Texture related work

Outline

I Features Extraction

1) Gabor

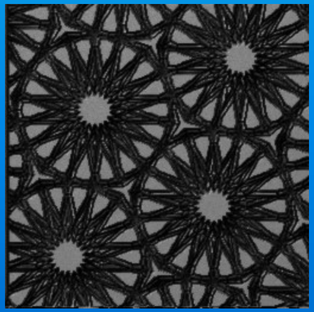
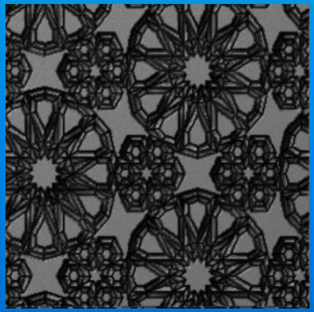
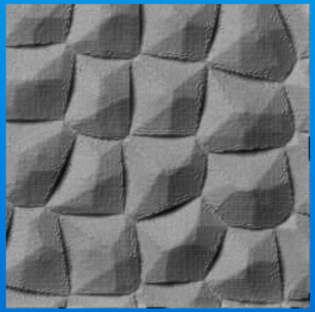
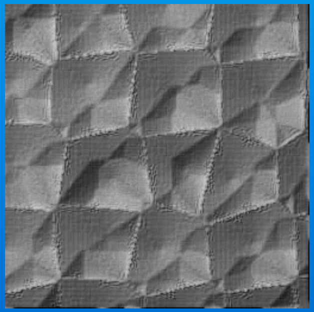
2) Local Binary Patterns

II Classification

Support Vector Machine

background

- A variety of techniques have been developed for measuring texture similarity.
- Most techniques calculate measures of image texture such as the degree of contrast, coarseness, directionality and regularity or periodicity, directionality and randomness.
- Gabor filter (or Gabor wavelet) is widely adopted to extract texture features from the images for image retrieval and texture classification , and has been shown to be very efficient.

1. Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific frequency and a specific direction.

2. Expanding a signal using this basis provides a localized frequency description, therefore capturing local features/energy of the signal.

3. Texture features can then be extracted from this group of energy distributions. The scale (frequency) and orientation tunable property of Gabor filter makes it especially useful for texture analysis.

For a given image I(x, y) with size P*Q, its discrete Gabor wavelet transform is given by a convolution :

$$G_{mn}(x, y) = \sum \sum I(x - s, y - t)\, \psi^*_{mn}(s, t)$$

Where s and t are the filter mask size variables, and ψ^*_{mn} is the complex conjugate of ψ_{mn} which is a class of self-similar functions generated from dilation and rotation of the following mother wavelet:

$$\psi(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp[-\frac{1}{2}(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2})]\cdot\exp(j2\pi Wx)$$

Where W is called the modulation frequency.

The self-similar Gabor wavelets are obtained through the generating function :

$$\psi_{mn}(x,y) = a^{-m}\psi(\tilde{x},\tilde{y})$$

Where W is called the modulation frequency. The self-similar Gabor wavelets are obtained through the generating function :

$$\psi_{mn}(x, y) = a^{-m}\psi(\tilde{x}, \tilde{y})$$

Where m and n specify the scale and orientation of the wavelet respectively, with m = 0,1, …M-1,n = 0,1, … N-1,and

$$\tilde{x} = a^{-m}(x\cos\theta + y\sin\theta)$$
$$\tilde{y} = a^{-m}(-x\sin\theta + y\cos\theta)$$

Where a > 1 and θ = nπ/N.

We can obtain an array of magnitudes:

$E(m, n) = \sum\sum |G_{mn}(x, y)|$ m=0,1,……M-1; n=0,1,……, N-1; with applying Gabor filters on the image with different Orientation at different scale.

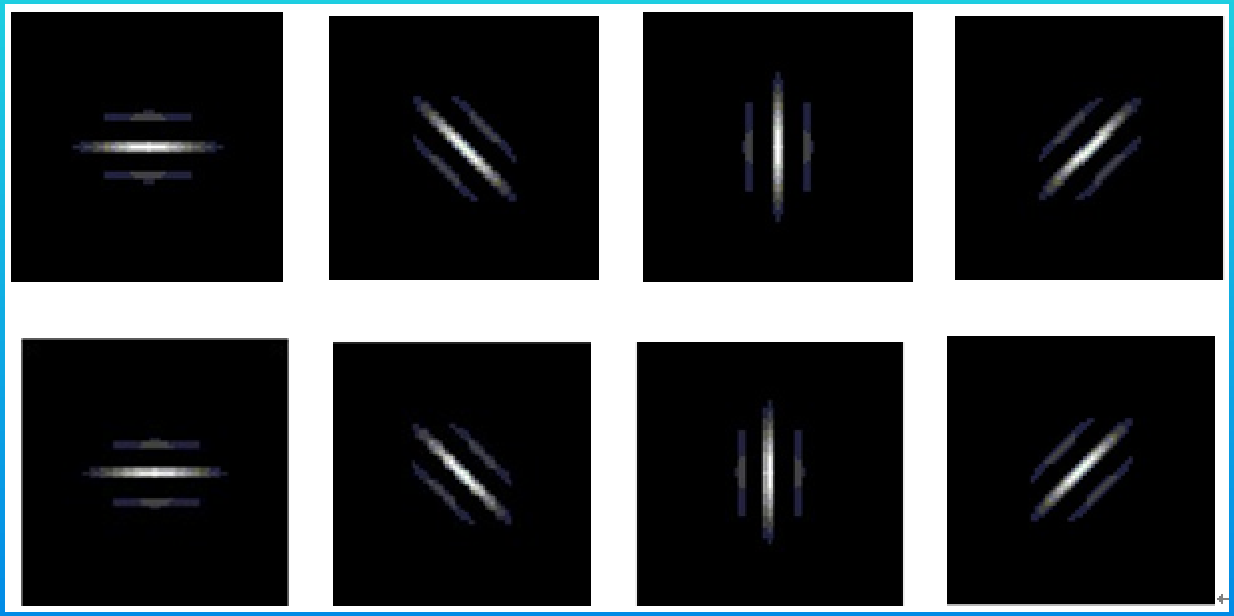
These magnitudes represent the energy content at different scale and orientation of the image.

It is assumed that we are interested in images or regions that have homogenous texture, therefore the following mean μ_{mn} and standard deviation σ_{mn} of the magnitude of the transformed coefficients are used to represent the homogenous texture feature of the region:

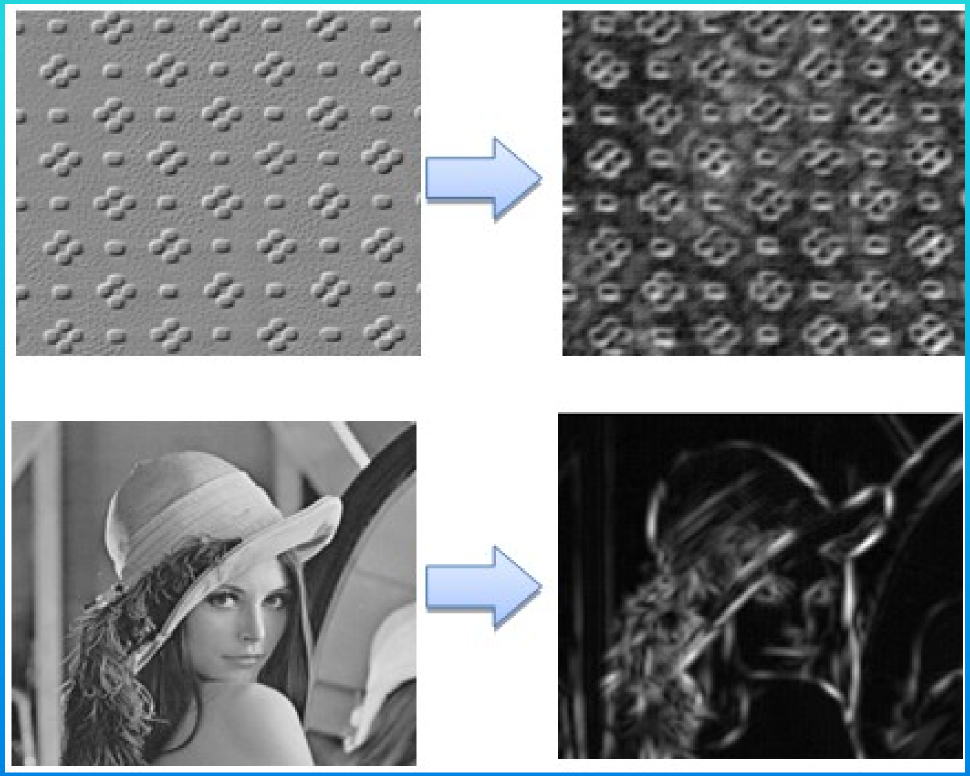
$$\mu_{mn} = \frac{E(m,n)}{P \times Q}$$

$$\sigma_{mn} = \frac{\sqrt{\sum_x \sum_y (|G_{mn}(x,y)| - \mu_{mn})^2}}{P \times Q}$$

The Gabor filter with eight different angles of the template image



Gabor filter filtering



Local Binary Patterns

The initial function as the auxiliary local contrast image, and is not a complete description of the characteristics.

Later promoted to an effective operator for texture description, measurement and extract image texture information locally, has invariance to the light.

Face recognition

Gesture recognition

Face detection

Dynamic textures

……

Achieving Gray Scale Invariance

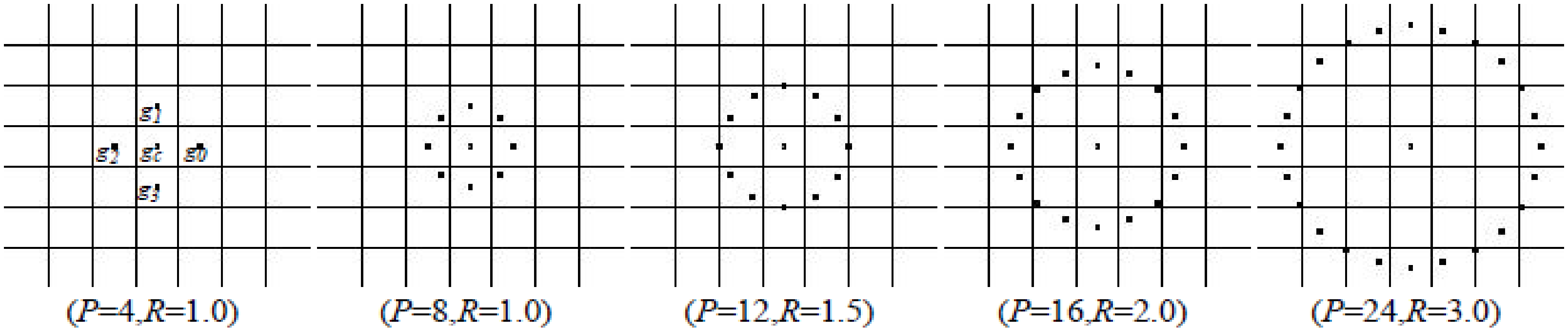


Fig. 1. Circularly symmetric neighbor sets for different (P,R).

Achieve the gray scale invariance by considering just the signs of the differences instead of their exact values:

$$T \approx t(s(g_0 - g_c), s(g_1 - g_c), \ldots, s(g_{P-1} - g_c))$$

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$$

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_0) 2^p$$

Achieving Rotation Invariance

To remove the effect of rotation, i.e. to assign a unique identifier to each rotation invariant local binary pattern:

$$LBP^{ri}_{P,R} = min\{ROR(LBP_{P,R}\ , i) \quad | \quad i = 0,1,\ldots,P\text{-}1\}$$

example

6	5	2
7	6	1
9	8	7

thresholded

1	0	0
1		0
1	1	1

weights

1	2	4
128		8
64	32	16

Pattern = **11110001**

LBP = 1 + 16 +32 + 64 + 128 = **241**

Figure 1. Calculation of the LBP

LBP=31

Achieving Rotation Invariance

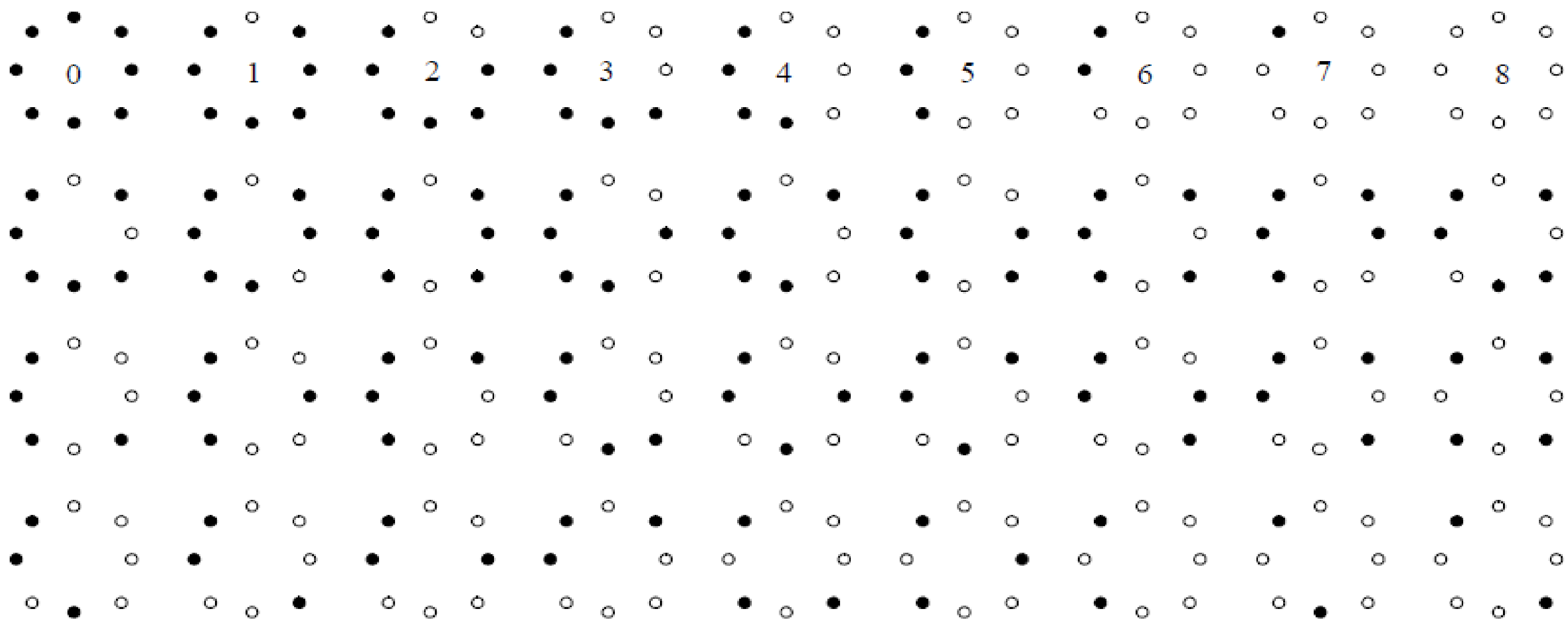


Fig. 2. The 36 unique rotation invariant binary patterns that can occur in the circularly symmetric neighbor set of $LBP_{8,R}^{ri}$. Black and white circles correspond to bit values of 0 and 1 in the 8-bit output of the operator. The first row contains the nine 'uniform' patterns, and the numbers inside them correspond to their unique $LBP_{8,R}^{riu2}$ codes.

- **Nonparametric Classification Principle**

$$L(S, M) = \sum_{b=1}^{B} S_b \log M_b$$

where *B* is the number of bins, and *Sb* and *Mb* correspond to the sample and model probabilities at bin *b*, respectively.

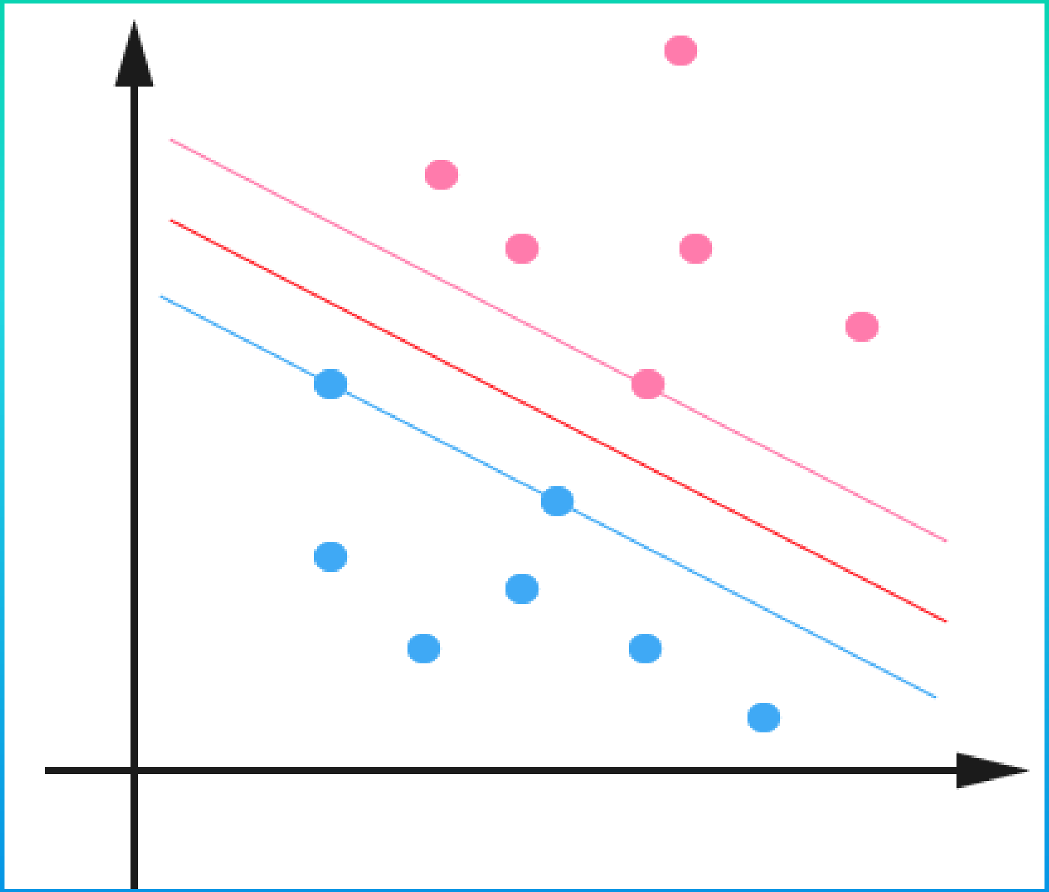
$$G(S, M) = 2\sum_{b=1}^{B} S_b \log \frac{S_b}{M_b} = 2\sum_{b=1}^{B} [S_b \log S_b - S_b \log M_b]$$

Support vector machine

- Support vector machine have strong theoretical foundations and excellent empirical success. They have been applied to tasks such as handwritten digit recognition, object recognition, and texture classification.

Support vector machine (SVM) is divided into two parts, one is support vector (in simple terms, is to support the plane of hyperplane, divided the two categories of vector points), other is the "machine", the "machine" is an algorithm.

In the field of machine learning, some algorithms as a machine, and support vector machine (SVM) itself is a kind of supervised learning method, it is widely used in the statistical classification and regression analysis.



SVM classification of online (plane) support vector is support vector, the line in the middle (surface) is the optimal classification plane.

Although the principle of support vector machine (SVM) is complex, but there are lots of mature library, including Taiwan university professor Lin libSVM to do the best.

We put the training data into corresponding good specific format and application in libSVM given training methods, then we can get the model. We can classify images with this model.

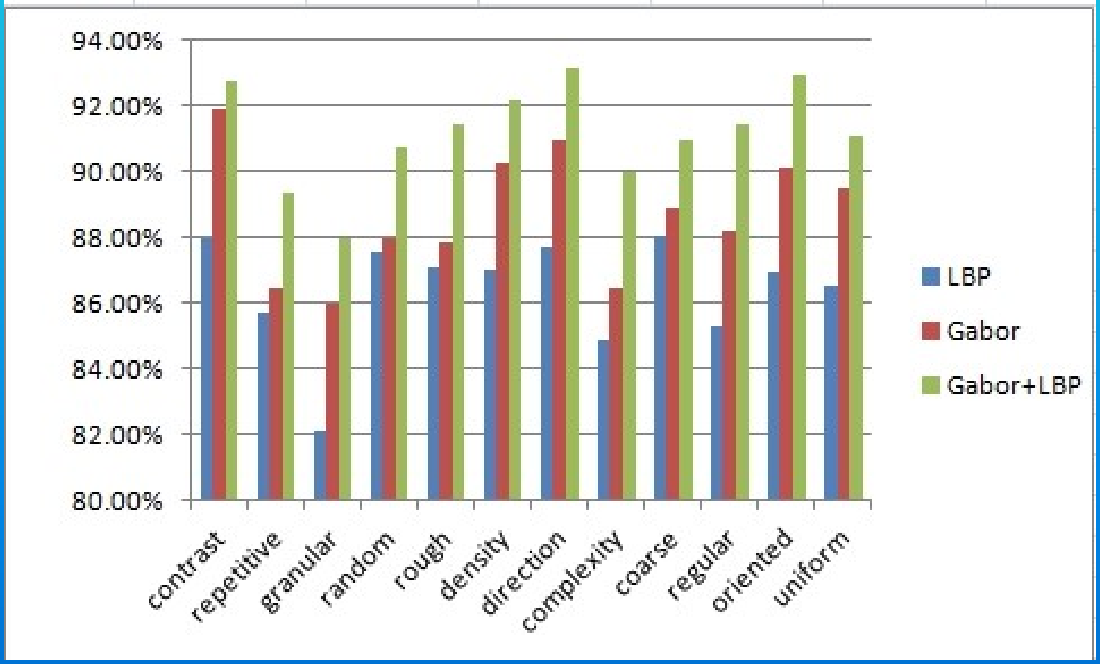
Support vector machine (SVM), show many unique advantages, it is to solve the small sample, nonlinear and high dimensional pattern recognition performance is good.

Compared with k-Nearest Neighbor (KNN), class sample size is large KNN efficiency is very low, and the efficiency of SVM is much better than the KNN, because it does not need to distance with all known samples, only need more support vector.

We generated 450 samples using 23 generation methods.

In order to obtain twelve-dimension perceptual features ,we trained 12 support vector machine models for prediction with Gabor features and LBP features.

Table shows leave-one-out accuracy.



Reference

- Content-based Image Retrieval Using Gabor Texture Features
- Multiresolution Gray Scale and Rotation Invariant Texture Classification with Local Binary Patterns
- Least Squares Support Vector Machine Classifiers