Pum-Riang Thai Silk Pattern Classification using Texture Analysis

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Abstract. Pum-Riang is a type of Thai silk with many patterns. Only experts can identify these patterns on sight. In order to help the general public who are interested in Pum-Riang silk, we propose an automatic Pum-Riang pattern detection using texture analysis. The process is divided into the feature extraction step, feature extraction step, and classifier training step. For each step, we compare various methods and parameters when applicable. The best model is evaluated on a separate test set. It achieves the perfect accuracy of 1.0, indicating that all test samples are correctly classified.

Keywords: Image mining · Texture analysis · Image processing.

1 Introduction

Pum-Riang is a type of Thai silk with elaborate patterns. It is made in Pum-Riang Sub-district in Surat Thani Province in southern Thailand. Historically, clothes made of Pum-Riang Silk is only worn by Thai royalties and aristocrats. Nowadays they can be worn by everyone, although they are typically reserved for special occasions such as weddings or religious ceremonies. Pum-Riang silk is made with specific patterns, some of which are shown in Figure 1. Because there are numerous patterns available that look alike, only experts can identify the name of the pattern on sight. To help the general public with the identification of Pum-Riang silk pattern, we propose an automated classification using texture analysis.

Many image processing techniques have been developed for various computer vision tasks. For our problem of pattern classification, texture analysis techniques are directly applicable. We use Local Binary Pattern (LBP) as well as two techniques based on LBP as our feature extraction method: Rotated Local Binary Pattern (RLBP) and Complete Local Binary Pattern (CLBP). For feature selection, we compare three methods: Chi-squared, information gain, and gain ratio, as well as find out the optimal number of features. Seven types of classifiers are compared: decision tree, naive Bayes, Bayesian network, averaged one-dependence estimators (AODE), support vector machine, logistic regression, and artificial neural network.

The rest of the paper is organized as follows. Section 2 presents related work. Section 3 presents the design of our Pum-Riang Thai silk pattern classification

(a) Ratchawat Chome Yai (b) Ratchawat Chome Lek

(c) Creuwal (d) Dok Pikul (e) Kao Lam Tud

Fig. 1: Various types of Pum-Riang silk.

framework. Section 4 presents the evaluation methods and results. Finally, Section 5 concludes the paper.

2 Previous Work

Singh et al. use CLBP, LBP, and Color Coherence Vector (CCV) as the texture analysis method to classify human facial expressions [9]. Multi-class support vector machine is used as the classifier. The overall prediction accuracy is 86.4%, 84.1%, and 75.8% for CLBP, LBP, and CCV, respectively.

Automatic detection of defects on fabrics has been studied widely studied. Chakraborty et al. propose a method of recognizing and identifying defects in silk fabric [1]. The average intensity of the grayscale image is analyzed, and the image is thresholded to produce a binary image where pixels corresponding to defects have value of 1. Fourier transform is then used to separate the fabric's patterns from the defects. The defects are then classified into one of three categories using artificial neural network: high, medium, and low lousiness. Classification accuracy is very good at 98.56%. Ngan et al. propose wavelet-based methods for defect detection on patterned fabric [8]. The results suggest that a combination of wavelet transform and golden image subtraction method produce the best detection rate. Other techniques used include morphological filters [6] and LBP [10].

Soo Jeon et al. propose a system for automatic recognition of woven fabric patterns using artificial neural network [4]. However, rather than the color pattern, the focus is on the fine weaving patterns such as thread density and warp and weft counts. As patterns in Pum-Riang silk are created using different thread colors, their approach is not directly applicable to our task. Kuo et al. use fuzzy C-means clustering to group fabric weave patterns [5]. However, the resulting clusters have not been evaluated in a classification setting. Furthermore, the photos were obtained using a high-resolution scanner, which makes it less convenient for the user of the system, compared to using a digital camera.

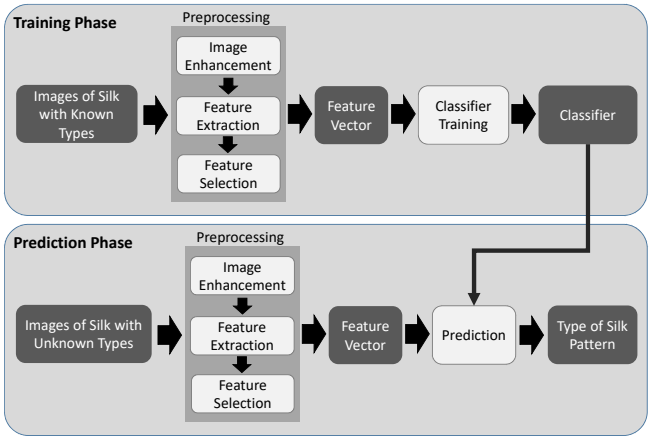

Fig. 2: Overall diagram showing different steps of the image analysis.

3 Design

The overview of our framework is shown in Figure 2. The process can be divided into two overall phases: training phase and prediction phase. In the training phase, the training dataset containing images of silk with known pattern types is used to train a classifier. In the prediction phase, given an image of silk with unknown pattern type, we use the classifier to predict the silk pattern type. In both phases, the raw images first need to go through the preprocessing steps, which consist of image enhancement, feature extraction, and feature selection. The resulting feature vectors are then used to train a classifier using various machine learning methods. We will now describe these steps in more detail.

3.1 Image Enhancement

Patterns used in Pum-Riang silk are made using two main colors. Some patterns such as Dok Pikul contain patterns that utilize additional colors, but these patterns are small when compared to the main patterns. For each pattern, the two main colors may vary. To simplify the later steps, we transform the two main colors to black and white for all images. This is done by thresholding the pixel value. For this work, the threshold is set manually by the user, although it is possible to develop a method that determines the appropriate threshold without human input.

3.2 Feature Extraction

As the number of pixels in an image is in the millions, it is impractical to directly use them as the features to train a classifier. Therefore, we need to extract useful features from the raw pixels. We use and compare the following

three texture analysis techniques which have been successfully applied in other related problems: Local Binary Pattern (LBP), Rotated Local Binary Pattern (RLBP), and Complete Local Binary Pattern (CLBP).

Local Binary Pattern (LBP) Local Binary Pattern assigns a value to each pixel, representing the local pattern near that pixel. After assigning a value to every pixel, a vector representing the count of pixels with each unique local pattern is computed and used as the extracted features. It has been found that LBP provides powerful features for texture classification. In this work, we compute LBP using eight adjacent pixels as the neighbors.

Rotated Local Binary Pattern (RLBP) Rotated Local Binary Pattern is an extension to LBP to make it rotation invariant [7]. Patterns can be rotated simply because the object is not properly oriented when the photo is taken, and this should not affect the features used for classification. RLBP orients each local pattern by always starting the computation from the neighbor whose difference to the central pixel is maximum. A histogram vector is then computed in the same way as LBP and used as the final feature vector for the image.

Complete Local Binary Pattern (CLBP) Both LBP and RLBP capture only the sign of the difference between each pixel and its neighbors. Guo et al. proposed Complete Local Binary Pattern (CLBP) which extends LBP by also including the magnitude of the differences as well as the gray level of the center pixel itself [3].

3.3 Feature Selection

After the feature extraction step, we have 2^N features for LBP and RLBP, and $2 \cdot 2^N + 2$ features for CLBP. Not all features are helpful for classification, as some may capture patterns that are similar across different silk patterns. The goal of the feature selection step is to identify important features and remove the rest in order to reduce model training time and reduce the effects (such as overfitting) that noise in the feature set may have on the prediction accuracy.

There are three main approaches in feature selection: wrapper, filter, and embedded. In the wrapper approach, the model is trained on different subsets of the features and the prediction accuracy is compared. This is computationally expensive and has a risk of overfitting. In the filter approach, a simple filter is used to evaluate and rank the features directly. In the embedded approach, the feature selection method is embedded into the specific model's training algorithm. For this work, we employ the filter approach as it can be used for all classifiers and is not too computationally expensive. Three filters are used and compared: Chi-square, information gain, and gain ratio.

3.4 Classifier Training

Once we have the appropriate feature vector for each image, the feature vectors are used to train a classifier. We train and compare 7 different classifiers in order to select the best one. The classifiers compared are decision tree, naive Bayes, Bayesian network, averaged one-dependence estimators (AODE), support vector machine, logistic regression, and artificial neural network. Each classifier's hyperparameters are left at the default settings, according to Weka's implementation.

4 Evaluation

4.1 Methodology

Our evaluation is separated into three parts: comparing feature extraction methods, comparing feature selection methods, and comparing classifiers. The feature extraction methods are implemented in Matlab while feature selection and classifier training are done using Weka [2].

Dataset We visited fabric stores in Pum-Riang Sub-district in Surat Thani Province in Thailand and took 60 photographs of each of the following five patterns of Pum-Riang silk: Ratchawat Chome Yai, Ratchawat Chome Lek, Creuwal, Dok Pikul, and Kao Lam Tud.

Although the photographs were taken carefully, some are slightly rotated while some others contain reflected light. These imperfections are not explicitly correct as they represent conditions that are likely to happen in the real world, and the methods need to be able to handle them.

For each pattern, 10 samples are separated and used as the test set (50 samples total). The remaining 50 samples for each pattern (250 total) are used as the training set as well as for comparisons of different feature extraction methods, feature selection methods, numbers of features, and classifiers. For these comparisons, 10-fold cross-validation is used as the evaluation method. The metrics reported are area under the ROC curve (AUC), accuracy (AC), sensitivity (SN), specificity (SP), precision (PR), and F-measure (FM).

4.2 Feature Extraction

In this section, we compare three feature extraction methods for texture classification: Local Binary Pattern (LBP), Rotated Local Binary Pattern (RLBP), and Complete Local Binary Pattern (CLBP). The feature selection method is fixed as information gain ratio, the number of features after feature selection is fixed as 60, and the classifier used is artificial neural network. The results are shown in Table 1.

Using AUC as the main criteria, CLBP performs best, although the differences are small. This indicates that the magnitude of the difference between neighboring pixels and the center pixel carries important information for prediction.

Table 1: Prediction accuracy for each feature extraction method.

Method	AUC	AC	SN	SP	PR	FM
LBP	0.998	0.984	0.984	0.996	0.984	0.984
RLBP	0.993	0.948	0.948	0.987	0.944	0.946
CLBP	**1.000**	**0.980**	**0.980**	**0.995**	**0.980**	**0.980**

Table 2: Prediction accuracy for each feature selection method.

Method	AUC	AC	SN	SP	PR	FM
Chi-squared	0.999	0.980	0.980	0.995	0.950	0.980
Information gain	0.999	0.976	0.976	0.994	0.976	0.976
Gain ratio	**1.000**	**0.980**	**0.980**	**0.995**	**0.980**	**0.980**

4.3 Feature Selection

In this section, we compare three feature selection methods: chi-squared, information gain, and information gain ratio (abbreviated as gain ratio). The feature extraction method is fixed to CLBP, the number of features is fixed as 60, and the classifier used is artificial neural network. The results are shown in Table 2.

Using AUC as the main criteria, information gain ratio gives the best results, although the differences are small again.

4.4 Number of Features

When feature selection is performed, the desired number of features can be controlled by the user. Smaller number of features lead to faster training and prediction, but the prediction accuracy may suffer. In this section, we vary the number of features and compare the prediction performance as well as training time. The numbers of features included in the comparison range from 10 to 100, in increments of 10. The feature extraction method is fixed to CLBP, the feature selection method is information gain ratio, and the classifier used is artificial neural network. The results are shown in Table 3.

Training time grows quickly with the number of features, although there is still some variance. Highest AUC is achieved with 60 features. However, if lower training time is desired, 10 features provide similar prediction accuracy while requiring much lower training time.

4.5 Classifier

In this section, we compare the performance of the following classifiers: decision tree, naive Bayes, Bayesian network, AODE, support vector machine, logistic regression, and artificial neural network. The feature extraction method is fixed to CLBP, the feature selection method is information gain ratio, and the number of features is 60. All classifiers used are part of the Weka data mining software,

Table 3: Prediction accuracy for different numbers of features, as well as training time taken to build the classifier.

Number of Features	**AUC**	**AC**	**SN**	**SP**	**PR**	**FM**	**Training Time (seconds)**
10	0.999	0.944	0.944	0.986	0.944	0.944	10.36
20	0.998	0.972	0.972	0.983	0.972	0.972	34.68
30	0.999	0.980	0.980	0.995	0.980	0.980	81.56
40	0.999	0.976	0.976	0.994	0.977	0.976	175.78
50	0.999	0.976	0.976	0.994	0.977	0.976	248.56
60	**1.000**	**0.980**	**0.980**	**0.995**	**0.980**	**0.980**	**1585.78**
70	0.999	0.984	0.984	0.996	0.984	0.984	1921.93
80	0.998	0.976	0.976	0.994	0.976	0.976	3183.28
90	0.998	0.976	0.976	0.994	0.976	0.976	1199.77
100	0.998	0.984	0.984	0.996	0.984	0.984	1927.74

Table 4: Prediction accuracy for various classifiers, as well as training time taken.

Classifier	**AUC**	**AC**	**SN**	**SP**	**PR**	**FM**	**Training Time (seconds)**
Decision tree	0.967	0.912	0.912	0.978	0.913	0.912	0.00
Naive Bayes	0.993	0.920	0.920	0.980	0.922	0.919	0.00
Bayesian network	0.994	0.916	0.916	0.979	0.917	0.915	0.00
AODE	0.996	0.952	0.952	0.988	0.952	0.952	0.01
Support vector machine	0.992	0.980	0.980	0.995	0.980	0.980	0.10
Logistic regression	0.978	0.978	0.978	0.960	0.990	0.960	12.70
Artificial neural network	**1.000**	**0.980**	**0.980**	**0.995**	**0.980**	**0.980**	**1585.78**

with all hyperparameters left at the default values [2]. The results are shown in Table 4.

The classifier that achieves highest prediction accuracy is artificial neural network, with AUC of 1.000. However, it has by far the highest training time. With bigger datasets or more stringent time constraints, AODE and support vector machine may be better choices, as they achieve similar prediction accuracy but with only a fraction of the training time.

4.6 Prediction Performance on Test Set

The previous comparisons are made using 10-fold cross validation on the training set. In order to accurately measure the prediction accuracy, the best model is evaluated on the held-out test set, which contains 10 samples for each pattern, making the total 50 samples. The best model uses CLBP as the feature extraction method, information gain ratio as the feature selection method, 60 features, and artificial neural network as the classifier.

The model achieves an accuracy of 1.0, indicating that all test samples are classified correctly. This gives us the confidence that the proposed model will be

able to classify the five types of Pum-Riang silk accurately. The model can be further developed into an application that anyone can use to find out the type of Pum-Riang silk.

5 Conclusion

This paper proposes an automated classification of Pum-Riang Thai silk pattern using texture analysis. The process can be divided into three steps: feature extraction, feature selection, and classifier training. For each step, we compare different methods and parameters in order to find the optimal setting. We find that the best setting overall is CLBP as the feature extraction method, information gain ratio as the feature selection method, number of features equal to 60, and artificial neural network as the classifier. The model achieves the perfect prediction accuracy of 1.0 when evaluated on the held-out test set. This shows that the proposed method is effective for classifying the five types of Pum-Riang Thai silk.

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