Spectral Histogram Model for Texton Modeling and Texture Discrimination

by Liu and Wang (2002)

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Spectral Histogram Overview

- Filter response distribution as a quantitative definition of texton (texture element) pattern.
- Stochastic generation of images with similar spectral histogram signature.
- Use of χ^2-distance for comparing spectral histograms.
- Texture segmentation using spectral histograms: comparison to human psychophysics.

Texture Perception

- Texture perception is an important component in early visual perception.
- Texture discrimination is near effortless.
- Textons: basic elements that make up textures:
  - Elongated blobs define by color, orientation, etc.
  - Line terminators
  - Line crossings
  - Local closure
- Textons are hard to describe formally.

Texture Synthesis

- Given probability distributions based on local correlation, use statistical sampler to generate (synthesize) individual textures.
- Local statistical methods not good for dealing with realistic textures containing large-scale features.
- Image pyramid approach can be used to deal with such an issue.

Spectral Histogram

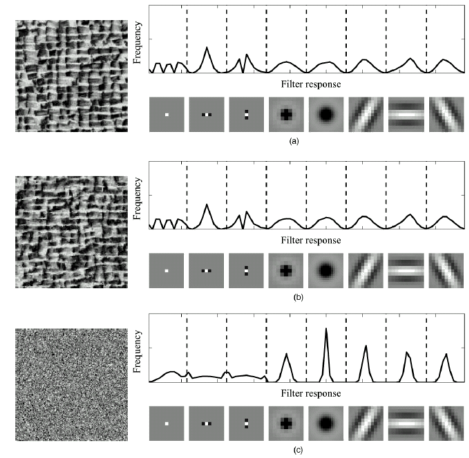
- Image window $\mathbf{W}$
- Filters $\{F^{(\alpha)}, \alpha = 1, 2, ..., K\}$.
- Filter response $\mathbf{W}^{(\alpha)} = F^{(\alpha)} * \mathbf{W}$.
- Response histogram $H_{\mathbf{W}}^{(\alpha)}$
- Spectral histogram: response histograms of all filters

$$H_{\mathbf{W}} = \left(H_{\mathbf{W}}^{(1)}, H_{\mathbf{W}}^{(2)}, ..., H_{\mathbf{W}}^{(\alpha)}, ..., H_{\mathbf{W}}^{(K)}\right)$$

- Difference measure: χ^2

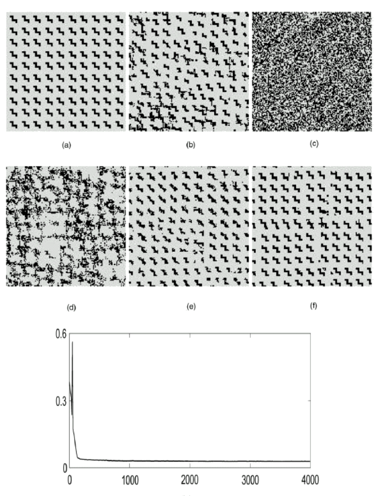
$$\chi^2\left(H_{\mathbf{W}_1}, H_{\mathbf{W}_2}\right) = \frac{1}{K}\sum_{\alpha=1}^{K}\sum_{z}\frac{\left(H_{\mathbf{W}_1}^{(\alpha)}(z) - H_{\mathbf{W}_1}^{(\alpha)}(z)\right)^2}{H_{\mathbf{W}_1}^{(\alpha)}(z) + H_{\mathbf{W}_1}^{(\alpha)}(z)}$$

Examples of Spectral Histogram



- Similar for similar (but not identical) textures, different for different textures.

Spectral Histgrams as Texton Patterns

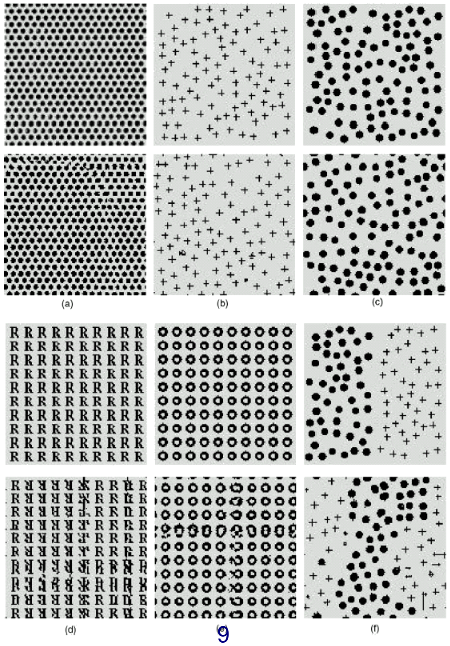


- Synthesize texture based on spectral histogram from observed image. Use of Gibbs sampler to reduce differences in SH.

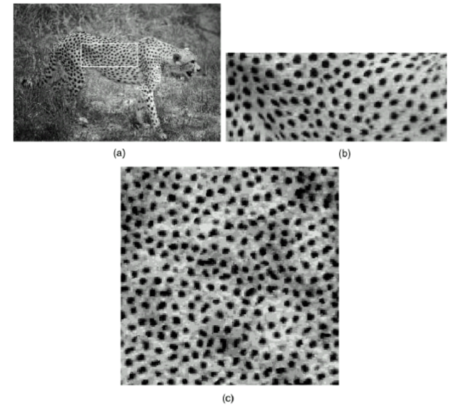
Texture Synthesis Algorithm

For a binary input texture, compute $H_{\text{obs}}^{(\alpha)}$, $\alpha = 1, \ldots, K$.
Initialize $\mathbf{I}_{\text{syn}}$ as a binary white noise image and $\lambda_i^{(\alpha)} \leftarrow 0$.
Repeat
For each pixel location $\vec{v}$ in $\mathbf{I}_{\text{syn}}$, do
$\mathbf{I}_{\text{black}} \leftarrow \mathbf{I}_{\text{syn}}$, $\mathbf{I}_{\text{black}}(\vec{v}) \leftarrow 0$, $\mathbf{I}_{\text{white}} \leftarrow \mathbf{I}_{\text{syn}}$, $\mathbf{I}_{\text{white}}(\vec{v}) \leftarrow 1$.
Compute $H_{\mathbf{I}_{\text{black}}}^{(\alpha)}$ and $H_{\mathbf{I}_{\text{white}}}^{(\alpha)}$, $\alpha = 1, \ldots, K$.
$E_{\text{black}} \leftarrow \sum_{\alpha=1}^{K} \sum_{i=1}^{L^{(\alpha)}} \lambda_i^{(\alpha)} \times H_{\mathbf{I}_{\text{black}}}^{(\alpha)}(i)$,
$E_{\text{white}} \leftarrow \sum_{\alpha=1}^{K} \sum_{i=1}^{L^{(\alpha)}} \lambda_i^{(\alpha)} \times H_{\mathbf{I}_{\text{white}}}^{(\alpha)}(i)$
$P_{\text{black}} \leftarrow \exp(-E_{\text{black}})/(\exp(-E_{\text{black}}) + \exp(-E_{\text{white}}))$.
$\mathbf{I}_{\text{syn}}(\vec{v}) \leftarrow 0$ with probability P_{black} and $\mathbf{I}_{\text{syn}}(\vec{v}) \leftarrow 1$ with $1 - P_{\text{black}}$.
$\lambda_i^{(\alpha)} \leftarrow \lambda_i^{(\alpha)} + \tau(H_{\mathbf{I}_{\text{syn}}}^{(\alpha)}(i) - H_{\text{obs}}^{(\alpha)}(i))$.
Until $\sum_{i=1}^{L^{(\alpha)}} |H_{\mathbf{I}_{\text{syn}}}^{(\alpha)}(i) - H_{\text{obs}}^{(\alpha)}(i)| \leqslant \epsilon$ for $\alpha = 1, 2, \ldots, K$.

Texture Synthesis Results



Synthesis of Natural Textures

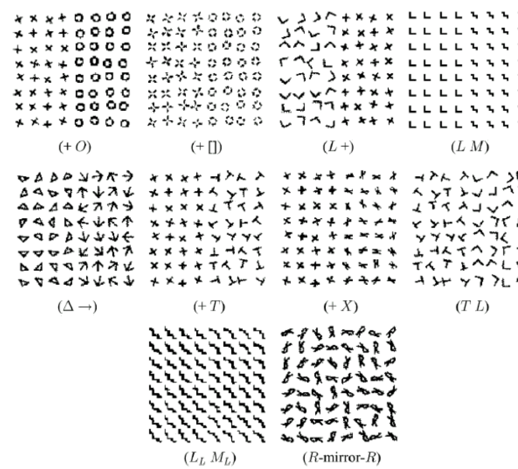


- Similar approach works for natural textures.

Interim Summary

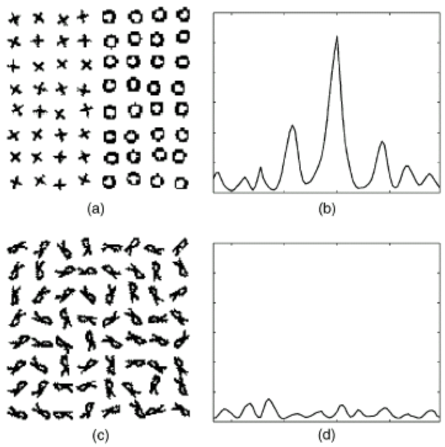
- Spectral histograms "capture a level of image description that is sensitive to certain types of spatial information such as orientation, scale, and density, while oblivious of geometrical properties."

Texture Discriminability in Humans



- Humans respond differently to different texture combinations.
- Some stand out more than others.

Texture Discriminability with Spectral Histograms



- Results are consistent with human psychophysics.

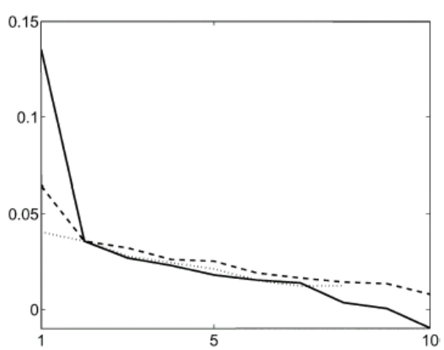
Texture Discriminability with Spectral Histograms

Table 1
Texture discrimination scores

Texture pair	Texture discriminability		
	Human data (Kröse, 1986)	Malik and Perona results (Malik & Perona, 1990)	Spectral histogram results
(+ O)	100	407	0.135
(+ [])	88.1	225	0.036
(L +)	68.6	203	0.027
(L M)	n.a.	165	0.023
(Δ $\rightarrow$)	52.3	159	0.018
(+ T)	37.6	120	0.015
(+ X)	30.3	104	0.014
(T L)	30.6	90	0.004
(L_L, M_L)	n.a.	85	0.001
(R-mirror-R)	n.a.	50	−0.01

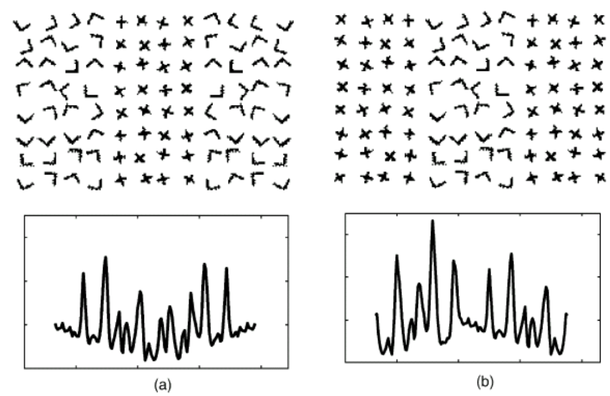
- Results are consistent with human psychophysics.

Texture Discriminability with Spectral Histograms



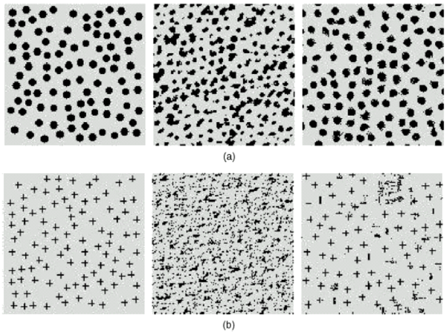
- Dots, dashes: psychophysical data
- Solid line: spectral histogram

Asymmetry in Texture Discrimination



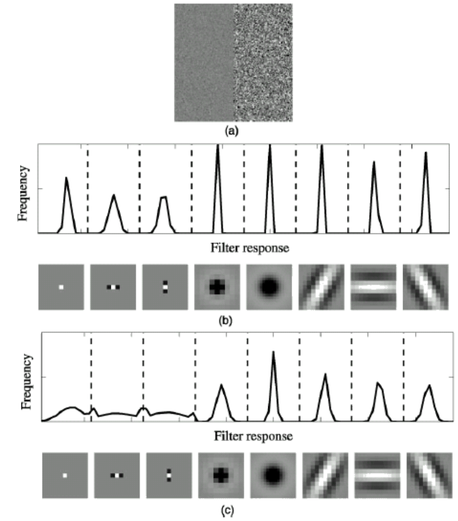
- Asymmetry is found in texture discriminability even when the constituent textures are the same.
- SH discriminability scores are: (a) 0.005 and (b) 0.018.

Comparison to Other Texture Synthesis Methods



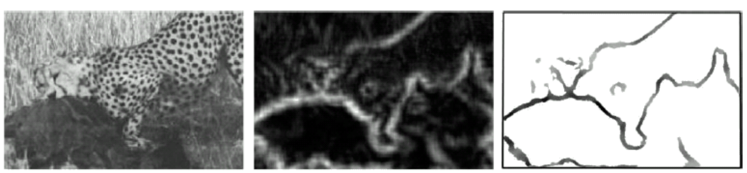
- Original; Heeger and Bergen (1995); Spectral histogram

Discrimination Based on 2nd-order Moment



- Texture made of response distributions of same mean but different variance: SH can discriminate these.

Texture Boundary Detection



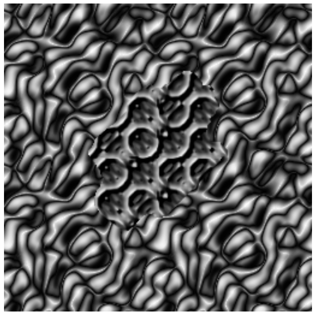
(a) (b) (c)

- Calculate texture gradient based on χ^2 distance in adjacent regions.

Discussion

- Filter selection
- Texture segregation
- Biological plausibility
  - Filters: no problem
  - Histograms: sketchy

Discussion (YC)



- What is a texture?
- Why did the visual system evolve to be sensitive to textures?
- See Oh and Choe (2006) for details.

References

Liu, X., and Wang, D. (2002). A spectral histogram model for texton modeling and texture discrimination. *Vision Research*, 42:2617–2634.

Oh, S., and Choe, Y. (2006). Segmentation of textures defined on flat vs. layered surfaces using neural networks: Comparison of 2D vs. 3D representations. *Neurocomputing*. In press.