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Image Texture Classification using Gray Level Co-Occurrence Matrix Based Statistical Features

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Abstract

In this paper, a novel texture classification system based on Gray Level Co-occurrence Matrix (GLCM) is presented. The texture classification is achieved by extracting the spatial relationship of pixel in the GLCM. In the proposed method, GLCM is calculated from the original texture image and the differences calculated along the first non singleton dimension of the input texture image. Then the statistical features contrast, correlation, energy and homogeneity are calculated from both the GLCM. The extracted features are used as an input to the K Nearest Neighbor (K-NN) for classification. The performance of the proposed system is evaluated by using Brodatz database and compared with the methods PSWT, TSWT, the Gabor transform, and Linear Regression Model. Experimental results show that the proposed method produces more accurate classification rate of over 99%.

Indexterms: Texture Classification, K nearest neighbor, gray level co-occurrence matrix, Brodatz album.

1. Introduction

The most important task in image processing and pattern recognition is the classification of texture images. Over the years, extensive researches have been made for the classification of texture images. A novel texture classification method via patch-based sparse texton learning is presented in [1]. Specifically, the dictionary of textons is learned by applying Sparse Representation to image patches in the training dataset. The SR coefficients of the test images over the dictionary are used to construct the histograms for texture classification. A new approach to extract global image features for the purpose of texture classification using dominant neighborhood structure is proposed in [2]. Features obtained from the local binary patterns (LBPs) are then extracted in order to supply additional local texture features to the generated features from the dominant neighborhood structure.

Texture classification by modeling joint distributions of local patterns with Gaussian mixtures is proposed in [3]. Local texture neighborhoods are first filtered by a filter bank. Without further quantization, the joint probability density functions of the filter responses are then described parametrically by Gaussian mixture models (GMMs). The classification performance of several feature extraction and classification methods for exotic wood texture images are described in [4]. The Gray Level Co-occurrence Matrix, Local Binary Patterns, Wavelet, Ranklet, Granulometry, and Laws' Masks will be used to extract features from the images.

Local Binary Pattern (LBP) algorithm is a typical texture analysis method combined with structural and statistical texture. Completed modeling of Local Binary Pattern (CLBP) is presented in [5], which is composed by the center gray level, sign components and magnitude components. A texture descriptor algorithm called invariant features of local textures (IFLT) is described in [6]. IFLT generates scale, rotation and illumination invariant descriptors from a small neighborhood of pixels around a centre pixel or a texture patch. The texture classification using the fusion of decisions from different texture classifiers is described in [7]. The classifier that use for classify the extracted features is Support Vector Machines (SVMs). A novel modality invariant texture descriptor which is built by modifying the standard procedure for building LBP is described in [8].

The wavelet transform is an important multi-resolution analysis tool has already been commonly applied to texture analysis and classification. A novel, efficient, and effective Refined Histogram (RH) for modeling the wavelet sub-band detail coefficients and a new image signature based on the RH model for supervised texture classification is described in [9]. Texture classification using discrete cosine transform and approach for soft computing tool is described in [10]. As DCT works on gray level images, the color scheme of each image is transformed into gray levels. Then DCT is applied on the gray level images to obtain DCT coefficient. These DCT coefficient are use to train the neural network. Wavelet based image texture classification using local energy histograms are proposed in [11].

This paper is organized as follows. The brief review about GLCM and K-NN classifier are described in Section 2. The proposed texture classification algorithm is described in Section 3. Experimental results are presented in Section 4. Several traditional techniques and the proposed method are compared. Finally, the conclusion is summarized in Section 5.

2. Methodology

The proposed system for texture classification is built based on GLCM and by applying KNN as classifier. In this following section the theoretical background of all the approaches are introduced.

2.1. GLCM

Texture is one of the important characteristics used in identifying objects or regions of interest in an image. A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix.

Gray level co occurrence matrix (GLCM) is the basis for the Haralick texture features. This matrix is square with dimension N_g, where N_g is the number of gray levels in the image. Element $[i,j]$ of the matrix is generated by counting the number of times a pixel with value i is adjacent to a pixel with value j and then dividing the entire matrix by the total number of such comparisons made. Each entry is therefore considered to be the probability that a pixel with value i will be found adjacent to a pixel of value j.

$$G = \begin{bmatrix} p(1,1) & p(1,2) & \dots & p(1,N_g) \\ p(2,1) & p(2,2) & \dots & p(2,N_g) \\ . & . & \dots & . \\ . & . & \dots & . \\ p(N_g,1) & p(N_g,2) & \dots & p(N_g,N_g) \end{bmatrix} \quad (1)$$

2.2. K-NN Classifier

In pattern recognition, the k-nearest neighbor algorithm (K-NN) is a method for classifying objects based on closest training examples in the feature space. K-NN is a type of instance-based learning where the function is only approximated locally and all computation is deferred until classification. In K-NN, an object is classified by a majority vote of its neighbors, with the object being assigned to the class most common amongst its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of its nearest neighbor. The neighbors are taken from a set of objects for which the correct classification is known. This can be thought of as the training set for the algorithm, though no explicit training step is required.

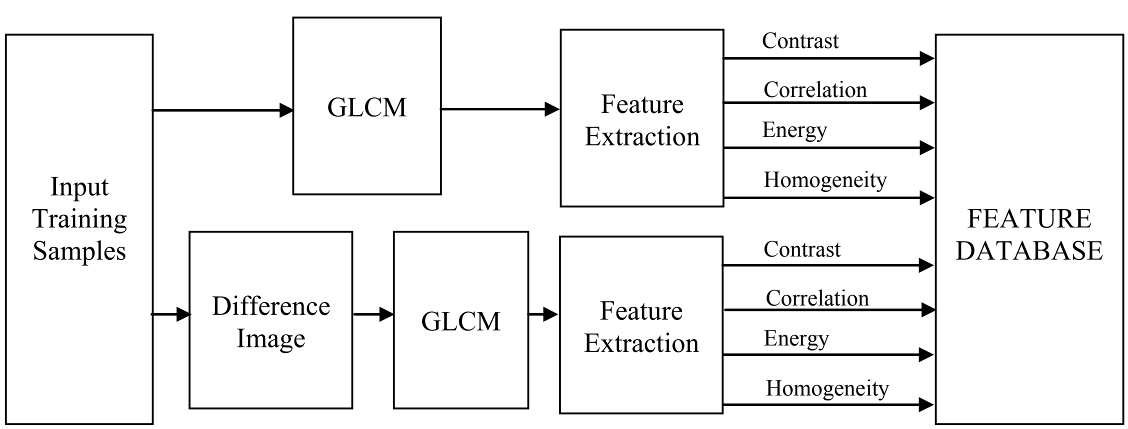
3. Proposed Method

The proposed system mainly consists of two stages, which include the feature extraction stage and the classification stage. All the stages are explained in detail in the following sub sections.

3.1. Feature Extraction Stage

Feature extraction is a critical pre-processing step for pattern recognition and machine learning problems. In the proposed approach, the GLCM features derived from the original texture image combined with the same GLCM features derived from the difference image are used as features to classify the digital texture images. The Feature Extraction stage of the proposed texture classification system based on GLCM is shown in Fig 2.

Figure 2: Feature extraction stage of the proposed texture classification method



3.2.1. GLCM

Feature Extraction

The GLCM is normalized so that the sum of its elements is equal to 1. Each element (*i*,*j*) in the normalized GLCM is the joint probability occurrence of pixel pairs with a defined spatial relationship having gray level values *i* and *j* in the image. Let us consider *p* is the normalized GLCM of the input texture image. Contrast is a measure of the intensity contrast between a pixel and its neighbor over the whole image and given by the equation (1) and the measure of how correlated a pixel is to its neighbor over the whole image is given by the equation (2).

$$contrast = \sum_{i,j} |i-j|^2 \ p(i,j)^2 \tag{1}$$

$$correlation = \frac{(i-\mu i)(j-\mu j)\,p(i,j)}{\sigma_i \sigma_j} \tag{2}$$

The energy is the sum squared element in the normalized GLCM and given by the equation (3) and the homogeneity in equation (4) is a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$Energy = \sum\nolimits_{i,j} \ p(i,j)^2 \tag{3}$$

$$Homogeneity = \sum_{i,j} \frac{p(i,j)}{1+|i-j|} \tag{4}$$

3.2. Classification Stage

In the classification phase, the two GLCM which is derived from the given unknown texture image and the differences calculated along the first non singleton dimension of the unknown texture image. The feature vector of the unknown texture image is obtained from both the GLCM. Then this vector is processed with the features in the database generated in the feature extraction stage. Textures were classified using a KNN classifier, in which the distance between the features and the corresponding features in the database was calculated using the Euclidean distance. The classification performance is measured as the percentage of test set images classified into the correct texture class. The classification algorithm is as follows.

Algorithm I: Classification Algorithm

[Input] unknown texture image and the feature database

[Output] the index of texture to which this unknown texture image is assigned

1) Calculate the GLCM (X) of the input unknown texture image
2) Calculate the spatial features of X by using eqn. (1) to (4).
3) Calculate the GLCM (Y) of difference image.
4) Calculate the spatial features of Y by using eqn. (1) to (4).
5) Fuse all the eight (8) features.
6) Apply KNN classifier and find the class of the unknown texture image by using the FEATURE DATABASE.

4. Experimental Results

In this section, the performance of the texture classification algorithm based on the proposed method is verified. To evaluate the performance of the proposed system, many computer simulations and experiments with 40 Brodatz texture images are performed and all the texture images are shown in Fig 3. Every Brodatz texture image is of size 640x 640 pixels with 256 gray levels. From each original image, 256 sample images of size 128x128 are extracted with an overlap of 32 pixels between vertical and horizontal direction. For each texture image, all the 256 images are separated into two set and 40 images are randomly selected as training set and the remaining 216 images as testing set. The performance of the proposed system is compared with Linear Regression Modal [12], TSWT [13], GLCM [14], GLCM with Wavelet [15], Gabor transform [16] and F16b [17]. Table 1 shows the Comparison of different texture classification method with the proposed method.

Figure 3: Brodatz texture images used in the experiments

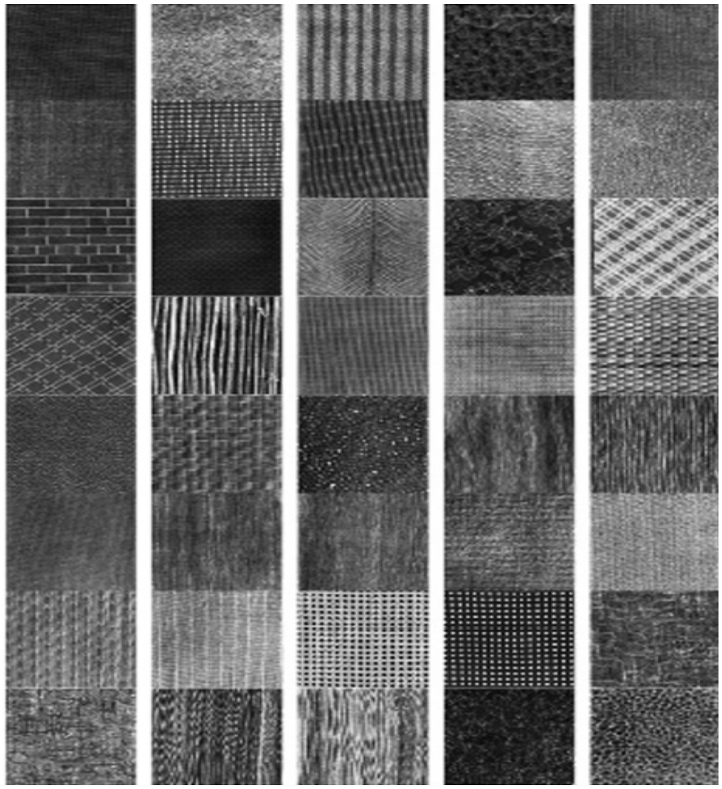


Table 1: Comparison of different texture classification method with the proposed method

ID	Proposed method	Linear Regression Model	F16b	Wavelet and GLCM	TSWT	PSWT	Gabor	Gabor and GLCM
D6	100	100	95.122	100	88.225	68.596	67.639	70.941
D9	99.61	97.531	80.488	95.122	50.941	39.136	24.151	24.583
D11	100	97.531	68.298	85.366	55.756	39.074	28.395	30.54
D14	100	93.827	100	100	90.154	73.318	80.201	74.429
D16	100	98.765	95.122	100	95.278	74.799	51.914	46.173
D17	100	95.062	80.488	97.651	60.509	44.398	43.719	38.333
D20	100	98.765	95.122	100	98.241	88.812	68.673	95.139
D21	100	100	100	100	100	96.343	99.753	92.963
D22	92.588	93.827	92.683	97.561	84.969	68.889	68.312	58.349
D24	95.313	98.726	70.732	95.122	58.249	42.207	29.907	33.981
D26	100	98.765	97.561	100	92.114	68.858	42.762	68.102
D34	100	98.765	97.561	100	81.728	70.833	68.688	85.201
D36	99.609	100	95.122	100	65.679	51.25	26.096	23.38
D41	99.609	90.123	82.927	92.683	45.324	33.827	19.738	17.593
D46	100	98.765	100	100	96.96	90.278	63.457	72.052
D47	100	98.765	100	100	97.886	74.367	36.852	65.602
D51	100	96.296	100	100	92.207	69.228	22.022	33.47
D53	100	96.296	100	100	92.577	70.247	41.682	49.259
D55	100	97.531	78.049	100	83.704	57.238	24.63	32.269
D56	100	86.42	97.561	100	91.574	73.133	45.139	43.41
D57	100	98.765	51.22	87.802	75.725	60.694	65.216	65.17
D64	100	98.765	100	100	94.383	61.713	38.287	43.148
D66	100	93.827	100	97.561	87.315	73.58	43.796	39.259
D68	100	93.827	100	92.683	87.361	62.685	33.148	26.62
D76	100	96.296	92.683	97.561	67.022	46.713	21.867	41.466
D77	98.828	98.765	97.561	100	77.824	47.824	47.515	35.401

Table 1: Comparison of different texture classification method with the proposed method - continued

D78	100	98.765	85.366	92.683	67.963	46.142	23.935	32.176
D79	100	96.296	80.488	90.244	61.188	43.688	21.713	28.056
D80	97.656	100	85.366	87.805	62.114	37.253	20.617	20.123
D82	99.219	98.765	65.854	100	73.904	50	34.306	54.469
D83	100	100	70.732	100	71.019	39.182	29.414	44.506
D85	96.484	97.531	87.805	100	62.901	38.92	22.052	26.929
D101	100	98.765	100	100	100	38.904	88.364	96.579
D102	100	97.531	100	100	90.478	87.809	36.296	77.716
D103	99.609	98.765	100	100	99.907	90.571	69.398	62.299
D104	96.094	98.765	100	100	99.846	92.114	61.142	68.318
D105	96.484	98.296	82.927	95.122	76.049	54.815	36.451	37.284
D106	91.016	95.062	95.122	92.683	66.343	52.346	28.488	34.336
D109	99.609	97.531	92.683	90.244	66.235	39.676	43.657	40.957
D111	100	100	87.805	80.488	56.991	44.059	24.753	32.222
Average	**99.043**	**97.151**	**90.061**	**96.707**	**79.166**	**61.588**	**43.429**	**48.995**

5. Conclusion
In this paper, a new method for classification of texture images based on GLCM is presented. The proposed method considers the spatial relationship of pixels in the GLCM which gives better classification rate than the PSWT, TSWT, the Gabor transform, and Linear Regression Model. The statistical features contrast, correlation, energy and homogeneity are used as features in the proposed method and robust KNN classifier is used for texture classification. Our future work is to extend the proposed method to colour texture classification and texture segmentation.

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