Visual Texture Analysis: From Similarity To Material Properties

CASIS, LLNL
May 13, 2015

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LLNL-PRES-670573
This work was performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under Contract DE-AC52-07NA27344. Lawrence Livermore National Security, LLC

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- Rene van Egmond, TU Delft
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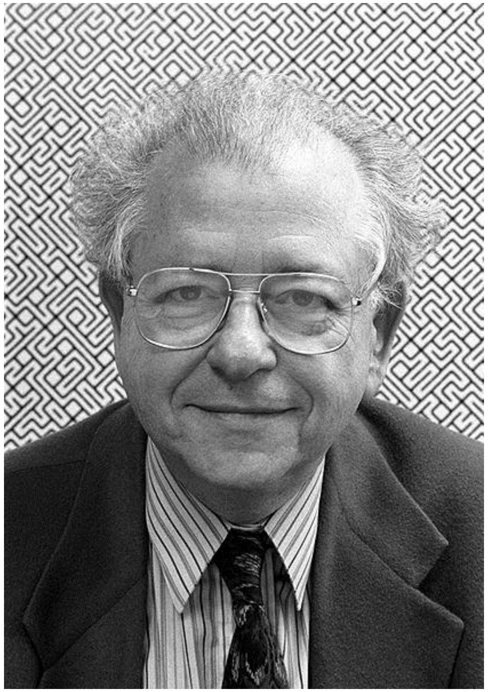
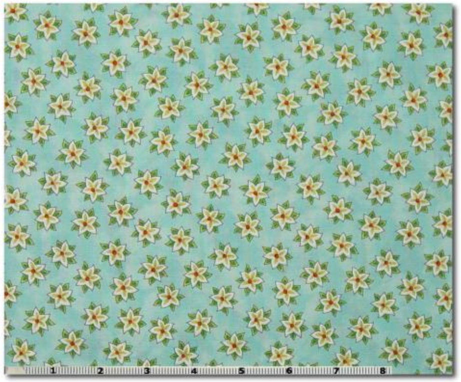
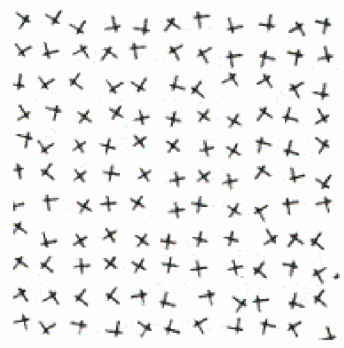
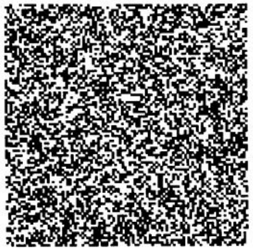
- Yuanhao Zhai, Univ. of Michigan
- Randy Roberts, LLNL
- NNSA, SONY Labs

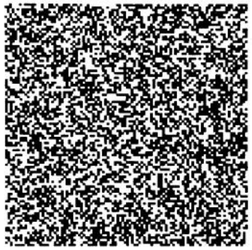
What is Texture?









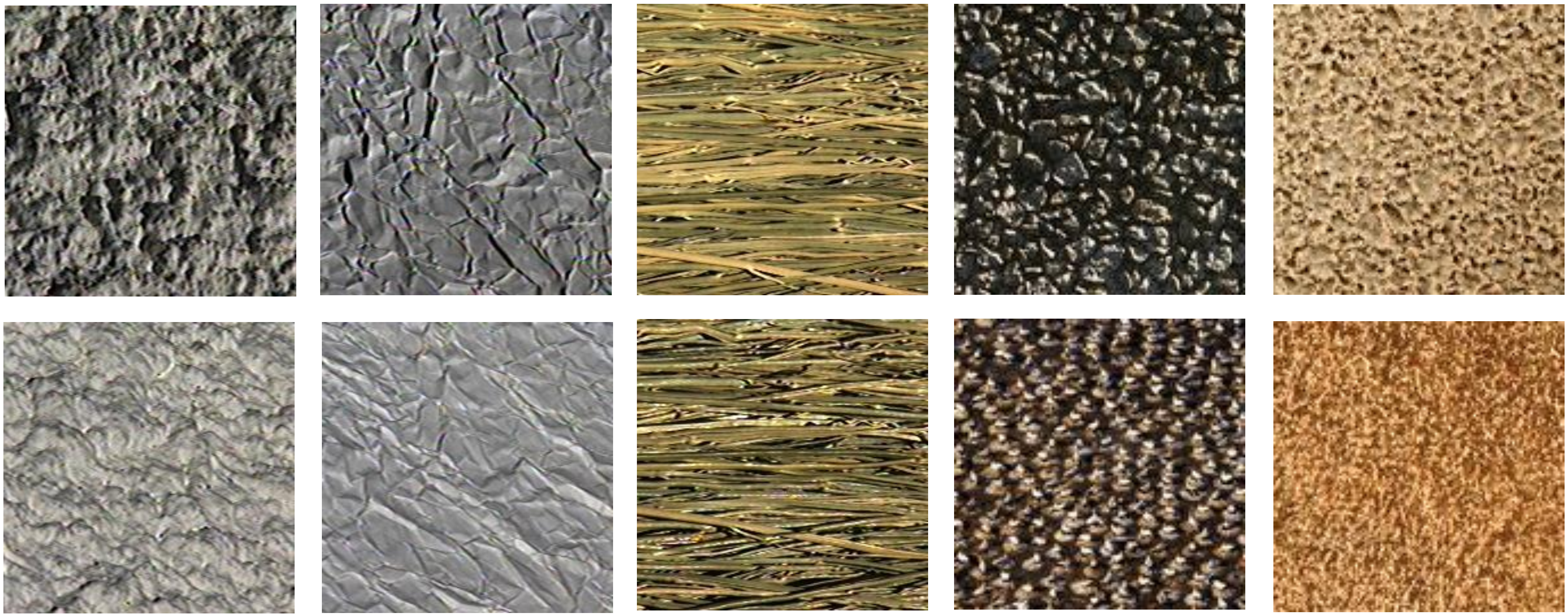


What is Texture?

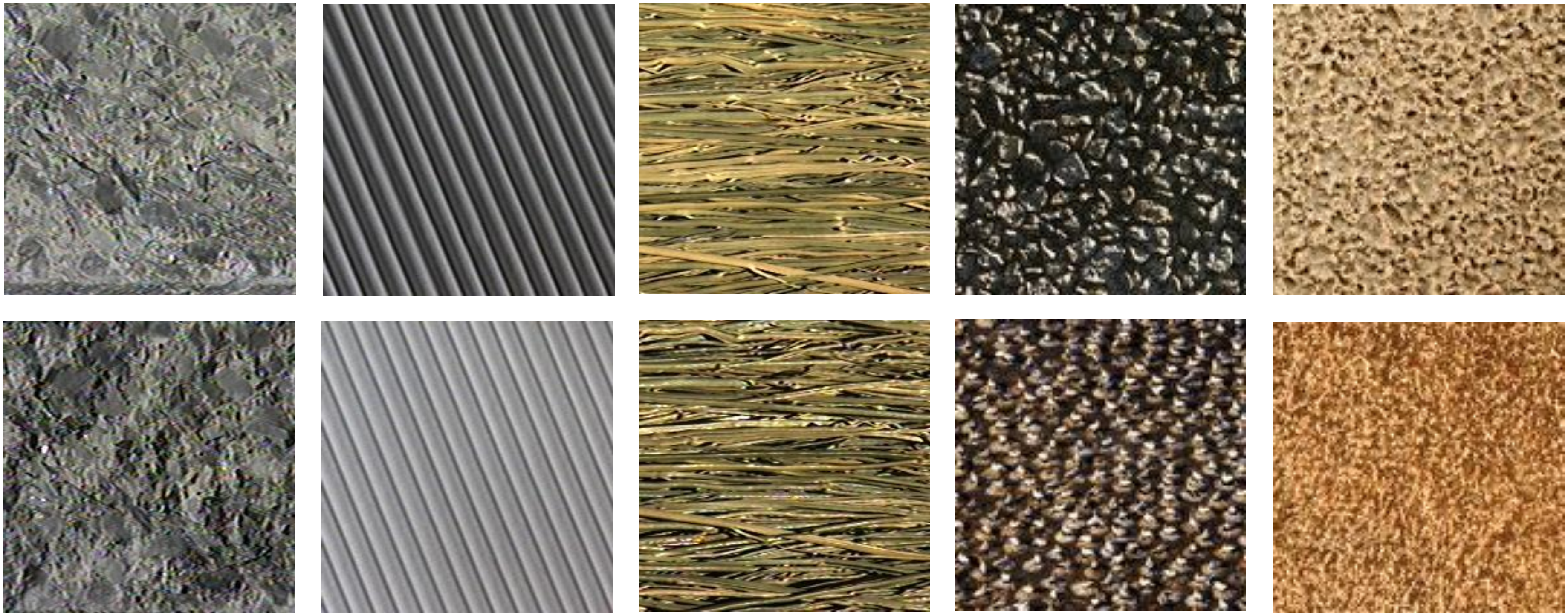
- “An image of visual texture is spatially homogeneous and typically contains repeated structures, often with some random variation, e.g., random positions, orientations or colors.” [Portilla & Simoncelli]

Texture Similarity

Material Identification



Material Identification



Texture Similarity and Identification Applications

- Content-Based Indexing and Retrieval
- Compression
- Visual to tactile conversion
- Semantic Information Extraction

Texture Similarity and Identification Applications

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  - Retrieval of similar textures

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Texture Similarity and Identification Applications

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  - Retrieval of similar textures
- Compression
  - Perceptually lossless
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Texture Similarity and Identification Applications

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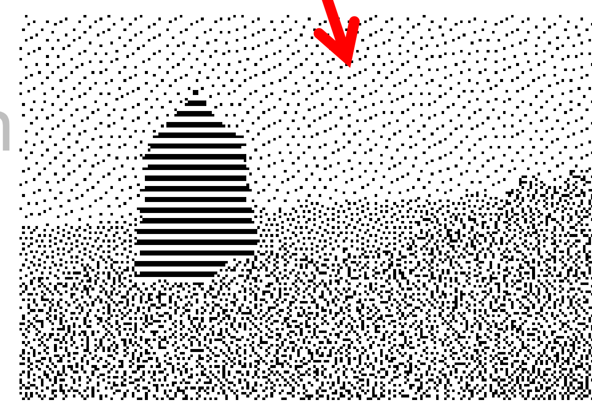
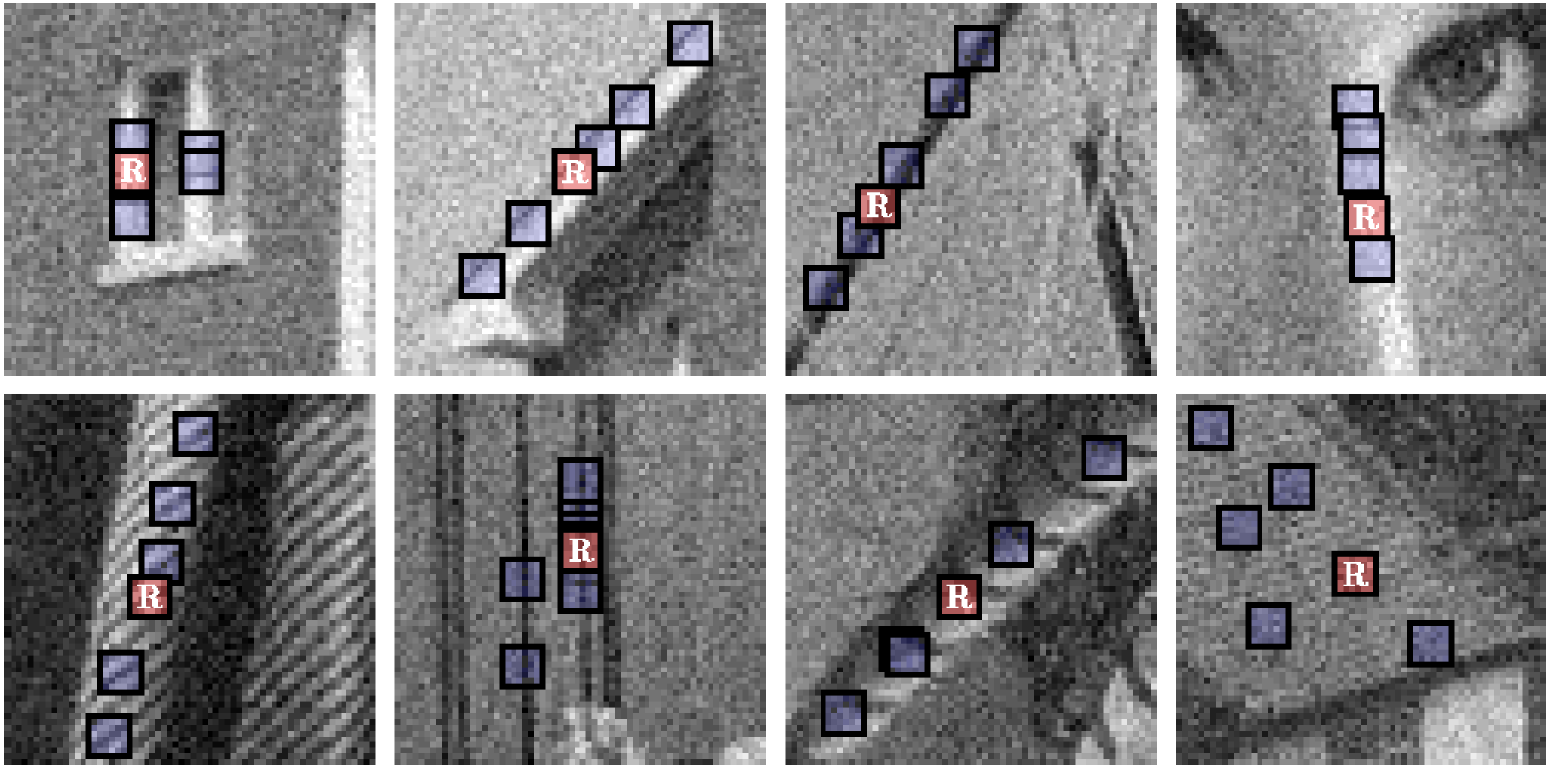


Texture Similarity and Identification Applications

- Content-Based Indexing and Retrieval
  - Retrieval of similar textures
- Compression
  - Perceptually lossless
  - Structurally lossless
  - Perceptually lossy
- Visual to tactile conversion
- Semantic Information Extraction
  - Computer vision: Focus on objects rather than material perception and texture [Adelson, HVEI'01]

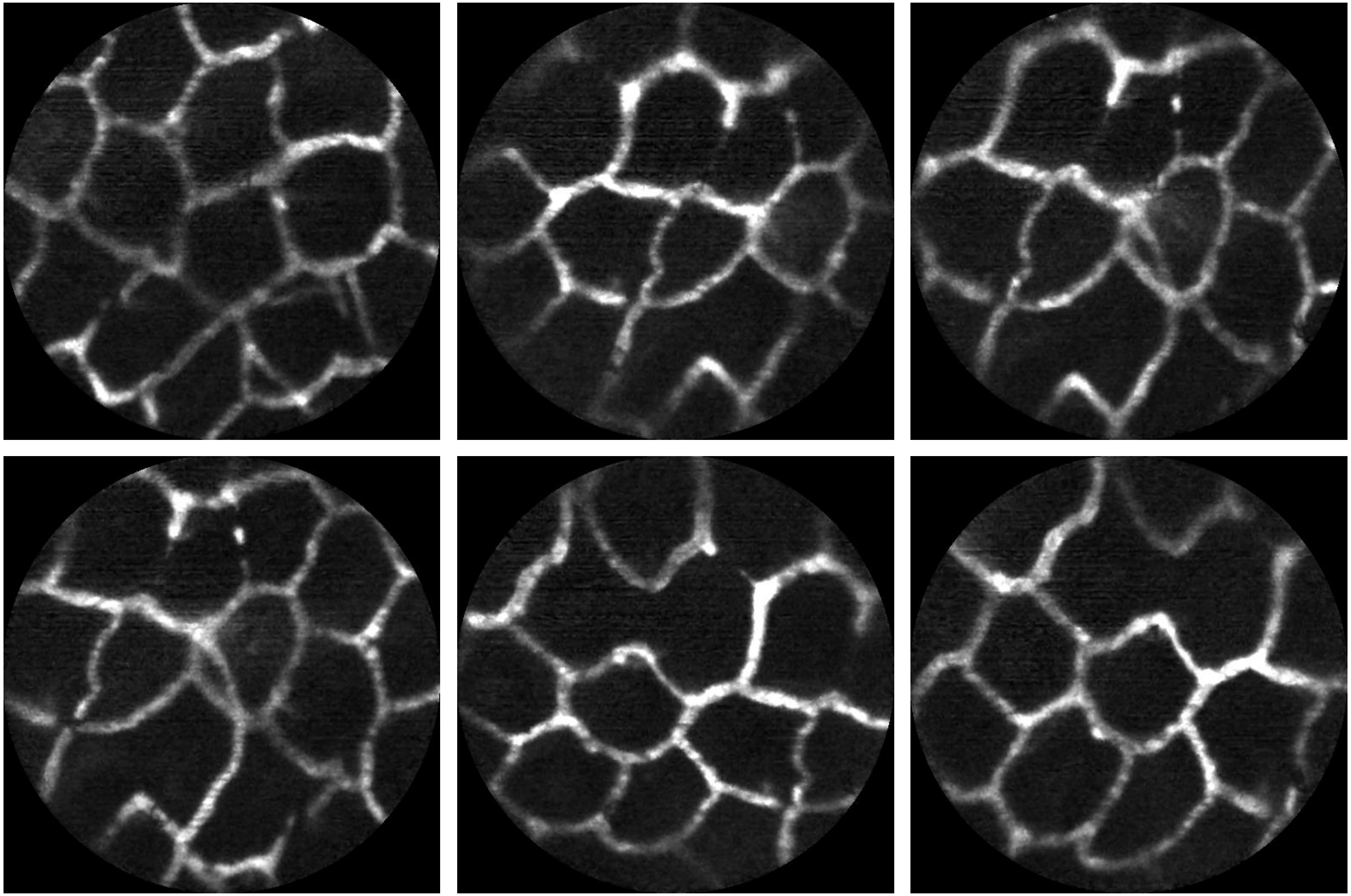
Restoration Based on Nonlocal Self-Similarity



Create groups of similar patches associated with a given "reference" block

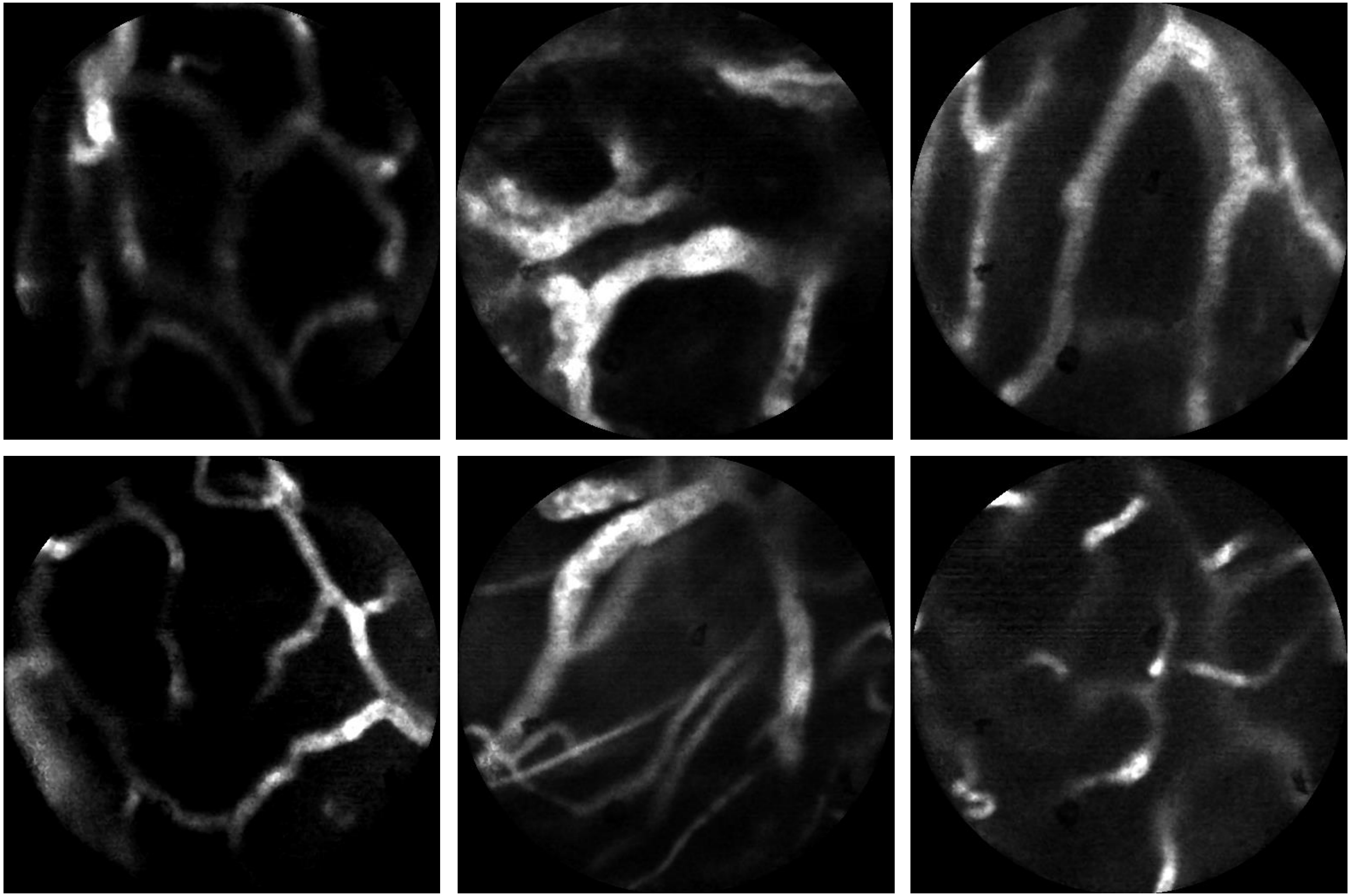
Dabov, Foi, Katkovnik, Egiazarian, "Image denoising by sparse 3D transform-domain collaborative filtering", IEEE T-IP, 2007

Microvascular Image Classification



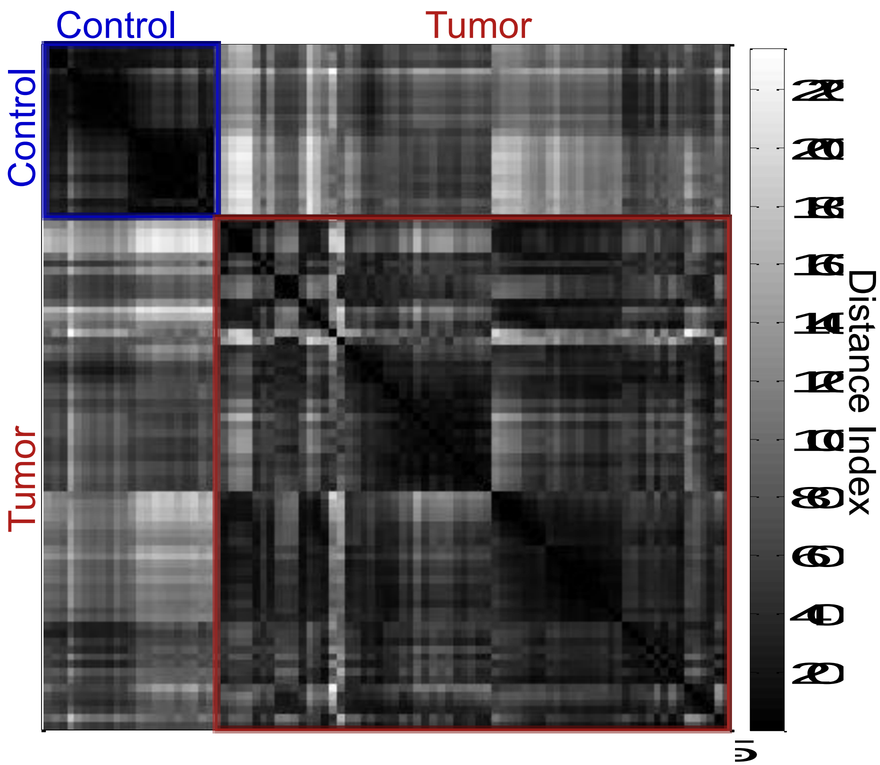
Control Mucosa Images – Sarah Ruderman

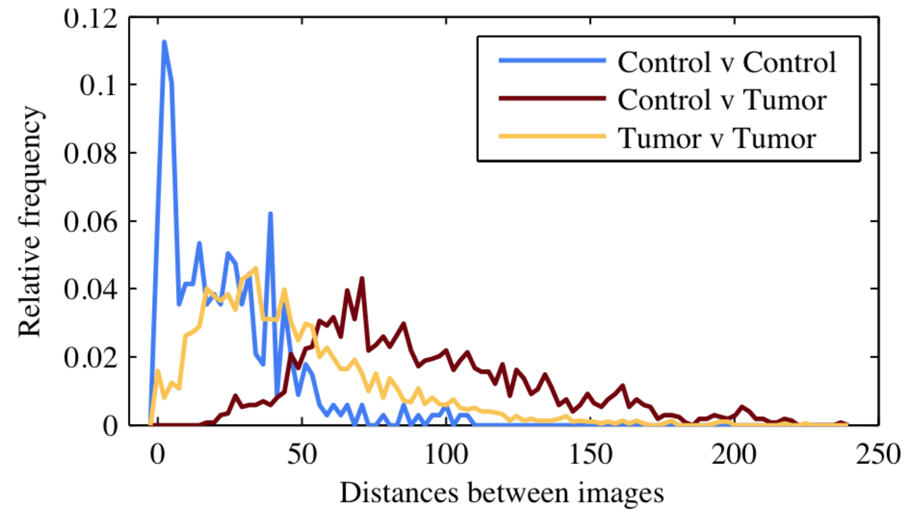
Microvascular Image Classification



Tumor Vasculature Images – Sarah Ruderman

Microvascular Image Classification

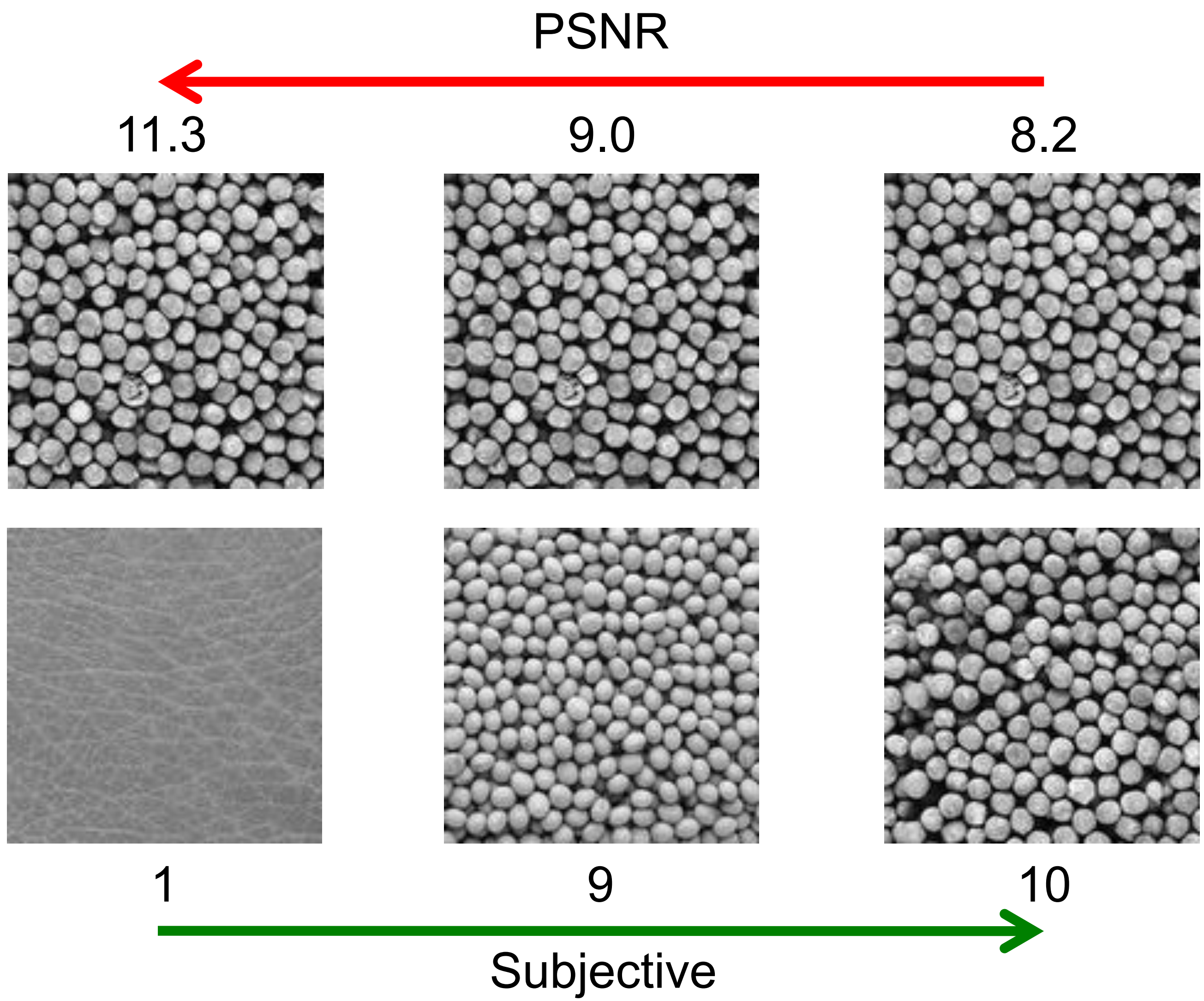




The darker the more similar

Huib de Ridder, Rene van Egmond
Faculty of Industrial Design Engineering
Delft University of Technology

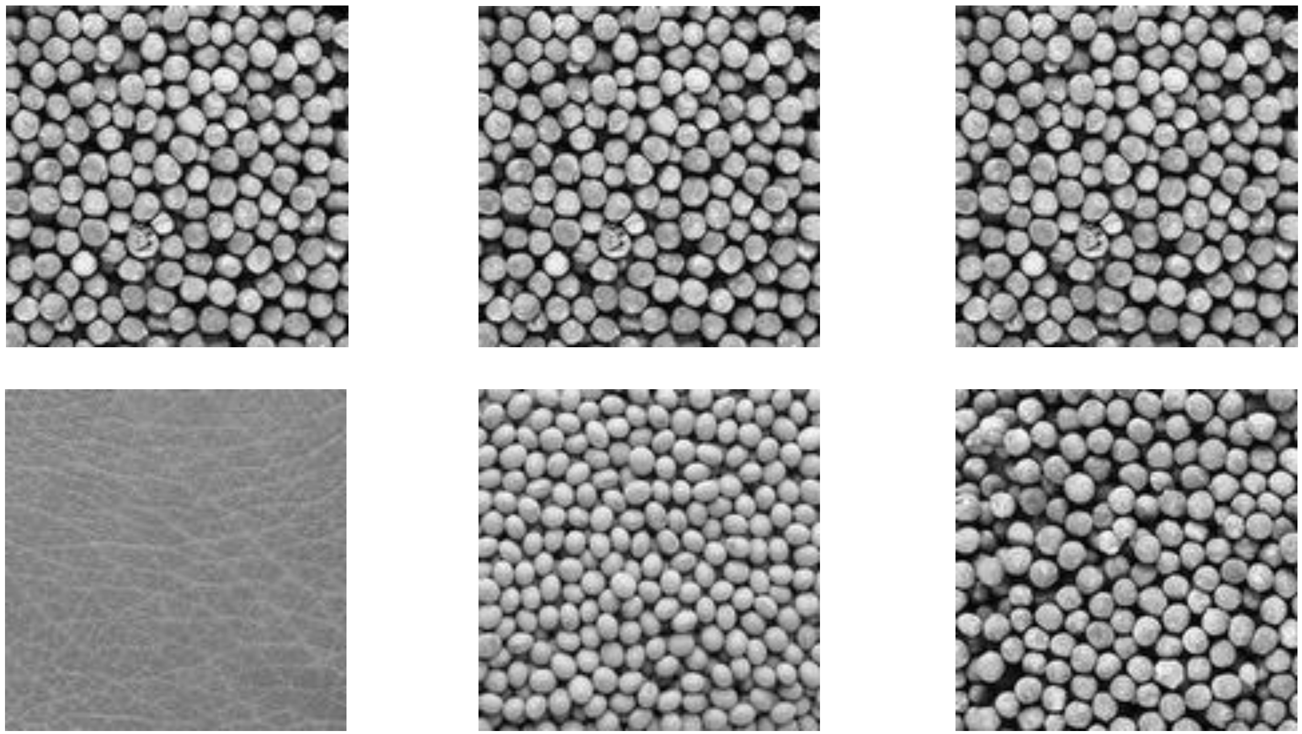
Subjective vs. Objective Texture Similarity



Subjective vs. Objective Texture Similarity

STSIM-2 global

0.83 0.96 0.98

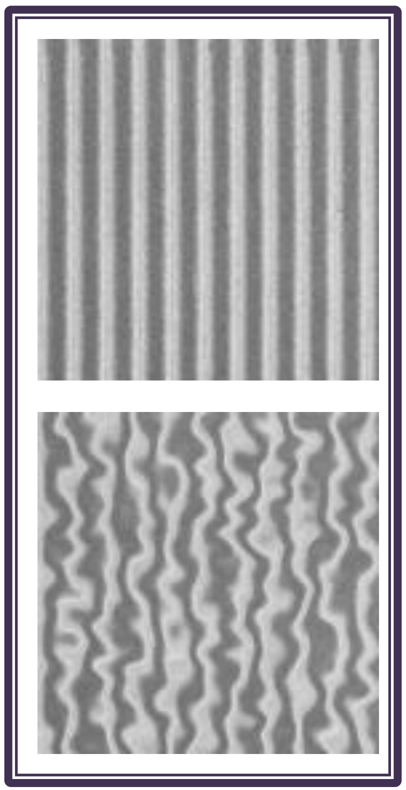


1 9 10

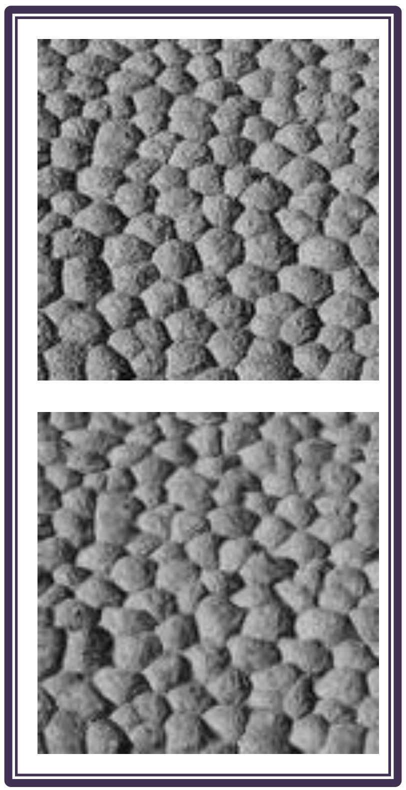
Subjective

Texture Similarity – PSNR?

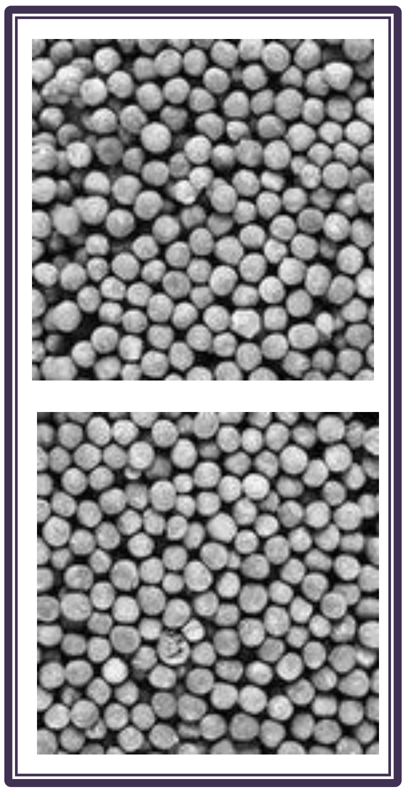
17.5



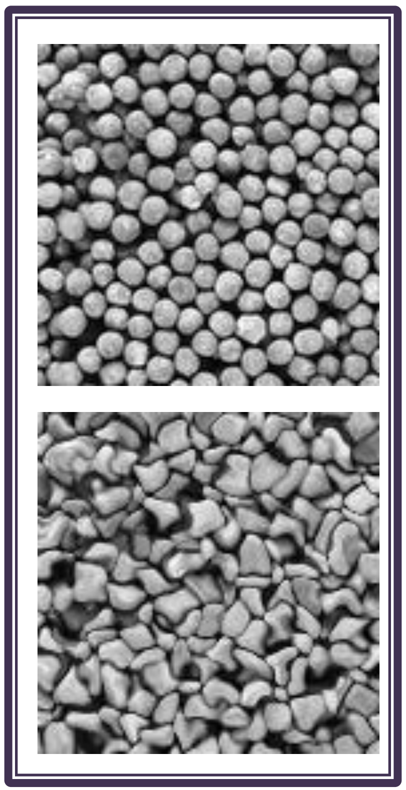
17.4



8.2

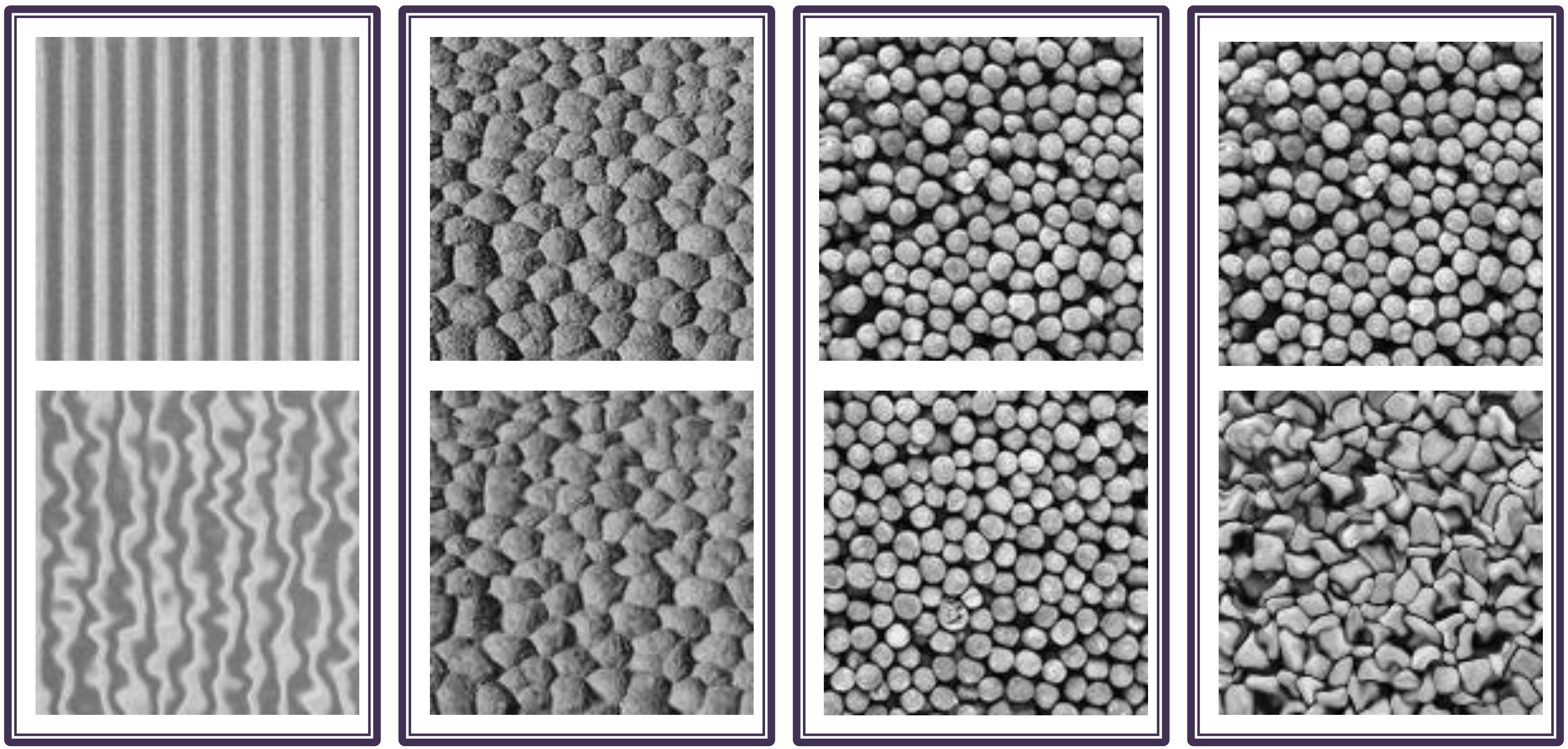


10.4



Texture Similarity – STSIM-2 global

0.83 0.99 0.98 0.96



Separating Grayscale and Color



- Different subjects put different emphasis on structure and color composition for texture similarity
- Separate metrics for grayscale and color [Zujovic, ICIP'09]
  - Use grayscale component to isolate/approximate structure
  - Structure in chrominance?
  - End user/application decides how to combine
- Can develop more effective metrics separately

SSIMs – Grayscale

$$l(\mathbf{x},\mathbf{y}) = \frac{2\,\mu_x\,\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}$$

$$c(\mathbf{x},\mathbf{y}) = \frac{2\,\sigma_x\,\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}$$

- Compare local image statistics

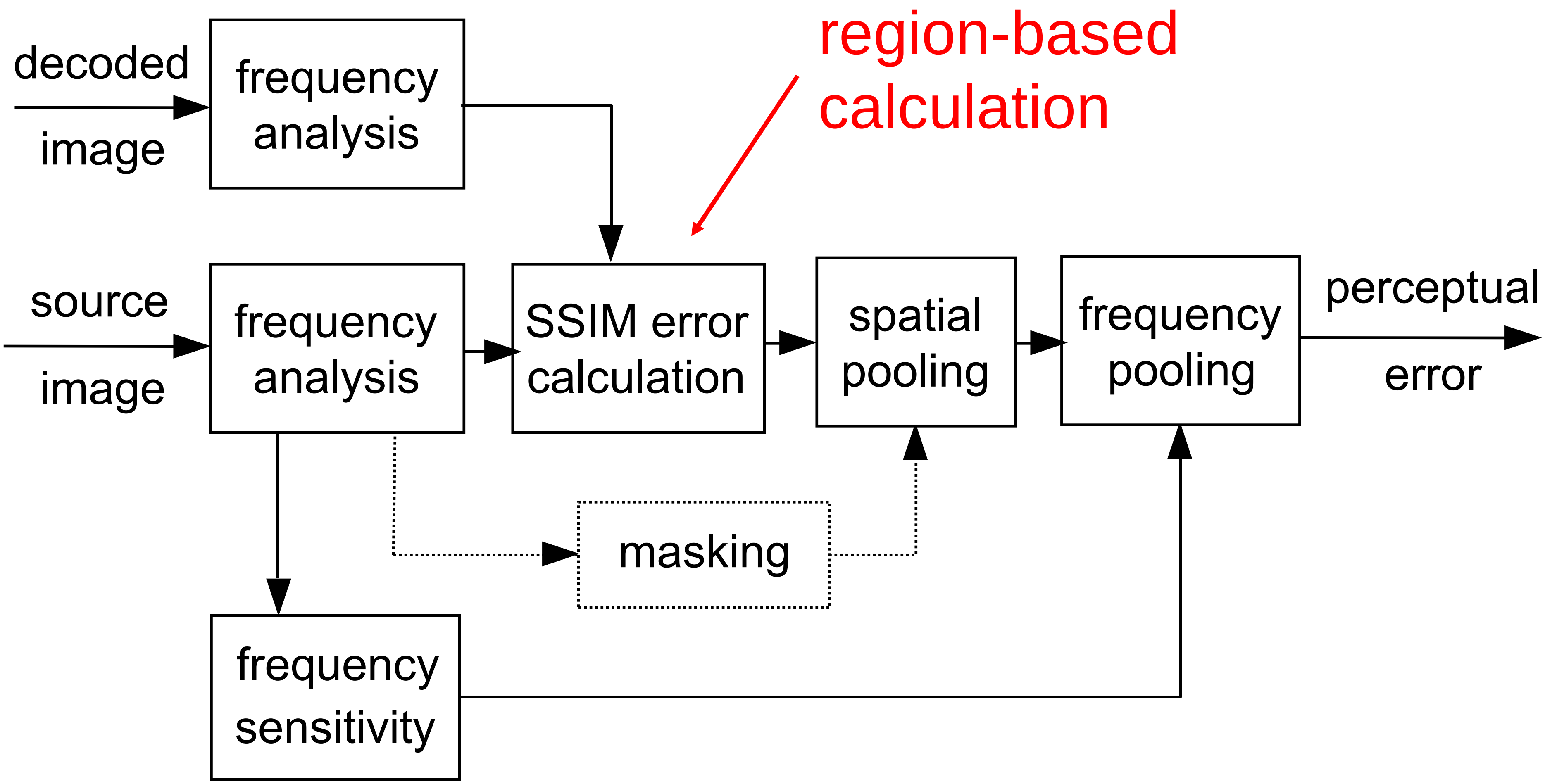
$$s(\mathbf{x},\mathbf{y}) = \frac{\sigma_{xy} + C_3}{\sigma_x\,\sigma_y + C_3},$$

- Point-by-point

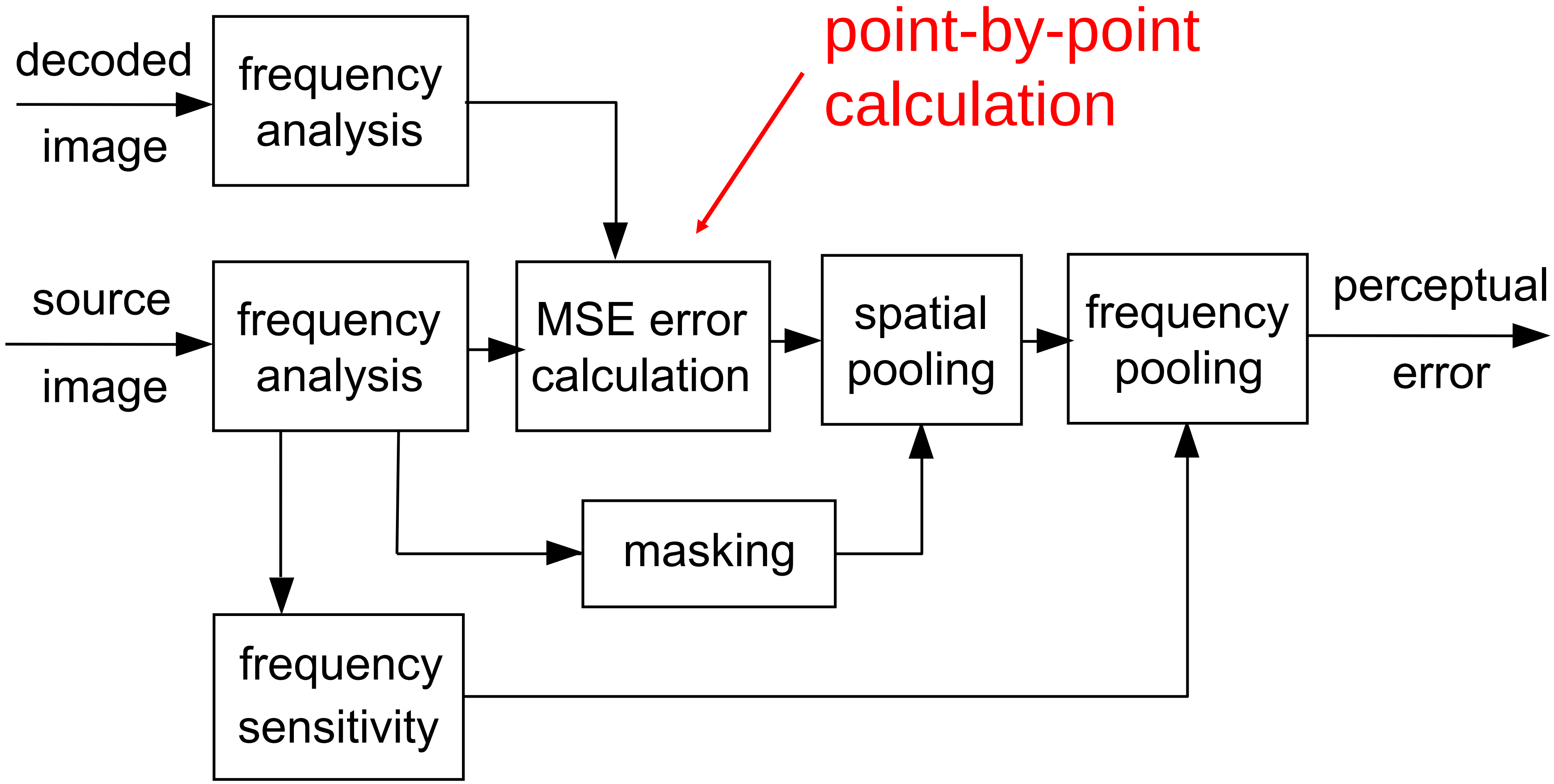
$$\mathrm{SSIM}(\mathbf{x},\mathbf{y}) = [l(\mathbf{x},\mathbf{y})]^{\alpha} \cdot [c(\mathbf{x},\mathbf{y})]^{\beta} \cdot [s(\mathbf{x},\mathbf{y})]^{\gamma}$$

Based on papers by Z. Wang, A.C. Bovik, H.R. Sheikh, and E.P. Simoncelli

CW-SSIM (Perceptually-Weighted)



Perceptual Quality Metrics



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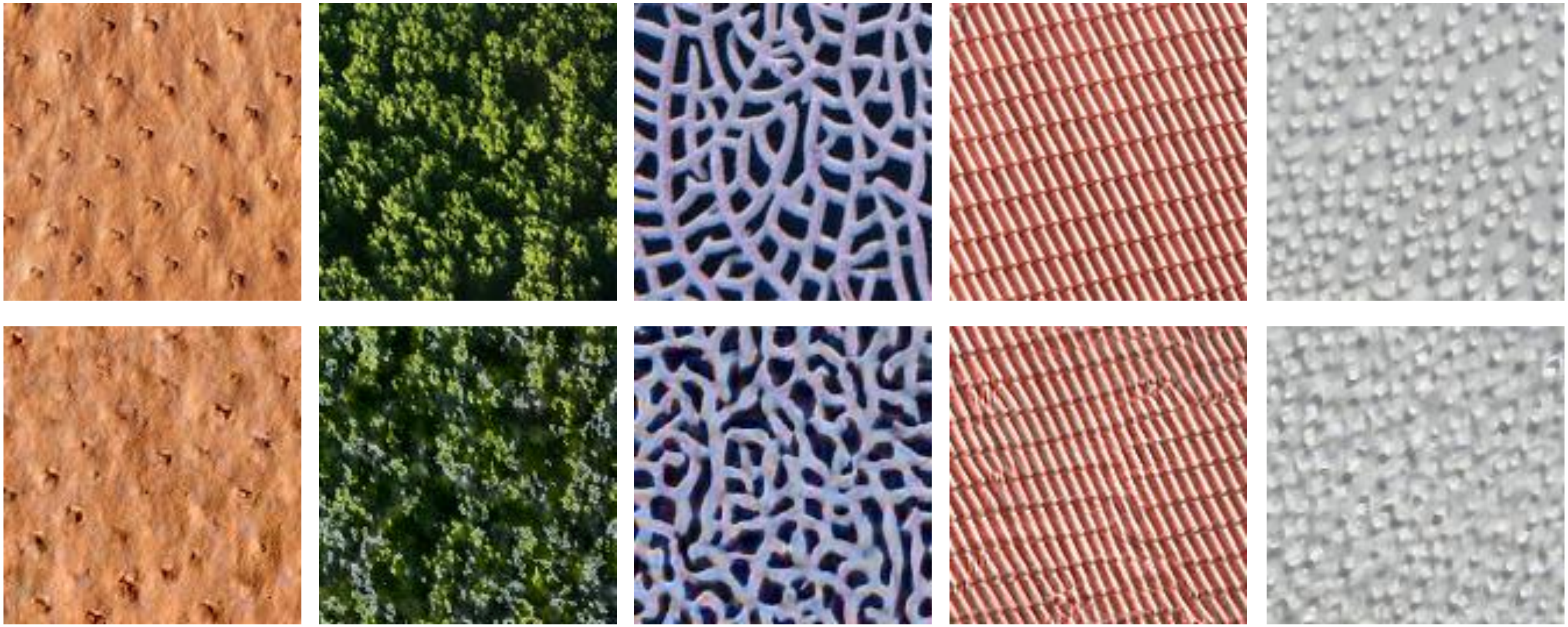
Structural Texture Similarity Metrics Grayscale

- No point-by-point comparisons
  - Drop structure term
- Local image statistics
  - Mean and variance
  - First order correlation coefficients
  - Crossband correlations
- Texture synthesis [Portilla&Simoncelli’00]

J. Zujovic, T.N. Pappas, D.N. Neuhoff, T-IP’13

Portilla and Simoncelli'00



- Universal parametric statistical model
- Necessary and sufficient parameters

STSIM-2: Subband Statistics

- To compare images $\mathbf{x}$ and $\mathbf{y}$:
- For each subband $\mathbf{x}^k$ and $\mathbf{y}^k$ find:
- Means μ_x^k, μ_y^k and standard deviations σ_x^k, σ_y^k
- Horizontal autocorrelations

$$\rho_x^k(0,1) = \frac{E\{(x_{i,j}^k - \mu_x^k)(x_{i,j+1}^k - \mu_x^k)\}}{(\sigma_x^k)^2}, \rho_y^k(0,1)$$

- Vertical autocorrelations $\rho_x^k(1,0), \rho_y^k(1,0)$
- Crossband correlations

$$\rho_{|x|}^{k,l}(0,0) = \frac{E\{(|x_{i,j}^k| - \mu_{|x|}^k)(|x_{i,j}^l| - \mu_{|x|}^l)\}}{\sigma_{|x|}^k \sigma_{|x|}^l}, \rho_{|y|}^{k,l}(0,0)$$

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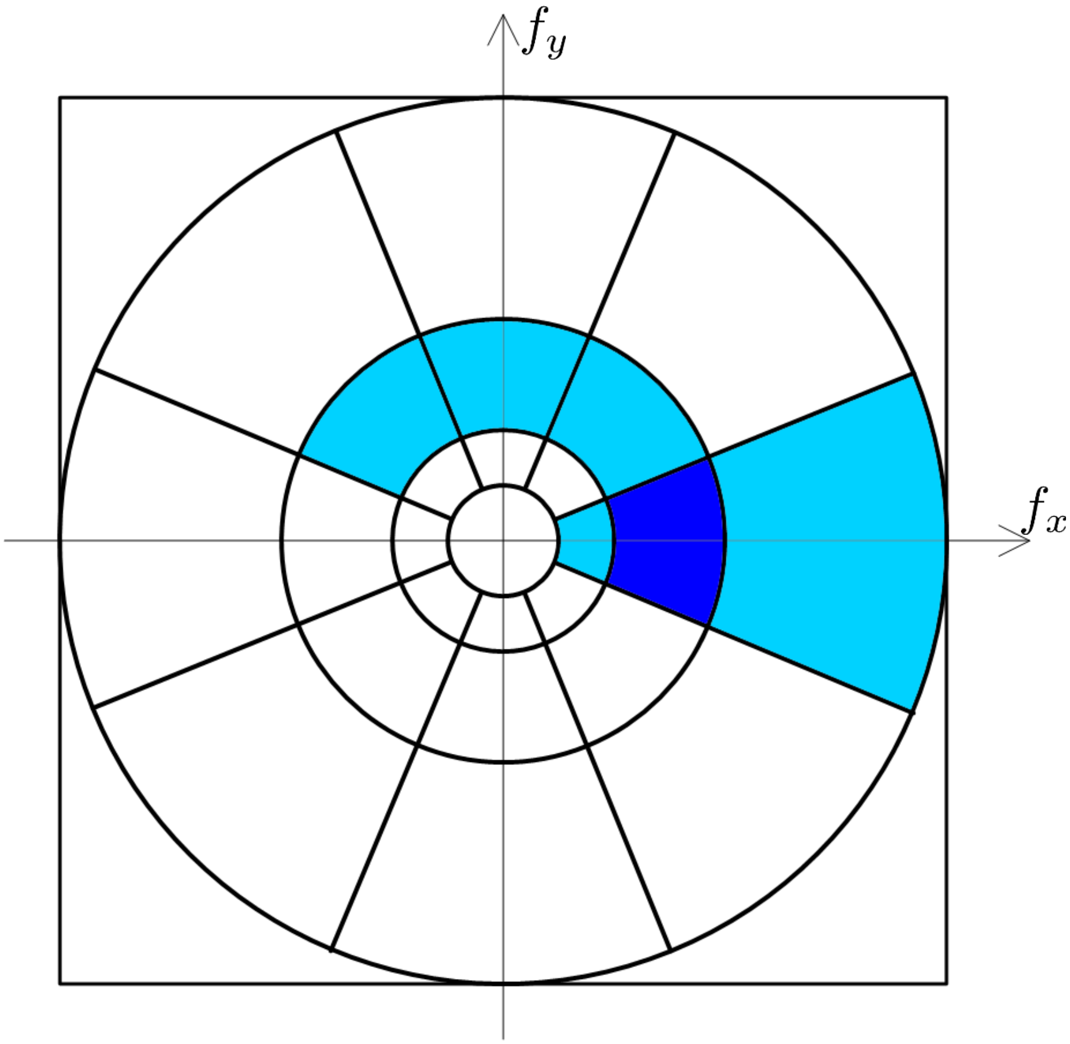
STSIM-2: Crossband Correlations



STSIM-2: Comparing Statistics

$$l^k_{\mathbf{x},\mathbf{y}} = \frac{2\mu^k_{\mathbf{x}}\mu^k_{\mathbf{y}} + C_0}{(\mu^k_{\mathbf{x}})^2 + (\mu^k_{\mathbf{y}})^2 + C_0} \qquad c^k_{\mathbf{x},\mathbf{y}} = \frac{2\sigma^k_{\mathbf{x}}\sigma^k_{\mathbf{y}} + C_1}{(\sigma^k_{\mathbf{x}})^2 + (\sigma^k_{\mathbf{y}})^2 + C_1}$$

$$c^k_{\mathbf{x},\mathbf{y}}(0,1) = 1 - 0.5|\rho^k_{\mathbf{x}}(0,1) - \rho^k_{\mathbf{y}}(0,1)|$$

$$c^k_{\mathbf{x},\mathbf{y}}(1,0) = 1 - 0.5|\rho^k_{\mathbf{x}}(1,0) - \rho^k_{\mathbf{y}}(1,0)|$$

$$c^{k,l}_{\mathbf{x},\mathbf{y}}(0,0) = 1 - 0.5|\rho^{k,l}_{|\mathbf{x}|}(0,0) - \rho^{k,l}_{|\mathbf{y}|}(0,0)|$$

J. Zujovic, T.N. Pappas, D.N. Neuhoff, T-IP'13

STSIM-2: Pooling

$$q^k_{\text{STSIM-1}}(\mathbf{x},\mathbf{y}) = (l^k_{\mathbf{x},\mathbf{y}})^{\frac{1}{4}}(c^k_{\mathbf{x},\mathbf{y}})^{\frac{1}{4}}(c^k_{\mathbf{x},\mathbf{y}}(0,1))^{\frac{1}{4}}(c^k_{\mathbf{x},\mathbf{y}}(1,0))^{\frac{1}{4}}$$

$$q_{\text{STSIM-2}}(\mathbf{x},\mathbf{y}) = \frac{1}{N+N_C}\left(\sum_{k=1}^{N} q^k_{\text{STSIM-1}}(\mathbf{x},\mathbf{y}) + \sum_{i=1}^{N_C} c^{k_i,l_i}_{\mathbf{x},\mathbf{y}}(0,0)\right)$$

J. Zujovic, T.N. Pappas, D.N. Neuhoff, T-IP'13

STSIM: Mahalanobis distance

- For each image, form feature vector consisting of all statistics for all subbands, including cross-correlations:

$$F_{\mathbf{X}} = (f_{1,\mathrm{x}}, f_{2,\mathrm{x}}, \ldots, f_{M,\mathrm{x}}), \quad F_{\mathbf{Y}} = (f_{1,\mathrm{y}}, f_{2,\mathrm{y}}, \ldots, f_{M,\mathrm{y}}), \quad M = 82$$

- Compute Mahalonobis distance

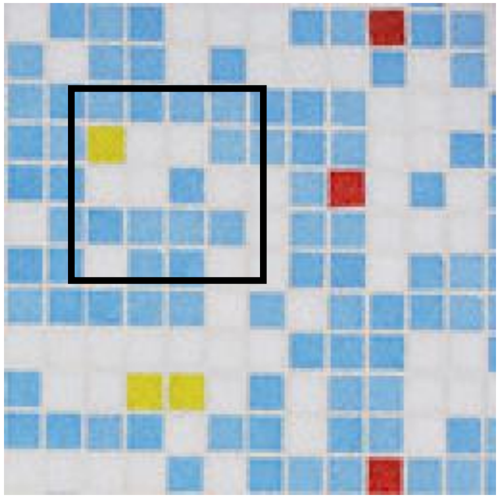
$$Q_{\mathrm{STSIM-M}}(x,y) = \sqrt{\sum_{i=1}^{M} \frac{(f_{i\mathrm{x}} - f_{i\mathrm{y}})^2}{\sigma_{fi}^2}} = f_x^T M f_y$$

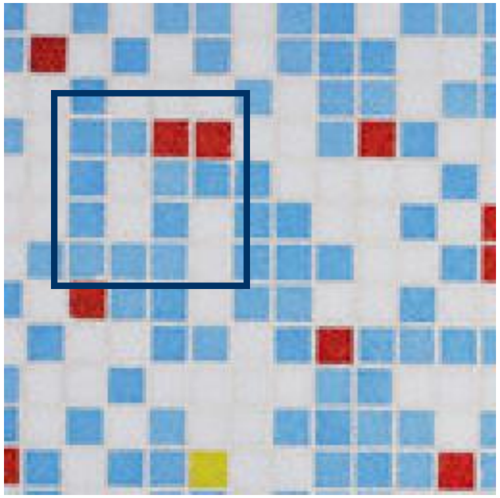
where $\sigma_{f_i}^2$ is the (overall or intra-class) variance of i^{th} statistic across all images in the database.

J. Zujovic, T.N. Pappas, D.N. Neuhoff, T-IP'13

M. Maggioni, G. Jin, A. Foi, T.N. Pappas, ICIP'14

Local versus Global





Color Composition Similarity

- Traditional methods
  - Raw color histogram comparisons
- Our approach
  - Remove unnecessary color detail
    - Extract dominant colors
    - Using adaptive clustering [Pappas'92]
  - Use more sophisticated distance metric
    - EMD [Rubner'00], OCCD [Mojsilovic'02]
  - Use "perceptually uniform" color space (L*a*b*)

Zujovic, Pappas, Neuhoff, ICIP'09

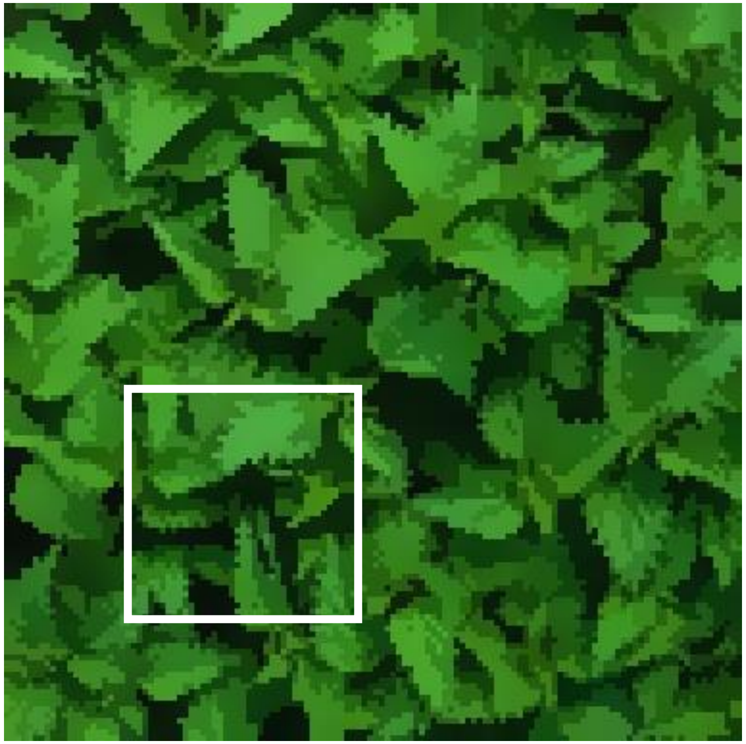
Color Composition Similarity

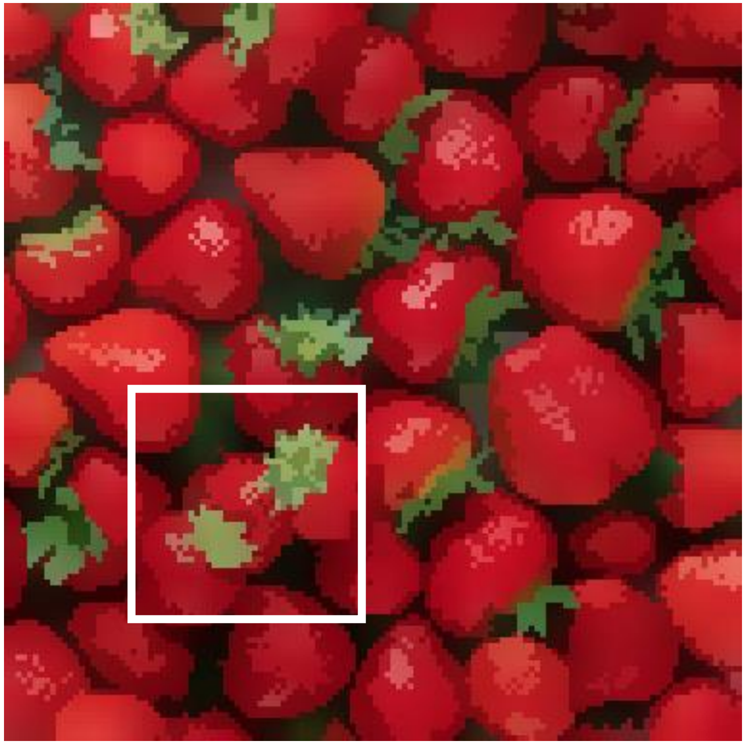
Original images

Color Composition Similarity

ACA Local Averages

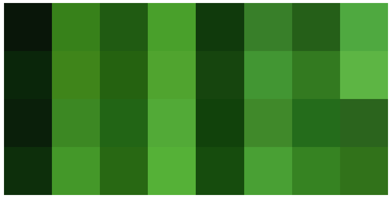
Color Composition Similarity



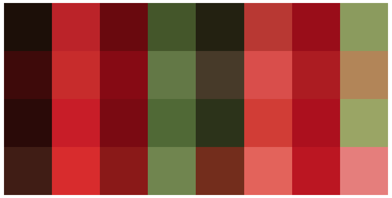


ACA Local Averages

Color Composition Similarity



ACA Local Averages
plus K-means



Optimal Color Composition Distance

- Minimum cost graph matching problem
- Quantize percentages of colors into "units"
- Example: 5% units = 20 units total

Image x

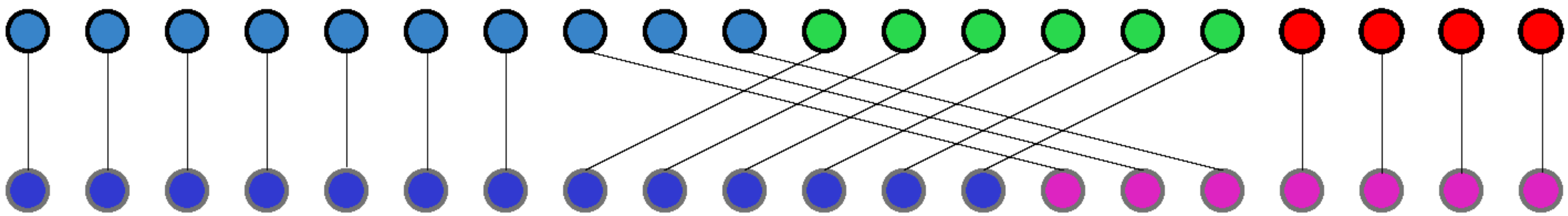
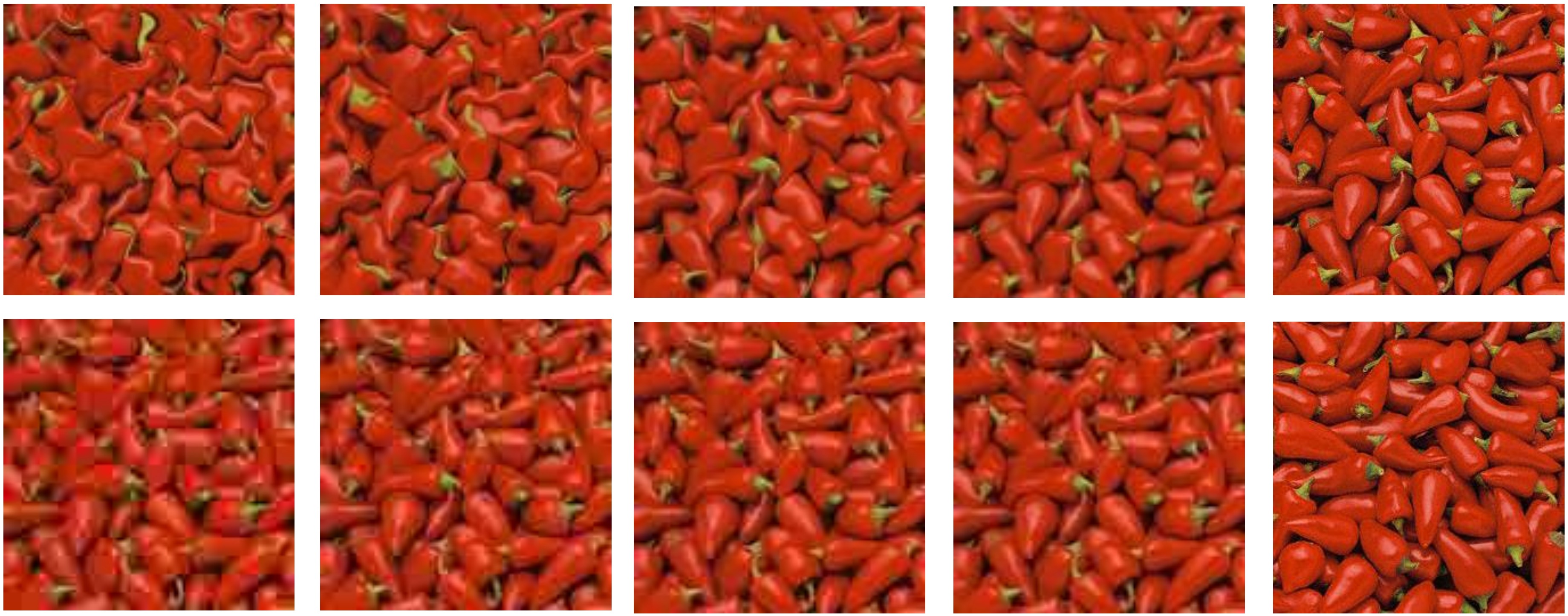


Image y

Texture Similarity Metric Evaluation

Poor agreement among subjects (ICC = 0.66) – Rank correlation?

Testing Domains for Texture Similarity



monotonic distortion identical

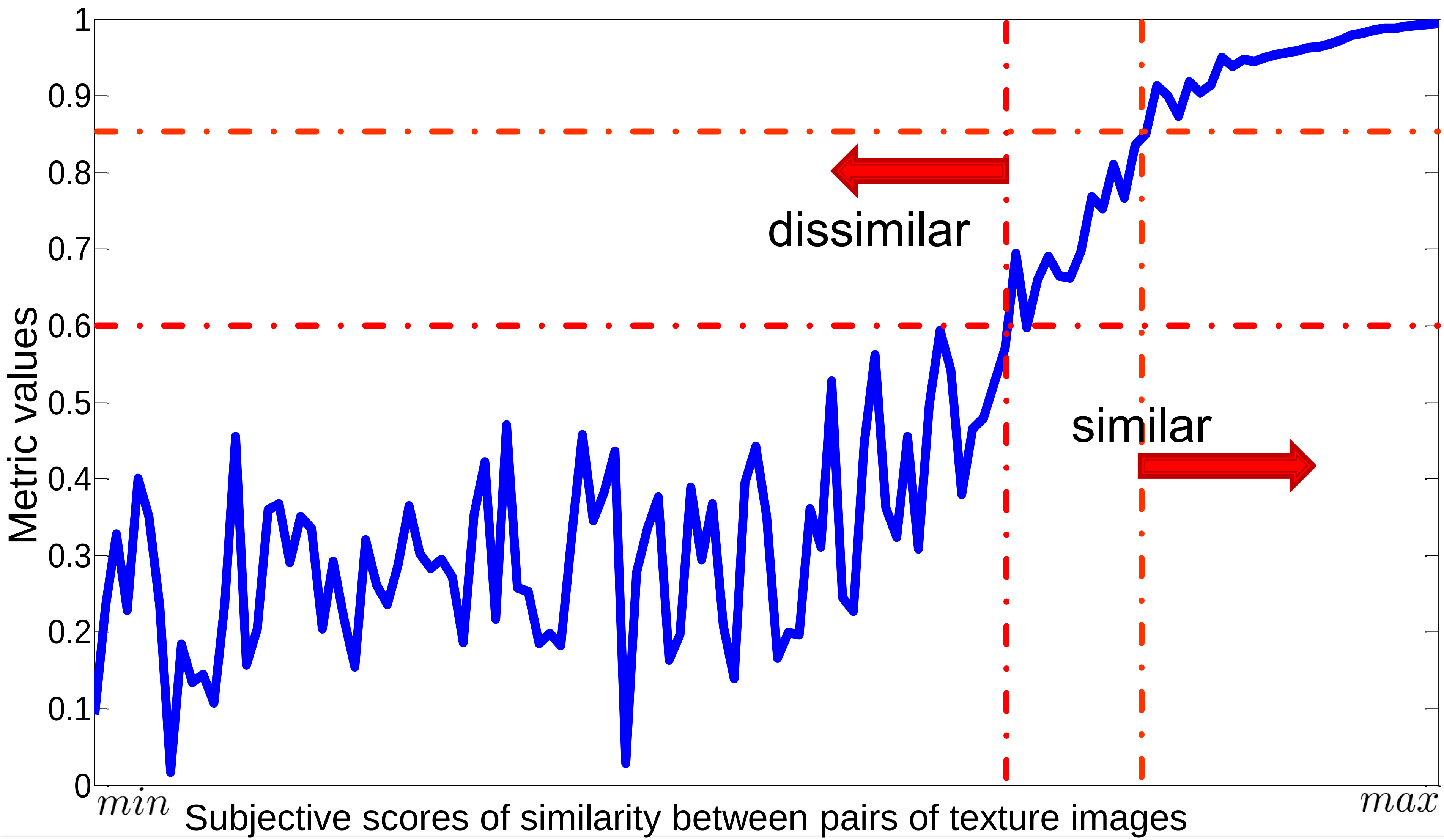
Testing Domains for Texture Similarity

dissimilar similar identical

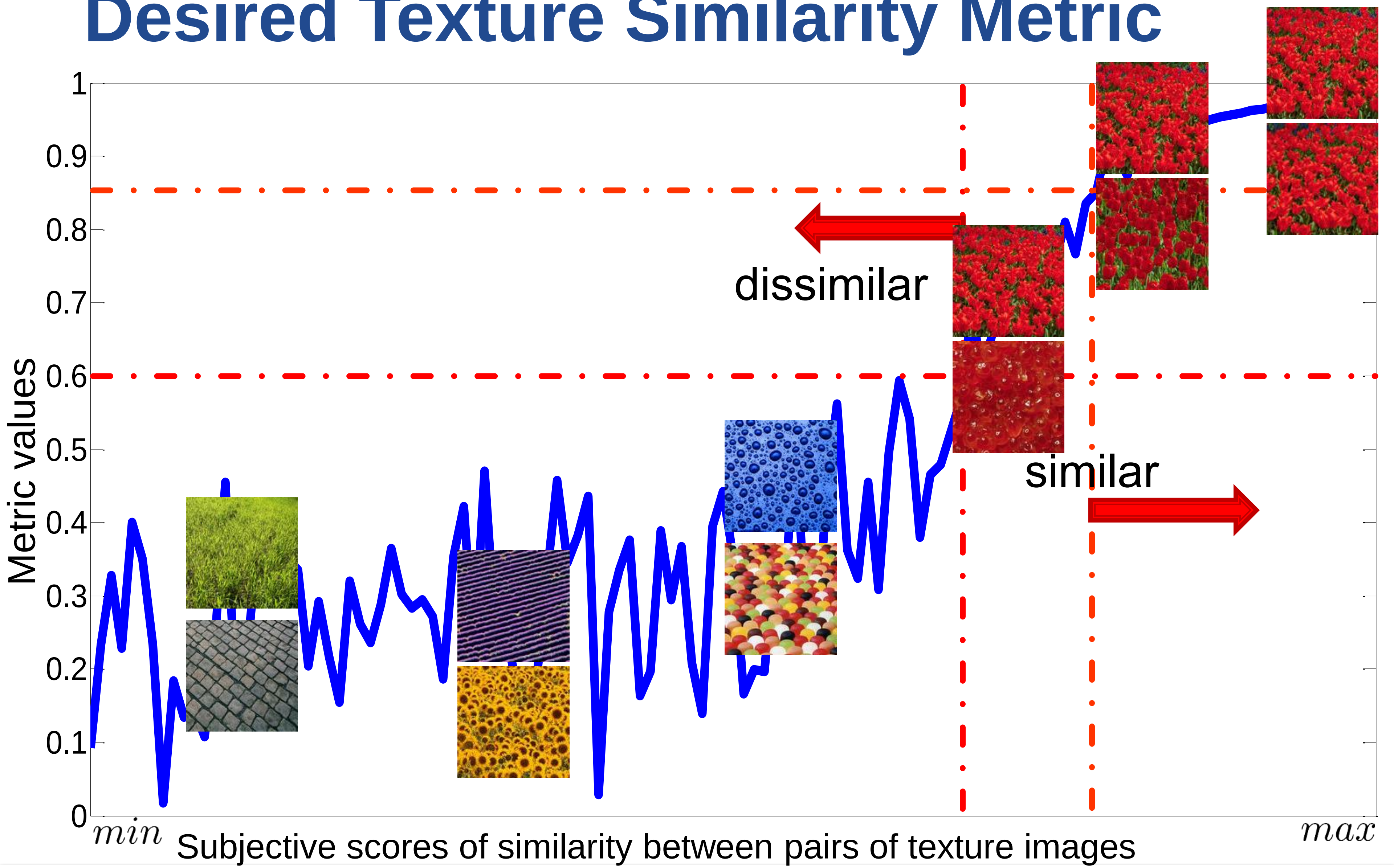
Testing Domains for Texture Similarity

- Limitations/Capabilities of Human Perception
- Application Requirements
- Testing Domains
  - Quantify (perceptually) small amounts of distortion
  - Similar vs. dissimilar
  - Retrieval of “identical” textures
- Absolute scale/threshold?

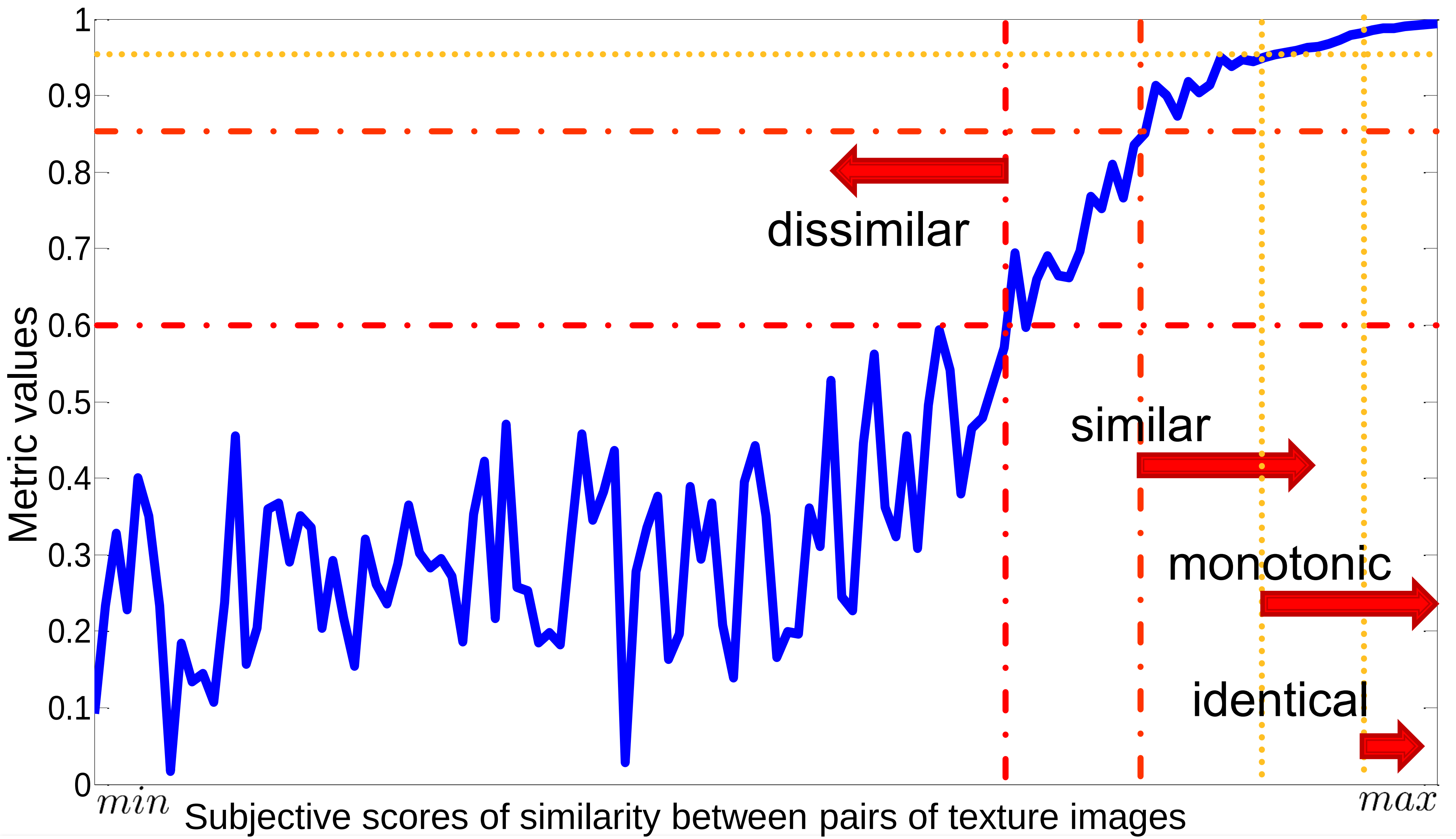
Desired Texture Similarity Metric



Desired Texture Similarity Metric

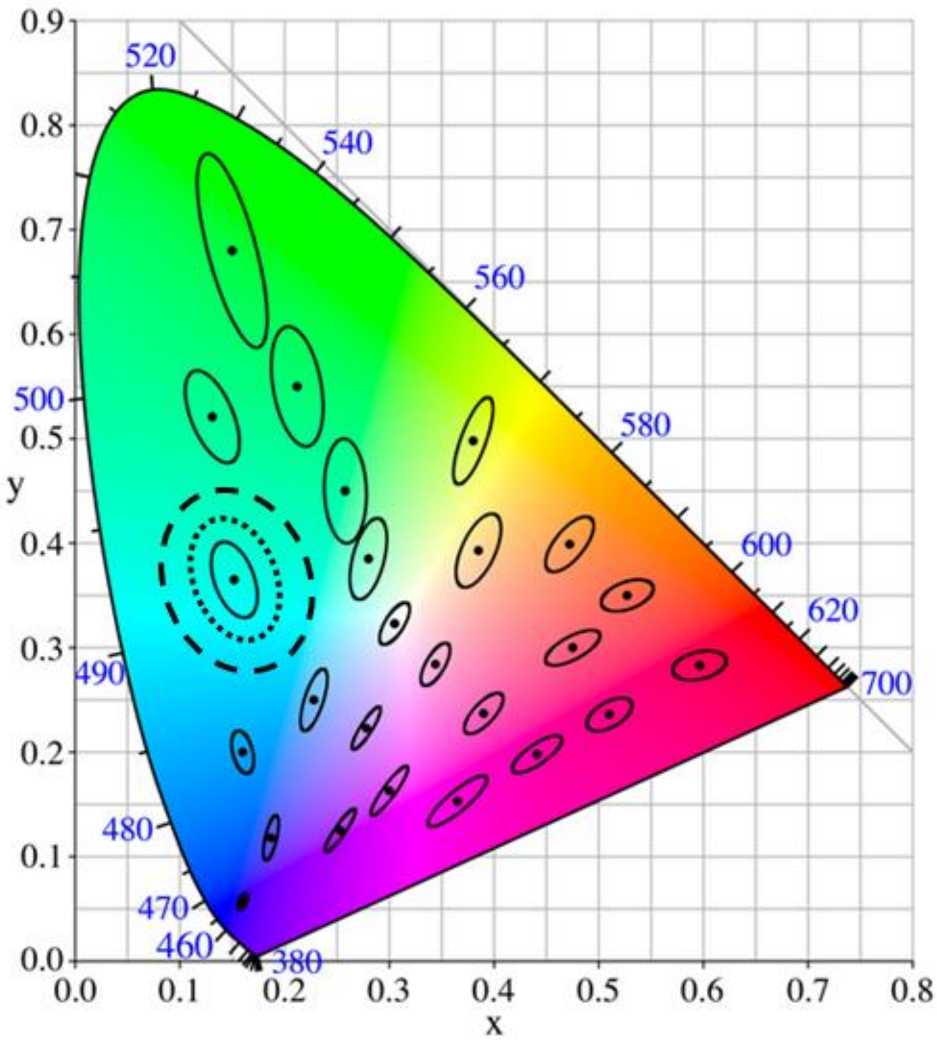


Desired Texture Similarity Metric



Color Analogy: MacAdam Ellipses

- Color:
  - JNDs
  - Cannot quantify large perceptual distances
- Texture:
  - JNDs can be obtained by existing perceptual quality metrics (solid)
  - “Ellipses” of similar textures (dashed)
  - “Ellipses” of identical textures (dotted)



Testing Domains for Texture Similarity

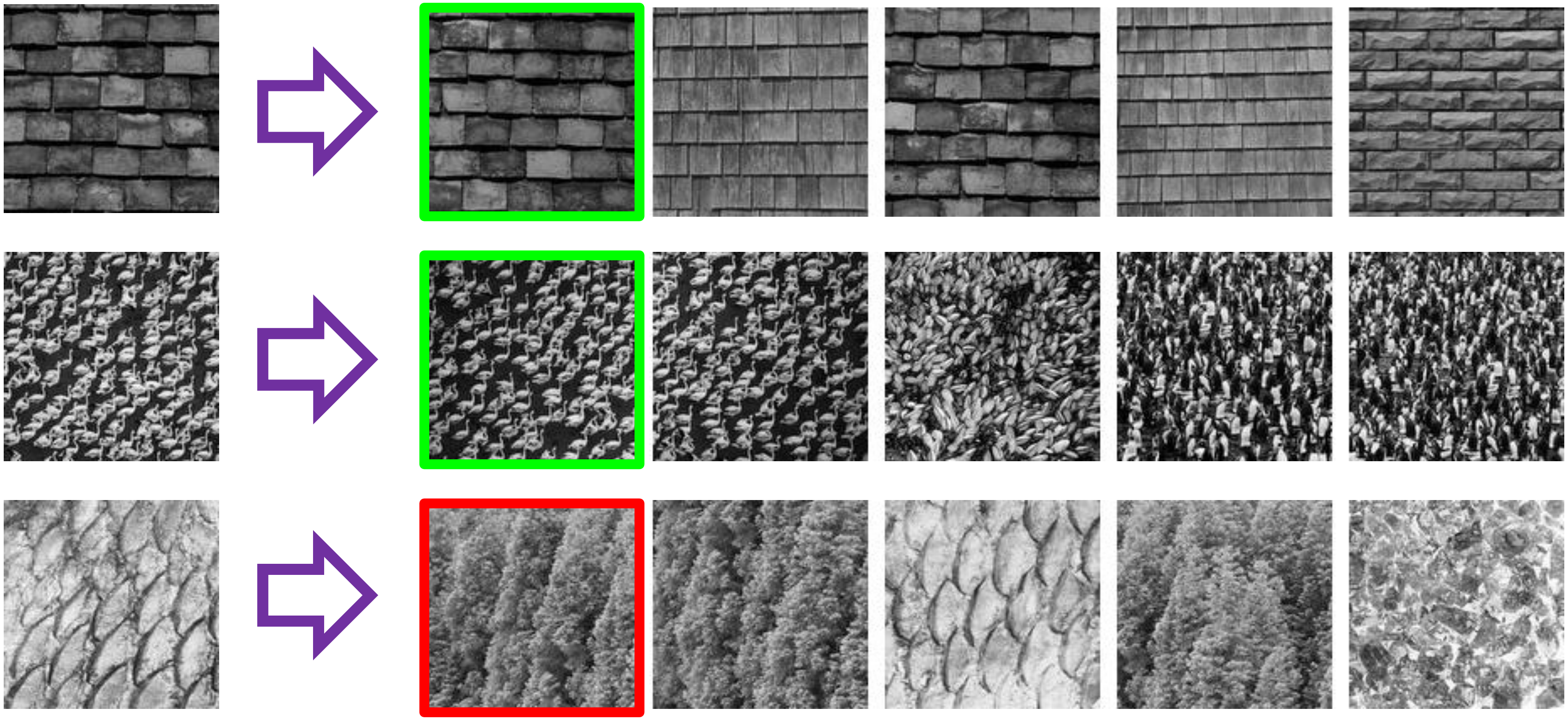
- Different domains require
  - Different metric evaluation criteria
  - Different subjective and objective tests
  - Different texture similarity metrics?
- Retrieval of “identical” textures
  - Known-item search
- Similar vs. dissimilar textures
- Quantify (perceptually) small amounts of distortion

J. Zujovic, T.N. Pappas, D.N. Neuhoff, H. de Ridder, R. van Egmond JOSAA’15

Building The Database

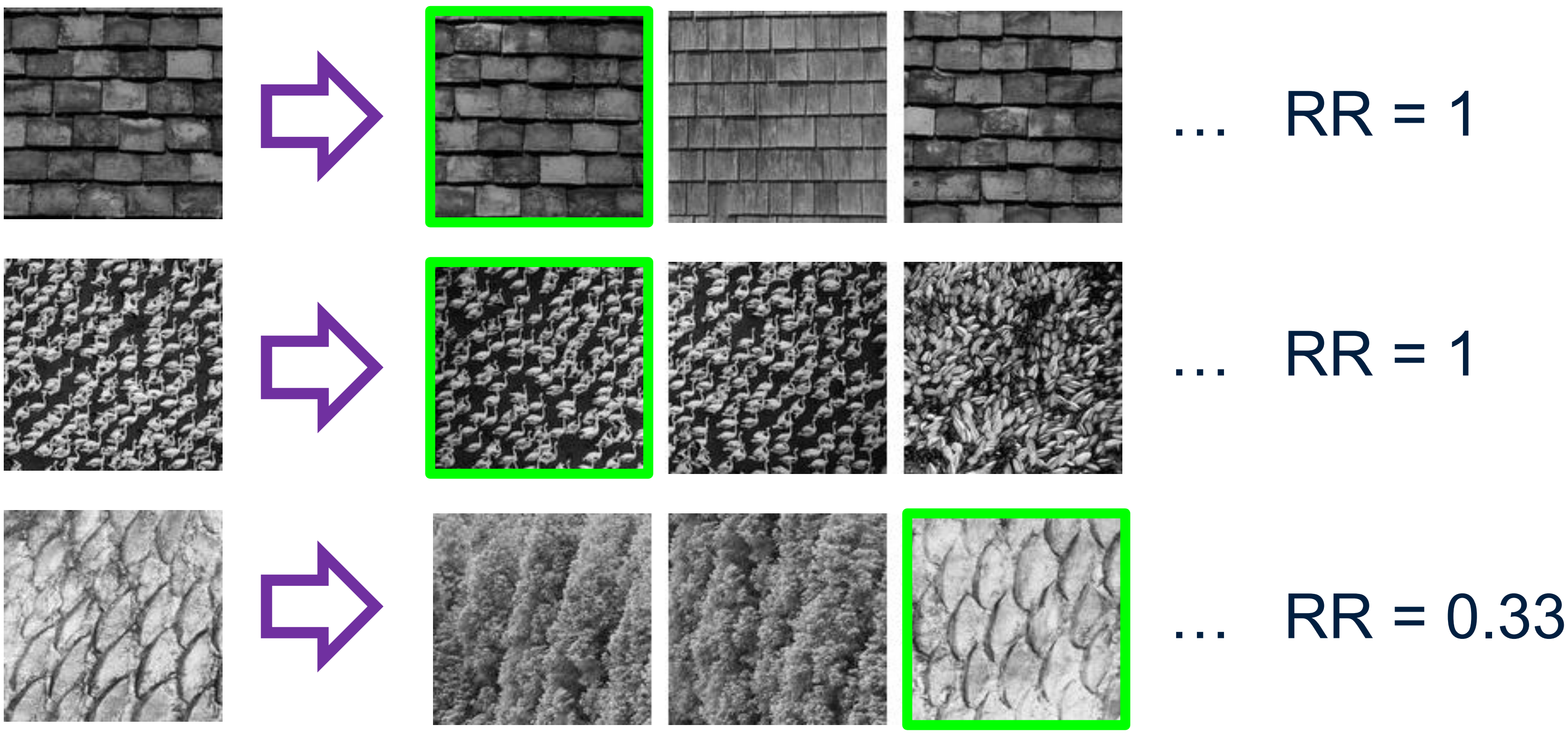
Precision at One

- Measures how many times the first retrieved texture was the correct one



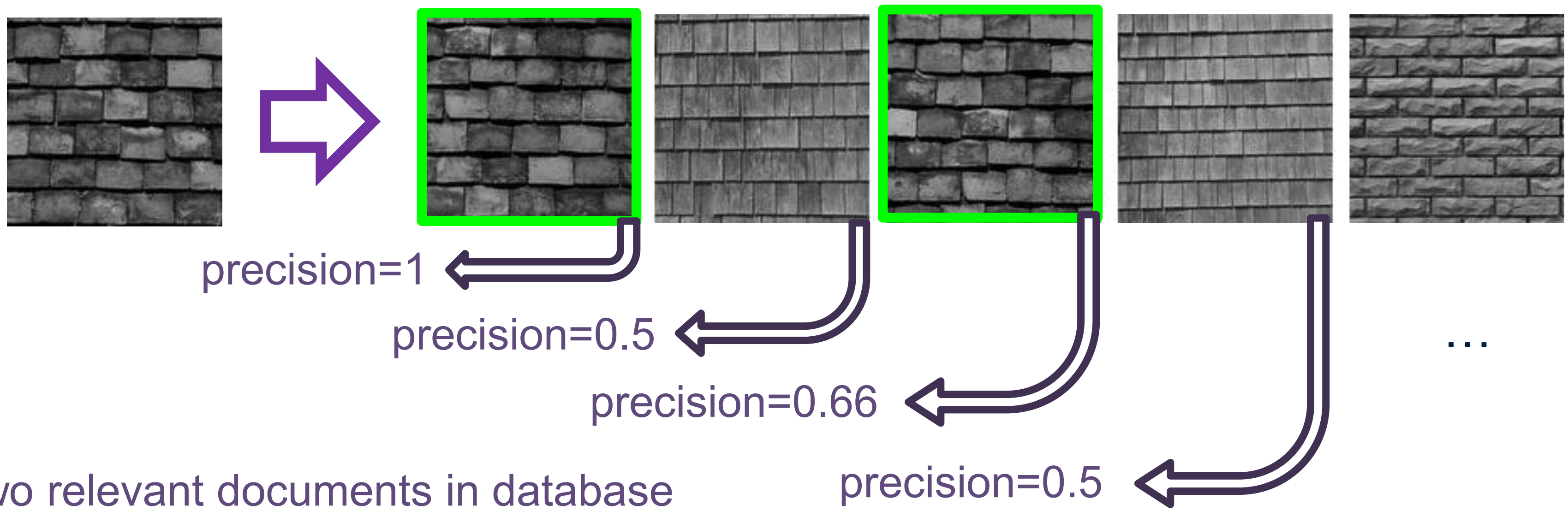
Mean Reciprocal Rank (MRR)

- Measures the average inverse rank of the first correct retrieved image



Mean Average Precision (MAP)

- Measures average precision when cutoff is made at 1^{st}, 2^{nd},…, N^{th} retrieved image



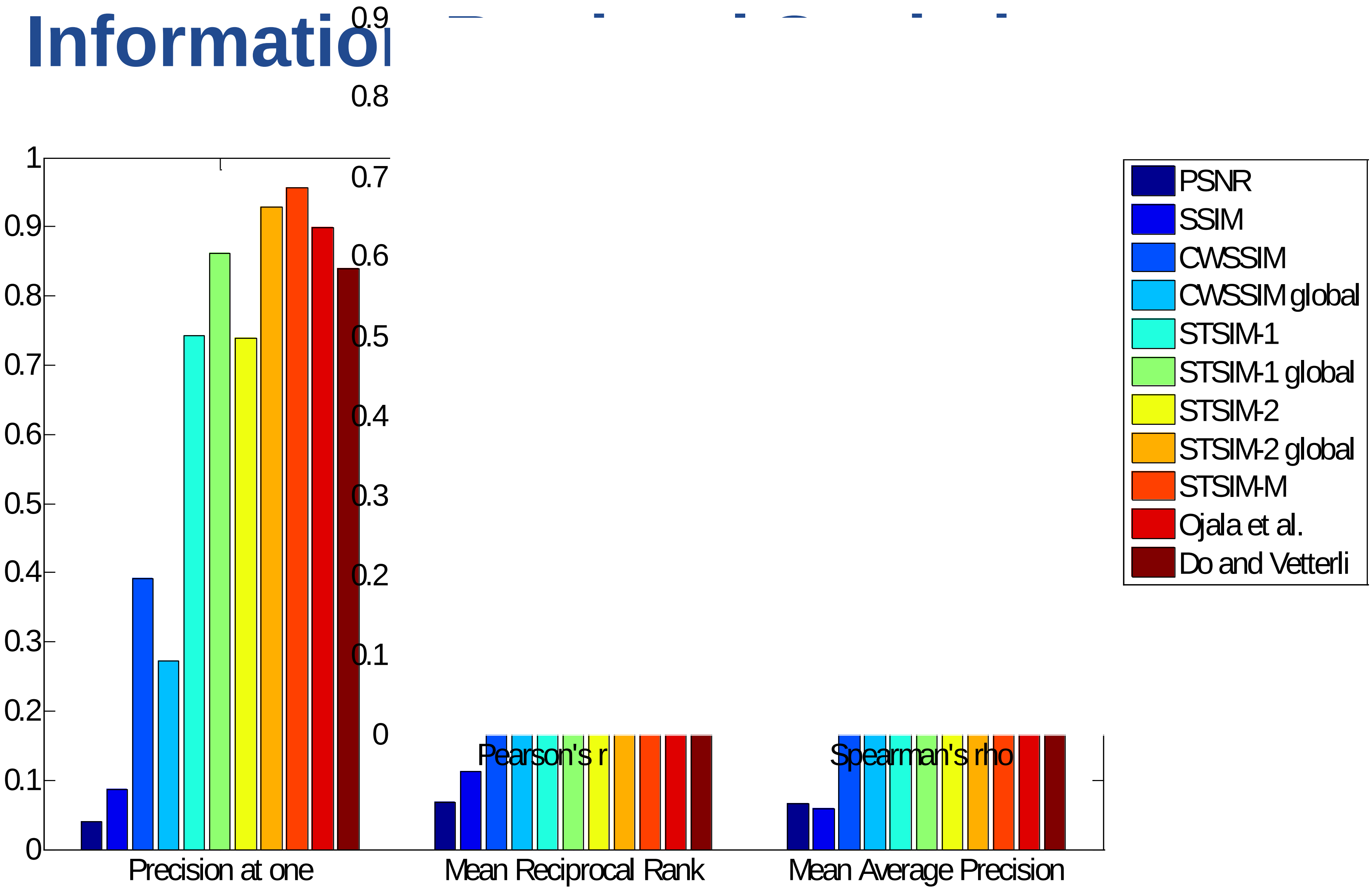
two relevant documents in database

indicator that document was relevant

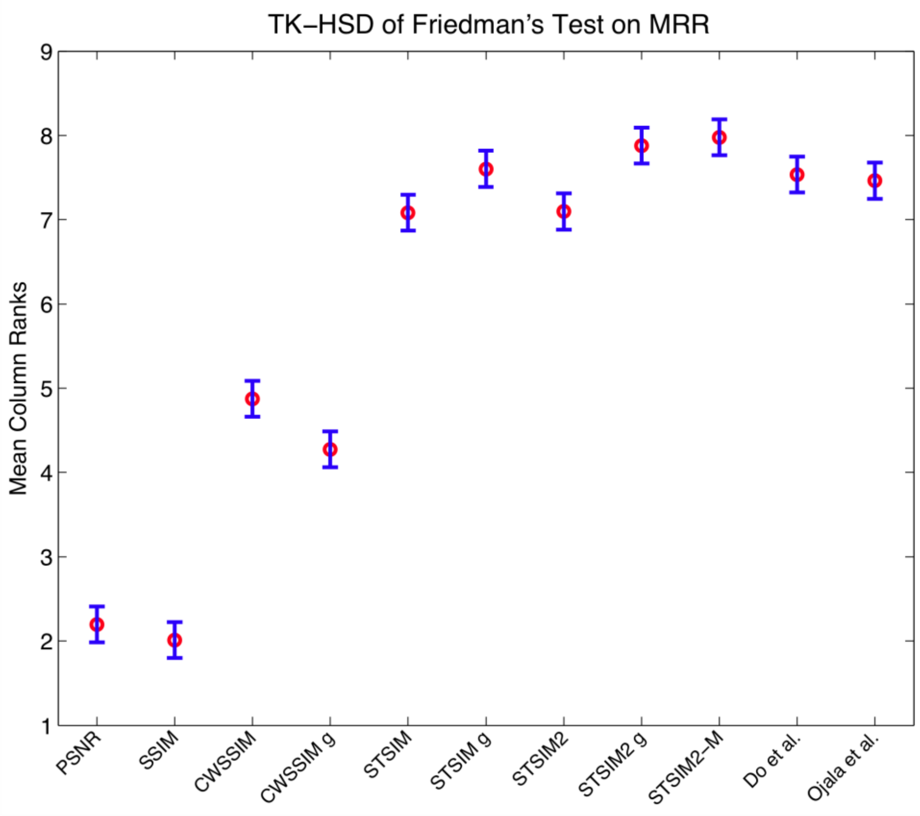
$$AP = 0.5*(1*1 + 0.5*0 + 0.66*1 + 0.5*0 + \ldots) = 0.83$$

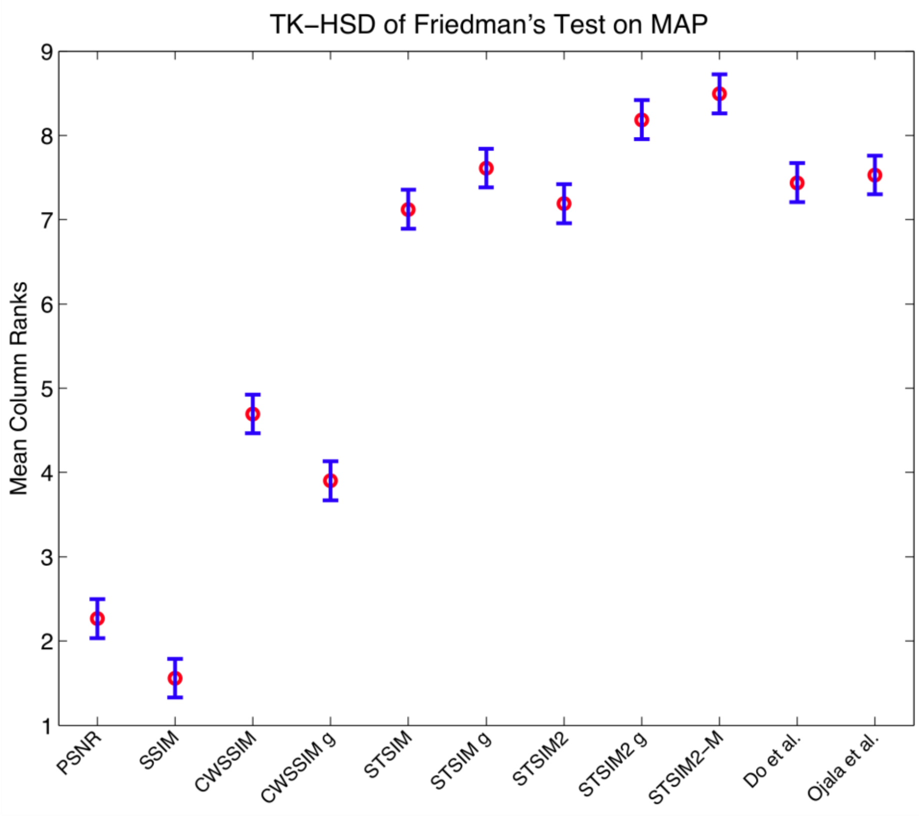
precision after first retrieved document

Informatio


0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Pearson's r
Spearman's rho
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Precision at one
Mean Reciprocal Rank
Mean Average Precision
PSNR
SSIM
CWSSIM
CWSSIM global
STSIM-1
STSIM-1 global
STSIM-2
STSIM-2 global
STSIM-M
Ojala et al.
Do and Vetterli

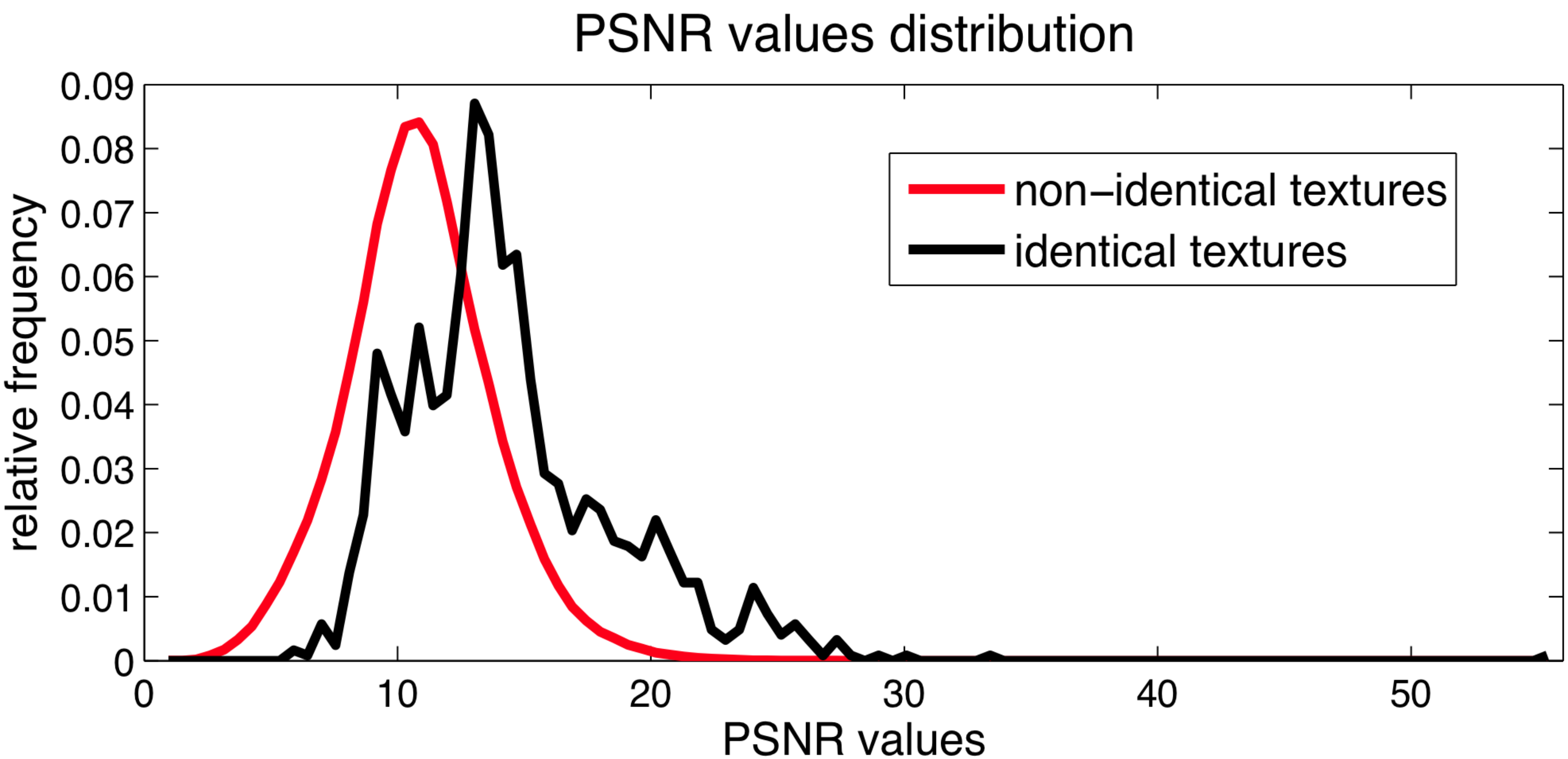
Statistical Validation



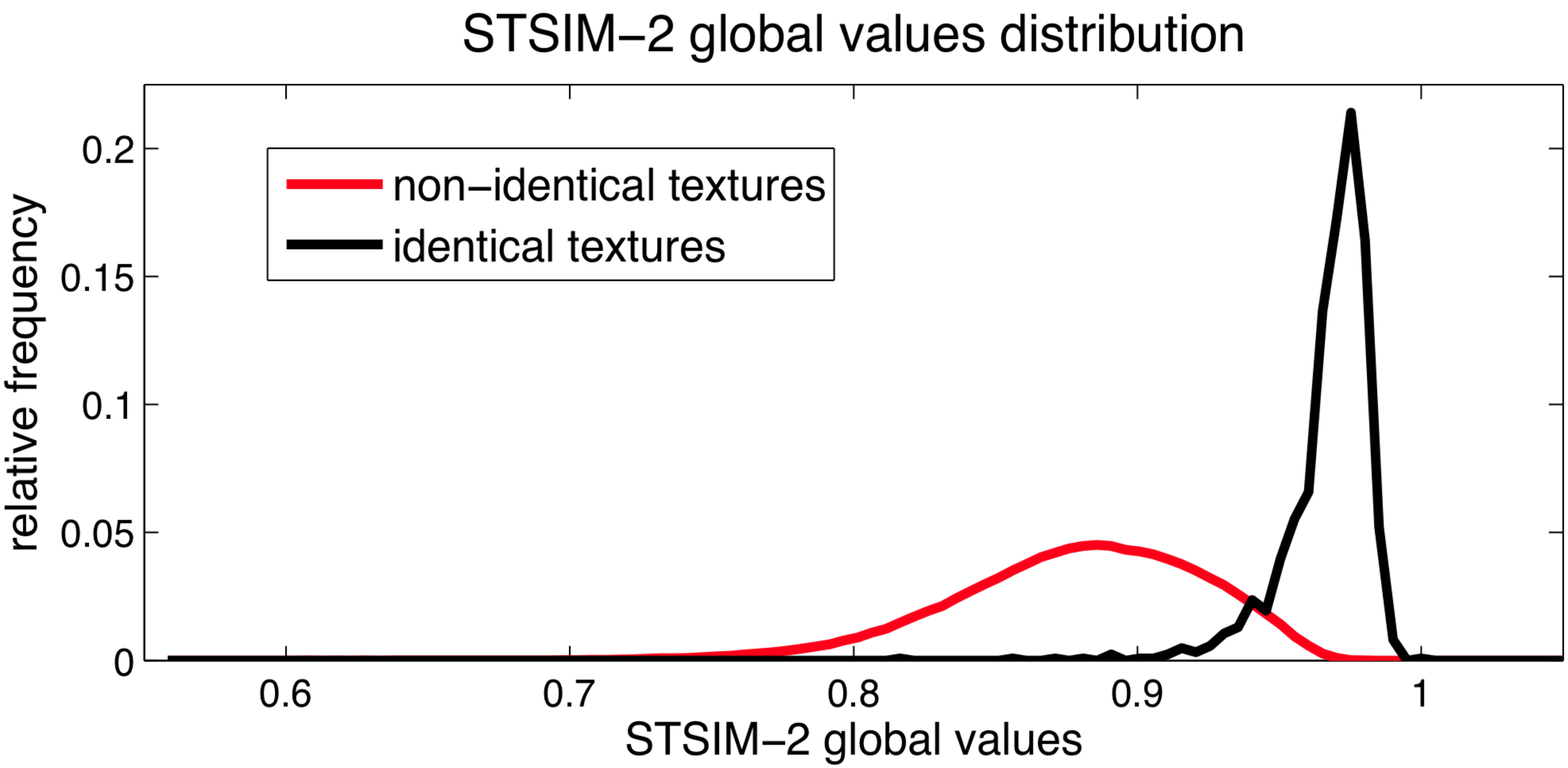


- P@1: Cochrane's Q test
  - Applied to each pair of metrics to determine statistical significance

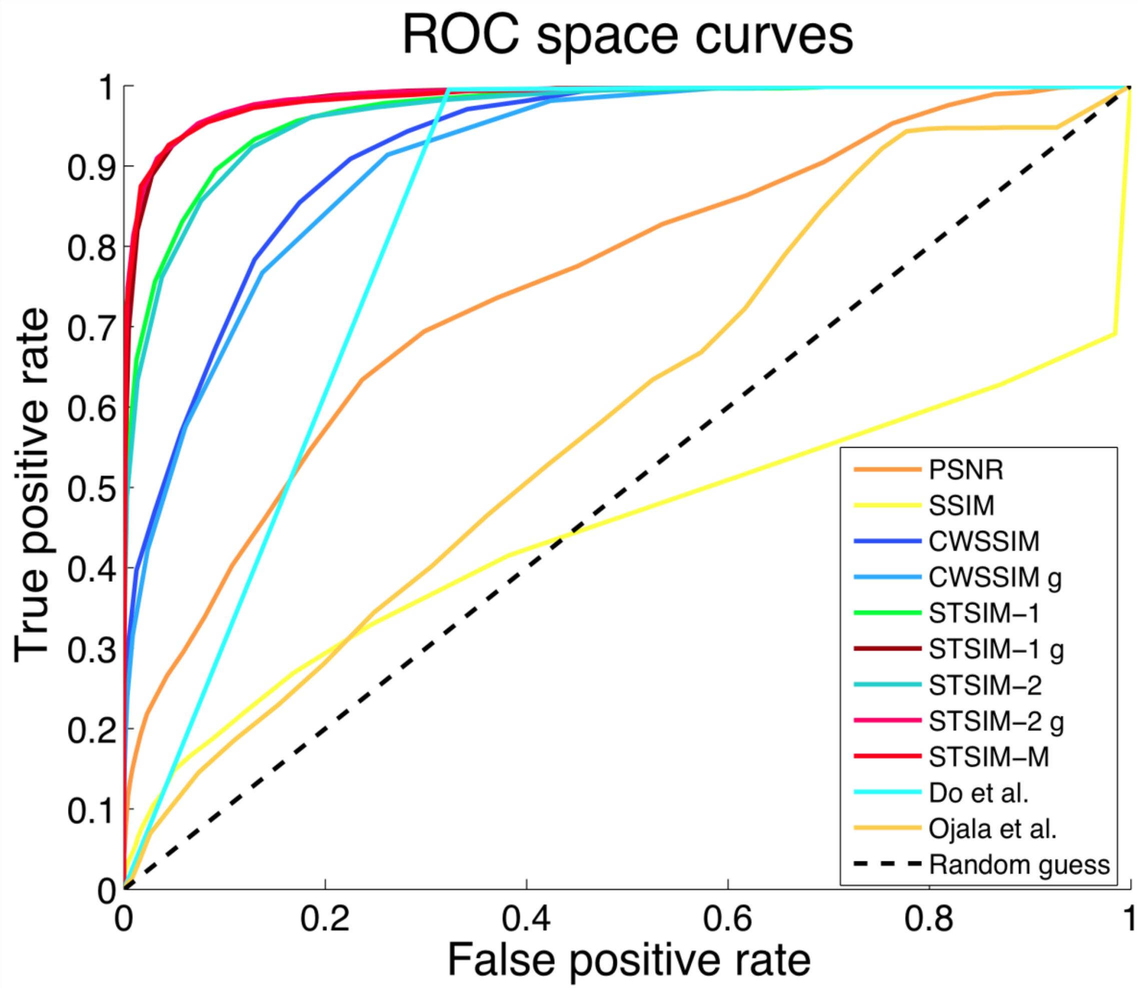
Receiver Operating Characteristic – ROC



Receiver Operating Characteristic – ROC



Receiver Operating Characteristic – ROC



Testing Domains for Texture Similarity

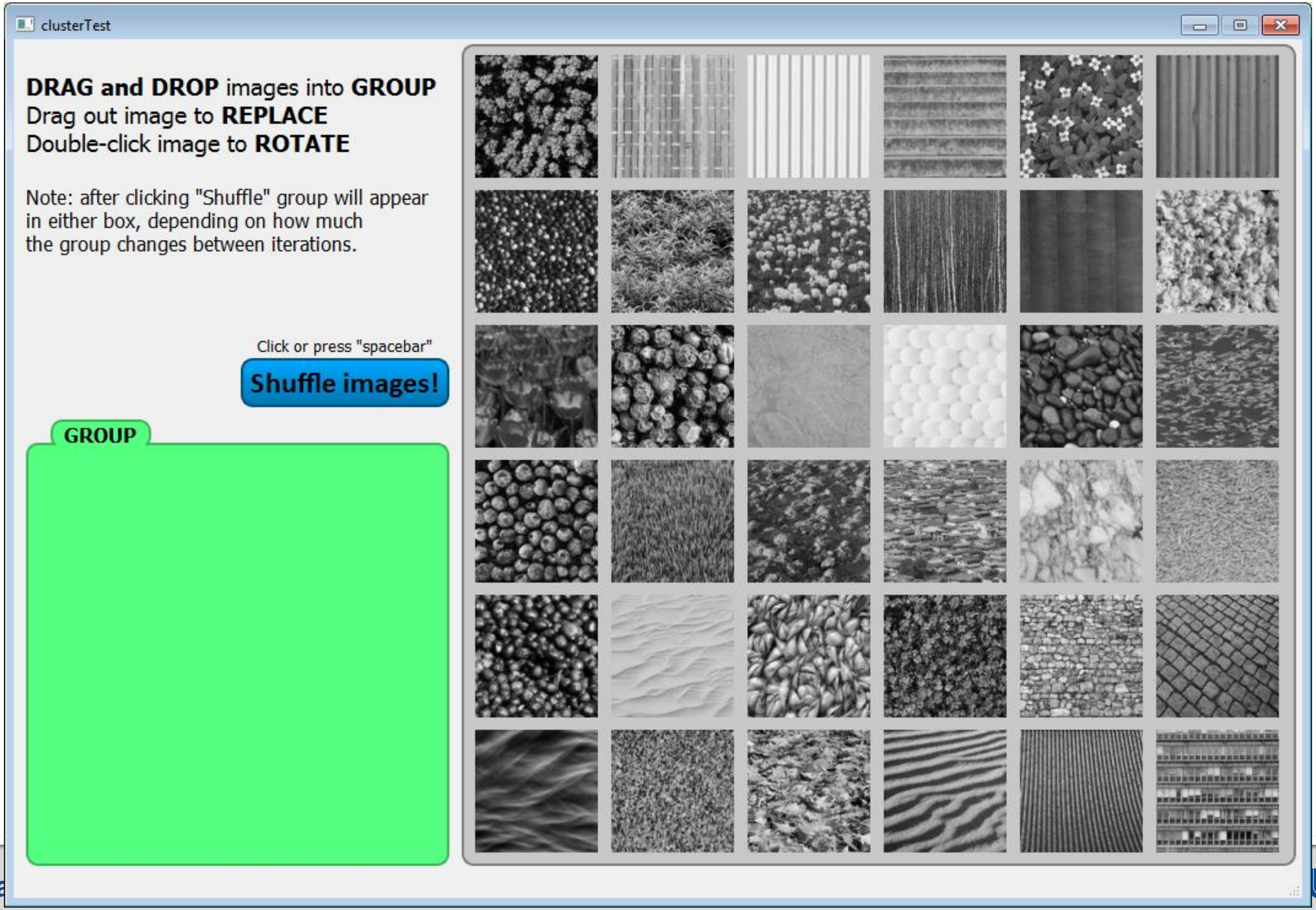
- Different domains require
  - Different metric evaluation criteria
  - Different subjective and objective tests
  - Different texture similarity metrics?
- Retrieval of “identical” textures
  - Known-item search
- Similar vs. dissimilar textures
- Quantify (perceptually) small amounts of distortion

Finding Clusters of Similar Textures

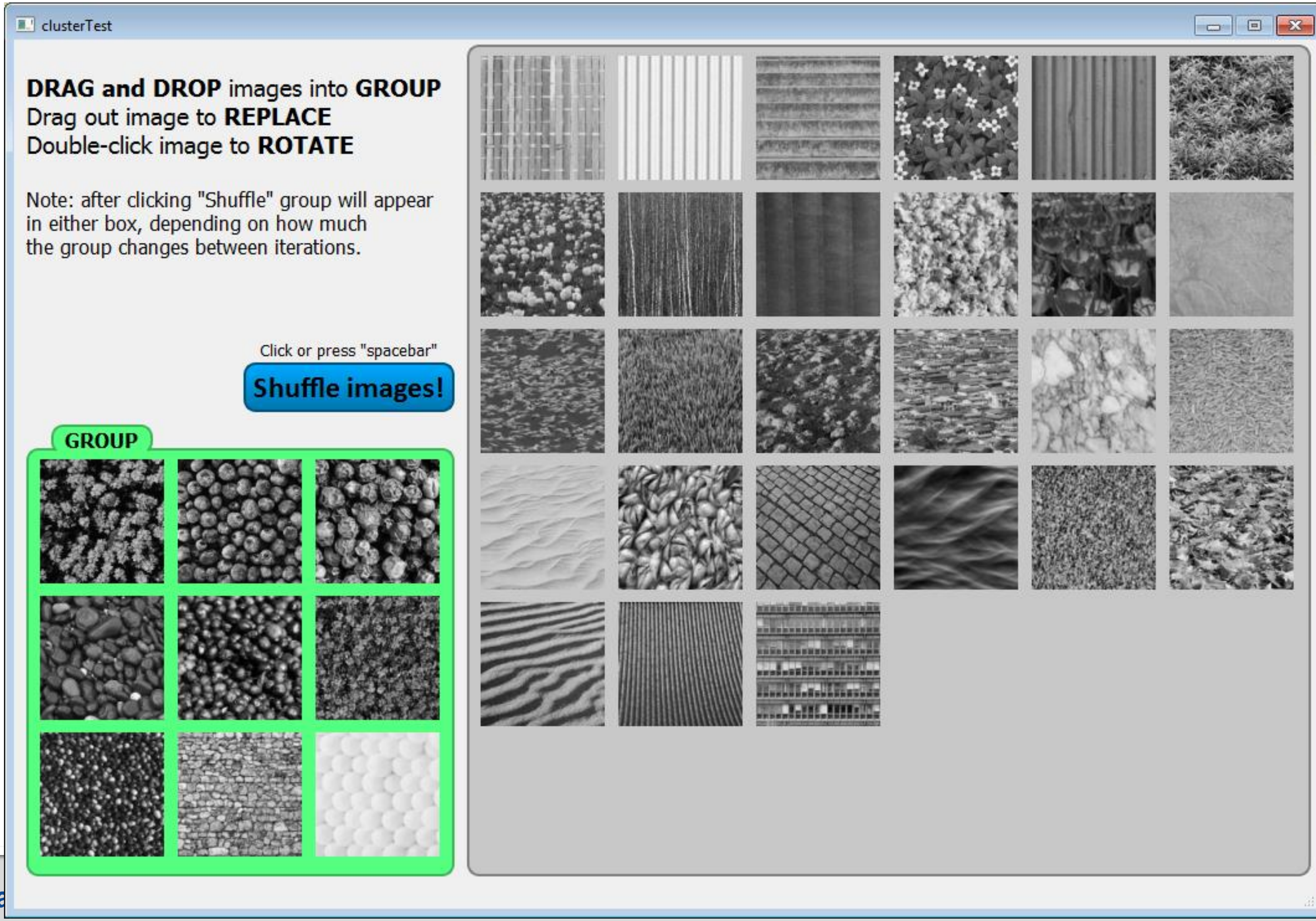
- Goal: find clusters of similar textures
  - Similar within clusters
  - Dissimilar across clusters
- Relatively large database
  - Difficult to see and compare all images at once
- ViSiProG: Visual Similarity by Progressive Grouping
  - Build similarity groups one at a time
  - Build each group in a step-by-step fashion
  - Each user builds multiple clusters
  - Combine results from different users

Zujovic, Pappas, Neuhoff, de Ridder, van Egmond, JOSAA'15

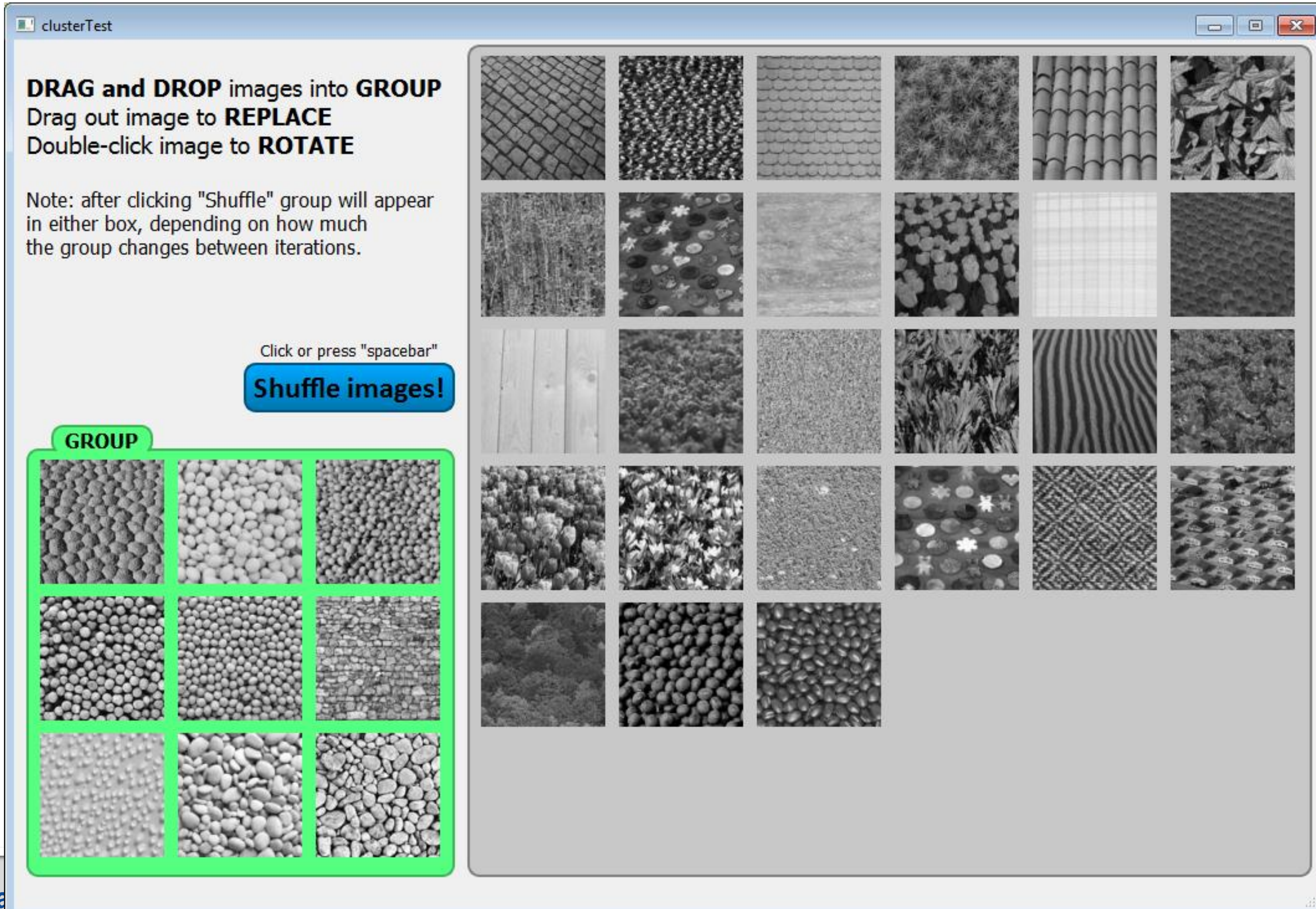
ViSiProG – Grayscale



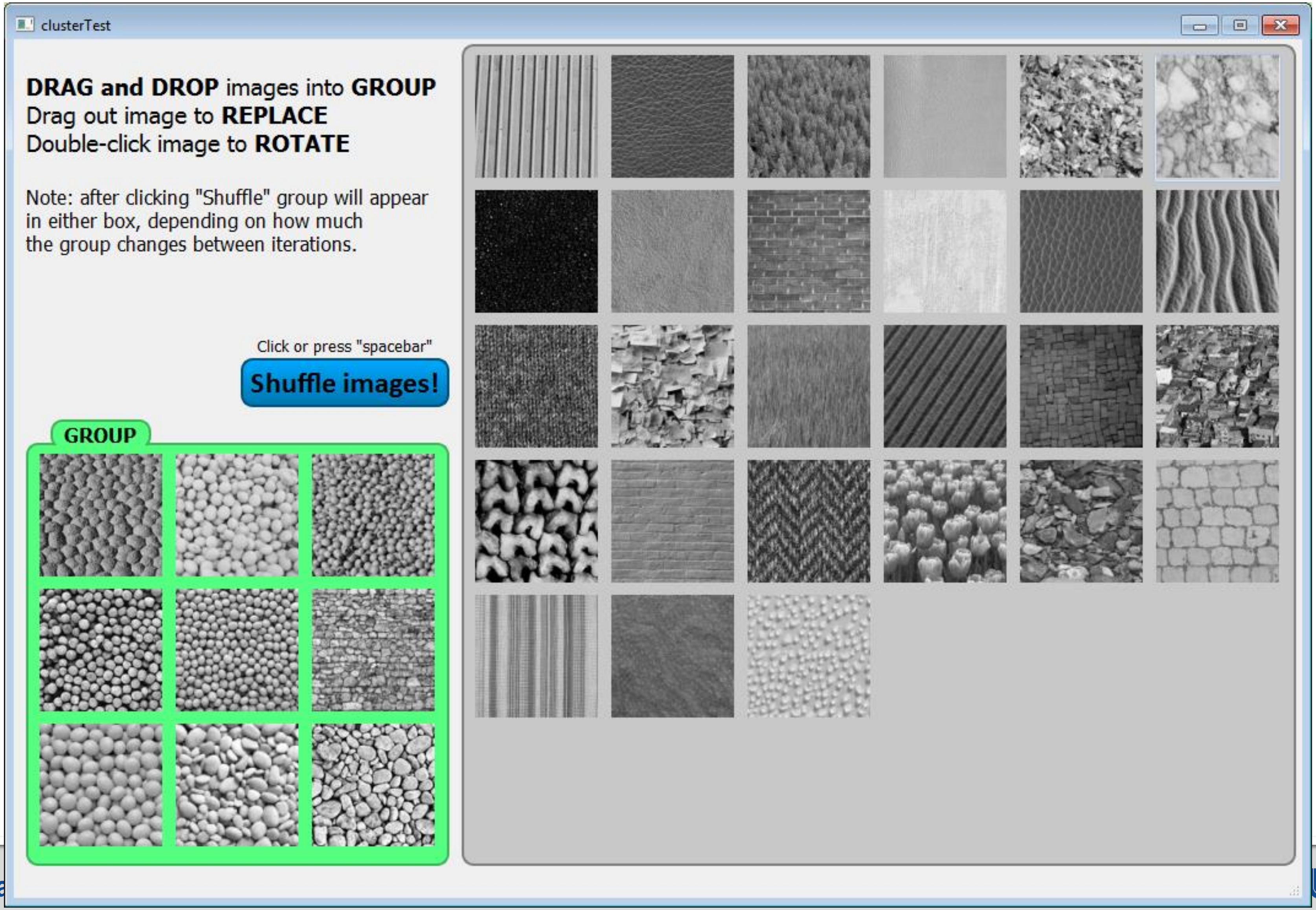
ViSiProG – Grayscale



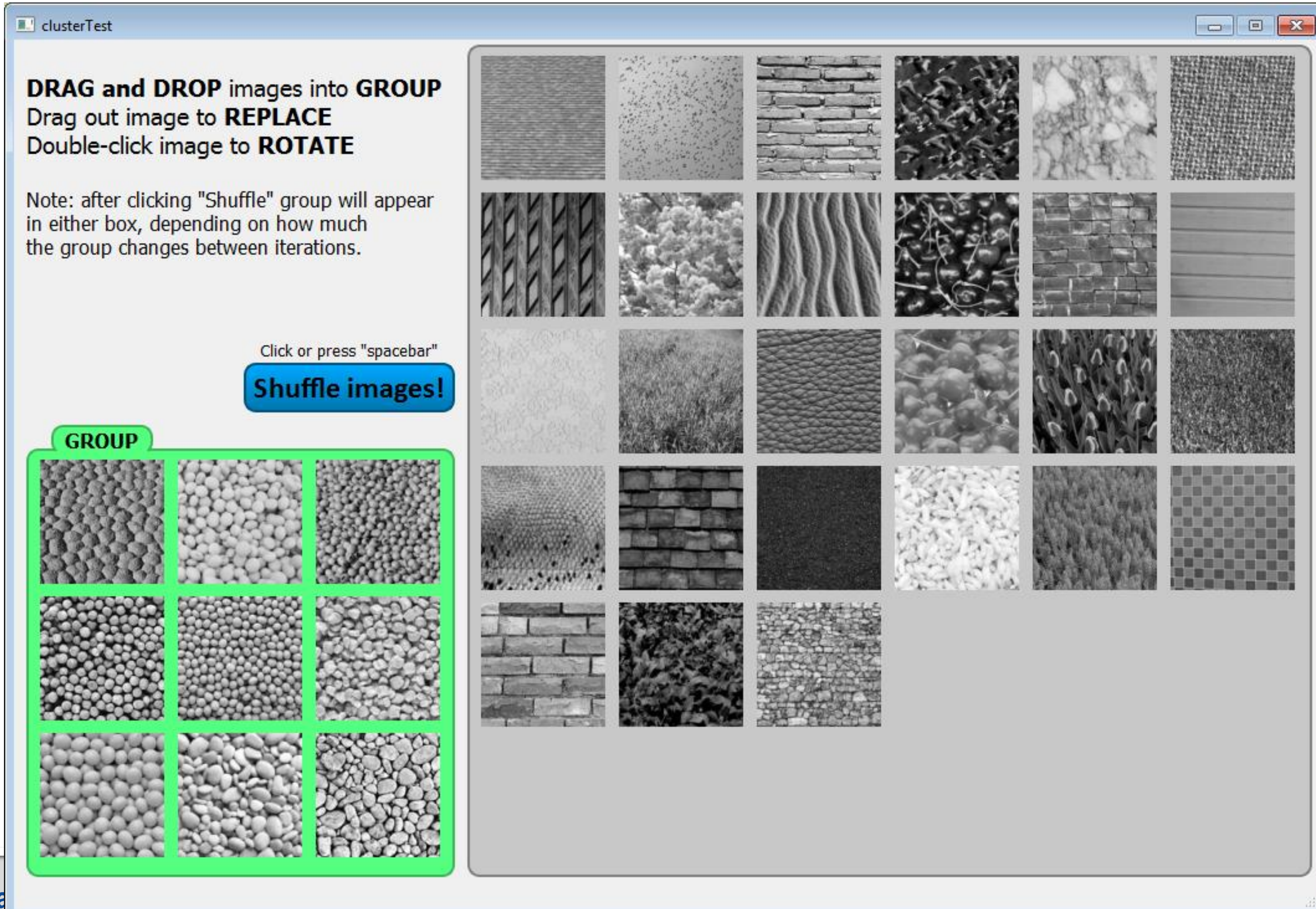
ViSiProG – Grayscale



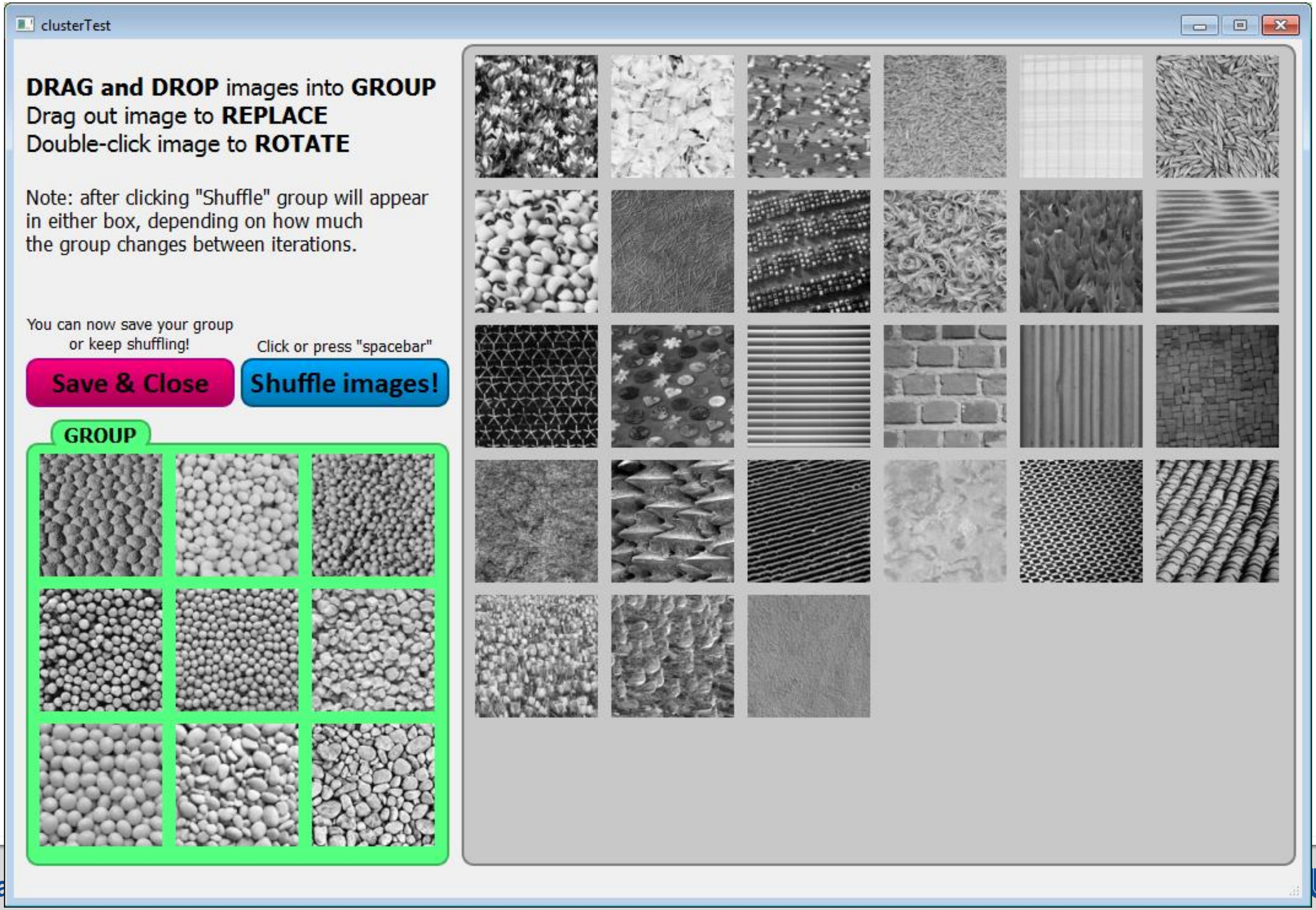
ViSiProG – Grayscale



ViSiProG – Grayscale



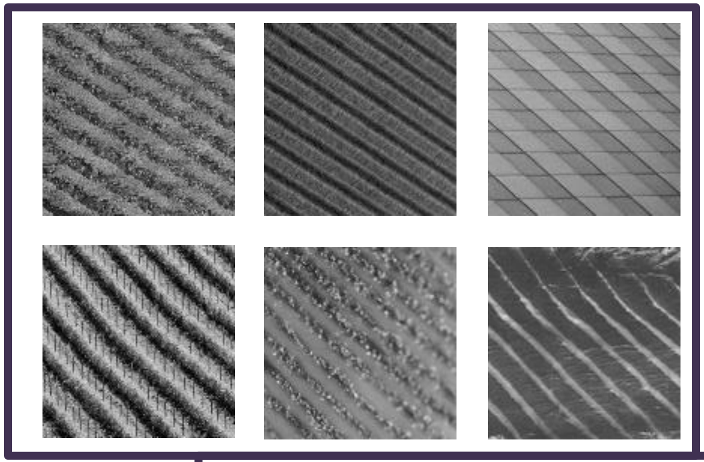
ViSiProG – Grayscale

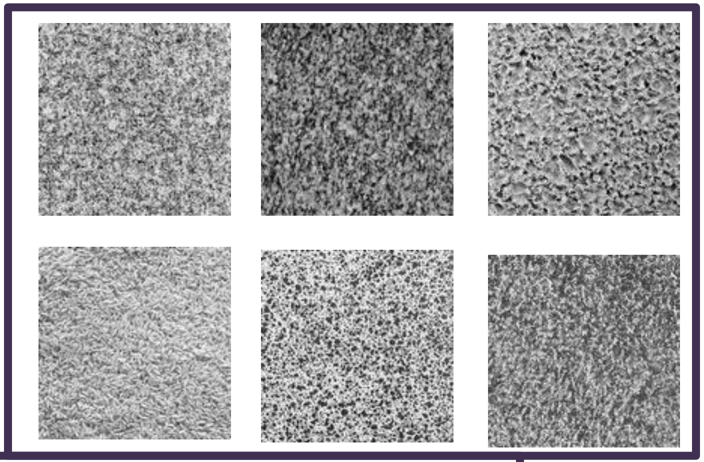


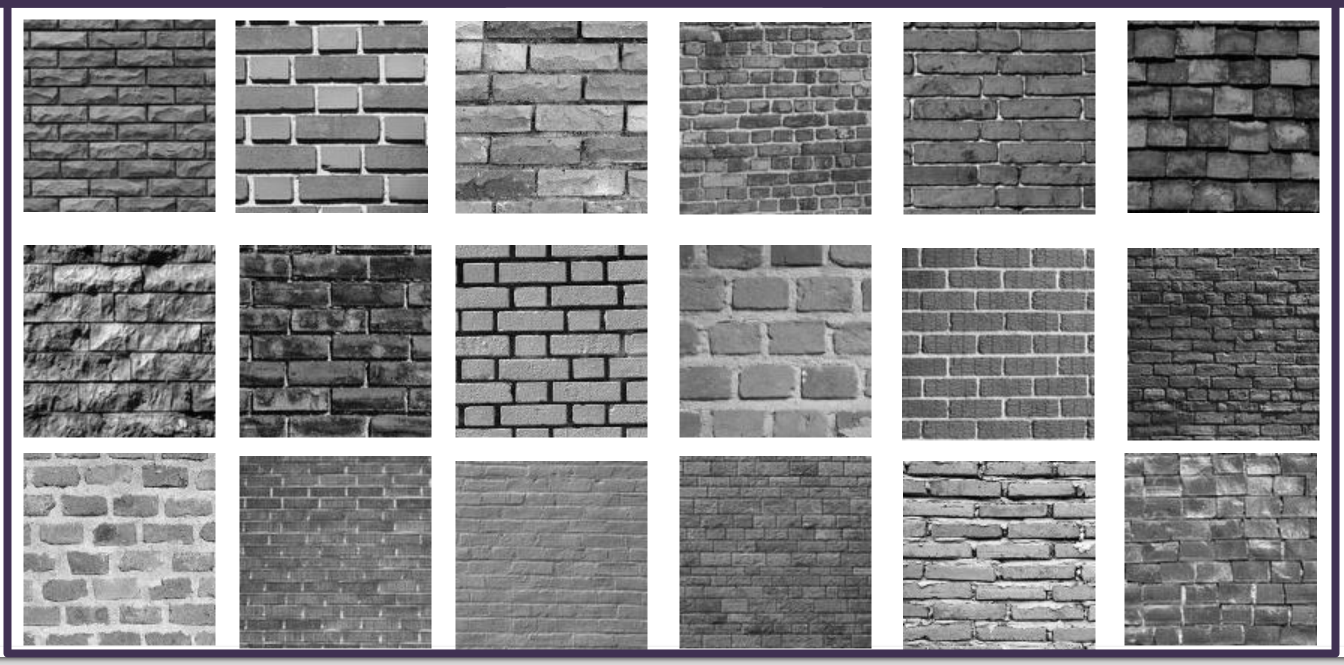
Finding Clusters of Similar Textures

- 246 grayscale images
- Subjects asked to form groups of 9 similar images
- Formed similarity matrix
  - Only 134 images were selected in a group
- Used spectral clustering to analyze results
  - Cluster the data based on human similarity scores

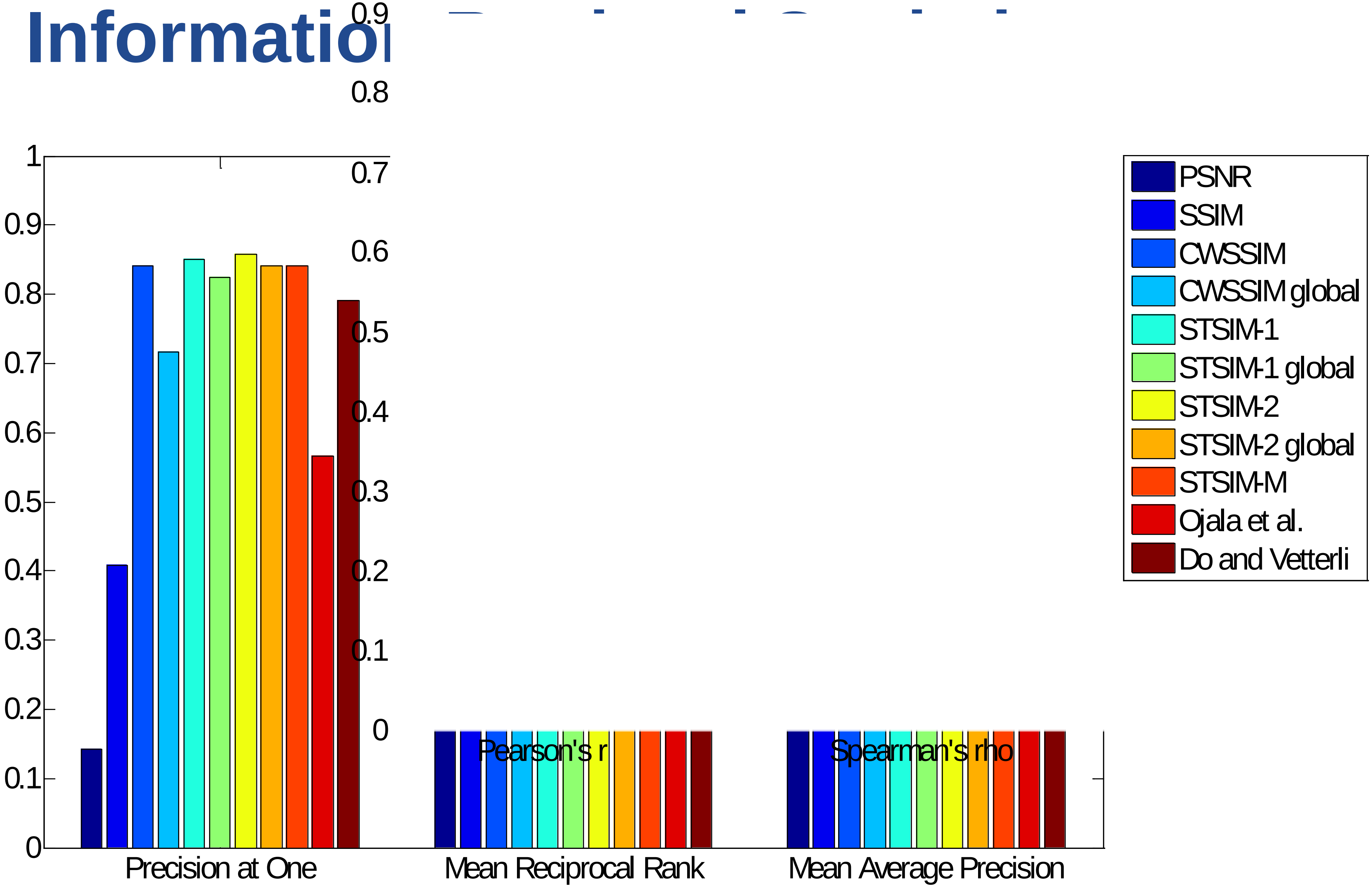
Similarity Clusters Examples





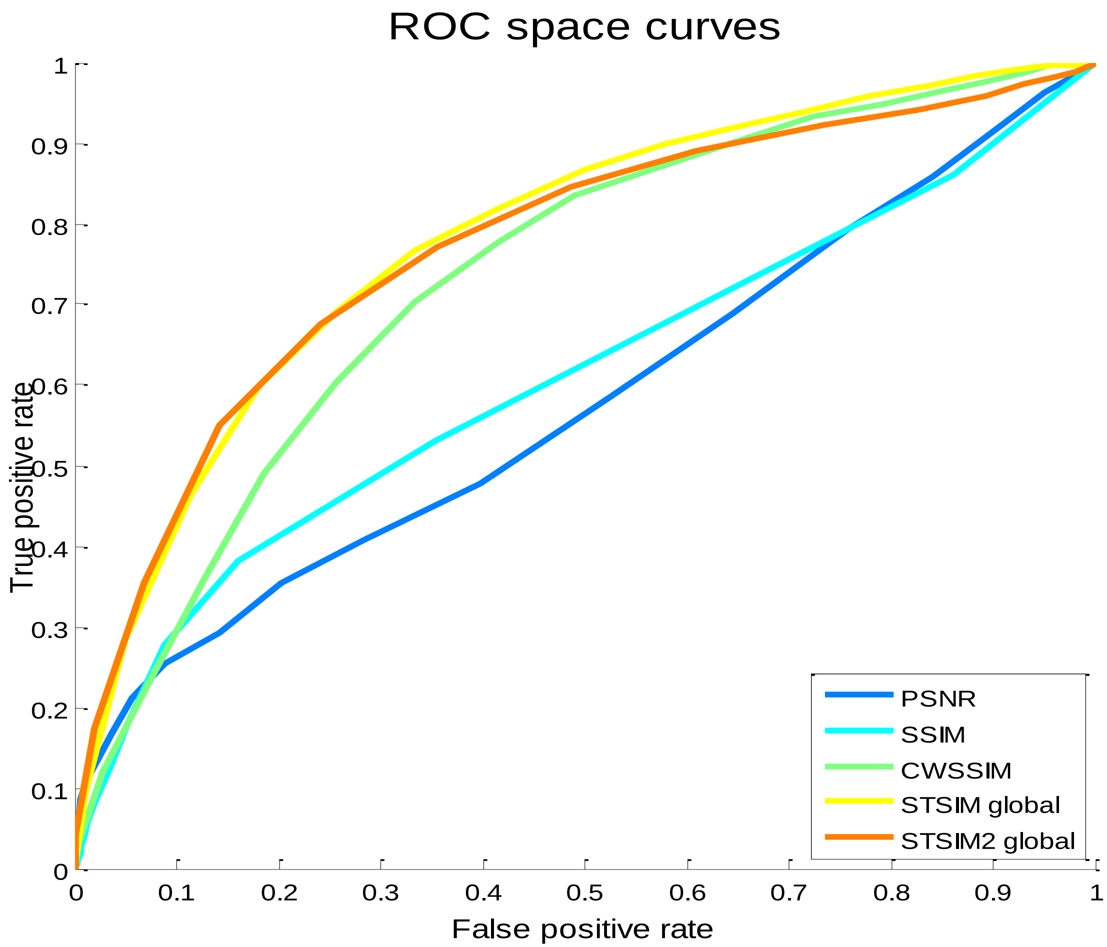


Informatio

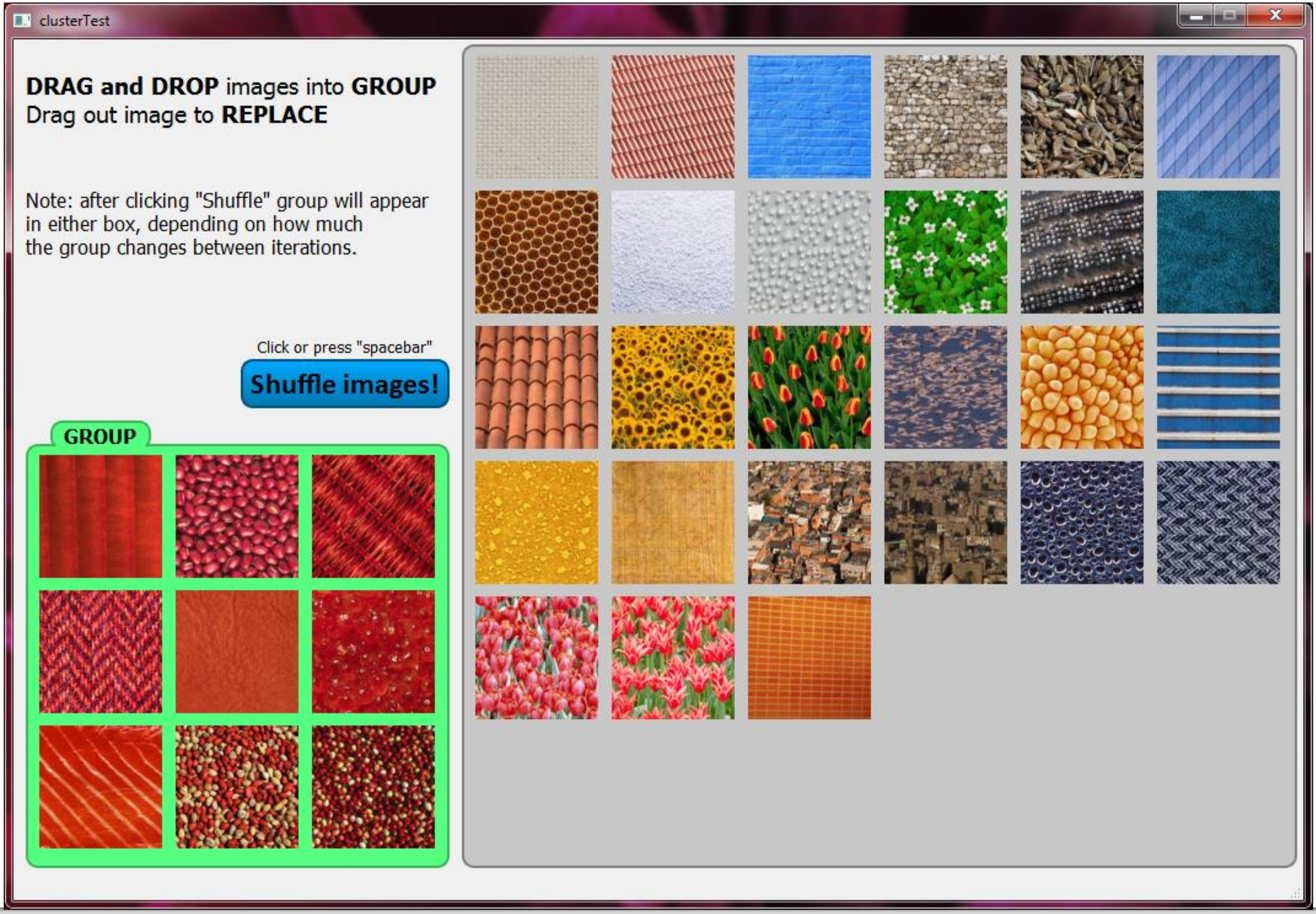


1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Precision at One
Mean Reciprocal Rank
Mean Average Precision
Pearson's r
Spearman's rho
PSNR
SSIM
CWSSIM
CWSSIM global
STSIM-1
STSIM-1 global
STSIM-2
STSIM-2 global
STSIM-M
Ojala et al.
Do and Vetterli

Receiver Operating Characteristic – ROC



ViSiProG – Color Composition



Similarity Clusters Examples

Testing Domains for Texture Similarity

- Different domains require
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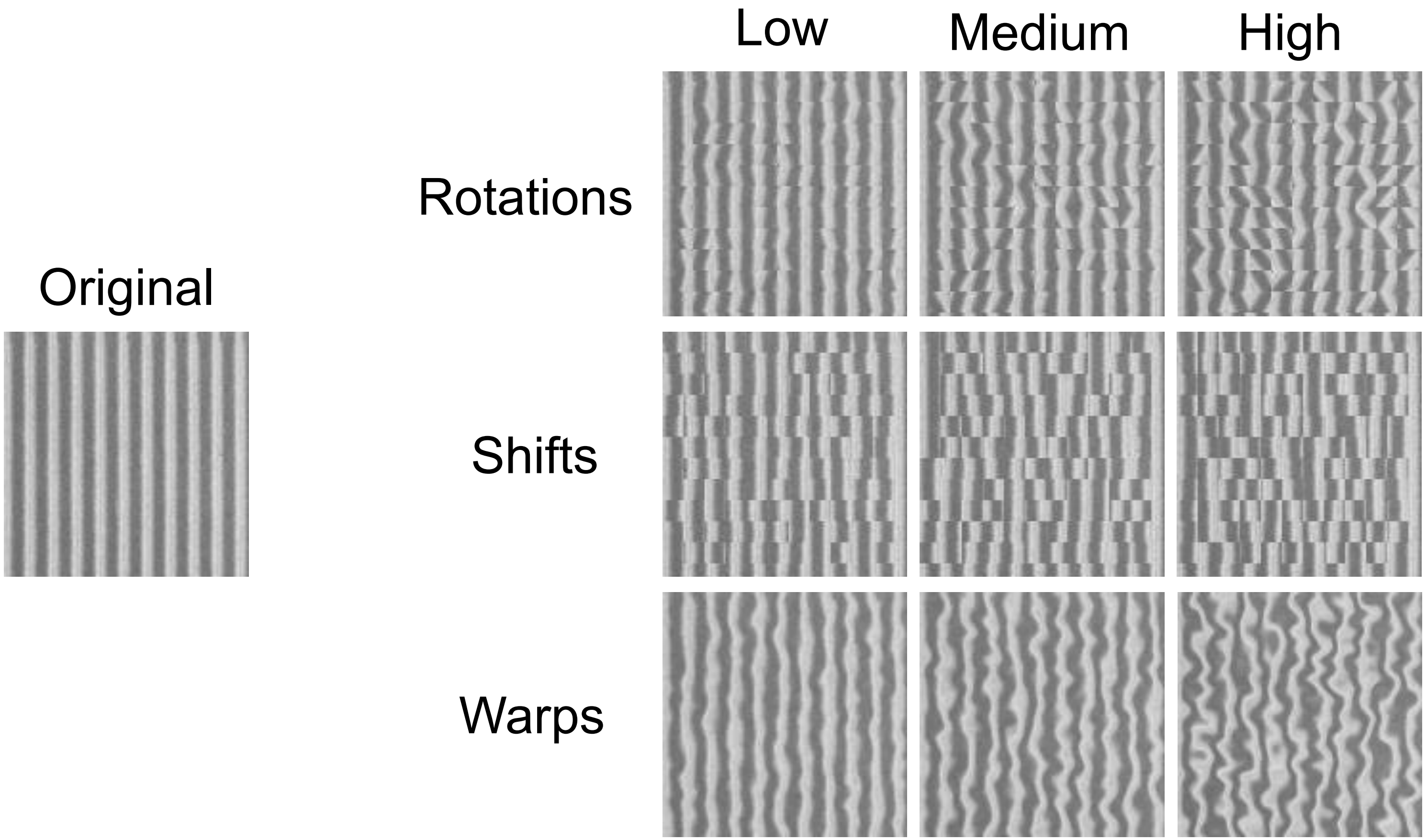
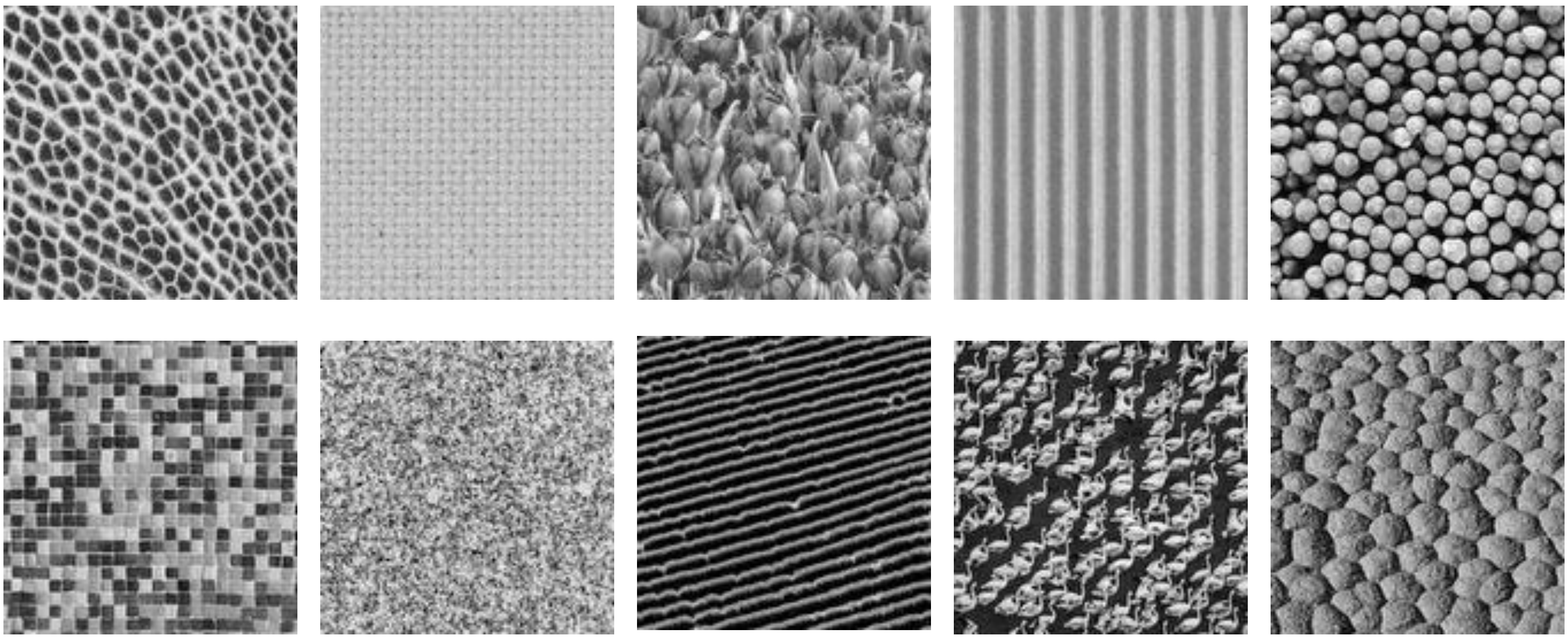
  - Different subjective and objective tests
  - Different texture similarity metrics?
- Retrieval of “identical” textures
  - Known-item search
- Similar vs. dissimilar textures
- Quantify (perceptually) small amounts of distortion

Distortion Quantification

- Subjects asked to rank the distortions from “best” to “worst”



Original Database



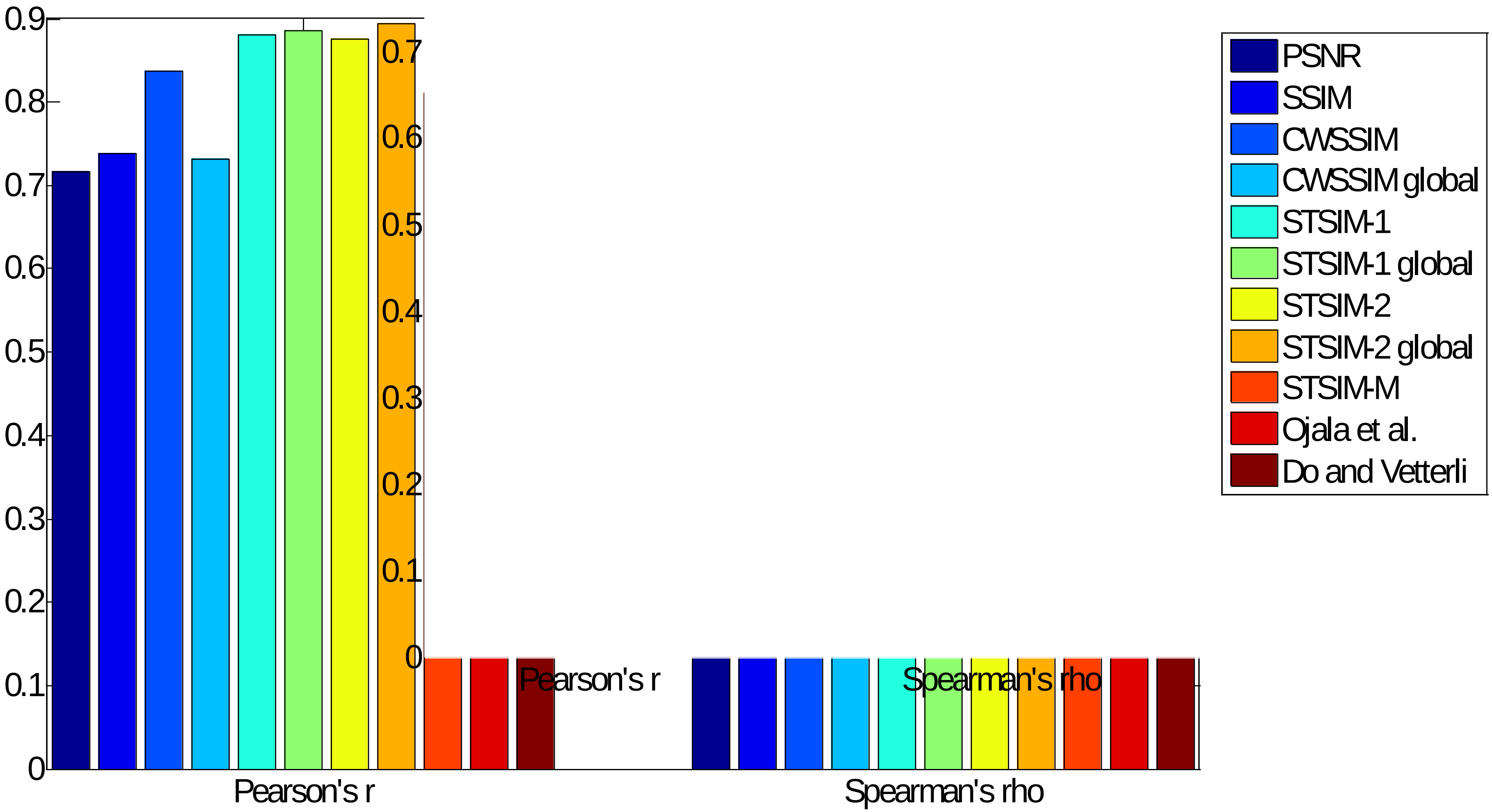
Analyzing the Results

- Subjective similarity scores:
  - Average ranks (Borda's rule)
  - Thurstonian scaling
  - Multidimensional scaling

- Qualitatively similar results

- Correlate with objective (metric) scores

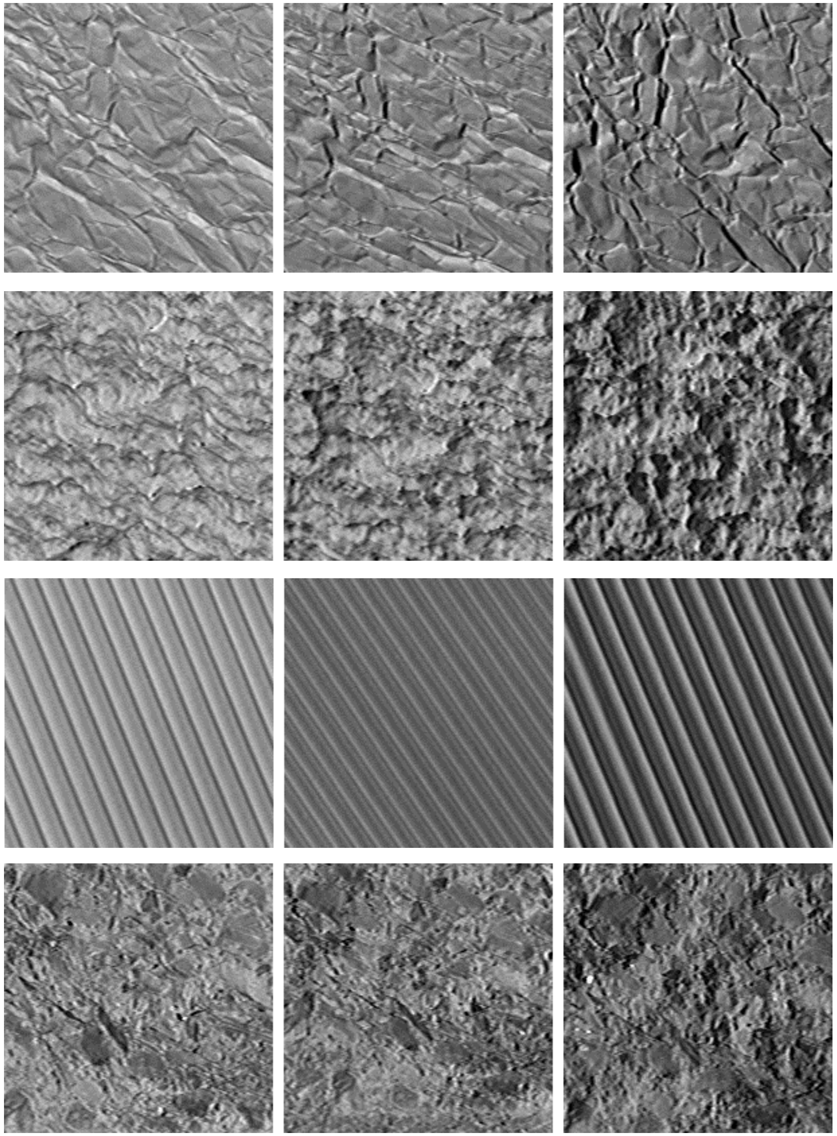
Analyzing



0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Pearson's r
Spearman's rho
PSNR
SSIM
CWSSIM
CWSSIM global
STSIM-1
STSIM-1 global
STSIM-2
STSIM-2 global
STSIM-M
Ojala et al.
Do and Vetterli

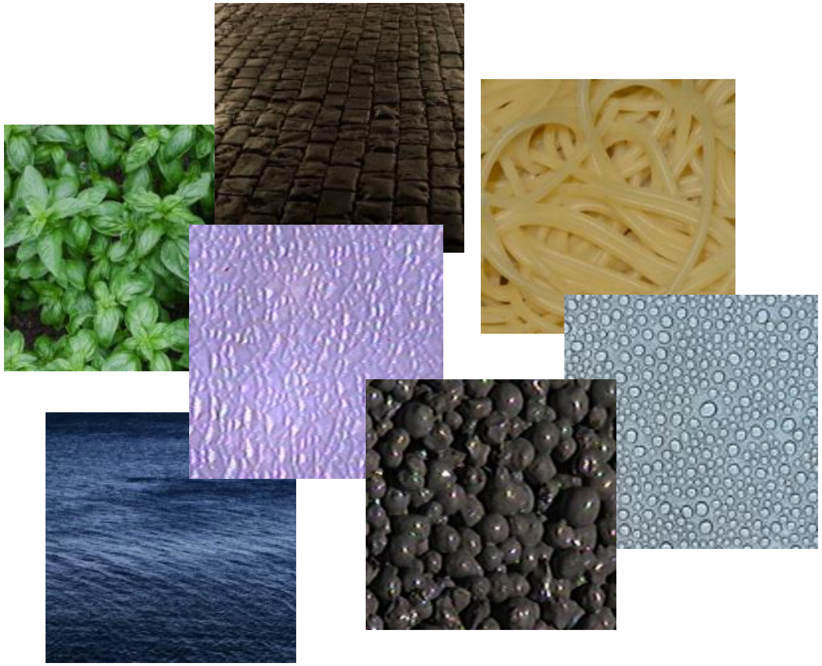
Material Properties

- Texture appearance depends on
  - Material (reflectance, transmittance)
  - Surface geometry
  - Lighting (color, direction, …)
  - Viewing angle
- Difficult to separate
  - “Inverse Optics” approach
  - Computationally intensive
- Rely on natural texture statistics
  - Ecological approach
  - Fast
  - Works most of the time, but …
  - Can make errors (illusions)



Material Properties

- Rely on natural image statistics to estimate specific attributes
  - Roughness
  - Glossiness
  - Directionality
  - Regularity
  - Scale
- Can be estimated/compared outside quantitative range of STSIMs
- Provide strong clues about material properties



Material Properties

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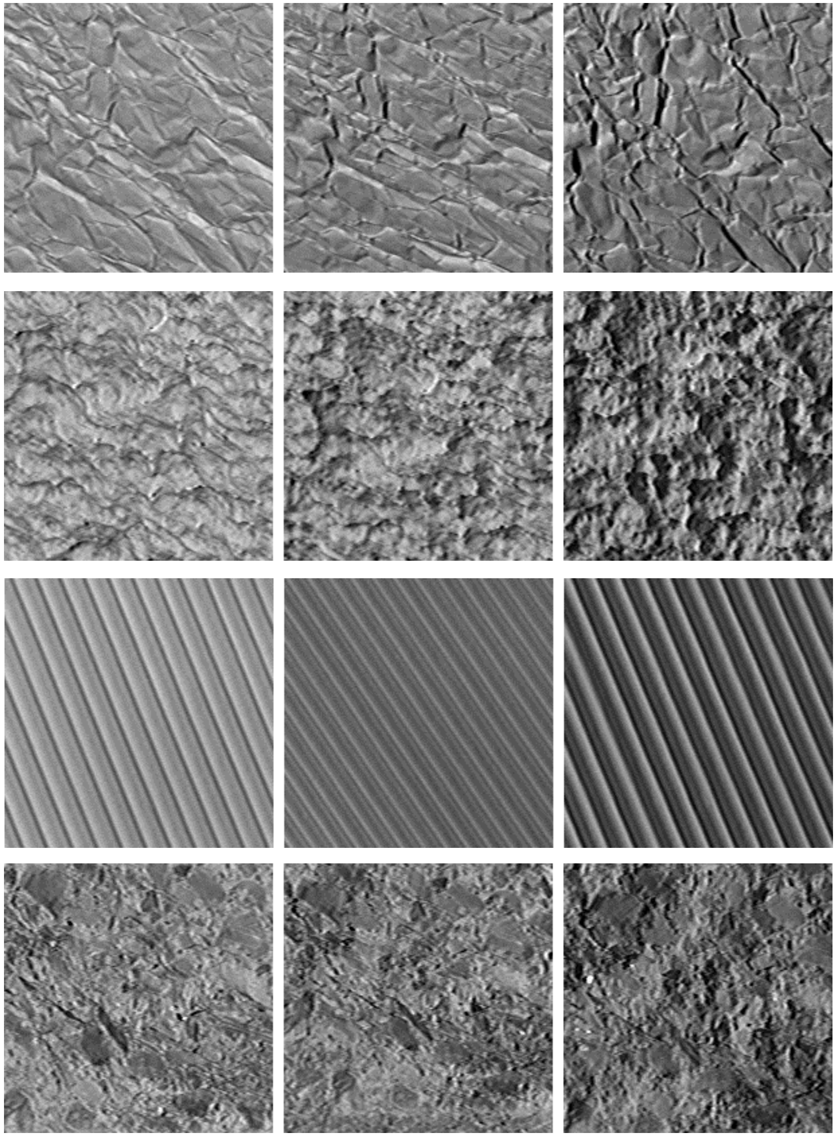
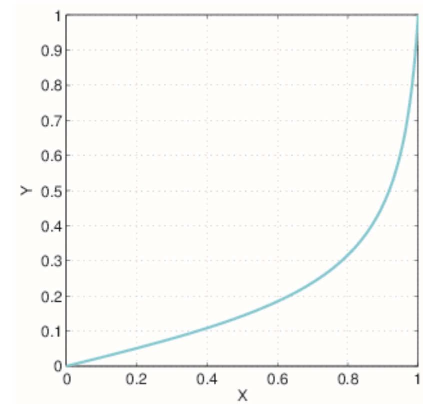


Manipulation on Statistics

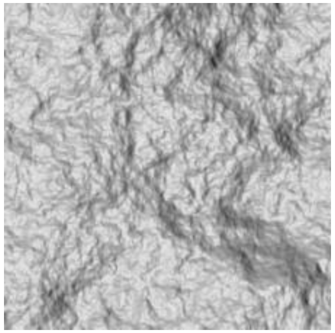
Input Texture → **Statistical analysis**

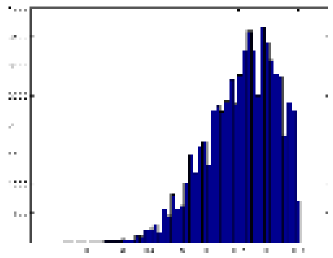
Example: Skewness hypothesis (Motoyoshi et al., 2007)



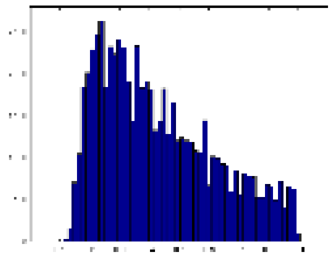
Statistics manipulation → **Gloss manipulation**

Example: λ-curve transformation (Wijntjes & Pont, 2010)

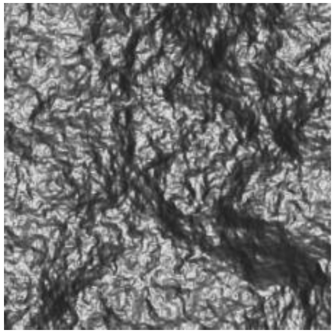




Negative skewness



Positive skewness



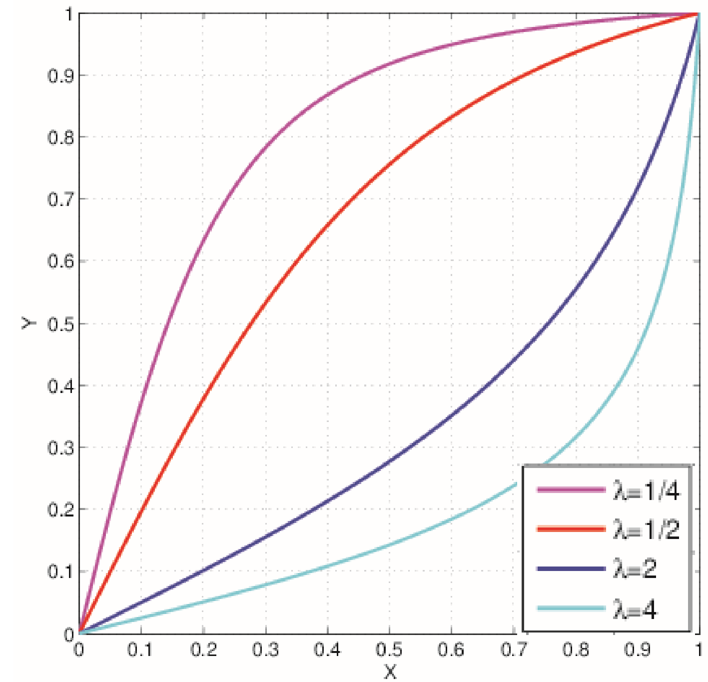
λ-curve Transformation

$$Y = \frac{X}{\sqrt{X^2 + \lambda(1 - X^2)}}$$

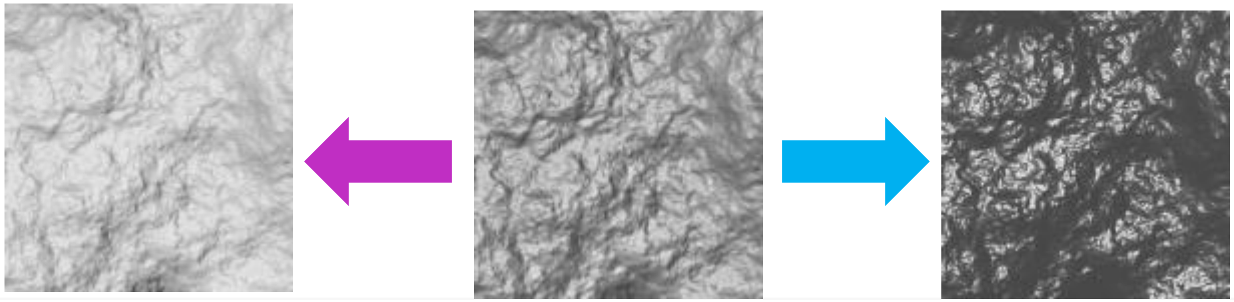
$X, Y \in [0, 1]$ **Input, output values**

$\lambda \in (0, +\infty)$ **Stretch degree in relief depth**

Stretches a Lambertian surface in depth; affects skewness of the luminance histogram



Lambertian surface



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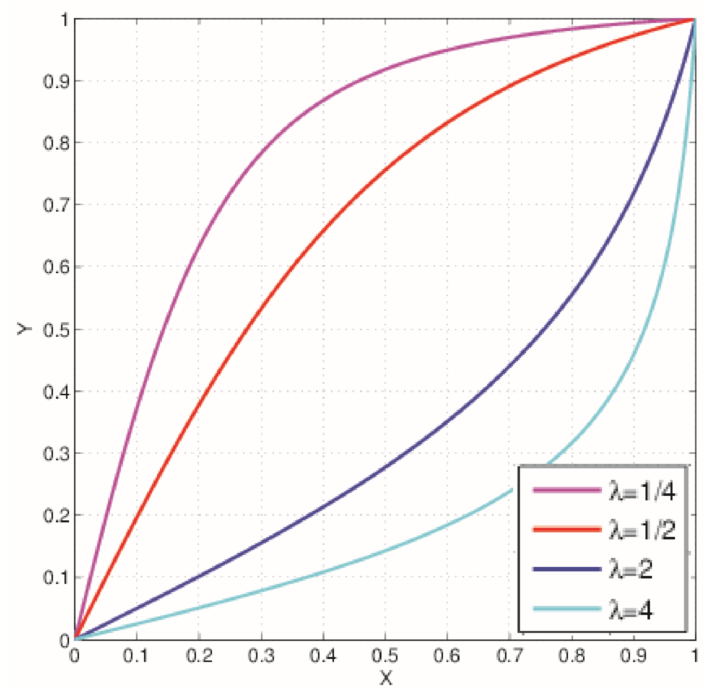
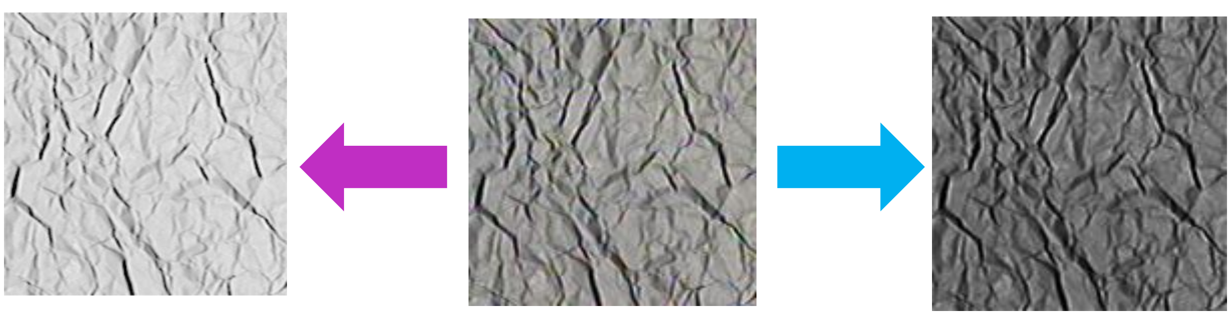


Natural surface



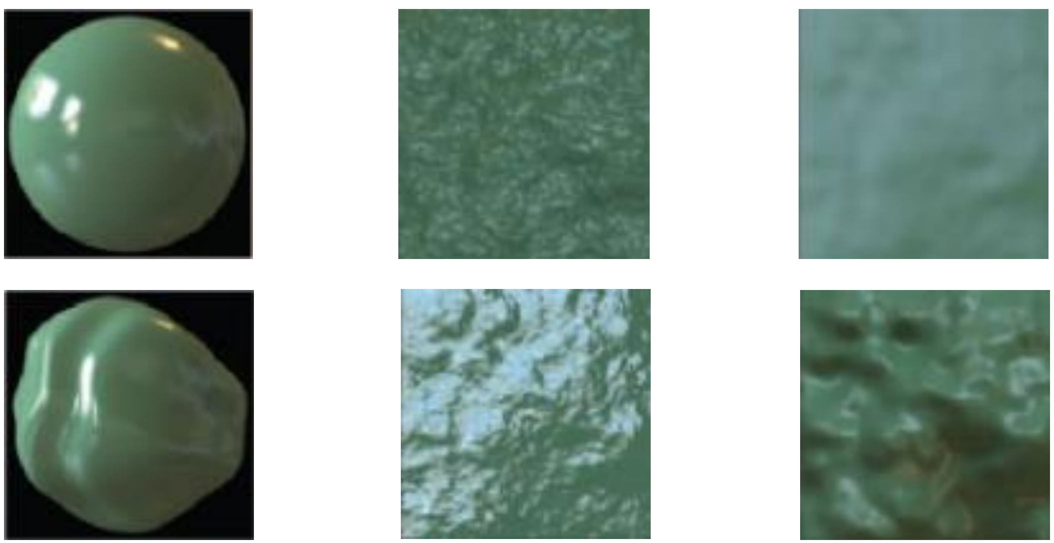
Glossier?

Manipulation on Image Cues

Alternative approach (Marlow and Anderson, 2013):

Input Texture ⇨ **Image cue manipulation** ⇨ **Gloss manipulation**

Image cues: specular coverage, specular contrast, specular sharpness



specular sharpness | specular coverage | specular contrast

Synthetic images: hard to do on natural textures

Motivation

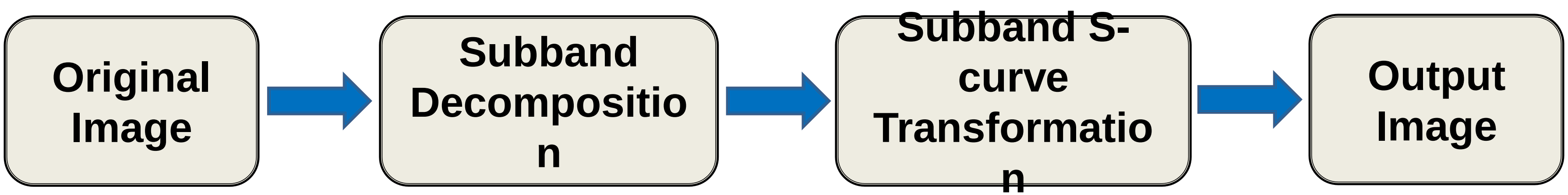
Even though we have multiple gloss related attributes:

- manipulation of gloss is constrained by surface geometry and illumination direction
- it is difficult to control these attributes at the perceptual level

Goal

- Transformation method to manipulate visual gloss of natural textures
- Without constraints on surface geometry and illumination conditions
- Investigate the relation between perceived gloss and perceived contrast

Method

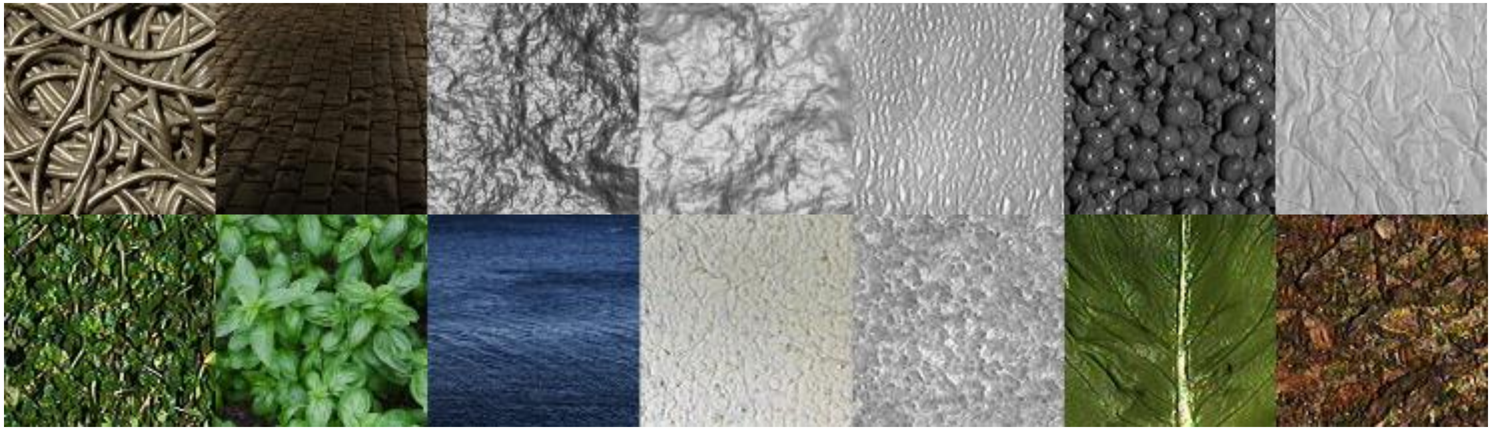


Subjective experiments

- Test the relation between perceived gloss and perceived contrast as you apply the S-curve transformation
- Test whether contrast adjustment could compensate for the gloss difference generated by illumination directions

Stimuli

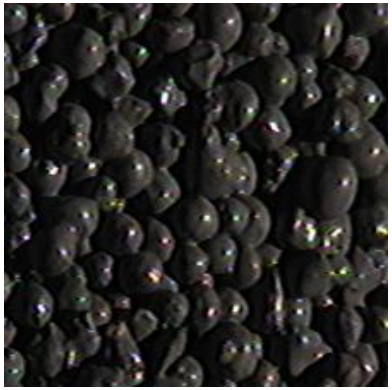
- Collection of natural and synthetic textures (256x256)
- Corbis website (natural, color)
- Pictures of black and white spaghetti (natural, color)
- CUReT texture database (natural, color and grayscale)
  - Illumination: 0.196 radians and 0.589 radians in polar angle
- Synthesized Lambertian surfaces: Rendered Brownian surfaces (grayscale)
  - Illumination: 0 and 50 degrees in polar angle



Examples

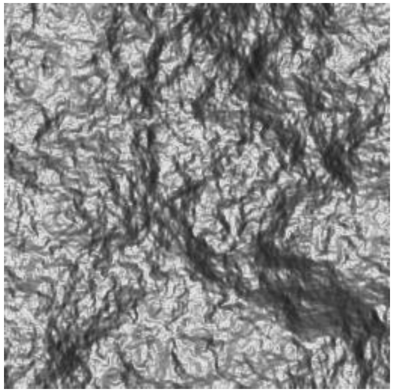
CUReT

0.196 radians



0.589radians

Lambertian



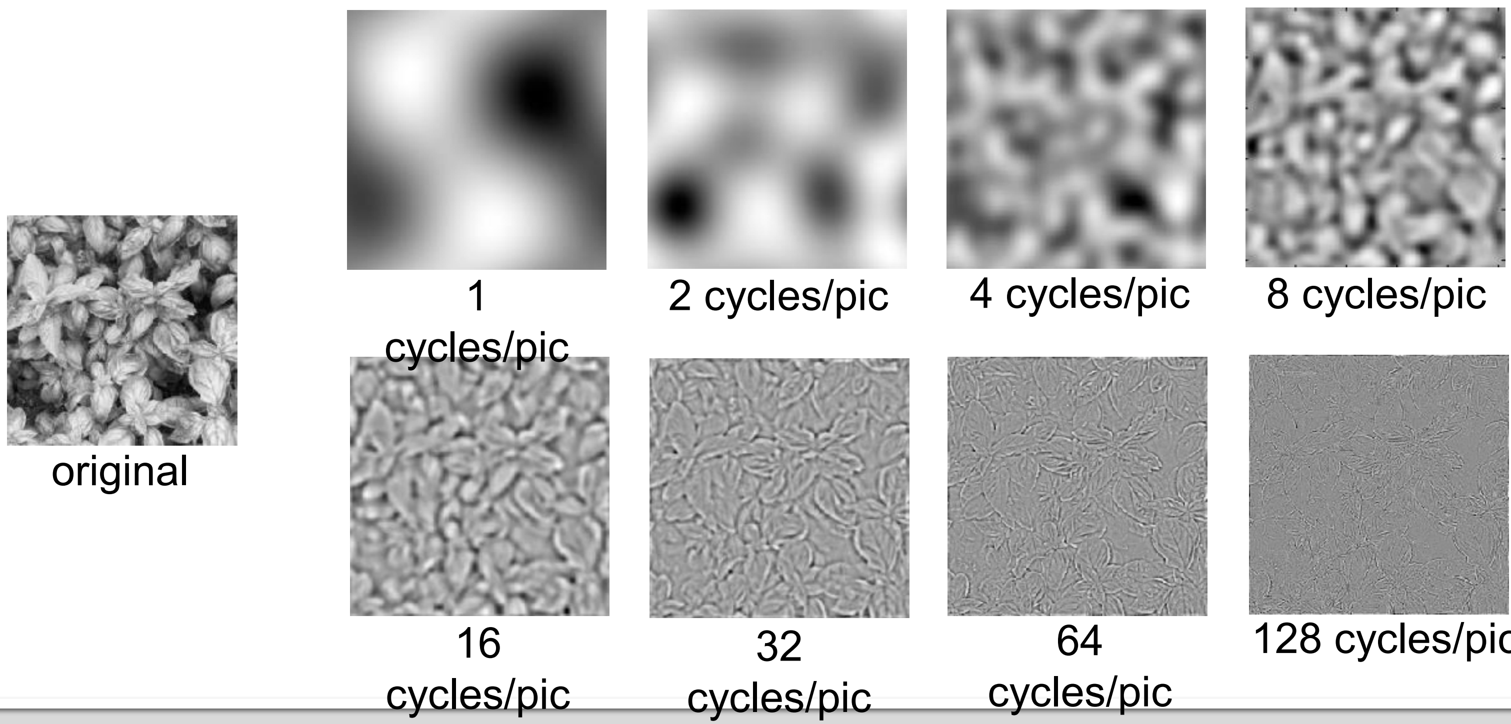
0 degrees

50 degrees

Image decomposition

Raised cosine-log filters of one-octave bandwidth centered at 2^k cycles/picture.

$$G_k(f) = \begin{cases} 0.5 + 0.5\cos(\pi \log_2 f - \pi k)\,, & if\ 2^{k-1} < f < 2^{k-1} \\ 0, & otherwise \end{cases}$$



S-curve Transformation

$$Y = \mu - \frac{\mu - X}{\sqrt{\alpha^2(\mu - X)^2(1 - 1/s^2) + 1/s^2}}$$

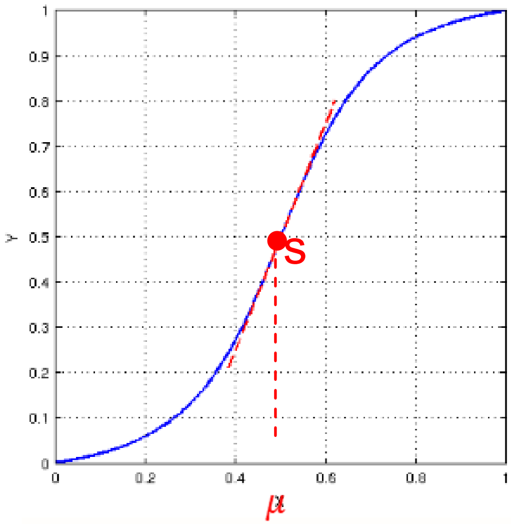
$\boldsymbol{X, Y \in [0, 1]}$ **Input value, output value**

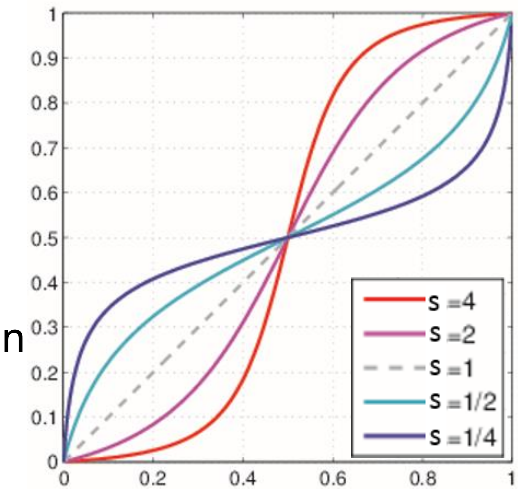
$\boldsymbol{\mu \in (0, 1)}$ **Mean of input values**

$\mathbf{S} \in (\mathbf{0}, \infty)$ **Slope of the curve when** $\boldsymbol{X = \mu}$

$$\boldsymbol{\alpha = \begin{cases} 1/(1-\mu), & if\ X \geq \mu \\ 1/\mu, & if\ X < \mu \end{cases}}$$

s is the sole control parameter controlling the transformation

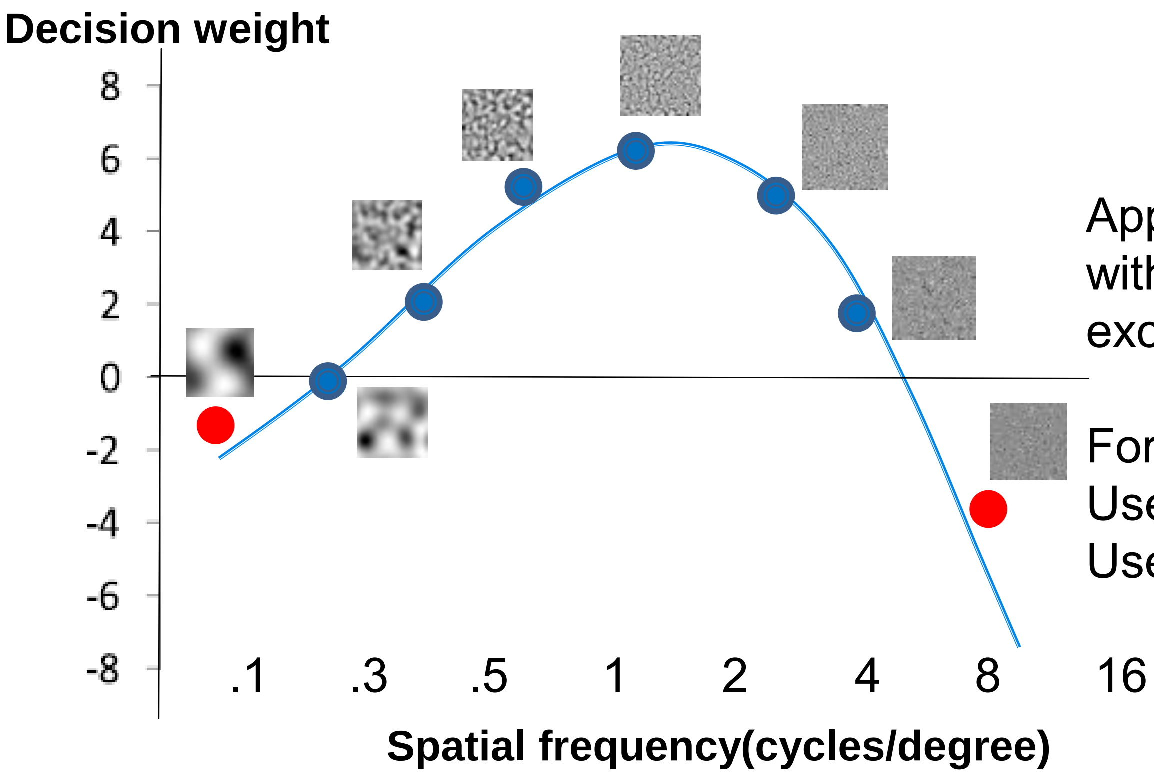




S-curve with different s values

Perceived Contrast Weighting Scheme

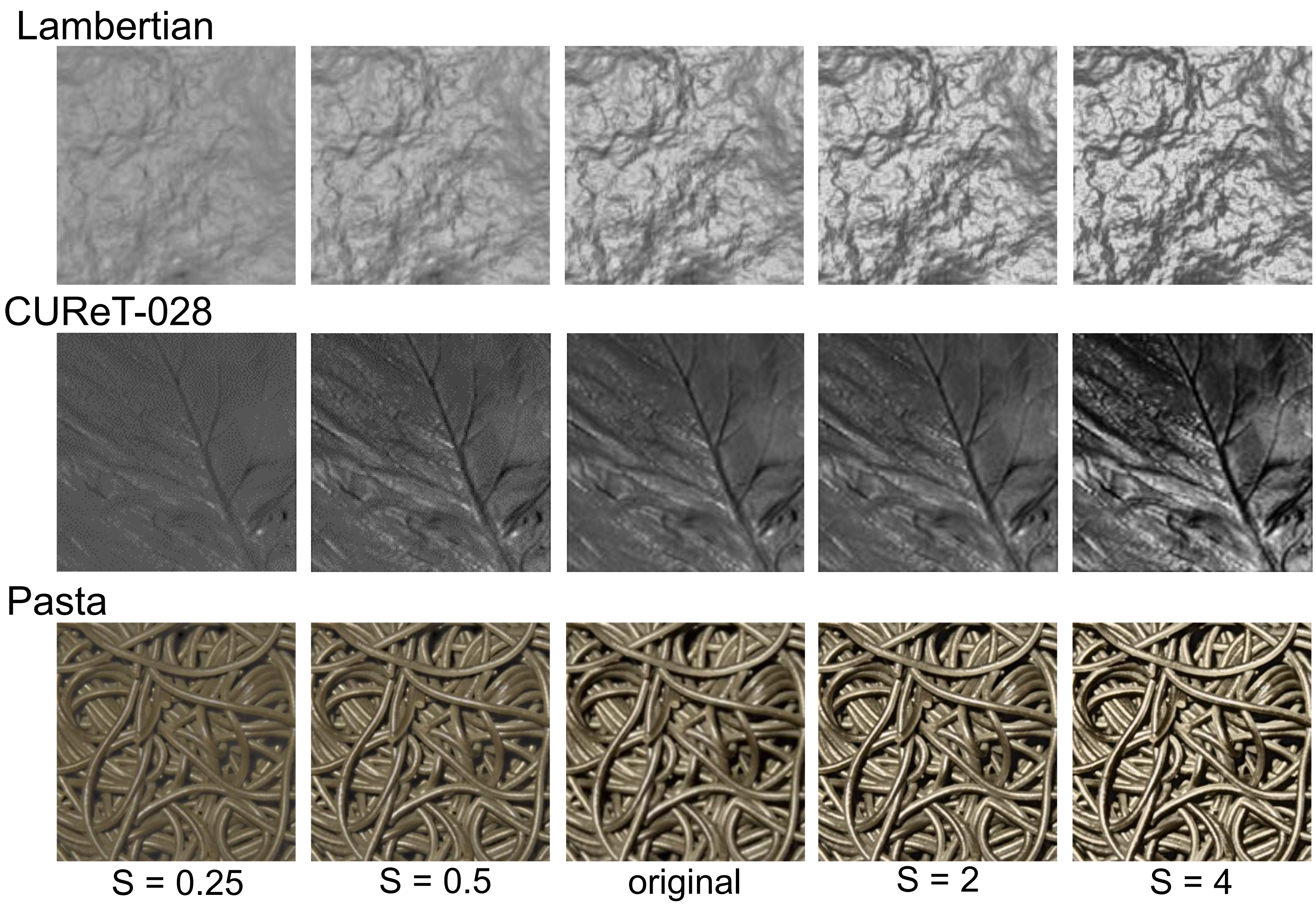
Haun & Peli, 2013:
How do different spatial frequencies contribute to the overall perceived contrast?
Weighting scheme for overall perceptual effect on contrast: Spatial frequencies around the peak of CSF (1-6 cycles/degree) contribute most to contrast perception, low and high frequency bands contribute less.



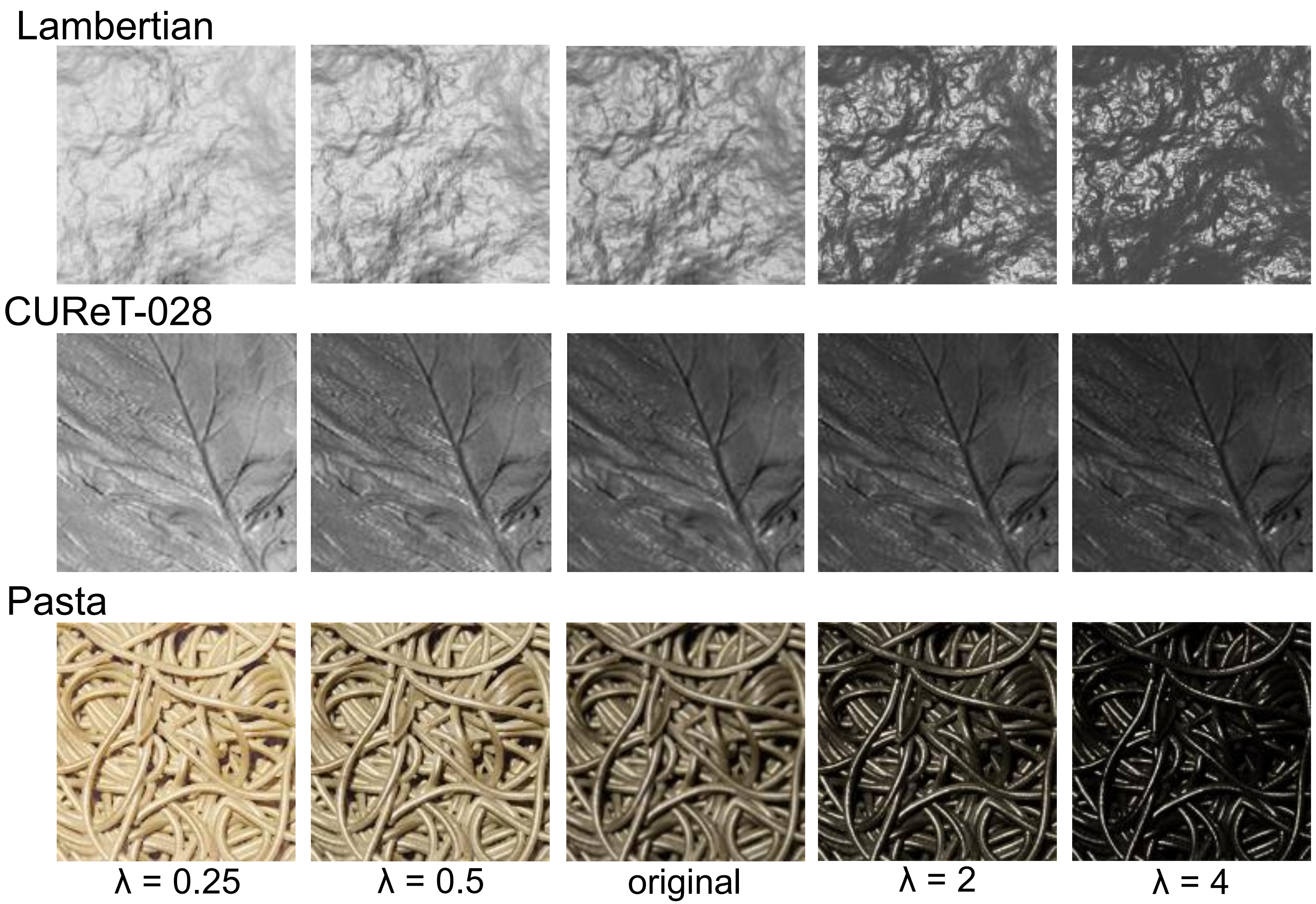
Apply the S-curve transformation with slope S to all frequency bands except the low and high bands

For low and high bands:
Use slope 2 S when S > 1
Use slope .5 S when S < 1

S-curve Transformed Images



λ-curve Transformed Images

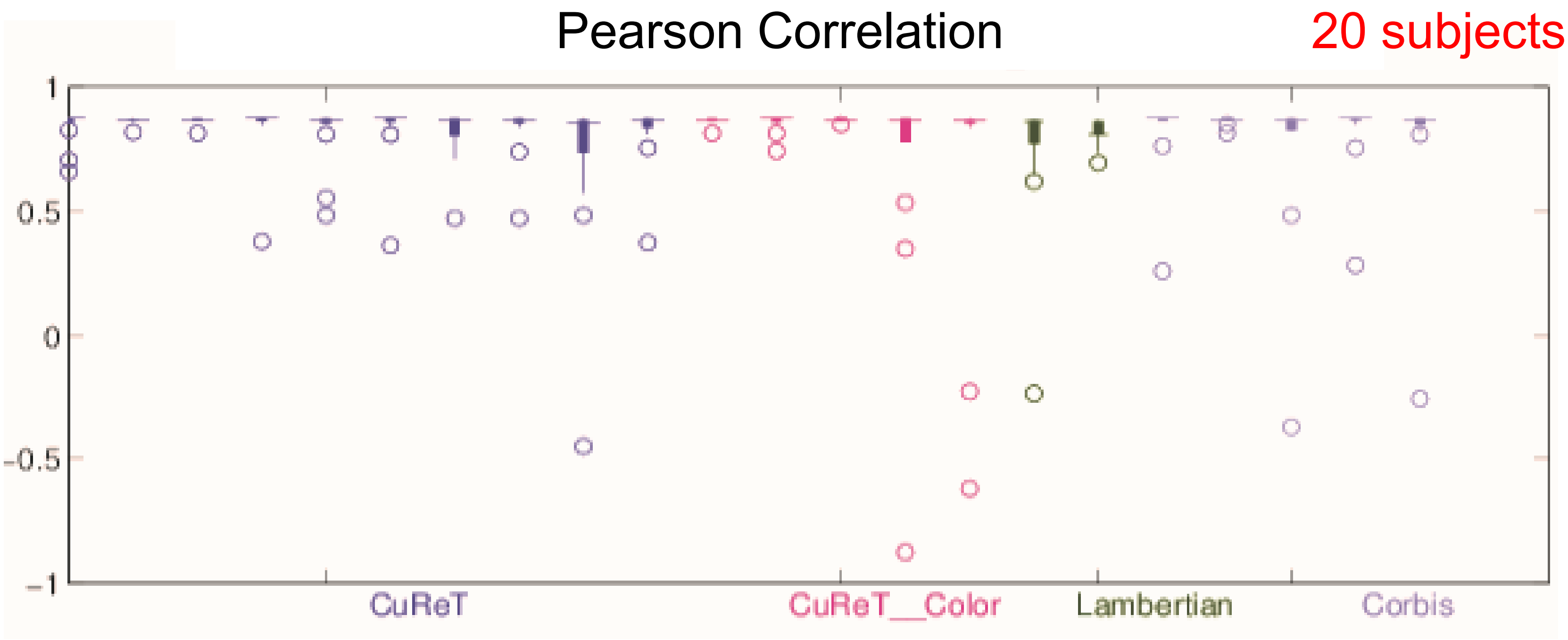


Graphical User Interface: Experiment I

Session 1: Arrange images in order of decreasing gloss
Session 2: Arrange images in order of decreasing contrast

Each trial: Original and six S-curve or λ-curve transformed images in random order
(Use one transformation, S or λ, in each trial)
Random order of curves, random order of images

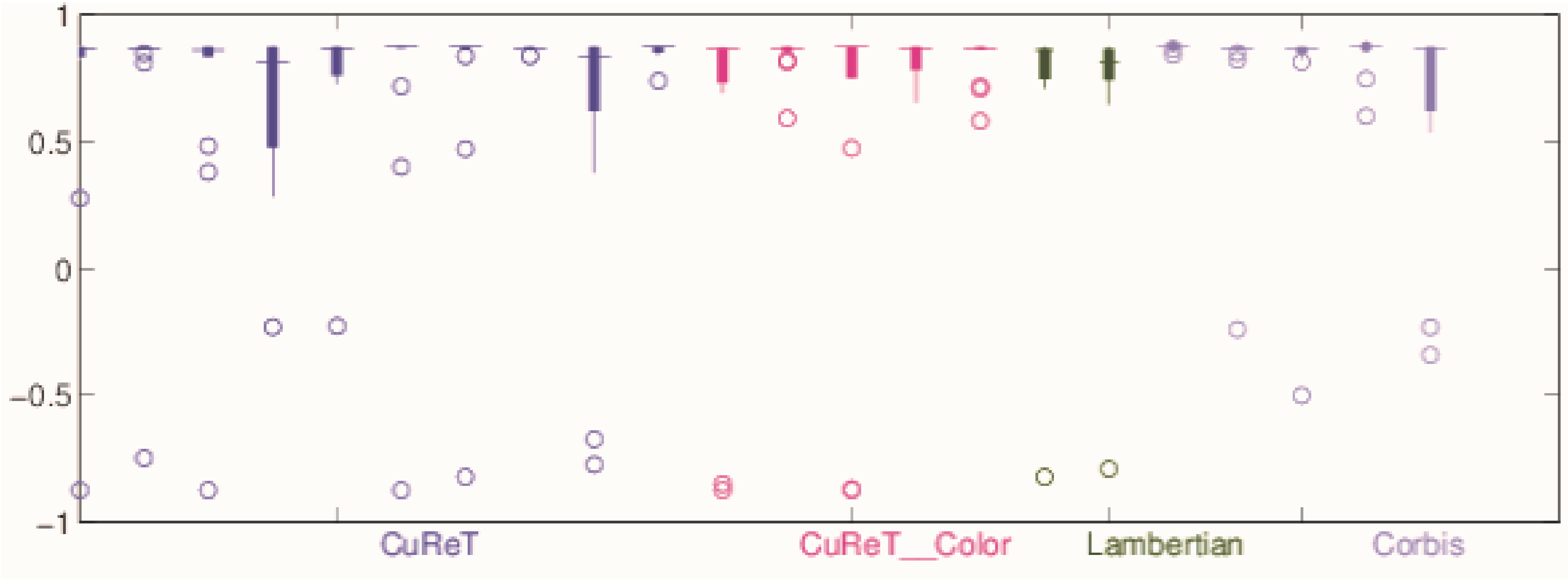
Correlation between S-Curve and Perceived Contrast



- Strong positive correlation between perceived contrast and slope of S-curve

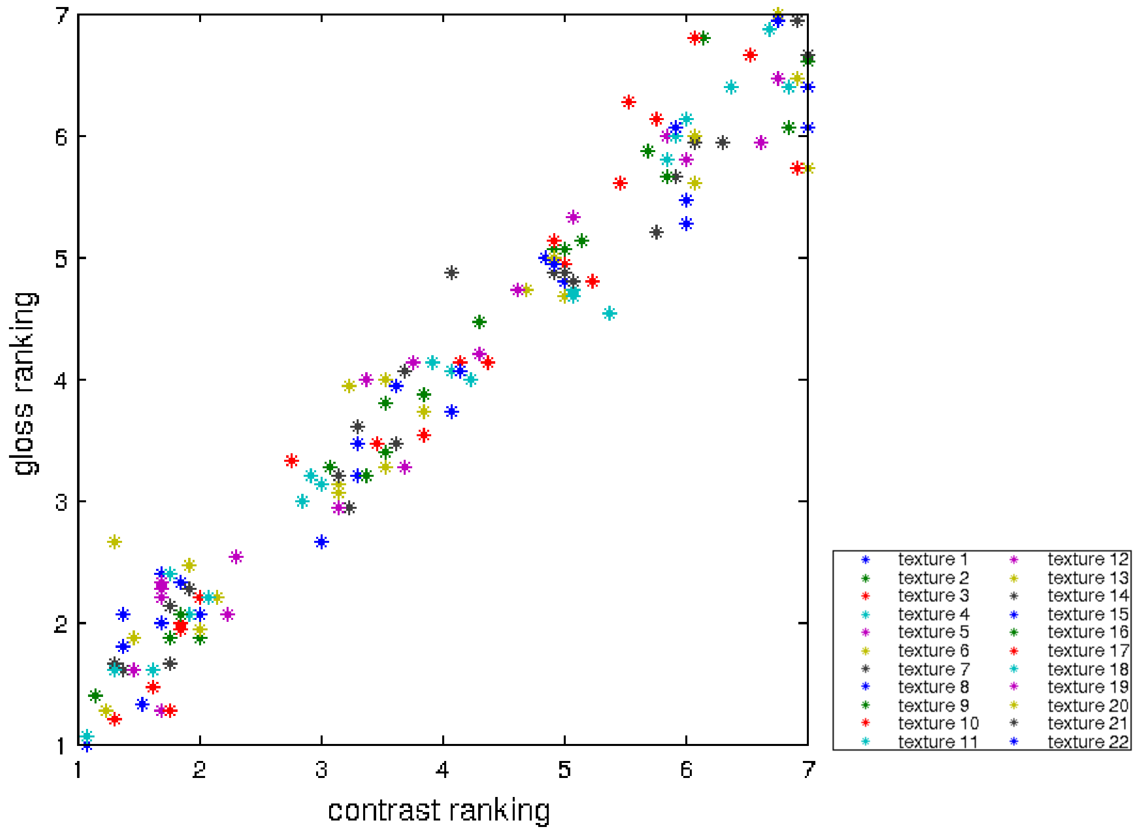
Correlation between S-Curve and Perceived Gloss

Pearson Correlation 20 subjects



- Positive correlation between perceived gloss and slope of S-curve
- But larger variation than contrast
- Perceived contrast and perceived gloss are closely related
- Do people respond to systematic changes rather than gloss or contrast?

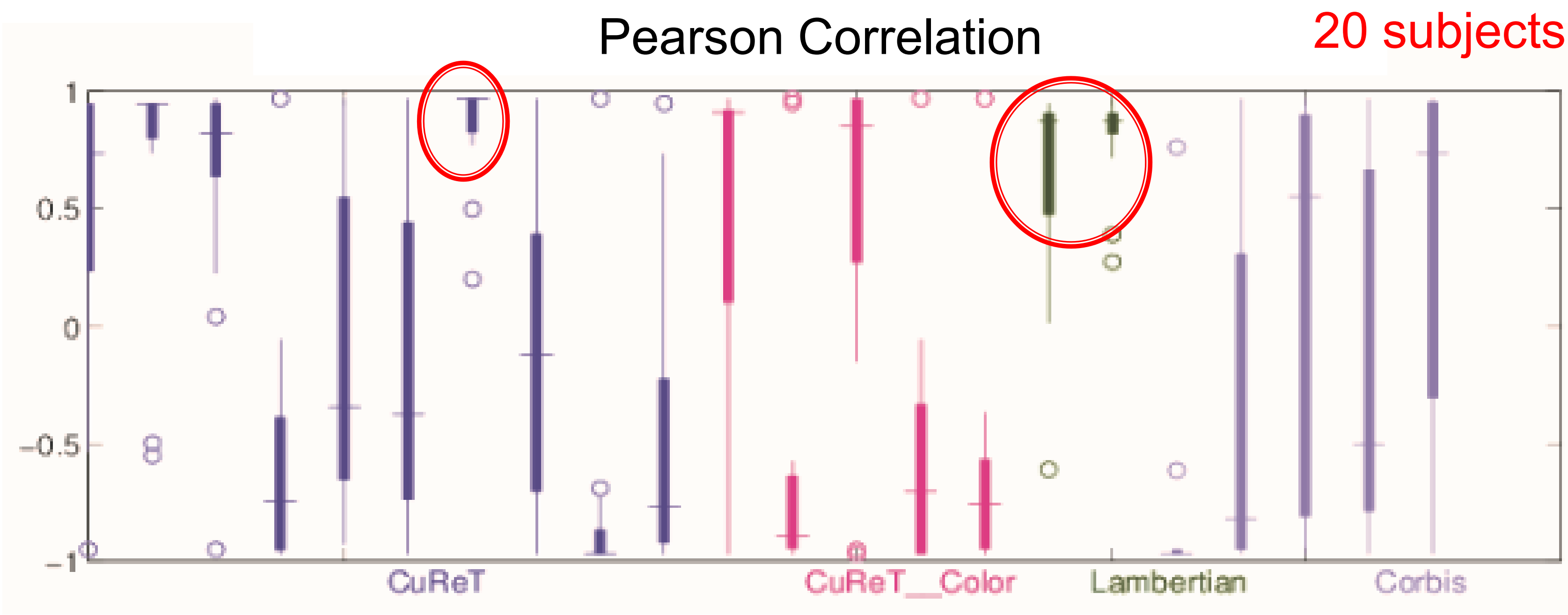
Relation between Perceived Gloss and Perceived Contrast



Average rankings between contrast and gloss in s-curve transformation

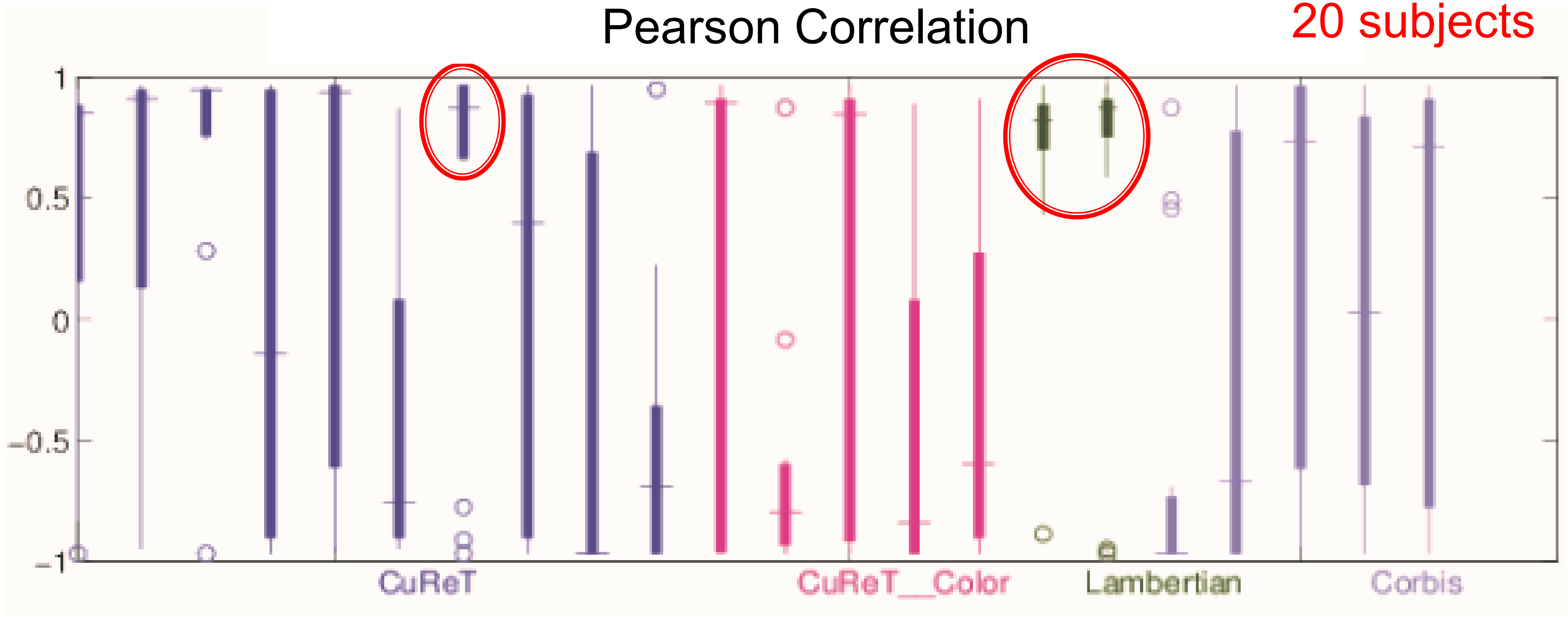
- Within the S-curve transformation, perceived gloss is positively correlated with perceived contrast across different types of textures.

Correlation between λ-curve and Perceived Contrast



- Very little correlation between perceived contrast and slope of λ-curve
- Except for synthetic Lambertian surfaces

Correlation between λ-curve and Perceived Gloss

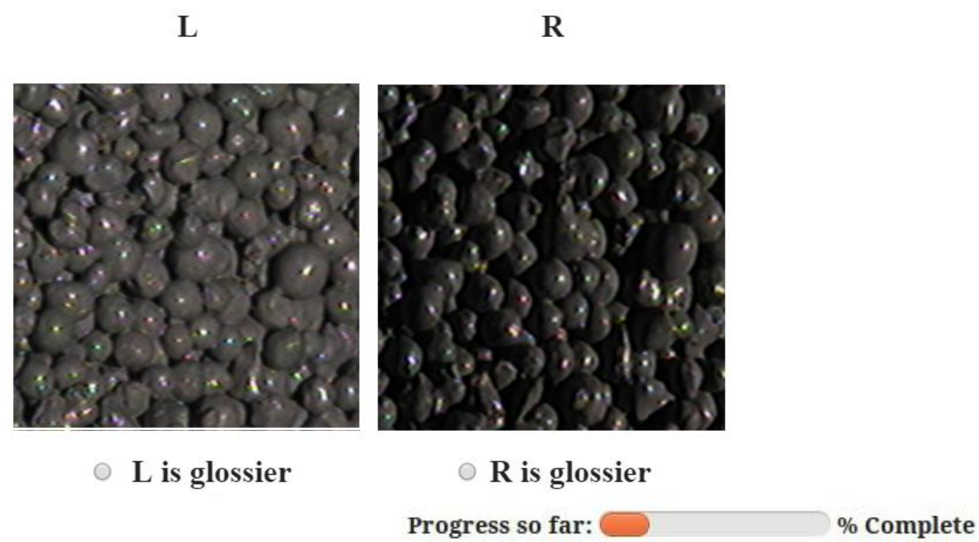


- Very little correlation between perceived contrast and slope of λ-curve
- Except for synthetic Lambertian surfaces
- Controlling histogram skewness, the λ-curve is not sufficient to manipulate the perceived gloss of natural textures

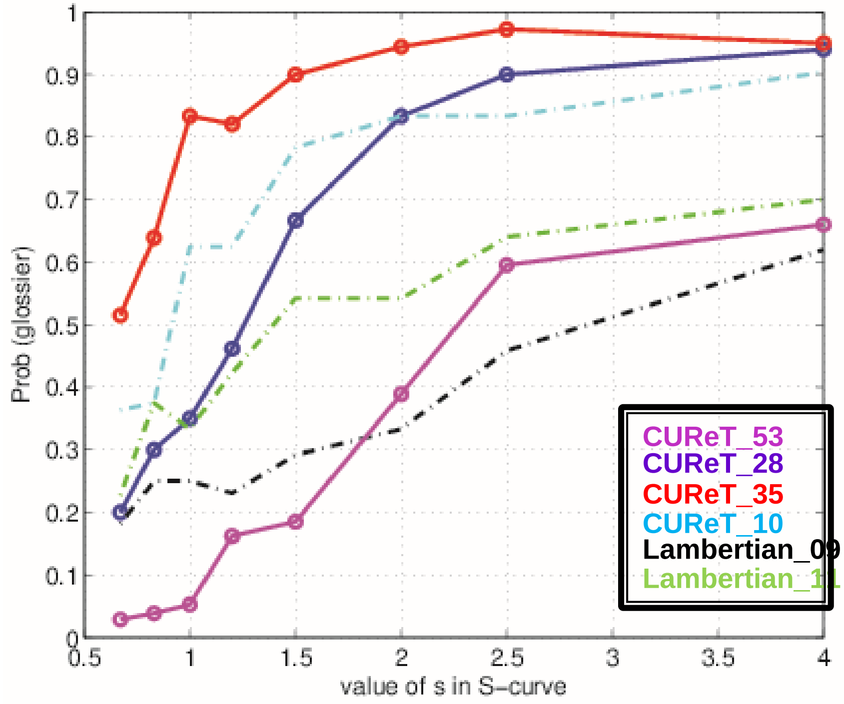
Graphical User Interface: Experiment II

Gloss matching: Pairwise comparison

Each trial: one original image in oblique illumination direction and one S-curve transformed version in near-frontal illumination



Experimental Results



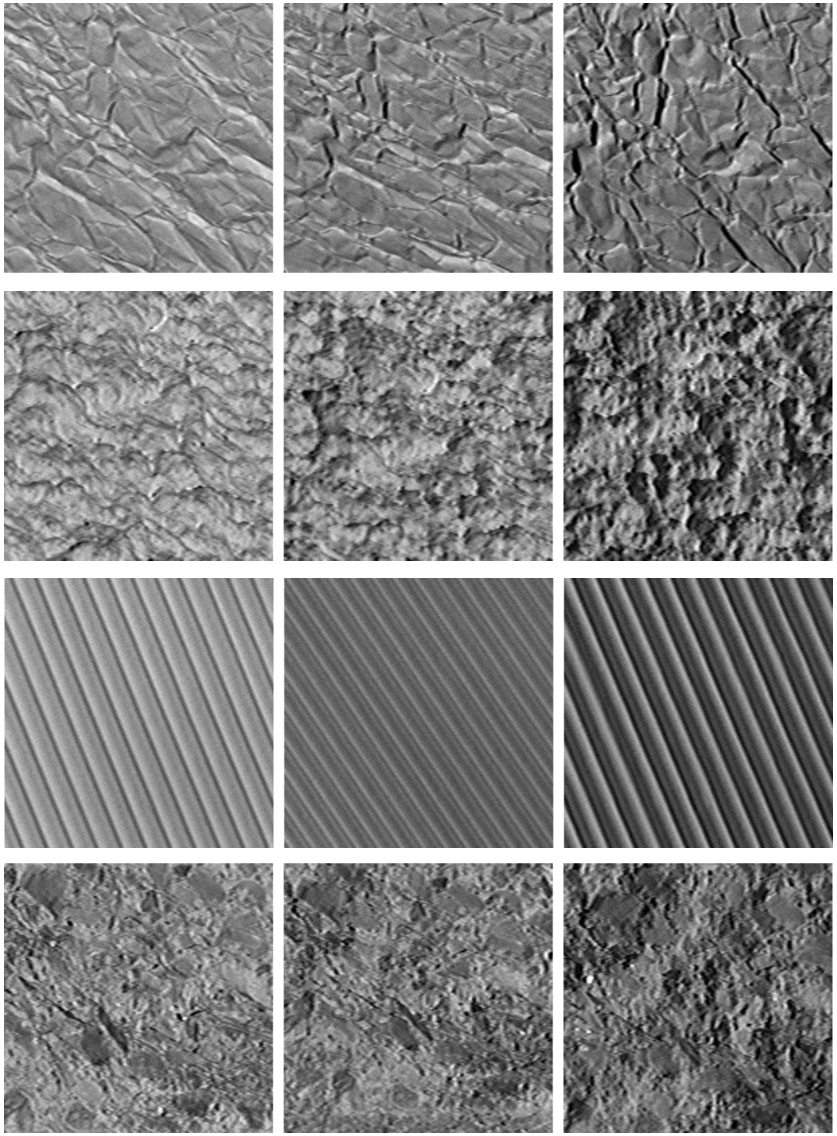
Probability that frontal illuminated texture was selected as glossier

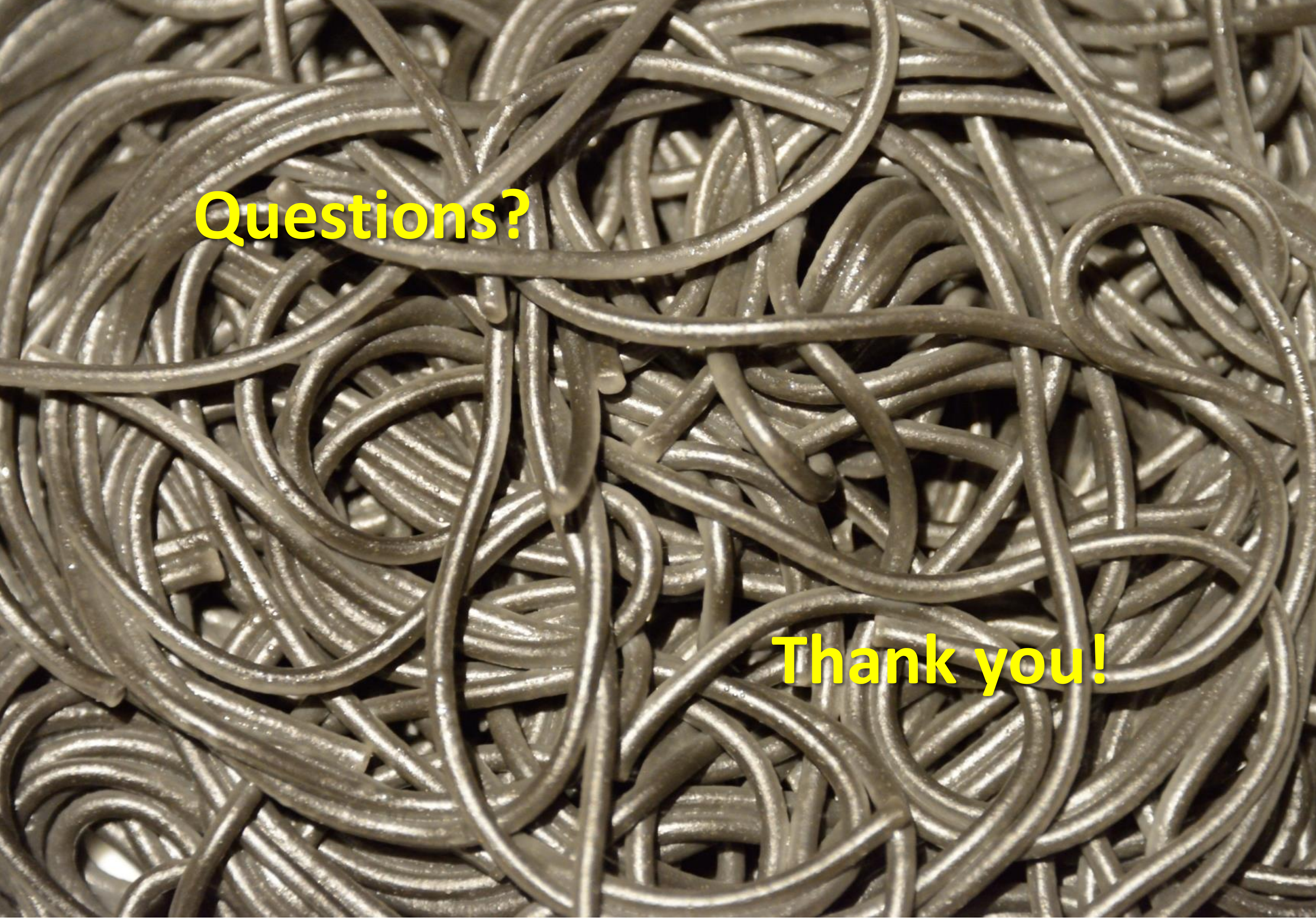
Conclusions

- We proposed a novel transformation method to manipulate the perceived gloss of natural textures with unknown geometry and illumination field.
- Natural textures behave differently than synthesized Lambertian surfaces.
- There is a strong positive correlation between perceived gloss and perceived contrast across different types of images including Lambertian surface.
- Contrast modification could compensate for gloss difference generated due illumination directions, within a certain range of directions

Material Properties

- Texture appearance depends on material, surface geometry, and lighting
- Difficult to separate
- Rely on image statistics to estimate specific attributes
  - Roughness
  - Glossiness
  - Directionality
  - Regularity
  - Scale
- Can be estimated/compared outside quantitative range of STSIMs
- Provide strong clues about material properties




Questions?
Thank you!

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