$ with the curvelet window
3. Wrap the product around the origin
4. Apply inverse 2D FFT to wrapped product to collect curvelet coefficients for each scale and angle

Example Curvelets

Figure: Frequency Domain

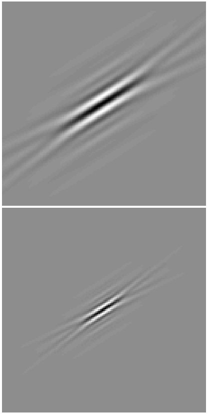


Figure: Spatial Domain

Global Feature Extraction (Sampling)

MEAN Calculate the mean of coefficients on $n \times n$ grid, concatenate across scales and angles

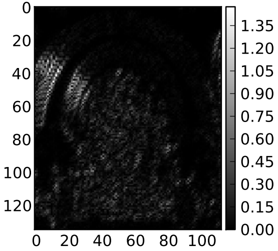


Figure: Curvelet coefficients at a specific scale and angle

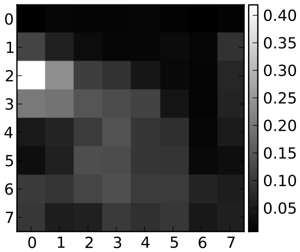


Figure: Mean values on an 8×8 grid

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

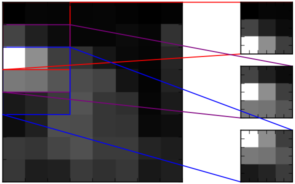


Figure: 8×8 mean coefficient grid sampled using 3×3 window

- 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 of features in database images
- $k = 1000$ clusters sufficient
- 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 Distance $d_{EUCL}(p,q) = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2}$

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

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

$\Rightarrow$ Amplify rare features, suppress common features

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

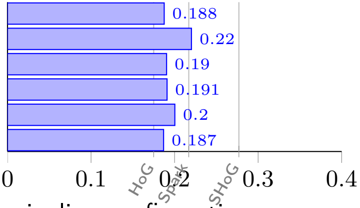
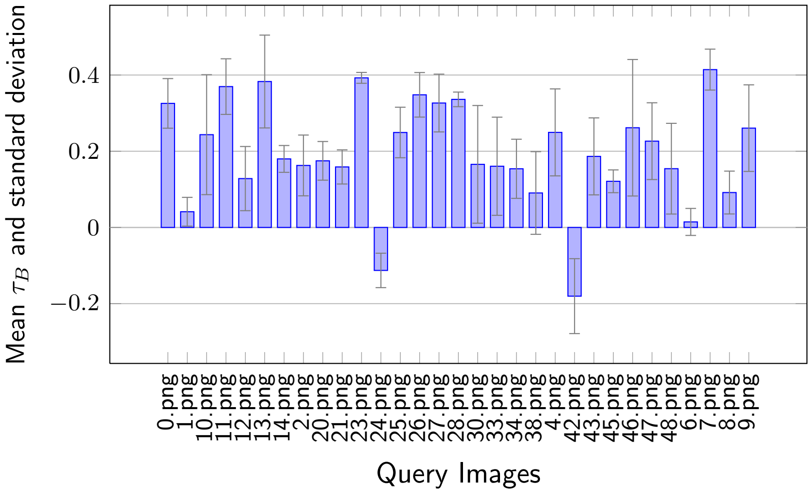


Table: Best performing pipeline configurations

Cross-Domain Distribution



Intra-Domain Dataset

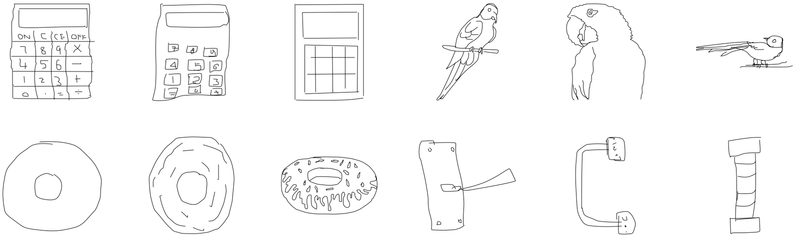


Figure: Example sketches from four categories from "How do humans sketch objects?", Eitz et al., 2012

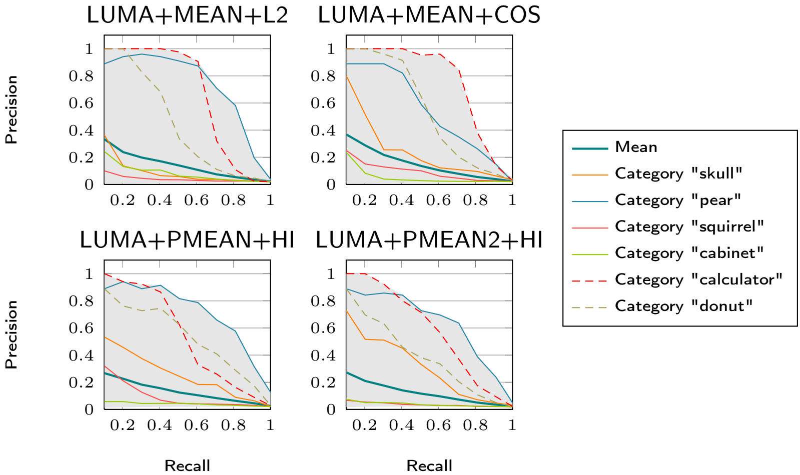
Intra-Domain Benchmark

- 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



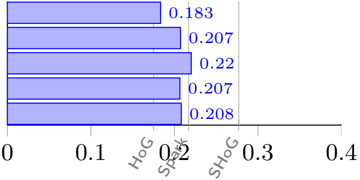
Discussion and Conclusions

- 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
- Very dependent on the nature of the images

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

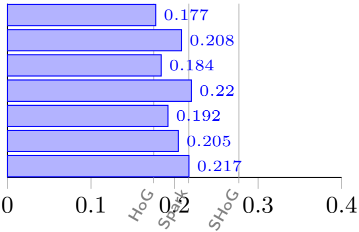
Cross-Domain Parameter Variation: Angles

Preproc.	Sampling	N_s	N_θ	Metric	Mean τ_B correlation coefficient
CANNY	PMEAN	4	4	HI	0.183
CANNY	PMEAN	4	8	HI	0.207
CANNY	PMEAN	4	12	HI	0.22
CANNY	PMEAN	4	16	HI	0.207
CANNY	PMEAN	4	20	HI	0.208



Cross-Domain Parameter Variation: Grid and Patch Sizes

Preproc.	Sampling	G	P	Metric	Mean τ_B correlation coefficient
CANNY	PMEAN	5	2	HI	0.177
CANNY	PMEAN	6	2	HI	0.208
CANNY	PMEAN	8	2	HI	0.184
CANNY	PMEAN	8	3	HI	0.22
CANNY	PMEAN	8	4	HI	0.192
CANNY	PMEAN	12	3	HI	0.205
CANNY	PMEAN	12	4	HI	0.217



Cross-Domain Parameter Variation: Canny Sigma

Preproc.	Sampling	σ	Metric	Mean τ_B correlation coefficient
CANNY	PMEAN	0.5	HI	0.193
CANNY	PMEAN	1.0	HI	0.214
CANNY	PMEAN	1.5	HI	0.22
CANNY	PMEAN	2.0	HI	0.218
CANNY	PMEAN	2.5	HI	0.187