Directional Filterbank for Texture Image Classification

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Introduction

- Rotation invariant texture classification is a critical and un-solved problem in machine vision.
- A number of methods have been proposed:
  - Madiraju and Liu (1994): using eigen-analysis of local covariance of image blocks to obtain 6 rotation invariant features, e.g. roughness, anisotropy etc.
  - Porter and Canagarajah (1997): creating circularly symmetric Gaussian Markov random field model in wavelet domain.
  - Charalampidis and Kasparis (2002): extracting roughness features in directional wavelet domain based on steerable wavelet.
  - Do and Vetterli (2002): using Gaussian Hidden Markov Tree to model cross-scale wavelet coefficients in steerable wavelet domain. Covariance matrices in HMT are replaced by eigenvalues to achieve rotation invariance.

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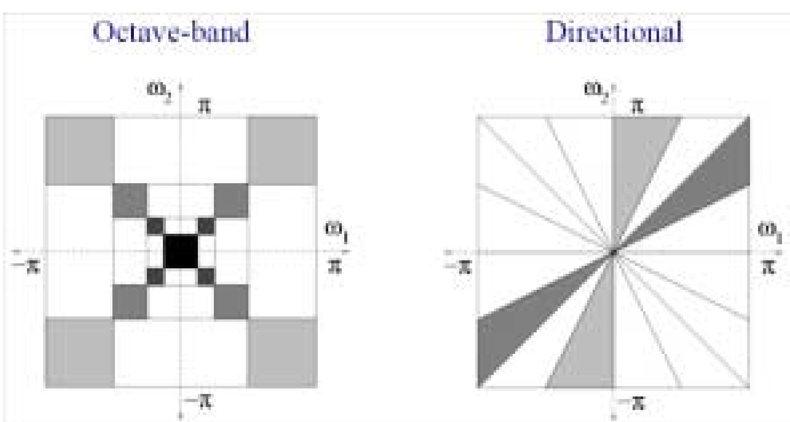
A New Method

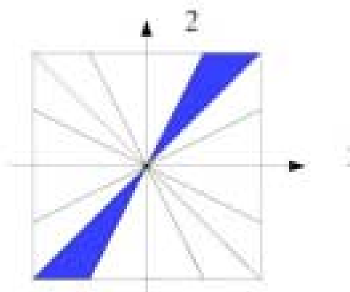
- Motivation:
  - Existing methods frequently provide low and inconsistent performance.
  - We like to explore the potential of a new critically sampled directional filter bank (CSDFB).
  - Preliminary work by Rosiles and Smith (2001) using this directional filter bank revealed promising results on non-rotated texture classification.
- Approach:
  - Exploring relationship between texture orientation and coefficient distributions in CSDFB.
  - Extracting principal axes from joint distribution of coefficients from all directional subbands.
  - Classification based on Support Vector Machine (SVM)

CSDFB

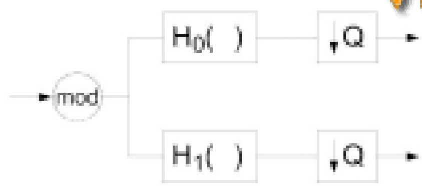
- 2-D directional filter bank



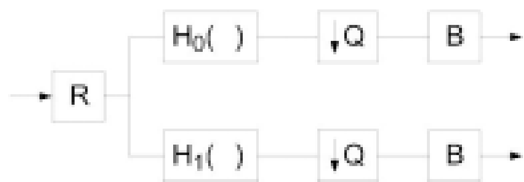
CSDFB



(a)



(b)



(c)

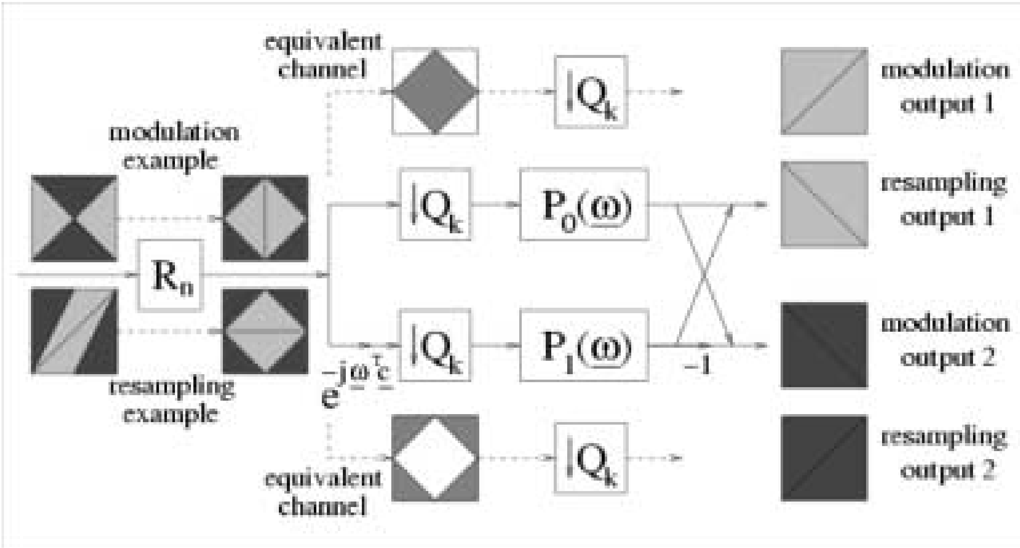
- The directional partition of the frequency plane can be achieved through successive applications of two critically sampled filter bank decompositions.

CSDFB

- Critically sampled directional filter bank is based on the pair of a diamond-shape lowpass filter and its complimentary highpass filter.
  - At the first stage decomposition, the input image is modulated (frequency shifted) by **Mod** before entering the filter bank.
  - At the following stages, the frequency resampling (skewing) matrix **R** reshapes the diamond passband into different parallelogram passbands, and together with the passbands of the previous stages these will produce wedge-shaped passbands
- The CSDFB can be efficiently implemented through separable filtering.

CSDFB

- Two band DFB

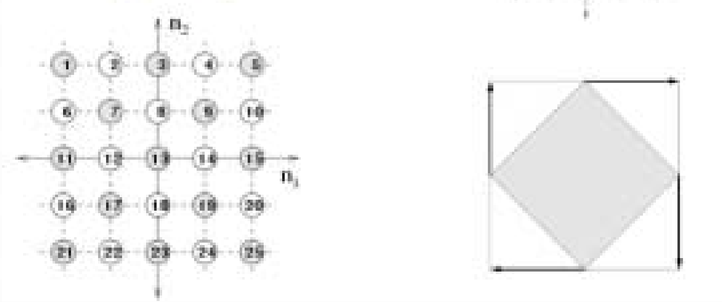


CSDFB

- Directional downsampling operator Q

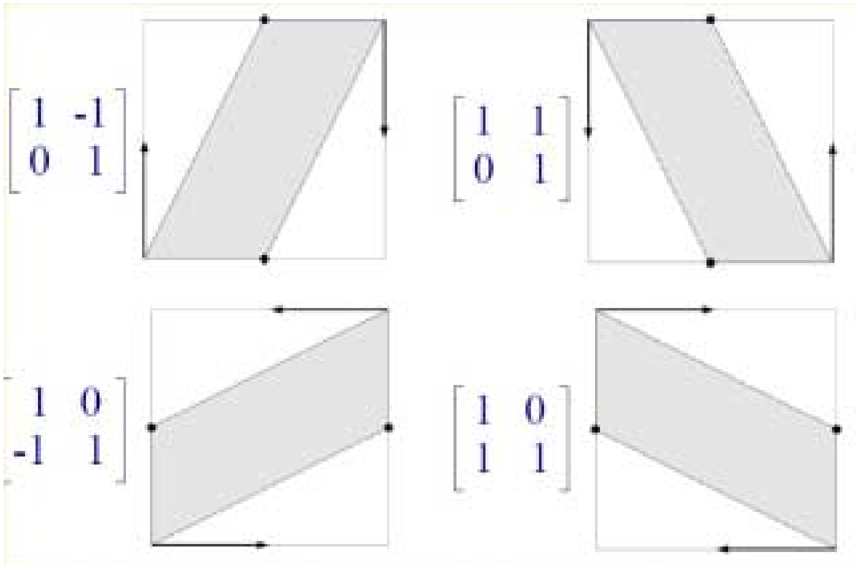
$$y[n] = x[Mn]$$

$$M = \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}$$



CSDFB

- Frequency resampling operator R



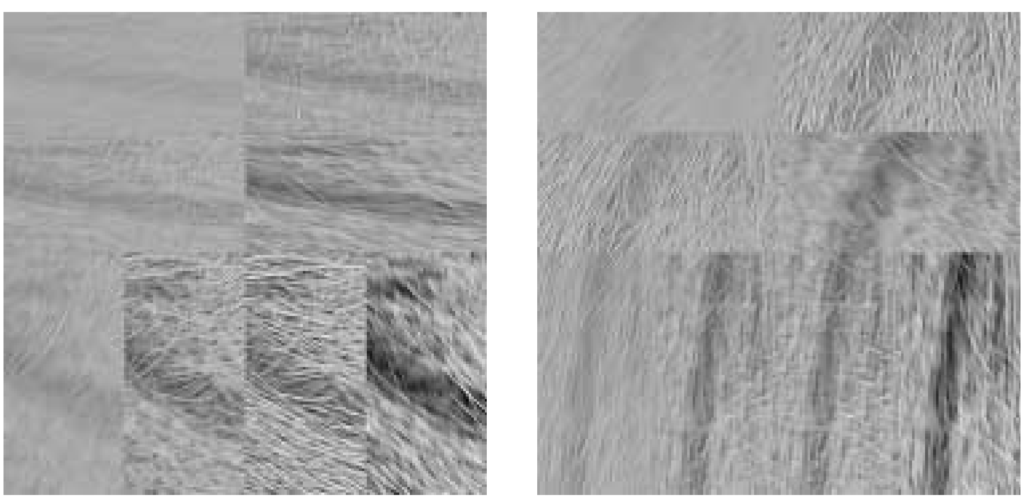
Feature Generation

- The probability distribution of coefficients from all directional subbands is modeled as a single multivariate Gaussian density.
  - One coefficient is taken from each directional subband at the same location to form an N-dimensional observation vector.
  - All coefficients within each subband are scanned, which generates the observation sequence.
  - The vector sequence is used to estimate the covariance matrix of the multivariate Gaussian density.
- The covariance matrices of different images belonging to that same class will generally cluster in the N-dimensional space (N=num. directional subbands).

Rotation Inside Subbands

- As original image being rotated in space, the filtered image inside each subband is also rotated by the same angle.
- However the magnitude level of the coefficients inside each specific subband many change. For example (as shown in the next page):
  - If a texture image has strong orientation feature along direction **d1**, the directional subband corresponding to **d1** will have the strongest response;
  - Now if this image is rotated to direction **d2**, the directional subband corresponding to **d2** will have the strongest response.

CSDFB Domain Texture

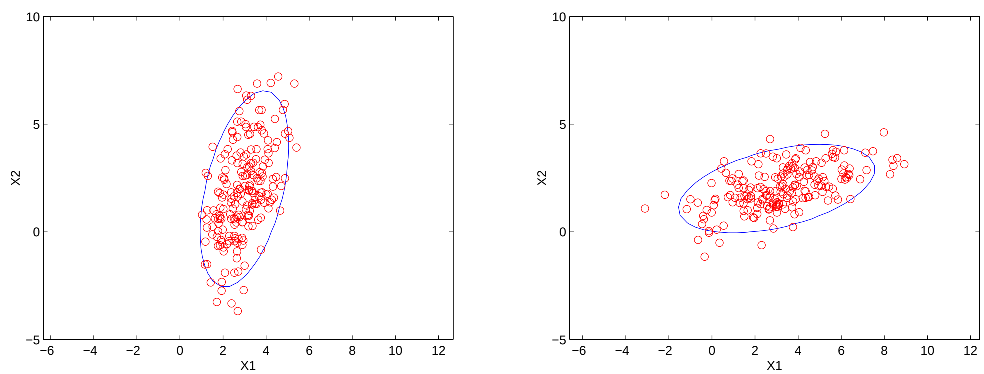


- An 8-band directional subband decomposition of the image STRAW rotated at different angles (30^{o} and 120^{o}).

Rotation Invariant Feature

- An image rotation will increase the magnitude level of certain subbands, and decrease the others.
- Reflecting into the covariance matrix, the rotation will shift the principal axes of the N-dimensional density (as illustrated in the next page).
- However the lengths of the principals axes can be considered as invariant.
  - Since the overall image energy is not changed, when some direction getting stronger, other direction will get weaker.
- Therefore the lengths of the principal axes of the N-D density can be used as rotation invariant feature.
- These principal axes can be calculated through eigen-analysis of the N-D covariance matrices.

Bivariate Gaussian Example



- A conceptual example of a bivariate Gaussian distribution with energy shift caused by rotation, i.e. a strong **x2** direction is changed to a strong **x1** direction.

Support Vector Machine

- SVM is a binary linear classification method which attempts to find a hyperplane that can separate samples from two classes with the largest margin.
- Given a training sample/vector sequence $\{\mathbf{x}_i \in \Re^n, i=1, 2, \ldots, N\}$. For each $\mathbf{x}_i$, a class indicator $y_i \in \{-1, 1\}$ classifies x_i into one of two classes.
- For linearly separable dataset, the hyperplane can be expressed as

$$f(\mathbf{x}) = \sum_{i=1}^{N} \lambda_i y_i (\mathbf{x}_i \cdot \mathbf{x}) + b,$$

where $\mathbf{x}$ is the testing sample, and λ_i, b are the solution of a quadratic optimization problem that maximize the separating margin, and

$$\sum_{i=1}^{N} \lambda_i y_i = 0,$$

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Support Vector Machine

- Based on this $f(\mathbf{x})$, the testing sample $\mathbf{x}$ will be classified into one of two classes according to the sign of $f(\mathbf{x})$.
- For linear non-separable dataset, both $\mathbf{x}$ and $\mathbf{x}$ can be projected onto a high dimensional space through a mapping function $\Phi(\cdot)$, and if this function satisfies

$$\Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}) = \kappa(\mathbf{x}_i, \mathbf{x})$$

the hyperplane function becomes

$$f(\mathbf{x}) = \sum_{i=1}^{N} \lambda_i y_i \kappa(\mathbf{x}_i, \mathbf{x}) + b,$$

- The binary SVM can be extended to multi-class classification in pair-wise fashion.

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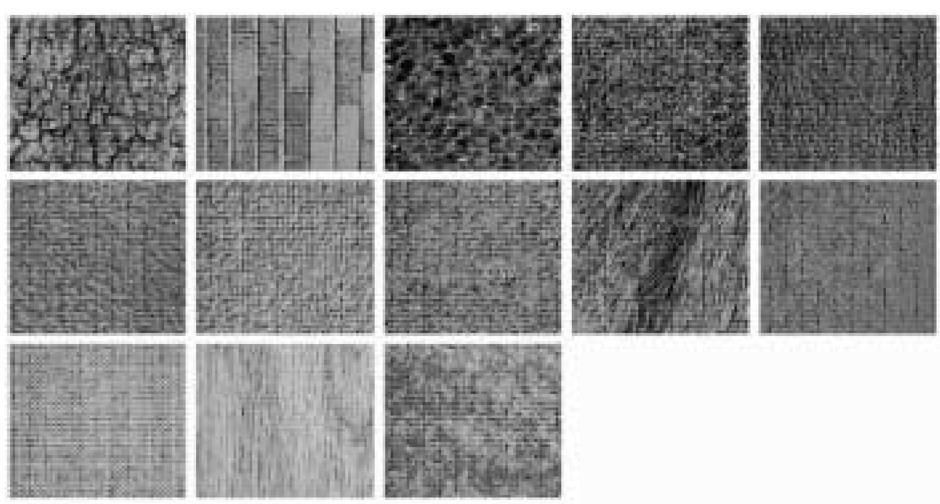
Experiment

- The Brodatz texture dataset is used.
- This dataset contains 13 classes of images with size of 512x512.
- Each class was digitized once for each of the seven rotation angles, i.e. 0^{o}, 30^{o}, 60^{o}, 90^{o}, 120^{o}, 150^{o} and 200^{o}.
- In the training and test, each 512x512 image is partitioned into 4x4 subimages, producing 4x4x7 = 112 subimages.
- 11 training images are randomly selected from the 0^{o} (non-rotated) subimages for each class.
- 8-band CSDFB and one splitting is applied to get 16 subbands for each subimage.

Experiment Results

- Brodatz texture dataset



Experiment Results

- System variants include:
  - SVM on 16-D feature vectors.
  - SVM on 8-D feature vectors. The 8–D vector is obtained by only keeping the eight most significant eigen-values after the eigen-analysis. It represents a computational advantage.
- The results are compared with those reported by Rosiles and Smith (2001), where the same CSDFB was used for non-rotated texture classification, and feature vectors consist of variance from each subband.
- <u>Unlike some previous works that only reported the results on selected rotation angles with selected subimages, all test results are reported here!</u>

Classification Results

texture	SVM-16	SVM-8	var. vec.[8]
bark	0.8614	0.8416	0.5644
brick	0.0792	0.0891	0.0300
bubble	0.8911	0.8911	0.6039
grass	0.8911	0.8911	0.6634
leather	0.7327	0.5743	0.3267
pigskin	0.5149	0.6436	0.1584
raffia	0.4554	0.4059	0.1683
sand	0.8416	0.8416	0.9010
straw	0.7525	0.6337	0.4158
water	0.7426	0.5644	0.0396
weave	0.9505	0.9406	0.0396
wood	0.7030	0.6832	0.0495
wool	0.7525	0.7030	0.1188

Table 1. Classification performance of rotated texture images averaged over all seven different angles.

Classification Results

Rotation	SVM-16	SVM-8	var. vec.[8]
0^o	0.8154	0.7846	0.8000
30^o	0.7500	0.7067	0.3400
60^o	0.6058	0.5577	0.2010
90^o	0.7067	0.7212	0.2500
120^o	0.6538	0.6394	0.2060
150^o	0.6587	0.6010	0.3120
200^o	0.8221	0.7548	0.4180

Table 2. Classification performance of images at different rotation angles averaged over all thirteen classes.

Conclusion

- A new rotation invariant texture classification method is introduced.
- It takes the advantage of directional energy compaction from CSDFB.
- A rotation invariant feature vector was designed for the directional subband coefficients.
- Experiment results are promising.
- Yet, certain problems with this method need further investigation, including the poor performance with certain type of texture images, e.g. BRICK and RAFFIA.