



西安电子科技大学

基于视皮层方位选择特性的模版提取 及其在质量评价中的应用

吴金建

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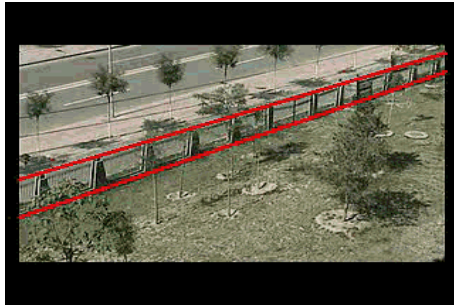
<http://web.xidian.edu.cn/wjj/index.html>



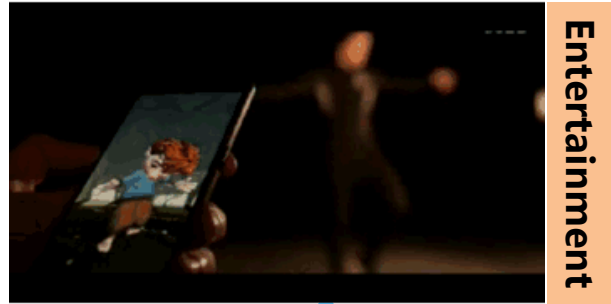
- ❑ **Background: Local Structural Descriptors**
- ❑ **The Orientation Selectivity Mechanism**
- ❑ **The Visual Pattern Modeling**
- ❑ **Image Content Extraction**
- ❑ **Application 1: Texture Classification**
- ❑ **Application 2: Quality Assessment**
- ❑ **Conclusion**

Background: Local Structural Descriptors

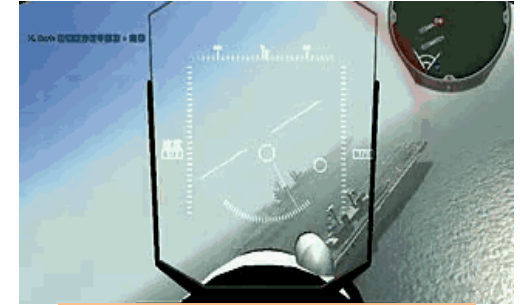
Video/Image is everywhere (more than 80% info. that we received)



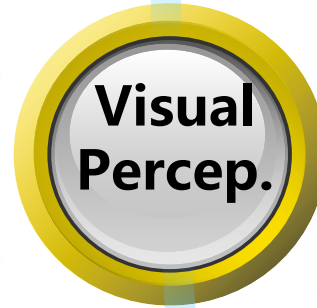
Social Security



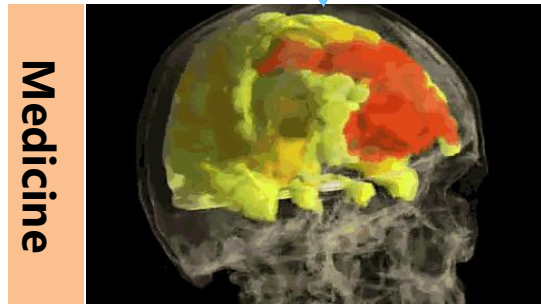
Entertainment



National Defense



Biometrics



Medicine



Manufacturing

Background: Local Structural Descriptors

How does the computer understand the digital images?



161	152	136	91	64	
157	151	125	78	53	
151	143	105	59	35	



How does the computer
extract information
from these digital values?

- Global descriptor:
 - Color
 - Entropy
 - ...
- Regional descriptor:
 - Edge
 - Contour
 - ...
- Local descriptor:
 - Corner (SIFT)
 - Texton (LBP)
 - ...

Background: Local Structural Descriptors

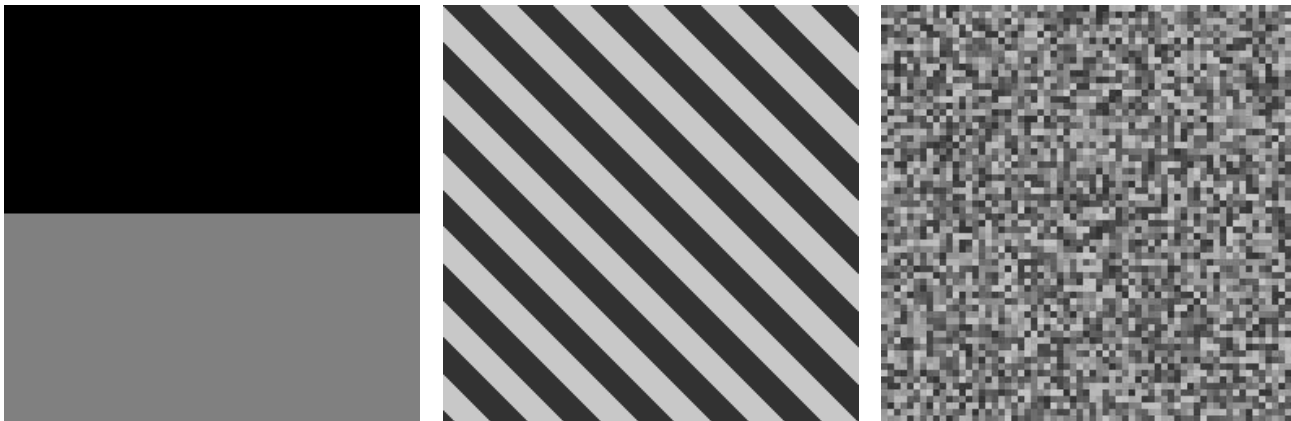
Local structural descriptor:

- The human visual system (HVS) is extremely adaptive to extract structures for image perception and understanding.
- The HVS is sensitive to luminance changes:
 - First order statistic values, e.g., mean, variance, etc.
 - The gray-level difference (luminance contrast)...

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Similar luminance changes, while quite different structure.

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Background: Local Structural Descriptors

Spatial distribution within neighbor pixels:

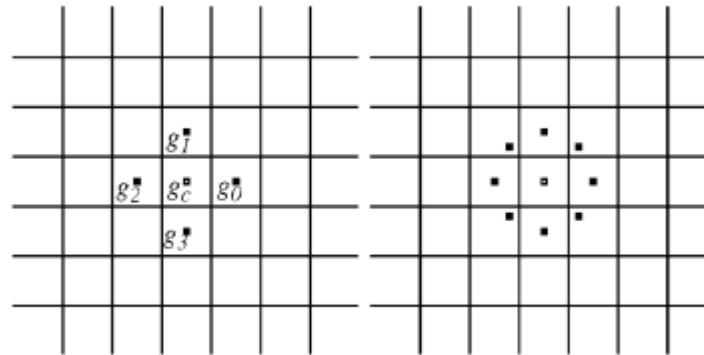
- The spatial joint distribution is analyzed with the co-occurring pixel values from neighborhood;
- By using the signed gray-level differences, the famous local binary pattern (LBP) is introduced.



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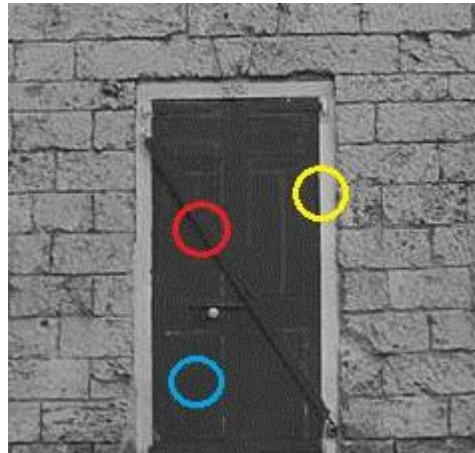


- ◆ The LBP succeeds in describing the spatial correlation of the structure.
- ◆ However, the signed gray-level difference procedure is too sensitive to disturbance.

Background: Local Structural Descriptors

Visual orientation:

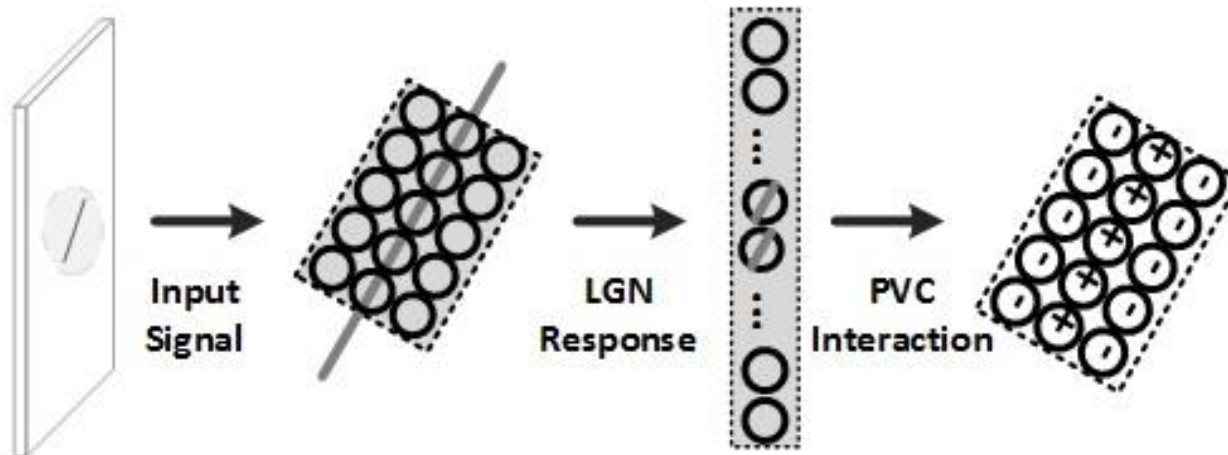
- The HVS is sensitive to visual orientation.
- Orientation information has been widely used in structural descriptor:
 - SIFT, HOG, etc.
- The HVS exhibits substantial orientation selectivity for scene perception.





The OS mechanism in the primary visual cortex :

- The HVS responds preferentially to the edge regions of an input scene;
- Because neurons in the primary visual cortex (especially in layer 4) exhibit substantial orientation selectivity

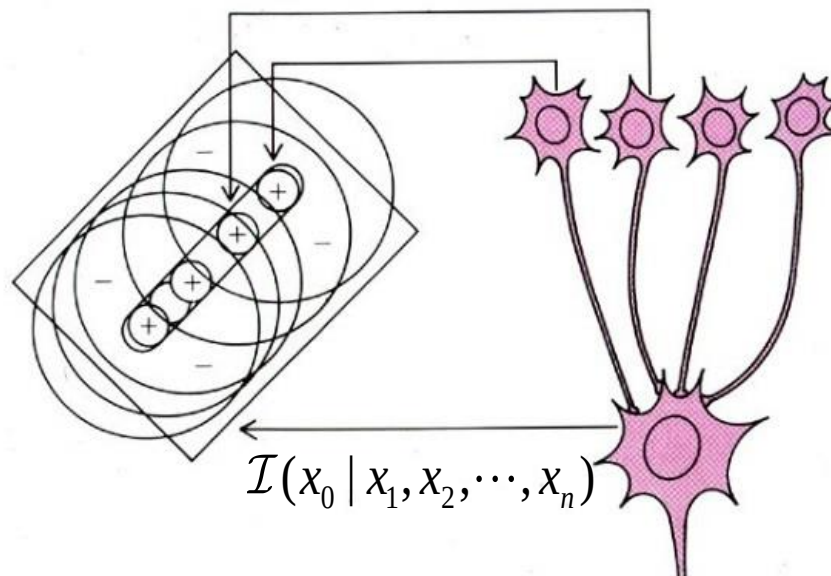




The OS mechanism in the primary visual cortex :

- Orientation selectivity arises from the arrangement of neuron interaction;

$$\mathcal{A}(\mathcal{I}(x | \mathcal{X})) = \mathcal{A}(\mathcal{I}(x | x_1, x_2, \dots, x_n))$$



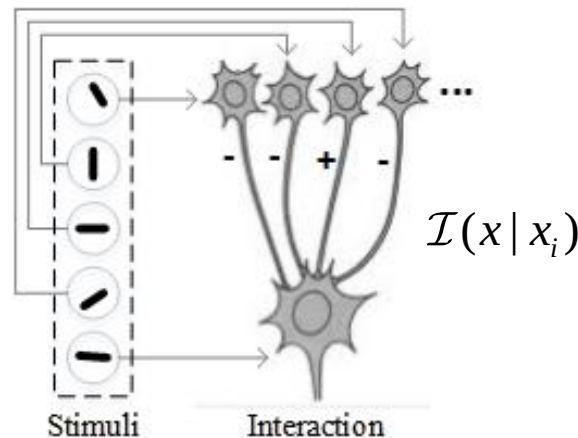
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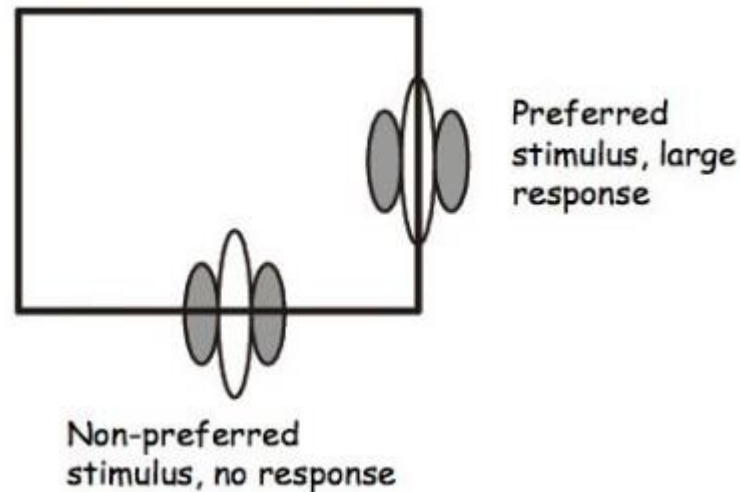
- For simplicity, only consider the synapses between the central cell and its excited cells;

$$\mathcal{A}(\mathcal{I}(x | \mathcal{X})) \approx \mathcal{A}(\mathcal{I}(x | x_1), \mathcal{I}(x | x_2), \dots, \mathcal{I}(x | x_n))$$



The OS modeling : Interaction

- The interaction between two cortical neurons:
 - **Excitation** if with similar preferred stimuli/orientations;
 - **Inhibition** if with dissimilar preferred stimuli/orientations.

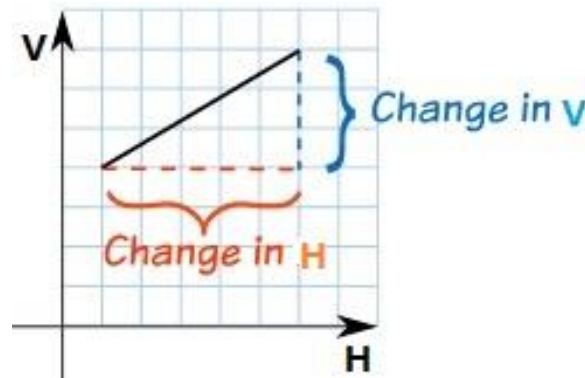




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$$\theta(x) = \arctan \frac{\mathcal{L}_v(x)}{\mathcal{L}_h(x)}$$





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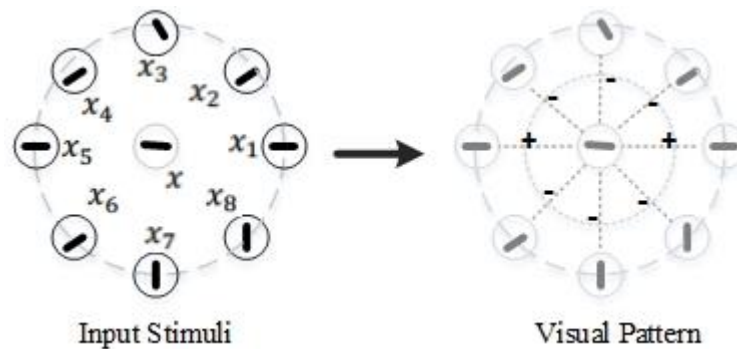
- Interaction between two pixels:

$$\mathcal{I}(x | x_i) = \begin{cases} + & \text{if } |\theta(x) - \theta(x_i)| < \mathcal{T} \\ - & \text{else} \end{cases}$$

The OS modeling : OS based visual pattern

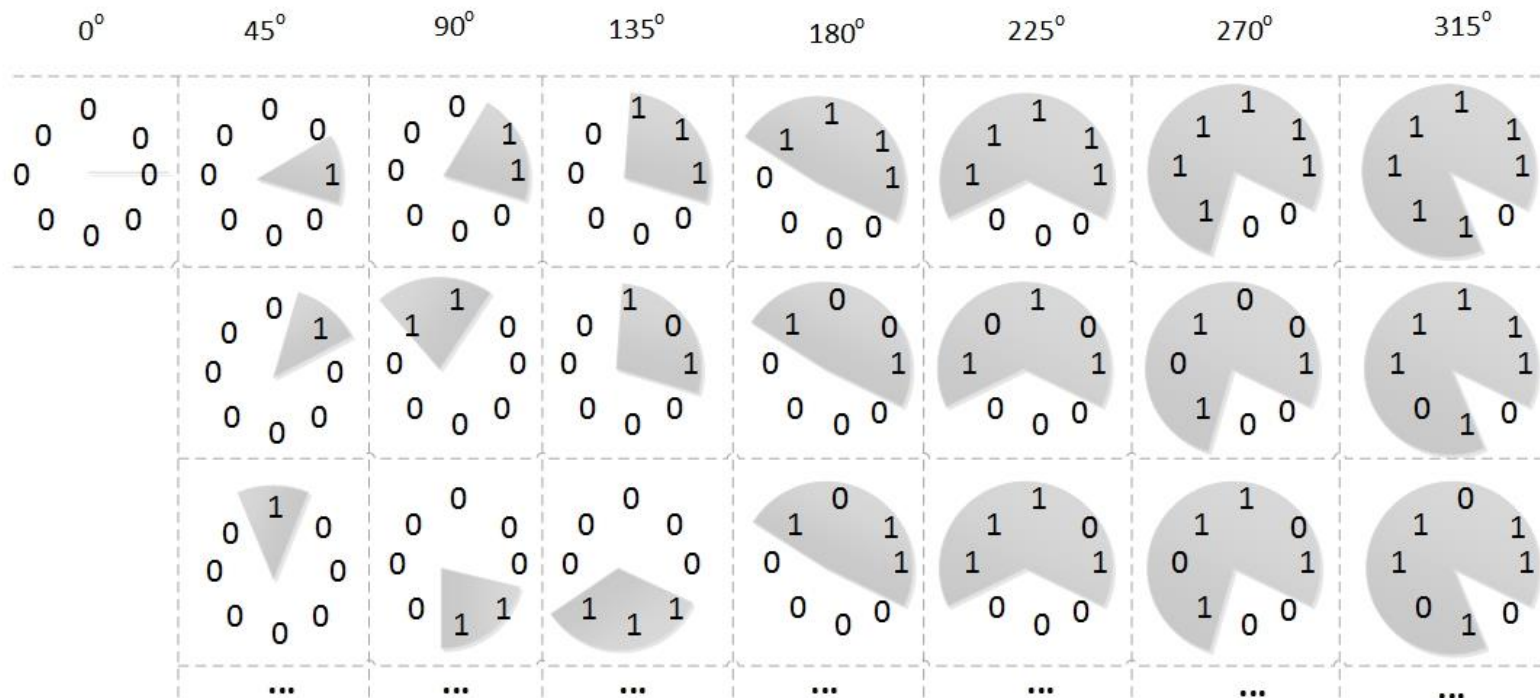
- The arrangement of interactions among the central pixel and its surrounding pixels:

$$\mathcal{P}(x | \mathcal{X}) = \mathcal{A}(\mathcal{I}(x | x_1), \mathcal{I}(x | x_2), \dots, \mathcal{I}(x | x_n))$$



The OS modeling : fundamental pattern extraction

- Too many original patterns: the number of pattern increases exponentially with the neighbor number.
- Pattern reduction: fundamental pattern
 - Patterns with same excitatory subfield represent similar response





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- Too many original patterns: the number of pattern increases exponentially with the neighbor number.
- Pattern reduction: fundamental pattern
 - Patterns with same excitatory subfield represent similar response
- Fundamental patterns:
 - A N-neighborhood local receptive field corresponds to N sector domains of the excitatory subfield;
 - E.g., for an 8-neighborhood, there are 8 excitatory subfield, $\{0^\circ, 45^\circ, 90^\circ, 135^\circ, 180^\circ, 225^\circ, 270^\circ, 315^\circ\}$

OS based structure extraction:

- A successful image structure descriptor should effectively represent:
 - Intensity change;
 - Spatial distribution.
- The OS based pattern: represents the spatial distribution.
- For intensity change representation: gradient magnitude,

$$\mathcal{M}(x) = \sqrt{(G_h(x))^2 + (G_v(x))^2}$$

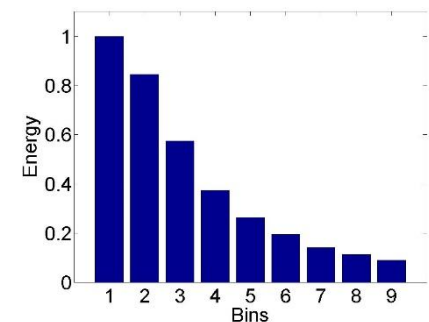
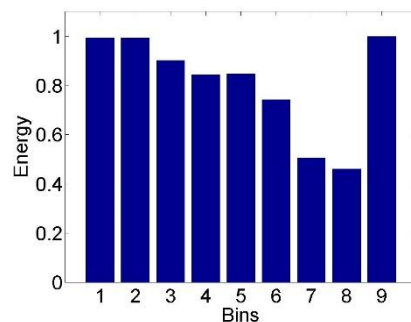
OS based structural histogram:

- Mapping an image into a structural histogram: with both OS based pattern and gradient magnitude, the structural information is extracted:

$$H_w(k) = \sum_{x=1}^N \mathcal{M}(x) \delta(\mathcal{P}_f(x), \mathcal{P}_f^k)$$

where:

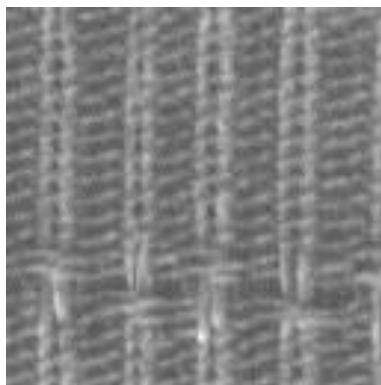
$$\delta(\mathcal{P}_f(x), \mathcal{P}_f^k) = \begin{cases} 1 & \text{if } \mathcal{P}_f(x) = \mathcal{P}_f^k \\ 0 & \text{else} \end{cases}$$



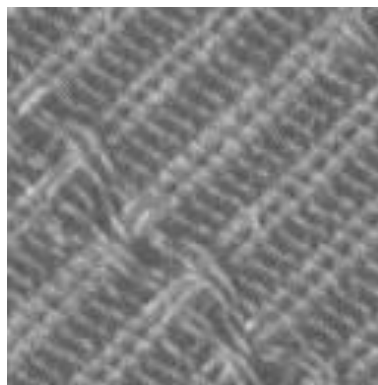
Application 1: Texture Classification



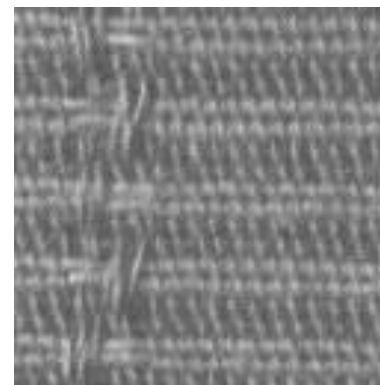
Rotation invariance:



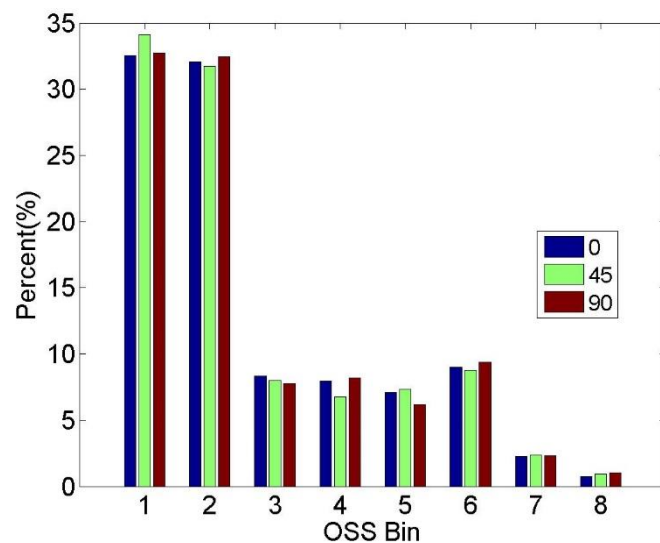
0°



45°



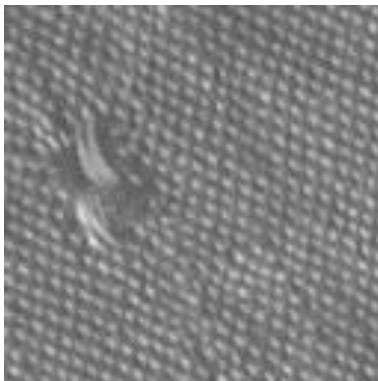
90°



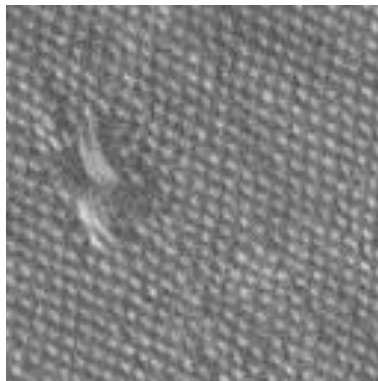
Application 1: Texture Classification



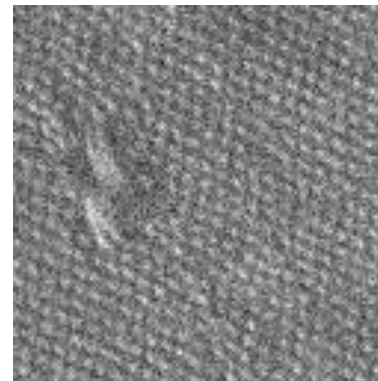
Robustness:



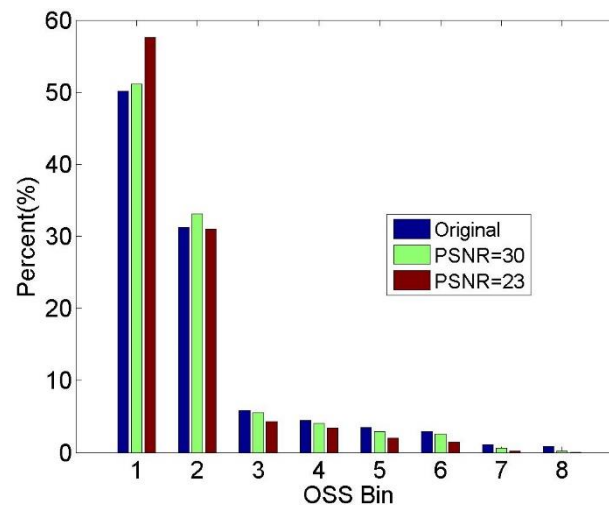
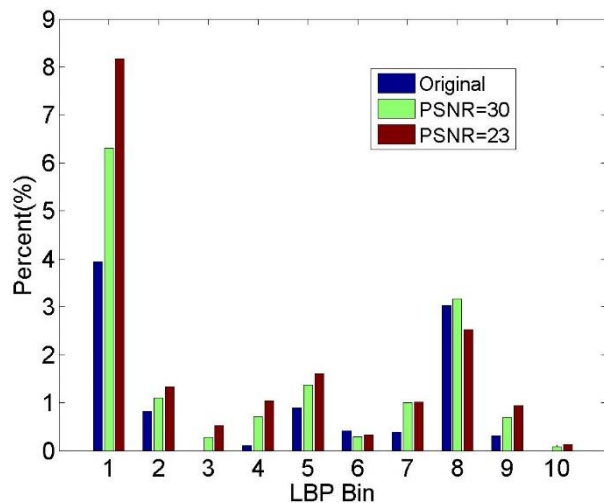
Original



PSNR=30dB



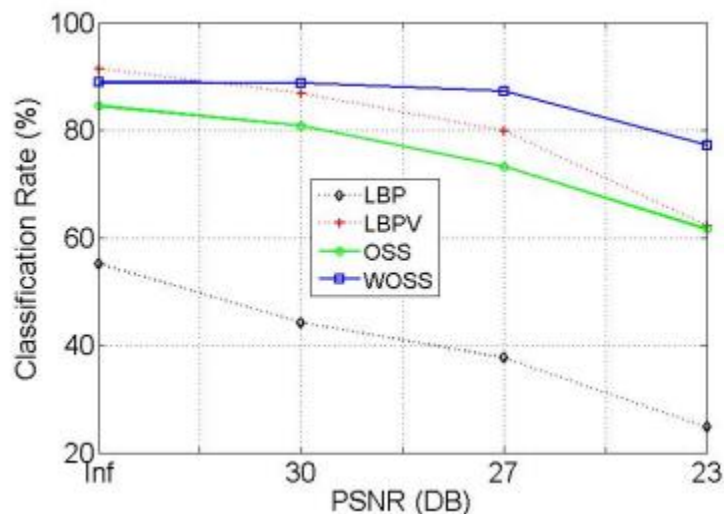
PSNR=23dB



Texture Classification:

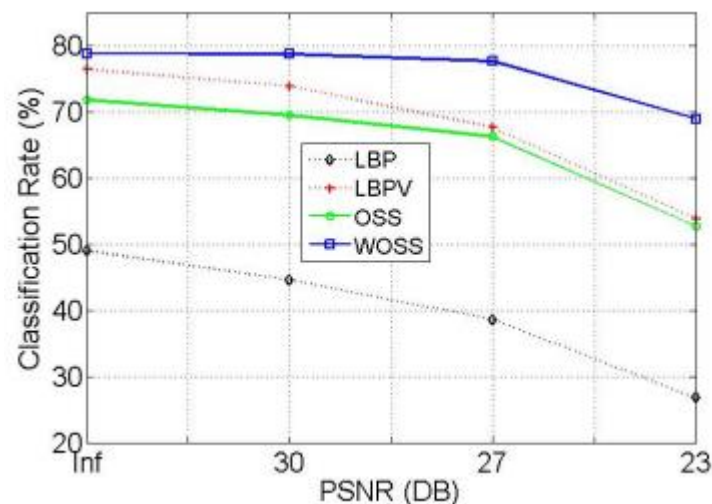
- TC10 database:

- Training: images under 'inca' illumination and '0°' angle (480 images);
- Testing: the other images (480×8 images).



- TC12 database:

- Training: same as that in TC10;
- Testing: images under 't184' and 'horizon' illuminations and nine angles ($480 \times 2 \times 9$ images).



Application 2: Quality Assessment



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Structural degradation caused by different distortions:



Application 2: Quality Assessment



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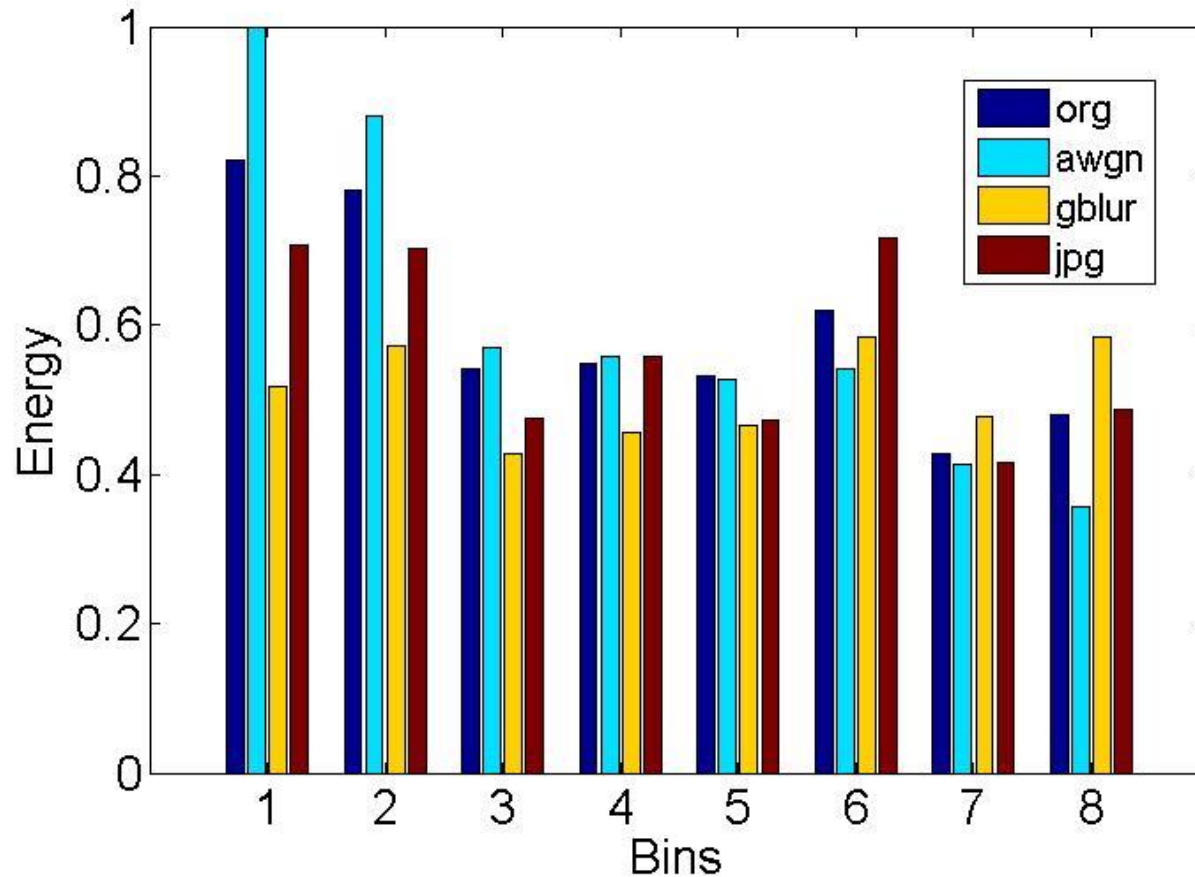
Though under a same level of noise, their qualities are different.



Application 2: Quality Assessment



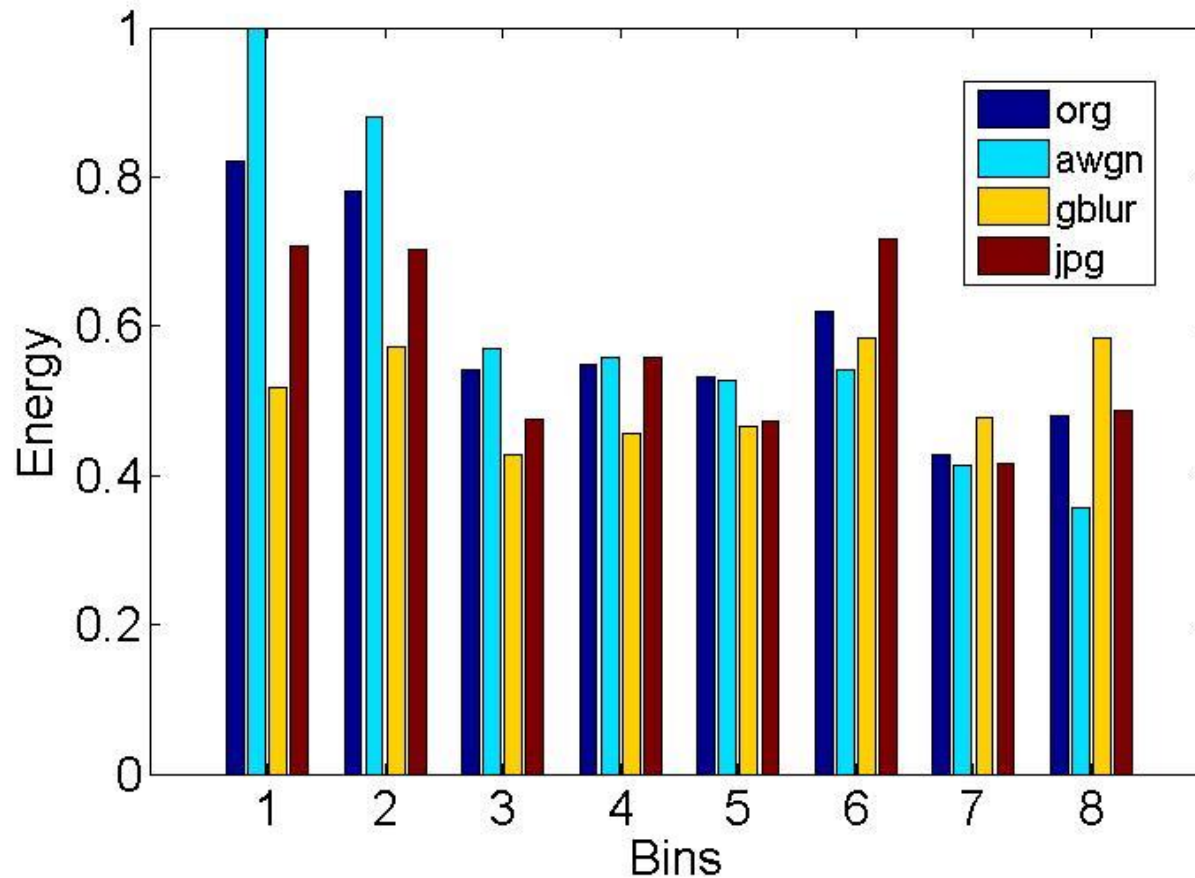
Structural degradation caused by different distortions:



Application 2: Quality Assessment



Structural degradation caused by different distortions:



Different distortion types cause different structural degradation

Application 2: Quality Assessment



Quality assessment according to structural degradation:

Performance on LIVE database

Dist.	Algo. Crit.		RR				FR			
		OSS	RRED [22]	WNISM [21]	RRVIF [38]	PSNR	SSIM [2]	MSSIM [39]	FSIM [40]	
No. of scalars		16	16	18	2	N	N	N	N	
j2k	CC	0.932	0.952	0.924	0.932	0.896	0.941	0.957	0.978	
	SRCC	0.921	0.946	0.920	0.950	0.889	0.936	0.953	0.971	
	RMSE	8.91	7.74	6.18	5.88	11.0	8.51	4.69	5.22	
jpg	CC	0.958	0.959	0.876	0.895	0.860	0.951	0.943	0.984	
	SRCC	0.944	0.953	0.851	0.885	0.841	0.944	0.942	0.983	
	RMSE	8.91	9.08	7.71	7.15	14.5	9.89	5.33	5.72	
awgn	CC	0.979	0.946	0.890	0.957	0.982	0.969	0.974	0.965	
	SRCC	0.972	0.946	0.870	0.946	0.985	0.963	0.973	0.965	
	RMSE	5.58	9.08	7.29	4.66	4.334	6.901	3.65	7.34	
gblur	CC	0.972	0.956	0.888	0.955	0.784	0.874	0.955	0.969	
	SRCC	0.962	0.952	0.915	0.961	0.782	0.894	0.954	0.971	
	RMSE	4.19	5.42	7.22	4.66	11.5	8.96	4.69	4.57	
ff	CC	0.924	0.895	0.925	0.944	0.890	0.945	0.947	0.946	
	SRCC	0.907	0.918	0.923	0.941	0.890	0.941	0.947	0.950	
	RMSE	10.4	12.7	6.25	5.42	13.0	9.36	5.30	9.21	
overall	CC	0.863	0.827	0.710	0.725	0.872	0.904	0.943	0.960	
	SRCC	0.865	0.830	0.703	0.732	0.876	0.910	0.945	0.963	
	RMSE	12.4	15.3	18.4	17.6	13.4	11.7	9.09	7.68	

Application 2: Quality Assessment



Quality assessment according to structural degradation:

Overall performance on CSIQ and TID databases

DB	Algo. Crit.	RR				FR			
		WOSS	RRED [22]	WNISM [21]	RRVIF [38]	PSNR	SSIM [2]	MSSIM [39]	FSIM [40]
CSIQ	CC	0.901	0.695	0.696	0.698	0.800	0.815	0.900	0.928
	SRCC	0.895	0.773	0.705	0.733	0.806	0.838	0.914	0.940
	RMSE	0.113	0.189	0.189	0.182	0.158	0.152	0.115	0.098
TID	CC	0.782	0.712	0.572	0.535	0.573	0.641	0.842	0.886
	SRCC	0.759	0.702	0.495	0.500	0.579	0.627	0.853	0.890
	RMSE	0.829	0.943	1.101	1.134	1.100	1.03	0.723	0.623

- In this paper, a novel structure descriptor is introduced.
- Inspired by the orientation selectivity mechanism in the primary visual cortex, the interactions among neurons are analyzed.
- By mimicking the excitation/inhibition in a local receptive field, a novel visual pattern is proposed to describe the spatial correlation among pixels.
- Taking both the luminance change and visual pattern into account, a novel structural descriptor is designed.
- Applications on texture classification and quality assessment demonstrate the effectiveness of the proposed structural descriptor.

- Jinjian Wu, et al., "Orientation Selectivity based Visual Pattern for Reduced-Reference Image Quality Assessment", **Information Science**, vol.351, pp.18-29, July 2016. (source code is available at <http://web.xidian.edu.cn/wjj/index.html>)
- Jinjian Wu, , et al., "Visual Orientation Selectivity based Structure Description", **IEEE TIP**, Vol. 24, No. 11, PP. 4602-4613, Nov. 2015.
- Jinjian Wu, et al., “Reduced-Reference Image Quality Assessment with Orientation Selectivity based Visual Pattern”, IEEE ChinaSIP 2015, Chengdu, Sichuan.
- Jinjian Wu, et al., “Visual Pattern Degradation based Image Quality Assessment”, OIT’2015, Beijing, China.
- Jinjian Wu, et al., "Orientation Selectivity based Structure for Texture Classification", SPIE /COS Photonics Asia Conference, 2014, Beijing, China.



Thanks