An Approach to Textile Recognition

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1. Introduction

Batik and Songket motifs (Ismail, 1997) 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.

The motifs themselves are usually highly stylised abstract designs derived from nature or mythology. The interesting thing about them, from the point of pattern recognition, is that the patterns are non-repeating but unmistakably belong to the same category; that is, according to the general theme of the non-repeating motifs, they belong to the same textile. Therefore, the pattern identification would have to be by example; making this ideal for content-based image retrieval and recognition.

While there are other approaches that try to classify individual patterns within the textile motifs, we approach problem as a form of "macro textures". Texture can be described as patterns of "non-uniform spatial distribution" of pixel intensities, that is to say that, intensity patterns are varying across space. In a similar manner, the Batik and Songket individual patterns vary across the textile but maintaining a similar theme. Therefore we adapt the approach for texture recognition and expand it to account for macro level variation as opposed to at pixel level. We are able to get good results on it, and considered among the best results reported.

In this paper, we will be using test images will be from a collection of traditional Batik and Songket design motifs. They will be used as input for performing classification and recognition by extending previous research on textile and texture recognition. The collection consists of 180 different samples (Ismail, 1997), sourced from 30 different texture classes (6 samples per class). Refer to Figure 1 for samples of the classes used in this paper.

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 (Davis, 1981; Walker et al., 1997) to represent the textures. Textures can be described as patterns of “non-uniform spatial distribution” of gray scale pixel intensities. Allam et. al (1997), citing Wezka et al. (1976) , and Conners and Harlow (1980) found that co-occurrence matrices yield better results than other texture discrimination methods. Haralick (1973) 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. 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 (Walker et al., 1997). Practical applications of GLCM in image classification and retrieval include iris recognition (Zaim et al., 2006), image segmentation (Abutaleb, 1989) and CBIR in videos (Kim et al., 1999).

For use in colour textures, Arvis et al. (2004) have introduced a multispectral variation to the GLCM calculation that supports multiple colour channels, by separating each pixel’s colour space into RGB components, and uses pairings of individual colour channels to construct multiple co-occurrence matrices.

We will be using the six RGB multispectral co-occurrence matrices – generated by separating each colour pixel into its Red, Green, and Blue components. RGB colour space is selected as opposed to others such as YUV and HSV, as it yields a reasonable (Chindaro et al., 2005) 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 (Davis et al., 1981). Allam et al. (1997) 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. (2006a, 2006b) have worked on 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" (Jamil et al., 2006a). Other approaches to textile recognition include using regular texel geometry (Han et al., 2009)

3. Description of approach

3.1 Co-occurrence Matrices in Image Representation

A source image with 256 possible colours is defined as I(x, y), with (x, y) determining the pixel coordinates, and the restriction of pixel values overlapping print: given by $0 \leq I(x, y) \leq 255$. The multispectral co-occurrence matrix (Arvis, 2004) represents the total number of pixel pairs in I(x, y) having a colour value i (from the channel a), and value j (from channel b).
A vector **T** may separate the pixel pairs 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. The reason that we introduce the vector **T** is to provide some degree of freedom when dealing with textures of a different scale (macrotextures have a larger **T**, microtextures on the other hand need a smaller **T**). To yield a co-occurrence matrix with rotation-invariance (to deal with all possible orientations of neighbouring pixels), the set of all possible t_x and t_y values must satisfy $x^2 + y^2 = r^2,\ r \in Z$, representing a fixed distance from the centre pixel.
Therefore, a co-occurrence matrix from channels a and b (a, b ∈ {R, G, B}) in I(x, y), separated by a vector **T** is represented mathematically as:

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

An elements of the above matrix, $c_{ab}(i_a, j_b)$ has the mathematical definition:

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

i_a and j_b are intensity values from channels a and b respectively, **T** is the distance vector as defined in (1) and $x, y \in I$. δ is is the Kronecker Delta.
Each of the six individual multispectral matrices, C_{ab} (a, b ∈ {R, G, B}) is converted to a grayscale image (having 256 possible shades of gray), $G_{ab}(i, j)$, such that $0 \leq i, j \leq 255$. 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 normalization, $min(c_{ab}(i,\ j))$ will have $g_{ab} = 0$, while $max(c_{ab}(i,\ j))$ has $g_{ab} = 255$. Histogram equalization is applied to improve the contrast of the generated matrices, which will improve visibility of outlying values in the graphical representation of the matrices.
Images in the same texture class will have a similar combination of six matrices which is distinct to a particular class (figure 2).

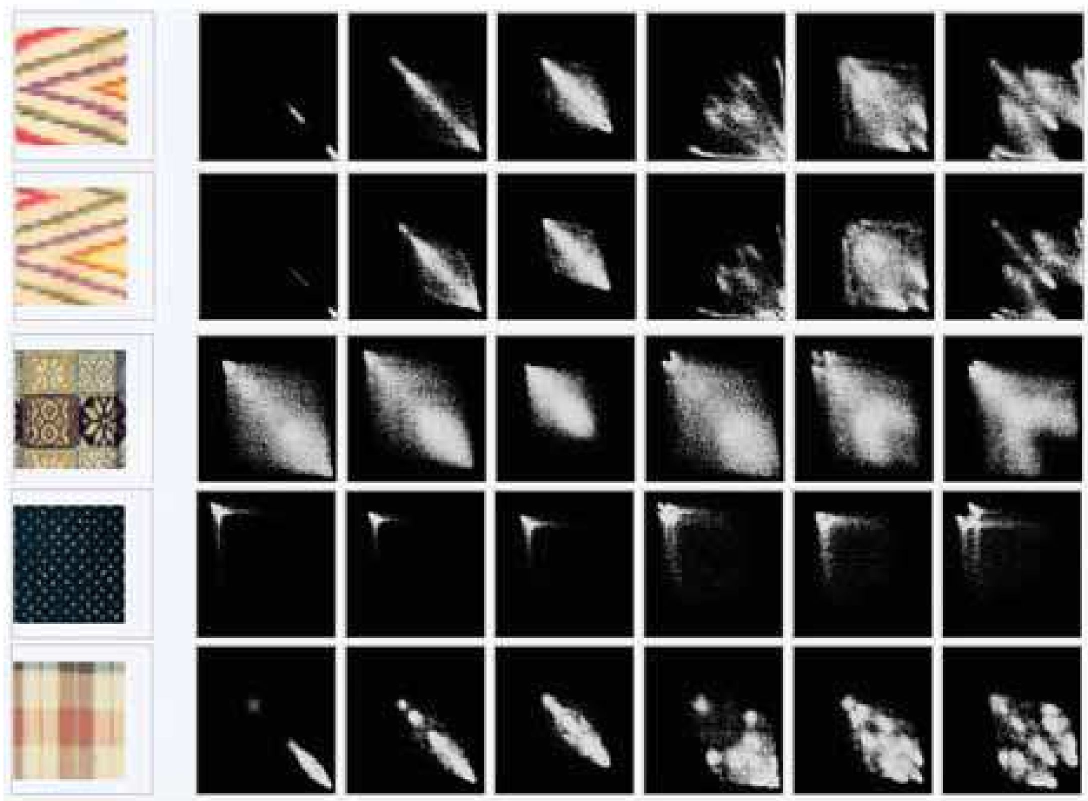

Fig. 2. Multispectral RGB co-occurrence matrices for 'Batik' motifs. Each row shows: 'Batik' motif and its corresponding matrices from the RR, GG, BB, RG, GB, and BR channels.

3.2 Orthogonal polynomial decomposition

We use orthogonal polynomials as a means of representing the information found in the co-occurrence matrices. Most GLCM or multispectral co-occurrence matrix-based methods of texture recognition uses a set of 'summary statistics' summarizing important textural features found in a particular image's matrix. Examples would be the five common features (Arvis, 2004) are derived from Haralick's (1973) original set of thirteen.
See et al. (2008) 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 (Wang et al., 1998) and Hermite (Krylov et al., 2005) 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 (See et al., 2008; Kotoulas et al., 2005). We propose the usage of "shape" information from the multispectral matrices, by means of orthogonal polynomial decomposition, as a basis in texture recognition and classification. The decomposition coefficients would be larger but they contain more textural information as compared to the summarized set of 5 common Haralick features.
The Tchebichef orthogonal polynomial is used for the purposes of decomposition of the multispectral matrices. In the research of See et al. (2008), the Tchebichef orthogonal polynomial outperforms other polynomials in general, second only to the Discrete Cosine Transform which is used as the basis for comparison. Other orthogonal polynomials have limitations which render them unsuitable for decomposing our multispectral co-occurrence matrices. Specifically, Krawtchouk moments only work for binary images, Hahn only work for specific cases in which the foreground is significantly whiter than the background, and Poisson-Charlier generally yields unsatisfactory results [15]. Hence, the Tchebichef orthogonal polynomial is ideal for decomposing the six generated multispectral co-occurrence matrices and using the resulting moment coefficients as basis for texture discrimination.
The limited finite expansion of the moments allow only prominent features to be preserved while discarding those moments which carry little or no information. 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.
The transformation of image intensity into moment orders is defined mathematically as M_{pq} (See et al,. 2008):

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

$0 \le p, q, x, y \le N-1$; $m_n(x)$ 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 (See et al, 2008):

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

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

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

where m_n is the n-th Tchebichef polynomial, $\rho(n)$ the rho function and $w(x)$ the weight function. Further details can be found in See et al (2008).

4. Classification

Firstly we compared the compared the results obtained from the Batik/Songket database and the VisText database. Images used are 100-by-100 pixel samples. For the 'Batik'/'Songket' database, 132 images from 16 different classes are used; for the VisTex database, 200 images from 40 different classes are used. A pixel radius of one unit, i.e. $r = 1$ is used for the construction of the multispectral matrices as it has been identified from prior research in GLCM to give optimum results. This results in 256 x256 GLCM matrices per image. We also need to compare the results obtained from varying orders from the discrete orthogonal polynomials.

For comparing two sample images S and T, we need to calculate the distance the visual representation S_{ab} and the visual representation T_{ab} ($a, b \in \{R, G, B\}$). The distance between the N^2 pairs of coefficients would have to be calculated. The distance(S_{ab}, T_{ab}) is defined as the Euclidean distance in the N^2 dimension between coefficients of S_{ab} and T_{ab}. Once the six distances for each of the six multispectral representations have been obtained, the final difference score, diff(S, T) is then obtained from the Euclidean distance (in the 6th dimension) of these six values. Hence, the smaller diff(S, T), the more similar S and T are ,diff(S, T) is 0 iff S=T; and diff(S, T) is symmetrical.

The k-nearest neighbor classifier is used to evaluate our findings, where k = 3. In order to estimate the moment order to use, we tested it from order 5 to 20. The percentage of correct classifications for the DCT and Tchebichef methods applied to our two data sets, versus the number of moment orders used in the process, is given in Figure 2 below. The best success rate was found using the Tchebichef orthogonal polynomial, with 10 as the best order of moments used. Some of these results have appeared in Cheong & Loke (2008a, 2008b). Overall the results using Vistex is better than using the Batik image database.

The Tchebichef orthogonal polynomial the reconstructed multispectral matrices strike a balance between preserving the shape of the matrices' visual representation and a good degree of variance when matching with other samples. DCT also creates a good approximation of the matrix pattern, however its reconstructions create a more rigid pattern while discarding certain outlying values visible in the matrix; this rigidity allows little room for error and will sometimes reject similar patterns. An order of 10 seems to allow for adequate intra-class variance. Lesser orders fail to capture the matrix shape well; greater orders result in a detailed reconstruction lacking in variance, causing certain samples to be rejected as false negatives.

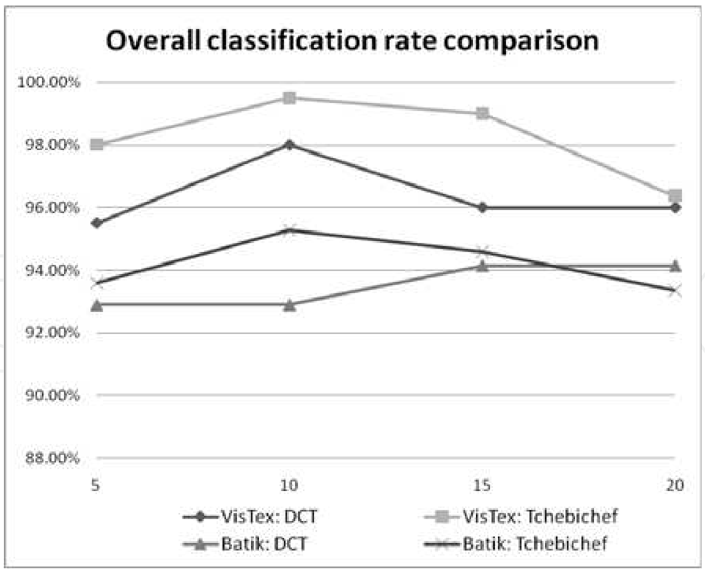

Fig. 2. Graph of average classification rate vs. number of moment orders used, for all sample data with both DCT and Tchebichef methods.

The best results we obtained (Figure 2) was using the 3kNN at 99.5% for VisTex textures and 95.28% for the Batik/Songket motifs.
Using Weka (Witten et al., 2005), we tested with various other classification methods to see if further improvements can be obtained using the best Tchebichef polynomial decomposition moment order set of 10. We also increased the number of samples to 180 encompassing 30 classes.
We used two unsupervised clustering algorithms and two supervised classifiers 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 neighbour, 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) (Kohavi, R., 1995).
The k-means algorithm by McQueen (1967) 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 (Hochbaum et al., 1985) is an implementation of an algorithm by Hochbaum and Shmoys, cited in Dasgupta and Long (2005). It works “as a fast simple approximate clusterer” modeled after the naïve k-means algorithm. kNN (the k-nearest neighbour) classifier works by assigning a texture (whose class is yet unknown) to the class in which the majority of its k neighbours 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 neighbours. 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 (Korb et al. 2004). The results have improved from earlier results, increasing the classification rate from 95.28% to 99.44% using the BayesNet and to 97.78% using the 5kNN classifier. Even the FarthestFirst returned better results compared to earlier classification runs.

The results are presented below.

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%

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

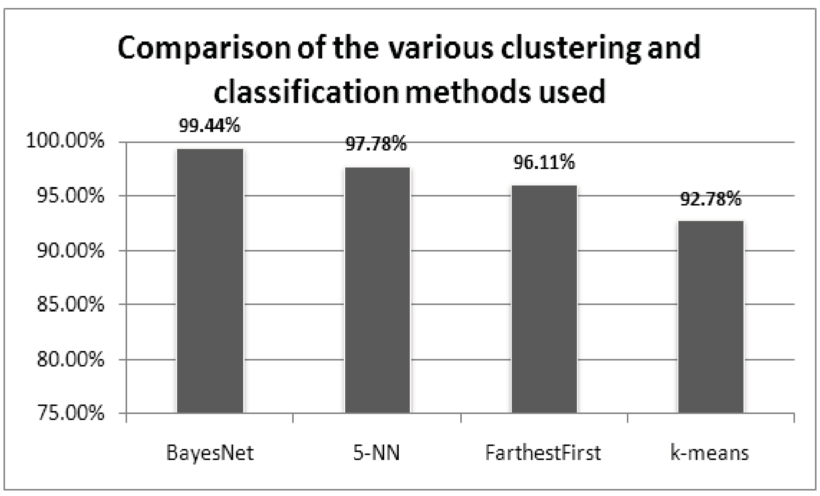

Fig. 3. Graph comparing the correct classification percentage for each of the four methods used

5. Dimension Reduction

The number of attributes generated, in order of 700, prompted us to study if the dimensionality can be reduced. As previously mentioned, using the Tchebichef orthogonal polynomial decomposition (with 10 moment orders) on 6 co-occurrence matrices yields a total of 726 attributes. The high number of attributes increases the complexity in storing the pattern descriptors. Another issue is the extended runtimes, deteriorating performance of the classification algorithms, and inefficiency of the knowledge discovery process due to irrelevant or redundant attributes, which could be compounded by the existence of a large number of samples in the knowledge base. Occam's Razor - in our case, the principle of using only the features that are necessary for textile classification - is the basis for our motivation to counter the 'curse of dimensionality'. Therefore, it is necessary to examine the effects of the reduced number of attributes on the accuracy of the classification.

If N is the number of moment orders used for the decomposition process then 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 $6N^2$. The Tchebichef orthogonal polynomial used in the decomposition of the 6 generated

multispectral matrices resulted in the many attributes in the order of 700. This resulted in 6(10+1)2 = 726 moment coefficients because 10th order moments were used.
We first generate the 726 moment coefficients on our set of 180 texture samples (each being 16.7 million colours, of size 100-by-100 pixels). The total number of classes is 30 with 6 samples in each class. The coefficient data obtained is fed into Weka (Witten et al., 2005) for classification (see 4.1). Five-fold cross validation was used for testing. The co-occurrence matrix coefficients are generated from the database of 180 sample images of 30 classes of 'Batik' and 'Songket' textures. The coefficients are then stored in CSV format and imported into Weka for further analysis.
InfoGain (Dumais et al., 1998), one of the simplest attribute ranking methods, work by determining the Shannon information After testing using the entire raw coefficients, we further tested with dimension reduction on the coefficients. Different attribute-selection filters are applied on the data to reduce the dimensions of the coefficient. For each filter, 'maximum attribute' parameter is set to values ranging from 2 to 16, i.e. reducing to dimension to 2 to 16. Experiments were performed using 5-fold cross-validation to classify the data.
The Weka FilteredClassifier and AttributeSelectionFilter options are used for this purposes to ensure that the same attribute selections are applied for training set and test set. The attribute-selection filters used are independent of the classification algorithms used. The list of filters selected were the ones used in Hall et al (2003) and (Deegalla et al. 2007). They are the Information Gain Attribute Ranking method (InfoGain), the RELIEF method, and finally Principal Components Analysis (PCA).
InfoGain (Dumais et al., 1998), one of the simplest attribute ranking methods, work by determining the Shannon information gain between an attribute and its class; the higher the information gain, the more relevant the attribute is. RELIEF (Kira et. al 1992; Konoeneko, 1994) randomly samples an instance from the data, locates its nearest neighbours and uses their attribute values in turn to update relevance scores for each attribute. The underlying principle behind RELIEF is that useful attributes are similar for instances of the same class, and vice versa.
Random projection (RP) (Bingham et al., 2001) uses a random matrix to project the original data set into a lower dimensional subspace. RP depends on the Johnson and Lindenstrauss theorem (Dasgupta et al., 2003) which states that any points in a d-dimensional Euclidean space can be mapped to a smaller k-dimensional Euclidean space while maintaining all pair-wise distance within an arbitrarily small factor.
PCA uses a linear transform to project the original attribute space to a lower dimensional subspace. Both PCA and RP are unsupervised in that class information is not required, whereas InfoGain and RELIEF are supervised, i.e. it uses class information for attribute selection.
For classification testing, we used the k-nearest neighbor lazy classifier (Aha et al., 1991), with k=1 (IB1) and k=3 (IB3), and the Bayesian Network (BayesNet) classifier. The k-nearest neighbor classifier works by assigning a sample to the class in which the majority of its k neighbors belong to. BayesNet in Weka constructs a Bayesian network from the data; by constructing a model to determine Bayesian probability of a single sample as belonging to a class. The advantage of BayesNet is that it can take into consideration the conditional dependency of attributes.

5.1 Dimension Reduction Results

The experimental results obtained via Weka are presented in the following figures 4-7.

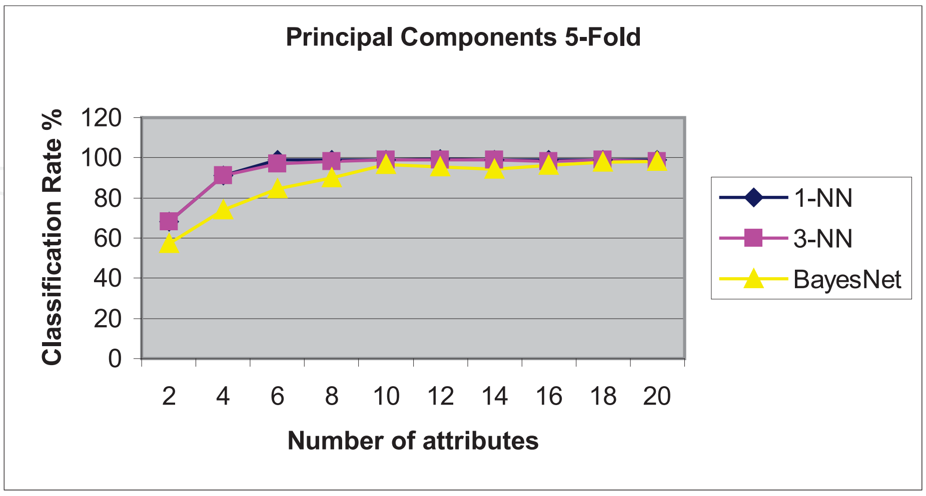

Fig. 4. Plot of classification rate versus number of attributes using Principal Components Analysis with 5-fold cross-validation.

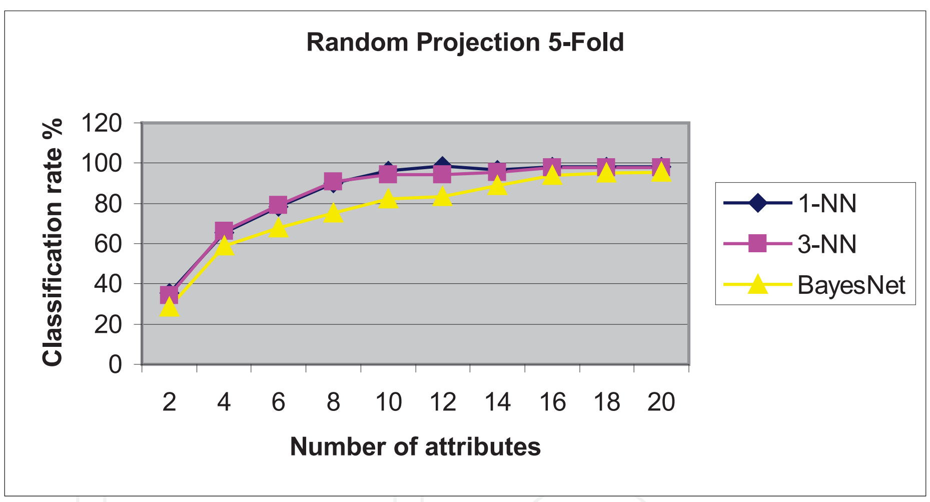

Fig. 5. Plot of classification rate versus number of attributes using Random Projection with 5-fold cross-validation.

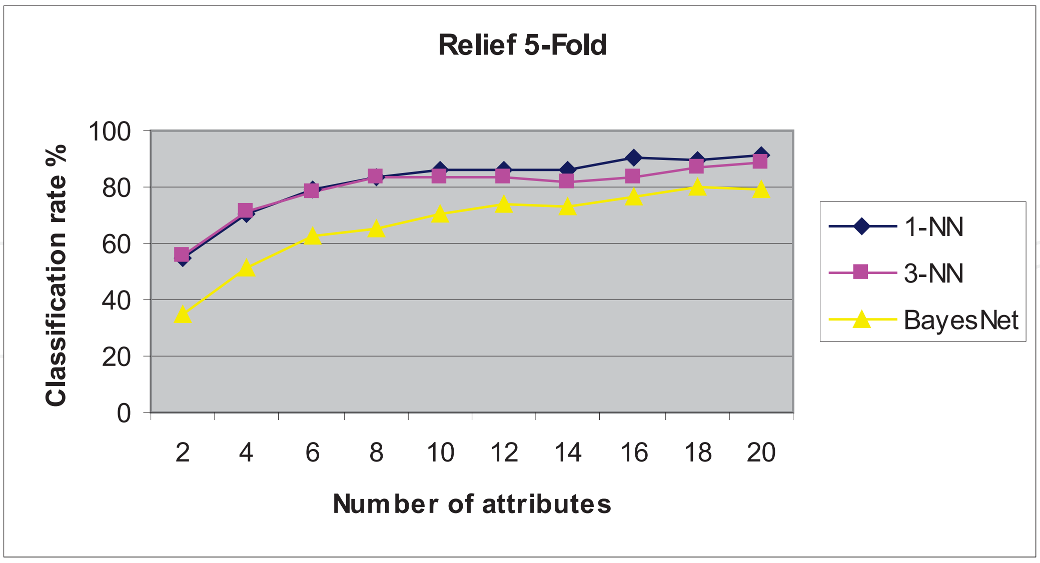

Fig. 6. Plot of classification rate versus number of attributes using RELIEF Attribute Evaluation with 5-fold cross-validation.

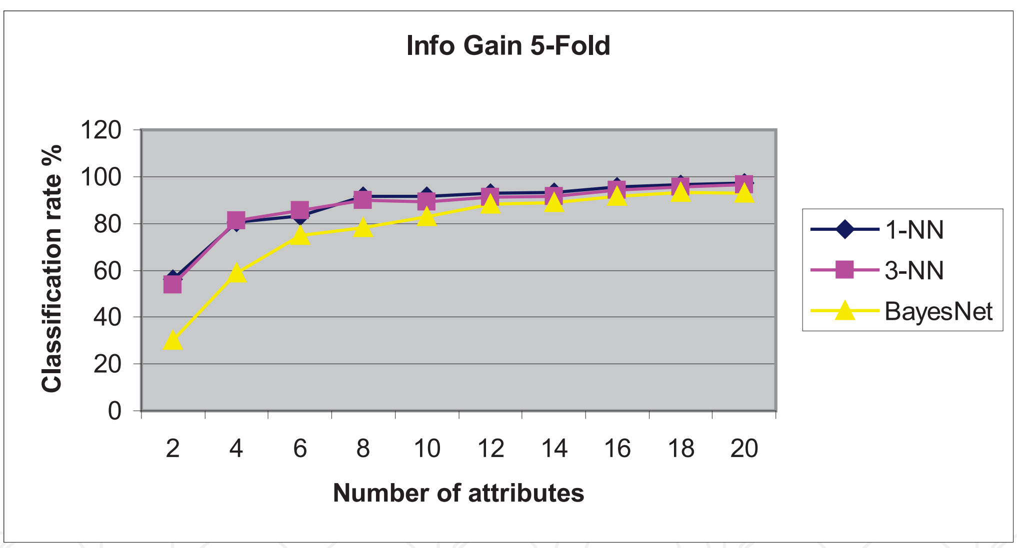

Fig. 7. Plot of classification rate versus number of attributes using Info Gain Attribute Evaluation with 5-fold cross-validation.

Results in figures 4-7 were obtained on the same data set using 5-fold cross validation. Results in figure 8 were obtained using a new test set of 60 samples, each class represented by 2 samples, and trained entirely on the data set used in the 5-fold cross validation test.

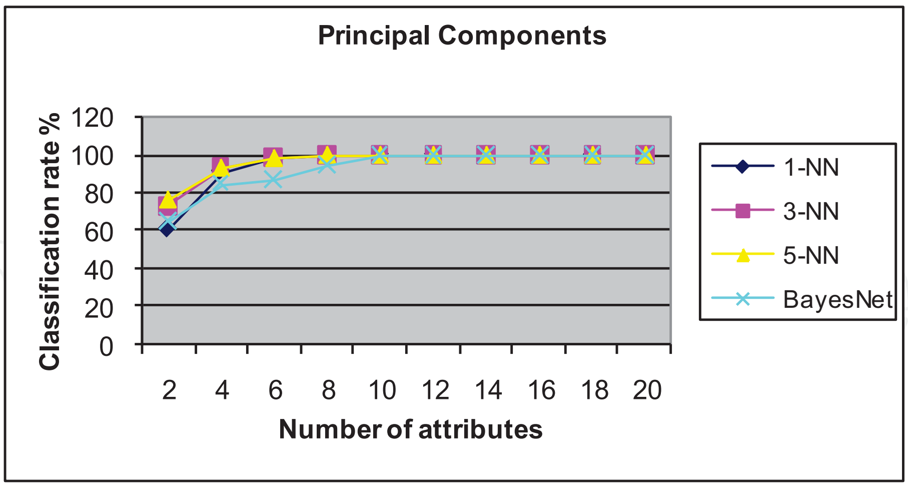

Fig. 8. Plot of classification rate versus number of attributes using Principal Components Analysis with new test data set.

The computation of the model using RP took the least time, ranging from 0.02-0.08 seconds. This was followed by Info Gain which took around 0.6s, RELIEF about 4s, and finally PCA which ranges around 8s.

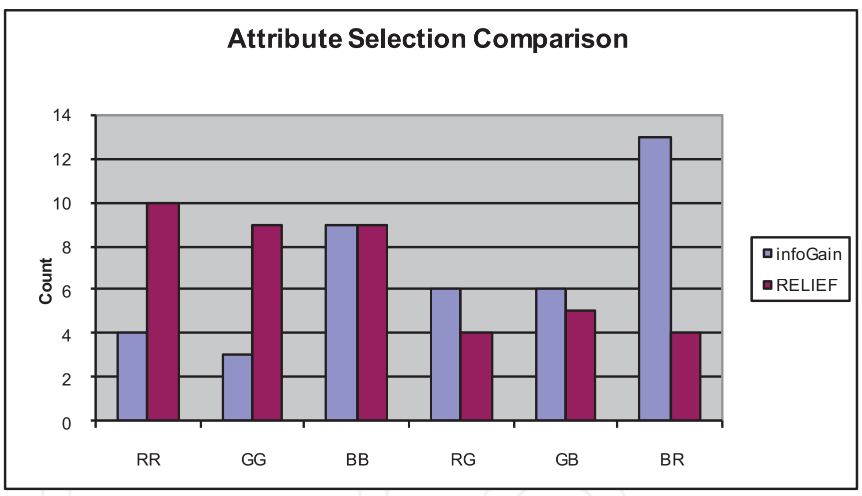

Fig. 9. Comparison of attribute selection of InfoGain and RELIEF

The results from dimension reduction are rather mixed. The supervised method of attribute reduction InfoGain and RELIEF returned the worse results. BayesNet did not particular work well on RELIEF. However the 1-NN returned respectable results using InfoGain attributes. Analyzing the attribute top 40 rankings from RELIEF indicate that it preferred attributes selected from the RR, BB and GG co-occurrence matrix whereas InfoGain preferred BB and BR attributes higher (see figure 9). There was considerable overlap in the BB, RG and CB.

The best results are obtained on unsupervised methods using subspace projection namely PCA and RP method. PCA returned the best results peaking at 8 attributes for 1-NN, 10 attributes for 3-NN, and 20 attributes for BayesNet, the results returned respectively are

98.9%, 98.9% and 98.3% correct classification rates. Random projection required twice the amount of attributes to reach their best values, for 1-NN and 3-NN at 16 attributes, and 20 attributes for BayesNet. The returned results are 98.3%, 97.8% and 95.6% correct classification rates respectively. The results on PCA reduction using 20 attributes only differs by only 1% using the full attribute set. The results using nearest neighbour classification in fact is better than obtained using the full attribute set.

The results obtained for PCA and RP are in agreement with the results obtained in (Deegalla et al., 2007), that is random projection requires a larger number of dimensions compared to PCA to achieve comparable results. In this case 1-NN and 3-NN classification peaked at around 8 attributes for PCA compared to 16 for RP. This is a significant reduction from 726 attributes needed in the original method. Even though nearest neighbour classification is not efficient for large datasets, this reduction in the number of attributes will increase the computational efficiency.

To confirm the results, we did additional testing on a new set of test data not included earlier. The data set consists of 30 classes with 2 samples in each class. This will also allow us to test if using a larger training set will increase the accuracy of the model. The results are in figure 8. The results showed that the results have improved when trained on a larger training set. 100% correct classification was achieved using 8 PCA attributes for 1-NN and 3-NN, while BayesNet reached 100% classification using 10 PCA attributes.

6. Discussion and Analysis

Prior research on the GLCM has focused predominantly on textures. Arvis et al. (2004) with their multispectral co-occurrence matrix method, with a 5-Nearest Neighbours classifier yielding a 97.9% percentage of good classification for VisTex textures. Previous research work involving color texture analysis using a combination of Gabor filtering and the multispectral method on the Outex (Ojala et al., 2002) database has yielded a rate of success of 94.7%. Allam's (1997) result of a 2% error rate 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, and we achieved between 98%-100% classification on Batik/Songket.

The results for 'Batik' and 'Songket' achieved here are among the best for such kinds of irregular textile patterns based on the limited prior research found. Our 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 that it is possible for many similar distributions to have the possibility of producing a similar value (Walker et al., 1995). An illustration of such a case is as follows, whereby the 5 common Haralick features combined with the 6 multispectral matrices yield a very low Euclidean difference even though the two samples (below, figure 10) are of visually different texture, highlighting the inadequacy of the statistical measure especially in non-uniform and colored texture images.

However, for development of a successful end-user application, some issues still need to be addressed, namely lighting variation and scale.

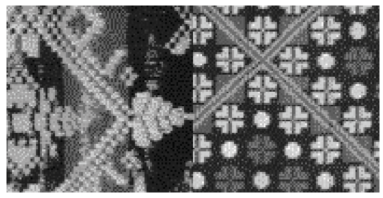

Fig. 10. Sample of two images with similar Euclidean distance using Haralick features.

Textile design motifs such as those found in these 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 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 (Cheong et al., 2008). 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.

Fig. 11. (Top) The full Batik cloth. (Bottom) Sampled regions used for training are not identical but bear "family resemblance".

The results indicate that nearest neighbour classification perform slightly better than BayesNet. This is probably because the textile patterns that we used are not identical, nor are they, considered on the whole, statistically uniform. They are more akin in a "family resemblance" manner (Wittgenstein, 1953). This can be explained by that no sample within the same class shares all the features, but each sample in the class shares overlapping features with each neighbours (see figure 11). Or as Wittgenstein puts it: "Something runs through the whole thread - namely the continuous overlapping of those fibres".
Reduction from 726 to 8 attributes means that only 1.1% of the original information is significant for classification. Arvis (2004), which achieved 97.9% on VisTex textures, still required 30 attributes based on 5 measures specified on each colour pair co-occurrence matrix. Based on the results presented here a reduction of down to 2% from the original attributes is adequate for classification.

7. Potential Applications

A simple non-textual access to textile patterns is capable of opening up a wealth of applications. For designers it could unlock their creative potential, by using access to textile pattern collection for inspiration or to stimulate innovation. One such project is Fashion and Apparel Browsing for Inspirational Content (FABRIC) (Ward et al., 2008). They could use it compare the designs, or to study them by browsing, or to survey the trend. It could also be used to avoid copyright issues, and to distinguish one's work by stamping their uniqueness on it.

There are also cultural aspects to it, because an accessible collection of patterns could be used for archival purposes, storing the narrative, the times and trends of particular groups of people through history, as well as charting the changes. It would be useful for understanding historical trends, as many of the patterns may shed different narratives throughout their history. In the Malay Archipelago, textiles, apart from artistic expression are also linked to religious and cultural beliefs. The patterns in the textile are a means of communication between the human and spirit world, and play a significant role in birth and death rites, whereby it is thought that the more powerful patterns, the more potent protection they offer (Hout, 1999).

Commercially an efficient method of comparing and recognizing textile patterns could spur the application of visual comparison shopping for fashion and clothing. A visual-based search engine could let shoppers select similar items based on colour, shape and pattern, in addition to price. Useful categories for such comparison shopping include shoes, handbags, and clothing. A usage scenario would that a shopper has some clothes of a particular pattern, but would like a matching pattern for the shoes, or sees a pattern that he or she likes, and wants possibly a matching pattern for shoes or clothing. This could be extended to mobile-based comparison shopping. In this scenario, the mobile phone camera snaps an image of the pattern, and the online store searches for similar items available.

8. 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. While Haralick's measures (1973) have been successfully applied to texture recognition, it is not so good for non-uniform patterns like textile motifs.

We have shown that a significant reduction in attributes down to about 2% of the original attributes contributed only slight deterioration of classification rate.

This makes this approach, combined with an appropriate attribute selection scheme, suitable for fast content-based retrieval applications, not only for traditional Batik and Songket textile motifs, but other design motifs where the patterns are overlapping in similarity. In particular, the application of principal components attribute reduction provided the highest accuracy at a higher computational cost. If computational cost is an issue, then the random projection method returned respectable results, the next best compared to other methods tested.

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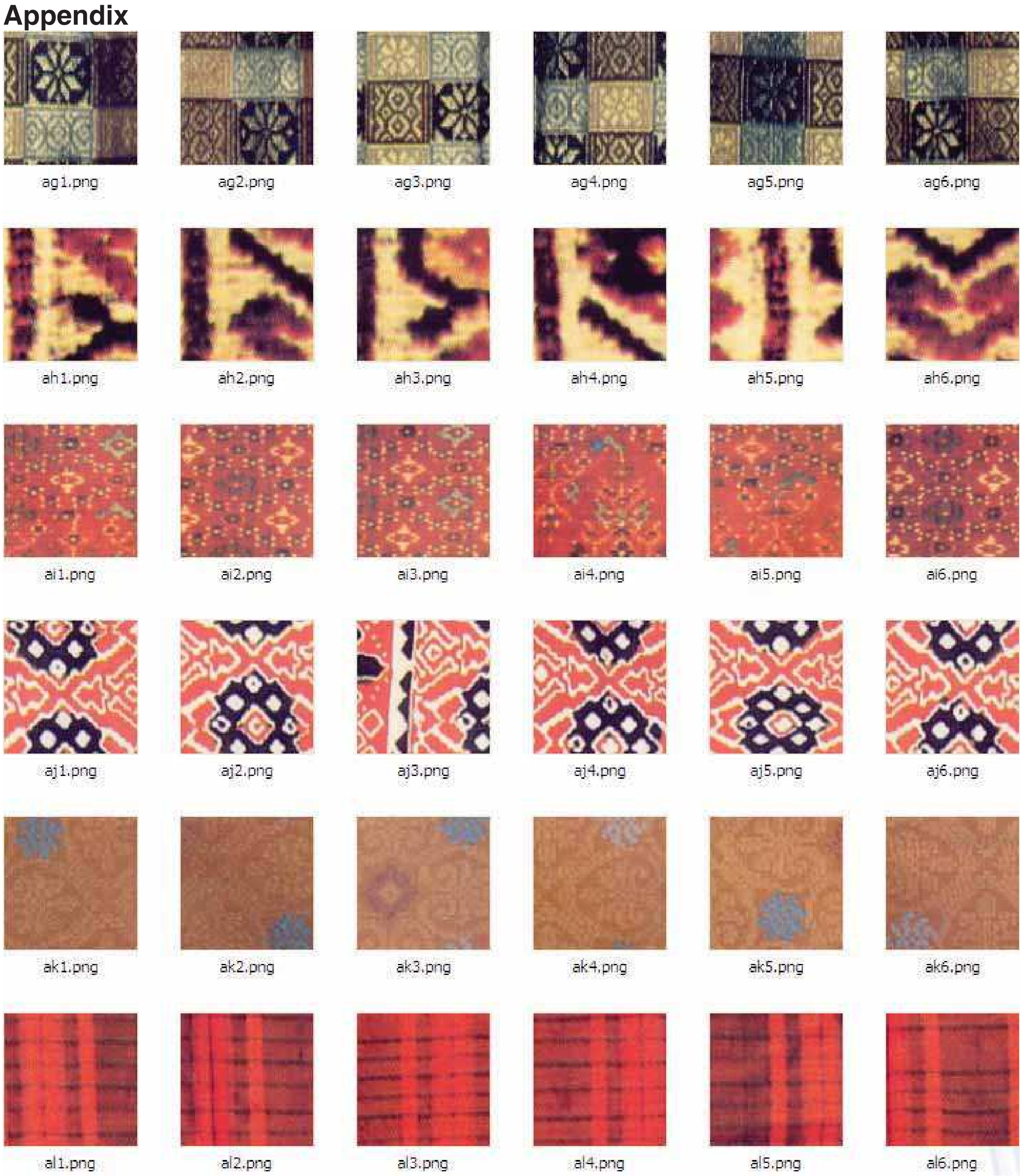
Appendix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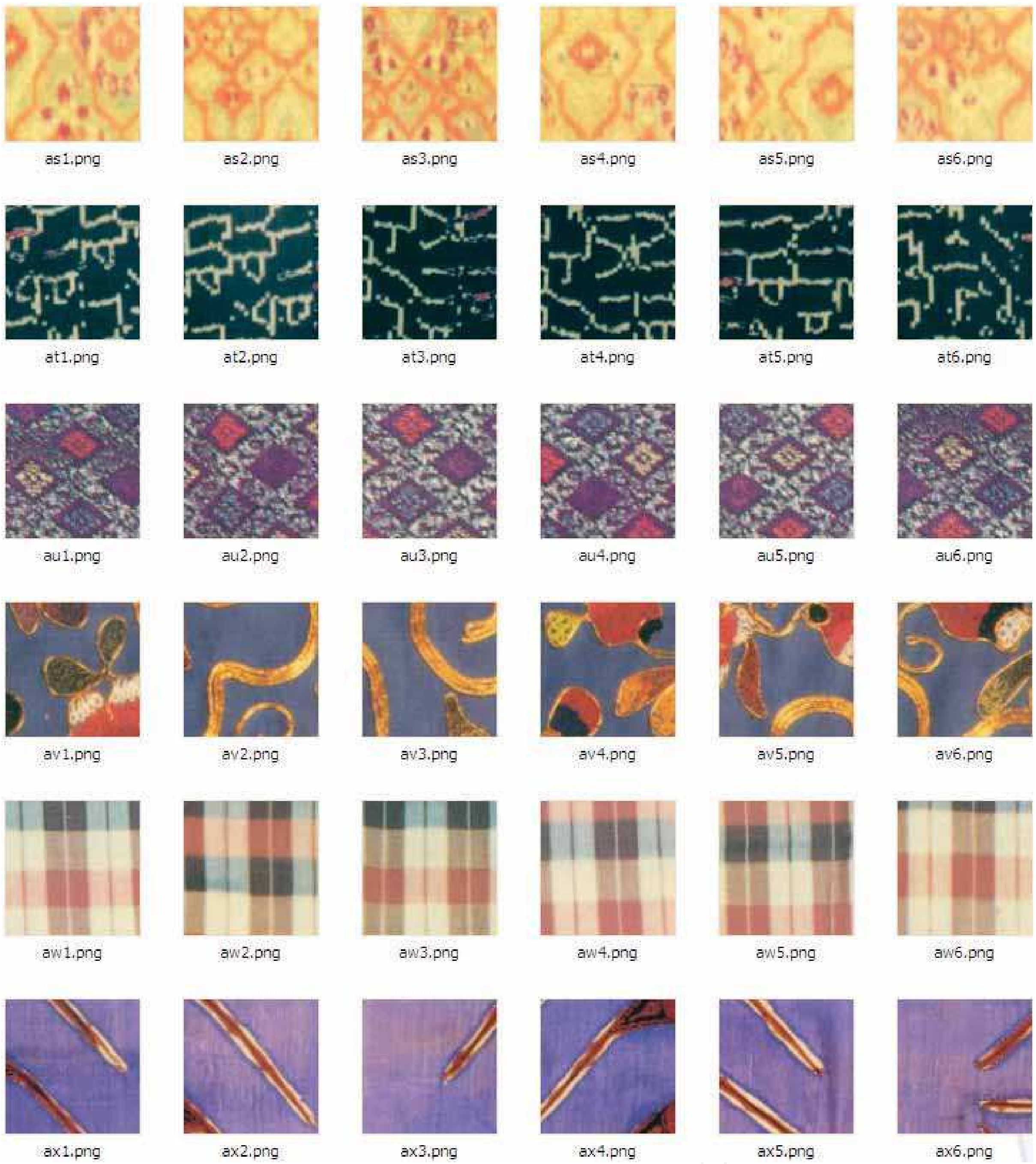
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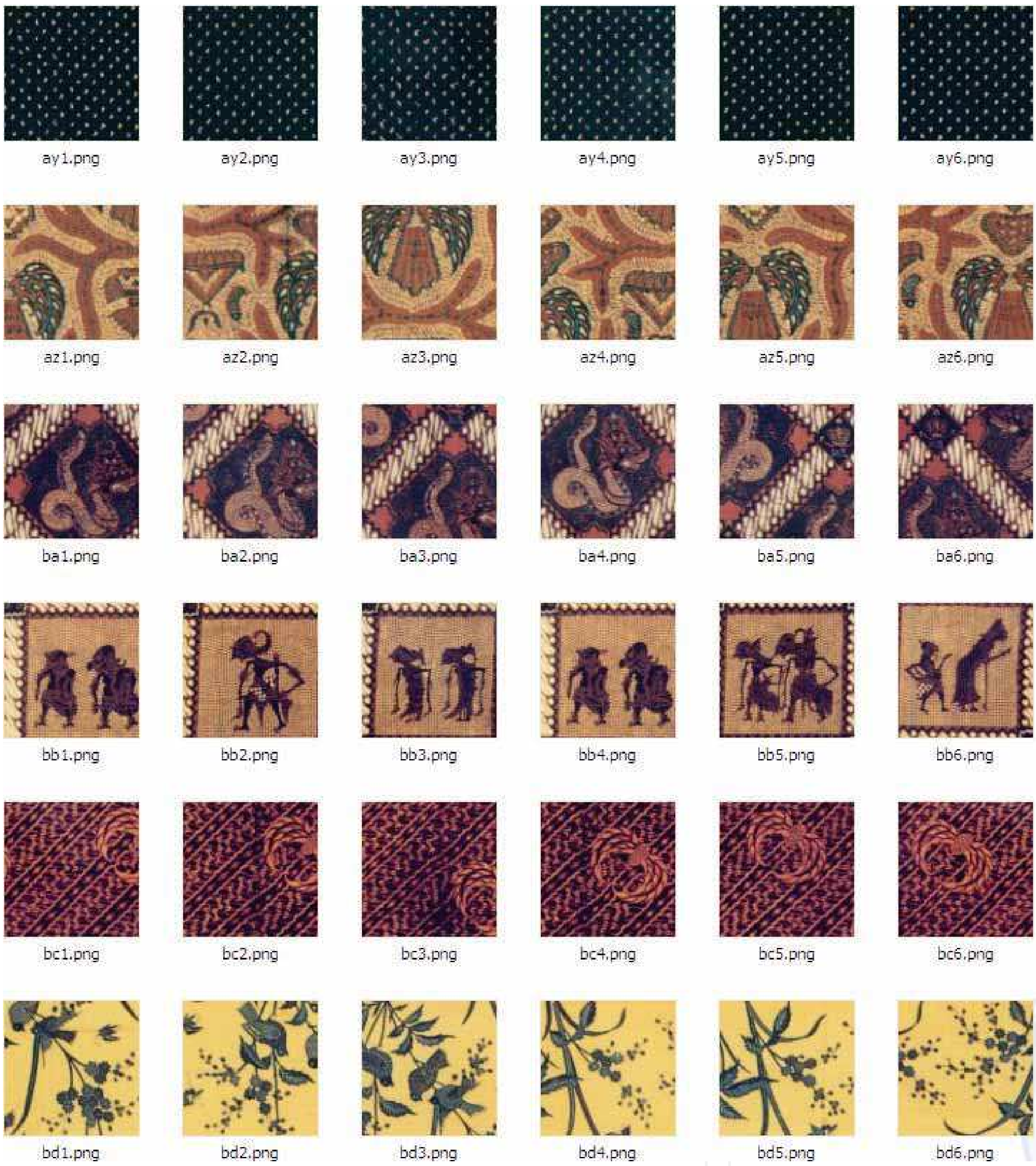
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For more than 40 years, pattern recognition approaches are continuingly improving and have been used in an increasing number of areas with great success. This book discloses recent advances and new ideas in approaches and applications for pattern recognition. The 30 chapters selected in this book cover the major topics in pattern recognition. These chapters propose state-of-the-art approaches and cutting-edge research results. I could not thank enough to the contributions of the authors. This book would not have been possible without their support.