Textile Recognition Using Tchebichef Moments of Co-occurrence Matrices

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Abstract. The existing use of summary statistics from co-occurrence matrices of images for texture recognition and classification has inadequacies when dealing with non-uniform and colored texture such as traditional 'Batik' and 'Songket' cloth motifs. This study uses the Tchebichef orthogonal polynomial as a way to preserve the shape information of co-occurrence matrices generated using the RGB multispectral method; allowing prominent features and shapes of the matrices to be preserved while discarding extraneous information. The decomposition of the six multispectral co-occurrence matrices yields a set of moment coefficients which can be used to quantify difference between textures. The proposed method have yielded very good recognition rate when used with the *BayesNet* classifier.

Keywords: texture recognition, texture classification, Tchebichef, orthogonal polynomial, co-occurrence matrix, GLCM, textile motifs.

1 Introduction

Batik and *Songket* motifs [1] are traditional Malaysian-Indonesian cloth designs, with intrinsic artistic value and a rich and diverse history. Despite having a history spanning centuries, they are still valued today for their beauty and intricacy, commonplace amongst today's fashion trends.

These patterns and motifs, however, defy a simple means of systematic cataloguing or indexing, and categorization. Linguistic terms are not accurate enough to identify or categorize - with sufficient accuracy - a particular textile motif; save for a few common design patterns, due to the diversity of patterns. Therefore, the pattern identification would have to be by example; making this ideal for content-based image retrieval and recognition.

In this paper, we will be using a collection of traditional *Batik* and *Songket* design motifs as input for performing classification and recognition by extending previous research on texture recognition. The collection consists of 180 different samples [1], sourced from 30 different texture classes (6 samples per class). Refer to Figure 1 for samples of the classes used in this paper.

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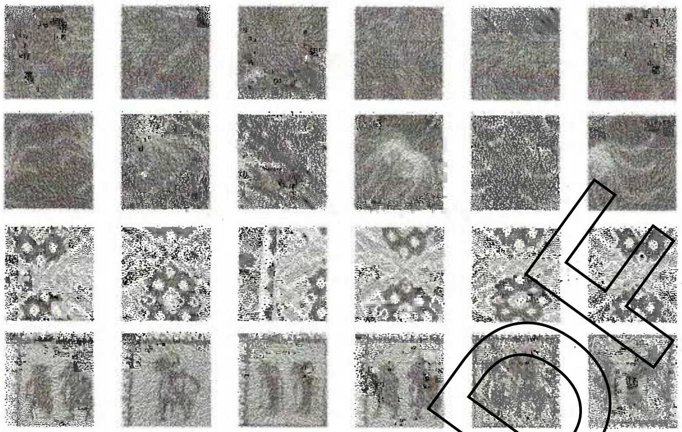

Fig. 1. Samples of texture motifs from 4 different classes used as sample data for this research

2 Related Work

Grey Level Co-occurrence Matrix or GLCM (also known as Spatial-dependence Matrix) has been known as a powerful method [2] to represent the textures. Textures can be described as patterns of "non-uniform spatial distribution" of grayscale pixel intensities [2]. Allam et. al [3], citing Wezka et al. [4], and Conners and Harlow [5] found that co-occurrence matrices yield better results than other texture discrimination methods. Haralick [6] achieved a success rate of approximately 84% by using the extraction and calculation of summary statistics of the GLCM found in grayscale images, having an advantage in speed compared with other methods [3]. Based on the good acceptance of GLCM approaches to texture recognition, in this research, we have adopted the use of GLCM as the basis for our textile motifs recognition. GLCM-based texture recognition have been used in combination with other techniques, including combining its statistical features with other methods, such as genetic algorithms [7]. Practical applications of GLCM in image classification and retrieval include iris recognition [8], image segmentation [9] and CBIR in videos [10].

For use in color textures, Arvis et al. [11] have introduced a multispectral variation to the GLCM calculation that supports multiple color channels, by separating each pixel's color space into RGB components, and uses pairings of individual color channels to construct multiple co-occurrence matrices. In this paper, we propose using the six RGB multispectral [11] co-occurrence matrices – generated by separating each colored pixel into its Red, Green, and Blue components. RGB color space is selected as opposed to others such as YUV and HSV, as it yields a reasonable [12] rate of success. The orthogonal polynomial moments for these six matrices are used as descriptors for the matrices in place of the summary statistics such as Haralick's measures [2]. Allam et al. [3] have also devised a method using orthonormal descriptors in their work on texture recognition on a 2-class problem, with a less than 2% error rate. Jamil et al. [13, 14] have worked retrieval of *Songket* patterns based on their shapes using geometric shape descriptors from gradient edge detectors. Their method achieved their best "precision value of 97.7% at 10% recall level and 70.1% at 20% recall level" [13, 14].

3 Description of Current Work

Mathematically, we define the source image as $I(x, y)$, where (x, y) determines the pixel coordinates, and $0 \leq I(x, y) \leq 255$. The multispectral co-occurrence matrix [11] represents the total number of pixel pairs in $I(x, y)$ having a color value i from the color channel a, and the value j from the color channel b. The pixel pairs in may be separated by a vector **T** where:

$$(x_2, y_2) = (t_x+x_1, t_y+y_1) \tag{1}$$

given (x_1, y_1) as coordinate of the first pixel, (x_2, y_2) for the second pixel [3].

We define a co-occurrence matrix of colors a and b $(a, b \in \{R, G, B\})$ dealing with pixel pairs in $I(x, y)$ separated by a vector **T** as:

$$C_{abt} = \begin{bmatrix} c_{abt}^{00} & \cdots & c_{abt}^{0j} \\ \vdots & \ddots & \vdots \\ c_{abt}^{i0} & \cdots & c_{abt}^{ij} \end{bmatrix} \tag{2}$$

We then define $c_{abt}(i_a, j_b)$ as:

$$c_{abt}(i_a, j_b) = \sum_{x,y} \sum_{(t_x,t_y)\in U} \delta[I(x, y) - i] \times \delta[I(x+t_x, y+t_y) - j] \tag{3}$$

given: i_a and j_b are intensity values from channels a and b respectively, **T** is the distance vector between the two pixels), δ the Kronecker Delta, and $x, y \in I$.

The set U of all possible t_x and t_y values satisfy the condition $x^2 + y^2 = r^2$; r being a fixed distance from the center pixel, $r \in \mathbf{Z}$; yielding a co-occurrence matrix with rotation-invariance.

Each of the six individual multispectral matrices, C_{ab} $(a, b \in \{R, G, B\})$ is converted to a grayscale image, $G_{ab}(i, j)$, such that $0 \leq i, j \leq 255$ (see Figure 1). The pixel intensity at any given position (i, j) correlates directly with the value in the co-occurrence matrix $C_{ab}(i, j)$, through the following equation:

$$g_{ab}(i, j) = \frac{c_{ab}(i, j)}{\max(c_{ab}(i, j))} \times 255 \tag{4}$$

After conversion $\min(c_{ab}(i, j))$ will have $g_{ab} = 0$, while $\max(c_{ab}(i, j))$ has $g_{ab} = 255$. However, outlying values (i.e. small values in C_{ab}) that contribute to the overall shape of the co-occurrence matrix will be lost during decomposition into moments. To solve this problem, the output image is then histogram-equalized to highlight such outlying values. By visual inspection of the generated matrices, images in the same texture class will have a similar set of the six matrices. For example, notice the similarity between the first two representations of multispectral matrices (samples of the same texture class) as opposed to other matrices (samples from different classes) in Figure 2.

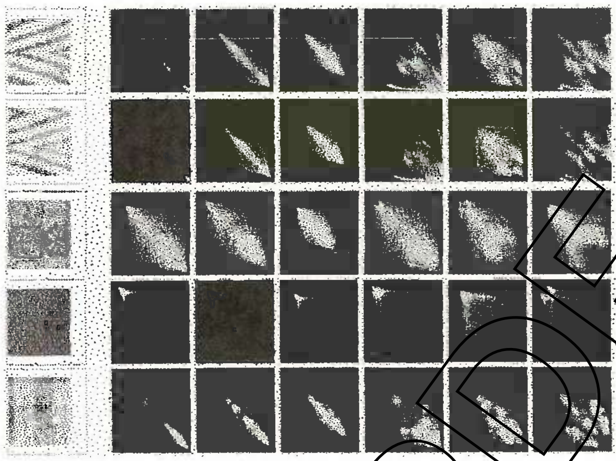

Fig. 2. Multispectral RGB co-occurrence matrices for 'Batik' motifs. Each row shows: 'Batik' motif and its corresponding matrices from the RR, GG, BB, RG, GB, and BR channels.

Current methods (using second-order statistics of co-occurrence matrices) compress the features of the matrix into a set of 'summary statistics' summarizing important textural features – Haralick [6] identified thirteen of them; five are commonly used [10, 11]. We propose to use the "shape" information from the multispectral matrices as a basis in texture recognition and classification. Such "shape" information can be seen as capturing more complete information rather than information such its skew, contrast, etc.

We introduce the usage of orthogonal polynomials as a means of representing the information found in the co-occurrence matrices. See et al. [15] have shown that discrete orthogonal polynomials such as the Tchebichef discrete orthogonal polynomial can be an effective way of representing any 2D function. Various orthogonal polynomial moments, such as Zernike [16] and Hermite [17] have been applied to texture classification. However, our approach differs in that we apply the orthogonal polynomial moments on the co-occurrence matrix image, not on the image directly. Our approach require that the multispectral co-occurrence matrices to be treated as an image, and hence can be represented as a series of image moments [12]. The limited finite expansion of the moments allow only prominent features to be preserved while discarding those moments which carry little or no information [15, 18]. The first few moments encode gross overall shape and other moments carry finer details; thus, by discarding higher moments, we are able to save on complexity while preserving the entire set of second-order textural statistics in the multispectral matrix.

This paper applies the Tchebichef method to decompose the six generated multispectral co-occurrence matrices and using the resulting moment values as basis for texture discrimination. Using the findings from See et al. [15], we can decompose the generated visual representation of the 6 multispectral matrices into a number of coefficients.

Mathematically, the following decomposition function transforms the matrices' image intensity into moment orders M_{pq} [15]:

$$M_{pq} = \frac{1}{\rho(p)\rho(q)} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} m_p(x) w(x) m_q(y) w(y) f(x, y) \tag{5}$$

where: $0 \leq p, q, x, y \leq N\text{-}1$; $m_n(x)$ is a set of finite discrete orthogonal polynomials, $w(x)$ the weight function, and $\rho(n)$ the rho function.

The Tchebichef polynomial is defined mathematically as [14]:

$$m_n(x) = n! \sum_{k=0}^{n} (-1)^{n-k} \binom{N-1-k}{n-k} \binom{n+k}{n} \binom{x}{k} \tag{6}$$

$$\rho(n) = (2n)! \binom{N+n}{2n+1} \tag{7}$$

$$w(x) = 1 \tag{8}$$

given: m_n is the n-th Tchebichef polynomial, $\rho(n)$ the rho function and w(x) the weight function. Let N be the number of moment orders used for the decomposition process. The total number of coefficients resulting from the decomposition process for each matrix is N^2. For the 6 matrices involved, the total number of coefficients per sample image is therefore $6(N)^2$. These are generated from the database of 180 sample images from 30 classes of 'Batik' and 'Songket' textures. The coefficients are then stored in CSV format and imported into Weka [19] for further analysis.

In Weka, two unsupervised clustering algorithms and two supervised classifiers are used to classify our sets of generated moment coefficients. The unsupervised clusterers are *IBk* (*k*-means with the *k* value set to the number of expected classes, i.e. 30), *FarthestFirst* (an optimized implementation of the *k*-means method); while the two supervised classifiers are *BayesNet* and *kNN* (*k*-nearest neighbor, with the *k* value set to 5). All of them use default parameters as defined in Weka. For the supervised classifier, we use 10-fold cross-validation to automatically partition the test and training data: the collection of sample data is partitioned into 10 mutually-exclusive partitions (called folds) [20].

The k-means algorithm by McQueen [21] works to partition our sample data (unsupervised) into *k* distinct clusters. The naïve K-means algorithm does so by minimizing total intra-cluster variance; in the context of our methods, it tries to identify the samples which minimize the variance within a particular texture class, thereby properly grouping these samples by texture class. *FarthestFirst* [19] is an implementation of an algorithm by Hochbaum and Shmoys [19], cited in Dasgupta and Long [22]. It works "as a fast simple approximate clusterer" modeled after the naïve k-means algorithm. kNN (the k-nearest neighbor) classifier works by assigning a texture (whose class is yet unknown) to the class in which the majority of its *k* neighbors belong to. In this case, we compare the linear distance between a texture sample and each of its *k* (we fix the value of k=5) neighbors, finally assigning it a class based on the majority of its 5 neighbors. The *BayesNet* Bayesian network learning algorithm in Weka uses the K2 hill-climbing strategy to construct a Bayesian network from the given coefficient data; by constructing a model to determine Bayesian probability of a single sample image as belonging to a class.

4 Experimental Results

For the purposes of this paper, the Tchebichef polynomial decomposition is performed with moment orders, N = 10, as it was previously determined to have the best degree of accuracy with the least processing time [23]. The following table shows the experimental results obtained in Weka [18].

Table 1. Experimental results as determined in Weka for each of the four methods

Method	Samples	Correct	Incorrect	Percentage
Supervised: *BayesNet*	180	179	1	99.44%
Supervised: 5NN (*kNN*)	180	176	4	97.78%
Unsupervised: *FarthestFirst*	180	173	7	96.11%
Unsupervised: k-means (*IBk*)	180	167	13	92.78%

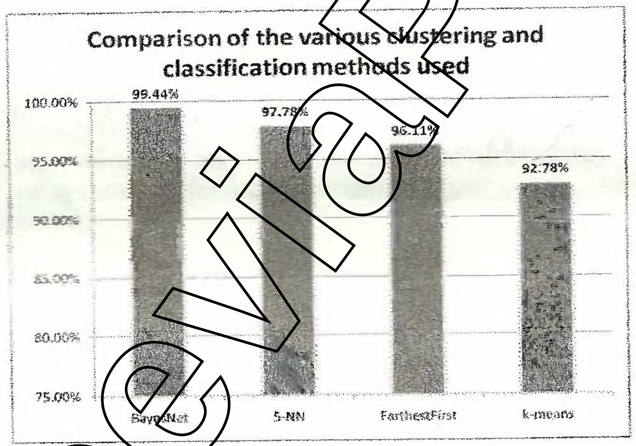

Fig. 3. Graph comparing the correct classification percentage for each of the four methods used

5 Discussion and Analysis

Prior research on the GLCM has focused predominantly on textures. Arvis et al. [11] with their multispectral co-occurrence matrix method, with a 5-Nearest Neighbors classifier yielding a 97.9% percentage of good classification for VisTex [24] textures. Previous research work involving color texture analysis using a combination of Gabor filtering and the multispectral method on the Outex [25] database has yielded a rate of success of 94.7% [25]. Allam's result of a 2% error rate [3] differs in the fact it is only applied to a 2-class problem, restricted to grayscale texture. This differs in our motivation of using the "shape" of the co-occurrence pattern.

The results for 'Batik' and 'Songket' achieved here are among the best for such kinds of textile patterns based on the limited prior research found [13, 14]. Experimental tests on co-occurrence matrices using summary statistics suggest that summary statistics may not always capture the full representation of the co-occurrence matrix: the rationale being many similar distributions having the possibility of producing a similar value [26] and resulting in a lower success rate [6]. Design motifs such as those found in textiles tend to have a more non-uniform distribution in the GLCM as opposed to textures. This also makes it difficult to be captured by Haralick's summary statistics [6] as the "shape" information is not adequately represented. Our method has the best success rate using the Tchebichef orthogonal polynomial, with 10 order of moments used [23]. This is due to the fact that with Tchebichef, the reconstructed matrices strike a balance between preserving the shape of the matrices' visual representation and a good degree of variance when matching with other samples.

6 Conclusion

We have successfully demonstrated the multispectral co-occurrence matrices method for use in the recognition of *Batik* and *Songket* design motifs and introduced the use of the Tchebichef orthogonal polynomial to decompose each of these matrices into a series of moments as a means to capture more complete second-order pixel statistics information. The advantage to this method is having a good degree of accuracy as compared to the use of summary statistics which is commonly used in GLCM research. We have also shown that this method is viable in matching non-uniform design motifs as opposed to only textures. This makes our approach suitable to be used in image retrieval applications for not only traditional *Batik* and *Songket* textile motifs but other design motifs.

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