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Photometric Stereo-based Woven Fabric Pattern Recognition Using Wavelet Image Scattering

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ABSTRACT

The weave pattern is a crucial factor that enhances the strength and stability of the fabric. Pattern recognition of woven fabric based on vision methods has been widely developed. In this research, woven fabric's basic weaving pattern recognition is based on photometric stereo images. First, six images of woven fabric were taken, each with a different direction of light. Next, an unbiased photometric stereo algorithm was used to reconstruct the six images. This paper used 23 grayscale photometric stereo images measuring 400 x 300 pixels. Augmentation techniques were carried out to produce 458 images consisting of 240 plain woven images, 159 twill woven images, and 60 satin woven images. The training data set consists of 367 images, and testing consists of 192 images. The feature extraction method uses wavelet image scattering and classification using Principal Component Analysis (PCA) and Support Vector Machine (SVM). The wavelet image scattering method effectively extracts texture features of photometric stereo images of diverse woven fabrics, while the PCA and SVM methods successfully classify the basic woven fabric patterns. The results of recognizing the basic woven fabric pattern using PCA and SVM classification obtained an accuracy of 98.57%.

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1. INTRODUCTION

Woven fabric is produced by interweaving the warp and weft yarns perpendicularly, and the crossing of the warp and weft is called float. There are two types of float: warp float refers to the warp passing over the weft, and weft float refers to the weft passing over the warp. The basic weave is often repeated in the pattern [1]. Plain, twill, and satin weave are some of the most basic patterns. The weave pattern enhances the fabric's strength, stability, and visual appeal [2]. Traditional methods for identifying weave patterns rely on manual analysis, which is time-consuming and expensive. Hence, creating an automated webbing pattern recognition system that exhibits exceptional efficiency and robustness is imperative. Weave pattern recognition relies on float analysis and the relationship between warp and weft. However, the color, diameter, and relationship between yarns vary. Furthermore, the automated approach should possess high accuracy and the ability to apply to many fabrics.

Various computer vision and image processing studies employ techniques that automatically recognize weave patterns [3-5]. Typically, there are two methods to recognize woven fabric patterns. At first, the fabric is categorized into basic woven patterns. The second method involves locating and classifying the floats to identify the weave patterns.

Classification-based methods [6, 7], extracting every feature of the fabric image, employ classification methods, such as support vector machine (SVM) and probabilistic neural network (PNN), to categorize basic weave patterns. These approaches can categorize basic weave patterns but cannot process fabrics with unfamiliar patterns, thereby exhibiting limitations in generalization and flexibility. The most common way is to find the float's position and identify the float type. Because of the periodicity of woven patterns, methods use the frequency domain [8, 9] to identify floats. Nevertheless, the power spectrum frequently produces noise and is difficult to analyze because of the uneven dispersion of the yarns.

Furthermore, the space domain method uses gray image projection [4] and gray line profiles [10]. Then, the Hough transform detects the tilt angle caused by the image position [11]. The method applies to solid color fabrics with poor accuracy on complicated colors and patterned fabrics. After finding the float accurately, the next step is binary classification. [12, 13] used the geometric shape of the float to categorize the float, but the geometric shape is highly comparable in certain fabrics, causing a high error in classification. Therefore, some methods of texture analysis, like GLCM, are used to get float features [4], active grid model (AGM) [14], and optical coherence tomography (OCT) [15]. These methods need images of fabrics with a high resolution, thus requiring a high specification and adequate fabric image acquisition system. After fabric feature extraction, Fabrics are categorized using techniques such as Fuzzy C-means Clustering (FCM) [1, 4, 16], Back Propagation Neural Network [18], and pattern database [18]. These classification methods rely heavily on feature extraction, and some floats require information about surrounding floats, so a single float cannot easily classify features.

In recent years, due to its excellent ability to extract features, the Convolutional Neural Network (CNN) has been extensively used for pattern recognition issues like object classification [19, 20] and defect detection [21, 22]. Boonsirisumpun et al. [20] and Xiao et al. [16] used CNN to classify fabric patterns used in automotive and knitted fabric patterns. A multi-task CNN finds floats and classifies float types for woven pattern recognition. [23] They developed a multi-task CNN to overcome the counting problem. While numerous conventional automated techniques relying on image processing have made certain advancements in weaving pattern recognition, They have some adaptability and efficiency limitations to unknown types of woven fabric patterns [2]. In addition, multi-task CNN methods are complex, making it difficult to train and learn from CNN models thoroughly. In addition, the CNN method requires a lot of data for learning, but it isn't easy to acquire empirical truth [24].

Based on photometric stereo, this research recognizes basic woven fabric patterns (plain, twill, and satin). A photometric stereo fabric image is an image that has depth texture, and a texture feature extraction method is needed to distinguish irregularity, uniformity, smoothness, and so on [25]. Extraction of texture features using wavelet image scattering has several advantages, including not being affected by rotation, scaling, and deformation in photometric stereo images; this method can maintain the distinguishable properties of each class. Then, a suitable and efficient method for feature selection must be developed. Principal component analysis (PCA) is among them because the technique efficiently applies dimensionality reduction. Furthermore, using SVM, this method has good generalization ability for small sample classification cases.

2. RESEARCH METHOD

Based on photometric stereo, this research recognizes basic woven fabric patterns (plain, twill, and satin). The block diagram is shown in Figure 1.

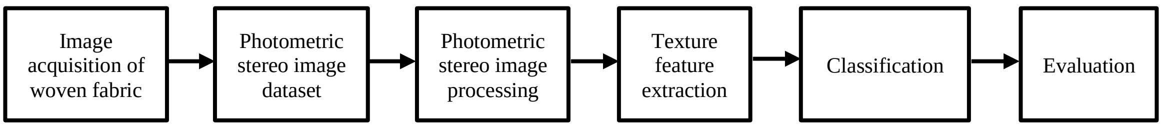
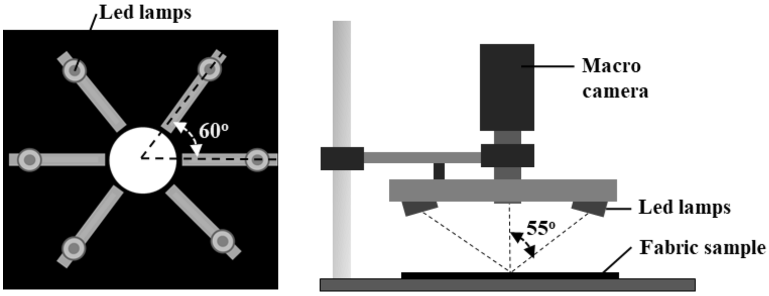


Figure 1. Block diagram of photometric stereo-based basic woven fabric pattern recognition

The work begins with acquiring woven fabric images from different light source directions, resulting in six woven fabric images of 400 x 300 pixels. Next, the reconstruction of the 3D surface structure from six images using an unbiased photometric stereo algorithm is performed. Then, the photometric stereo image is processed with augmentation techniques to increase the dataset. Then, the texture features are extracted using wavelet image scattering. The next stage is classification using PCA and SVM. The last stage is to evaluate the qualification results by calculating the accuracy of the woven fabric pattern recognition.

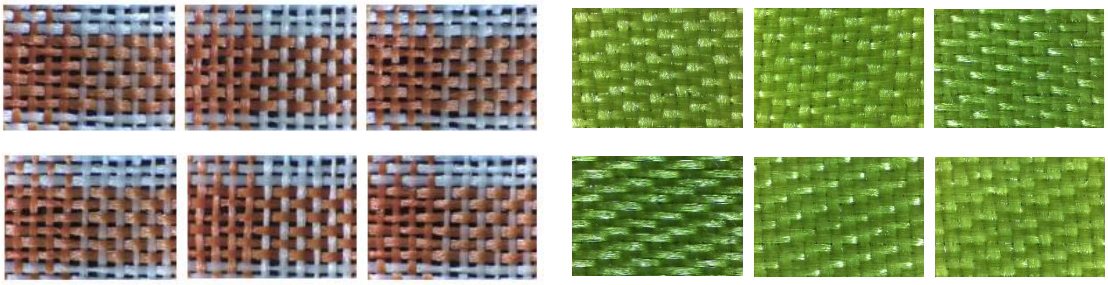
2.1. Image Acquisition of Woven Fabric

The process of acquiring woven fabric images with different light source directions using a SONY IMX307 macro camera, as shown in Figure 2, resulted in six woven fabric images measuring 400 x 300 pixels with varying light directions, as shown in Figure 3. Figure 3a presents plain weave, and Figure 3b presents satin weave. A data set of 23 woven fabric samples was obtained with 12 samples of plain weave, eight samples of twill weave, and three samples of satin weave.



(a) (b)

Figure 2. Image acquisition system for woven fabric samples with variations in lighting directions (a) under the light source view, (b) side view of the image recording device.

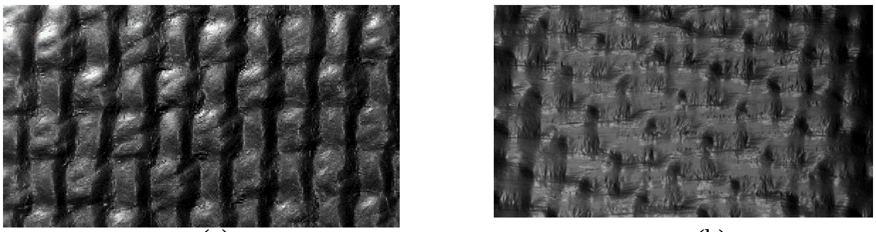


(a) (b)

Figure 3 Six images of woven fabrics with varying light directions (a) Plain weave and (b) Satin weave.

2.2. Photometric Stereo Image Dataset

The dataset of photometric stereo images of woven fabrics used in this paper were 23 samples with 12 samples of plain weave, eight samples of twill weave, and three samples of satin weave. The photometric stereo image is a grayscale image measuring 400 x 300 pixels. In our previous work [26], we reconstructed the 3D surface of woven fabric using an unbiased photometric stereo algorithm. Some examples of woven photometric stereo image datasets are shown in Figure 4. Figure 4a presents plain weave, and Figure 4b presents satin weave.



(a) (b)

Figure 4. Photometric Stereo image dataset of woven fabric (a) Plain weave and (b) Satin weave.

Previous woven pattern recognition studies still use 2D woven fabric images, so there are several weaknesses, including only being able to classify basic woven patterns, float detection errors due to using binary classification, inability to be applied to fabrics with complex colors and patterned fabrics, high errors in the classification process, and difficulty in float classification. To overcome the weakness of using 2D woven fabric images, 3D stereo photometry images are used for woven fabric pattern recognition. Extraction of texture features using wavelet image scattering is expected to maintain the distinguishable properties of each class.

2.3. Image Augmentation

Image augmentation involves several image transformations, including skewing, scaling, and inversion, to make different images from the whole set of images, thereby multiplying the dataset [27]. By employing augmentation, the overall quantity of dataset images increases, thus allowing the model to train effectively [28]. In this research, several augmentation techniques are applied to the image, such as horizontal inversion, shift, and rotation (fixed angle of 15° starting from 0°, 15°, 30°, and 45°). From 23 samples of photometric stereo images with 12 samples of plain weave, 8 samples of twill weave, and 3 samples of satin weave. An illustration of image augmentation is shown in Figure 5.

In the photometric stereo image dataset of 458 images, to ensure that no data leakage occurs during the augmentation process, a data splitting strategy is performed. First, divide the dataset into a training set of 387 images (80%) and a testing set of 92 images (20%) before performing augmentation, then ensure that augmentation of the same image is only in one of the sets and not both. The training set of 367 images consists of plain weave 192 images, twill 127 images, and satin 48 images. At the same time, the testing set of 92 images consists of 48 plain woven images, 32 twill images, and 12 satin images—a schematic diagram of the separation augmentation process, as shown in Figure 6.

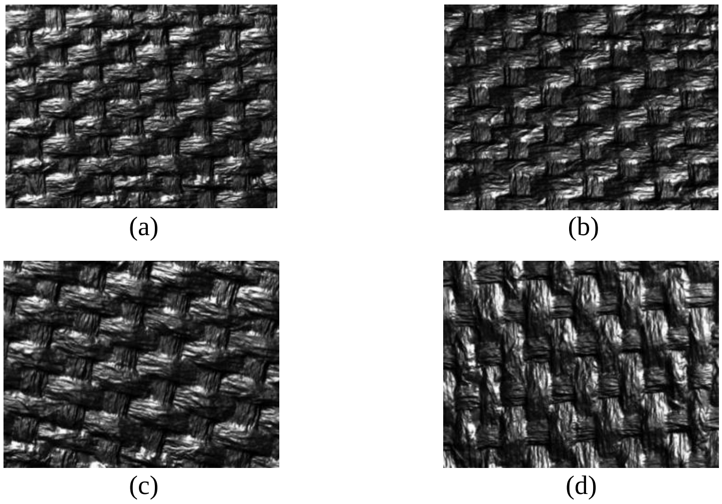


Figure 5. Various augmentation techniques are applied to plain weave photometric stereo images: (a) Original image, (b) Shift, (c) Rotate, and (d) Horizontal flip.

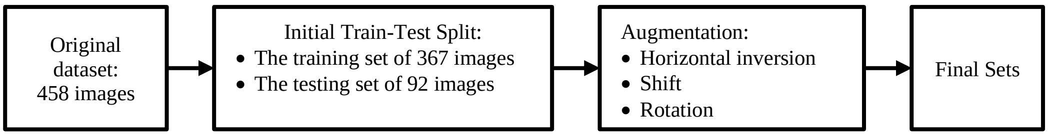


Figure 6. Diagram of the separation augmentation process.

2.4. Texture Feature Extraction using Wavelet Image Scattering

This paper uses the wavelet image scattering method or wavelet scattering network to feature the extraction of photometric stereo fabric images with 3D surface texture (depth). In photometric stereo images, wavelet image scattering is unaffected by rotation, scaling, and deformation. Besides, this method can maintain the distinguishable properties of each class [29]. Wavelet image scattering can also be considered a deep convolutional network, and convolution is performed along spatial, rotational, and scale variables. In this feature extraction, the filters used are scaled and rotated wavelets. In addition, three main jobs are carried out to make a deep network. Figure 7 shows an example of the functions carried out by wavelet image scattering.

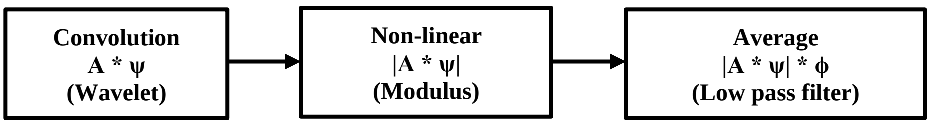


Figure 7. Stages of the wavelet scattering transform [30].

Textural, spectral, and contextual features are the three basic elements of pattern recognition. Texture features contain spatial information of intensity variations within a band [31]. Several features are introduced to capture texture information from an image. This paper uses wavelet image scattering to extract the texture features of photometric stereo-woven fabric images. Wavelet image scattering is applied to each channel of the stereo photometric grayscale image, and then the scattering coefficients are applied to each channel to form the final result. An illustration of wavelet image scattering for texture feature extraction of photometric stereo woven fabric image is shown in Figure 8.

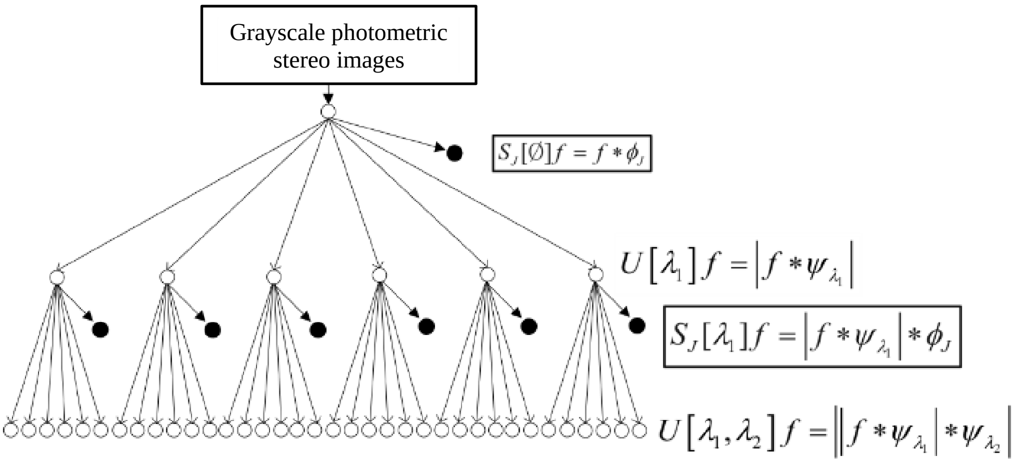


Figure 8. Application of wavelet image scattering to grayscale photometric stereo images [32].

2.5. Classification with PCA and SVM

The main idea of PCA is to reduce the dimension of a set of images with many interrelated variables while maintaining as much variation as possible in the set of images. PCA computation reduces to the solution of the eigenvalue/eigenvector problem for positive semidefinite symmetric matrices [33]. In this paper, eigenvalues were varied to obtain variations in classification accuracy.

After classification with PCA, the classification accuracy results will be compared using SVM. Finding the hyperplane's location is the core of the SVM learning process. The main goal of the function f(x) is to be obtained by the classifier to determine the hyperplane [34]. SVM is a binary classifier specifically designed to categorize samples into two classes. So, SVM must be extended to solve multiple classes [6]. In this paper, SVM configuration is used with kernel functions using polynomials, and polynomial orders are carried out to obtain variations in classification accuracy.

The direct multi-class SVM method solves one optimization problem concurrently, including all classes. Finding many separating hyperplanes (one for every class) such that for every data point, the margin between the end and the hyperplane matching the proper class is greater than the margins for the other classes is the aim. Multiple decision functions, each corresponding to one class, are introduced here and optimized collectively. The decision function for class *k* can be written as:

$$f_k(x) = w_k^T x + b_k \tag{1}$$

where w_k and b_k Are the parameters for class *k*. During classification, the class with the largest decision value is chosen.

2.6. Evaluation of Classification Results

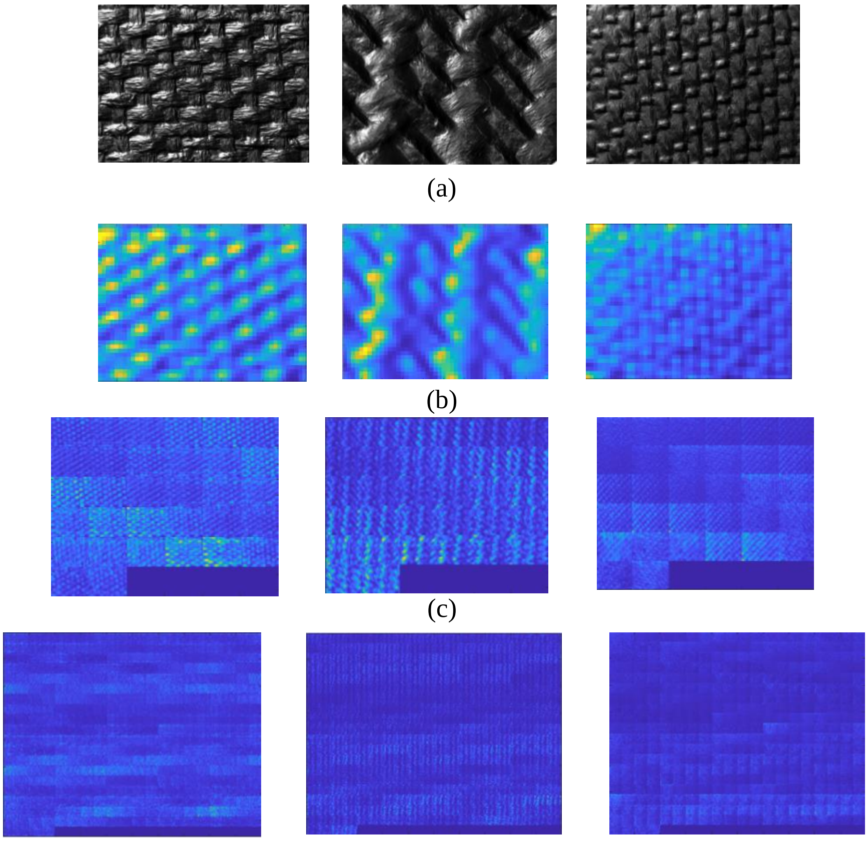
Accuracy is the most frequently employed evaluation metric in classification. Accuracy is the number of correct predictions divided by the total number of predictions. The equation used to calculate classification accuracy is as follows [35].

$$Classification\ accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} x100 \tag{2}$$

3. RESULTS AND DISCUSSION

The texture feature extraction process uses wavelet image scattering unaffected by rotation, scaling, and deformation in photometric stereo images [29]. Then, for training and testing, image augmentation is used [27] to increase the total number of dataset images and produce a set of different images. The training process used 367 grayscale photometric stereo images, and the testing process used 192 images. Furthermore, the classification process for plain, twill, and satin weaves will be done using PCA and SVM.

An example of the results of texture feature extraction of photometric stereo images of woven fabrics with wavelet image scattering for each layer is shown in Figure 9. Figure 9a shows woven fabric's grayscale photometric stereo image for plain, twill, and satin weaves. Figure 9b-d shows the scattering transformation of the first, second, and third layers for plain, twill, and satin weaves. The mean and variance of each scattering-transformed image are used as features, resulting in 367 scattering features.



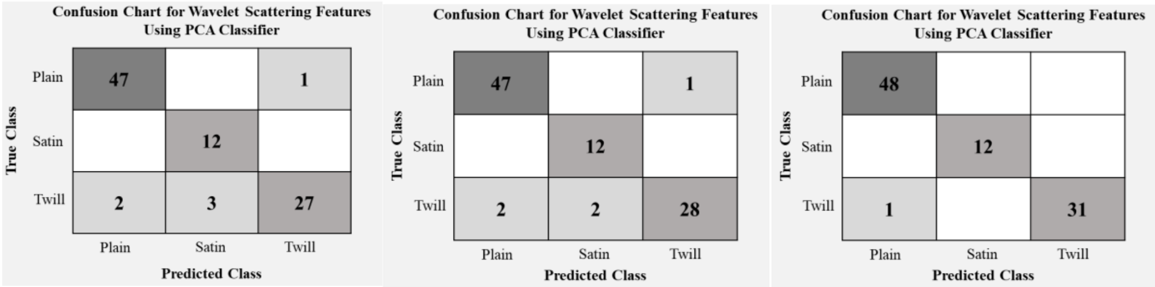
(a) (b) (c) (d)

Figure 9. Texture feature extraction results of photometric stereo images of plain, twill, and satin woven fabrics with wavelet image scattering for each layer (a) Photometric stereo grayscale image, (b) first layer scattering transformation, (c) second layer, (d) third layer.

Based on Figures 9(c) and 9(d), there are blank panels in the scattering transforms; this can be favorable to the feature extraction results, including removing uninformative high-frequency noise, thus helping to retain only the most stable and important features, filtering complex inputs into simpler and more meaningful representations, resulting in effective feature extraction. It can capture stable features, such as texture or shape, that are resistant to small deformations or noise.

3.1. Classification with PCA

Principal component variance is represented by the eigenvalues obtained from the covariance matrix. Components with large eigenvalues are those that capture greater volatility in the data. Small eigenvalues are indicative of less significant components that PCA frequently discards. A confusion matrix is generated to visualize the predictions provided by the PCA model on the test dataset and to comprehend the number of classified images. Rows and columns show the classes that were correctly predicted and those that were incorrectly predicted. The results of the confusion matrix are shown in Figure 10. Figure 10a shows the result of the confusion matrix with eigenvalue = 6, Figure 10b shows the result of the confusion matrix with eigenvalue = 7, and Figure 10c shows the result of the confusion matrix with eigenvalue = 8. The accuracy of PCA classification results with eigenvalue variations is shown in Table 1.



(a) (b) (c)

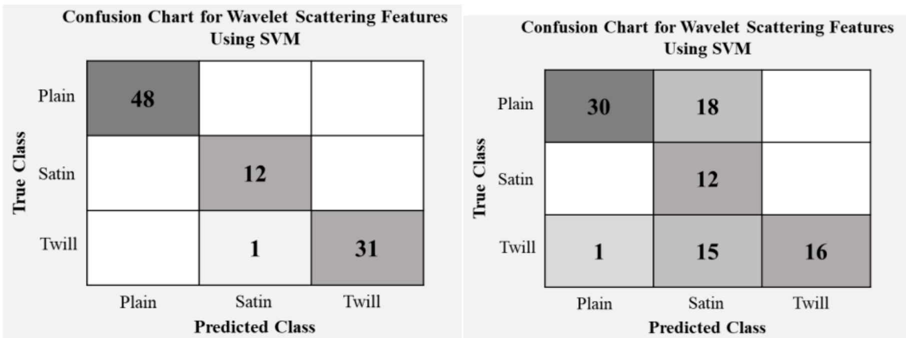
Figure 10. Confusion matrix for plain, satin, and twill weaves with PCA classification.

Table 1. PCA classification results with eigenvalue variations

No	Eigenvalue	Woven pattern	Accuracy (%)	Accuracy average (%)	Precision (%)	Recall (%)
1	6	Plain	96.4	91.4	94.10	90.78
		Twill	79.2			
		Satin	100			
2	7	Plain	96.4	92.85	95.14	92.73
		Twill	83.3			
		Satin	100			
3	8	Plain	100	98.57	98.96	99.32
		Twill	95.8			
		Satin	100			

3.2. Classification with SVM

In this paper, SVM configuration is used with kernel functions using polynomials, and polynomial orders are carried out to obtain variations in classification accuracy. Non-linear decision boundaries in feature space are produced using polynomial kernels. Decision boundaries are made more difficult by high-degree polynomials. Decision boundaries are made simpler and more broadly applicable by low-degree polynomials. The results of the confusion matrix are shown in Figure 11. Figure 11a shows the confusion matrix results with polynomial order = 1 and 2, and Figure 11b shows the confusion matrix results with polynomial order = 3. The accuracy of SVM classification results with variations in polynomial order is shown in Table 2.



(a) (b)

Figure 11. Confusion matrix for plain, satin, and twill weaves with SVM classification.

Table 2. SVM classification results with variations in polynomial order

No	Order of the polynomial	Woven pattern	Accuracy (%)	Accuracy average (%)	Precision (%)	Recall (%)
1	1 and 2	Plain	100	98.57	98.96	97.44
		Twill	100			
		Satin	95,8			
2	3	Plain	35,7	51.42	70.83	74.48
		Twill	100			
		Satin	33,3			

The feature extraction method using wavelet image scattering is effectively applied to the texture of photometric stereo images of woven fabrics with depth variations in their surface structure. The wavelet image scattering method can extract as many as 367 scattering features from 80% of the photometric stereo images trained so that the classifier method used in this paper using PCA and SVM can classify the basic woven pattern of woven fabric with high accuracy. In addition, using the wavelet image scattering method does not require a segmentation process to extract features. The classification accuracy results obtained by PCA and SVM are 98.57%. In the PCA method, the best accuracy is obtained when using eigenvalue 8, while in the SVM method, the best accuracy is obtained when using polynomial order 1 and 2. In terms of computation time, PCA is faster than SVM.

The primary woven pattern recognition research results are compared with other research results, as shown in Table 3. Li et al. [6] suggested using LBP and GLCM for extracting features from woven fabrics. The experimental fabrics comprise plain, twill, and satin weaves. It obtained 45 groups of woven cloth pictures, each measuring 200x200 pixels at 600 dpi. They then employed SVM as a classifier to categorize different types of woven fabrics. Their proposed approach has an accuracy rate of 87.77%. Kuo [36] used the CIE-Lab color model and co-occurrence matrix to extract features and subsequently utilized the SOM network for classification. The image that was taken has 600 by 600 pixels. There are six different kinds of fabric: plain weave, twill weave, smooth weave, single jersey, double jersey, and non-woven fabric. The maximum achieved classification accuracy was 92.63%. Meng et al. [2] achieved an accuracy of 92.97% using a multi-task and multi-scale convolutional neural network (MTMSnet). The dataset is randomly partitioned into three segments: 600 images for training, 100 images for validation, and the remaining 100 images for testing. To identify texture features, Xiao et al. [16] proposed a method based on TILT and HOG. The knitted fabric structure dataset comprises 13,600 images sourced from various places of 400 fabric pieces, encompassing both the face and reverse sides. A training sample set contains 11,200 images, while the remainder serves as the test sample set. The classification was performed using FCM clustering. Their method obtained an accuracy of 94.57%.

Table 3. Comparison of woven pattern recognition research results

Authors	Method		Accuracy (%)
	Feature extraction	Classification	
[6]	LBP + GLCM	SVM	87,77
[36]	CIE + Co-occurrence matrix	SOM	92,63
[2]	MTMSnet	MTMSnet	92,97
[16]	TILT + HOG	FCM	94,57
This work	Wavelet image scattering	PCA + SVM	98,57

As shown in Table 3, the wavelet image scattering method with PCA and SVM classification has high accuracy compared to other methods. Wavelet image scattering methods effectively extract diverse woven fabric pattern features; PCA and SVM methods successfully perform primary woven fabric pattern classification. Furthermore, the augmentation technique increases the image data's variety, improving the model's overall performance.

4. CONCLUSION

This paper used 23 grayscale photometric stereo images measuring 400 x 300 pixels. Augmentation techniques were carried out to produce 458 images consisting of 240 plain woven images, 159 twill images, and 60 satin images. The 458 photometric stereo image dataset is divided into two randomly selected sets, one for training (80%) and one for testing (20%). The training set of 367 images consists of plain weave 192 images, twill 127 images, and satin 48 images. At the same time, the testing set of 92 images consists of 48 plain woven images, 32 twill images, and 12 satin images. The feature extraction method uses wavelet image scattering and classification using PCA and SVM. The wavelet image scattering method effectively extracts texture features of photometric stereo images of diverse woven fabrics, while the PCA and SVM methods successfully classify the basic woven fabric patterns.

The results of basic weave pattern recognition using PCA classification obtained an accuracy of 98.57% with one twill weave pattern detected in the plain weave pattern. SVM classification obtained an accuracy of 98.57% with one twill weave pattern detected in the satin weave pattern. In the PCA method, the best accuracy is obtained when using an eigenvalue of 8, while in the SVM method, the best accuracy is obtained when using polynomial orders 1 and 2. Considering the classification accuracy results obtained, the PCA and SVM classification methods are proposed in this paper, considering the classification model configuration and computation time.

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