Texton Theory in Computer Vision

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Acknowledgement

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Problem Statement

- To classify images of materials on the basis of their texture appearance without imposing any constraints on, or requiring any a priori knowledge of, the viewing or illumination conditions.

Texture and Texton

- **Texture**
  No operational definition of texture. It varies based on different approaches of texture analysis.
- **Texton**
  It is fundamental micro structures of natural images (and videos).
- **Texture analysis**
  1- Statistical Approach
  2- Structural Approach
  3- Fourier Approach

2D and 3D Texture

- **2D texture**

  Flat texture
  Viewpoint and illumination are assume constant

- **3D texture**

  Appearance changes dramatically due to different viewpoint and lighting settings

Figure 1 : Same patch of material of "Crumpled Paper" imaged under three different lighting and viewing conditions

Motivation

- Classifying textures from single images under such general conditions is a very demanding task.
- Textured materials often undergo a sea change in their imaged appearance with variations in illumination and camera pose.

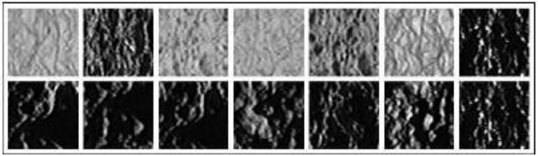

Figure 2 : The changed in image appearance of the same texture with variation in imaging conditions.

Experimental Setup

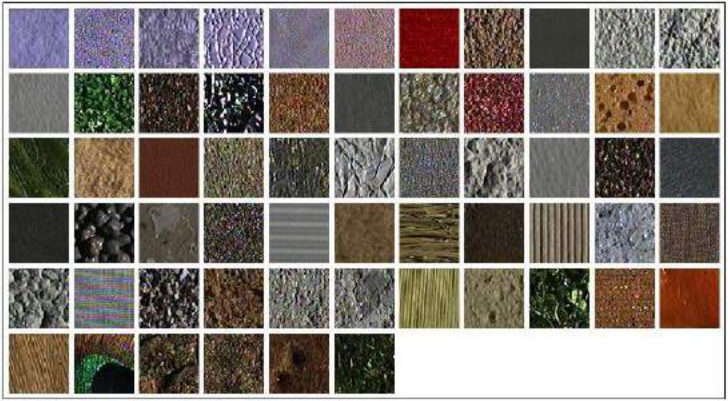

Figure 3 : One image of each of the textures present in the Columbia-Utrecht database. Only a central 200*200 region is shown.

Algorithm I

Stage 1: Generating the texton Dictionary

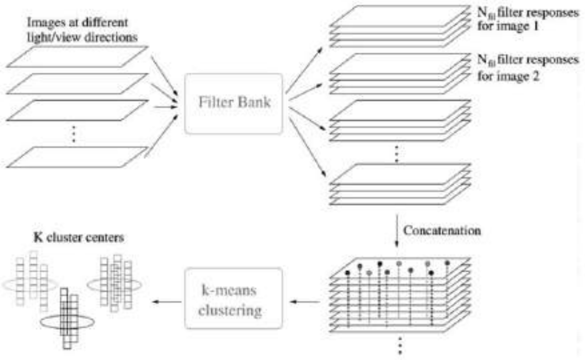

Figure 4 : Learning the texton dictionary

Algorithm II

Stage 2: Model generation

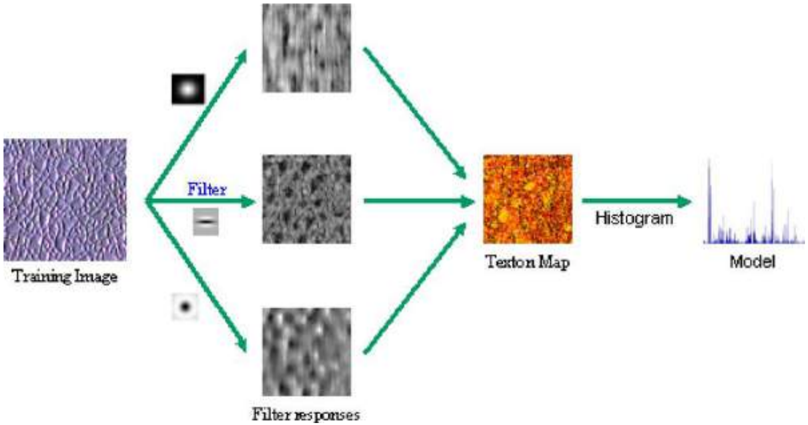

Figure 5 : Learning a model from given training image

Algorithm III

Stage 3: Classification stage

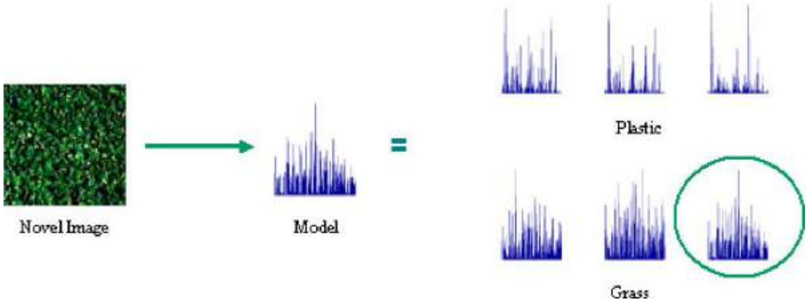

Figure 6 : Classification of a novel image

Algorithm IV

- In Classification stage a nearest neighbour classifier is used and the chi-squared statistic employed to measure distances
- **Distance between two histograms**
  Chi-Square distance:

$$\chi^2(h_1, h_2) = \frac{1}{2} \sum_{n=1}^{bins} \frac{(h_1(n) - h_2(n))^2}{h_1(n) + h_2(n)} \tag{1}$$

LM Filter Bank [1]

Leung and Malik work

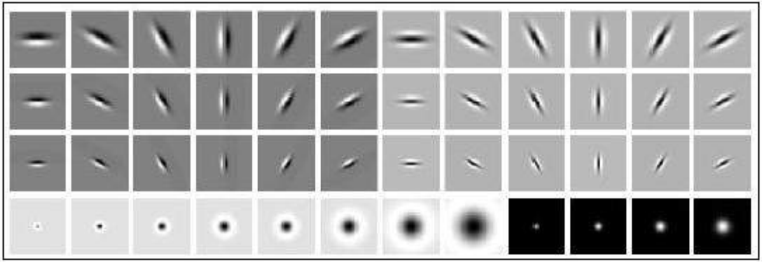

Figure 7 : Mixture of edge bar and spot filters at multiple scale and orientations.It has total 48 filters-2 Gaussian derivative filters at 6 orientation and 3 scales 8 Laplacian of Gaussian filters and 4 Gaussian filters

The Maximum Response(MR)Filter Bank [2]

Varma and Zisserman work

- Only 8 filter responses are recorded by taking, at each scale,the maximum response of anisotropic filters across all orientations

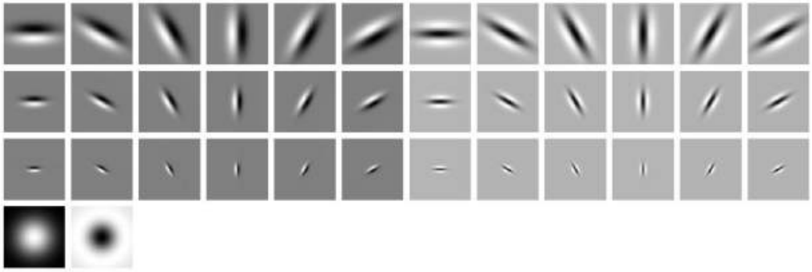

Figure 8 : The RFS (Root Filter Set) filter bank consist of two anisotropic(an edge and a bar filter at 6 orientation and 3 scales) filters and 2 rotationally symmetric ones(a Gaussian and a Laplacian of Gaussian)

LM vs MR filters [2]

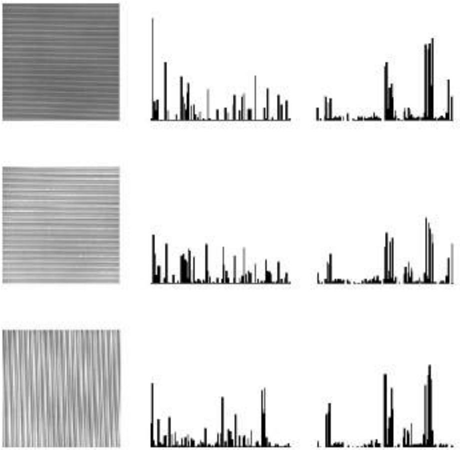

Figure 9 : Classification of rotated textures.Column 1 shows three images of Ribbed paper texture.Column 2 shows the textons histograms using LM filter bank.Column 3 shows textons histogram using the MR filter bank

Results

Filters	Dimension	Invariance	Number of texture classes 20	40	61
S	13	Rot.	96.30%	95.27%	94.62%
LMS	48	None	96.08%	93.75%	93.44%
LML	48	None	98.04%	96.47%	96.08%
RFS	38	None	98.37%	96.36%	96.08%
MR8	8	Rot.	97.83%	96.41%	96.40%
MR4	4	Rot.	94.13%	92.07%	90.73%
MRS4	4	Scale, Rot.	96.41%	94.08%	93.26%

Table 1 : Comparison of classification rates for varying number of texture classes for each of the filter set

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Reducing the Number of models

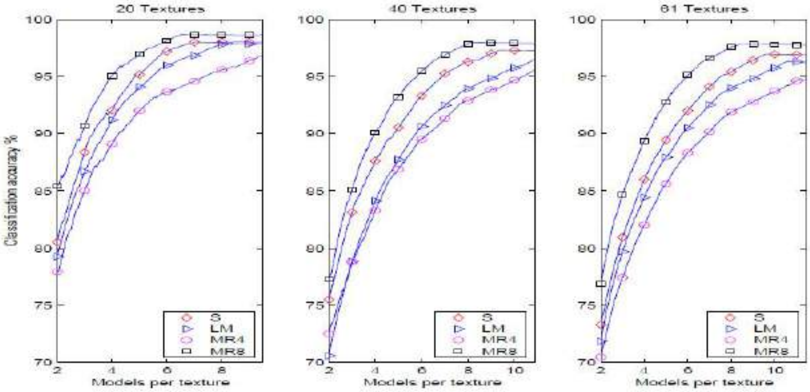


Figure 10 : Classification rates for models selected by the Greedy algorithm for 20,40 and 61 textures

Are Filter Banks Necessary? [3-4]

- **Markov Chain**
- A sequence of random variables $x_1, x_2, x_3, ...x_n$
- x_t is a state of model at time t

$$\boxed{x_1} \rightarrow \boxed{x_2} \rightarrow \boxed{x_3} \rightarrow \boxed{x_4} \rightarrow \boxed{x_5}$$

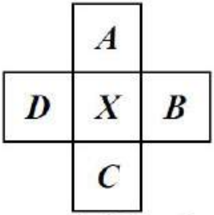
- **Markov assumption:** each state depends only in previous one $P(X_t|X_{t-1})$
- The above is actually first order markov chain
- An N^{th} order markov chain: $P(X_t|X_{t-1}, ..., X_{t-N})$

Markov Random Field

- a generalization of Markov Chain to two or more dimensions
- **First order MRF**

  Probability that pixel X takes certain value given the values of neighbours A,B,C,D

  P(X|A,B,C,D)



MRF (Markov Random Field) Classifier [3-4]

- Model changes from joint pdf of filter responses to joint pdf of row pixel intensities computed over all N×N patches in image:

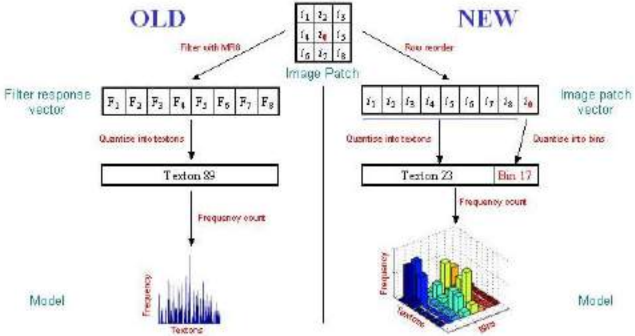


Figure 11 : The MRF representation

Results

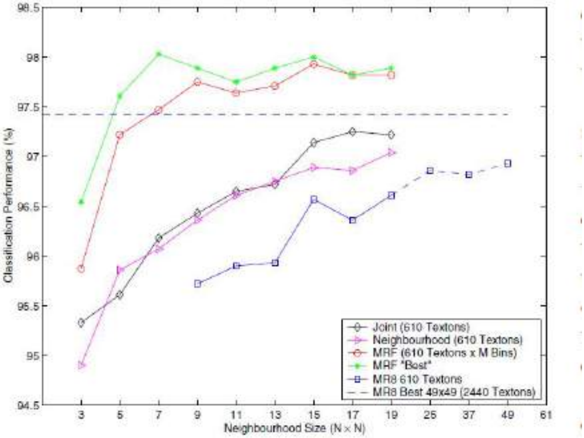


Figure 12 : The variation in classification performance as size of the neighborhood changes

Results: Scale and Rotation Invariance

Scale: Select 4 textures for which scaled data is present. Add scaled images to (a) test set and (b) training + test set of selected textures

	Naturally Scaled		Synthetically Scaled x 2	
	Test Only	Training + Test	Test Only	Training + Test
MRF	93.48%	100%	65.22%	99.73%
MR8	81.25%	99.46%	62.77%	99.73%

MRF not adversely affected by scaling. Can cope with scale changes at least as well as MR8

Rotation Invariance: Use circular neighbourhoods and correct for local orientation before forming feature vectors

N x N	Rot. Inv. N'hood	Not Inv. N'hood	Rot. Inv. MRF	Not Inv. MRF
7 x 7	96.36%	96.08%	97.07%	97.47%
9 x 9	96.47%	96.36%	97.25%	97.75%

Table 2 : The effects of scale and rotation

Conclusion

- The blurring (e.g. Gaussian smoothing) in many filters means that fine local detail can be lost.
- Superior classification results can be obtained by using compact, local neighbourhoods and without the use of filter banks.

References I

[1] Leung, Thomas and Malik, Jitendra *Representing and Recognizing the Visual Appearance of Materials Using Three-dimensional Textons*. International Journal of Computer Vision, 2001

[2] M Varma and A.Zisserman , *A Statistical Approach to Texture Classification from Single Images*. International Journal of Computer Vision, volume 62, 2005

[3] M Varma and A.Zisserman , *Texture classification: Are filter banks necessary?*. IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2003

[4] M Varma and A.Zisserman, *A statistical approach to material classification using image patch exemplars*.IEEE transactions on pattern analysis and machine intelligence, volume 31, 2009

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Thanks