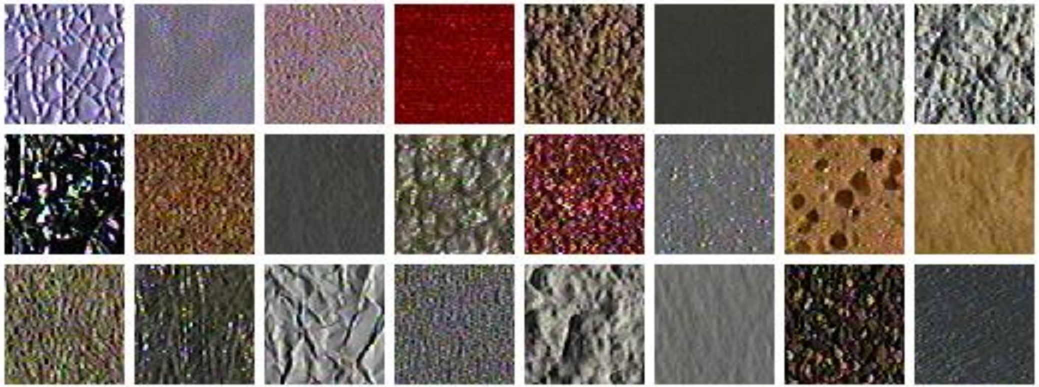
Texture and Material Recognition

2014 February 27

Material Recognition

Similar to texture recognition.



CURET Texture Database

Flickr Material Database (there are masks)

FMD

10 classes (Fabric Foliage Glass Leather Metal Paper Plastic Stone Water Wood)

100 images per class

50 images used for training

Today

1. Presenting two papers on local features for texture and material recognition

2. Designed local features

3. Trained to fit a test set by SVM

4. Tested on Flickr Materials Database

First Paper

Recognizing Materials Using Perceptually Inspired Features

Lavanya Sharan · Ce Liu · Ruth Rosenholtz · Edward H. Adelson

IJCV 2013 version of 2010 CVPR paper

57.1% on FMD (up from 44.6%)

Humans can do 84.9%

Second Paper

Pairwise Rotation Invariant Co-occurrence Local Binary Pattern

Xianbiao Qi · Rong Xiao · Jun Guo · Lei Zhang

ECCV 2012

57.4% on FMD

Third Paper

Toward Robust Material Recognition for Everyday Objects

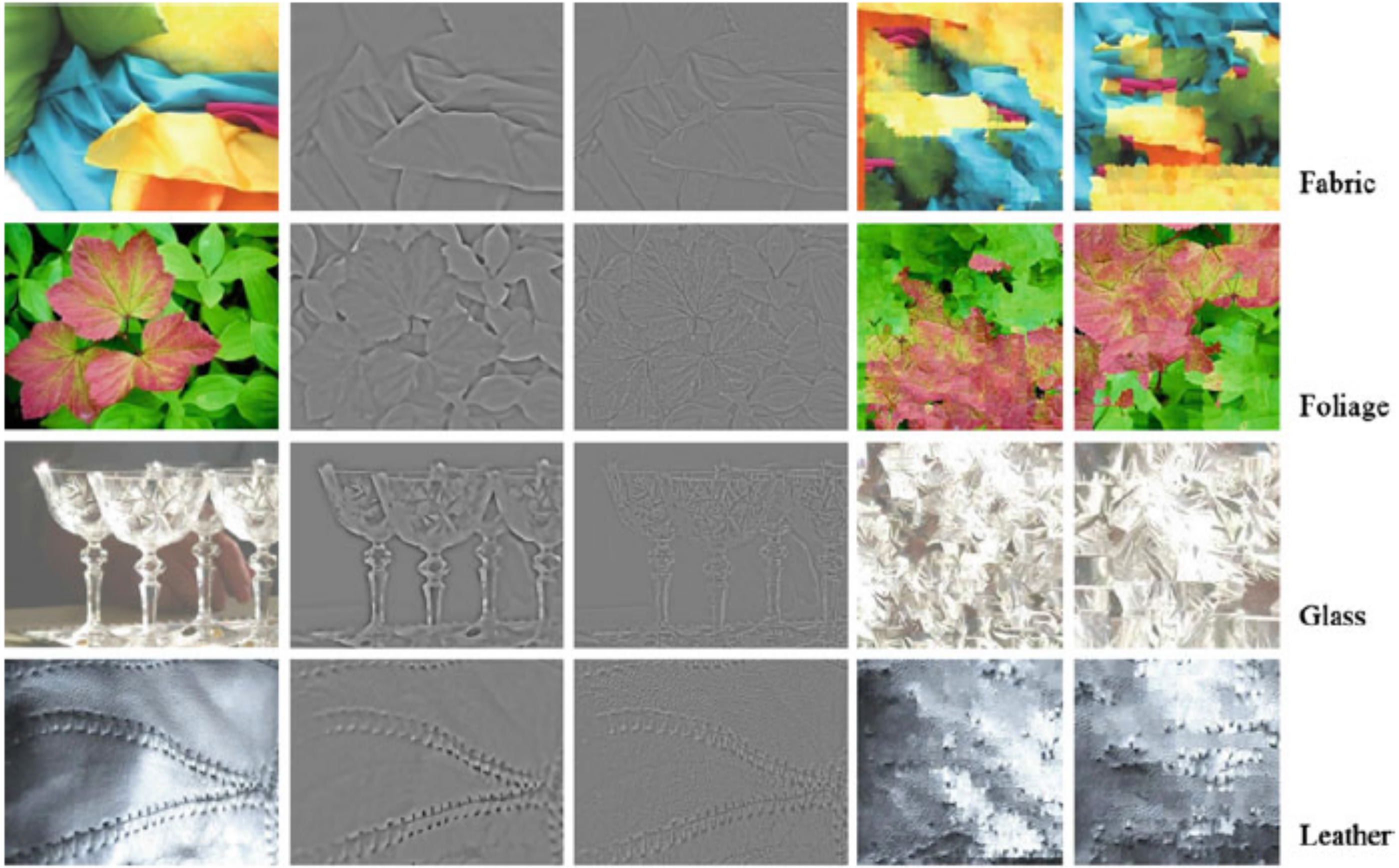
Diane Hu · Liefeng Bo · Xiaofeng Ren

BMVC 2011

54% on FMD

Lots of Stuff

First Paper



5 MTurk Human Experiments

Humans

2,500 people in MTurk study, 500 per experiment.

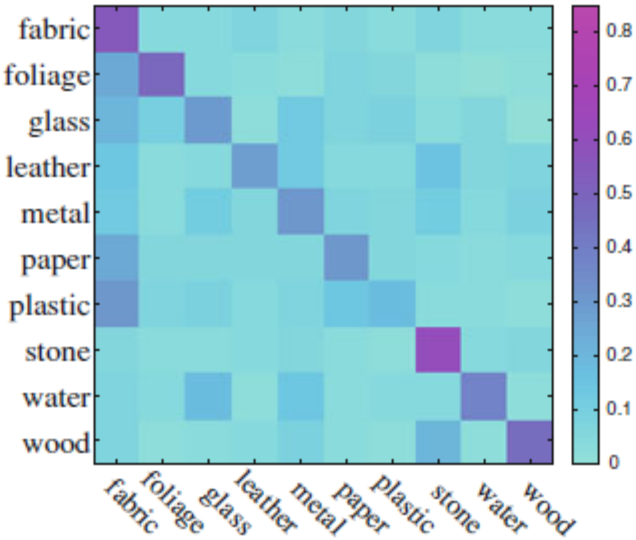
84.9% on original images

65.3% bilateral filtered

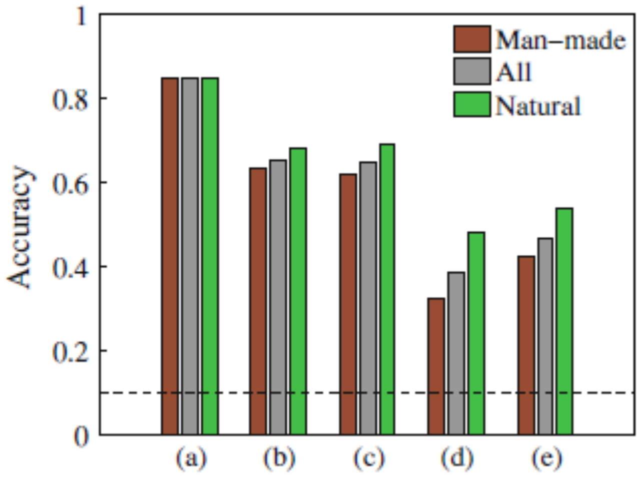
64.8% high-pass filtered

38.7% synthesized 15x15 (big drop, global to local)

46.9% synthesized 30x30



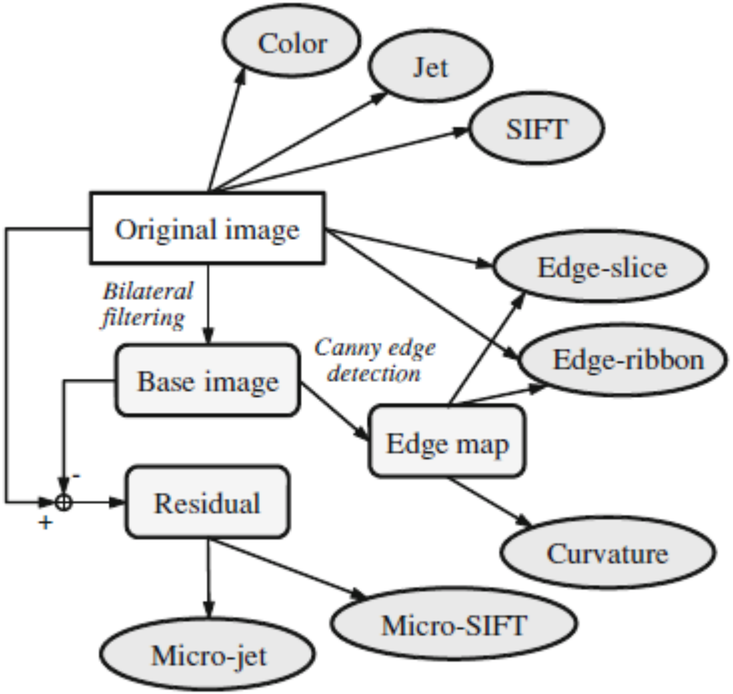
(e) Synthesized 30×30 (46.9%)



(f) Average recognition rate

Category matters

Feature Generation

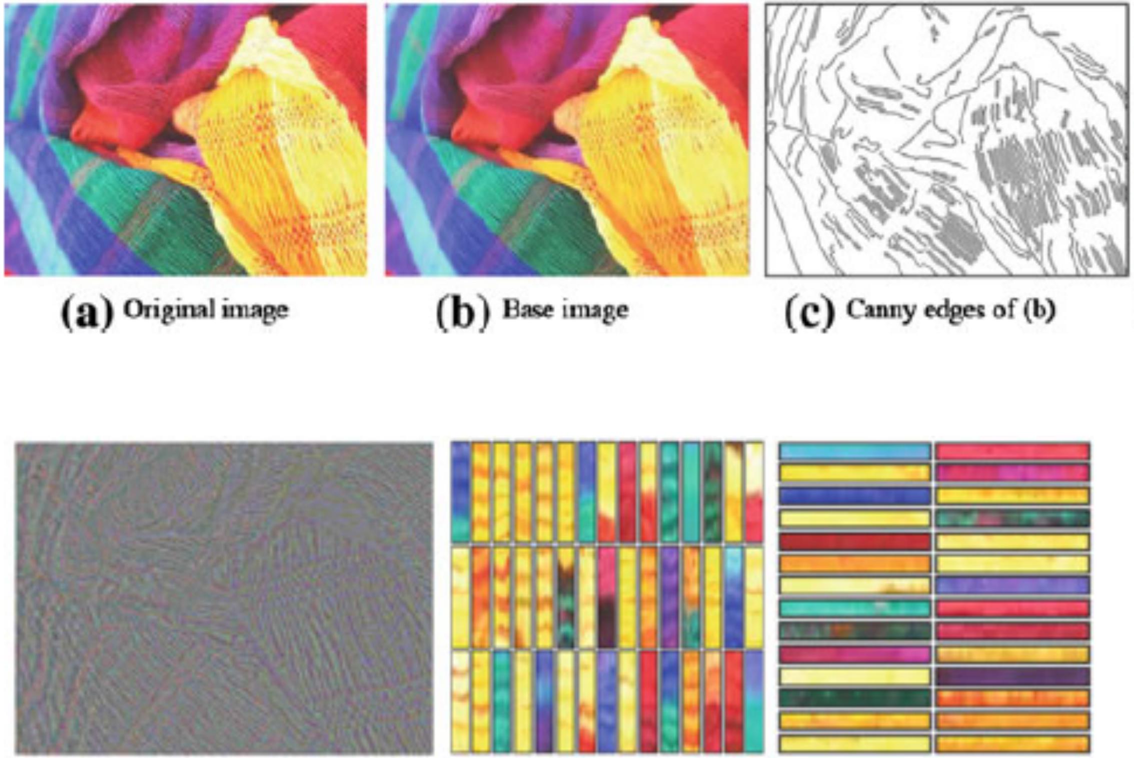


Color and texture features on original images (color, Jet, SIFT)

Edge-based features (slice, ribbon, curvature)

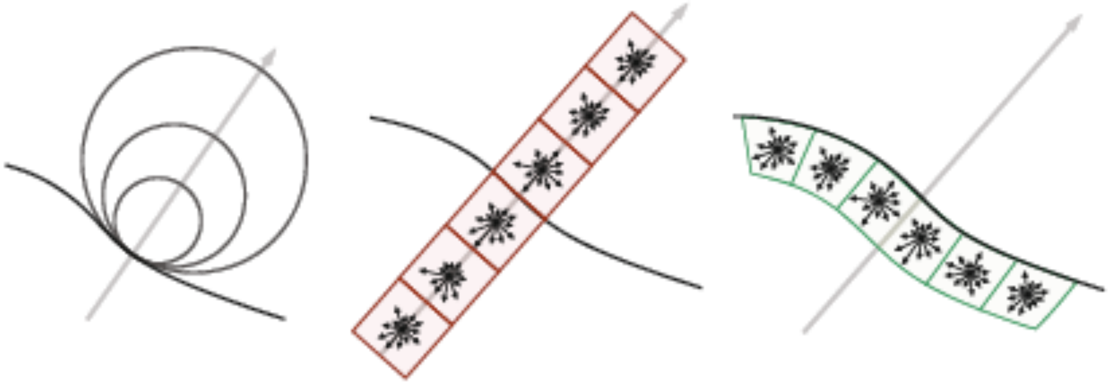
Texture features on bilateral residual (Jet, SIFT)

(Will not cover all these features)



(a) Original image (b) Base image (c) Canny edges of (b)

(d) Residual image: (a)-(b) (e) Edge-slice samples (f) Edge-ribbon samples



(a) Curvature (b) Edge-slice (HOG) (c) Edge-ribbon (HOG)

Fig. 9 (a) We computed the curvature of edges at three spatial scales to measure outline shape information. (b), (c) We computed HOGs over 6 cells defined near the edges in images to measure reflectance information

Feature Dictionary

k-means to cluster 8 features into codewords and concatenate all feature codewords into a single dictionary.

Feature name	Dim	Average # per image	# of clusters
Color	27	6326.0	150
Jet	64	6370.0	200
SIFT	128	6033.4	250
Micro-jet	64	6370.0	200
Micro-SIFT	128	6033.4	250
Curvature	3	3759.8	100
Edge-slice	72	2461.3	200
Edge-ribbon	72	3068.6	200

Latent Dirichlet Allocation

(aLDA method not described here because it doesn't work)

aLDA vs. SVM	44.6% vs. 57.1%

SVM

Form histogram of words and apply binary SVM with histogram intersection. One-versus-all.

$$c(h) = \sum_i a_i k(h, h_i) + b$$

$$k(h, h_i) = \sum_{j=1}^{|\mathbb{D}|} \min\Big(h(j), h_i(j)\Big).$$

Feature Importance

SIFT, color, curvature, edge-ribbon, micro-SIFT, jet, edge-slice, micro-jet.

SIFT+color can achieve 50.2%

(but, small number of images)

Etc

Further results and conclusions ...

Local Binary Patterns

Second Paper

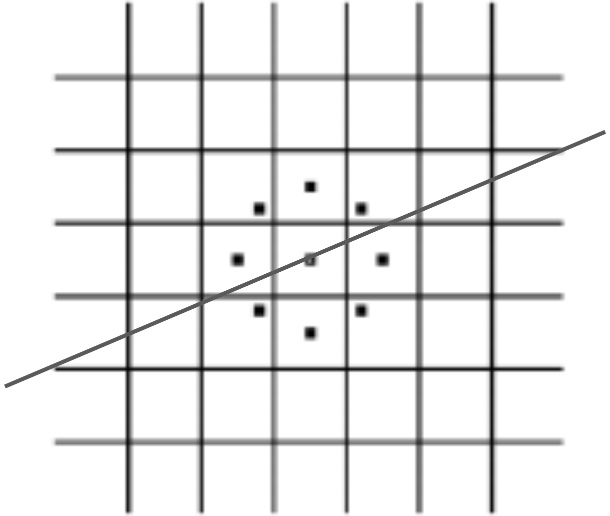
Local Binary Pattern (Ojala 2002)

Invariant to mean value, maps rotation to barrel shifts.

Pattern 11110000 is an edge.

58 patterns <= 2 transitions.

Histogram of 59 or 10 bins



(P=8,R=1.0)

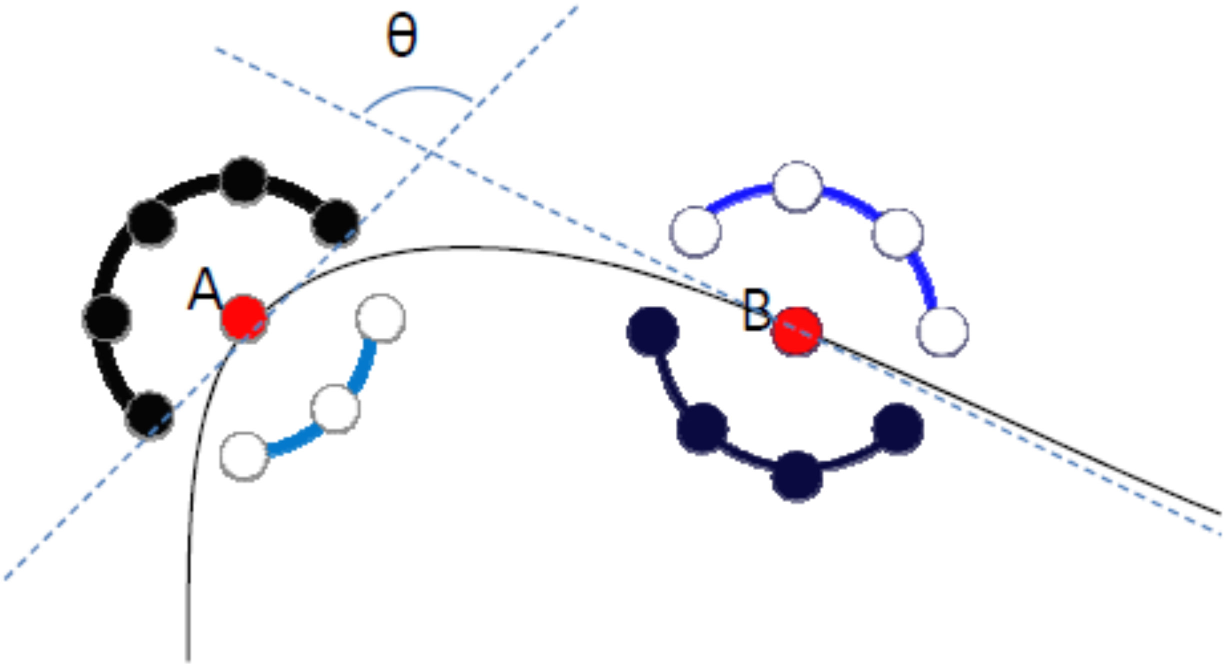
PRI-coLBP

In short:

A pair of local binary patterns, gradient aligned at 3 scales.

Trained by SVM/PCA/RBF or SVM/additive kernel approximation

Idea



2D Histogram

Calculate the rotation invariant uniform LBP codeword for point A. Calculate the uniform LBP codeword for point B. Accumulate into 2D histogram.

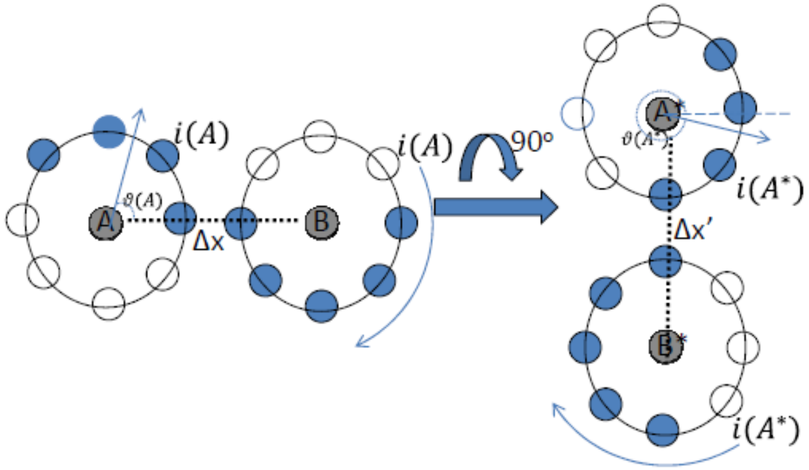


Fig. 2. An illustration of pairwise rotation invariant. For the left pairs, we first determine orientation $i(A)$ of the reference point A, then we compute the uniform pattern of B according to $i(A)$, we get co-patterns $[(00001111)_{RU}, (01111100)_U]_{co}$. For the rotated pairs in the right side, we could also get the same co-patterns.

$$H_{4,8} \leftarrow H_{4,8} + |\nabla_A| + |\nabla_B|, \quad H \in \mathbb{R}^{10\times 59}$$

Extension

Rotation Invariance. Define a local frame at A with local gradient as first axis. Define position of B in this frame.

Evaluate B at three scales and two orientations, along and cross gradient. (edge-ribbon, edge-slice?)

Add RGB, we have 4D histogram. Feature vector has dimension 3*6*10*59 = 10620.

PCA

Feature vector is sparse and can be reduced to 120-150 dimensions (empirically).

Texture Classification

Methods	Brodatz(3)	CUReT(46)	KTH-TIPS(40)
PRI-CoLBP$_0$	**96.6%**	98.6%	98.3%
PRI-CoLBP$_0$(PCA)	96.0%	**99.2%**	**98.8%**
PRI-CoLBP$_0$(AKA)	**96.8%**	98.5%	97.6%
Nguyen et al.[18]	96.1%	—	95.7%
Zhang et al.[14]	95.9%	95.3%	96.1%
VZ-Patch[16]	92.9%	98.0%	92.4%
Caputo et al.[17]	95.0%	98.5%	94.8%
Lazebnik et al.[19]	88.2%	72.5%	91.3%
MSLBP[5]	91.6%	96.3%	92.2%

Material Recognition

Methods		50
Single Feature	SIFT [21]	35%
	MSLBP	43.5%
	Kernel Descriptor in [20]	49%
	PRI-CoLBP$_g$	**56.5%±1.8**
	PRI-CoLBP$_g$(PCA)	**55.2%±1.8**
	PRI-CoLBP$_g$(AKA)	**57.4%±1.7**
Multiple Features	Liu et al. CVPR 2010 [21]	44.6%
	Hu et al. BMVC 2011 [20]	54% ±2.0

Oxford Flower

Single Features	20	30	Multiple Features	20	30
SIFT boundary [7]	32.0%	–	Ito et al. [4]	53.2%	–
HSV [7]	43.0%	–	Nilsback et al. [7]	72.8%	–
HOG [7]	49.6%	–	Yuan et al. [23]	74.1%	–
SIFT internal [7]	55.1%	–	Nilsback's thesis [8]	76.8%	–
CoHED [4]	48.2%	–	Grabcut [9]	77.0%	–
MSLBP	52.0%	–	Chai et al.[9]	80.0%	–
MSDS [9]	69.5%	73.4%	PRI-CoLBP$_g$ + MSDS	**84.2%**	**87.1%**
Kanan et al [24]	71.4%	75.2%			
PRI-CoLBP$_g$	**79.1%**	**82.3%**			

Conclusion

1. MIT group got a big boost just by changing their learning method.

2. Pairwise LBP capturing an equivalent quantity of material information?