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Texture Information in Run-Length Matrices

Xiaoou Tang

Abstract—We use a multilevel dominant eigenvector estimation algorithm to develop a new run-length texture feature extraction algorithm that preserves much of the texture information in run-length matrices and significantly improves image classification accuracy over traditional run-length techniques. The advantage of this approach is demonstrated experimentally by the classification of two texture data sets. Comparisons with other methods demonstrate that the run-length matrices contain great discriminatory information and that a good method of extracting such information is of paramount importance to successful classification.

Index Terms—Pattern classification, run-length matrix, texture analysis.

I. INTRODUCTION

Texture is the term used to characterize the surface of a given object or region and it is one of the main features utilized in image processing and pattern recognition. Many texture analysis methods have been developed over the past few decades [2], [7]–[11], [14].

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The author is with the Department of Information Engineering, the Chinese University of Hong Kong, Shatin, Hong Kong (e-mail: xtang@alum.mit.edu).
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One such method characterizes texture images based on run-lengths of image gray levels. First introduced by Galloway [7], the *run-length method* has not been widely accepted as an effective texture analysis approach. Several comparison studies conducted by Weszka *et al.* [15] and Connors and Harlow [4] have shown that the run-length features are the least efficient texture features among a group of traditional texture features, such as the co-occurrence features, the gray level difference features, and the power spectrum features. Applications of the run-length method have been very limited compared to other methods.

In this correspondence, we investigate the run-length method with a new approach. By using a multilevel dominant eigenvector estimation algorithm and the Bhattacharyya distance measure for feature extraction, we demonstrate that texture features extracted from the run-length matrix can produce great classification results. Experimental comparison with the widely used co-occurrence method and the recently proposed wavelet method show that the run-length matrices contain sufficient discriminatory information and that a good method of extracting such information is crucial to a successful classification.

This work is organized into four sections. Section II introduces the original definition of the run-length matrix and several of its variations, then reviews the traditional run-length features and describes the new run-length feature extraction algorithm. Section III presents the texture classification experimental results. The conclusions are summarized in Section IV.

II. METHODOLOGY

be the maximum run length. The four new matrices are defined as follows.

1) *Gray Level Run-Length Pixel Number Matrix*:

$$p_p(i, j) = p(i, j) \cdot j. \quad (1)$$

Each element of the matrix represents the number of pixels of run-length j and gray-level i . Compared to the original matrix, the new matrix gives equal emphasis to all length of runs in an image.

2) *Gray-Level Run-Number Vector*:

$$p_g(i) = \sum_{j=1}^N$$

$$p(i, j). \quad (3)$$

This vector represents the sum distribution of the number of runs with run length j .

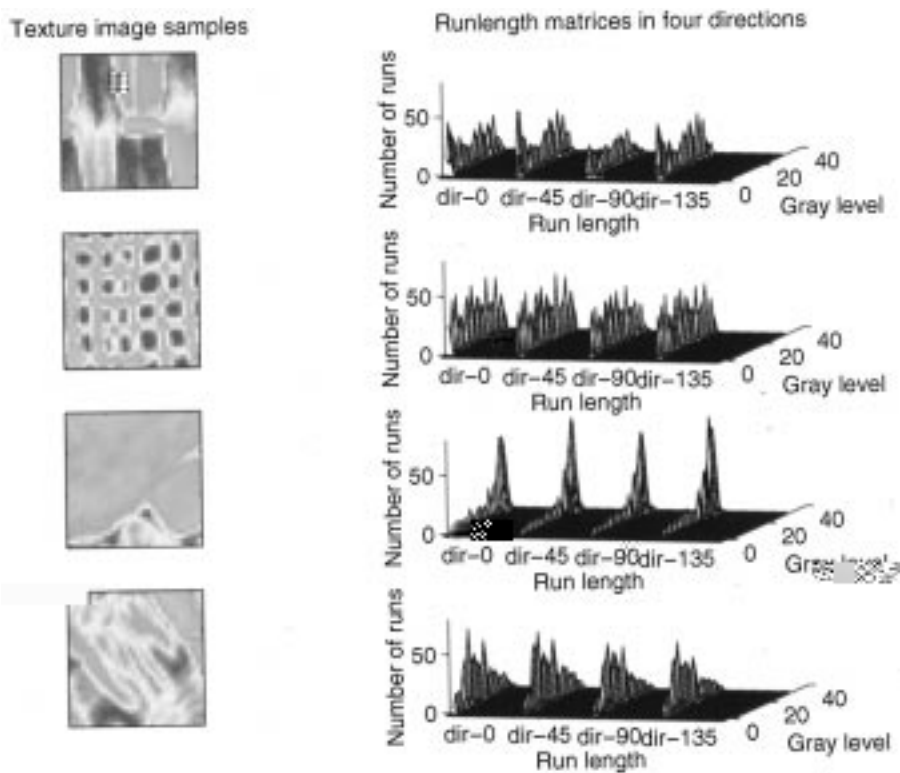


Fig. 1. Four directional run-length matrices of several Brodatz texture samples. Each image sample is of size 32×32 with 32 gray levels. The four directional (0° , 45° , 90° , and 135° directions) run-length matrices are combined into a single matrix. The left-most column of each directional matrix is the run-length-one vector, which has much larger values than the other columns.

4) Gray-Level Run-Length-One Vector:

$$p_o(i) = p(i, 1). \tag{4}$$

Fig. 1 shows the four-directional run-length matrices of several natural texture samples. Notice that the first column of each of the four directional run-length matrices is overwhelmingly larger than the other columns. This may mean that most texture information is contained in the run-length-one vector. The advantages of using this vector are that it offers significant feature length reduction and that a fast parallel run-length matrix computation can replace the conventional serial searching algorithm. For example, the positions of pixels with run-length one in the horizontal direction can be found by

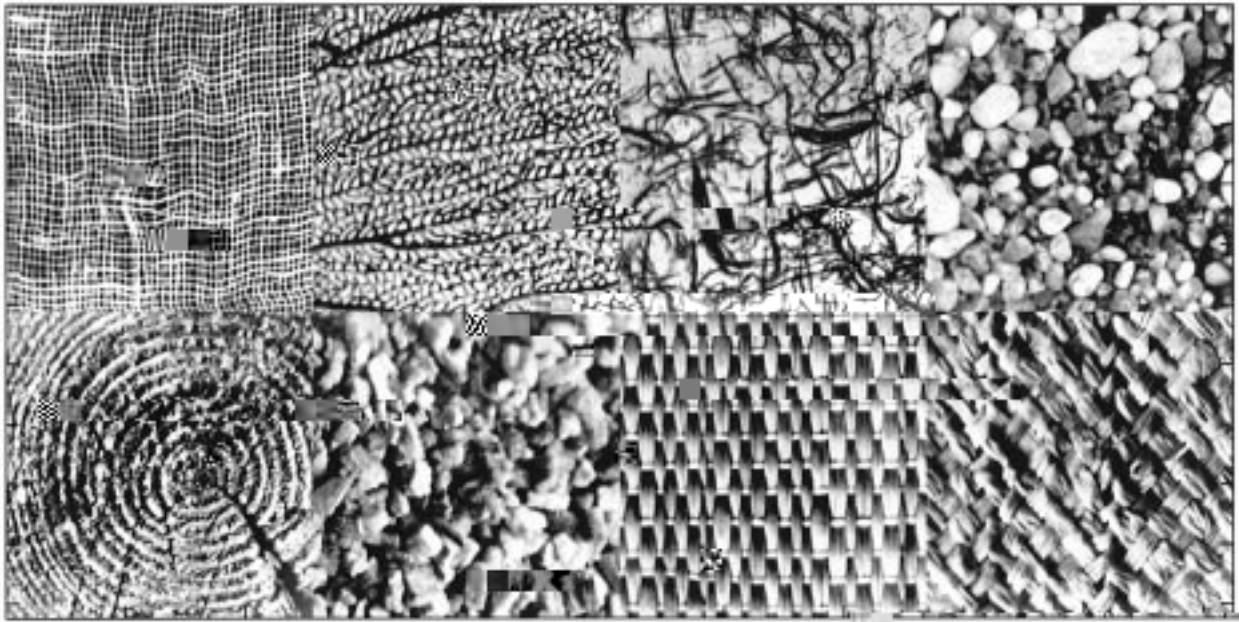


Fig. 3. Eight Brodatz textures. Row 1: burlap, seafan, rice paper, pebbles23. Row 2: tree, mica, straw, raffia.

3) *Gray-Level Nonuniformity (GLN)*:

GLN =

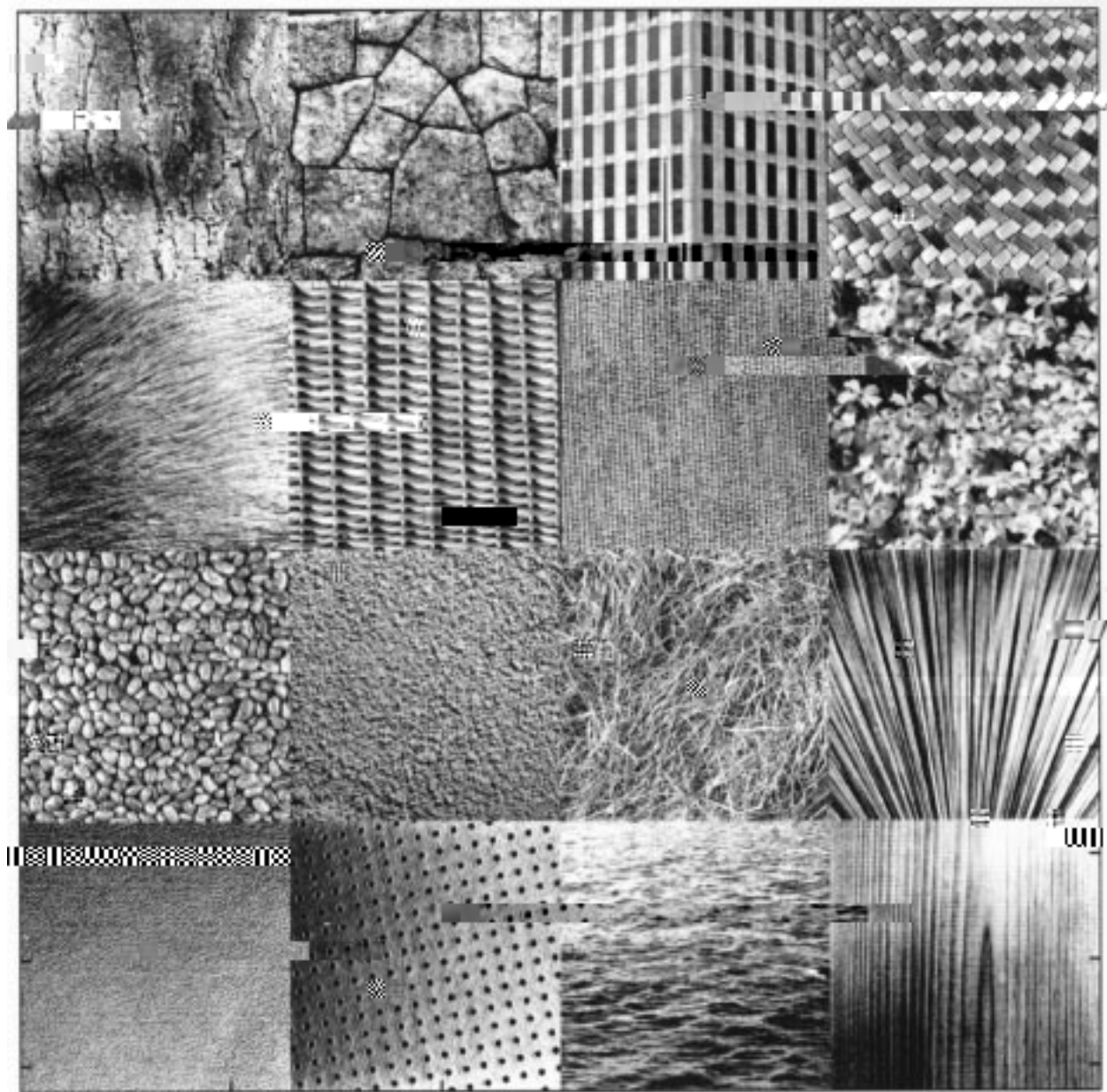


Fig. 4. Sixteen Vistex textures.

TABLE I
BRODATZ TEXTURE CLASSIFICATION RESULTS USING THE NEW FEATURE SELECTION METHOD ON THE TRADITIONAL RUN-LENGTH FEATURES

Feature name	Original feature length	Number of selected features	Correct classification rate		
			Training data	Testing data	All data
G5	20	12	88.5	74.9	78.6
C2	8	8	61.2	41.8	47.0
D4	16	16	84.4	59.1	65.8
...

in the first few columns of the matrix. Moreover, because of the correlation between the short-run section and the long-run section, using only the first few columns as the feature vector will also preserve most of the information in the long-run section. Another advantage of using only the first few columns is that the fast parallel

run-length matrix computation algorithm described in Section II-A can be used.

To further reduce the feature vector dimension and to decorrelate neighboring element values in the matrices, we use the principal component analysis method, also called Karhunen–Loeve transform

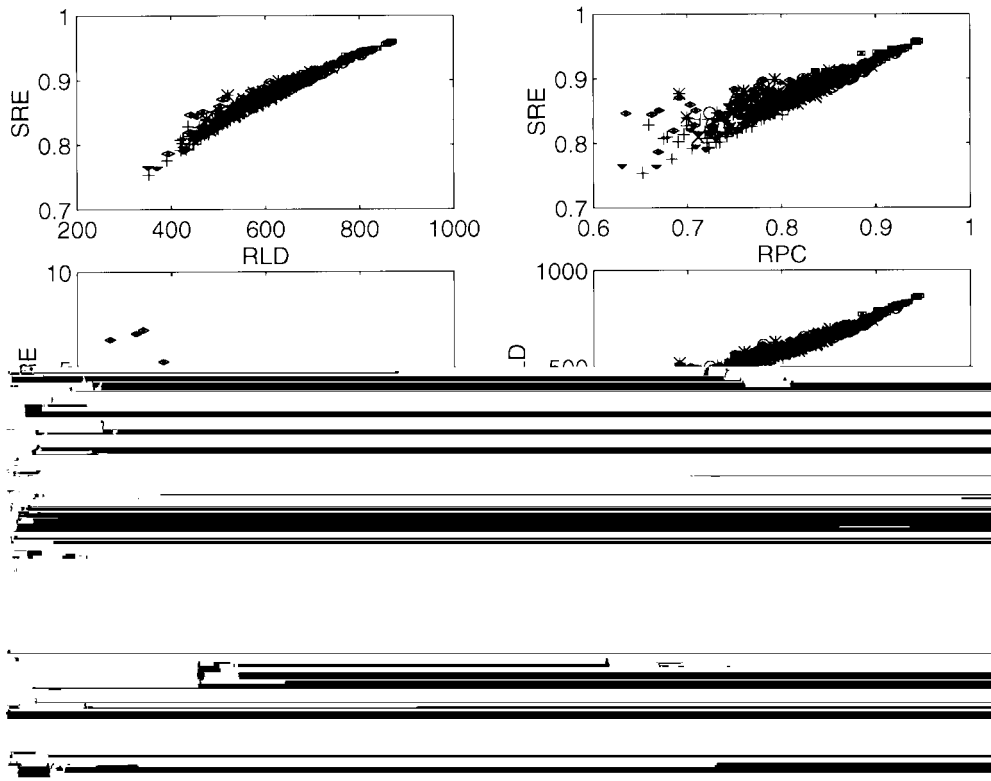


Fig. 5. Scatter plots of several highly correlated traditional run-length texture features of the eight Brodatz textures. Due to overlap, not all eight class symbols can be discerned.

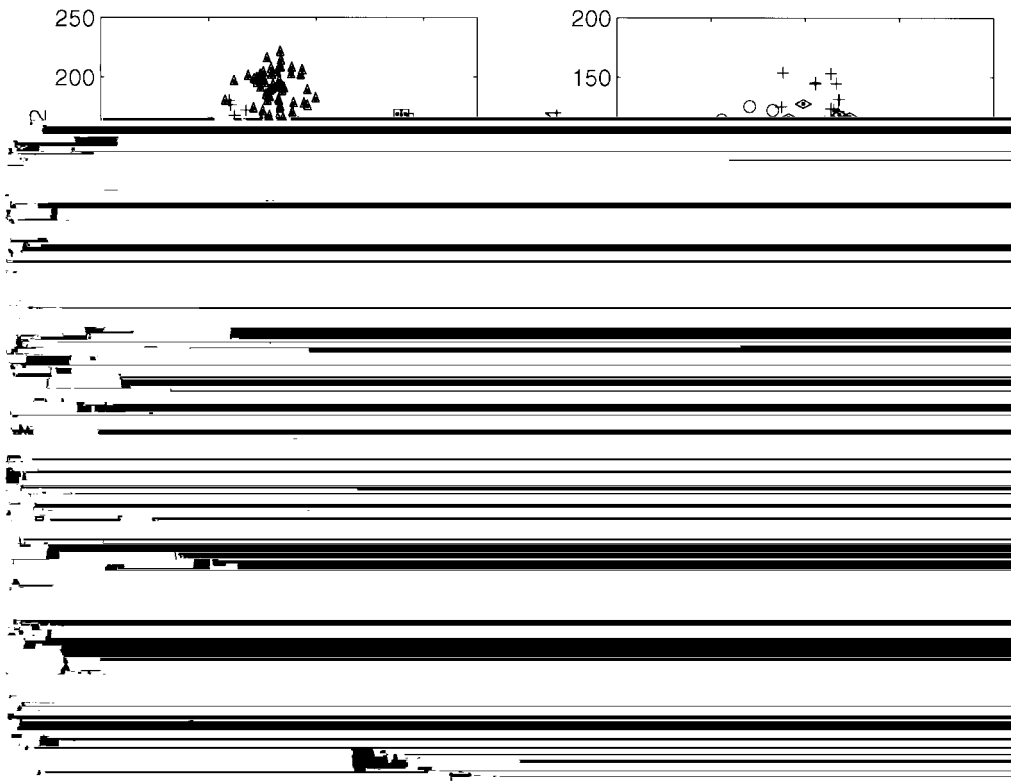


Fig. 6. Scatter plots of the top eight features extracted by applying an MDEE transform on the original run-length matrices of the Brodatz textures. Linearly separable clustering is observed for most of the eight texture classes.

TABLE II
BRODATZ TEXTURE CLASSIFICATION RESULTS USING
THE NEW DOMINANT RUN-LENGTH MATRIX FEATURES

Feature name	Original feature length	Number of selected features	Correct classification rate		
			Training data	Testing data	All data
p: columns 1:4	512	17	99.9	96.8	97.6
4096	4096	18	99.9	99.0	99.5

TABLE III
VISTEX TEXTURE CLASSIFICATION RESULTS USING THE
NEW DOMINANT RUN-LENGTH MATRIX FEATURES

Feature name	Original feature length	Number of selected features	Correct classification rate		
			Training data	Testing data	All data
p: columns 1:4	512	17	99.9	96.8	97.6
4096	4096	18	99.9	99.0	99.5

To avoid this problem, we use a new multilevel dominant eigenvector estimation method developed in [12]. By breaking the long feature vector into $g = n/k$ groups of small feature vectors of length k ,

$$A = \begin{bmatrix} B_1 \\ B_2 \\ \vdots \\ B_g \end{bmatrix} \tag{24}$$

where

$$B_g = \begin{bmatrix} x_1((g-1)k+1) \cdots x_{((g-1)k+1)} \\ \vdots \\ x_1(gk) \cdots x_{(gk)} \end{bmatrix}$$

we can perform the KLT on each of the g group short feature vector set B . Then a new feature vector is formed by the first few selected dominant eigenfeatures of each group. The final eigenvectors are

(KLT), and then use the Bhattacharyya distance measure to rank the eigenfeatures according to their discriminatory power.

1) *Multilevel Dominant Eigenvector Estimation (MDEE) Method:*
To compute the KLT, let x be a feature vector sample. We form an n by m matrix

$$A = \begin{bmatrix} x_1(1)x_2(1) \cdots x_n(1) \\ x_1(2)x_2(2) \cdots x_n(2) \\ \vdots \\ x_1(n)x_2(n) \cdots x_n(n) \end{bmatrix} \tag{22}$$

where n is the feature vector length and m is the number of training samples. The eigenvalues of the sample covariance matrix are computed in two ways, depending on the size of the feature vector. If the feature vector length n is a small number, eigenvalues are computed by a standard procedure. The sample covariance matrix is estimated by

$$W = \frac{1}{m} \sum_1^m (x - \mu)(x - \mu)^T = \frac{1}{m} AA^T \tag{23}$$

where μ is the mean vector. The eigenvalues and eigenvectors are computed directly from W . However, for the feature vector formed by the four directional run-length matrices, n is a large number. For a neighborhood of 32×32 with 32 gray levels, n can reach a maximum of 4096, producing a covariance matrix of size 4096×4096 . Direct computation of the eigenvalues and eigenvectors becomes impractical.

features. By directly using part or all of the run-length matrix as a feature vector, much of the texture information is preserved. This approach is made possible by the utilization of the multi-level dominant eigenvector estimation method, which reduces the computation complexity of KLT by several orders of magnitude. Combined with the Bhattacharyya measure, they form an efficient feature selection algorithm.