Texture Descriptor Comparison

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December 13, 2018

1 Introduction

Image texture represents an image area contributing repetition of patterns pixel intensities arranged in some structure ways. They give us information about the spatial arrangement of color or intensities in an image whose spatial distribution creates visual patterns with distinctive characteristics, such as roughness, repetitiveness, directionality, and granularity.

There exist different approaches to extract and represent textures; they can be classified into texture signatures, frequency-based models, space-based models and statistical models.These approaches are known as texture descriptors and depending on textures problem to classify, a proper selection of the descriptors can significantly improve the classification performance. Thus, a comparative evaluation between different texture descriptors is nessary in order to choose the most appropriate descriptor for a particular application.

This report presents a comparative evaluation and statistical study of 5 texture descriptors: Gabor Filter Banks (GFB), Haar Wavelet Transform (HWT), Daubechies-4 wavelet transform (Daub-4), Local Binary Pattersn (LBP) and Gray-Level Co-occurrence Matrix (GLCM). The comparision is made by computing the classification accuracy of numerical datasets generated by the texture descriptor and by the means of three classifications algorithms: Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Naive Bayes (NB).

Texture descriptors are applied in texture datasets containing, in some cases more than several images with interesting features and challenges, such as viewpoint changes, differances in scale, illumination, and rotation.

The rest of the report is organized as follows, In section.2 the texture descriptors definitions and the theoretical basis of the used descriptors are presented. In section.3 the methodology of texture description and the calssification process are described. Section.4 shows the experimental results and the statistical significance. Section.5 presents a discussion of the results.

2 Texture Descriptors

2.1 Gabor Filter Banks

A 2-D Gabor filter is a linear filter which impulse response is a sinusoidal function modulated by a Gaussian envelope [5]. The Gabor functions are defined in both the spatial domain and the frequency domain. The general form in the spatial domain is given by:

$$g(x, y) = \frac{F^2}{\pi\gamma\eta} e^{-F^2[(\frac{x'}{\gamma})^2+(\frac{y'}{\eta})^2]} e^{i2'}$$

with:

$$x' = xcos\theta + ysin\theta,$$
$$y' = -xsin\theta + ycos\theta$$

where
F : is the central frequency of the filter.
θ : is the angle between the direction of propagation of the sinusoidal wave and the x axis.
γ and η : are the standard deviations of the Gaussian envelope in the dimensions x and y, respectively.

The term Gabor filter bank contains multiple Gabor filters with different orientations and frequencies to extract features of an image, by the proper selection of the filter mentioned above. Depending of the parameters, the filters will analyze in different ways the spatial and frequency domain [5][4].

Different approaches have been used in the state-of-the-art to tackle the problem of Gabor parameterization and its influence in different tasks, such as classification and segmentation [4][3]

2.2 Wavelet Transform

Wavelet are functions which are formed by two resulting coefficients, given by the wavelet functions $\psi(x)$ and the scaling function $\phi(x)$ in the time domain. The wavelet function applies a low pass filter to the signal $u(t)$ resulting in the *appriximation* coefficients and the scaling function applies a high pass filter which results in the *detail* coefficients[10]

In general, the wavelet transform represents a continuous signal $u(t)$ in time domain as an expansion of coefficients, proportional to the inner product between the signal and different scaled and translated of the mother wavelet function[11], defined by:

$$\psi_{a,b} = \frac{1}{\sqrt{a}}\psi(\frac{t-b}{a})$$

where a and b are the scaling and shifting parameters, respectively.

In image processing, Discrete Wavelet Transforms (DWT) are applied due to the properties of the images, especialy, Haar and Daubechies wavelet transforms are more common than the others.

2.2.1 Haar Wavelet Transform

The Haar Wavelet Transform (HWT) is one of the simplest of the DWT. In HWT a function is multiplied against the Haar wavlet with different shifts and scales [12]. The Haar wavelet function is defined as

$$\psi(x) = \begin{cases} 1 & 0 \leq t \leq \frac{1}{2}, \\ -1, & \frac{1}{2} \leq t \leq 1, \\ 0, & \text{othewise} \end{cases}$$

Its scaling function is given by:

$$\psi(x) = \begin{cases} 1 & 0 \leq t < 1, \\ 0 & \text{otherwise} \end{cases}$$

2.2.2 Daubechies Wavelet Transform

The Daubechies wavelets are a family of orthogonal wavlets with compact support and a varying number of vanishing moments. These define discrete wavelet transformations[12]. The Daubechies scaling coefficients are defined by:

$$\textstyle\sum_{k=0}^{h_k-1}(-1)^k h_k k^m = 0$$

where:
k : Is the parameter of vanishing moments.
h_k : Are the scaling coefficients.

For integers $m = 0, 1, 2, ... \frac{N_k}{2} - 1$.

The scaling equation for a four-coefficients wavelet is[12]:

$$\Phi(t) = h_0\Phi(2t) + h_1\Phi(2t-1) + h_2\Phi(2t-1) + h_3\Phi(2t)$$

And the corresponding wavelet function is defined as:

$$\psi(t) = h_3\Phi(2t) - h_2\Phi(2t-1) + h_1\Phi(2t-2) - h_0\Phi(2t-3)$$

For the Daubechies-4 wavelet transform (Daub-4), to find h_k, the following nonlinear system of equations must be solved:

$$\begin{gathered} h_0 + h_1 + h_2 + h_3 = 2 \\ \mathrm{h}_0^2 + h_1^2 + h_2^2 + h_3^2 = 2 \\ \mathrm{h}_0 - h_1 + h_2 - h_3 = 0 \\ \text{-1}\mathrm{h}_1 + 2h_2 - 3h_3 = 0 \end{gathered}$$

2.3 Local Binary Patterns

The Local Binary Pattern (LBP) descriptor extracts micropatterns that are invariant to loal grayscale in the image. Given a pixel c with gray value g_c, the LBP is computed by thresholding the difference between the gray values of its p neighbors $g_{n}{}_{n=1}^{p-1}$ (distributed on a circle of radius r pixels) and g_c by using the step function $s(x)$. A binary vector of p bits is extracted by concatenating the binary gradient directions[1] [2]. The LBP operator is given by:

$$LBP_{r,p}(c) = \sum_{i=1}^{p-1} s(g_i - g_c)2^i$$

where

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

2.4 Gray Level Co-occurrence Matrix

Gray Level Co-occurrence Matrix (GLCM) is the matrix of relative frequencies $P_{\theta,d}(d_1, d_2)$. It describes how frequently two pixels with gray-levels I_1, I_2 appear in the window separated by a distance d in direction θ which varies in four directions that represent horizontal diagonal, vertical, and minus diagonal by $0^o, 45^o, 90^o$ and 135^o respectively.

The second-order statistic defines textural features which are derived from co-occurrence matrix, and reach represents certain image properties as coarseness, contrast, homogeneity and texture complexity.

3 Methodology

GFB, HWT, Daub-4, LBP and GLCM descriptors were compared against each other. These descriptors were applied in the next well-known benchmark texture datasets[15]:

- Kylberg texture Dataset: This dataset contains textured surfaces including fabrics, stone, grain, sesame seeds, and lentils. It contains 4480 576x576 resolution images with 28 different number of classes
- KTH-TIPS 2: Images of material are presented in this dataset, such as crumpled, aluminum foil, sandpaper, sponge, styrofoam, linen, corduroy, cotton, brown bread, orange peel, and cracker.

The experiment methodology in this paper consists of the following steps:

1. All images were resized to 128x128 by linear interpolation, to reduce computational cost.
2. All datasets were processed by all of the texture descriptors considered. The value of parameters of each descriptors is given below.
3. Depending on the texture descriptor, the feature vectors are computed and from these, a numberical dataset is created and labeled

   GFB: The number of Gabor Filters in the GFB(T_f) is given by $n_f x n_o = 40$; namely, number of frequencies is 5 corresponding with wavelength from 2 to 6 and number of orientation varies from 0 to $2 * \pi$ with $\frac{\pi}{4}$ step. The Gabor transform of an input image (I) is computed for each filter f_i where $i \in \{1, ..., T_f\}$. The mean u_{f_i} and the standard deviation σ_{f_i} of each transformed image are used as elements of the feature vector $\overrightarrow{V}$[5].

$$\overrightarrow{V} = (u_{f_1}, \sigma_{f_1}, u_{f_2}, \sigma_{f_2}, u_{f_3}, \sigma_{f_3}, ..., u_{f_i}, \sigma_{f_i})$$

HWF and Daub-4: The resulting 2-D array of wavelet coefficients constains 4 bands of data LL, HL, LH and HH where L is a Low-pass filter and H is a High-pass filter.
The LL band can be processed once again by the wavelet tranform, producing even more subbands.
The mean $u_{subband}$ and the standard deviation $\sigma_{subband}$ are used as elements of the feature vector $\overrightarrow{V}$

$$\overrightarrow{V} = (\mu_{LH_1}, \sigma_{LH_1}, \mu_{HH_1}, \sigma_{HH_1}, \mu_{HL_1}, \sigma_{HL_1}, \\ ...\mu_{LH_k}, \sigma_{LH_k}, \mu_{HH_k}, \sigma_{HH_k}, \mu_{HL_k}, \sigma_{HL_k})$$

LBP: Given a texture image, an LBP pattern can be computed at each central pixel c in a neighborhood. The texture can be cahracterized by the distribution of LBP patterns. The histogram of these binary numbers is then used as feature vector [1] [2]

GLCM: By computing mean GLCM of a given texture image at four different orientations, Haralick features is computed. Set of Haralick features extracted from mean GLCM such as contrast, correlation, energe is used as feature vector.

4. The labeled numerical datasets are classifed by three different classification algorithms: SVM with GridSearch algorithm, *polynomial* and rbf kernels with various parameters; KNN with K = 5 and Gaussian Näive Bayes (NB)

4 Experiment Result

The table that illustrates the accuracy of each descriptor with corresponding classifier and dataset.

Descriptor	Classifier	Dataset	Accuracy
GFB	SVM	Kylberg	0.991
		KTH-2	0.937
	NB	Kylberg	0.943
		KTH-2	0.555
	KNN	Kylberg	0.965
		KTH-2	0.787
Haar	SVM	Kylberg	0.927
		KTH-2	0.8
	NB	Kylberg	0.900
		KTH-2	0.547
	KNN	Kylberg	0.879
		KTH-2	0.728
DB4	SVM	Kylberg	0.922
		KTH-2	0.781
	NB	Kylberg	0.899
		KTH-2	0.516
	KNN	Kylberg	0.889
		KTH-2	0.714
LBP	SVM	Kylberg	0.563
		KTH-2	0.160
	NB	Kylberg	0.866
		KTH-2	0.374
	KNN	Kylberg	0.819
		KTH-2	0.611
GLCM	SVM	Kylberg	0.689
		KTH-2	0.650
	NB	Kylberg	0.754
		KTH-2	0.571
	KNN	Kylberg	0.611
		KTH-2	0.601

Table 1: Experiment result

This table presents average result of descriptors in each dataset.

Dataset	Descriptor	Avg.Accuracy
Kylberg	GFB	0.966
	Haar	0.902
	DB4	0.903
	LBP	0.749
	GLCM	0.685
KTH-2	GFB	0.759
	Haar	0.692
	DB4	0.670
	LBP	0.382
	GLCM	0.607

Table 2: Average result

5 Conclusions

In this work I presented a statistical comparison of the performance of four image texture descriptors for pattern classification: HWT, DB4, LBP, GFB and GLCM, tested on well-known texture datasets, with different classification algorithms. Therefore, I have found sufficient evidence to say that, for the considered experimental settings and metrics using SVM as pattern classification algorithm which gives the most accuracy for two dataset at GFB, Haar and DB4 descriptor; therefore, the best descriptor was GFB.

References

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