New Texture Similarity Metrics

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CSP Seminar

Oct 23, 2014

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Northwestern: Thrasos Pappas, Jana Zujovic,

Xiaonan Zhao, Guoxin Jin

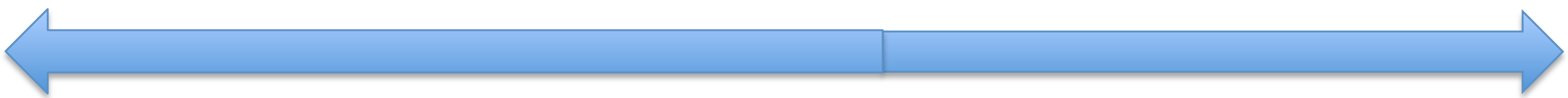
My Interests in Perceptual Similarity Measures

- Going way back
  - Lossy source coding (data compression)
  - Audio coding for digital jukebox
  - Image coding for FAX transmission
  - Halftoning
- Recent
  - Compressing images containing texture
  - Textured image retrieval
  - Texture classification

Research Spectrum: Analytical to Qualitative

much of my work

this work



analytical

qualitative

Precise mathematical formulations
Idealized, tractable models
Idealized, tractable performance measures
Definitions, derivations, theorems, proofs
Provably good methods/algorithms.
Clear understanding of how/why things work
Limited practical relevance

Rough formulations
Vague, qualitative models
Actual real-world data
Vague definitions
Intractable performance measures
Ad Hoc algorithms
Proof is in the pudding; success is in the eye of the beholder
Basis of success/failure not so clear
Direct practical relevance

Uses of Image Metrics

- Assess performance of image processing methods/systems.
  - Eliminate burden of human subjective assessments.
- Enable optimization (rare outside of MSE based metrics)
- Serve as a component of an image processing system
  - Restoration
  - Content based image retrieval
  - Classification
  - Lossy compression/coding
  - Question: If a metric is used as a system component, can it also be used to judge the performance of the system?

This talk

- Some metrics symmetrically assess similarity, i.e., $S(X,Y) = S(Y,X)$.
- Some (asymmetric) metrics assess quality of Y as reproduction of X.
- "No reference metrics" assess quality of Y all by itself.
- Almost none are "metrics" in the mathematical sense.

This talk

Goals of Image Similarity Metrics

- Reflect human perception/judgments
  - produce values monotonically related to human scoring
- Low computational and/or conceptual complexity
- Analytical tractability to permit analytical optimization (rare)
- Make system that uses it as a component work well
- Specialize to individual applications
- Possible invariance properties to have or not
  - rotation
  - spatial scaling
  - amplitude scaling (contrast)
  - amplitude shifting

This talk

Testing/Assessing Image Metrics

- Correlate metric values with subjective assessments by people
- Assess the performance of a system that uses the metric
  - Retrieval
  - Compression
  - Classification
  - Restoration

This talk

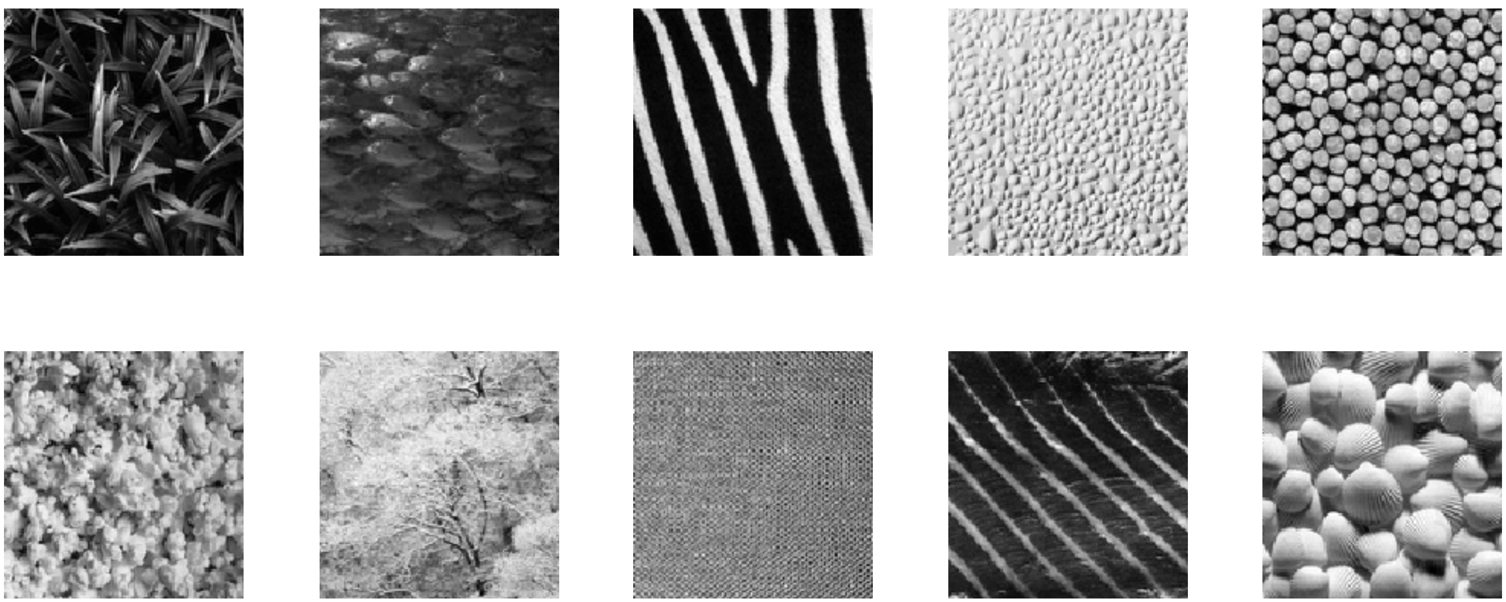
Our Goal: Similarity Metrics for Texture

- What is texture?

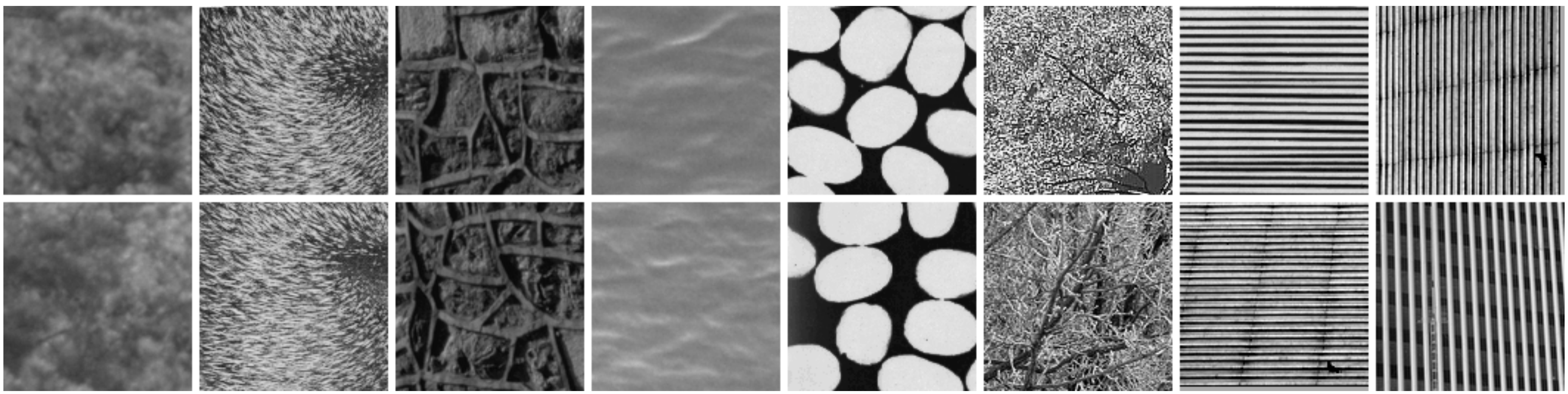
  "Loosely speaking, texture images are spatially homogeneous and consist of repeated elements, often subject to some randomization in their location, size, color, orientation, etc."

  [Portilla, Simoncelli, *Int. J. Comput. Vis.*, Oct. 2000]

- Textures are images for which point-by-point metrics like MSE are least relevant. (MSE can be very large for "identical" textures.)



Examples of “Similar Textures” that are not similar in MSE



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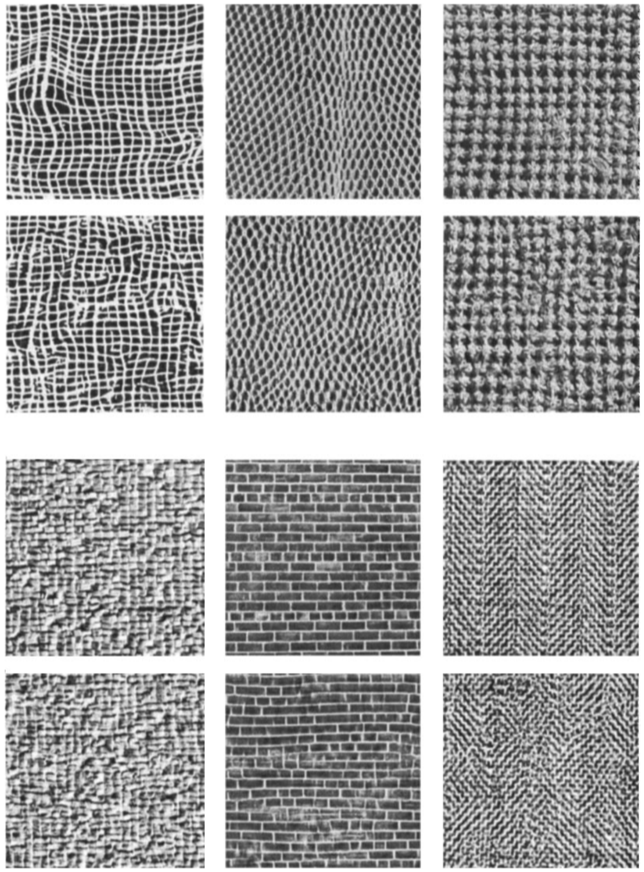


Figure 14. Synthesis results on photographic pseudo-periodic textures. See caption of Fig. 12.

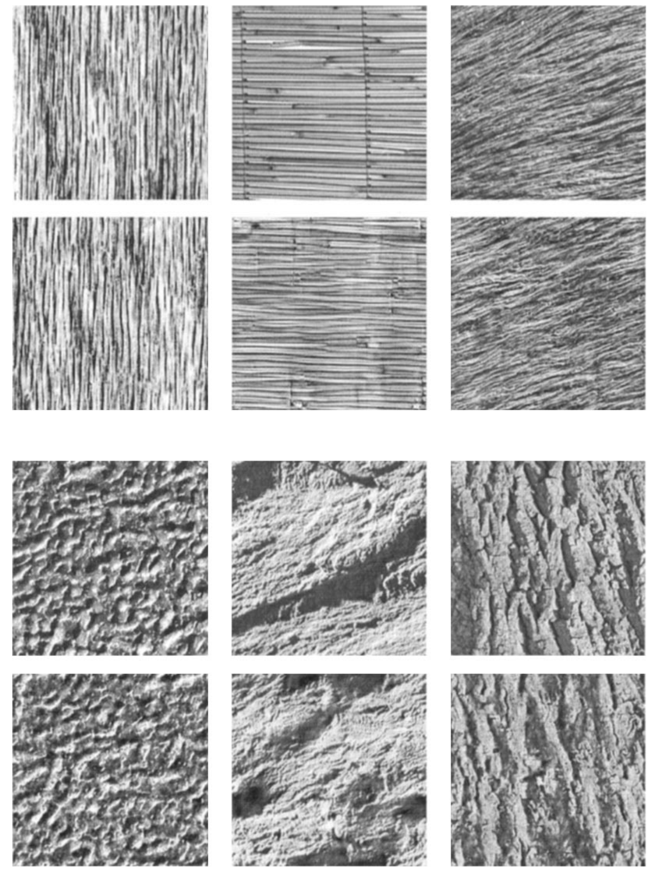


Figure 15. Synthesis results on photographic aperiodic textures. See caption of Fig. 12.

Image Metric Themes

- Much recent interest in metrics of the following types
  - Structural Similarity Image Metrics
    - SSIM: [Wang, Bovik, Sheikh, Simoncelli, *IEEE Tr. Im. Proc.*, 2004]
  - Local Pattern Metrics for texture similarity (my term)
    - Local Binary Patterns (LBP): [Ojala, Pietikainen,Maenpaa, *IEEE Tr. PAMI*, 2002]
  - Both of these are, largely, sliding statistic/feature based, instead of point-by-point comparison based
  - Both are applicable to textures

- This talk: Two new metrics of texture similarity, one of each type
  - STSIM: Structural Texture Similarity Metric
  - LRI: Local Radius Index

Outline

- Review
  - Point-by-point metrics
  - SSIM (Structural Similarity Metric)
- STSIM (Structural Texture Similarity Metric): new SSIM type metric:
  - Performance in identical texture retrieval and image compression
- Review
  - LBP (Local Binary Patterns)
- LRI (Local Radius Index): new local-pattern metric
  - Performance in identical texture retrieval and image coding
- RI-LRI (Rotation invariant LRI):
  - Performance in texture classification
- Concluding remarks

Review: Point-by-Point Metrics

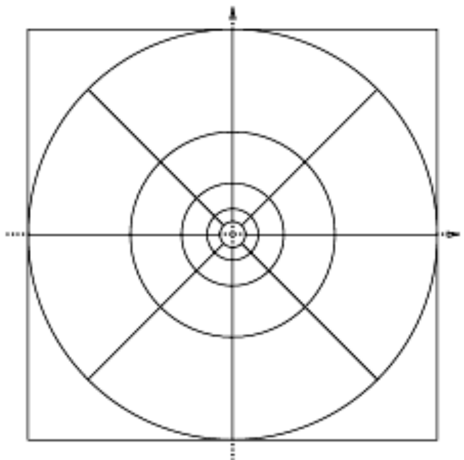
- Given N x N image X and reproduction Y
- MSE: $$\text{MSE}(X,Y) = \frac{1}{N^2}\sum_i \left(X_i - Y_i\right)^2$$
- Frequency weighted MSE: $$\text{FW-MSE}(X,Y) = \frac{1}{N^2}\sum_j w_j\left(\overline{X}_j - \overline{Y}_j\right)^2$$

$\overline{X}$ and $\overline{Y}$ are coefficients in a transform or subband decomposition

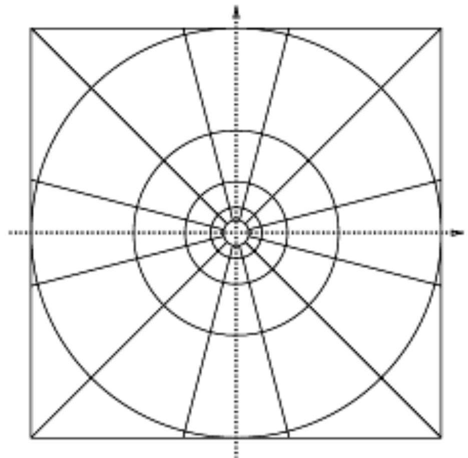
Weight w_j can depend on sensitivity of visual perception to changes in coef. $\overline{X}_j$ and the value of $\overline{X}_j$ and neighboring $\overline{X}_j$'s, i.e. w_j can reflect masking effects.

Some Frequency Decompositions

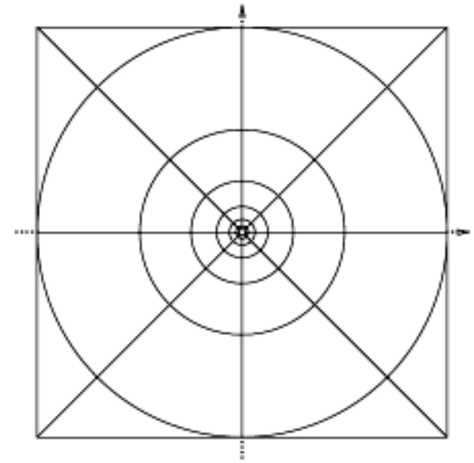
Cortex (Watson'87)



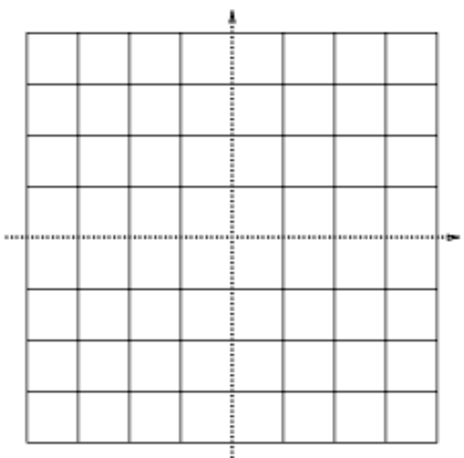
Cortex (Daly'92)



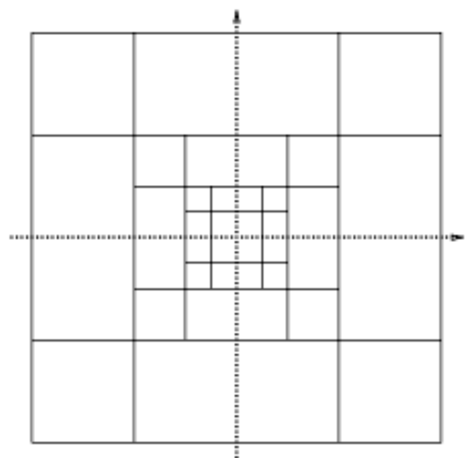
Lubin'91



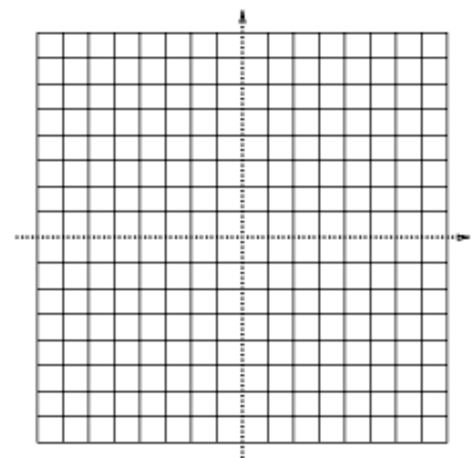
4x4 Subband



Wavelet



8x8 DCT



Review: The Original SSIM[1]

- Given images X and Y, to compute SSIM(X, Y):
  - Slide NxN window across each in steps of s, e.g. $N = 8$ to 32, $s = N/2$
  - For n-th window position, compute:
    - *luminances* (means) $m_{X,n} = \frac{1}{N^2}\sum_i X_{n,i}$ $\quad m_{Y,n} = \frac{1}{N^2}\sum_i Y_{n,i}$
    - *contrasts* (variances) $c^2_{X,n} = \frac{1}{N^2}\sum_n \left(X_{n,i} - m_{X,n}\right)^2$ $\quad c^2_{Y,n} = \frac{1}{N^2}\sum_n \left(Y_{n,i} - m_{Y,n}\right)^2$
    - statistic similarities: $M_n = \frac{2\, m_{X,n}\, m_{Y,n} + \varepsilon}{m^2_{X,n} + m^2_{Y,n} + \varepsilon}$ $\quad C_n = \frac{2\, c_{X,n}\, c_{Y,n} + \varepsilon}{c^2_{X,n} + c^2_{Y,n} + \varepsilon}$

      $\frac{\text{geom. mean}}{\text{arith. mean}}$
    - *structure* (crosscorrelation): $S_n = \dfrac{\frac{1}{N^2}\sum_i \left(X_{n,i} - m_{X,n}\right)\left(Y_{n,i} - m_{Y,n}\right) + \varepsilon}{c_{X,n}\, c_{Y,n} + \varepsilon}$
    - window similarity: $W_n = \left(M_n\, C_n\, S_n\right)^{1/3}$
  - Pool window similarities over all positions: $\mathrm{SSIM}(X,Y) = \frac{1}{\#\,\text{positions}}\sum_n W_n$
  - $0 \leq \mathrm{SSIM} \leq 1$. 1 = highest quality, 0 = lowest

[1]Wang, Bovik, Sheikh, Simoncelli, *IEEE Tr. Im. Proc.*, 2004

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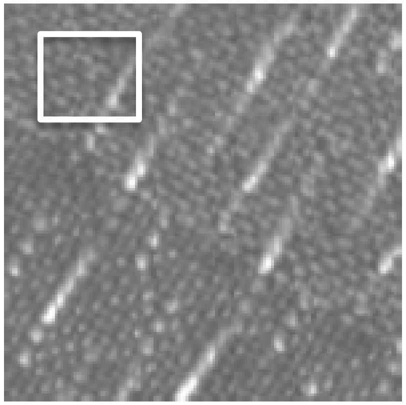
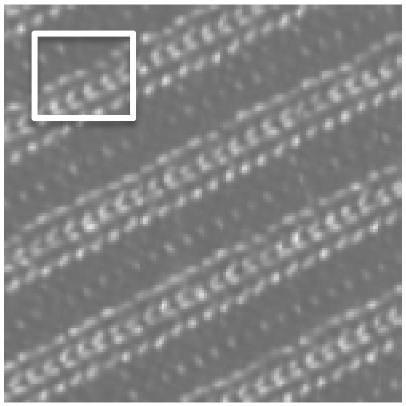
      geom. mean / arith. mean
    - *structure* (crossc X $$\frac{\frac{1}{N^2}\sum_i \left(X_{n,i} - m_{X,n}\right)\left(Y_{n,i} - m_{Y,n}\right) + \varepsilon}{\quad}$$



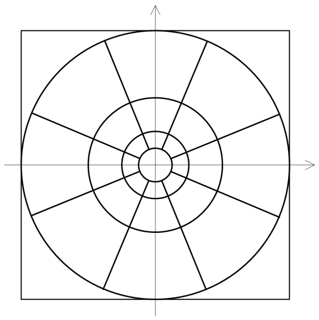
    - window similarity: $S_n)^{1/3}$
  - Pool window similar s: S — ns $\sum_n W_n$
  - $0 \leq$ SSIM ≤ 1. 1 = lowest



WHY?

[1] Wang, Bovik, Sheikh, Simoncelli, *IEEE Tr. Im. Proc.*, 2004

SSIM Improvements



- CW-SSIM (Complex Wavelet SSIM)[1]
  - Apply SSIM (without luminance) to 7x7 windows of each subband of *steerable pyramid* wavelet/subband decomposition,
  - For example, 12 bands, 3 scales, 4 orientations, no lowpass or highpass bands.
  - Magnitude of the structure/crosscorrelation terms
  - Pool over subbands.
  - Advantage: Does not penalize small spatial shifts, rotations, scalings.
- Many other improved versions of SSIM

[1]Sampat, Wang, Gupta,. Bovik & Markey, *IEEE Tr. Im. Proc.*, Nov. 2009

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Thrasos Pappas

Jana Zujovic

STSIM for Textured Images

- Structural Texture Similarity Metric (STSIM)[1]
  - Start with CW-SSIM (based on steerable pyramid decomposition)
  - Discard "structure" terms –-- they are not even "statistics"
  - Add lag 1 autocorrelations as statistics

horizontal

$$\rho_{H,n} = \frac{\frac{1}{N^2}\sum_{i,j}\left(X_{n,i,j} - m_n\right)\left(X_{n,i,j+1} - m_n\right)^*}{c_{X,n}^2}$$

vertical

$$\rho_{V,n} = \frac{\frac{1}{N^2}\sum_{i,j}\left(X_{n,i,j} - m_n\right)\left(X_{n,i+1,j} - m_n\right)^*}{c_{X,n}^2}$$

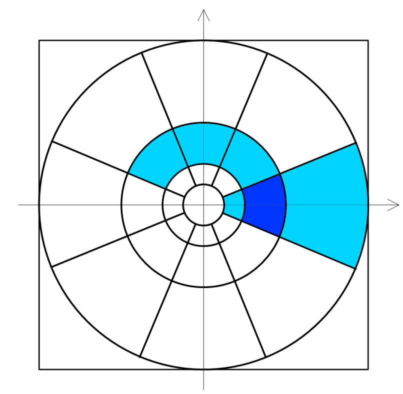
  - Autocorrelation similarity: $R_{H,n} = 1 - \frac{1}{2}\left|\rho_{X,H,n} - \rho_{Y,H,n}\right|$
  - 56 statistics total
  - Geometric mean pooling of statistic similarity for each window position
  - Arithmetic average pooling over window positions
  - Or, for homogeneous textures, treat entire image as one window

[1]Zhao, Reyes, Pappas, Neuhoff, ICIP, Oct. 2008

STSIM2[1] for Textured Images

- To STSIM, add
  - Add interband crosscorrelations (of magnitudes) between bands of pyramid decomposition of image *X*. Same for *Y*.

$$l_n^{(k,l)} = \frac{\frac{1}{N^2}\sum_i \left(\left|X_{n,i}^{(k)}\right| - m_n^{(k)}\right)\left(\left|X_{n,i}^{(l)}\right| - m_n^{(l)}\right)}{c_{X,n}^{(k)}\, c_{X,n}^{(l)}}$$



  - Between
    - all pairs of bands within each scale
    - bands at adjacent scales with same orientation
  - Same similarity scoring as for autocorrelations
  - 82 statistics total
  - Geometric mean pooling of statistic similarity for each window position
  - Arithmetic average pooling over window positions
  - Or, for homogeneous textures, treat entire image as one window

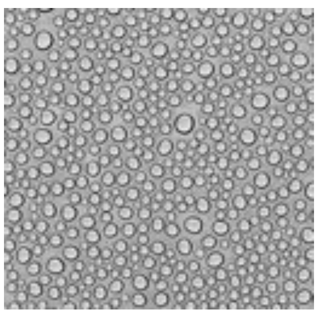
[1] Zujovic, Pappas, Neuhoff, *IEEE Tr. Im. Proc.*, 2013.

Metric Test: Identical Texture Retrieval[1]

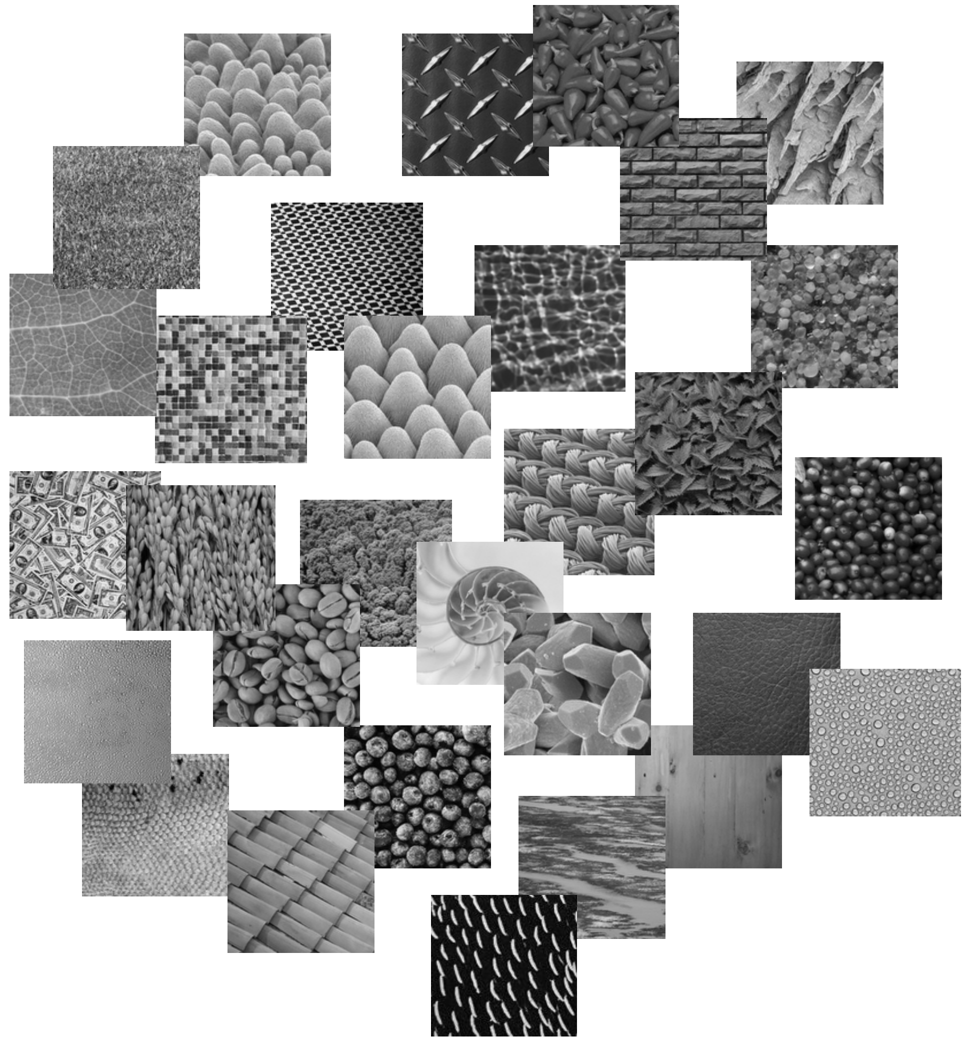
- Test metric as component of a retrieval system.
  - Given database of textures partitioned into classes of "identical textures", find closest texture in database to query image.
- Goodness of metric:
  - "Precision@1" = % of queries for which closest image is in same class.
- No subjective evaluations needed!

[1]Zujovic, Pappas, Neuhoff, *IEEE Tr. Im. Proc.,* 2013

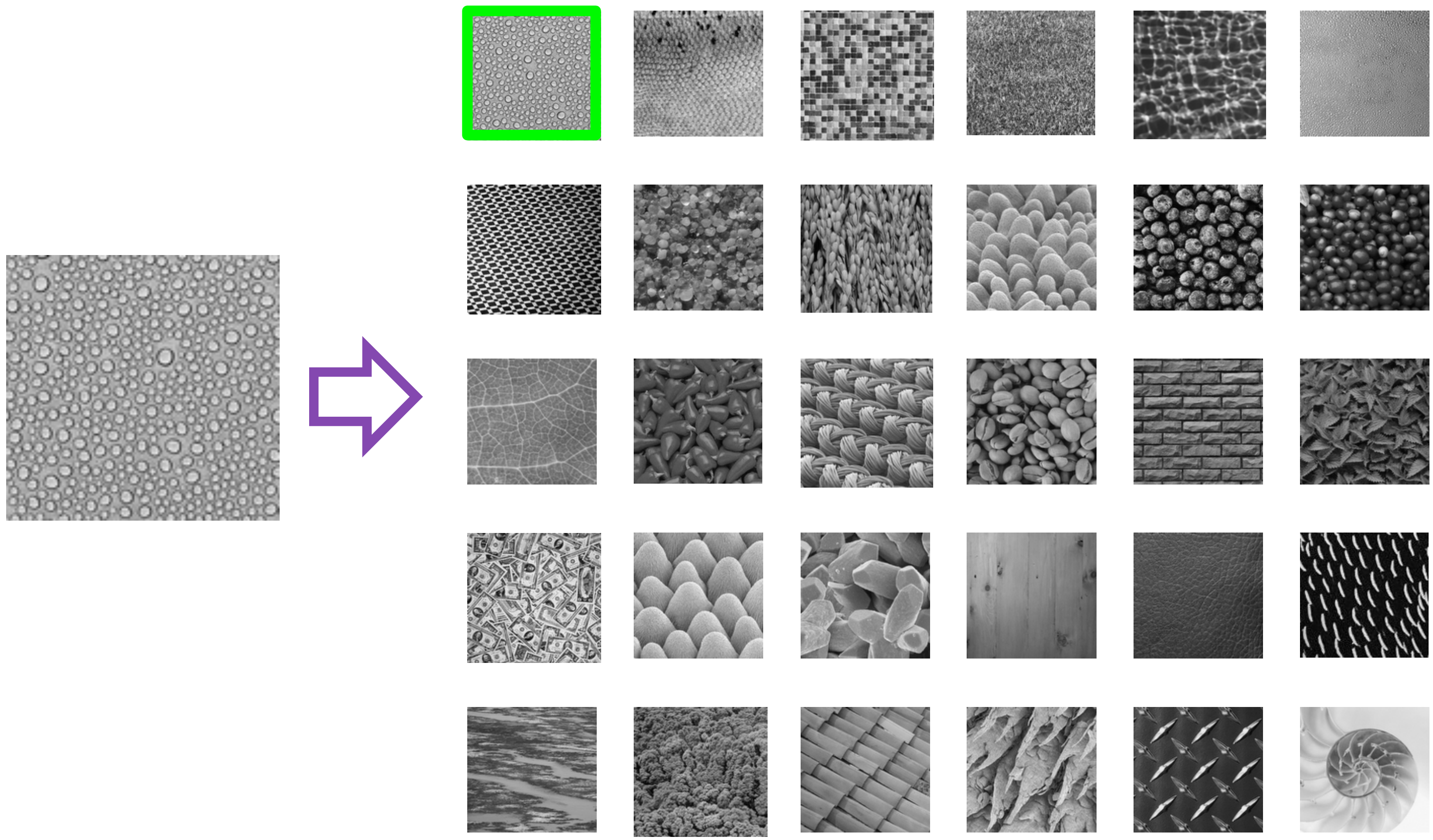
Identical Texture Retrieval:
Find Closest Image to Query in Database



?

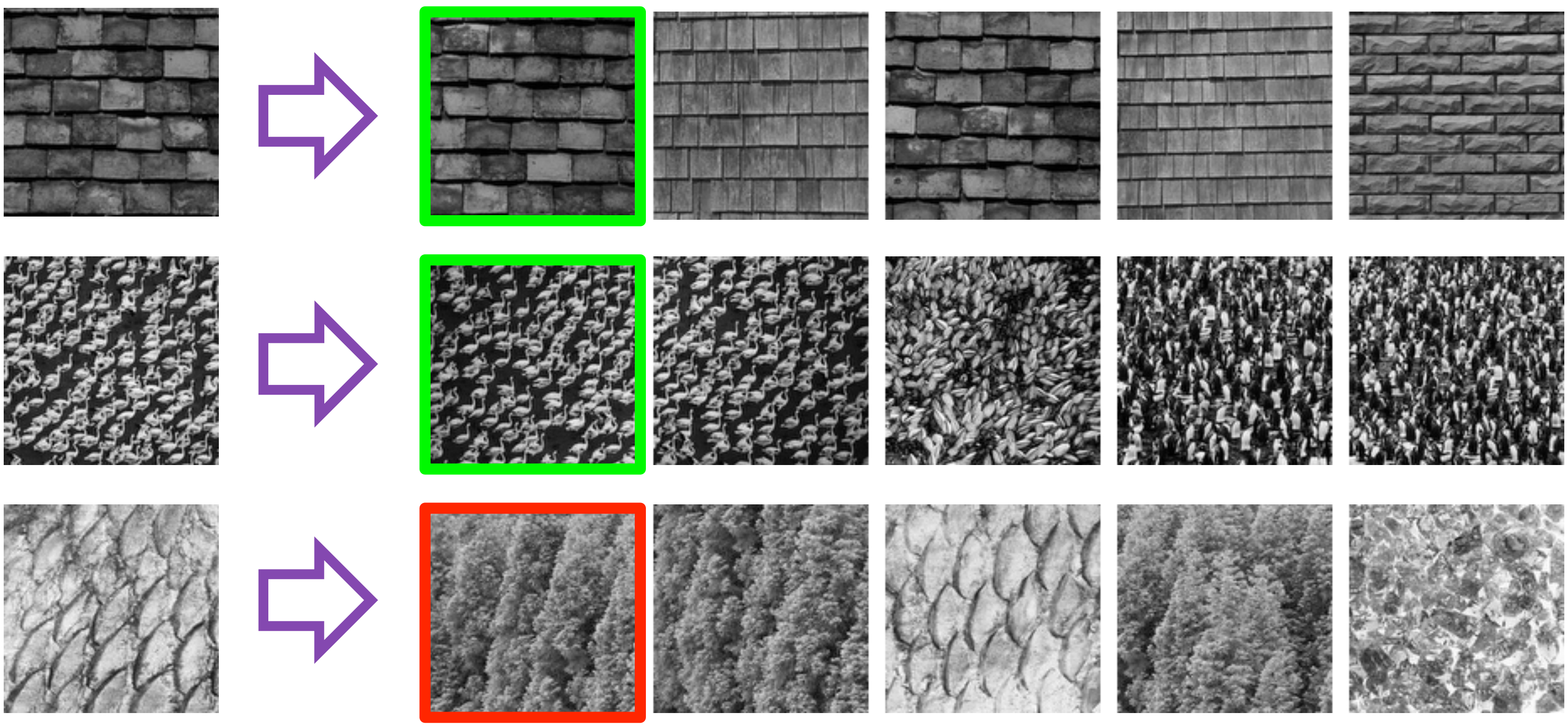


Order Database by Metric Similarity



Precision @ One

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



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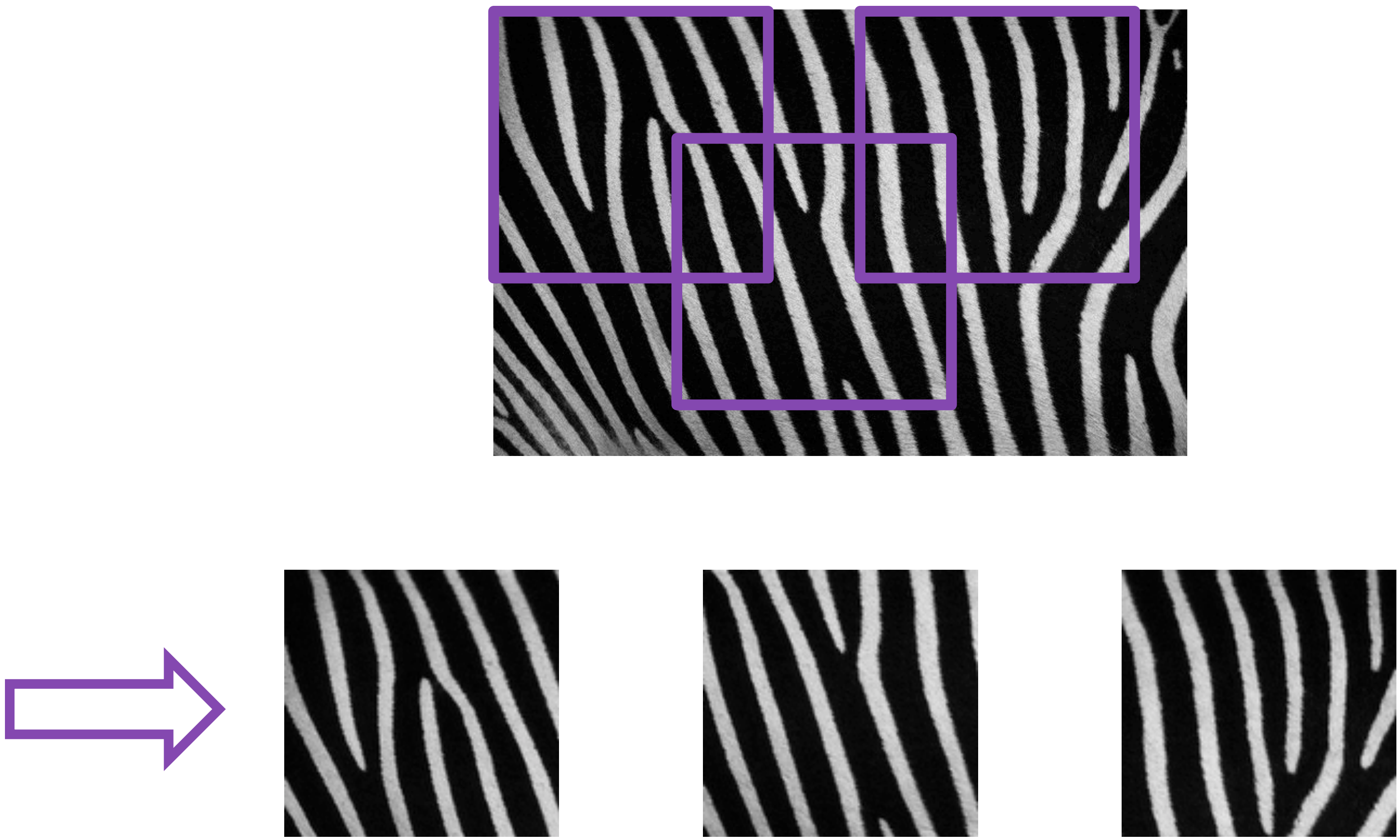
- Corbis-based database: 1181 textures in 425 “identical” classes.

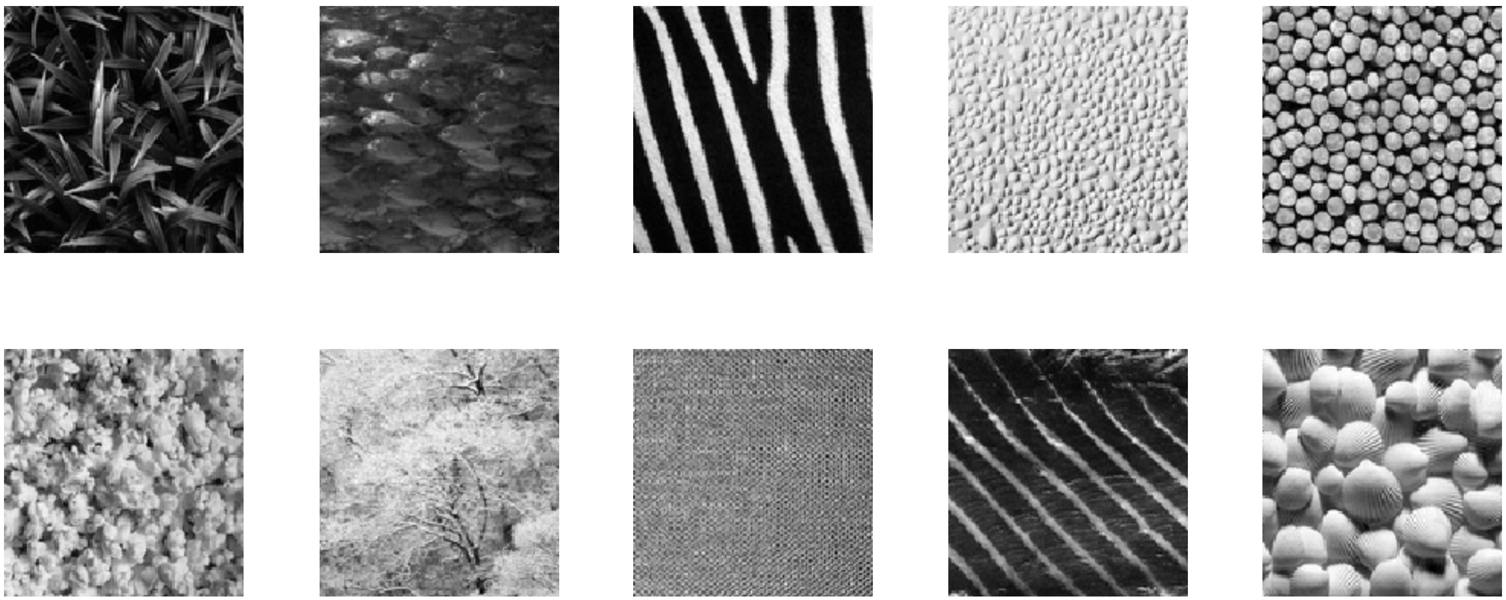
  Each class formed by extracting several 128x128 textures from one homogeneous larger texture image.

[1]Zujovic, Pappas, Neuhoff, *IEEE Tr. Im. Proc.*, 2013

Building the Database



Sample Images in Corbis Database



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- Results

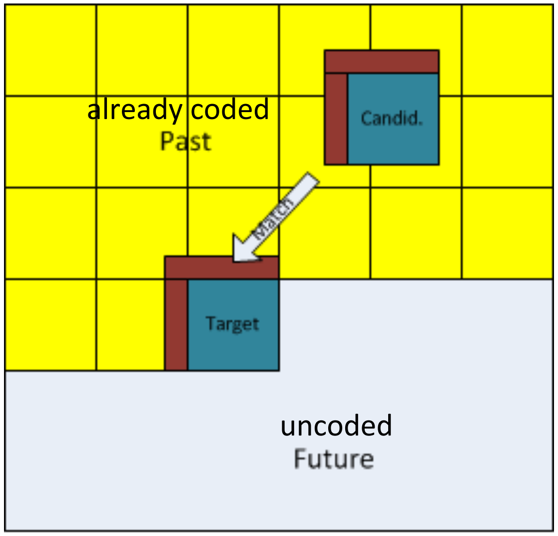
PSNR	SSIM	CW-SSIM	CW-SSIM global	STSIM	STSIM global	STSIM 2	STSIM2 global	STSIM-M global
4%	9%	39%	27%	74%	86%	74%	93%	96%

- Similar results for other performance measures that take into account location of other siblings in the ordering of textures according to distance from query.

[1]Zujovic, Pappas, Neuhoff, *IEEE Tr. Im. Proc.*, 2013

Another Test: Matched Texture Coding (MTC)[1]

- Consider encoding current block, e.g., 32x32, by pointing to a previously encoded block.
- If no sufficiently good previous block, encode with JPEG.
- Key to success is a texture similarity metric for judging if a candidate previous block is sufficiently good.
- Other issues:
  - Search strategy
  - Blending around blocks to avoid blocking artifacts.



- Notes:
  - Textured blocks require the most bits when coded with a pixel-accurate criteria.
  - Whereas the eye is maximally forgiving to changes in a textured block.
  - Goal of MTC is "structurally lossless", rather than "perceptually lossless": Decoded image might look different viewed next to original, but has "equal quality".

- [1]Jin, Zhai, Pappas, Neuhoff, ICIP, 2012.

Encoding at 0.34 bits/pixel

MTC

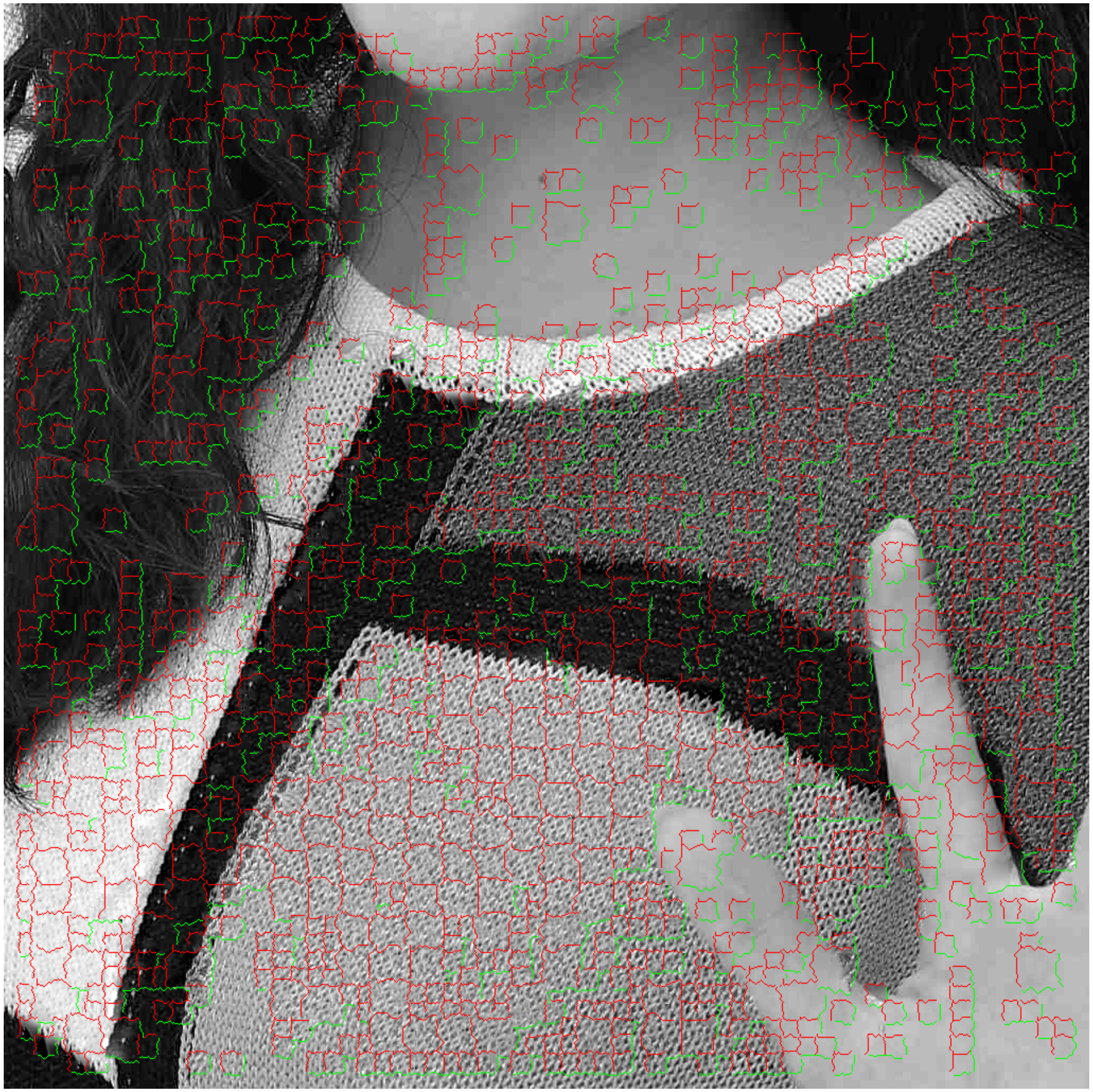
JPEG

Structurally Lossless?

original

MTC

MTC @ 0.37 bpp



blending seams of matched-texture blocks

- red – matched-texture block to right or below
- green - blending seam between texture block and JPEG

MTC @ 0.37 BPP

	32x32 matched-texture	16x16 matched-texture	8x8 JPEG	Overall
fraction of image coded	20.5%	23.6%	55.9%	100%
coding rate within block, bpp	0.03	0.11	0.61	
contribution to total, bpp	0.006	0.026	0.34	0.37

- Recall key ideas:
  - Matched-texture coding saves bits,
  - And saved bits can be used to improve JPEG coding
  - Which in turn leads to better matched-texture coding, by improving quality of available candidates

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LBP (Local Binary Patterns)[1]

- Another approach to computing sliding-window statistics
- Intended for texture classification, where rotation invariance is required. (In contrast for identical texture retrieval and MTC coding, rotations should be penalized monotonically.)

- For each image, compute LBP Index at each pixel,
- LBP Feature = histogram H of LBP Indices.
- LBP Metric

LBP(X, Y) = similarity of histograms H_X and H_Y as measured by divergence of H_X wrt H_Y

$$= \sum_i H_Y(i) \log \frac{H_Y(i)}{H_X(i)}$$

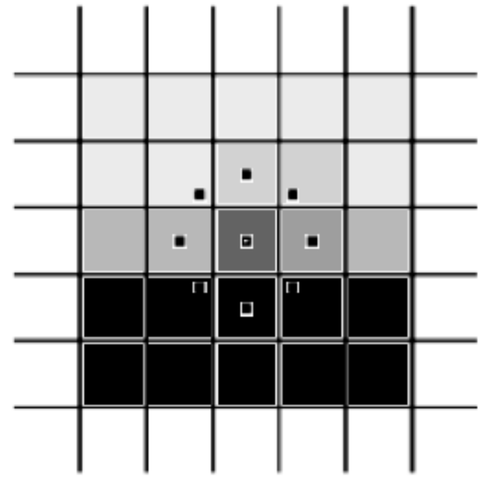
[1] Ojala, Pietikainen, Maenpaa, *IEEE Tr. PAMI*, 2002

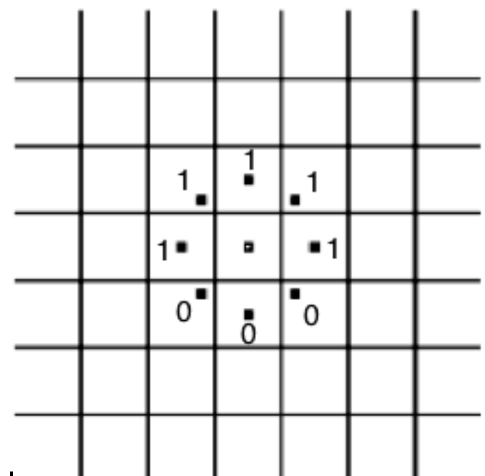
LBP Indices and Feature for Image *X*

- Parameters *r*, *P*.
  - For pixel x_i , let $y_1,\ldots,y_P$ denote image values at *P* equally spaced points on circle of radius *r* centered at *i*-th pixel. Interpolate as needed.
  - Form *P*-dimen'l binary pattern vector $b_1,\ldots,b_P$ with
    $$b_j = \begin{cases} 1, & \text{if } y_j > x_i \\ 0, & \text{else} \end{cases}$$
  - Circularly shift $b_1,\ldots,b_P$ to maximize # leading 0's.
  - Assign integers 0,…,*P* to *uniform* patterns:

00000000	00000001	00000011	…	11111111
0	1	2		P

  - Assign P+1 to all other patterns.
  - LBP index at pixel i = assigned integer
  - LBP index provides circular pattern information
  - Rotation invariant, and gray-scale invariant
  - LBP Feature = histogram of LBP indices for all pixels, which provides frequencies of circular patterns.





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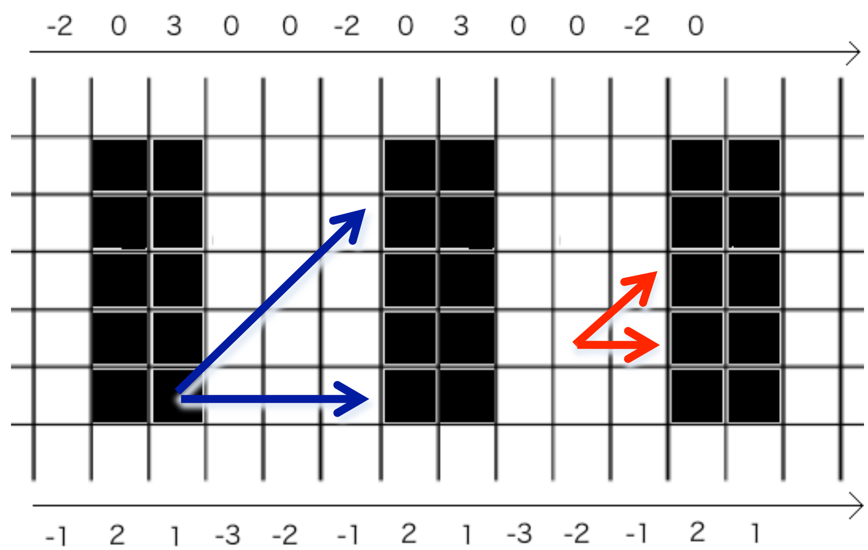
Yuanhao Zhai

New Feature: Local Radius Index (LRI)[1]

- Basic ideas:
  - Generally speaking, a texture contains repetitive smooth elements delineated by edges.
  - One meaningful characteristic of a homogeneous texture is the distribution of distances between adjacent edges at some particular angle.
  - LRI produces 8 such histograms -- one for each neighboring direction.

- Two types of LRI:
  - LRI-A: measures widths of Adjacent smooth regions, i.e. inter-edge distances, in each given direction.
  - LRI-D: measures Distances from pixels to nearest edge, i.e., to boundary of next smooth region, in each given direction.



[1]Zhai, Neuhoff, Pappas, ICASSP, 2013.

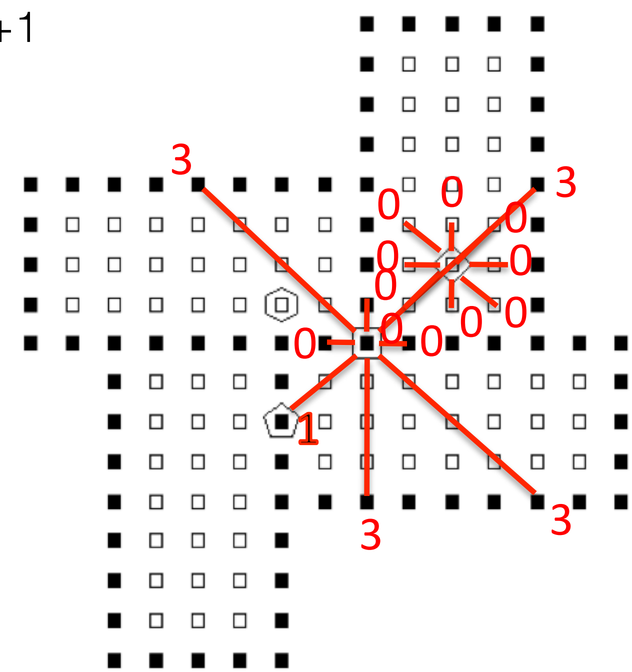
LRI-A

- LRI-A Indices

For i-th pixel x_i and directions $d = 1,\ldots,8$,
let $a_1, a_2, a_3, \ldots$ denote successive Adjacent pixels in direction d.

$$
\begin{aligned}
L_d &= 0\,, \quad \text{if } |x_i - a_1| \le \text{threshold } T \\
&= k\,, \quad \text{if } a_j > x_i + T \text{ for } j = 1,\ldots,k, \text{ but not } k{+}1 \\
&= -k\,, \quad \text{if } a_j < x_i - T \text{ for } j = 1,\ldots,k, \text{ but not } k{+}1
\end{aligned}
$$

Limit max value of L to K and $-K$, respectively.



- LRI-A Feature for image X:

Histograms: $H_1,\ldots, H_8$ for indices $L_1,\ldots,L_8$,

- Threshold T: Determines what is an edge, and controls noise sensitivity. Typically, $T = \sigma/2$.

- Size limit K: Limits size of texture elements detected by LRI, and reduces computation. Typically, $K = 4$.

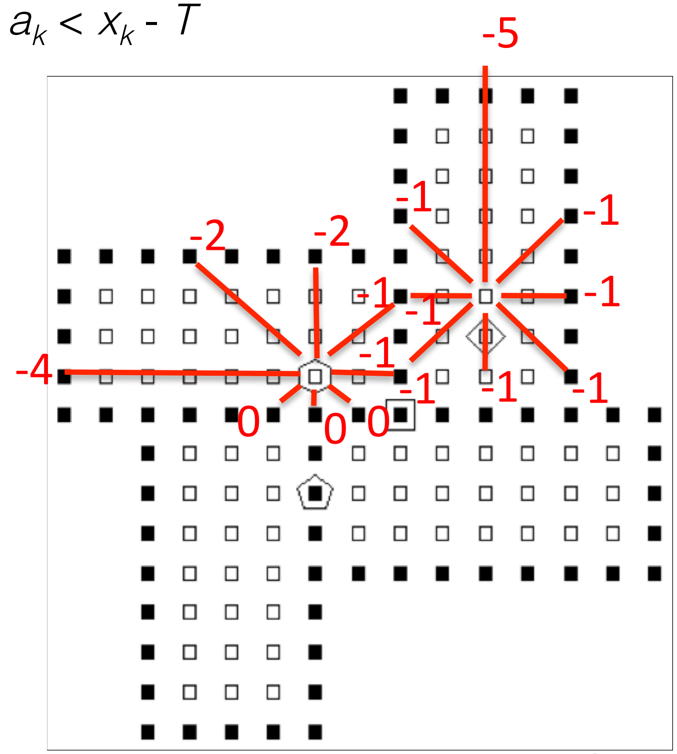
LRI-D

- LRI-D Indices

  For i-th pixel x_i and directions $d = 1,\ldots,8$,
  let $a_1, a_2, a_3, \ldots$ denote successive adjacent pixels in direction d

$$
\begin{aligned}
L_d &= 0, \quad \text{if } |x_i - a_1| > T, \\
&= k, \quad \text{if } |x_i - a_j| \le T, \text{ for } j = 1,\ldots,k\text{-}1 \text{ and } a_k > x_k + T \\
&= -k, \quad \text{if } |x_i - a_j| \le T, \text{ for } j = 1,\ldots,k\text{-}1 \text{ and } a_k < x_k - T
\end{aligned}
$$

  Limit max value of L to K and $-K$, respectively.



- LRI-D Feature for image X:

  Histograms: $H_1,\ldots, H_8$ for indices $L_1,\ldots,L_8$,

- Threshold T: Determines what is an edge, and controls noise sensitivity. Typically, $T = \sigma/2$.

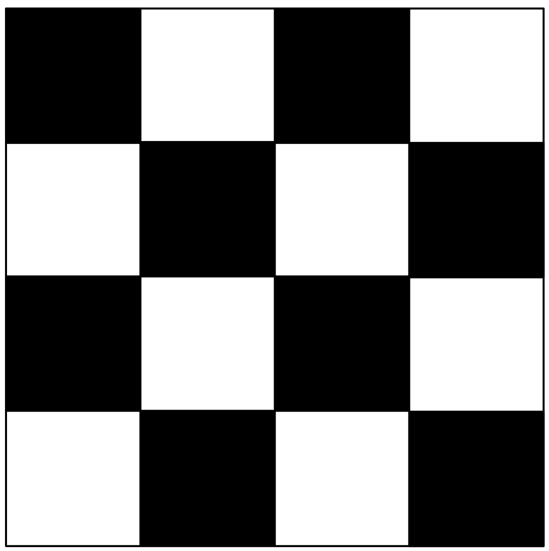
- Size limit K: Limits size of texture elements detected by LRI, and reduces computation. Typically, $K = 4$.

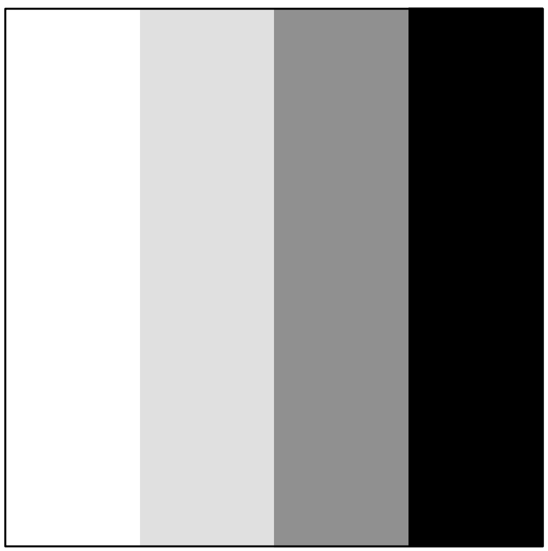
Comments

- LRI-A vs. LRI-D:
  - LRI-A index $L_{i,d}$ measures size of adjacent texture element, if there is one. It is zero at i unless there is edge adjacent to i in direction d.
  - LRI-D index $L_{i,d}$ measures dist. from i to nearest edge in direction d. It usually decreases by 1 one when moving in direction d from i.
  - Hence, LRI-A values are sparser. LRI-D values are more correlated/ redundant.
- LRI and LBP are complementary:
  - LBP provides angular pattern info; no direction or element size info.
  - LRI provides direction and size info; no angular pattern info.

Why Do LRI Indices Have "±" Signs?

- Without signs, the following have same horizontal LRI histograms:

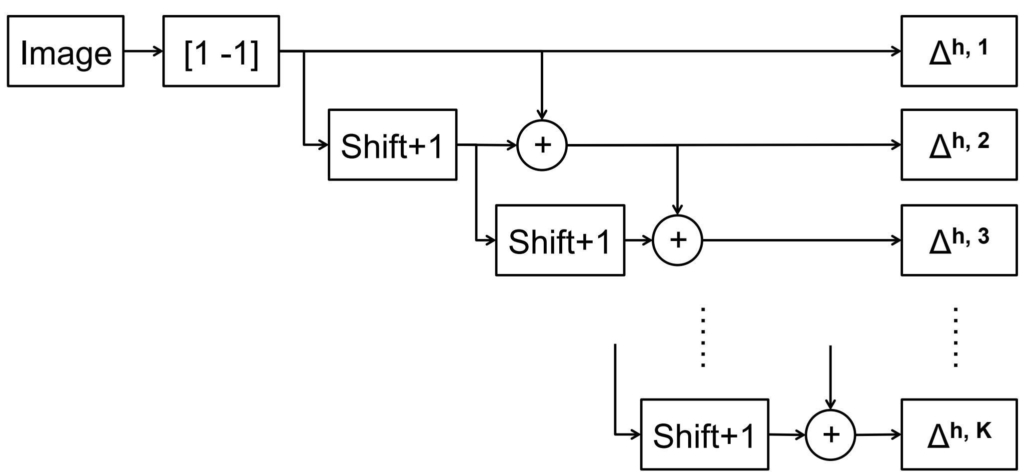




Computation of LRI Indices

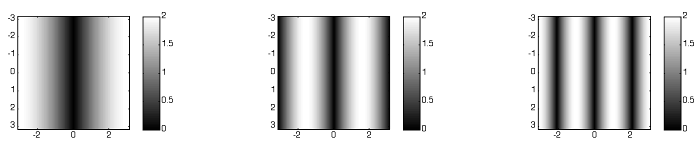
- Fast algorithm:
  - Precalculate & store pairwise differences between all pairs of pixels separated by k =1, …, K in unsigned directions d (horiz, vert, diag, anti-diag)
  - Pairwise differences are then used to compute LRI indices.
  - ~$4K$ operations per pixel.
  - Pairwise differencing in direction d of pixels separated by k can be viewed as a filtering,

    e.g., h = [1 0 0 0 -1] is impulse response of horizontal filter for k = 4.
  - Filtering can be done in simple recursive fashion:



Pixel Differencing Filters Create De Facto Subband Decomposition

- Pairwise differencing in direction d of pixels separated by k can be viewed as a filtering.
- The $4K$ filters comprise a simple multiscale, multiorientation subband decomposition, with 4 orientations and K scales.
- Example: Frequency response for 3 scales in horizontal direction:



- Might use this decomposition instead of steerable pyramid; requires much less computation

Texture Similarity Metrics Based on LRI

1. Purely LRI-based similarity metric:
   - LRI feature: Combine 8 histograms into vector of dim. 8 x (2*K*+1)
   - Compare similarity of the vectors obtained for images *X, Y* with divergence.

$$\sum_i H_Y(i)\log\frac{H_Y(i)}{H_X(i)}$$

Texture Similarity Metrics Based on LRI

2. Combine/pool LRI with other features:

   a. LBP

      – Use 8 nearest neighbor pixels, without interpolating values on circle.

   b. Luminance (mean) μ

      – Comparison term: $$M(X,Y) = \left(\frac{\max\left(|\mu_X - \mu_Y|,\ 10 \right)}{256} \right)^2$$

      – Penalizes only mean differences larger than 10.

   c. Subband Contrast Distrib'n (SCD) $\sigma_1^2, \ldots, \sigma_{12}^2$ from steerable filter.

      – Comparison term: $$SCD(x,y) = \prod_{b=1}^{12} \frac{2\sigma_{x,b}\sigma_{y,b} + \varepsilon}{\sigma_{x,b}^2 + \sigma_{y,b}^2 + \varepsilon}$$

   c'. Subband Contrast Distrib'n (SCD_f) $\sigma_1^2, \ldots, \sigma_{4K}^2$ from pairwise differencing filters, which are much simpler to compute since filtering is already done.

Texture Similarity Metric Based on LRI

- New LRI-based texture similarity metric:

$$LRI^{+} = LRI \times LBP^{1.1} \times M \times \left(\tan\left((1\text{-}SCD)\,\pi/2\right)\right)^{1.2}$$

  - Metric is nonnegative with zero meaning identical, and a small value meaning similar.
  - LBP computed from pixel differences with few add'l computations.

- Complexity:
  - Leaving aside subband costs, STSIM2 (with a global window, which is the simplest version), requires approximately 500 operations per pixel.
  - LRI and SCD requires 16 and 36 operations per pixel, respectively.
  - Steerable filter pyramid needs 14 FFTs, each with $5 \log N$ op's per pixel.
  - With SCD_f, no transform needed for LRI^+, beyond that needed for LRI.
  - Conclusion: LRI^+ with SCD_f is at least 10 times faster than STSIM2.

Metric Test 1: Identical Texture Retrieval

Corbis-derived database

CW-SSIM	STSIM 2	STSIM 2 global	STSIM M global	LPB (8,1)	LRI-A	LRI-D	SCD	LRI^+-a	LRI^+-b	LRI^+-b
39	74	93	96	90.0	91.8	83.2	83.7	98.7	98.1	99.0

LRI-A, LBP, M, SCD

LRI-A, LBP, M, SCD_f

LRI-D, LBP, M, SCD

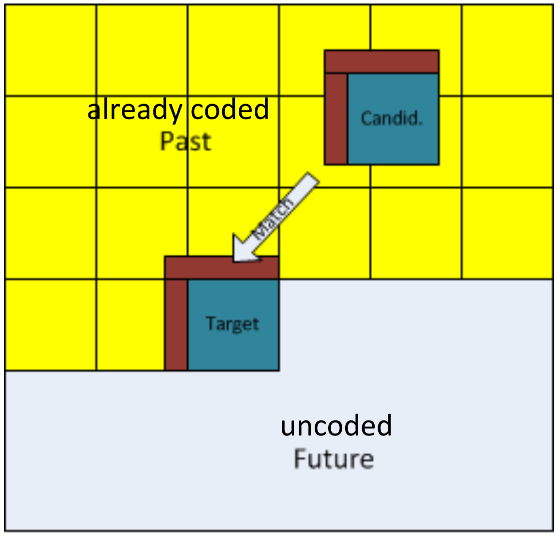
Notes:

- LRI-A > LBP by themselves.
- LRI-A > LRI-D by themselves.
- LRI-A ≈ LRI-D when combined with other features.
- LRI^+_b is simplest of LRI^+ methods
- Combining features exploits complementarities

Metric Test 2: MTC

- Consider encoding current block, e.g., 32x32, by pointing to a previously encoded block.
- If no sufficiently good previous block, encode with JPEG.
- Key to success is a texture similarity metric for judging if a candidate previous block is sufficiently good.

- Use LRI^{+}_{b} instead of STSIM2



original: 1024x1024

JPEG coded

all encodings at 0.18 bpp

MTC coded with STSIM2

MTC coded with LRI_b

- STSIM2 & LRI^{+}_{b} give similar performance.
- LRI-based coder runs ~6 times faster.

Outline

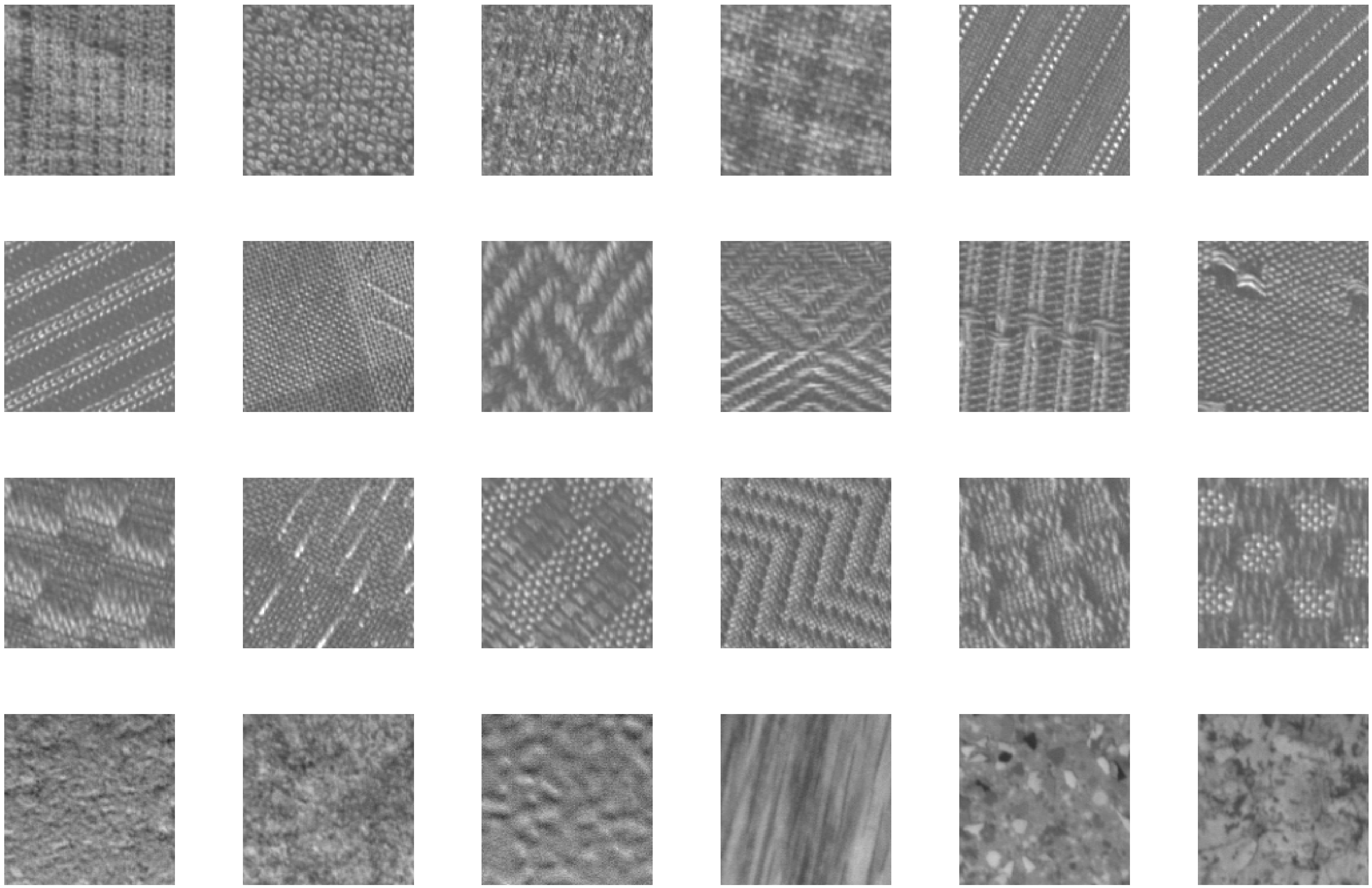
- Review
  - Point-by-point metrics
  - SSIM (Structural Similarity Metric)
- STSIM (Structural Texture Similarity Metric): new SSIM type metric:
  - Performance in identical texture retrieval and image compression
- Review
  - LBP (Local Binary Patterns)
- LRI (Local Radius Index): new local-pattern metric
  - Performance in identical texture retrieval and image coding
- RI-LRI (Rotation invariant LRI):
  - Performance in texture classification
- Concluding remarks

Yuanhao Zhai

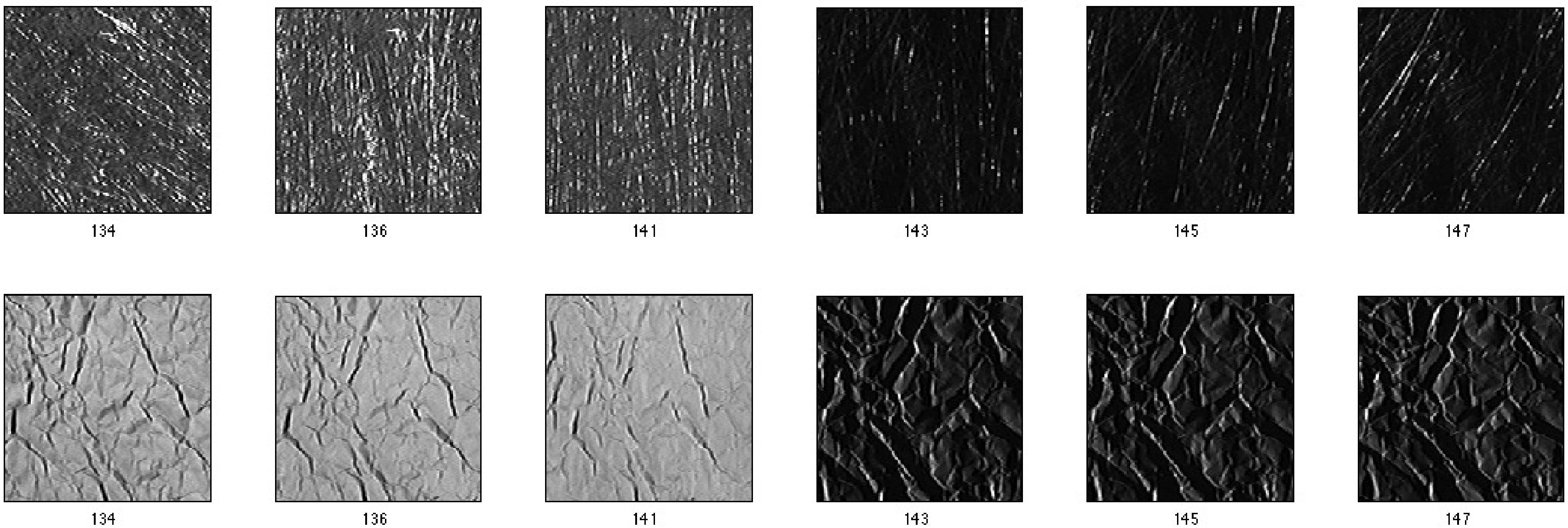
Metric Test 3: Texture Classification

- Problem: Given examples of *K* texture classes and a query from an unknown one of these classes, identify the class of the query.
- Common approach: *M nearest neighbors* (*M-NN*)
  - Measure the "distance" of query to each example in each class.
  - Decide the class that occurs the most among the *M* closest examples.
- Use a texture similarity metric to determine "distance"
- The goodness of a similarity metric is judged by the classification accuracy that results, expressed as a percent.
- OUTEX and CUReT databases are de facto "standards" for testing texture metrics in classification.
- Texture classification cannot presume texture has known orientation. So metric must be rotation invariant.
- LBP is rotation invariant. LRI is not.
- Gray-scale invariance might also be desired.

Samples of OUTEX Database

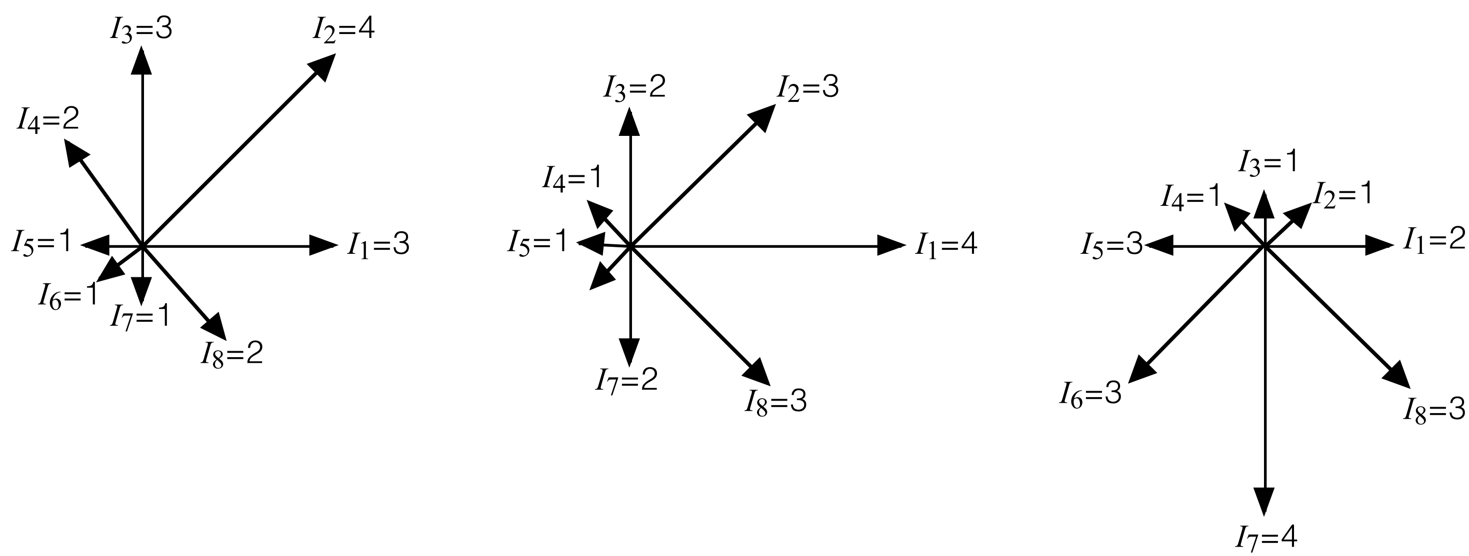


Samples of CURet Database



RI-LRI (Rotation Invariant LRI)[1]

original LRI indices



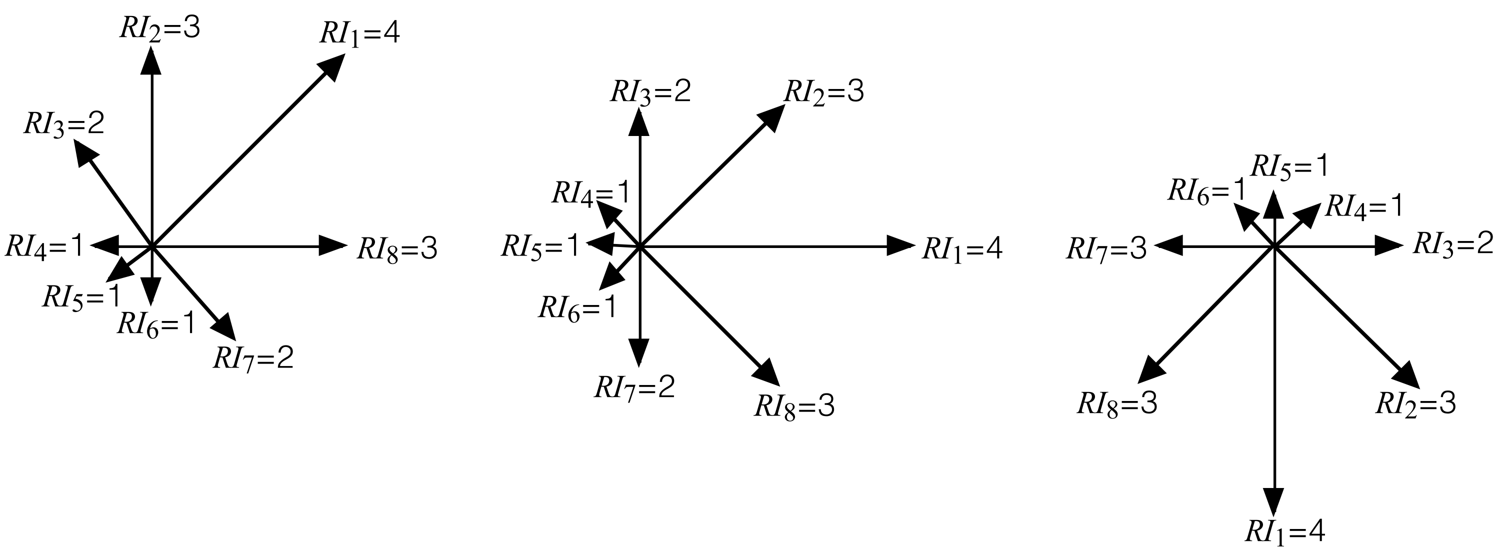
Now, H_1 is histogram of indices RI_1 in dominant directions.

H_2 is histogram of indices adjacent to dominant directions, etc.

[1]Zhai, Neuhoff, Pappas, ICIP, 2014.

RI-LRI (Rotation Invariant LRI)[1]

rotation invariant LRI indices



Now, H_1 is histogram of indices RI_1 in dominant directions.

H_2 is histogram of indices adjacent to dominant directions, etc.

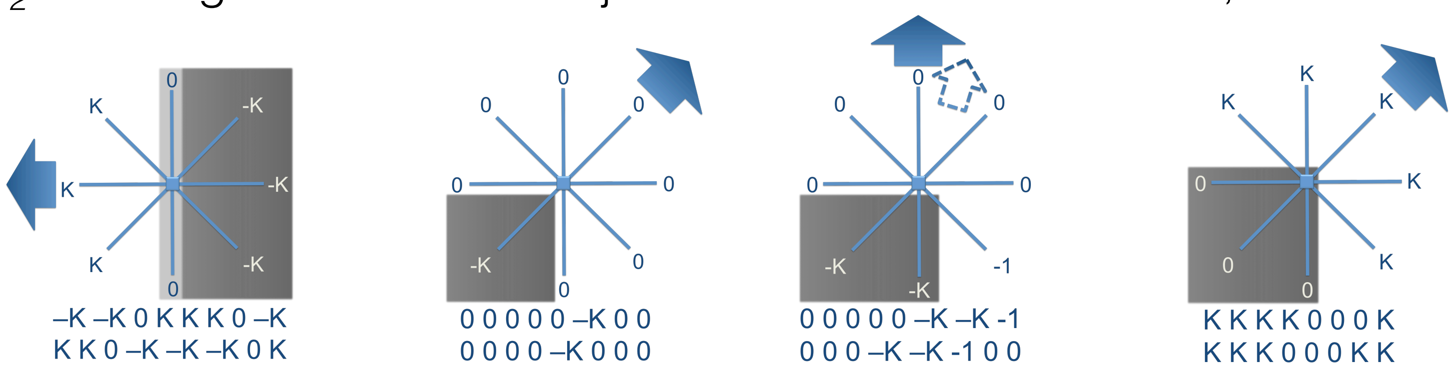
[1]Zhai, Neuhoff, Pappas, ICIP, 2014.

RI-LRI (Rotation Invariant LRI)[1]

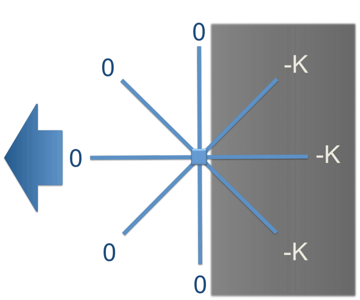
- To make LRI rotation invariant, for each pixel i,
  - For each pixel i estimate dominant direction: $D_i = \text{angle}\left(\sum_{d=1}^{8} I_{i,d} \times \phi_d\right)$
    where $[\phi_1,\ldots,\phi_8] = [1, 1+j, j, -1+j, -1, -1-j, -j, 1-j]$
  - Circularly shift pixel i's LRI indices, $I_{i,1},\ldots,I_{i,8}$, forming $RI_{i,1},\ldots,RI_{i,8}$, such that $RI_{i,1}$ is the index in direction closest to the dominant direction D_i :

$$RI_{i,d} = I_{i,\,1+(d-1+\overline{D}_i) \bmod 8}$$

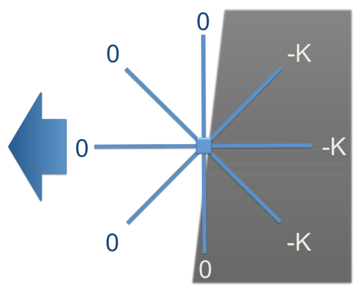
    where $\overline{D}_i$ is D_i rounded to nearest multiple of $\pi/4$.
  - Now, H_1 is histogram of indices in dominant directions.
  - H_2 is histogram of indices adjacent to dominant directions, etc.



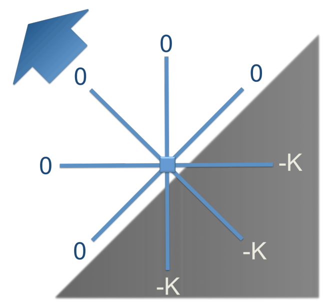
[1]Zhai, Neuhoff, Pappas, ICIP, 2014.



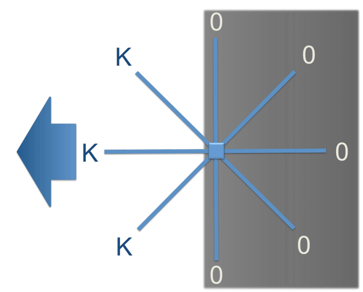
–K –K 0 0 0 0 0 –K
0 0 0 –K –K –K 0 0



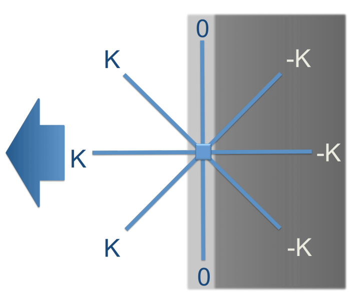
–K –K 0 0 0 0 0 –K
0 0 0 –K –K –K 0 0



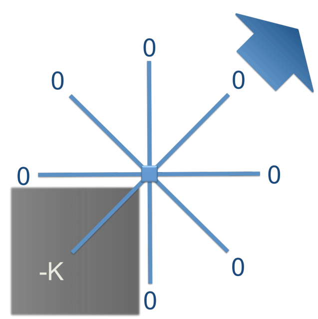
–K 0 0 0 0 0 –K –K
0 0 0 –K –K –K 0 0



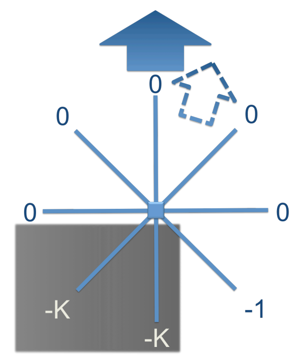
0 0 0 K K K 0 0
K K 0 0 0 0 0 K



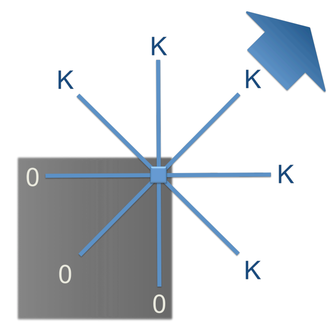
–K –K 0 K K K 0 –K
K K 0 –K –K –K 0 K



0 0 0 0 0 –K 0 0
0 0 0 0 –K 0 0 0

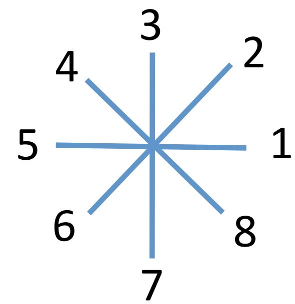


0 0 0 0 0 –K –K -1
0 0 0 –K –K -1 0 0



K K K K 0 0 0 K
K K K 0 0 0 K K

RI-LRI Feature Vector



- Observations:
  - Most distinctive information is in dominant direction (d=1), opposite direction (d=5), & orthogonal directions (d=3,7).
  - Orthogonal directions (1 & 3), (5 & 7) contain correlated information.
- LRI Feature Vector is 2-D histogram
  - For each m,n between $-K$ and K

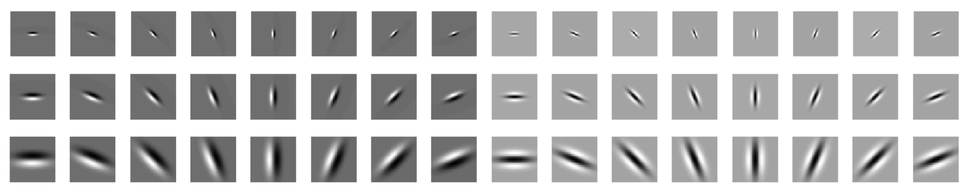
$$H(m,n) = \left[\#\text{pixels s.t. } (RI_{i,1}, RI_{i,3}) = (m,n)\right] + \left[\#\text{pixels s.t. } (\mathrm{RI}_{i,5}, \mathrm{RI}_{i,7}) = (m,n)\right]$$

  - Feature Vector length = $(2K+1)^2$. (Typically, $K = 4$)

Feature	Complexity		Feature	Complexity
LBP(8,1) w/o interp.	30		LBP(8,1)	90
LRI (K = 4)	36		LBP(16,2)	242
RI-LRI (K = 4)	47		LBP(24,3)	394

RI-LRI^{+} Metric Based on RI-LRI

- Combine RI-LRI with
  - LBP ((8,1) no interpolation)
  - RI Subband Contrast Distribution (RI-SCD)
    - Motivated by LEBC[1], measure variances $s_1^2, \ldots, s_{48}^2$ from subband decomposition generated by "edge" (first deriv.) and "bar" (second deriv.) filters with 3 scales and 8 orientations.



scale 3

scale 2

scale 1

    - To attain rotation invariance, for each scale and choice of "edge" or "bar" arrange the 8 variances in decreasing order.
    - RI-SCD similarity of images: $\text{RI–SCD}(X,Y) = \prod_{i=1}^{48} \frac{2\, s_{X,i} s_{Y,i} + \varepsilon}{s_{X,i}^2 + s_{Y,i}^2 + \varepsilon}$
- RI-LRI^{+}:

$$\text{RI-LRI}^{+} = (\text{RI-LRI})^{0.7} \times \text{LBP}^{0.4} \times \big(1-(\text{RI-SCD})\big)^{1.3}$$

Metric Test: Texture Classification

- OUTEX database: percent accuracy averaged over 3 test scenarios

LBP (8,1)	RI-LRI (K=4)	VZ-Joint	VZ-MR8	DLPB +NGF	CLBP	DNS +LBP	LEBC	RI-LRI^{+}
71.8	84.9	91.8	93.0	94.1	96.7	95.5	98.7	98.4

- CUReT database: percent accuracy

LBP (8,1)	RI-LRI (K=4)	VZ-Joint	VZ-MR8	CLBP	DNS +LBP	LEBC	RI-LRI^{+}
80.8	91.9	97.7	97.8	97.0	95.0	98.5	98.1

- RI-LRI^{+} (with 139-dim'l feature vector) is nearly as good as LEBC (with 1280-dim'l feature vector).
- RI-LRI^{+} uses 1-NN, i.e., Nearest Neighbor classification

Concluding Remarks

- New texture features: LRI, RI-LRI
- New texture similarity metrics:
  - STSIM, STSIM2 –-- SSIM-type
  - LRI, LRI^+ ---- local pattern type
  - RI-LRI, $RI\text{-}LRI^+$ ---- local pattern type, rotation invariant
- State-of-the-art performance in
  - Identical texture retrieval
  - Texture classification
  - MTC compression
- Order of magnitude lower dimensionality of feature vector than similarly performing feature vectors.

Current Work

- LRI based on “genuine” edge detectors, e.g., Canny
- Analytically predict LRI histograms on periodic texture patterns
- Study sensitivity of LRI to noise
- New pooling methods

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